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Entitled:

Automatic date fruit sorting system based on machine learning and visual features

Presented by:
BOUMARAF Ibtissam

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In front of the Jury committee composed of:

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BOUMARAF Ibtissam

Dedication

From the depths of my heart, I dedicate this work to all who hold a special place in my life.

To My Parents

I dedicate this thesis to my parents, **Abdelhamid** and **Tibani Baya**. Their unwavering support, love, and encouragement have been the cornerstone of my academic journey. My father's steadfast belief in my abilities inspired me to pursue a doctorate. I owe my success equally to my extraordinary mother's boundless patience and faith in me.

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BOUMARAF Ibtissam

ملخص

تحتل سوق التمور الجزائرية مكانة اقتصادية كبيرة، حيث تحتل المرتبة الثالثة عالميًا في إنتاج التمور. ومع ذلك، هناك فجوة كبيرة بين قدرتها الإنتاجية وصادراتها. وينبع هذا الإشكال من طرق الفرز اليدوية التقليدية البطيئة والمعرضة للخطأ والتي تتطلب الكثير من العمالة، وكذا تعتمد على الفحص البصري لعوامل الجودة المختلفة. تهدف هذه الأطروحة إلى معالجة هذه القيود من خلال الاستفادة من الشبكات العصبية التلافيفية (CNNs) لأتمته فرز التمر. تتضمن الشبكات العصبية التلافيفية معلومات تتجاوز بيانات الرؤية أحادية المنظور، مما يخلق حلاً أكثر فعالية. يستخدم نهجنا المبتكر مجموعة بيانات متعددة الوسائط تجمع بين ميزات من وجوه متعددة للتمر جنبًا إلى جنب مع بيانات التصوير الحراري وقياس الوزن، مما يوفر تمثيلًا أكثر ثراءً وشمولية لكل ثمرة تمر. تتعمق هذه الأطروحة في ثلاث مساهمات رئيسية تستكشف وتوضح فعالية هذه الأساليب القائمة على الشبكات العصبية التلافيفية.

المساهمة الأولى توضح فعالية نهج متعدد الوسائط مع الشبكات العصبية التلافيفية، حيث تحقق دقة اختبار تبلغ 94٪ باستخدام نموذج VGG16 من خلال دمج جميع المعلومات في مدخل بيانات مرئي واحد. تبحث المساهمة الثانية في دمج البيانات متعددة الوسائط باستخدام تقنيات الاندماج المتأخر. في السيناريو الأول، يتم تصنيف التمر بناءً على صور من أربع زوايا. يوسع السيناريو الثاني السيناريو الأول من خلال دمج مما سبق مع الصور الحرارية وقياسات الوزن. تسلط النتائج الضوء على التحسين الكبير في الدقة الذي لوحظ عند دمج ميزات إضافية في السيناريو الثاني. تتعامل المساهمة الأخيرة مع قيود تحليل وجه واحد ومجموعات البيانات الصغيرة. تقترح طريقة لدمج المعلومات من وجوه متعددة للتمر وتستخدم وظيفة التبديل لزيادة حجم مجموعة البيانات. تعمل هذه المقاربة على تحسين دقة التصنيف بشكل كبير، حيث يصل نموذج VGG16 المضبوط بدقة تامة (100٪) مع دمج أربعة وجوه، مما يبرز إمكانات تقنيات تكبير حجم البيانات لمعالجة القيود المرتبطة بمجموعات البيانات المحدودة. في الختام، توضح هذه الأطروحة إمكانات الشبكات العصبية التلافيفية (CNNs) جنبًا إلى جنب مع دمج البيانات متعددة الوسائط. من خلال الاستفادة من المعلومات من أربع صور مرئية تلتقط وجوهًا مختلفة لثمرة التمر، تعمل الطريقة المقترحة على تحسين دقة وكم المعلومات حول الثمرة بأكملها. يمهد هذا الطريق لإحداث ثورة في الفرز الآلي للتمر الجزائري، مما يؤدي في النهاية إلى مستقبل أكثر كفاءة ودقة لسوق التمور الجزائرية.

الكلمات المفتاحية: الشبكات العصبية التلافيفية (CNNs)، التمر، تصنيف الصور، دمج البيانات متعددة الوسائط، التصوير متعدد الزوايا، التصوير الحراري، التعلم بالنقل، قياس الوزن.

Abstract

The Algerian date market holds significant economic potential, ranking third in global date production. However, a substantial gap exists between its production capacity and date fruit exports. This limitation stems from slow, error-prone, and labour-intensive traditional manual sorting methods that rely on visual inspection of various quality factors. This thesis addresses these limitations by leveraging Convolutional Neural Networks (CNNs) to automate date fruit sorting. CNNs incorporate information beyond single-view visual data, creating a more efficient solution. Our novel approach utilizes a multimodal dataset that combines features from multiple fruit faces alongside thermal imaging data and weight measurements, providing a richer and more comprehensive representation of each date fruit. The thesis delves into three key contributions that explore and demonstrate the effectiveness of these CNN-based approaches. The first contribution demonstrates the effectiveness of a multi-modal approach with CNNs, achieving 94% testing accuracy using a VGG16 model by combining all information into one visual data input. The second contribution investigates multi-modal data fusion with late fusion techniques. In Scenario I, fruits are classified based on four-view images. Scenario II extends scenario I by incorporating thermal images and weight measurements. The results highlight the significant accuracy improvement observed when incorporating additional features in Scenario II. The final contribution addresses the limitations of single-face analysis and small datasets. It proposes a method to combine information from multiple fruit faces and utilizes permutation functions to increase dataset size. This approach significantly enhances classification accuracy, with a fine-tuned VGG16 model achieving perfect accuracy (100%) with merged four faces, highlighting the potential of data augmentation techniques to address limitations associated with limited datasets. In conclusion, this thesis demonstrates the potential of Convolutional Neural Networks (CNNs) combined with multi-modal data fusion. By leveraging information from four visual images capturing different faces of the date fruit, the proposed approach enhances the accuracy and richness of information about the entire fruit. This paves the way for revolutionizing automated Algerian date fruit sorting, ultimately leading to a more efficient and accurate future for the Algerian date fruit market.

Keywords: Convolutional Neural Networks (CNNs), Date Fruit, Image Classification, Multi-modal Data Fusion, Multi-view Imaging, Thermal Imaging, Transfer Learning, Weight Measurement.

Résumé

Le marché des dattes en Algérie présente un potentiel économique important, se classant troisième dans la production mondiale de dattes. Cependant, un écart important existe entre sa capacité de production et ses exportations de fruits de dattes. Cette limitation découle de méthodes traditionnelles de tri manuel lentes, sujettes aux erreurs et à forte intensité de main-d'œuvre, qui reposent sur l'inspection visuelle de divers facteurs de qualité. Cette thèse vise à remédier à ces limitations en exploitant les Réseaux Neuronaux Convolutifs (CNN) pour automatiser le tri des fruits de dattes. Les CNN intègrent des informations au-delà des données visuelles à vue unique, créant ainsi une solution plus efficace. Notre approche novatrice utilise un ensemble de données multimodal qui combine des caractéristiques de plusieurs faces de fruits ainsi que des données d'imagerie thermique et des mesures de poids, offrant une représentation plus riche et plus complète de chaque fruit de datte. La thèse explore trois contributions clés qui explorent et démontrent l'efficacité de ces approches basées sur les CNN. La première contribution démontre l'efficacité d'une approche multimodale avec les CNN, atteignant une précision de test de 94% en utilisant un modèle VGG16 en combinant toutes les informations en une seule entrée de données visuelles. La deuxième contribution examine la fusion de données multimodales avec des techniques de fusion tardive. Dans le scénario I, les fruits de dattes sont classés sur la base d'images à quatre vues. Le scénario II étend le scénario I en incorporant des images thermiques et des mesures de poids. Les résultats mettent en évidence l'amélioration significative de la précision observée lors de l'incorporation de fonctionnalités supplémentaires dans le scénario II. La dernière contribution aborde les limitations de l'analyse à visage unique et des petits ensembles de données. Elle propose une méthode pour combiner les informations de plusieurs faces de fruits et utilise des fonctions de permutation pour augmenter la taille de l'ensemble de données. Cette approche améliore considérablement la précision de classification, avec un modèle VGG16 affiné atteignant une précision parfaite (100%) avec quatre visages fusionnés, ce qui met en évidence le potentiel des techniques d'augmentation de données pour remédier aux limitations associées aux ensembles de données limités. En conclusion, cette thèse démontre le potentiel des Réseaux Neuronaux Convolutifs (CNN) combinés à la fusion de données multimodales. En exploitant les informations de quatre images visuelles capturant différentes faces du fruit de datte, l'approche proposée améliore la précision et la richesse des informations sur l'ensemble du fruit de datte. Cela ouvre la voie à la révolution du tri automatisé des dattes algériennes, conduisant finalement à un avenir plus efficace et précis pour le marché des dattes en Algérie.

Mots-clés: Réseaux Neuronaux Convolutifs (CNNs), Fruit de Datte, Classification d'Images, Fusion de Données Multi-modales, Imagerie Multi-vue, Imagerie Thermique, Apprentissage par Transfert, Mesure de Poids.

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LIST OF ABBREVIATIONS

CNNs Convolutional Neural Networks

VGG Visual Geometry Group

FAOSTAT Food and Agriculture Organization Corporate Statistical Database

TSS Total Soluble Solids

Ph Potential of Hydrogen

USDA United States Department of Agriculture

SStd Substandard

UNECE United Nations Economic Commission for Europe

CODEX Codex Alimentarius Commission

ANNs Artificial Neural Networks

AI Artificial Intelligence

k-NN k-Nearest Neighbors

SVMs Support Vector Machines

PCA Principal Component Analysis

ReLU Rectified Linear Unit

Lr Learning Rate

SGD Stochastic Gradient Descent

Adam Adaptive Moment Estimation

RMSprop Root Mean Square Propagation

AUC Area Under the Curve

ROC Receiver Operating Characteristic

MCC Matthew's Correlation Coefficient

MLP Multi-Layer Perceptron

RGB Red, Green, Blue

HSV Hue, Saturation, Value

SSC Soluble Solids Content

DM Dried Matter

LDA Linear Discriminant Analysis

IR Infrared

List of Publications

International Journal Paper

- Ibtissam BOUMARAF, Abdelhamid DJEFFAL, Sarah SETTA, and Abdelmalik TALEB-AHMED, IMPROVING DATE FRUIT SORTING WITH A NOVEL MULTIMODAL APPROACH AND CNNS, International Journal of Advances in Soft Computing and its Application, 15, 3(2023), 190-206. doi: 10.15849/IJASCA.231130.13.

International Conference Papers

- Ibtissam BOUMARAF, Abdelhamid DJEFFAL, Abou Bakr Seddik DRID, DESIGNING SORTING DATES MACHINE USING EMBEDDED SYSTEM, Second International Conference on Electrical Engineering ICEEB2018, December 2-3 2018, Biskra, Algeria.
- Ibtissam BOUMARAF, Mohamed Aymene SLIMANE, Abdelhamid DJEFFAL, MULTIFACE AND INFRARED IMAGES FOR HIGH DATES SORTING PRECISION, 11th International Conference on Information Systems and Advanced Technologies, 22–23 December 2021, Annaba, Algeria.

Workshops

- Abdelhamid DJEFFAL, Ibtissam BOUMARAF, TRI DES DATTES A BASE DE CARACTERISTIQUES APPROFONDIES, Workshop International sur la durabilité des systèmes de production phoenicicoles en Algérie, Université de Biskra, 6 et 7 Décembre 2016.
- Ibtissam BOUMARAF, Abdelhamid DJEFFAL, and Abdelmalik TALEB-AHMED, AUTOMATING DATE FRUIT SORTING: A MULTI-MODAL FUSION AND DEEP LEARNING APPROACH, in 1st workshop on Advances in Deep Learning for Images and Immersive Technologies (ADL2IT), 10-12 October 2023.

Poster

- Ibtissam BOUMARAF, Abdelhamid DJEFFAL, AUTOMATIC DATE SORTING SYSTEM BASED ON AUTOMATIC LEARNING AND VISUAL CHARACTERISTICS, 1st Ph.D Days, JDITA'2018, Biskra, Algeria, January 28-30, 2018.

Chapter 1

INTRODUCTION

1.1 Context

The Algerian government is making significant efforts to diversify its economy, focusing on the agricultural sector. Algeria's agricultural development policy strongly focuses on increasing food production and improving quality. The ultimate goal is to modernize and develop the agricultural industry to achieve self-sufficiency and increase exports [1].

Among Algerian agricultural products, dates are important, ranking second after olives. Despite being one of the world's largest date producers, Algeria's presence in the international market is relatively modest. In 2022, global statistics ranked Algeria as the third largest date producer, reflecting its agricultural prowess [2]. However, despite this impressive production capacity, Algeria's date fruit exports must catch up to its production capabilities. In 2021, Algeria ranked seventh globally in date exports, highlighting a significant gap between production and export levels and indicating untapped potential to expand its global market share [3]. Despite offering high-quality date products with a wide range of options, Algeria still needs help gaining a stronger foothold in international competition.

The post-harvest sorting of dates is a crucial yet challenging step that significantly impacts marketability. This meticulous process requires careful size, shape, colour, and defect assessments. While traditionally relying on human workers' exceptional vision and precision, manual sorting is often tedious, error-prone, and time-consuming. These limitations pose a significant obstacle in the date fruit industry, prompting the need for automated solutions. The agricultural sector faces a critical challenge in ensuring efficient and consistent sorting of high-value crops. Traditional sorting methods, which frequently rely on manual labour, face limitations that impede productivity and product quality. They are inherently time-consuming and labour-intensive, affecting overall throughput and constraining the capacity to meet market demands. Human sorters rely on visual inspection and experience, leading to inconsistencies and variability in sorting outcomes.

These inconsistencies can result in a mix of product grades within a group, impacting marketability and revenue.

1.2 Motivation and Objectives

Traditional sorting methods in the food industry, particularly agriculture, are labour-intensive and often yield inconsistent results. Deep learning systems offer a transformative solution to address these issues. By automating the sorting process, these systems can reduce manual labour and enhance efficiency. Additionally, deep learning, especially systems utilizing Convolutional Neural Networks (CNNs), can detect subtle visual cues that human sorters might miss, leading to more thorough and consistent quality assessments.

Numerous researchers have explored the application of deep learning to date fruit classification (sorting and grading). Used architectures like VGG16, AlexNet, VGG-19, Inception-v3, and MobileNetV2 have achieved impressive results in classifying date fruits (for tasks like maturity, type, and harvesting decisions)[4–7]. Existing research primarily focuses on single-perspective image data and may not capture the full spectrum of quality variations within a date type [4, 7]. However, these studies have certain limitations. They primarily focused on classifying different types of date fruits or evaluating their ripeness stages, often neglecting sorting based on the quality grade of a specific date fruit type. Furthermore, they prioritized applying the latest deep learning technologies without necessarily delving deeper into data collection to detect external and internal features according to international quality standards. Another significant limitation is that these studies generally considered only one side of the fruit, which can lead to errors in detecting defects on other sides. This thesis aims to address these gaps by developing a comprehensive and effective deep learning-based system for automatically sorting and grading date fruits.

The proposed system will consider multiple fruit aspects, incorporate thermal imaging, and measure the weight of the date fruit to enhance defect detection and provide a more accurate assessment of fruit quality. Improving the efficiency and accuracy of the sorting process will significantly enhance Algeria's competitiveness in the global market in terms of date exports.

1.3 Thesis Contributions

All the above considerations lead this thesis to address the challenge of delving deeper into the characteristics of date fruits. We will accomplish this goal by integrating various data sources, such as images taken from different perspectives, internal characteristics, and weight measurements. The research will then explore the most effective strategies to fuse this multimodal data and leverage the power of deep learning models to achieve superior classification performance.

We compiled a custom dataset to develop an automated Algerian date fruit sorting and grading system. This dataset encompasses two prevalent varieties, Deglet Noor and Mech Degla, with each variety further categorized into different quality grades. The key contributions of this thesis are as follows:

1. ***Improving date fruit sorting with a novel multimodal approach and CNNs:***

   In this contribution, we introduce a unique technique to classify each variety type of date fruit in our dataset into five grades. Each date fruit has four images of four faces, a thermal image, and a weight measure. We use a two-step data preparation strategy to effectively utilize these varied data sources.

   Firstly, we capture the overall visual appearance by converting the four visual images to grayscale and then averaging them. This process creates a single grayscale image representing the average visual characteristics from all fruit sides.

   Secondly, we implement a "Customized Image Channel" strategy, which combines the averaged grayscale image with the thermal image and the weight measurement of the fruit. These combined channels serve as the input for various convolutional neural network architectures. These crucial data preparation steps play a crucial role in achieving accurate and efficient classification using CNNs (VGG16, ResNet50, InceptionV3, and CNN model from scratch). By reducing noise, simplifying data representation, and ensuring consistency, these steps significantly improve the quality and reliability of the automated date fruit sorting process.

2. ***Multimodal Data Fusion and Deep Learning for Automated Date Fruit Classification:***

   In this contribution, we explore the concept of multimodal data fusion for accurately classifying date fruits. We propose a late-fusion technique that combines multiple sources of information in two different scenarios.

   Firstly, we employ the fusion of convolutional neural networks (CNNs) trained on four images taken from different sides of the date fruit. Combining these multiple-face images, we aim to represent the fruit's visual features comprehensively.

   In the second scenario, we explore the fusion of these multiple-face images with thermal imaging data and the weight information of the date fruit. Thermal images provide valuable temperature-related information, which can offer insights into the internal properties and ripeness of the date fruit. By incorporating the weight data, we leverage the additional physical attributes of the fruit. By integrating this multimodal data into the classification process, we aim to enhance the accuracy and robustness of the classification system. To assess the efficacy of our suggested multimodal data fusion methodology, we employ commonly used pre-trained models, including VGG16, ResNet50, MobileNet, and a custom CNN design, all of which have extensive recognition for their proficiency in visual identification tasks.

3. ***Optimizing Date Fruit Classification Through Multi-View Imaging and Deep Learning:***

   This contribution presents a novel approach for high-precision date fruit classification, significantly advancing the sorting process. We focus on enriching the dataset and capturing more comprehensive information by capturing four images of each date fruit from different sides. These images are then processed to create a representation that preserves data integrity while preparing the data for a convolutional neural network (CNN) training phase. Our customized CNN architecture leverages sophisticated techniques like dropout regularization to prevent overfitting and fine-tunes a pre-trained VGG16 model for optimal performance. Additionally, we employ a permutation function to explore the significance of using multiple views to generate all possible configurations of these facial elements. By applying the same techniques to datasets with one, two, and three faces, we will demonstrate the effectiveness of incorporating multiple views for improved classification accuracy.

Finally, our contributions aim to enhance the accuracy and reliability of Algerian date fruit classification, offering valuable benefits for date fruit exporters and consumers.

1.4 Thesis Structure

The thesis structure comprises two distinct parts:

Part I, entitled "Background and Literature Review," establishes the foundational knowledge for the research. Chapter 2 provides a comprehensive overview of date fruit fundamentals, encompassing growth stages, existing classifications, prominent Algerian varieties, and established quality assessment standards. Chapter 3 delves into the core concepts of machine learning pertinent to image classification. In contrast, Chapter 4 reviews the application of artificial intelligence within the agricultural sector, specifically focusing on existing date fruit classification techniques utilizing both traditional and deep learning approaches.

Part II, titled "Contributions," showcases the novel research conducted within this thesis. Chapter 5 details a multimodal approach that leverages CNNs for automated date fruit sorting, including data preparation steps and the methodology employed to convert multiple input sources into a unified image representation. Chapter 6 investigates multimodal data fusion using concatenation with deep learning for automated date fruit classification. Chapter 7 explores classification optimization through multi-view imaging and deep learning, employing techniques such as merging and permutation functions. Finally, Chapter 8 presents a comprehensive conclusion summarizing the critical contributions of the thesis and proposing several directions for future research.

Part I:

Background and Literature Review

Chapter 2

Date Fruit Sorting

2.1 Introduction

The date palm tree is known scientifically as Phoenix dactylifera. It plays a role in the oasis ecosystem of regions and holds great importance in agricultural production in dry and semi-dry areas. It serves as an element within the oasis environment, playing an economic and social function for local communities by producing date fruits. Additionally, the presence of date palms contributes to the stability of the Algerian Sahara, home to over 3 million residents. Dates are popular and nutritious locally and enjoy international acclaim for their high-energy content [8].

This chapter offers an overview of date fruits, covering aspects such as growth stages, classifications, and global significance, emphasising Algerian varieties. It delves into the grading and sorting processes and the stringent quality standards that adhere to producers and regulatory bodies.

2.2 Overview of Date Palms

The date palm (Phoenix dactylifera) occupies a significant position in the history and cultures of arid and desert regions, particularly in the Middle East and North Africa. These resilient trees thrive in some of the harshest environments on Earth and have earned admiration for sustaining communities by providing shelter, food, and raw materials. As a result, they have become iconic symbols in various societies [9].

A date palm can grow up to 20 metres in height and continue to produce dates for up to 200 years, provided it remains disease-free and unaffected by drought, which can destroy palm groves that have thrived for decades. The tree has a cylindrical trunk adorned with a stipe (a group of tough leafy fronds) and a crown of slender pinnate leaves measuring 4 to 7 metres. The date flower appears in large, airy clusters. Date palms typically begin to bear fruit around age 5, with an average annual production of

400 to 600 kg per tree, which can persist for up to 60 years [10]. The schematic diagram of a date palm tree is illustrated in Figure 2.1.

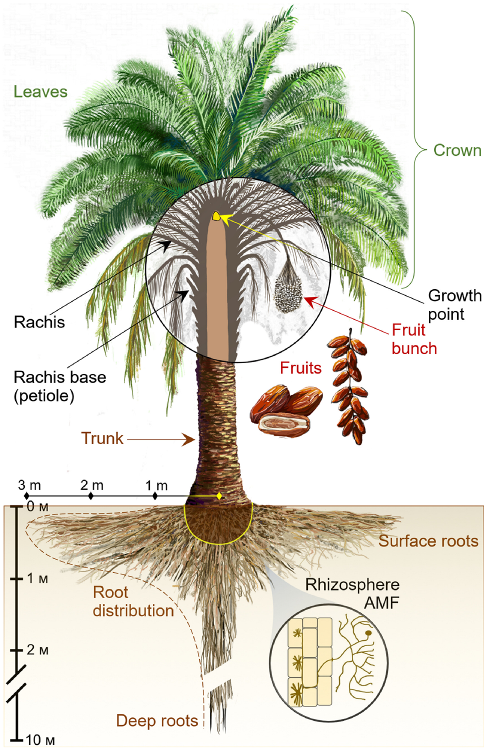


Figure 2.1: Morphological features of a date palm tree [11]

The cultivation of dates, a globally beloved fruit enjoyed across Africa, North and South America, and Asia, is intricately tied to its historical roots in the Middle East and the Maghreb. An impressive 90% of the world's date production emanates from these regions, reflecting its cultural centrality and economic importance [12], [13], [14]. This section will further explore global date palm production and Algerian date fruit production in diverse regions.

2.2.1 Global Date Palm Production

The ten countries leading in date palm production, according to FAOSTAT 2022, are Egypt, Saudi Arabia, Algeria, Iran, Pakistan, Iraq, Sudan, United Arab Emirates, Oman, and Tunisia [15]. This order reflects their significant role in shaping global date palm cultivation. Starting with Egypt and ending with Tunisia, this list shows how various factors, such as geography and climate, influence each country's contribution. In particular, Saudi Arabia, Algeria, and Iran play crucial roles in date palm production globally. For a visual representation, refer to Figure 2.2, which illustrates the top 10 date fruit producers. This graphic helps us understand each country's hierarchy and importance in the global date palm industry.

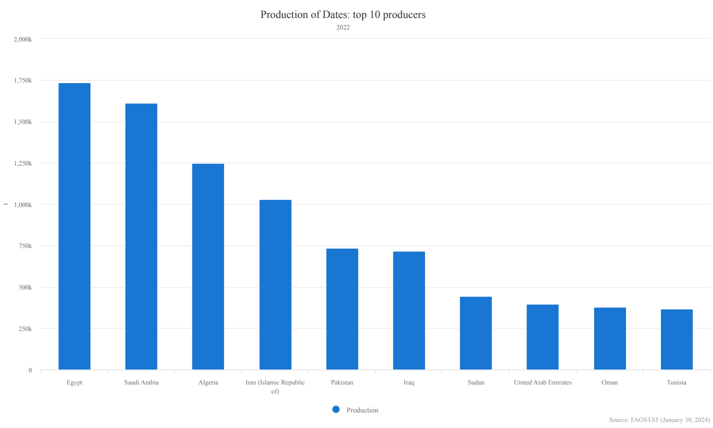


Figure 2.2: Charting the Top 10 Date-Producing Nations [15]

2.2.2 The Date Palm in Algeria

Despite being one of the world's top date producers, Algeria's presence in the international market remains relatively modest. In 2022, global statistics ranked Algeria as the third-largest date producer, a testament to its agricultural prowess. According to a recent report by the Food and Agriculture Organization of the United Nations (FAO), Algeria produced over 1.4 million tonnes of dates in 2022, a 7 % increase from the previous year [2].

Despite this impressive production capacity, Algeria's date exports must catch up to its production capabilities. In 2021, Algeria ranked seventh globally in date exports, with a total volume of 76.9 thousand tonnes valued at 79 million dollars [3].

On the cultivation front, date palms in Algeria thrive in various oases in the hot and arid southern regions. They are found from the west near Morocco to the east by Tunisia-Libya and from the Saharan Atlas in the north to places like Reggane in the southwest, Tamanrasset in the central part, and Djanet in the southeast. There are about a thousand types of date palms, with three main areas known for having different varieties. Wild palms, known as "Khalts," grow randomly in oases, providing a valuable resource for selecting new cultivars known for their premium dates and resistance to bayoud disease. Date palms spread out in an east-west pattern, with most remaining in their original areas. In the eastern part of Algeria, a popular variety called Deglet Nour is well-liked for export, constituting almost half of all date palms planted there. Some varieties, such as Degla Beida and Tinnaser, are sent to sub-Saharan African countries; Export-oriented varieties like Hmira find their way to countries like Russia and China, while new introductions like Tafezwin are gaining traction in South America. Meanwhile, within Algeria, the Bentqbala variety reigns supreme in the eastern Ghardaïa market, reflecting local preferences. Agaz, a variety harvested early in Tidikelt in the west, performs well in the markets of Ouargla and Ghardaïa [16]. Table 2.1 presents the most cultivated varieties of date fruit in different regions of Algeria.

Region	Number of cultivars	Most common cultivars
West		
Atlas	70	Ghares, 'Asyan, Feggus
Saoura	80	Feggus, Hartan, Cherka, Hmira, Deglet Talmine
Gourara	230	Hmira, Tinnaser, Taqerbuch
Touat	190	Tgazza, Aghamu, Taqerbuch
Tidikelt	60	Tgazza, Taqerbuch, Cheddakh, Aggaz
Center		
El-Menia	70	Timjuhart, Ghars, Timedwel
M'Zab	140	Azerza, Ghars, Deglet Nour, Taddela, Bentqbala
East		
Ouargla	70	Ghars, Deglet Nour, Degla Beida
Oued Righ	130	Deglet Nour, Ghars, Degla Beida
Souff	70	Deglet Nour, Ghars, Degla Beida, Mich Degla
Zibans	140	Deglet Nour, Ghars, Degla Beida, Mich Degla
Aures	220	Buzrur, 'Alig, Buhles, Mich Degla
Tassili	180	Tanghimen, Tabanis, Khadaji

Table 2.1: Cultivar Inventory in the Three Date Palm Regions of Algeria [16]

2.3 Comprehensive Overview of Dates

The date palm tree generously yields its sweet and nutritious fruit, the date, which has been a cherished food for centuries. Dates are a natural health snack packed with carbohydrates, fibre, vitamins, and minerals. These antioxidant powerhouses help fight oxidative stress and inflammation in the body. Dates boast incredible versatility in the kitchen, enjoyed fresh or dried [17].

On the botanical front, date fruit is an elongated or rounded drupe with a single seed. It comprises a fine cellulosic envelope known as the pericarp or skin and a mesocarp that is more or less fleshy with variable consistency. The mesocarp consists of a peripheral zone with a sustained colour and compact texture, an inner zone of a lighter shade and a fibrous texture called the endocarp. The endocarp forms a membrane surrounding the seed [18]. Figure 2.3 shows date fruit compositions.

2.4 Developmental Growth Stages of Dates

Date fruit development involves five maturity stages over approximately 6–8 months, as shown in Figure 2.4. These stages include [20]:

- **Hababouk (Loulou):** The initial stage, lasting 4 to 5 weeks after pollination, features round-shaped fruit with a whitish-cream colour and green stripes.
- **Kimri (Bleh):** Within the first 17 weeks, young, elongated fruit with a greenish

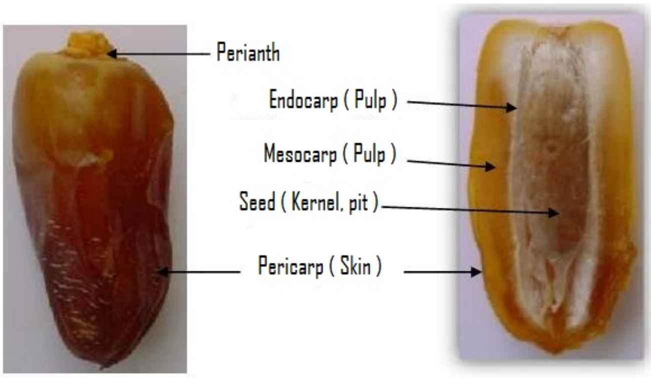


Figure 2.3: Date fruit compositions [19]

colour, hard texture, and high moisture appears. Although unsuitable for direct consumption, people use this fruit to make chutney or pickles.

- **Kalal (Bser):** During the next six weeks, the date fruit reaches maximum size and weight, transitioning to yellow, purplish pink, or red, depending on the cultivar. The sugar content increases, making dates suitable for raw consumption or processing into jam, butter, or date-in-syrup.

- **Rutab (Martouba):** In the following four weeks, dates lose water, becoming softer, sweeter, and darker in colour (light brown). Sucrose converts to reducing sugars, marking the beginning of ripening. Rutab stage dates are consumed fresh or processed into various products.

- **Tamar:** The final two weeks involve the fruit gaining maximum total solids, high sweetness, low astringency, a dark brown colour, soft texture, and a wrinkled shape. These dates have good storage stability due to their low moisture and high sugar content [21].

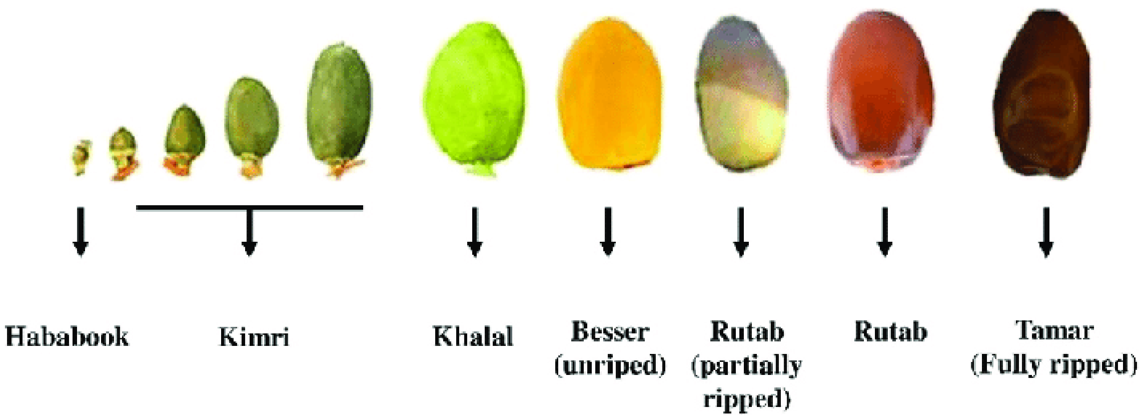


Figure 2.4: Date fruit stages [22]

2.5 Date Fruit Classifications

Date fruits can be classified into three primary categories based on their texture: soft, semi-soft, and dry dates. Espiard (2002) pointed out that these categories are determined by the variation in texture observed in dates. Munier's quality index, introduced in 1973 and known as "r," further aids in classification. This index assesses the fruit's stability degree, resulting in the following classification [23, 24]:

- **Soft dates:** Soft dates typically contain over 30% moisture, low levels of sucrose, but high amounts of reducing sugars (glucose and fructose), and $r < 2$.
- **Semi-soft dates:** Semi-soft dates have a moisture content ranging from 20% to 30%, with 18% to 30% sucrose and 45% to 54% reducing sugars, and $2 < r < 3.5$.
- **Dry dates:** Dry dates have moisture levels below 20% and nearly equal proportions of sucrose and reducing sugars, ranging from 33% to 46%, and $r > 3.5$.
- At $r = 2$, the stability of the fruit is optimal, and its suitability for preservation is highly appreciated.

2.6 Date Fruit Varieties in Algeria

The Algerian palm tree has a diversity of varieties, which present dates of varying shapes and characteristics, categorised into three distinct groups [25]:

2.6.1 Commercial Varieties of Dates

Deglet Noor is the most famous date fruit type that is revered nationally and internationally in Algeria. It makes up almost half of all dates grown in the country. These dates are soft and look nice. When ready to eat, they turn shiny brown and have smooth skin with wrinkles. Inside, they are soft and fibrous, but they taste perfect. People all over love Deglet Noor dates because they look and taste great, making them an excellent choice for snacks and desserts [23].

2.6.2 Common Dates

Common Algerian varieties dominate the southwest regions, constituting a significant portion of the market. Examples include Mech Degla, Ghars, and Degla Beida, each with distinct features [26]:

- **Mech Degla:** It exhibits a sub-cylindrical form, with slight elongation and flattening at its base. It displays a light beige hue when it reaches maturity, accompanied by a subtle brownish tinge. The outermost layer, the epicarp, exhibits a wrinkled texture, lack of shine, and fragility. The mesocarp is not succulent in its inner composition, presenting a white colouration, dry consistency, and a mealy texture.

- **Ghars:** Ghars can be described as a type of date fruit with a notably tender texture when fully mature. It exhibits a yellow hue in its early stage, becomes honeyed during the rutab stage, and assumes a dark brown colour when fully ripe. The epicarp is characterised by its glassy appearance, glossy finish, adhesive properties, and slight wrinkling. The mesocarp consists of a pulpy material that feels soft and fibrous.

- **Degla-Beidha:** The object's shape is tapering, with a flattened side on the perianth and a narrowed end on the opposite side. During the maturation stages, its colour is yellow, then transitions to a light brown or beige hue once it is fully ripe. The outer layer, known as the epicarp, is thick and smooth. The middle layer, the mesocarp, possesses a fleshy consistency that is dry and mealy texture. The calyx, which is flat in shape, presents a colouration ranging from yellow to orange and exhibits a solid adherence to the flesh.

2.6.3 Secondary Dates

The category of secondary dates includes cultivars that are less prevalent or facing endangerment, with more than 150 varieties identified. Notable examples include Hamra, Timnaceur, Tegaza, Tezerzait, and Takerboucht. Takerboucht is particularly noteworthy for its resistance to Bayoud disease, making it particularly interesting to researchers and cultivators [25].

In the study of Algerian date fruit varieties, researchers have identified significant differences in characteristics such as maturity, harvest date, average size, and sugar content among cultivars [26, 27]. Table 2.2 presents a comparative analysis of four prominent cultivars: Deglet-Nour, Mech Degla, Ghars, and Degla-Beidha.

Characteristics	Cultivar			
	Deglet−Nour	**Mech Degla**	**Ghars**	**Degla−Beidha**
Image				
Meaning of the name	Finger of light	Date that is not Deglet Nour	Pasty and sticky	White date
Importance	Most responded in Algeria (≈ 53%)	Abundant	Abundant in the palm groves of South−East Algeria	Abundant in all palm groves of South−East Algeria (≈ 37%)
Maturity	October November	October	August September	October
Harvest date	November December	November	September	October
Average date size	L = 4.34 cm, l = 1.7cm	L= 2.85 cm, l=1.58cm	L =4.36, l = 1.8cm	L = 2.85 cm; l =2cm
Date inner diameter	1.2cm	1.04 cm	1.3cm	1.14 cm
Average date weight	11.84 g	5.68 g	9.75g	18.75 g
Average pulp weight	10.92 g	4.74g	8.6g	18.06 g
Ratio (pulp/date)	0.93	0.83	0.88	0.96
Total Sugars	71.37%MS	80.7%MS	62.4%MS	74%MS
TSS	71%	65%	53.4 %	79.50%
pH	5.546	5.67	6.16	5.18
Moisture content	25.52%	13.93%	23	17.45%
Sucrose	46.11% MS	51.40 %MS	5%MS	30.36

Table 2.2: Comparative Characteristics of Four Date Cultivars: Deglet-Nour, Mech Degla, Ghars, and Degla-Beidha [26, 27]

2.7 Grading and Sorting Process

Sorting and grading are crucial to ensuring market readiness and maintaining quality consistency for date fruits. The sorting process involves carefully removing defective fruits and categorising them based on size, maturity, texture, colour, and shape. Manual labour typically handles this process. In contrast, grading focuses on aspects like size, weight, visual defects, skin condition, uniformity of colour, and absence of decay or damage [22].

International standards like Codex and U.S. Grades establish quality criteria, which help standardise grading practices (see section 2.8.2). Although sorting aims to segregate fruits based on their characteristics, grading/classification plays a central role in categorising fruits into distinct groups to meet diverse market demands [22].

Despite being labour-intensive and time-consuming, the manual nature of sorting and grading processes remains prevalent in all countries, posing challenges in post-harvest operations. In South Algeria, for example, a single grader can typically handle around 200 kilograms of dates during an 8-hour shift. However, this capacity doubles to 400 kilograms when using conveyor belts, although it is essential to ensure that the belts do not move faster than approximately 9 metres per minute [17].

Understanding their maturity stages is essential to sorting and grading date fruits, from rapid growth to complete ripening. Furthermore, variations in chemical composition, including sugar levels and dietary fibre, significantly influence these processes [20].

Mechanical methods, such as sorting on moving belts or crates, complemented by manual approaches illustrated in Figure 2.5, contribute to improving the efficiency of date fruit sorting and grading, thus ensuring uniformity and quality between batches [28].

a. Date Grading in Iraq, Oman [17]

b. Sorting dates [29]

Figure 2.5: Manual date sorting and grading process.

2.8 Quality Assessment

Dates, revered as versatile and nutritionally rich fruit, boast myriad distinct qualities that significantly contribute to their overall desirability. The assessment of date fruit quality is a multifaceted process that considers consumer preferences and the rigorous standards set by producers. Striking a balance between these perspectives ensures that dates meet consumers' taste preferences and align with the stringent criteria set forth by regulatory bodies and international trade agreements.

2.8.1 Consumer Perspective

For consumers, taste and texture are the most essential qualities of dates. A study supports this, revealing that consumers rank taste as the primary factor influencing their purchase intent. Additionally, the texture of dates is a crucial factor affecting consumer preferences. Furthermore, the colour of dates plays a significant role in consumer perception [30]. Consumers often use visual colour evaluation to determine dates' perceived freshness and ripeness. It is essential for date fruit producers to prioritise taste, texture, and colour to meet consumer expectations and drive purchase intent. In addition to taste, texture, and colour, other essential qualities of dates include their size and the presence or absence of defects [31].

2.8.2 Producers Perspective

From the producers' perspective, ensuring the consistent quality of the dates is not just a commitment to consumer satisfaction but also a strategic imperative to maintain competitiveness in the market. Meeting and surpassing industry standards are indispensable for building trust within the supply chain, cultivating a robust brand reputation, and securing access to international markets. Implementing rigorous quality control measures, including morphological and physicochemical evaluations, empowers producers to adhere to established benchmarks, comply with regulatory requirements, and maintain the integrity of their products. After harvesting, various tasks within the date fruit industry are essential to prepare the date fruit for the subsequent packaging step. The sorting and grading process represents a crucial step in which workers segregate the dates according to the standards established by international organisations.

2.8.3 USDA Standards for Date Grades

The recent standards for grading dates, developed by the United States Department of Agriculture (USDA), provide a comprehensive framework that meticulously outlines sorting criteria, including colour, uniformity, absence of defects, character, and score.

This section explores the U.S. grading system for dates and classifies date fruits based on distinct characteristics and quality standards [32]:

- **Grade A (or U.S. Fancy)**: This category includes whole or pitted dates of a single variety with good colour, nearly uniform size, minimal defects, and a positive overall character (Total Score over 90 score points).
- **Grade B (or US Choice)**: Whole or pitted dates of one variety fall into this class, featuring reasonably good colour, moderate uniformity in size, a moderate level of defects, and a satisfactory character (Total score of about 80 score points).
- **Grade B (dry) or US Choice (dry)**: This category pertains to whole dry dates intended for processing. The criteria include reasonably good colour, moderate uniformity in size, moderate defects, and a satisfactory character (Total Score of about 80 score points).
- **Grade C (or US standard)**: This grade encompasses whole or pitted dates (excluding dry dates for processing) of one variety or date pieces/macerated dates. The characteristics include pretty good colour, moderate uniformity in size (except for pieces), moderate defects, and a satisfactory character (Total Score of about 70 score points).
- **Grade C (Dry) or U.S. Standard (Dry)**: Whole dry dates intended for processing belong to this class, exhibiting fairly good colour, moderate uniformity in size, a moderate level of defects, and a satisfactory character (Total Score of about 70 score points).
- **Substandard or Cull Date Fruit**: This category refers to dates that do not meet the criteria of US Grade C or US Standard (dry), as described in Section 798 of the California Agricultural Code. Cull dates are affected by various defects such as insect infestation, decay, mould, fermentation, souring, dirt, or other foreign material, damage from black scald, side spots, and improper ripening (total score below 60 score points).

The standards established by the United States for grading and sorting dates define quality standards using a scoring system. The numerical representation of each scored factor is expressed on a scale of 100. Table 2.3 represents the maximum points assignable to these factors.

To ensure the consistent application of these grade standards, each inspector needs to gain experience under the guidance of individuals knowledgeable in date sorting, and each factor is represented numerically as detailed as follows [32]:

Factors	Points
Color	20
Uniformity of Size	10
Absence of defects	30
Character	40
Total Score	100

Table 2.3: Score Points for Classification Factors [32]

- **Colour:** The colour-scoring procedure allows for flexible sample sorting within the appropriate grade. Grade A requires a sample with "good colour," typically any shade of amber consistent with the variety. For Grade B, uniform, typical amber is essential, but some variations in date fruit are acceptable. Grade C requires a relatively uniform colour, typical amber for whole and pitted dates, along with consistency of colour in date fruit. Dates burnt to a cherry-red colour due to over-hydration are addressed under defects, not colour. Specific score thresholds determine the final grade within each classification. Table 2.4 is provided for assigning scores based on colour requirements.

Classification	Score Points	Marked Variation
A	20	Over 0% to 1%
	19	Over 1% to 3%
	18	Over 3% to 5%
B and B Dry	17	Over 5% to 8%
	16	Over 8% to 10%
C and C Dry	15	Over 10% to 15%
	14	Over 15% to 20%
Substandard	13 or less	Over 20%

Table 2.4: Scoring Points for Date Classification Based on Color [32]

- **Uniform Size:** It is crucial in grading whole and pitted date styles.
  - "A" classification, dates that are practically uniform in size can receive a score of 9 or 10 points, with the criteria that not more than 10%, by weight, should deviate conspicuously from the average size of the dates in the container.
  - The "B" classification, of reasonably uniform size, allows for a score of 8 points, with a limit of 15% deviation from the average size.
  - Classification "C" allows a score of 7 points for a fairly uniform size, with a limit of 20% deviation.
  - The "SStd (Substandard)" classification applies to dates failing the requirements of the "C" classification, receiving a score of 0 to 6 points and graded as Substandard.

- **Absence of Defect:** Defects in dates are classified based on various characteristics, affecting their appearance, edibility, or quality:

1. Damaged by Discolouration: Presence of a dark area visible through the skin, more than one-fourth (1/4) inch wide, of natural origin.
2. Damaged by Broken Skin: Any rupture exposing the flesh, with the shortest dimension of the exposed area at least three-sixteenths (3/16) inch.
3. Damaged by Checking: Fine lines from water injury covering at least one-fourth of the date's surface.
4. Seriously Damaged by Checking: Heavy lines from water injury covering a significant portion of the date's surface.
5. Damaged by Deformity: Abnormal shape significantly deviating from the variety's typical form.
6. Damaged by Puffiness: Soft, pliable skin separated from the flesh in a balloon-like fashion over a substantial portion of the date's surface.
7. Seriously Damaged by Puffiness: Dry, hard skin separated from the flesh over a significant portion of the date's surface.
8. Damaged by Scars: Blemishes affecting the exterior, not less than three-sixteenths (3/16) inch in the shortest dimension.
9. Damaged by Sunburn: Light-coloured area scarred by sun heat, not less than three-sixteenth inch in the shortest dimension.
10. Damaged by Insect Injury: Blemishes resulting from insects or mites affect at least one-fourth of the date's surface.
11. Damaged by Improper Hydrating: Injury from excessive heat or incomplete hydrating process.
12. Damaged by Mashing: Physical injury partially mangling the flesh while keeping the date whole.
13. Damaged by Mechanical Injury: Excessive trimming or similar injury affecting appearance or eating quality.
14. Damaged by Lack of Pollination: Manifested by absence of a pit or thin, immature appearance.
15. Damaged by Blacknose: Severe checking causing dark, crusty, dry flesh over a significant area.
16. Damaged by Side Spot: Circular dark area extending into the flesh, affecting a minimum area.

17. Damaged by Black Scald: Collapse, death, and blackening of flesh along the side, often with a bitter taste.
18. Damaged by Improper Ripening: Pronounced evidence of green shrivel or puffy flesh due to climatic or cultural issues.
19. Damaged by Other Defects: Any injury or defect not defined, materially affecting appearance, edibility, or quality.
20. Affected by Souring: Breakdown of sugars into alcohol and acetic acid by yeasts and bacteria.
21. Affected by Mold: Visible presence of mold.
22. Affected by Dirt: Presence of any quantity of dirt.
23. Affected by Insect Infestation: Presence of dead insects, insect parts, or excreta.
24. The presence of any quantity of such substance is the condition that is influenced by foreign material.
25. The state of decomposition is a condition that is influenced by decay.

The classification of dates based on the presence of defects includes:

- **"A" classification:** Practically free from defects, scoring 27 to 30 points.
- **"B" Classification:** Reasonably free from defects, scoring 24 to 26 points.
- **"C" Classification:** Fairly free from defects, scoring 21 to 23 points.
- **"SStd" Classification:** Fail to meet requirements, scoring 0 to 20 points, is graded as substandard.

- **Character:** The quality and attributes of dates are subject to various interconnected factors, such as their development, fleshiness, softness, ripeness, dryness, and semi-dry or dry calyx ends.

  - **Development** refers to the fruit size and maturity growth stage.
  - **Fleshiness** pertains to the thickness of the date material relative to its size.
  - **Softness** indicates the lack of firmness in the date flesh, which is often influenced by the moisture content and the breakdown of the structure of the cell wall, both of which are essential for complete ripening.
  - **Ripeness** signifies the extent to which the cell wall structure of the date flesh has been broken down. Fully ripened dates exhibit translucency, pliability, and a lack of woody texture, often achieved through partial drying.

- **Dryness** is related to the moisture content of the date, which affects its texture and firmness.
- **The presence of semi-dry or dry calyx ends** describes the texture, firmness, or dryness of the date, often categorized as semi-dry or dry ends, which can impact overall quality.

The classification of dates based on their character includes:

- **A Classification:** Dates with good character receive a score of 36 to 40 points. They are well-developed, well-fleshed, and soft, or they ripen sufficiently to develop these qualities within 15 days. The presence of semi-dry or dry calyx ends should be minimal.
- **B Classification:** Dates with a reasonably good character score of 32 to 35 points. They should be pliable and well-developed, with no more than 10% of the dates having semi-dry or dry calyx ends.
- **C Classification:** Dates with a fairly good character score of 28 to 31 points. They are pliable, fairly well-developed, and fleshed, with no more than 20% of the dates having dry calyx ends.
- **SStd Classification:** Dates that fail to meet the requirements receive a score of 0 to 27 points and are graded as substandard.

2.8.4 UNECE Standard DDP-08

UNECE Standard DDP-08 is a standard developed by the United Nations Economic Commission for Europe (UNECE) Working Party on Agricultural Quality Standards to ensure the marketing and commercial quality control of dates. The standard categorises dates into three classes: "Extra" Class, Class I, and Class II, based on the following criteria [33]:

- Dates must be devoid of abnormal external moisture and foreign smells or tastes.
- The dates' condition should allow for effective marketing and commercial control.
- Quality and size tolerances are allowed in each lot for produce that falls short of the minimum requirements for the specified class.
- Switzerland does not allow a tolerance exceeding 6% for produce damaged by pests.
- Each package must contain uniform contents, including only dates of the same origin, quality, and variety.
- Each package's minimum weight of dates should be 4.0 g.

2.8.5 The CODEX STAN 143-1985

CODEX STAN 143-1985 sets quality standards for commercially prepared whole dates, both pitted and unpitted. Here is a summary of the grading and classification standards. Dates are assigned a grade based on overall quality: "Choice", "Standard", or "Substandard" [34]:

- **Choice:** Dates that possess exceptional quality, devoid of any major defects, display uniformity in size, colour, and distinctive flavour and texture.

- **Standard:** Dates that exhibit good quality, allowing for slight defects and minor variations in size and colour, while still meeting the market's expectations.

- **Substandard:** Dates that do not conform to either the "Choice" or "Standard" categories, primarily due to more significant defects, deviations in colour and size, or compromised characteristics.

Dates are classified according to various factors:

- Style: Pitted or unpitted.

- Moisture content: Dry, semi-dry, or moist.

- Ripeness: Fully ripe or semi-ripe.

- Size: Extra-large, large, medium, small.

- Blemishes: Slight, serious, free of blemishes.

- Variety: for example, Deglet Noor, Medjool, and Barhi.

2.9 Conclusion

Dates hold significant importance, particularly in numerous regions spanning Africa, the Middle East, and Asia, and they have recently emerged as a valuable commodity in global trade. In the past two decades, global date production has significantly risen. In 2022, production reached approximately 9.75 million metric tons [35], and this upward trend is expected to continue, as forecasted by the Food and Agriculture Organization (FAO).

The processing journey of dates encompasses various crucial stages, such as harvesting, cleaning, grading, sorting, packaging, and distribution to local or international markets. Consequently, ensuring the quality of date fruit has become essential, requiring strict adherence to international standards. These standards establish precise criteria and classifications, guiding producers and stakeholders in upholding quality standards throughout the supply chain.

However, numerous obstacles still need to be overcome in producing and trading date fruits, particularly postharvest handling technologies, food safety protocols, and quality assurance measures. This section offers a comprehensive analysis of date fruit production, covering aspects such as cultivation, the recognition of notable Algerian date varieties, postharvest sorting and grading techniques, and an investigation into international standards for quality assessment pertinent to date fruits.

Chapter 3

Machine Learning Fundamentals for Image Classification

3.1 Introduction

The ability to automatically classify images has become increasingly important in various fields. Image classification tasks involve training computer models to analyze visual data and assign appropriate categories to the content of images. This chapter delves into the fundamental principles of machine learning that empower these models to achieve impressive classification accuracy.

Delving into Deep Learning, a powerful subfield of machine learning, requires a solid understanding of its core concepts. We will begin by examining machine learning's fundamental approaches (supervised, unsupervised, reinforcement) to pave the way for tackling intricate image data.

The focus then shifts to Artificial Neural Networks (ANNs), the cornerstone of Deep Learning architectures. We will dissect the components of ANNs, including layers, weights, biases, activation functions, and optimization techniques. Next, we will explore Convolutional Neural Networks (CNNs), a specialized type of ANN designed explicitly for image classification tasks.

Finally, the chapter concludes by introducing essential metrics used to evaluate the performance of image classification models.

3.2 Overview of Machine Learning

Figure 3.1 highlights the intricate interplay between artificial intelligence (AI) and its crucial subfield, machine learning. Machine learning is at the forefront of technological advancement. It specializes in crafting algorithms and models that enable autonomous learning and decision-making processes. Unlike conventional programming paradigms reliant on pre-defined commands, machine learning empowers systems to dynamically adapt and evolve in response to the data they encounter.

Its algorithms are central to machine learning's efficacy. These algorithms harness extensive datasets to solve complex problems without explicit programming instructions. Notable among these algorithms are decision trees, support vector machines, and Bayesian networks, each offering unique pattern recognition and prediction approaches.

Deep learning, a specialized subset of machine learning, further enhances the field's capabilities by employing multi-layered models that simultaneously perform feature selection and model fitting. This approach has ushered in a new era of predictive modelling, enabling the development of sophisticated algorithms that outperform traditional methods.

Recent advancements in computational power have been instrumental in fueling the rapid progress of machine learning and deep learning techniques. This surge in computational capacity has facilitated the development of complex prediction models, leveraging architectures such as artificial neural networks, convolutional networks, and recurrent neural networks to achieve unprecedented levels of precision and performance [36, 37].

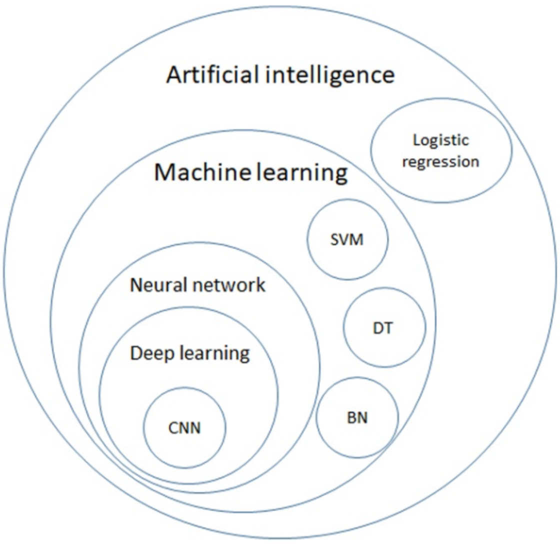


Figure 3.1: A Venn diagram illustrating the relationships between artificial intelligence (AI), machine learning (ML), neural networks, deep learning, and other algorithms within each category [37].

Machine learning algorithms are the backbone of modern technological advancements, permeating diverse applications such as image recognition, natural language processing, and recommendation systems. These algorithms enable systems to analyze complex data, recognize patterns, and make intelligent decisions without explicit human intervention. From identifying objects in images to understanding human language nuances, machine learning capabilities continue to fuel transformative breakthroughs, revolutionizing industries and improving everyday experiences [36].

3.3 Machine Learning Categories

Machine learning encompasses diverse algorithms designed to address a broad spectrum of problems. These algorithms can be broadly classified into three main paradigms: supervised learning, unsupervised learning, and reinforcement learning [36, 38–41]. Each paradigm adopts a distinct approach to the learning process, which we will discuss further. Figure 3.2 shows a visual representation of these machine learning paradigms.

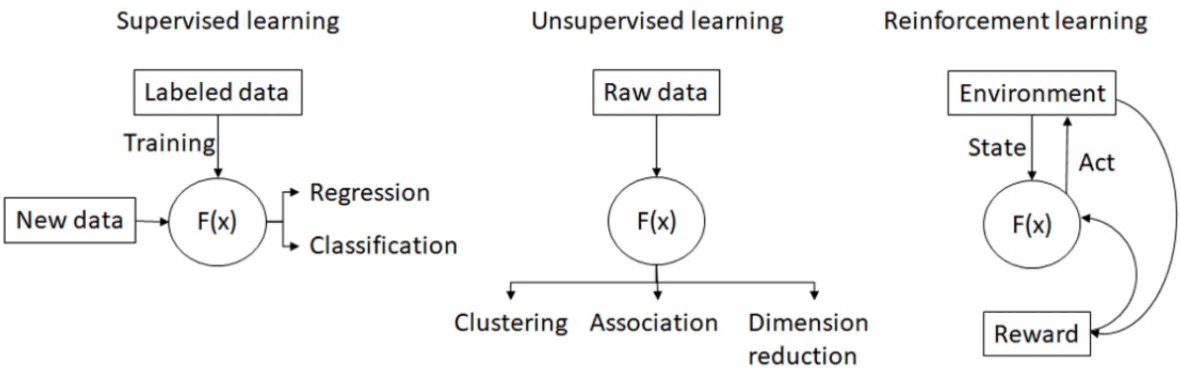


Figure 3.2: Types of Machine Learning [37].

3.3.1 Supervised Learning

Supervised learning is a fundamental division within machine learning dedicated to pattern recognition by establishing correlations between variables and known outcomes. This methodology primarily operates with annotated datasets, wherein the algorithm is endowed with training data comprising diverse characteristics (referred to as "X") and their corresponding accurate output values (referred to as "y"). This approach enables the algorithm to identify underlying patterns within the data and formulate a model capable of replicating these patterns when presented with new data instances [36, 40].

Researchers play a pivotal role in advancing supervised learning by curating labelled datasets that adjust network parameters through a direct comparison between input data and the desired output (target) values, facilitating the efficient education of the algorithm. Training the algorithm through labelled examples makes supervised learning ideal for tackling forecasting tasks like classification and regression. As Figure 3.3 illustrates, supervised learning excels when the target variable is categorical (classification) or continuous (regression). The overarching objective of supervised learning is to extract valuable insights from historical information in the form of labelled training data [37–39, 41].

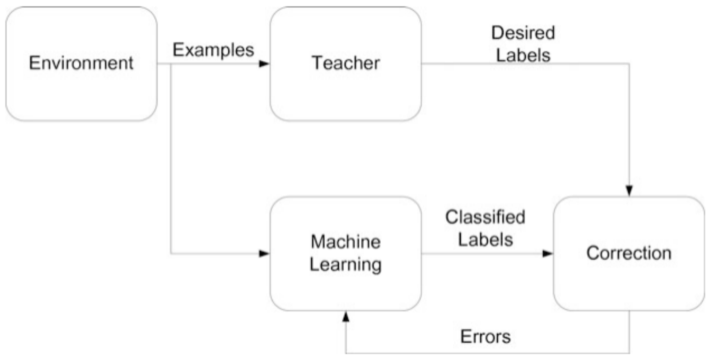


Figure 3.3: Supervised Learning Process [42]

3.3.1.1 Supervised Machine Learning Types

Supervised learning excels at making predictions based on labelled data. Two fundamental types of supervised learning techniques are regression and classification. Below, we delve into these essential techniques:

- **Regression** is a supervised learning technique that aims to establish the relationship between a dependent variable (the target for prediction) and one or more independent variables (the predictors). It predicts continuous outcomes like real estate prices, stock prices, or exam scores. Linear regression, the simplest form, fits a straight line to depict the relationship between the variables [39]. However, there is a wide array of other regression methods, and techniques like bagging in ensemble learning can help improve model accuracy [36, 43].

- **Classification** is a process that predicts categorical or nominal variables, dividing the output into specific classes based on the training data provided. This process entails categorizing the output into distinct classes according to the training data. This technique falls under supervised learning, in which the model gains insights from annotated data to classify fresh data into predetermined classes [36, 39, 43].

3.3.1.2 Common Supervised Learning Algorithms

The following section explores some of the most widely used supervised learning algorithms, highlighting their key features and each with its strengths.

- **Linear Regression** is a supervised learning technique used for forecasting, illustrating the relationship between a dependent variable (the target of prediction) and one or more independent variables (the predictors), assuming a linear connection. The process involves placing a straight line on a scatterplot containing the data points. The optimal line is the one that minimizes the overall distance between itself and all the data points [36, 40].

- **Decision Tree Algorithm** is a popular supervised learning technique used for both regression (predicting continuous values) and classification (predicting categories). It works by building a tree-like structure where each node represents a question or test on a data feature. The algorithm recursively divides the data into subsets based on the characteristic that best separates the data points according to the desired outcome (classification or prediction). This process continues until a stopping criterion is met, resulting in a tree with decision nodes (asking questions) and leaf nodes (containing the final predictions) [36, 40, 41]

- **Random Forest Algorithm** is an ensemble classifier that leverages the combined predictions of numerous decision tree classifiers. Each decision tree grows using a randomized subset of features and binary questions, resulting in diverse trees. After constructing the random forest by combining these trees, the model makes the final classification or prediction through a majority vote on the individual tree outputs [39, 40]. Compared to other algorithms, Random Forest requires minimal tuning. However, a potential drawback is the increased computational cost associated with a higher number of trees, which can sometimes lead to inaccuracies in the results [43].

- **K-Nearest Neighbors Algorithm (k-NN)** stands out for its simplicity and effectiveness. The core concept relies on the observation that data points with similar characteristics cluster closely together. This analogy is fundamental to how k-NN works: it predicts the class of an unlabeled data point by examining the k nearest labelled data points in the training set. Like neighbours in a community share characteristics, the k-NN algorithm predicts the class label of the unlabeled point based on the most frequent class label among its k-nearest neighbours. This process resembles a form of collaborative decision-making [39, 40].

- **Support Vector Machine Algorithm:** Vladimir Vapnik formulated the concept of support vector machines (SVMs), also known as support vector networks, in the early 1960s. Researchers use these supervised learning algorithms for regression and classification tasks. Further advancements occurred in the late 1990s through collaborations with Corinna Cortes, Chris Burges, Alex Smola, and Bernhard Scholkopf. SVMs aim to construct a discriminative hyperplane that effectively separates data points belonging to different classes. The input data is often projected into a higher-dimensional feature space to achieve better separability [43, 44]. The SVM algorithm creates one or more hyperplanes in this high-dimensional space to delineate (or partition) the data into distinct classes. This approach is particularly well-suited for datasets with a clear separation between classes. SVMs are known for their ability to handle high-dimensional data and model non-linear relationships between variables [36, 39].

3.3.2 Unsupervised Learning

Unsupervised learning focuses on unveiling latent patterns in data without explicit classification. By employing unsupervised learning algorithms, machines autonomously discern patterns and create labels, particularly useful in fields like fraud detection [40].

Unsupervised datasets lack associated targets, presenting unique challenges compared to supervised datasets, where predefined labels guide learning [38]. In this paradigm, algorithms autonomously segregate samples based on inputs, enabling tasks such as clustering and dimensionality reduction [36, 37].

In unsupervised learning, the focus shifts to autoassociation input information, which reduces data dimensionality. Driven solely by input data correlations, unsupervised learning uncovers significant patterns without external guidance [41].

Furthermore, unsupervised learning deviates from supervised learning by eschewing labelled data reliance and specific prediction anticipation. Instead, its objective is to elucidate natural groupings or patterns latent within data elements or records [39], as illustrated in Figure 3.4.

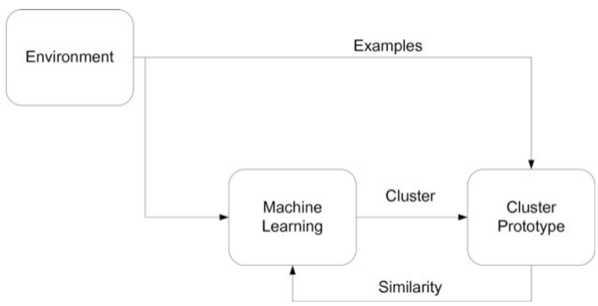


Figure 3.4: Unsupervised Learning Process [42]

3.3.2.1 Unsupervised Machine Learning Techniques

Unsupervised learning uncovers hidden patterns within unlabeled data, providing valuable insights for various applications. Here, we explore two essential techniques:

- **Clustering:** This task is grouping similar data points based on their characteristics. It enables the discovery of inherent structures within the data, forming clusters where objects within a cluster share a high degree of similarity. In contrast, objects in different clusters are more dissimilar. This technique is beneficial for analyzing large datasets and identifying previously unknown subgroups. K-means clustering is a popular method for achieving this partitioning, but various other clustering algorithms are available [36, 39, 40, 45].

- **Dimensionality Reduction:** This process involves reducing the number of features (dimensions) in a dataset while preserving the most critical information. By transforming high-dimensional data into a lower-dimensional space, dimensionality reduction simplifies it, making it easier to analyze and visualize. Additionally, it can enhance the efficiency of machine learning algorithms by mitigating the effects of the "curse of dimensionality." Principal Component Analysis (PCA) is a widely used method for dimensionality reduction, among many other available techniques [36, 39, 41, 45].

3.3.2.2 Common Unsupervised Learning Algorithms

After exploring the popular unsupervised learning techniques of clustering and dimensionality reduction, we explore two widely used algorithms for each technique: K-means clustering and Principal Component Analysis (PCA).

- **K-Means Clustering** is a popular unsupervised learning technique that divides data points into a predefined number (k) of clusters. The method optimizes the assignment of data points between clusters based on similarity. Initially, the process randomly selects k cluster centres or centroids. Each data point then assigns itself to the nearest centroid. The algorithm updates the centroids to align with the mean of the assigned data points. This cycle of reassigning data points and updating centroids continues until the centroids show little change, indicating convergence. This approach facilitates the discovery of underlying patterns in the dataset and is useful for tasks like data exploration, anomaly detection, and segmentation [36, 40].

- **Principal Component Analysis (PCA)** is a popular unsupervised dimensionality reduction approach. Its goal is to convert a dataset from a high-dimensional to a low-dimensional space while preserving as much of the original information (variance) as possible. The method achieves this by finding a new set of uncorrelated variables known as principal components (PCs), representing the directions of the highest variance in the data. These key components effectively indicate the most informative directions in the data. PCA provides various advantages, including data visualization in reduced dimensions, feature extraction for machine learning methods, and reducing the "curse of dimensionality" [36, 39].

3.3.3 Reinforcement Learning (RL)

Unlike supervised and unsupervised learning, which have predefined goals, reinforcement learning operates in an open-ended way. It does not require a pre-defined "correct answer" but instead learns through interacting with its environment. The learner (an agent) takes actions, receives feedback through rewards or penalties, and continuously refines its model based on these experiences, as illustrated in Figure 3.5. This iterative process mirrors how humans and animals learn through trial and error, constantly adapting their behaviour based on the outcomes of their actions [36, 39–41, 45].

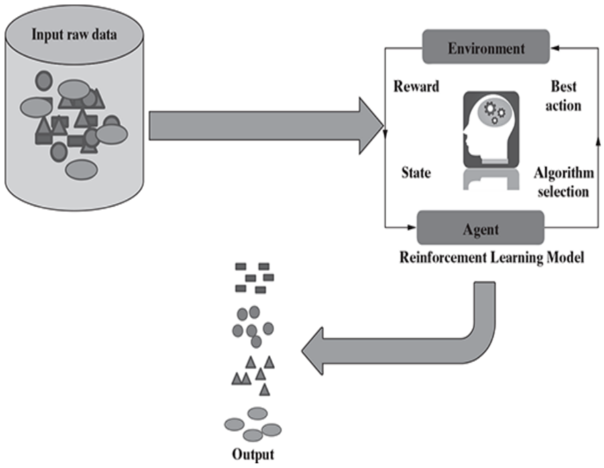


Figure 3.5: Reinforcement Learning Process [39]

3.3.3.1 Reinforcement Learning Types

Reinforcement learning (RL) equips agents to make optimal decisions in an environment by learning from rewards and penalties. However, the way agents acquire this knowledge differs between two main types [46]:

- **Model-Based Reinforcement Learning:** In model-based reinforcement learning, the agent comprehensively understands the environment, allowing it to predict the rewards of each action and prioritize those with the highest predicted rewards. This greedy method works best in static and predictable environments, where the agent builds an accurate model and uses it for efficient planning and strategy based on anticipated outcomes.

- **Model-Free Reinforcement Learning:** This type of reinforcement learning focuses on direct interaction with the environment. The agent does not rely on a pre-defined model but learns through trial and error. The agent explores different actions and observes the resulting rewards to gradually develop a strategy (policy) for maximizing future rewards in dynamic environments. There are two main approaches to categorize this method: value-based and policy-based.

3.3.3.2 Common Reinforcement Learning Algorithms

This section delves into two fundamental algorithms that play a crucial role in achieving this goal: Q-learning and SARSA. These algorithms and their variations form the backbone of many successful RL applications in robotics [36].

- **Q-learning:** This is a model-free, off-policy reinforcement learning algorithm. It utilizes a Q-function, which estimates the future reward an agent can expect by taking a specific action in a particular state. Through trial and error interactions with the environment, Q-learning updates this Q-function to learn the optimal policy (action selection strategy) for maximizing future rewards. Q-learning and its variations are the most commonly used RL methods in social robotics [36, 47].

- **SARSA (State-Action-Reward-State-Action):** This on-policy reinforcement learning algorithm estimates Q-values for actions in specific states by iteratively updating based on rewards and state transitions. Unlike Q-learning, SARSA uses the current policy to select the following action, influencing the Q-value updates for the initial state-action pair. This approach can lead to different learning paths and outcomes compared to Q-learning, as it follows the used policy [36, 45].

3.4 Deep Learning for Image Classification

Image classification using machine learning traditionally relied on feature extraction, a manual process in which experts select and extract essential image characteristics. This strategy had limitations:

- **Feature extraction:** It required extensive domain expertise, making it a time-consuming and challenging operation.

- **Insufficient Feature Representation:** Manually selected features often fail to capture the rich and complex information within images, thus limiting the accuracy of standard machine learning models.

Traditional methods in image classification often need help with complex data due to the need for manually-defined features. Deep learning overcomes this limitation by automatically learning these features directly from the data. With their multiple layers, deep neural networks excel at extracting progressively intricate characteristics from the image. This capability allows them to capture the image's underlying structure effectively. As a result, deep learning models often outperform traditional methods in image classification tasks, as demonstrated in Figure 3.6.This advancement can be attributed to two key factors: the availability of advanced hardware, such as powerful GPUs and specialized accelerators, which facilitate the training of complex models, and the development of innovative network architectures like Convolutional Neural Networks (CNNs). [48, 49].

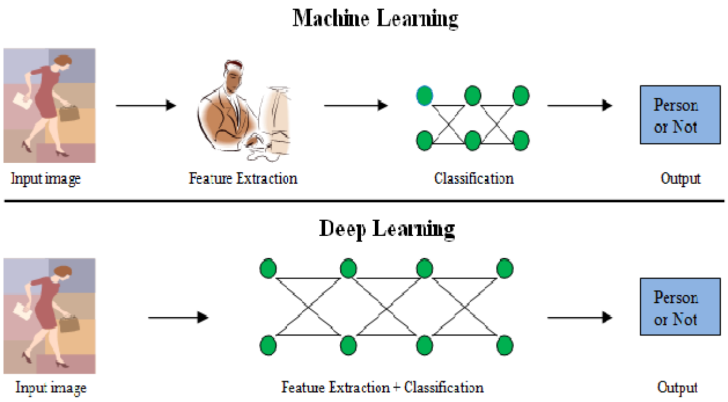


Figure 3.6: Machine Learning versus Deep Learning [50]

3.5 Artificial Neural Networks

Artificial neural networks (ANNs), the base of deep learning, have advanced long since their creation in the 1940s. They consist of perceptrons (processing units) structured into three layers: input (image data), hidden (information processing), and output (classifications). The complexity of the network is determined by its number of hidden layers and neurons [48, 51].

ANNs learn by training on labelled image data. The network learns to distinguish between classes by modifying connections in response to prediction errors. Deep ANNs perform feature extraction (automatically learning complicated features) and modelling non-linear relationships in image data, which are critical for effective classification [52].

Despite requiring significant computational resources and data, advancements in hardware (GPUs) and techniques like unsupervised pre-training improve the efficiency of deep ANN training for image classification. This foundation in ANNs paves the way for exploring the specialized architectures of deep learning models used in this field [49].

3.6 Artificial Neural Network Components

The essential building blocks of artificial neural networks (ANNs) define their structure and function. We will briefly review the main elements below:

- **Input Layer:** It acts as the network entry point, receiving the data's features (such as pixel intensities). Each feature has a corresponding node that feeds its value forward through connections to the next layer (often hidden). Notably, for one-dimensional data (e.g., Multilayer Perceptron), the input layer's shape must account for the training minibatch size. Ultimately, the input layer prepares the data for processing by subsequent layers, contributing to the final predictions at the output layer [53, 54].

- **Hidden Layers:** Artificial neural networks rely on hidden layers and internal processing stages in which interconnected neurons analyze and transform data. These layers progressively extract features, building on each other to uncover deeper patterns in the data. The number of hidden layers and neurons are crucial design choices tailored to the specific problem. Hidden layers, or "dense layers," are the engines that power neural networks' ability to learn and make predictions [40, 52, 55].
- **Output Layer:** It consists of neurons that transmit processed data to the external environment. In this layer, the network generates a response or prediction based on the input received from the input layer. The configuration of the ANN determines the type of final output, which can be continuous, binary, ordinal, or count. This output format depends on the activation function chosen for the neurons in the output layer [55].
- **Weights:** It represents the strength of connections between neurons. A lower weight indicates that the data passing through this connection has minimal impact on the final predictions. In contrast, a significant positive or negative weight modifies the information received by subsequent layers, which may impact predictions. This approach is similar to how brain cells communicate, with connections growing or decreasing as they acquire experience. As connections define specific brain regions activated or deactivated in response to processed informationConnections define brain regions activated or deactivated in response to processed information [51].
- **Biases:** It indicates the prediction baseline when all characteristics have zero values. In default prediction generation, bias can be a significant factor, mainly if some features are absent and have a zero value [51].
- **Activation Functions:** Neural networks rely on activation functions, which are the fundamental mechanisms within each neuron, to control the transformation of inputs into outputs. These functions act as calculators that process the combined influence of incoming neuron signals (weighted sum). After processing, activation functions determine whether the resulting value is significant enough to be passed on to the next layer. This thresholding process allows the network to focus on relevant information and introduces non-linearity, a critical factor in solving complex problems. Activation functions act as decision gates, determining which signals are strong enough to influence the network's overall prediction [51, 55].
  - **Sigmoid Function (Logistic Function):** It converts different inputs into probabilities ranging from 0 to 1. Its S-shaped curve introduces critical non-linearity for tackling complex tasks. The popularity of this function stems from

its alignment with probabilistic models and binary classifications. However, vanishing gradients, where error signals diminish during training, limit its effectiveness in deeper networks. Therefore, alternative activation functions may be necessary for deeper architectures. This function is represented as [51, 55]:

$$A(x) = \frac{1}{1 + e^{-x}}$$

.

- **Tanh Function:** It offers a compelling alternative to the sigmoid function in ANNs and DNNs. Both share a sigmoidal output curve, but Tanh's key advantage lies in its broader output range (-1 to 1) compared to sigmoid's 0 to 1. This seemingly minor difference translates to a significant benefit: Tanh is less susceptible to the vanishing gradient problem, a hurdle that hinders learning in deep networks. While not entirely immune, Tanh offers a clear advantage over sigmoid, potentially leading to faster learning [51, 55]. As shown in the equation below, the Tanh function is represented as:

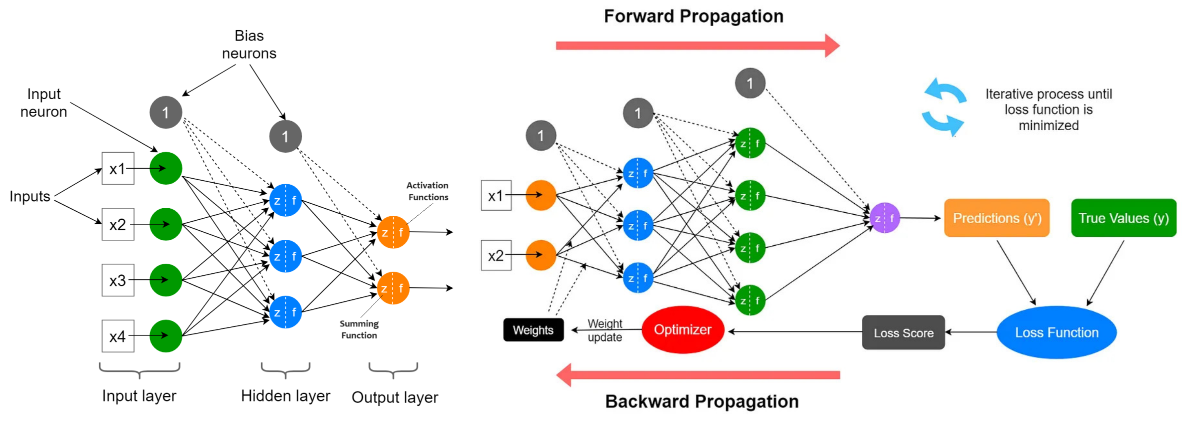
$$A = \left(\frac{2}{1 + e^{-2x}}\right) - 1$$

.

- **ReLU Function (Rectified Linear Unit):** has emerged as a dominant choice in artificial neural networks (ANNs) and deep neural networks (DNNs) due to its efficiency and ability to overcome limitations present in previous activation functions. Unlike sigmoid and Tanh functions with their sigmoidal curves, ReLU operates according to a segmented linear rule. For negative input values, ReLU outputs zero. However, for positive input values, ReLU maintains a linear relationship, essentially acting like a standard identity function $g(z) = \max(0, z)$ [55].
- **Softmax Function:** Similar to the sigmoid function, the softmax function manages categorical outcomes in multinomial labelling systems. It converts the model's outputs into a probability distribution, enabling more nuanced predictions [55, 56]. It can be defined as [56]:

$$f(x)_j = \frac{e^{x_j}}{\sum_{k=1}^{K} e^{x_k}}, \quad j = 1, \ldots, K.$$

- **Loss Function / Cost Function:** The loss function and cost function are conceptually similar. Both serve as quality checks, regularly assessing the difference between the network's predictions and actual values. The loss function calculates a specific error metric for each data point, providing valuable feedback on network performance. Iterative optimization procedures like gradient descent use this data to improve the network's internal parameters (weights and biases). Consider the loss function to be a teacher who regularly corrects the network's errors, allowing it to change and improve its predictions over time. The critical difference lies in scope: the loss function focuses on a single data point, while the cost function aggregates the error across the entire training dataset [39, 55].



a. b.

Figure 3.7: Artificial Neural Network Components: (a) Basic NN Layers [57], (b) An overview of the neural network training process [58].

3.6.1 Hyperparameters

Hyperparameters are essential for optimizing neural network performance and efficiency. These settings, determined before training, such as learning rate and regularization methods, influence how the model learns from data and adapts to unseen information.

- **Learning Rate:** It is a crucial hyperparameter in neural network training and determines the magnitude of steps taken during optimization. Typically defined as a small positive value (0.0 to 1.0), it controls the amount of weight adjustment per iteration, affecting both efficiency and convergence. A higher learning rate offers faster learning but risks suboptimal weights, while a lower rate allows for more precise adjustments and potentially leads to a global optimum. However, setting the learning rate too low may extend training or halt convergence, locking the model inefficiently. Therefore, selecting the correct learning rate is critical for balancing training speed with achieving an optimal solution [52, 59].

- **Regularisation:** It is a technique in machine learning that prevents overfitting, where a model learns to memorize training data rather than generalize well to new, unseen data. The aim is to encourage simpler models that perform better on out-of-sample data. There are several methods of regularisation, including L1 (Lasso penalization), L2 (Ridge penalization), L2-L1 (Elastic Net penalization), and the dropout method.

- The L1 regularization method compels numerous weights to assume zero value, encouraging a sparse distribution in the model's weights.
- L2 penalizes the squared values of the weights, shrinking them towards zero.
- L2-L1 regularisation strikes a balance between the L1 and L2 methods.
- The dropout method randomly turns off a certain percentage of neurons during training, preventing the network from becoming too dependent on specific neurons or features.

The choice of regularisation method depends on the specific characteristics of the data and the problem at hand. Ultimately, regularisation improves the model's performance and generalization capabilities, leading to better results on unseen data [52, 55].

3.6.2 Optimizers

Optimizers guide neural network training, ensuring efficient and effective learning tailored to the specific problem. Optimizers guide neural network training, ensuring efficient and effective learning tailored to the specific problem. Achieving this involves continuously fine-tuning the network's internal parameters (weights and biases) based on the calculated loss function. This function measures the discrepancy between the network's predictions and reality. The chosen optimization algorithm minimizes the loss function, leading to more accurate network predictions. Selecting the right optimizer is crucial, as different algorithms offer distinct strengths and weaknesses [51, 55].

- **Gradient Descent** is a workhorse optimizer in deep learning, helps models learn by iteratively adjusting weights based on the loss function (a guide for minimizing error). Each step refines the performance until the loss reaches a desired level, indicating an optimal configuration [51].

- **Stochastic Gradient Descent (SGD)** is a variant of the traditional gradient descent algorithm designed for faster training. Unlike standard gradient descent, which uses the entire dataset for each update, SGD utilizes a single data point (extreme case) or a small batch of data points (mini-batch) in each iteration. This approach allows SGD to process large datasets that would not fit in memory at once, potentially leading to faster convergence due to more frequent parameter updates [51, 52, 55].

- **Adaptive Moment Estimation (Adam)** has become dominant in deep learning optimization. Unlike traditional gradient descent algorithms that rely on a single, fixed learning rate for all parameters, Adam tackles a fundamental challenge: determining the optimal learning rate for each parameter within the network. This personalized approach leads to faster convergence and potentially superior performance [55].

- **Root Mean Square Propagation (RMSprop)** is a powerful optimizer that addresses the limitations of gradient descent. While gradient descent can struggle with oscillations, RMSprop incorporates momentum for smoother learning. Crucially, it also introduces adaptive learning rates. RMSprop adjusts the learning rate for each parameter based on its past behaviour, using recent gradient magnitudes to prevent excessive updates for noisy parameters and accelerate learning for stable ones. This approach leads to faster convergence and makes RMSprop a valuable tool for deep learning tasks [60].

3.7 Types of Artificial Neural Networks

Artificial neural networks (ANNs) are versatile machine learning tools. They come in many forms, each suited for specific tasks. This variety in structure allows them to tackle a wide range of problems. The following section will explore some of the common types of artificial neural networks:

3.7.1 Recurrent Neural Networks (RNNs)

The 1980s saw the emergence of Recurrent Neural Networks (RNNs), tailored specifically to excel with sequential data such as time series. Unlike standard neural networks, RNNs feature a unique looped structure within their hidden layers. This loop endows them with the ability to retain past information from preceding inputs, providing a "memory" crucial for tasks such as language translation (remembering a sentence's subject for subsequent verb translation) and discerning relationships between events, even when widely spaced in the sequence (as illustrated in Figure 3.8). This memory offers additional advantages, including parameter efficiency through parameter sharing across time steps and compatibility with convolutional layers for tasks involving sequential data with spatial information, such as image captioning. Despite encountering challenges like vanishing gradients during training, RNNs remain a potent tool for many applications reliant on sequence comprehension [61, 62].

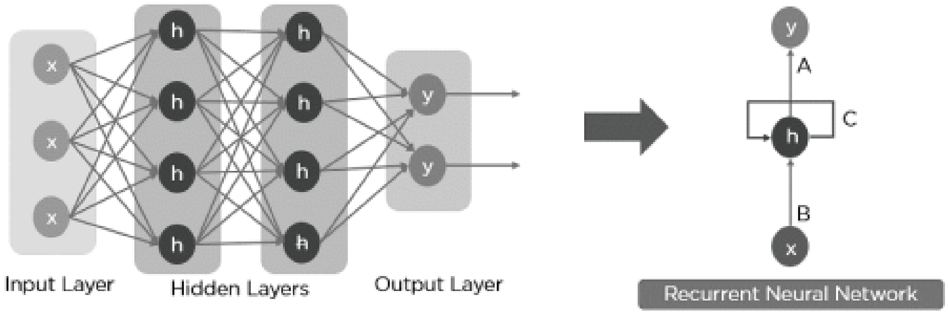


Figure 3.8: Recurrent neural network (RNN) architecture [36]

3.7.2 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are artificial neural networks inspired by the animal visual cortex, renowned for their success in image recognition and computer vision tasks. They have a unique architecture with neurons arranged in three dimensions, allowing them to process spatial relationships and reduce complexity. CNNs extract features from input data through convolution, using weight sharing to improve efficiency. They can directly work with raw images, simplifying tasks like image classification and object detection (Figure 3.9). However, their layered architecture makes design and maintenance more challenging, and training is computationally expensive and slower [62–64].

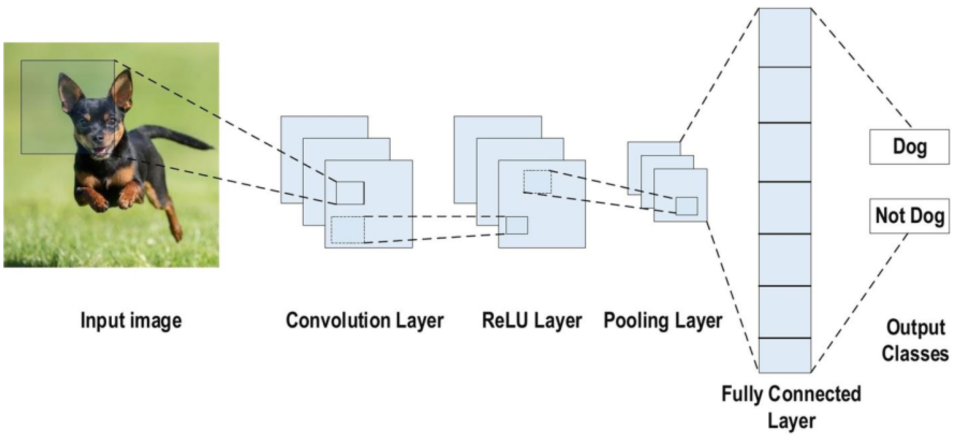


Figure 3.9: Example of CNN Architecture [65]

Convolutional neural networks (CNNs) consist of several vital layers that work together to extract and process features from input data. These layers include convolution, pooling, fully connected, and dropout layers, each serving a unique function in the network's architecture. Here is a brief overview of these essential components:

- **Convolution Layer** is the main component of any CNN, following the input layer and is where most computations occur. Here, multiple filters, small in height and width but spanning the entire image depth, scan across the input image. These filters act as feature detectors, searching for specific patterns within the image. By convolving the filters with the input, the convolutional layer generates feature maps that highlight the presence and location of these detected features within the image [50, 63, 66], As illustrated in Figure 3.10.

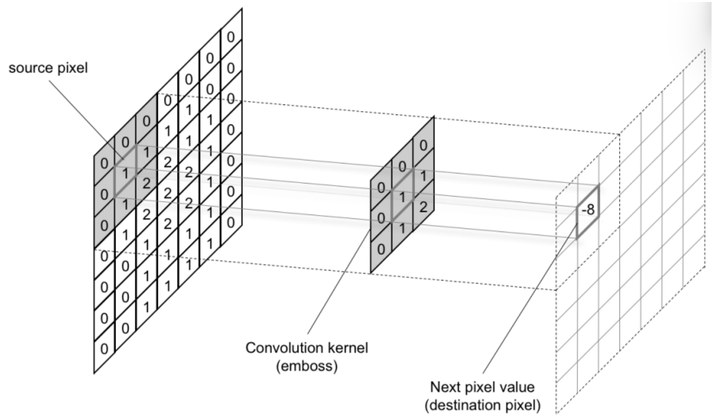


Figure 3.10: Diagram illustrating the convolution operation [51]

- **Pooling Layer**, situated between convolution layers, plays a pivotal role in reducing the spatial resolution of the feature maps. They effectively downsample the image by selecting the maximum or average value within defined pooling regions. Specifically, four principal types of pooling layers exist (Figure 3.11): Max pooling, which consistently chooses the most significant value in the region; Average pooling, which computes the mean within the region; Global max pooling, and Global average pooling [51, 54].

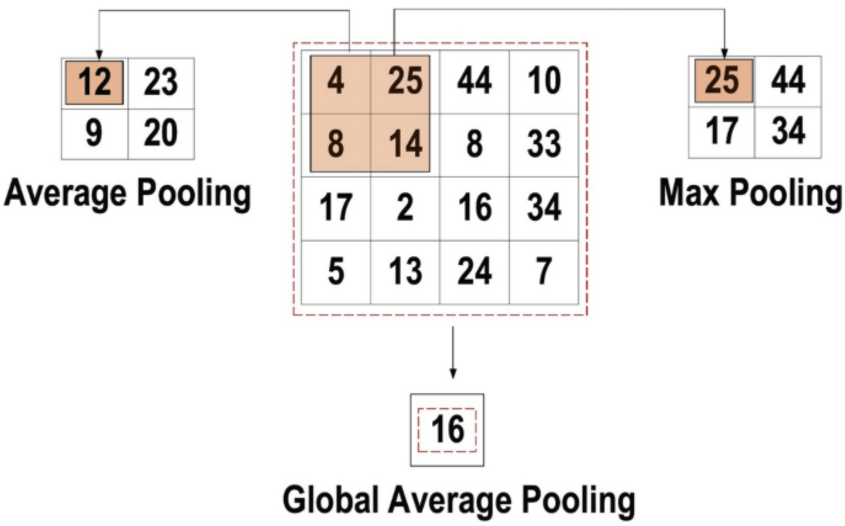


Figure 3.11: Example illustrating the pooling layer types [67]

- **Fully Connected Layer (FCN)** represents the final phase of a Convolutional

Neural Network (CNN), following the convolution and pooling layers. This specific layer requires a 1D vector as input, achieved by flattening the incoming 3D vector. The FCN is responsible for classification, and it combines information from previous layers to make predictions about the image category, providing probabilities for each classification. Every node in the FCN layer connects to all nodes in the previous layer, correlating with the number of target classes. Using the softmax activation function, the FCN produces probabilities for each target class, ensuring that the sum of all softmax values equals 1 [56, 62].

- **Dropout Layer** represents a common technique in convolutional neural networks (CNNs) to enhance model generalization and reduce overfitting. During training, approximately 50% of neurons undergo random deactivation, disrupting overly reliant connections and encouraging acquiring novel, distinct characteristics. As a result, the network is less prone to overfitting and demonstrates improved performance on unseen data [62].

3.7.3 Transfer Learning

Transfer learning utilizes pre-trained models, initially trained on extensive datasets like ImageNet, to address novel tasks, particularly in situations with limited data availability. Transfer learning significantly reduces the need to gather large amounts of new data by using the learned features from one domain in another. Adapting a pre-trained model's architecture, typically a deep CNN, to suit the new task involves replacing its output layer and fine-tuning it on the target dataset (Figure 3.12). This strategy has demonstrated its effectiveness in various domains, such as image classification, by training only the newly added layers, thus decreasing the time required for training and the data volume needed [56, 62, 68].

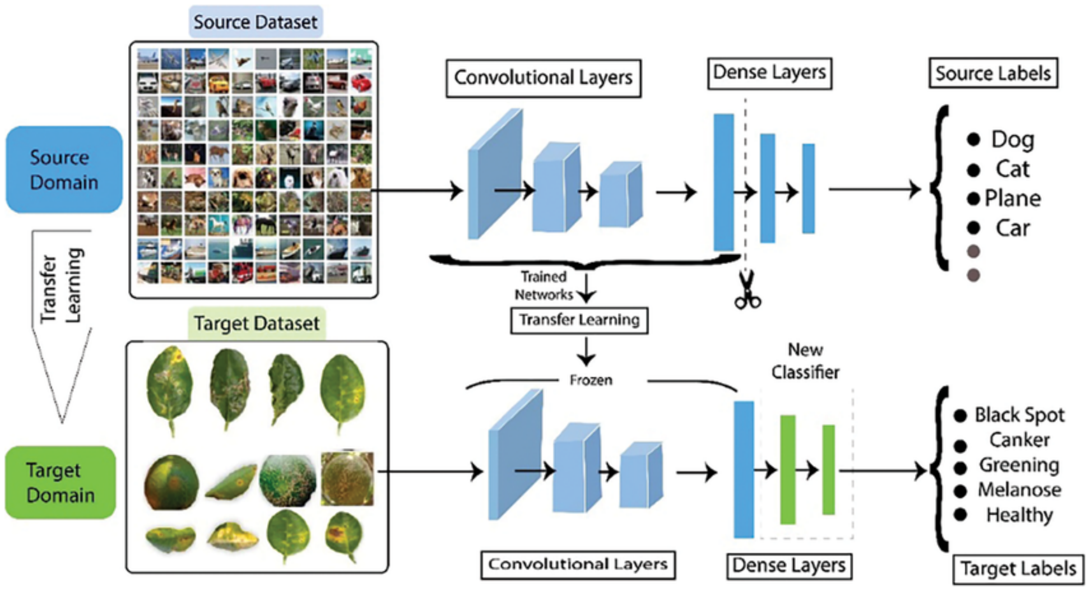


Figure 3.12: The architecture of transfer learning [69]

3.7.3.1 Pretrained CNN Architectures

Pretrained Convolutional Neural Network (CNN) architectures significantly advance deep learning by offering robust models adaptable to various tasks. Each architecture introduces unique innovations that enhance performance and suitability for different applications. Below, we explore some of the most influential pretrained CNN architectures.

- **VGGNet:** It devised by Simonyan and Zisserman from the University of Oxford in 2014, represents a significant advancement in CNN architecture. The model, available in configurations with 16 and 19 layers, employs 3x3 filters with a stride and padding of size one and 2x2 max pooling with a stride of 2. This strategic design reduces the number of parameters while improving the depth of the network. Despite reducing image size due to max pooling, the number of filters increases with each layer, ensuring robust feature extraction. VGGNet-16 features an astonishing 138 million parameters. However, its parameter uniformity remains commendable, with a consistent increase in filter count as the network deepens. This architectural simplicity (Figure 3.13), coupled with the use of small-sized filters, underscores VGGNet's popularity and efficacy in image classification tasks [52, 63, 66].

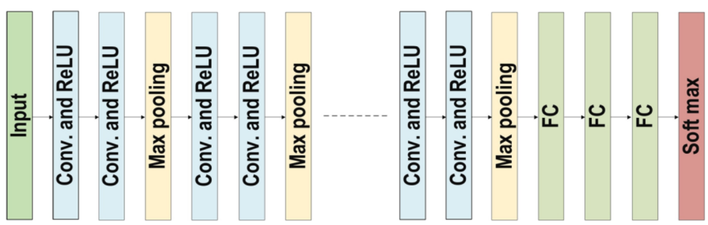


Figure 3.13: VGG16 architecture [65]

- **ResNet:** In 2015, He et al. from Microsoft Research introduced ResNet, a breakthrough architecture that achieved remarkable success in the ImageNet competition. This achievement challenged the conventional wisdom that increasing network depth leads to overfitting due to vanishing gradients or a high number of parameters. The core innovation of ResNet lies in its use of residual blocks. These blocks cleverly connect layers within the network, facilitating the flow of gradients during training and addressing the vanishing gradient problem prevalent in deep CNNs (Figure 3.14). By allowing the network to learn residual functions related to the layers' input, residual blocks allow efficient optimization and improved accuracy even with a greater network depth [52, 63, 66].

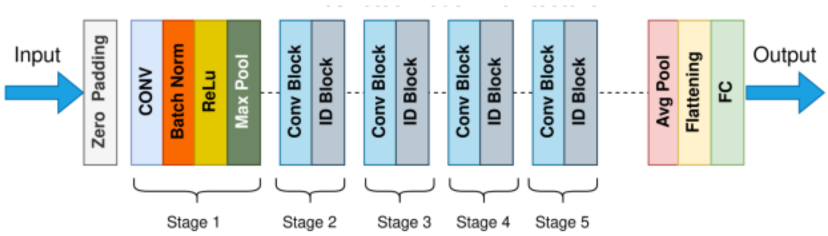


Figure 3.14: ResNet architecture [70]

- **GoogleNet Inception Module:** Szegedy et al. (2014) revolutionized CNNs with GoogleNet, featuring the groundbreaking Inception module. This innovation secured victory in the ImageNet image classification competition. At its core, the Inception module enables flexible layer utilization. Unlike traditional CNNs, Inception modules employ multiple filter sizes (kernels) within a single layer (e.g., 1x1, 3x3, 5x5). This design allows for the simultaneous detection of low-level details and higher-level abstractions, which improves classification performance. GoogleNet leverages parallel processing within Inception modules to efficiently create high-dimensional feature maps [52, 66].

- **MobileNetV2 Module:** It is a CNN architecture designed for mobile devices, featuring 32 initial convolution layers and 19 bottleneck layers. It offers robust performance with minimal memory consumption and facilitates fast transaction execution. Its predecessor, MobileNetV1, introduced Depthwise Separable convolution and gained recognition for its lightweight nature. Both models accept input images of 224 x 224 pixels or 300 x 300 pixels, making them suitable for SSD backbone networks. The critical innovation in MobileNetV2 is the 'Inverted Bottleneck Residual Block.' This block incorporates a bottleneck layer and a residual connection, allowing the network to process information more efficiently while maintaining accuracy [68, 71]. Figure 3.15 presents the architecture.

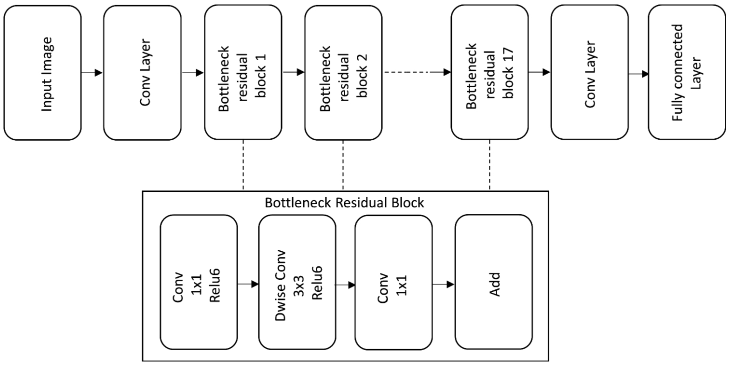


Figure 3.15: MobileNetV2 architecture [71]

3.7.3.2 Fine-tuning

Fine-tuning is crucial in transfer learning for convolutional neural networks (CNNs). This technique effectively leverages pre-trained models for new tasks, especially with limited data. It optimizes a pre-trained model by adjusting its final layers to fit the new task.

During fine-tuning, practitioners typically freeze the pre-trained model, which serves as a vital feature extractor, except for the final layers. They then train these final layers and any new classifier layers added for the specific task simultaneously. The objective is to progressively adjust the higher-level feature representations of the pre-trained model to fit the new classification task better. Fine-tuning allows the network to specialize its later layers for the new data while preserving the valuable general knowledge acquired during pretraining, thereby mitigating overfitting [71].

3.8 Evaluation Metrics

Assessing the effectiveness of an image classification model involves using a range of metrics to evaluate how well it can accurately predict. These metrics provide valuable insights into the strengths and weaknesses of the model, aiding in guiding its further development and optimization. Below are some commonly used metrics:

- **Confusion matrix** is a valuable tool for evaluating a model's performance by comparing predicted results against actual values. It provides a detailed breakdown of the model's predictions, including the number of true positives, true negatives, false positives, and false negatives. In addition, it offers information on the specific types of errors the model makes. Furthermore, the confusion matrix is the foundation for calculating various other metrics, such as accuracy, Precision, Recall, and specificity [72], as illustrated in figure 3.16. True Positive (TP) refers to correctly classified positive samples, while True Negative (TN) refers to correctly classified negative samples. False Positive (FP) indicates incorrectly classified positive samples, and False Negative (FN) indicates incorrectly classified negative samples [71].

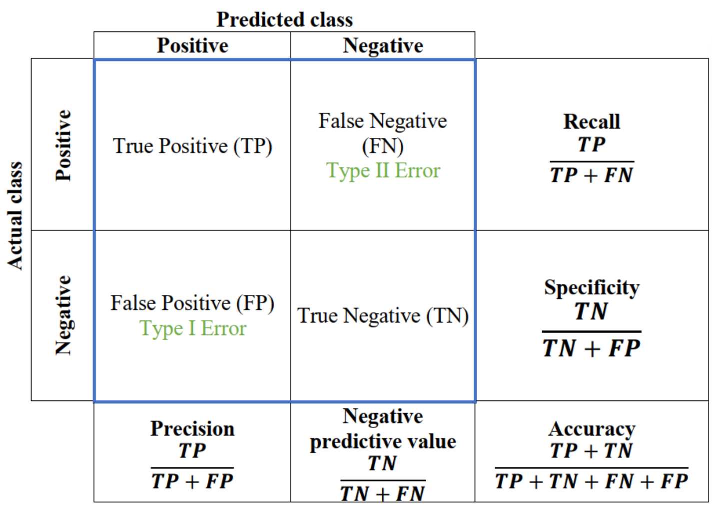


Figure 3.16: Confusion matrix with the equations for evaluation metrics [72]

- **Accuracy** quantifies the overall correctness of a model by dividing the total number of correct classifications, including both true positives and true negatives, by the total number of classifications performed. It provides a straightforward assessment of the model's accuracy, indicating how well it performs across all classes. Nonetheless, accuracy alone may not provide detailed insights into the model's performance on specific classes, mainly when dealing with imbalanced datasets or when focusing solely on positive or negative predictions, which is defined as follows [38, 39, 48]:

$$\text{Accuracy Score} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision**: Also known as a positive predictive value, measures the accuracy of optimistic predictions by determining the proportion of correctly predicted positive cases among all instances predicted as positive, as calculated as [65, 73]:

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (sensitivity)** focuses on a model's ability to identify all relevant positive cases within a dataset comprehensively. It calculates the proportion of actual positive instances the model correctly classified, providing insight into how well it captures true positives. [60, 65].

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-score** is a metric used in classification tasks to balance the model's performance between Precision and Recall. The F1 score aims to capture how well the model identifies true positives while also minimizing false positives. A high F1-score indicates a good balance between these two aspects [38, 39].

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **AUC - ROC Curve**: It is a graphical tool used to visualize the trade-off between True Positive Rate (TPR) (Recall) and False Positive Rate (FPR) (1-Specificity). A higher ROC curve indicates better performance, while a higher AUC indicates a better ability to distinguish positive from negative cases. The optimal operating point on the ROC curve minimizes the distance between correctly classifying positive and negative cases, determined by locating the nearest distance d to point (0, 1.0) in the curve [74].

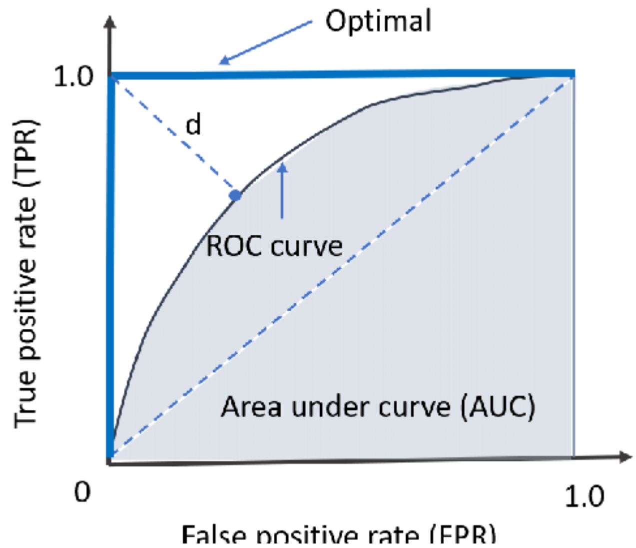


Figure 3.17: AUC - ROC Curve [74]

- **Cohen's kappa**: It is a metric used to assess agreement between two ratings. A high score (closer to 1.0) indicates strong agreement, meaning the ratings are similar. Conversely, a low score (closer to 0) suggests significant differences. It is beneficial for classification tasks with N distinct categories, where a good metric reflects how close the ratings are to achieving the same classification [75].

- **Matthew's correlation coefficient (MCC)** is a metric for evaluating classification models that consider all aspects of a confusion matrix (correct and incorrect classifications for both positive and negative cases). Introduced in 1975, MCC gained popularity in the 2000s and was used in various machine learning competitions [75]. MCC ranges from -1 to 1. 1 is perfect prediction, -1 is imperfect prediction, and 0 is random prediction. The formula for MCC is [38]:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (FN + TN) \times (FP + TN) \times (TP + FN)}}$$

3.9 Conclusion

This chapter has established the foundation of machine learning for image classification, focusing on Deep Learning and Convolutional Neural Networks (CNNs). We have explored various CNN architectures and underscored the importance of evaluating their performance using a variety of metrics. With ongoing advancements in CNN technology, we anticipate even greater accuracy and efficiency in automated sorting systems.

The next chapter will delve deeper into this dynamic field, investigating how researchers have utilized Deep Learning, CNNs, and other AI techniques to tackle similar challenges across diverse agricultural domains. Through thoroughly examining these studies, we aim to extract best practices applicable to our case study on automated date fruit sorting. This exploration will pave the way for developing a robust and efficient date fruit sorting system.

Chapter 4

Literature Review

4.1 Introduction

The agricultural sector is significantly transforming by integrating artificial intelligence (AI). This transformation drives automation and substantially improves quality control processes' efficiency, accuracy, and consistency. This chapter delves into the fascinating world of machine learning techniques applied to agricultural product classification, focusing on date fruit classification.

Section 4.2 explores Traditional Machine Learning versus Deep Learning Techniques, comparing their strengths and weaknesses. Traditional Machine Learning methods are known for their high interpretability but often require manual feature extraction. In contrast, Deep Learning Techniques, especially Convolutional Neural Networks (CNNs), excel by automatically learning features from raw data, enhancing classification accuracy.

Section 4.3 is dedicated to a Date Fruit Classification case study. We identify their respective advancements and limitations by meticulously analyzing traditional and deep learning approaches. This analysis involves a comprehensive review of the literature and practical experiments. We utilize comparison tables to present our findings, which can guide future research and help determine the most effective method for accurate date fruit categorization based on various quality parameters.

4.2 Application of Artificial Intelligence Systems in Agricultural Products

Artificial intelligence (AI) in agriculture has gained significant traction, particularly in classifying, sorting, and grading fruits and vegetables. This technology aims to enhance the efficiency, accuracy, and consistency of quality control processes. The literature reveals a wealth of research focused on developing AI systems for these tasks, utilizing traditional machine learning techniques and more advanced deep learning approaches. This section is divided into two subsections, each exploring this literature in detail.

4.2.1 Classification Using Traditional Machine Learning Techniques

Traditional machine-learning techniques have been widely employed in classifying and sorting agricultural products. Omidi Arjenaki et al. (2013) developed a machine vision system to sort tomatoes by shape, maturity, size, and defects, as outlined in their study [76]. The system utilized a CCD camera to capture images of the tomatoes. To differentiate between healthy, immature, and defective tomatoes based on colour, the researchers employed thresholding techniques, precisely the Otsu method, which achieved the best results in defect classification compared to other methods tested. Thresholds for other sorting tasks were established based on specific image features: minimum fullness for defect sorting, quartile values of eccentricity for shape sorting, 2-D area quartile values for size sorting, and the range of mean colour components for maturity sorting. The system was evaluated using 210 tomato samples and achieved individual accuracies of 84.4% for defect detection, 90.9% for shape classification, 94.5% for size classification, and an overall system accuracy of 90%.

In another study, D. Martínez Gila et al. (2015) [77] investigated the classification of olive batches (tree or soil) using image processing and machine learning techniques. Their study focused on three olive varieties (Picudo, Picual, and Hojiblanco) originating from Priego de Cordoba, Spain. The researchers used a combination of image processing and Principal Component Analysis (PCA) to extract relevant features from webcam images (Logitech QuickCam SphereTM), capturing 176 olives (77 from trees and 99 from soil). The classification was achieved using Fisher Discriminant Analysis, with wrinkles on the olive skin and colour being the primary features. This approach achieved high accuracy (over 98%).

The proposed work in [78] of M.M. Sofu et al. (2016) addresses the problem of designing an automatic apple sorting system using machine vision. This work proposes a system consisting of roller, transporter, and class conveyors combined with an enclosed cabin with machine vision, load cell, and control panel units. This type of fruit is sorted by its colour, size, weight, and then detected mechanical damages like scabs, stains and rot. They captured four (4) images of each apple rolling on the conveyor and used two channels, so it captured eight images at the same time. It used a C4.5 decision tree as a classifier, resulting in an average sorting accuracy rate of 73.96%.

Jyoti Jhawar (2016) [79] proposed an automated grading of oranges system which selected a Maharashtra orange variety of India as an experimental dataset. In this work, the oranges were classified into four classes(Not Ripe, semi-ripe, ripe and over ripe), and the system extracted only four features from the RGB image as a total number of pixels, the mean value of red, green and blue colours in the fruit. To achieve their goal or aim, they used three experiments (Nearest-Neighbor Prototype, Edited Multi-seed Nearest-Neighbor Technique which blended three techniques (edited nearest-neighbour, K-nearest-neighbor and K-means) which extracted two seed points for each class, and then the K-means algorithm evaluated these two seed points which calculate the distances using City block distance metric, the class of orange is the nearest value to the sample. The last technique is linear regression, which is used to predict the classes of maturity level of fruit. It used a three-feature red, blue, and green average to calculate a ripeness measure. This work achieved 92.93%, 89.90 %, and 97.98 % when using the Nearest Prototype, Edited Multi-Seed Nearest Neighbor, and Linear Regression, respectively.

Megha et al. (2016) [80] addressed the challenge of grading tomato quality in India by dividing their system design into hardware and software components. Using image processing techniques, they aimed to classify tomatoes based on defect and ripeness (Defective, Non-Defective, Ripe, Unripe). During the feature extraction and selection phase, nine statistical features were extracted using the MATLAB platform. These features included the colour mean, standard deviation, skewness for each colour channel (red, green, and blue) and colour texture features derived from the image's grey-level co-occurrence matrix (contrast, correlation, energy, and homogeneity). A multi-layer neural network classifier was employed for the classification. The system achieved high accuracy, correctly classifying tomato images as defective/non-defective and ripe/unripe with 100% and 96.47% accuracy, respectively.

Payman Moallem et al. (2017) [81] proposed a computer vision system to grade golden apples from Iran. This system tackles the apples' health status (healthy/ defective) and quality level (first-class, second-class, rejected). First, the system performs pre-processing steps to remove the stem and calyx regions, which can interfere with defect detection. Stem removal utilizes morphological methods for external stems and a Mahalanobis classifier for internal stems based on colour space analysis. Following pre-processing, the system extracts various features from the apple images, including statistical, textural, and geometric characteristics. These features are then fed into different classifiers, including Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), and K-Nearest Neighbor (KNN). The system achieved the highest recognition rate using the SVM classifier, reaching 92.5% accuracy for healthy vs. defective classification and 89.2% for three-class quality grading.

In the same year, Hosein Nouri-Ahmadabadi et al. [82] developed a sorting system of peeled pistachio into two classes of pistachio kernels (PK) and pistachio shells (PS) using a Support Vector Machine, for the extraction features step they converted an RGB colour space to HSV which using an H-component and Otsu thresholding method, a 30 colour features they used as input vector of the classifier system which used statistically indexed (the five indices ' Mean, Variance, Skewness, Rang, Kurtosis' for each sample in the images were extracted from the components of RGB and HSV colour spaces), for their implementation used 240 samples for training and validation and 120 samples for testing. Their system achieved 99,58% and 99,17% for training and testing accuracy, respectively.

Traditional machine learning models, such as decision trees and linear regression, offer simplicity and interpretability, making it easier to understand how decisions are made. They are effective with smaller datasets, which is beneficial when large amounts of labelled data are unavailable and generally require less computational power and resources than deep learning models, making them more accessible for implementation in environments with limited computational capacity. However, traditional techniques often rely on manual feature extraction, which can be time-consuming and may only capture some relevant data features.

Deep learning has emerged as a powerful alternative to address the limitations of traditional machine learning, such as the need for manual feature extraction. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated higher accuracy in image classification tasks due to their ability to learn and extract complex features from raw data automatically. The following subsection will delve into how deep learning techniques have been applied to classify and grade fruits and vegetables.

4.2.2 Classification Using Deep Learning Techniques

Deep learning techniques have revolutionized agricultural product classification by providing higher accuracy and robustness compared to traditional methods. The following research supports this.

In a study by Shadman Sakib et al. (2019) [83], the Fruits-360 dataset comprising 25 categories of fruits was utilized to train and evaluate a CNN-based classifier. The dataset, consisting of 14,258 training images and 3,565 testing images, encompassed a diverse range of fruit types. Using a CNN architecture with a batch size of 15 and an Adam optimizer with a learning rate of 0.002, the model achieved impressive results, boasting a training accuracy of 99.79% and a testing accuracy of 100%. These findings underscore the effectiveness of CNNs in fruit recognition tasks and highlight their potential for real-world applications in agriculture and the food industry.

Ranjit K.N. et al. (2019) [84] proposed a two-stage deep learning method for accurate fruit disease detection and classification. In the first stage, a novel quad-tree approach efficiently identifies potential disease regions by analyzing pixel homogeneity within image subsections. This approach reduces the computational burden in the subsequent stage. The second stage leverages a deep learning architecture with six hidden layers for disease classification. The model was trained on a substantial dataset of 40,000 images containing 1,000 diseased and non-diseased samples for each of the 20 fruit classes. The researchers used convolutional neural networks (CNNs) and a Stochastic Gradient Descent Momentum (SGDM) optimizer with a learning rate of 0.1 for 50 epochs to achieve optimal performance. This two-stage approach achieved significant accuracy, outperforming traditional classifiers (SVM, KNN) in detection and classification tasks. The study demonstrates the effectiveness of deep learning for automated fruit disease analysis, particularly its ability to handle many fruit classes while maintaining high accuracy. Notably, the reported accuracy was 0.86% before image segmentation (BS) and improved to 0.93% after segmentation (AS), highlighting the benefit of the preprocessing stage in identifying regions of interest.

Leveraging transfer learning, Juan Ponce et al. (2019) [85] conducted a study on the classification of olive-fruit varieties using Convolutional Neural Networks (CNNs). Their research focused on olive samples from Gibraleon, Spain, collected in 2018, including several olive varieties. The study evaluated several popular CNN architectures, including AlexNet, InceptionV1, InceptionV3, ResNet-50, ResNet-101, and Inception-ResNetV2, trained using the Adam optimizer with a learning rate 0.001. The dataset consisted of 2,800 samples, and each variety comprised 400 olive fruits. Preprocessing techniques, utilizing machine vision methods, were applied to extract features from the images. Among the CNN architectures, Inception-ResNetV2 demonstrated the highest average hit rate of 95.91% and exhibited superior average probability values for correct classification, demonstrating its effectiveness for olive variety classification. While all CNNs achieved notable performance, AlexNet and InceptionV1 displayed comparatively lower accuracy, suggesting limitations for this classification task. The study highlights the importance of fruit morphology as a pivotal feature for olive variety classification through CNN-based approaches.

Shuxiang Fan et al. (2020) [86] investigated an innovative approach for automated Apple defect detection using Convolutional Neural Networks (CNNs). Their study, conducted on apples from China in 2020, involved the classification of apples into normal and defective categories using both CNNs and Support Vector Machines (SVMs). For

SVMs, the means and standard deviations of the R, G, and B components were utilized as textural features. Meanwhile, the CNN approach incorporated textural features such as entropy, energy, correlation, contrast, and homogeneity, employing stochastic mini-batch gradient descent with a learning rate of 0.001 and a batch size of 16. Testing on a dataset comprising 200 apples revealed CNN's superior performance, achieving an accuracy of 96.5% compared to SVM's accuracy of 87.1%. Furthermore, independent validation confirmed CNN's effectiveness, achieving an accuracy of 92% with a processing time of under 72 milliseconds for six images of a single apple. Notably, the CNN-based method surpassed the traditional image processing approach (SVM), showcasing its potential for real-world implementation in fruit sorting machines owing to its high accuracy and efficiency.

Pandey et al. (2021) [87] investigated the potential of deep learning for mango cultivar recognition in India. Their study employed four pre-trained convolutional neural network (CNN) architectures: AlexNet, GoogLeNet, ResNet50, and VGG16. These models were evaluated on a dataset curated for Indian mangoes, encompassing nearly 1850 images representing 15 popular cultivars. The evaluation results demonstrated the effectiveness of transfer learning for this task. GoogLeNet achieved the highest F1 score (87.62%) with a low false positive rate (0.008), outperforming the other three CNN models (AlexNet: 85.88%, ResNet50: 86.61%, VGG16: 86.23%).

Tapia-Mendez et al. (2023) [88] executed a novel study classifying 32 distinct fruits and vegetables categories using advanced deep learning models, also examining their ripeness level. They used a dataset sourced from Kaggle, each labelled as either "fresh" or "rotten." Notably, the authors employed two prominent deep learning architectures, MobileNet V2 and InceptionV2, to develop dedicated models for each task: classification and ripeness assessment. Intriguingly, the MobileNet V2 model emerged as the standout performer across both tasks, showcasing its versatility and efficacy in fruit and vegetable analysis. Specifically, the MobileNet V2 model achieved an exceptional accuracy rate of 97.86% in classifying the 32 produce types, underscoring its robustness in distinguishing between a diverse range of fruits and vegetables. Moreover, in evaluating ripeness across 12 classes of fresh and rotten stages, the MobileNet V2 model demonstrated unparalleled precision, achieving a flawless accuracy rate of 100%. These findings underscore MobileNet V2's suitability and superiority for such applications, offering valuable insights into its potential for advancing the field of agricultural classification and assessment.

Deep learning techniques have significantly advanced the classification and sorting of agricultural products, offering several key advantages. Deep learning models, particularly Convolutional Neural Networks (CNNs), demonstrate high accuracy and robustness, particularly with complex and high-dimensional image data, effectively outperforming traditional methods. They automate feature extraction, eliminating the need for manual feature engineering and domain-specific knowledge. These models are scalable and adaptable, handling the ever-growing volumes of agricultural image data and fine-tuning pre-trained models for various agricultural products.

With advancements in hardware and algorithms, deep learning models can achieve real-time processing, facilitating on-the-fly classification and sorting in agricultural environments while remaining robust to variability in lighting and angle. However, deep learning techniques also have limitations, including high computational requirements, the need for large annotated datasets, complexity and interpretability challenges, and the risk of overfitting.

To better understand the differences between traditional machine learning and deep learning techniques, Table 4.1 summarising a comparison of the studies mentioned above is provided below.

Now that we have a comprehensive understanding of both traditional and deep learning techniques and their strengths and weaknesses in agricultural product classification, we can delve deeper into our study on date fruit classification. In the following section, we will embark on a meticulous analysis of this domain. We will explore the methodologies, datasets, feature extraction techniques, and classification algorithms employed in prior studies.

Through a comparative assessment of traditional machine learning models and deep learning architectures, we aim to identify the most optimal approach for accurately categorizing date fruits based on various quality parameters.

Authors (References)	Variety/Origin	Classes/Grades	Techniques (Models)	Parameters (Features)	Database (Samples)	Accuracy (%)
Omidi Arjenaki et al. (2013) [76]	Tomatoes (Iran)	Desirable/ Undesirable	Threshold Techniques	Shape (Eccentricity), Maturity (Color), Size (Area), Defects (Visual)	210	90.61
D. Martínez Gila (2015) [77]	Olives (Spain)	Tree or Soil	Fisher Discriminant Analysis	Wrinkles, Color	176	>98
M.M. Sofu et al. (2016) [78]	Apples (Turkey)	Golden, Starking Delicious, Granny Smith	Decision Tree (C4.5)	Colour, Size, Weight, Defect	183	73.69
Jyoti Jhawar (2016) [79]	Oranges (India)	Not Ripe, Semi Ripe, Ripe, Over Ripe	Multi-Seed Nearest Neighbor	Red, Green, Blue Color Mean	80 (Test)	89.9
			Linear Regression			92.93
			Nearest Neighbor			97.98
Megha Araker (2016) [80]	Tomatoes (India)	Defective/Non-Defective	Multilayer Neural Network	9 Color Stats, 12 Color Texture Features	520	100
		Ripe/Unripe				96.47
Moallem P (2017) [81]	Apples (Iran)	Healthy/Defected	SVM	16 Features (Statistical, Textural, Geometric)	120	92.5
		1st, 2nd Class, Rejected				89.2
Hosein Nouri-Ahmadabadi et al. (2017) [82]	Peeled Pistachios (Iran)	Pistachio Kernels / Shells	Support Vector Machine (SVM)	30 Color Features	360	99.17
Shadman Sakib et al. (2019) [83]	Fruits-360 Dataset	25 Categories	CNN	Batch Size 15, Adam Optimizer (lr=0.002)	14,258 Train / 3,565 Test	99.79 Train 100 Test
Ranjit K N et al. (2019) [84]	20 Fruit Types	Diseased, Non-Diseased	CNN (6 Layers)	SGD Momentum (lr=0.1), 50 Epochs	40,000	Before Seg: 0.86 After Seg: 0.93
Juan Ponce et al. (2019) [85]	Olives (Spain, 2018)	Different Varieties	AlexNet	Adam (lr=0.001)	2,800	89.9
			Inception-ResNetV2			91.81
			InceptionV1			94.86
			InceptionV3			95.33
			ResNet-50			94
			ResNet-101			95.91
Shuxiang Fan et al. (2020) [86]	Apples (China, 2020)	Normal/Defective	CNN		200 (Test)	96.5
			SVM	Textural Features (CNN), Color Stats (SVM)		87.1
Chanki Pandey et al. (2021) [87]	Mangoes (India)	15 Varieties	AlexNet	Not Specified	1,850	85.88
			GoogLeNet			87.62
			ResNet50			86.61
			VGG16			86.23
Tapia-Mendez et al. (2023) [88]	From Kaggle (Global)	32 Fruits and Vegetables	2x MobileNet V2 (Type , Ripeness)	Not Specified	3,360 (168 Test)	97.86
		(Fresh/Rotten)				100

Table 4.1: A Comparison Table Between Traditional and Deep Learning Techniques in Agricultural Product Classification

4.3 Date Fruit Classification: Traditional and Deep Learning Approaches

Dates hold significant economic and cultural value across various regions worldwide. As the demand for standardized quality and efficient processing methods increases, artificial intelligence (AI) systems rapidly transform the date fruit sorting and grading landscape. This section delves into the evolution of sorting techniques, highlighting the transition from traditional methodologies to the revolutionary impact of deep learning approaches. We will explore how AI empowers automated sorting systems, leading to greater consistency, efficiency, and ultimately, a higher quality of date fruit products reaching consumers.

4.3.1 Date Fruit Classification Systems Using Machine Learning

Traditional sorting and grading methodologies have long been the foundation for automated classification tasks in date fruit processing. Researchers have explored various techniques, ranging from statistical analysis to machine learning algorithms, for accurate and efficient sorting.

Djeffal et al. (2010) [89] investigated the application of Support Vector Machines (SVM) in automated classification tasks. Their study analysed single-view image images of dates, extracting length, width, colour, volume, and homogeneity features. These features were then used to train an SVM model capable of classifying dates into six categories (Standard, Fraza, Small Fruit Standard, Small Fraza Fruit, Stained Fruit, Boufarwa). Notably, the system achieved a high training accuracy of 98.85% on a dataset of 353 samples, demonstrating the potential of machine learning for automated date sorting.

In this context, Al Ohali (2011) [90] explored the application of computer vision technology for the automated grading and sorting of date palm fruits. Their innovative system used RGB images of date fruits to extract a comprehensive range of predefined external quality features. These encompassed critical attributes such as size, shape, colour, wrinkles, and the identification of defects such as bruises and bird pecks. Employing these extracted features, the researchers implemented a sophisticated back-propagation neural network classifier to categorize dates into three distinct quality tiers. Impressively, their system achieved an accuracy rate of 80% when tested on a sizable dataset comprising 1,200 training and 660 testing samples. This research underscores the potential of computer vision techniques in revolutionizing date fruit quality assessment and highlights the promise of improved efficiency and consistency in the date grading process.

The researchers Tavakolian et al. (2013) [91] successfully employed FT-NIR spectroscopy and advanced statistical analysis to achieve a significant breakthrough in date fruit processing. This technique enables the non-destructive classification of various date palm cultivars, focusing on discriminating between six cultivars (five Iranian date fruits and Tunisian Deglet Noor) with over 90% accuracy. Moreover, FT-NIR spectroscopy, coupled with the application of Partial Least Squares (PLS) analysis on aggregate data, showed promising potential for estimating critical quality parameters such as soluble solids content (SSC) and dried matter composition (DM). That eliminates the need for destructive testing, streamlining the sorting process and ensuring consistent quality. The real-time nature of FT-NIR spectroscopy makes it ideal for integration into date fruit processing facilities, enabling efficient quality control measures.

In 2014, Mohana et al. [92] introduced an innovative approach for grading Indian date fruit, categorizing them into six distinct grades based on surface hardness and size. The grades included hard surfaces with small and large sizes, semi-hard surfaces with small and large sizes, and soft surfaces with small and large sizes. Using a Sobel operator to capture the shape features, the authors employed perimeter, area, major-axis length, minor-axis length, eccentricity, and equidiameter measurements derived from the fruit's contour. Additionally, they utilized texture analysis, extracting features through Local Binary Pattern (LBP) mapping to compute mean and standard deviation values.

Mohana et al. employed three classification techniques for the grading process: the K-NN classifier, Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA) classifiers. Among these, the K-NN classifier demonstrated superior performance, achieving an accuracy of 96.45%. This robust accuracy surpassed the performance of the SVM and LDA classifiers, showcasing the effectiveness of the proposed grading methodology in accurately categorizing date fruit based on its distinctive characteristics.

Building upon the existing research on shape and texture analysis for date fruit classification, Ghulam Muhammad (2015) [93] investigated the use of Support Vector Machines (SVM) for classifying four distinct Saudi Arabian date varieties: Ajwah, Sagai, Sellaj, and Sukkary. His approach went beyond traditional methods by incorporating colour information alongside the standard shape and size features. Notably, the study achieved a remarkable classification accuracy of 98.1% using a combination of Weber Local Descriptor (WLD) texture descriptors, shape and size features, and the YCbCr colour space (with a dataset of 800 samples, 200 per variety). This finding highlights the potential of WLD descriptors as a powerful feature extraction method for accurate date variety classification, mainly when used in conjunction with SVM classifiers.

Oussama Aiadi et al. (2016) [94] delved into the classification of Algerian date fruit varieties, focusing on seven cultivars cultivated in Touggourt, Algeria, using Support Vector Machines (SVM). Their focus was on leveraging a combination of shape and colour features to achieve accurate classification. Comprising a dataset of 350 meticulously curated date fruit samples, the researchers meticulously partitioned 280 specimens for the learning phase and reserved 70 for rigorous testing. Notably, the SVM-based classification methodology exhibited remarkable prowess, boasting an impressive accuracy rate of 97.14%. Such high accuracy demonstrates the power of machine learning in identifying subtle differences among Touggourt date fruit varieties. Encouraged by this success, Aiadi et al. (2017) [95] explored an alternative approach, proposing a novel method for automatic date fruit classification using a Gaussian Mixture Model (GMM). Their study focused on ten Algerian date varieties (Ajina, Adam Deglet Noor, etc.) and employed a combination of colour histogram, texture, and shape features for classification. Utilizing a dataset of 5,000 date images and the Calinski-Harabasz index for cluster evaluation, their method achieved a high accuracy of 97.49%. This work highlights the potential of GMM for accurate date variety classification and emphasizes the effectiveness of combining multiple feature types.

Annamalai et al. (2018) [96] investigated date fruit classification based on hardness for three major Omani growing regions. Their study employed two machine learning approaches: Linear Discriminant Analysis (LDA) and Artificial Neural Networks (ANN). Feature extraction focused on histogram and texture characteristics, utilizing a dataset of 1,800 date fruit samples. The three-class model (soft, semi-hard, and hard) achieved classification accuracies of 66% and 71% for LDA and ANN, respectively. Interestingly, accuracy improved to 84% and 77% for LDA and ANN when using a simplified two-class model (combining soft and hard dates). This finding suggests that distinguishing between two hardness categories might be more efficient. Additionally, the study revealed that histogram features were more influential than texture features for hardness classification. Finally, the analysis of mean grey values indicated that hard dates were significantly brighter than softer varieties.

While traditional methodologies have achieved commendable results, they have limitations, as discussed in 4.2.1. Transitioning to deep learning for date fruit classification represents a paradigm shift. Deep learning offers the advantage of automated feature learning, enhancing accuracy and efficiency.

4.3.2 Application of Deep Learning in Date Fruit Classification

Building upon the foundation in section 4.2.2, deep learning emerges as a transformative force for agricultural processes, particularly in sorting. Convolutional Neural Networks (CNNs) have been at the forefront of this revolution, demonstrating remarkable effectiveness in automating and streamlining date fruit sorting. These CNN-powered systems achieve superior precision, significantly improving efficiency and accuracy compared to traditional methods. We will delve into specific examples of these studies to showcase the practical applications of deep learning in revolutionizing date fruit sorting.

Researchers Nasiri et al. (2019) [4] used image-based deep learning to conduct an innovative study on the automatic sorting of Shahani date cultivars from Iran. The study classified date fruits into four categories: Khalal, Rutab, Tamar, and defective dates. By employing the well-known VGG-16 convolutional neural network model, they achieved an impressive 96.98% classification accuracy. Their dataset comprised 1,300 high-quality images processed over 25 training epochs with the RMSProp optimizer. This approach demonstrates the transformative impact that advanced image-based deep learning methods can have on the automated sorting and grading of date fruits, paving the way for more precise and efficient agricultural practices.

Hamdi Altaheri (2019) [6] conducted a notable study to explore the effectiveness of deep learning models in classifying date fruits based on type, maturity stages, and readiness for harvesting, aiming to assist in the development of robotic harvesting systems in orchard environments in Saudi Arabia. Utilizing a large dataset of over 8,000 samples, divided into training and testing sets for both date type (4,530 training samples and 3,542 testing samples) and maturity stages (3,227 training samples and 3,420 testing samples), the study fine-tuned two deep learning architectures, VGG-16 and AlexNet. Trained using different learning rates (0.002 for VGG-16 and 0.0001 for AlexNet) and optimized with the Stochastic Gradient Descent (SGD) optimizer, the models employed data augmentation techniques to enhance robustness and generalisability. The VGG-16 model outperformed AlexNet across all categories, achieving 99.01% accuracy for date type classification, 97.25% for maturity classification, and 98.59% for harvest readiness classification, compared to AlexNet's 96.51%, 94.98%, and 95.51%, respectively. These results demonstrate the superior performance of VGG-16 in capturing intricate visual features necessary for accurate classification and suggest significant potential for developing automated systems for date fruit harvesting. Altaheri's research underscores the potential of deep learning models, particularly VGG-16, in automating date fruit classification and harvesting, with future research opportunities to integrate these models into fully automated robotic systems and to expand the dataset to improve robustness and adaptability.

Alhamdan et al. (2021) [97] conducted a comprehensive study to classify nine different types of Saudi Arabian date fruits using various convolutional neural network (CNN) models. Leveraging a dataset available on Kaggle comprising 1,658 samples, the research demonstrates the application of deep learning techniques to improve the accuracy and efficiency of date fruit classification. In their work, they developed and compared four different CNN models, each with distinct configurations and training parameters. The 48-4L model optimized with SGD at a learning rate of 0.001 achieved 96% accuracy without data augmentation or noise. The 65-4L model, using Adagrad with data augmentation and L2 regularisation, achieved 95% accuracy. The 70-4L model, utilizing Adam with a meagre learning rate and noise but without augmentation, achieved the highest accuracy of 97%. The 74-4L model, also using Adagrad with data augmentation and noise, had the lowest accuracy at 91%. These results indicate that different configurations and training strategies significantly impact the performance of CNN models in date fruit classification. The high accuracy rates across all models demonstrate the potential of CNNs in this application, although the specific approach and parameters need careful optimization to achieve the best results.

Dalila Pérez-Pérez et al. (2021) [98] conducted an in-depth study on the classification of Mexican dates harvested in 2020 to determine their ripeness. Using a dataset of 1,002 images categorized into ripe and unripe, they employed various state-of-the-art deep learning models, including pre-trained architectures such as VGG-16, VGG-19, Inception V3, ResNet-50, ResNet-101, ResNet-152, and AlexNet, and a custom CNN model built from scratch for comparison. The models were trained with different configurations, including epochs (25 and 400), batch sizes (64 and 128), and optimizers (Adam and SGD), with learning rates of 0.001 and 0.01. VGG-19 achieved the highest accuracy of 99.32%, highlighting its superior performance in classifying the ripeness of date fruits. While other models performed well, they did not match the accuracy of VGG-19. While useful as a baseline, the custom CNN outperformed the pre-trained models, demonstrating the advantage of leveraging pre-trained architectures for complex classification tasks. The study underscores the importance of selecting the exemplary model architecture and training parameters to achieve optimal performance in image classification tasks.

Khalied Albarrak et al. (2022) [7] conducted a pivotal study on classifying Saudi Arabian dates using advanced deep learning techniques, focusing on distinguishing between eight different classes of date fruits with the MobileNetV2 architecture. Utilizing a dataset of 1,717 date fruit samples, the researchers trained their model over 100 epochs with an adaptive learning rate, starting at 0.0001 and decaying by the number of epochs. Various preprocessing and model-tuning techniques, such as data augmentation, model checkpointing, and dropout, were employed to enhance performance. To evaluate their model, Albarrak et al. compared it against three other models: Model I, which used MobileNetV2 with a superficial classification layer of eight nodes, achieving 64% accuracy; Model II, which featured a more complex classification layer with five layers, achieving

85% accuracy; and Model III, which involved freezing the pre-existing layers for the first 20 iterations, resulting in 88% accuracy. The proposed model outperformed all three, achieving an impressive 99% accuracy, thanks to the integration of customized classification layers and advanced preprocessing and model tuning techniques.

A comprehensive comparison table has been compiled to explore date fruit classification methodologies, detailing the efficacy of traditional and deep learning approaches in date fruit classification (Table 4.2).

The studies conducted by Nasiri et al. (2019)[4], Altaheri (2019)[6], Alhamdan et al. (2021)[97], Pérez-Pérez et al. (2021)[98], and Albarrak et al. (2022)[7] collectively contribute valuable insights into the application of deep learning in date fruit classification. However, despite their notable achievements, certain common limitations persist across these works. One recurring constraint is the reliance on limited data, often single-sided images, which impedes the model's ability to capture all relevant fruit features. This limitation can lead to incomplete assessments and potentially inaccurate classifications, particularly concerning features that vary across different sides or angles.

Moreover, while these studies excel at classifying general quality parameters, they often need to pay more attention to the specific criteria outlined in international quality standards established by organizations such as the Food and Agriculture Organization. Integrating these standards into the classification process could enhance real-world applicability. Additionally, the exclusive use of RGB images limits the input data's scope, neglecting complementary information that could improve classification accuracy. Incorporating data such as weight measurements or internal defect detection using techniques like infrared imaging (IR) could offer a more comprehensive picture of fruit quality.

Despite these limitations, these studies represent significant advancements in date fruit classification using deep learning. By addressing these issues, we can unlock the full potential of this technology for developing even more robust and comprehensive systems in the future.

Reference (Authors)	Variety/Origin	Classes/Grades	Techniques (Models)	Parameters (Features)	Database (Samples)	Accuracy (%)
Djeffal et al. (2010) [89]	Biskra, Algeria	6	SVM	Length, width, color, volume, homogeneity	353 (training)	98.85
Yousef Al Ohali (2011) [90]	Saudi Arabia	3	Back-propagation Neural Network	Size, Shape, Color, Wrinkles, Defects	1200 (training), 660 (testing)	80
Mohammad Tavakolian et al. (2013) [91]	Iran and Tunisia	6 cultivars	PLS	Soluble solids, dry matter, firmness	600 (100/each cultivar)	92.3
Mohana et al. (2014) [92]	India	6 grades	K-NN	Shape, Texture	960	96.45
			SVM			91.66
			LDA			98.58
Ghulam Muhammad (2015) [93]	Saudi Arabia	4 types	SVM	Color, texture, shape, size	800 (200/each type)	98.1
Oussama Aidi et al. (2016) [94]	Touggourt, Algeria	7 varieties	SVM	Shape, colour	350 (280 training, 70 testing)	97.14
Aiadi et al. (2017) [95]	Algeria	10 varieties	GMM	Color histogram, texture, shape	5,000 images	97.49
Annamalai et al. (2018)[96]	Oman	3 grades (soft, semi-hard, hard)	LDA	Histogram, texture	1800	66 (three classes), 84 (two classes)
			ANN			71 (three classes), 77 (two classes)
Amin Nasiri et al. (2019) [4]	Iran (Shahani cultivar)	4 classes (Khalal, Rutab, Tamar, defective)	VGG-16	25 epochs, RMSProp optimizer	1300 images	96.98
Hamdi Altaheri (2019) [6]	Saudi Arabia	Type (5), Maturity (7), Harvest Decision	VGG-16	Lr =0.002 , SGD optimizer	8000	Type: 99.01%, Maturity: 97.25%, Harvest: 98.59%
			AlexNet	Lr= 0.0001, SGD optimizer		Type: 96.51%, Maturity: 94.98%, Harvest: 95.51%
Alhamdan et al. (2021) [97]	Saudi Arabia (available on Kaggle)	9 types	CNN : 48-4L: no augmentation/ no noise	SGD, lr = 0.001, Batch size: 32,Epochs: 200	1658	96
			CNN : 65-4L: with augmentation,no noise	Adagrad, lr= 0.01, L2=0.005, batch-size=50, epochs =1000		95
			CNN: 70-4L: without augmentaion/with noise	Adam, lr= 0.000001, epochs=1500		97
			CNN : 74-4L: with augmentation and noise	Adagrad		91
Dalila Pérez-Pérez et al. (2021) [98]	Mexico	Ripe/Unripe	VGG-16, VGG-19, Inception V3, ResNet-50, ResNet-101,ResNet-152, AlexNet,CNN from scratch)	Epochs = 25 and 400, Batch = 64 and 128, Optimizers = Adam, SGD, Learning rate =0.001, 0.01	1002 images	The best VGG-19 (99.32)
Khalied Albarrak et al. (2022) [7]	Saudi Arabia	8 classes	MobileNetV2	Adaptive Learning Rate, INITLR = 0.0001, decay = INITLT/EPOCHS, epochs=100	1717	99

Table 4.2: A Comparison Table Between Traditional and Deep Learning Techniques in Date Fruit Classification

4.4 Conclusion

This chapter provides a comprehensive overview of artificial intelligence's transformative impact on agricultural product classification, explicitly focusing on date fruit classification. By thoroughly exploring traditional machine learning and deep learning techniques, we have identified the strengths and limitations of these methods in automating classification processes.

The evolution of classification techniques for date fruits has been examined, showcasing the significant advancements achieved through the application of deep learning, particularly Convolutional Neural Networks. As we look to the future, the role of AI in agriculture appears bright, holding immense potential for further improving efficiency and accuracy in agricultural quality control processes. However, it is essential to acknowledge that relying solely on RGB images and limited datasets can restrict the model's ability to capture all relevant features. Therefore, utilizing larger, more diverse datasets and incorporating additional data points, such as weight or infrared imaging for internal defect detection, could offer a more comprehensive picture of fruit quality.

Additionally, integrating international quality standards into the classification process can further enhance the capabilities of classification systems, ultimately benefiting the agricultural industry and ensuring the delivery of high-quality products to consumers worldwide.

Part II:

CONTRIBUTIONS

Chapter 5

Improving date fruit sorting with a novel multimodal approach and CNN

5.1 Introduction

As the global popularity of date fruit rises, traditional sorting methods face significant challenges. These manual processes are time-consuming, prone to errors, and lead to inconsistent quality. This situation presents an opportunity to use AI innovation. Automating sorting with deep learning can revolutionize the industry, ensuring consistent quality and enhanced efficiency.

This chapter presents a solution to the limitations of traditional date fruit sorting by achieving a more efficient and accurate automated Algerian date sorting. We created our dataset, which contains two famous varieties: Deglet Noor and Mech Degla.

Our contribution focuses on developing a robust automated system based on multimodal data of date fruit. This system combines visual (RGB and thermal images) and physical data (weight) to provide a comprehensive characterization of each date fruit. By leveraging Convolutional Neural Networks (CNNs), the system extracts key features from this rich data and performs automated classification for sorting purposes. We will evaluate the system's performance using various metrics, demonstrating its effectiveness in addressing a critical challenge in the date fruit sorting process.

The remaining sections of this chapter will detail our research methodology, including dataset acquisition, proposed architecture, and data preprocessing techniques. We will also present experimental results and their significance and conclude with findings and potential future research directions.

This contribution was published in the International Journal of Advances in Soft Computing and its Applications in 2023. The published article is entitled Improving Date Fruit Sorting with a Novel Multimodal Approach and CNNs [1].

[1]http://ijasca.zuj.edu.jo/PapersUploaded/2023.3.13.pdf

5.2 The Proposed Method

Previous works on the date fruit classification have often relied on single RGB images, which do not capture the full range of visual and physical characteristics necessary for accurate and efficient sorting. These methods are limited by their inability to provide comprehensive data, leading to suboptimal performance in classification tasks. In response to these limitations, our proposed method leverages a combination of data modalities and deep learning techniques to improve the accuracy and efficiency of date fruit classification, as depicted in Figure 5.1.

Our proposed method begins with Data Acquisition and Preprocessing. We built a comprehensive dataset by collecting multiple data types for each date fruit: four RGB images captured from various angles to capture the fruit's visual characteristics, one thermal image to provide insights into internal properties such as maturity or defects, and weight data as a quantitative measure of size and potential maturity. During preprocessing, the RGB images are converted to grayscale to simplify the visual information, and image averaging is used to create a single image that represents the average visual properties, reducing noise and highlighting key features. We also customize the channel values, combining the grayscale image, thermal image, and weight data into a multi-channel format to enhance the deep learning model's ability to utilize diverse data.

The dataset is then divided into training (70%), validation (20%), and testing (10%) sets. In the Model Selection and Training phase, we experiment with various Convolutional Neural Networks (CNNs), including VGG16, InceptionV3, ResNet50, and a CNN model from scratch. These models are trained on the training set, with the validation set used to fine-tune the models and prevent overfitting. This process optimizes the models' ability to extract relevant features from the multimodal data for accurate classification.

In the Testing and Evaluation phase, we evaluate the trained models on the testing set using performance metrics such as accuracy, precision, and recall to assess their effectiveness comprehensively. Finally, we develop a practical application using the best-performing CNN model. This application classifies date fruits into specific varieties, such as Deglet-Noor and Mech-Degla. Each variety is graded into five grades based on quality. This method addresses the limitations of previous approaches by incorporating multiple data modalities and advanced deep learning techniques to achieve superior classification performance.

5.2.1 Dataset Acquisition

A comprehensive dataset is essential to train and evaluate deep learning models effectively. In our research, we constructed such a dataset encompassing two distinct Algerian date fruit varieties: Deglet Noor and Mech Degla, each categorized into five quality grades

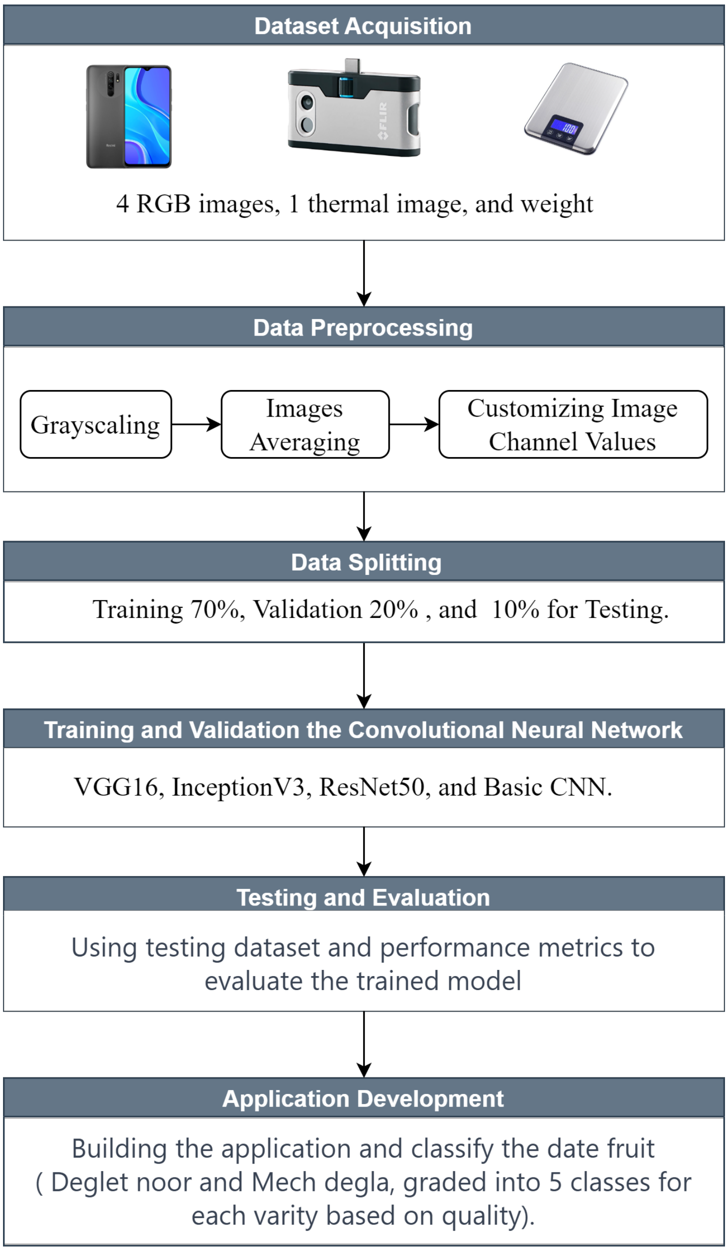


Figure 5.1: Flowchart Illustrating the Processing of Multimodal Data for Date Fruit Classification with CNNs

(Grades 1-5) based on visual appearance, internal properties, and weight, as illustrated in Figure 5.2.

To ensure our proposed multimodal classification system achieves reliable sorting results, we meticulously constructed a balanced dataset of 1,103 date fruits, encompassing both Deglet Noor and Mech Degla varieties. For Deglet Noor, we collected 109, 105, 69, 104, and 80 fruits in Grades 1-5, respectively. Similarly, Mech Degla is represented by 63, 120, 203, 140, and 110 fruits in Grades 1-5, respectively. We captured a rich data set for each fruit: four RGB images from various angles using an RGB camera for detailed visual information, a single thermal image using a FLIR camera to analyze internal characteristics, and weight measurements with a high-precision scale (as illustrated in Figure

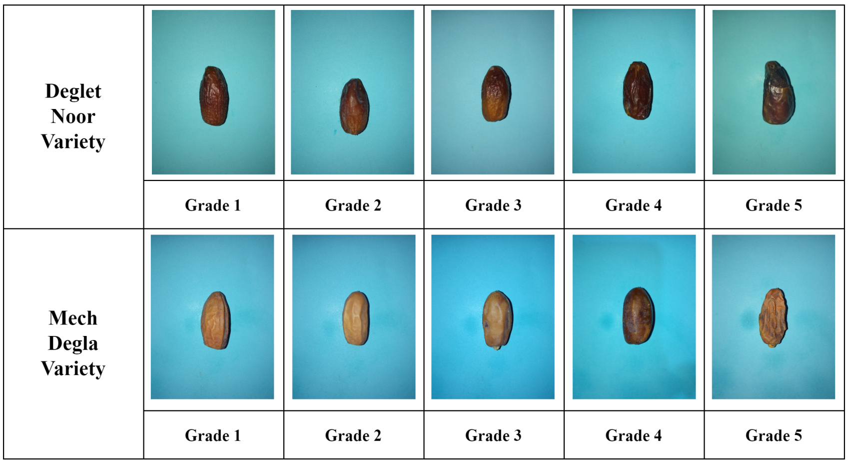


Figure 5.2: Examples of Date Fruit Varieties in Our Dataset (Deglet Noor and Mech Degla)

5.3). This diverse data collection forms the foundation for our multimodal data fusion model, enabling it to comprehensively characterize each date fruit and achieve accurate classification for automated sorting.

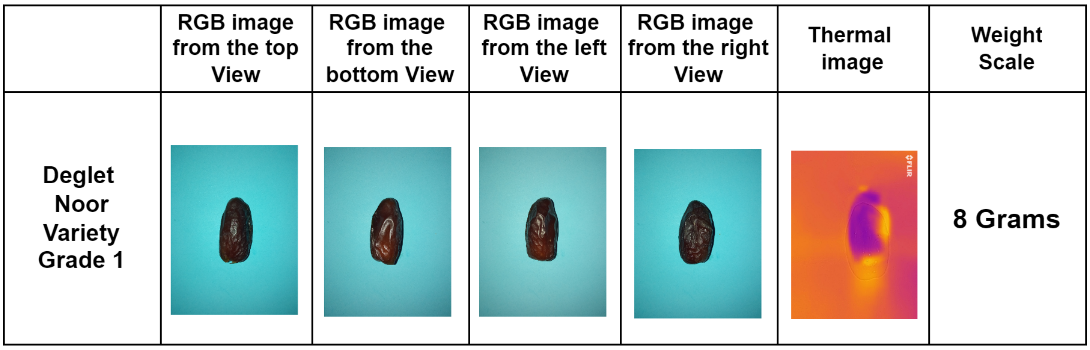


Figure 5.3: Example of a Deglet Noor Date Fruit (Grade 1) with Highlighted Features

The RGB images provided detailed visual characteristics, the thermal images offered insights into internal properties, and the weight data indicated size and maturity. We ensured high-quality image capture and consistency with a controlled setup that included consistent lighting from four fluorescent lamps, a uniformly coloured blue background, and no size restrictions during image capture to accurately reflect real-world scenarios.

This meticulous approach resulted in a comprehensive and well-balanced dataset suitable for training and evaluating deep-learning models for date fruit classification and quality grading.

5.2.2 Data Preprocessing

Data preprocessing is an essential stage in the machine learning workflow. It bridges the gap between raw data and the format required by specific algorithms. This stage involves a series of transformations that normalize and enrich the data to improve the effectiveness and efficiency of subsequent analysis.

In our study on date fruit classification using deep learning, we implemented a meticulous sequence of operations tailored to our multimodal dataset. This sequence consisted of three key steps designed to enhance the data representation and facilitate optimal model performance:

5.2.2.1 Image Grayscale Transformation

A crucial step in the data preprocessing stage involved applying a grayscale transformation to all the images captured for each date fruit. This dataset comprised four RGB images (GrayF1, GrayF2, GrayF3, and GrayF4) captured from various angles to provide a comprehensive view of the fruit's visual characteristics. Additionally, a thermal image (denoted as GrayIR) was captured with a FLIR camera to offer insights into internal properties such as maturity levels or defects (refer to Figure 5.2, and 5.3).

Grayscale transformation plays a significant role in our approach for several reasons: It reduces data dimensionality by converting RGB images, which have three colour channels (red, green, and blue), into a single intensity channel. This transformation significantly improves computational efficiency during image processing and model training. Additionally, grayscale transformation emphasizes shape and texture. However, it is essential to note that while a spot in the date fruit might appear relatively dark in grayscale, a healthy area might not show such a stark contrast. Due to grayscale conversions being based on brightness, original defects and healthy areas can influence their final grayscale intensity, as illustrated in Figure 5.4.

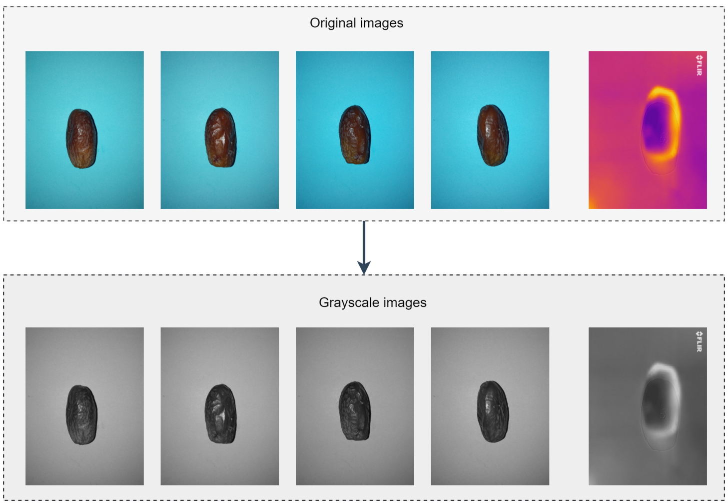


Figure 5.4: Example of Grayscale Conversion (RGB Image vs. Grayscale Image)

The process involves transforming RGB images into grayscale using a weighted sum of their red, green, and blue components, as specified in Equation Eq. 1. The weights reflect each channel's contribution to perceived brightness.

$$\text{Gray(img)} = 0.2989 \times \text{R(img)} + 0.5870 \times \text{G(img)} + 0.1140 \times \text{B(img)}. \qquad \text{(Eq. 1)}$$

This formula was applied to all images in our dataset, including the four RGB images (GrayF1, GrayF2, GrayF3, and GrayF4) and the thermal image (GrayIR), achieving a more efficient and potentially more informative data representation for our deep learning models.

5.2.2.2 Image Averaging

Following grayscale conversion, we incorporated image averaging into our data preprocessing workflow to address potential variations from capturing images from different angles of the date fruit. While capturing multiple views provides valuable information about the fruit's shape and texture, slight variations in perspective during image acquisition can introduce noise into the data. This noise might confuse the deep learning model.

Image averaging aims to mitigate this issue. We generate a new image incorporating information from all viewpoints by calculating the average pixel value across corresponding pixels in a set of images (one from each side of the fruit). It will reduce the impact of minor viewpoint inconsistencies and provide a more robust representation of the model by capturing the most prominent features.

The process involves four grayscale images (GrayF1, GrayF2, GrayF3, and GrayF4) captured from different angles of each fruit. For each pixel location (x, y) in the output image (denoted as $\text{Gray(x,y)}_{\text{avg}}$), we calculate the average of the corresponding pixel values from the four input images (mathematically represented by the formula in Equation Eq.2). This process generates a new image that amalgamates information from all viewpoints, effectively capturing the most salient visual features of the date fruit while reducing the impact of minor viewpoint inconsistencies, as illustrated in Figure 5.5.

$$Gray(x,y)_{\text{avg}} = \frac{Gray(x,y)_{F1} + Gray(x,y)_{F2} + Gray(x,y)_{F3} + Gray(x,y)_{F4}}{4} \qquad \text{(Eq.2)}$$

5.2.2.3 Customising Image Channel Values

In the final data preprocessing step, we create a custom image designed as input for our Convolutional Neural Networks (CNNs). This image combines information from three sources: the Grayscale Averaged Image, the Grayscale FLIR Image, and the weight of the date fruit.

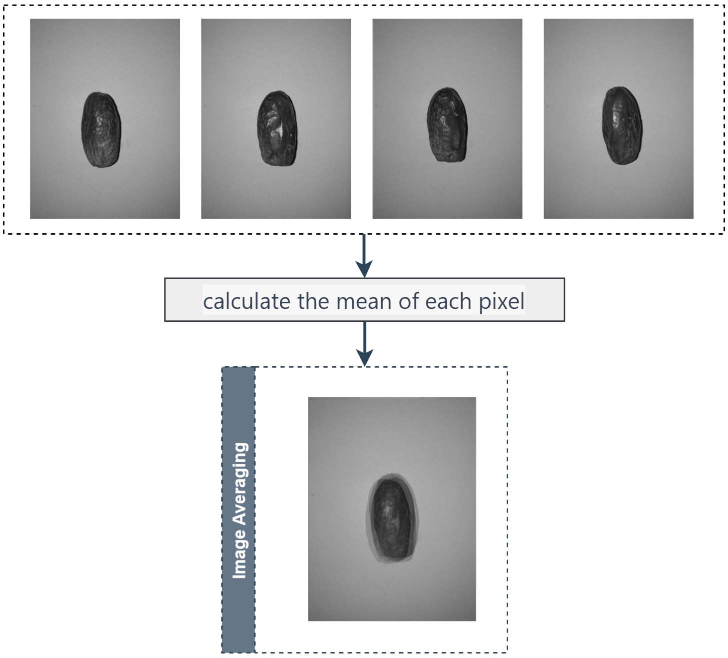


Figure 5.5: Image Averaging: From Four Grayscale Views to a Single Averaged Image

To create this three-channel image, we first ensure the FLIR image is resized to match the dimensions of the averaged grayscale image, achieving accurate alignment between the two images. Next, we construct a new image with red, green, and blue channels, each representing different information sources:

- **Red Channel:** Each pixel's red channel value is assigned the corresponding pixel value from the averaged grayscale image.

- **Green Channel:** Each pixel's green channel value is assigned the corresponding pixel value from the FLIR image.

- **Blue Channel:** Each pixel's blue channel value is determined by the fruit's weight, processed as follows:

  1. Normalize the original weight value ($\text{Weight}_{\text{original}}$) by subtracting 1 and dividing by 20.0, scaling the weights to a consistent range.

  $$\text{Normalized\_Weight} = \frac{\text{Weight}_{\text{original}} - 1}{20.0} \qquad \text{(Eq.3)}$$

  2. Multiply the normalized weight by 255 and round to the nearest integer, ensuring compatibility with typical image intensity ranges (0-255).

  $$\text{Scaled\_Weight} = \text{round}(\text{Normalized\_Weight} \times 255) \qquad \text{(Eq.4)}$$

This process is applied to each pixel in the new image, integrating visual and weight data into a single, cohesive three-channel image, as presented in Eq.5. This composite image allows the CNN to analyze the combined features and improve classification accuracy. Figure 5.6 illustrates the customizing image channel values.

$$
\begin{aligned}
\text{Resulting\_Image}(x,y) &= (R\_Value, G\_Value, B\_Value) \\
R\_Value &= \text{Gray}(x,y)\_avg \\
G\_Value &= \text{Gray}(x,y)\_IR \\
B\_Value &= \text{Scaled\_Weight}
\end{aligned}
\tag{Eq.5}
$$

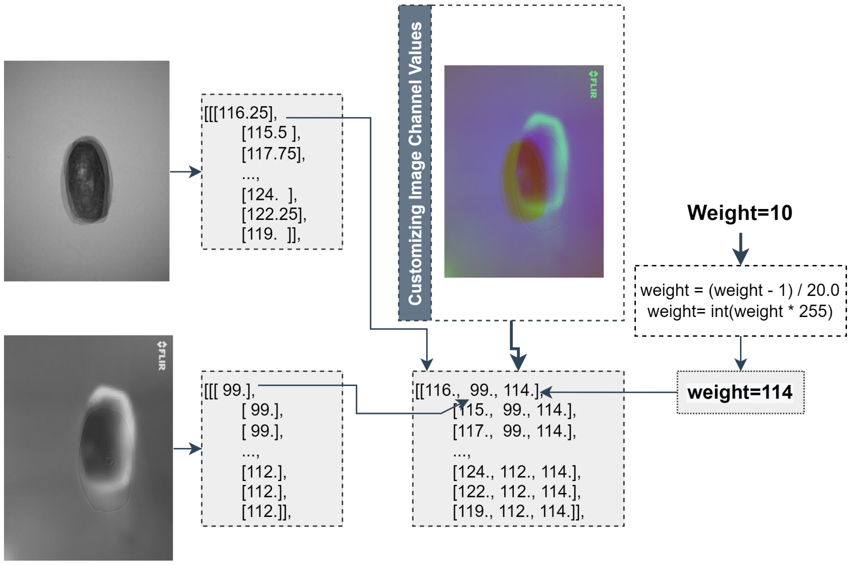


Figure 5.6: Customizing Image Channels: Assigning Red, Green, and Blue Values from Grayscale Images and Weight.

5.2.3 Model Conception

Following data preprocessing, we explored various deep-learning models to classify date fruit quality based on the custom three-channel images (averaged grayscale, FLIR image, and weight information). We employed two distinct approaches: transfer learning with pre-trained models and a custom-designed Convolutional Neural Network (CNN). We trained all models using the Adam optimizer with a learning rate of 0.00001, a batch size of 16, and an image size of 244 $\times$ 244 pixels, except for InceptionV3, which used a picture size of 299 $\times$ 299 pixels

5.2.3.1 Transfer Learning Approach

In the transfer learning approach, we utilized pre-trained models such as VGG16, InceptionV3, and ResNet50, renowned for their remarkable performance in image classification tasks, fine-tuning them on our dataset to adapt their learned representations to the specifics of date fruit quality classification. The architecture of the transfer learning approach is illustrated in Figure 5.7.

The architecture for all transfer learning models remained consistent in terms of hyper-parameters, with variations occurring in the selection of the base model. This architecture encompassed several key components:

- An Input Layer to receive the three-channel image data.
- A Pre-trained CNN (VGG16, InceptionV3, ResNet50) for feature extraction.
- A Global Average Pooling 2D layer to reduce spatial dimensions.
- Dropout layers (with a dropout rate of 0.2) to prevent overfitting.
- Dense layers for classification, with the final layer consisting of 10 neurons corresponding to the number of dates fruit quality classes, employing the Softmax activation function to provide class probabilities.

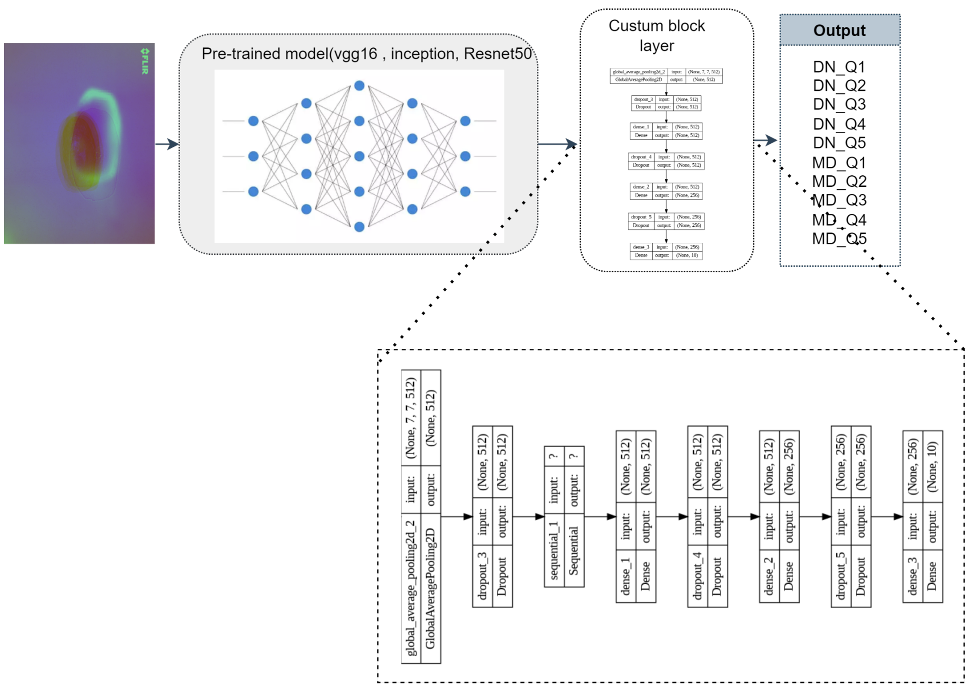


Figure 5.7: Transfer Learning Architecture for Date fruit Quality Classification.

5.2.3.2 Custom CNN Model

Furthermore, we examined the performance of a custom CNN model explicitly designed to classify date fruit quality. This model was constructed with convolutional layers, progressively extracting hierarchical features from the input data. The first convolutional layer utilized 64 filters of size (3x3) with the ReLU activation function, followed by subsequent layers employing 64 and 128 filters, respectively. Max-pooling layers were interspersed between convolutional layers to reduce spatial dimensions and focus on salient features. Dropout layers (with a dropout rate of 0.3) were included to mitigate overfitting during training. The Flatten layer then transformed the data into a one-dimensional vector, which was fed into Dense layers for classification. Like the transfer learning approach, the final Dense layer consisted of 10 neurons with Softmax activation, providing class probabilities for each image. The architecture of the Custom-CNN is depicted in Figure 5.8.

Layer (type)	Output Shape	Param #
conv2d_98 (Conv2D)	(None, 222, 222, 64)	1792
max_pooling2d_8 (MaxPooling2D)	(None, 111, 111, 64)	0
conv2d_99 (Conv2D)	(None, 109, 109, 64)	36928
max_pooling2d_9 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_100 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_10 (MaxPooling2D)	(None, 26, 26, 128)	0
conv2d_101 (Conv2D)	(None, 24, 24, 128)	147584
max_pooling2d_11 (MaxPooling2D)	(None, 12, 12, 128)	0
dropout_14 (Dropout)	(None, 12, 12, 128)	0
flatten_1 (Flatten)	(None, 18432)	0
dense_14 (Dense)	(None, 512)	9437696
dropout_15 (Dropout)	(None, 512)	0
dense_15 (Dense)	(None, 10)	5130

Figure 5.8: Custom CNN modelArchitecture for Date fruit Quality Classification.

5.3 Results and Discussion

This section presents the performance evaluation of the implemented deep learning models for date fruit quality classification. The experiments used Python 3.9.6 on a Windows 10 Pro machine with an Intel® Core™ i5-6200U CPU @ 2.30 GHz and 4.00 GB of RAM. TensorFlow and Keras libraries (versions 2.6.0) facilitated the model development and training process.

Four distinct deep-learning models were evaluated using a 70/20 training-validation data split. The performance metrics employed for evaluation were training accuracy and validation accuracy, and the results are presented in Table 5.1.

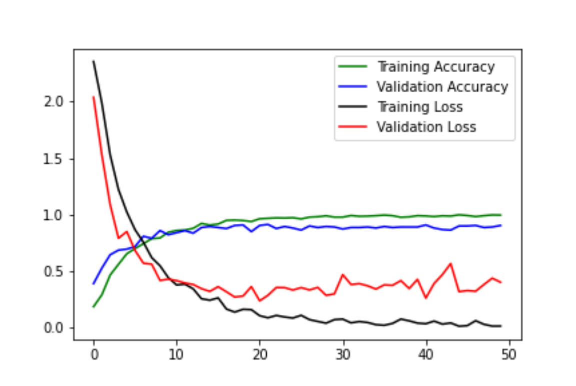
- **VGG16:** The VGG16 model achieved a training accuracy of 99.6% and a validation accuracy of 90.4%, with a training loss of 0.0153. As depicted in Figure 5.9(a), the loss function exhibits a significant decrease while the training accuracy significantly increases, indicating effective learning by the model. The validation loss and accuracy curves also demonstrate a similar trend, suggesting that the model is not severely overfitting to the training data. Notably, the validation accuracy remains consistently high (around 88% to 91%) after epoch 17, signifying robust generalization capability.

- **InceptionV3:** The InceptionV3 model attained a training accuracy of 100% but yielded a lower validation accuracy of 69.9%. Figure 5.9(b) illustrates an initial high loss and low accuracy for the model during training, followed by a gradual decrease and increase, respectively. While the validation set performance followed a similar trend, the accuracy consistently remained lower than the training accuracy, suggesting potential overfitting. The model achieved 100% training accuracy after only 7 epochs, indicating memorization of the training data and a validation accuracy of around 70%, suggesting limited generalizability to unseen data. The validation loss exhibits a decreasing trend until epoch 15, followed by an upward trend, further supporting the possibility of overfitting.

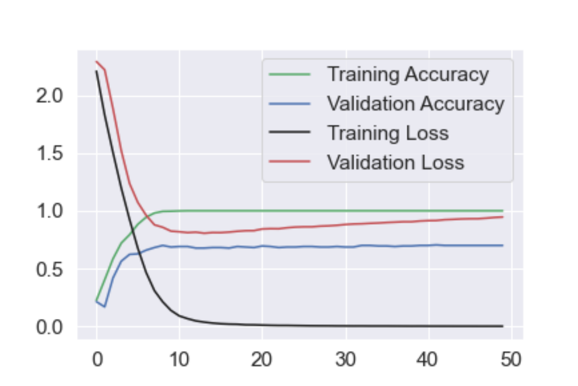
- **ResNet50:** The ResNet50 model achieved a training accuracy of 100%, but the validation accuracy plateaued at around 78%, indicating overfitting to the training set and potentially poor generalization ability. As shown in Figure 5.9(c), the loss and validation loss curves exhibit a similar decrease, signifying learning from the training data. However, the validation loss rises after epoch 10, suggesting the onset of overfitting. The model's complexity (50 layers) might contribute to the high training accuracy and overfitting behaviour.

- **Custom CNN model:** It achieved an accuracy of 87.5% during training and 81.4% during validation, with a training loss of 0.3893. As depicted in Figure 5.9(d), both training loss and accuracy improve with increasing epochs, indicating successful learning on the training data. The validation loss and accuracy curves also exhibit a positive trend, suggesting the model's ability to generalize effectively to unseen data and signifying its capability of performing well on both the training and validation sets.

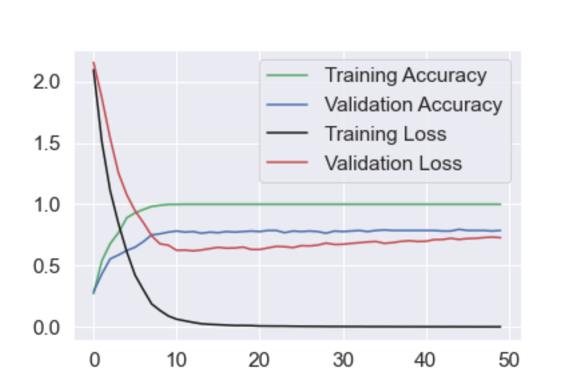
The performance of the trained models was further assessed on a separate 10% test dataset to evaluate generalizability to unseen data. Performance metrics employed for evaluation included Receiver Operating Characteristic (ROC) Area Under the Curve



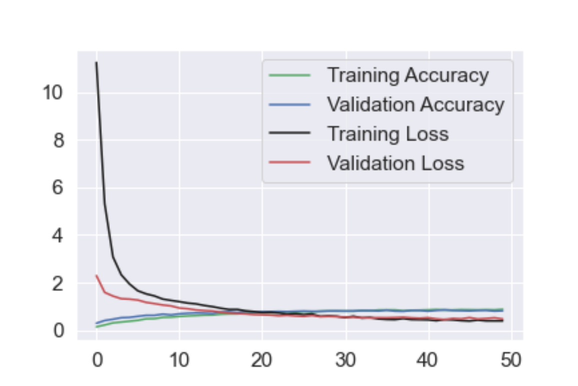
a. Accuracy and Loss of the VGG16 model.



b. Accuracy and Loss of the Inception V3 model.



c. Accuracy and Loss of the ResNet50 model.



d. Accuracy and Loss of the Custom CNN model.

Figure 5.9: Curves of Loss and accuracy during the model training for four models: (a) VGG16 (b) InceptionV3 (c) ResNet50 (d) Custom-CNN model.

Model Type	**Training results**		**Validation results**	
	Loss	**Accuracy (%)**	**Loss**	**Accuracy (%)**
VGG16	0.0153	99.6	0.4027	90.4
InceptionV3	0.0010	100	0.9461	69.9
ResNet50	0.0009	100	0.7274	78.64
Custom CNN model	0.3893	87.5	0.4684	81.4

Table 5.1: Training and Validation Results for Various Models.

(AUC), confusion matrix, Cohen's Kappa coefficient, Matthews Correlation Coefficient (MCC), precision, recall, F1-score, and accuracy.

- **VGG16:** The VGG16 model achieved outstanding performance across all classes, as evidenced by ROC AUC values close to 1.0 (Figure 5.10(a)). That suggests exceptional classification ability for all classes. The confusion matrix in Figure 5.11(a) further supports this observation, demonstrating high accuracy in predicting each class. Additionally, the model yielded a Kappa coefficient and MCC of 0.93 (Figure 5.12(a)), indicating an almost perfect level of agreement between predicted and actual labels.

Furthermore, as shown in Table 5.2, the F1-score of 93.69% demonstrates a desirable balance between precision (93.75%) and recall (93.69%). These metrics suggest that the model made few false positive predictions while correctly identifying a high proportion of actual positive instances. The overall accuracy of 93.69% indicates the model's success rate in making accurate predictions across all classes.

- **InceptionV3:** While the InceptionV3 model exhibited good performance with a ROC AUC score of 0.9609 (Figure 5.10(b)), the confusion matrix in Figure 5.11(b) reveals some variation in performance across classes. The Kappa coefficient and MCC of 0.7332 and 0.7359, respectively (Figure 5.12(b)), indicate a substantial, but not perfect, level of agreement between predicted and actual labels.

  Table 5.2 shows that the InceptionV3 model achieved a moderate balance between precision (80.56%) and recall (76.58%), reflected in the F1-score of 76.58%. The model made relatively few false positive predictions (precision) but demonstrated a moderate ability to identify actual positive instances (recall). The overall accuracy of 76.58% represents the model's success rate in making accurate predictions.

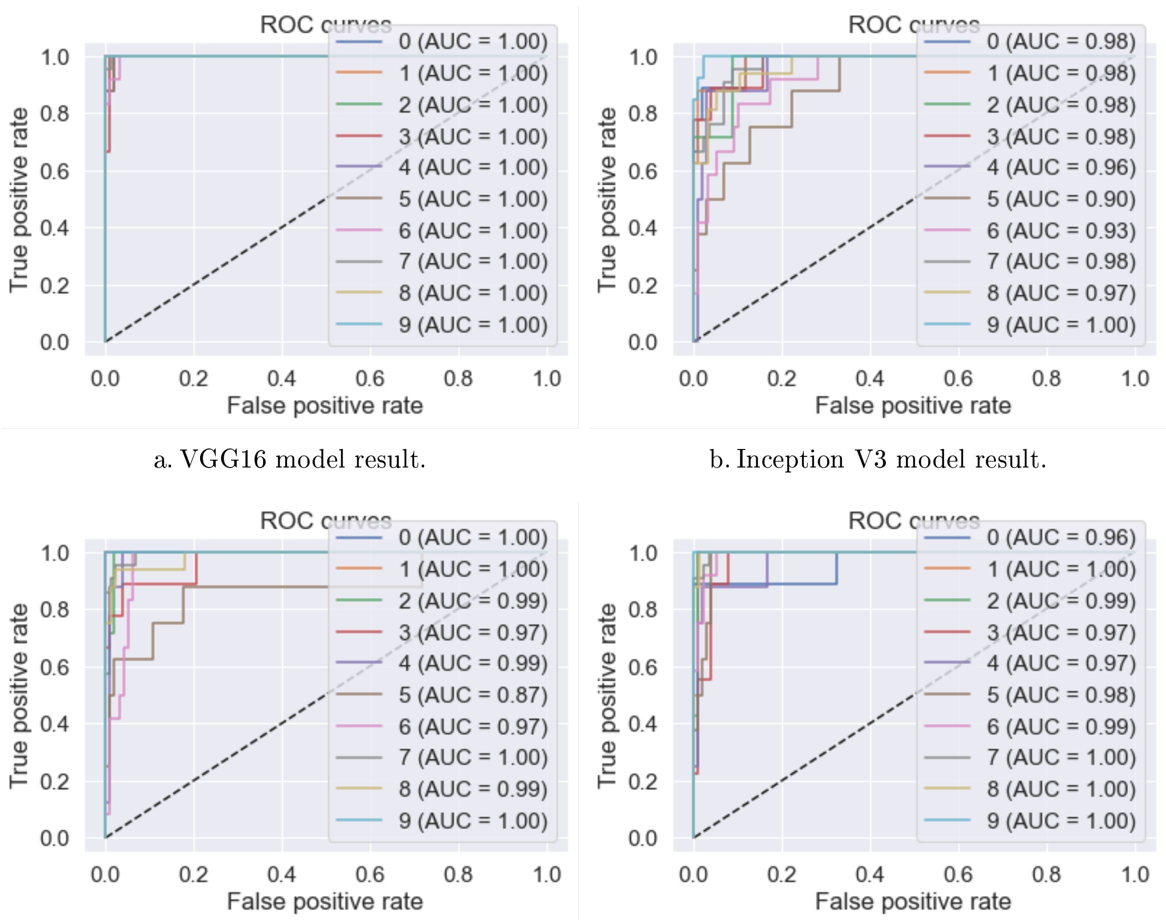
- **ResNet50:** The ResNet50 model achieved high performance in most classes, with perfect ROC AUC values for five classes and values exceeding 0.98 for most others (Figure 5.10(c)), indicating excellent classification ability across the majority of classes. The confusion matrix (Figure 5.11(c)) further reinforces this observation. The Kappa coefficient and MCC of 0.8259 and 0.8285, respectively (Figure 5.12(c)), suggest a substantial level of agreement between predicted and actual labels, although not perfect.

  Table 5.2 demonstrates good performance for the ResNet50 model across all metrics. The F1-score of 84.68% reflects a satisfactory balance between precision (87.50%) and recall (84.68%). The model made a few false positive predictions and correctly identified a high proportion of actual positive instances. The overall accuracy of 84.68% represents the model's success rate in making accurate predictions.

- **Custom CNN model:** It exhibited excellent performance in terms of ROC AUC values, with all classes exceeding 0.96 and most exceeding 0.98 (Figure 5.10(d)), which indicates the model's effectiveness in distinguishing between classes. The confusion matrix (Figure 5.11(d)) demonstrates moderate performance across all classes. The Kappa coefficient and MCC of 0.8263 and 0.8277, respectively (Figure 5.12(d)), suggest a substantial level of agreement between predicted and actual labels, although not perfect.

Table 5.2 shows that the CNN model performed well, achieving a moderate balance between precision (80.00%) and recall (84.68%), reflected in the F1-score of 84.68%. The model made relatively few false positive predictions and correctly identified a moderate proportion of actual positive instances. The overall accuracy of 84.68% indicates the model's high success rate in making accurate predictions.

The results, presented in Table 5.2 and Figure 5.13, revealed a clear distinction in performance between the models. VGG16 consistently achieved the highest values across most evaluation metrics, demonstrating its superiority in image classification for this specific task. VGG16 attained an F1-Score of 93.69%, precision of 93.75%, recall of 93.69%, accuracy of 93.69%, and a remarkable ROC AUC of 0.998, suggests VGG16's exceptional ability to correctly classify images and effectively differentiate between various classes within the dataset.



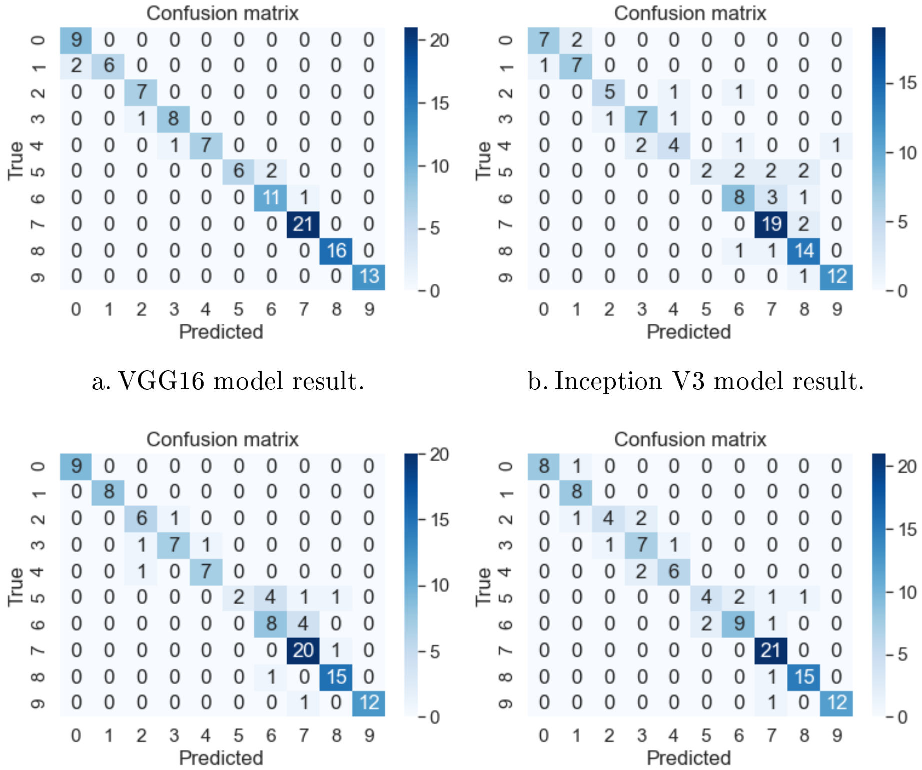
a. VGG16 model result.

b. Inception V3 model result.

c. ResNet50 model result.

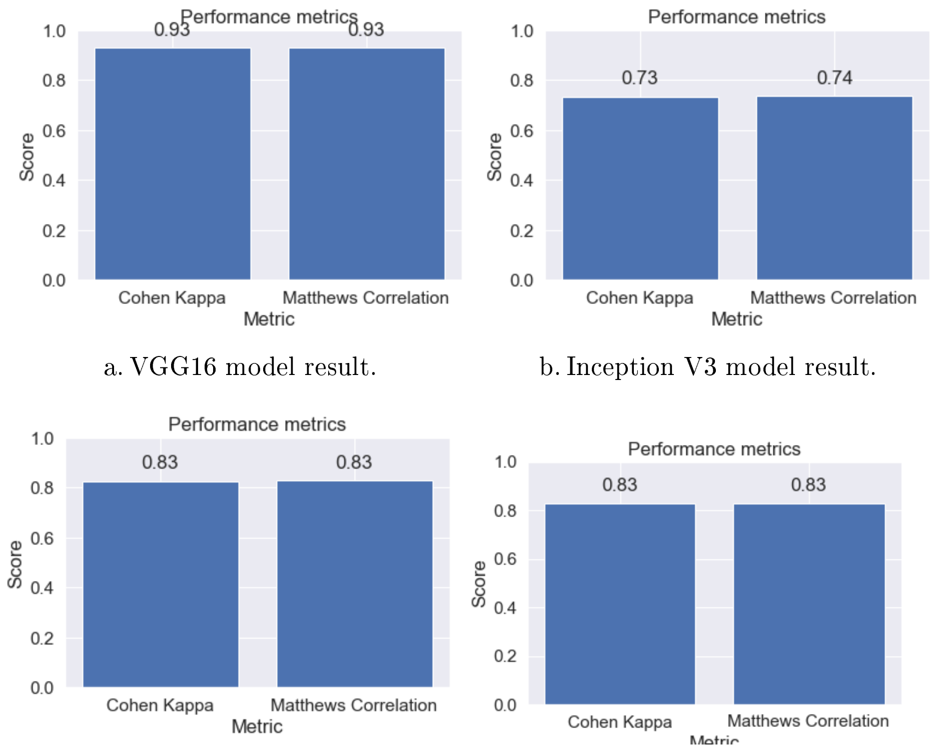
d. Custom CNN model result.

Figure 5.10: The ROC AUC curve for various models: (a) VGG16 (b) InceptionV3 (c) ResNet50 (d) CNN model from scratch.



a. VGG16 model result.
b. Inception V3 model result.
c. ResNet50 model result.
d. Custom CNN model result.

Figure 5.11: The confusion matrix for various models



a. VGG16 model result.
b. Inception V3 model result.
c. ResNet50 model result.
d. Custom CNN model result.

Figure 5.12: The Kappa and Matthews scores for various models

While all evaluated models achieved promising results, InceptionV3 presented the lowest performance across most metrics except precision. Its F1-Score (76.58%), recall (76.58%), accuracy (76.58%), and ROC AUC (0.9609) indicate a need for further investigation into its suitability for this particular task. While InceptionV3 might possess a more complex architecture than other models, its performance suggests potential challenges with generalizability to unseen data.

ResNet50 and The custom-CNN achieved comparable performance in terms of F1-Score (84.68% for both). However, a closer examination reveals that ResNet50 had a slight advantage in precision (87.50%) and Kappa (0.8259), potentially indicating a more balanced classification approach. Interestingly, the Custom-CNN model outperformed ResNet50 in ROC AUC (0.9837 vs. 0.9757), suggesting a potential advantage in discriminating between positive and negative classes.

The observed trends in performance during the testing phase mirrored those seen during validation, highlighting the effectiveness of validation in assessing model generalizability beyond the training data. VGG16 maintained its lead, while InceptionV3 continued to show the lowest performance, validating the importance of the validation step.

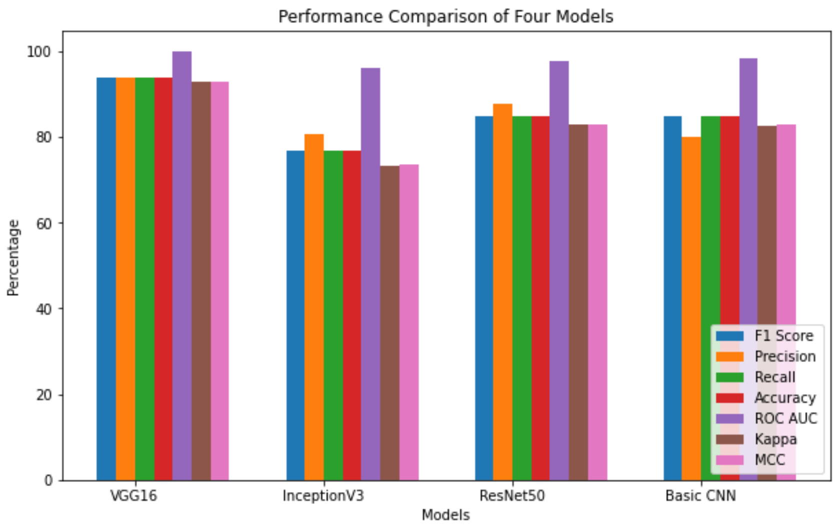


Figure 5.13: Performance Comparison of Four Models.

Model	F1-Score	Precision	Recall	Accuracy	ROC AUC	Kappa	MCC
VGG16	93.69%	93.75%	93.69%	93.69%	0.998	0.9287	0.9293
InceptionV3	76.58%	80.56%	76.58%	76.58%	0.9609	0.7333	0.7359
ResNet50	84.68%	87.50%	84.68%	84.68%	0.9757	0.8259	0.8285
Custom CNN model	84.68%	80.00%	84.68%	84.68%	0.9837	0.8263	0.8277

Table 5.2: Testing Results for Four Models.

The superior performance of VGG16 on unseen data highlights the importance of model selection for practical sorting applications. While InceptionV3 and ResNet50 boast more complex architectures, this complexity could lead to overfitting on the training data, hindering their ability to generalize to novel fruit characteristics encountered during real-world sorting. VGG16's simpler architecture likely contributed to its superior generalizability and effectiveness in sorting unseen date fruits.

This work underscores the critical role of model selection and evaluation strategies in achieving optimal performance for date fruit classification tasks. The choice of the model architecture and the effectiveness of hyperparameter tuning significantly impact the ability to classify images accurately. While VGG16 excelled in this instance, further research could explore advanced optimization techniques for other models and investigate methods to mitigate overfitting issues. Additionally, augmenting the dataset with more diverse and representative samples could further improve the generalisability and robustness of all models.

A Flask-based web application was developed to facilitate user interaction with the date fruit classification models. Users can upload thermal and four-face images of the date fruit for classification and input for the fruit's weight. The user interface (Figures 5.14 and 5.15) guides users through image selection and weight input before initiating the prediction process.

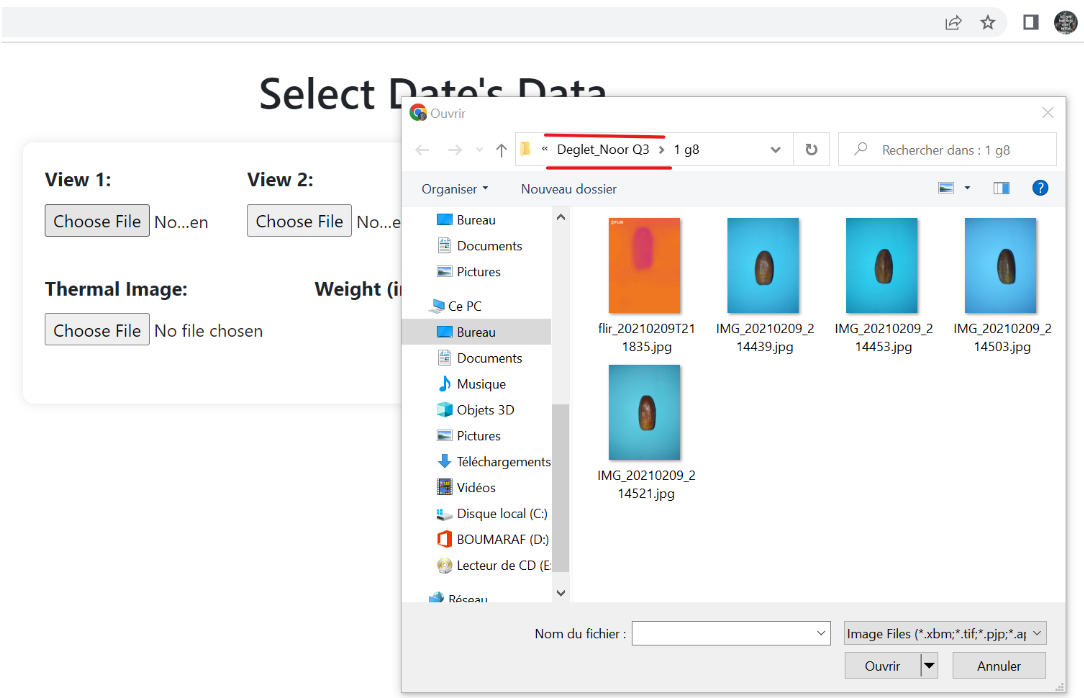


Figure 5.14: Step 1 - Selecting the date fruit to predict. The user selects both thermal and four-face images and inputs the fruit's weight.

The results are then presented within the application interface (Figure 5.16) as a table displaying the predicted class for the date fruit by each model (VGG16, InceptionV3, ResNet50, and CNN model from scratch). The evaluation confirmed the superior per-

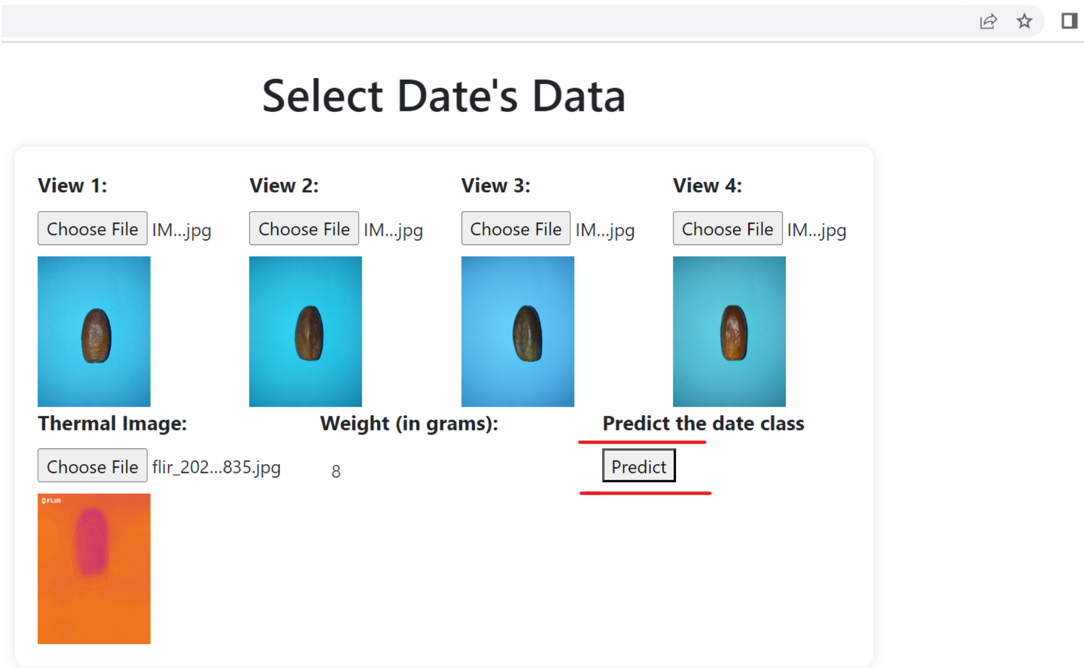
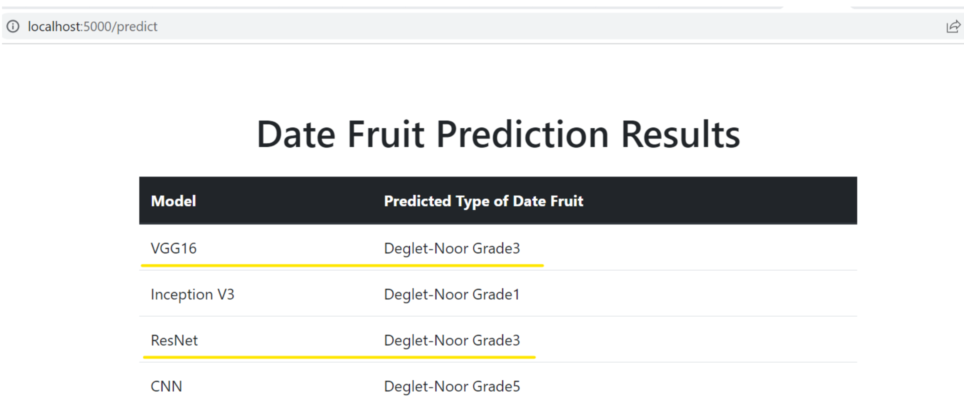


Figure 5.15: Step 2 - Displaying the data for prediction. This interface presents all the information the user enters, including the thermal and four-face images of the chosen date fruit and its weight. This information is used to predict the class of the date fruit.

formance of VGG16 for our date fruit classification task, as both VGG16 and ResNet50 correctly classified the Deglet Noor Q3 sample (Figure 5.16). The findings from the performance metrics analysis. These results suggest a potential benefit in using multimodal data (thermal, visual images, and the weight of the date fruit) to improve prediction accuracy.


localhost:5000/predict

Date Fruit Prediction Results

Model	Predicted Type of Date Fruit
VGG16	Deglet-Noor Grade3
Inception V3	Deglet-Noor Grade1
ResNet	Deglet-Noor Grade3
CNN	Deglet-Noor Grade5

Figure 5.16: Step 3 - Displaying the prediction results. This table shows the predicted class for the chosen date fruit made by each of the four models used in the experiment. The VGG16 and Resnet50 models predicted the class of the date fruit correctly, while the other models did not.

5.4 Conclusion

This contribution investigated the potential of using multimodal data, combined with convolutional neural networks (CNNs), to classify Algerian date fruit efficiently. A grayscale, image averaging, and customized image channel adjustment method was proposed to simplify and standardize the input data for CNN models, resulting in high accuracy rates during training (99.6%) and testing (94%).

Our experimentation revealed that the VGG16 model achieved the highest performance in classifying Algerian date fruit, with a testing accuracy of 94%. Conversely, the InceptionV3 model exhibited the lowest accuracy. While the ResNet50 and CNN from scratch models performed similarly, VGG16 emerged as the most effective choice for this task.

These findings suggest that the proposed approach has the potential to significantly improve the efficiency and accuracy of date fruit sorting compared to traditional manual methods. Automating the sorting process can reduce labour costs and processing time and enhance sorted fruit's consistency and quality, potentially increasing market value.

Further research could explore the impact of incorporating additional data modalities on classification accuracy and using other methodologies. Investigating advanced data augmentation techniques and hyperparameter optimization for the CNN models might improve performance.

Chapter 6

Multimodal Data Fusion and Deep Learning for Automated Date Fruit Classification

6.1 Introduction

Date fruit sorting is crucial for maintaining product quality and meeting consumer preferences. However, the diversity of date fruit types and grades challenges traditional manual sorting methods.

While machine learning and deep learning offer promising solutions, limitations exist, such as overfitting and sensitivity to data diversity and size. Our previous contribution encountered these limitations. Nevertheless, the potential of Convolutional Neural Networks (CNNs) in a multimodal fusion approach for date fruit sorting remains largely unexplored.

This chapter of our second contribution proposes a novel approach for automating date fruit sorting accuracy by integrating multimodal data through a late fusion technique. This technique combines information from various sources, including images from multiple angles, thermal imaging, and fruit weight. We explore the effectiveness of this approach using four established deep learning models (Custom-CNN, VGG16, ResNet50, and MobileNet) on a new dataset encompassing eight distinct date fruit grades (5 from Deglet Noor and 3 from Mech Degla).

This chapter is structured as follows: Section 6.2 details the proposed methods, Section 6.3 presents the experimental results and analysis, and the final section concludes with key findings and future directions.

6.2 Methodology

By collecting data from various modalities (visual images from multiple angles, thermal images, and weight), the system gathers a richer and more informative set of features for classification. This multimodal representation of the fruit creates a multi-dimensional profile, capturing details beyond visual appearance. This approach has the potential to significantly improve classification accuracy compared to methods that rely solely on RGB images. The steps involved in our methodology are summarized in Figure 6.1.

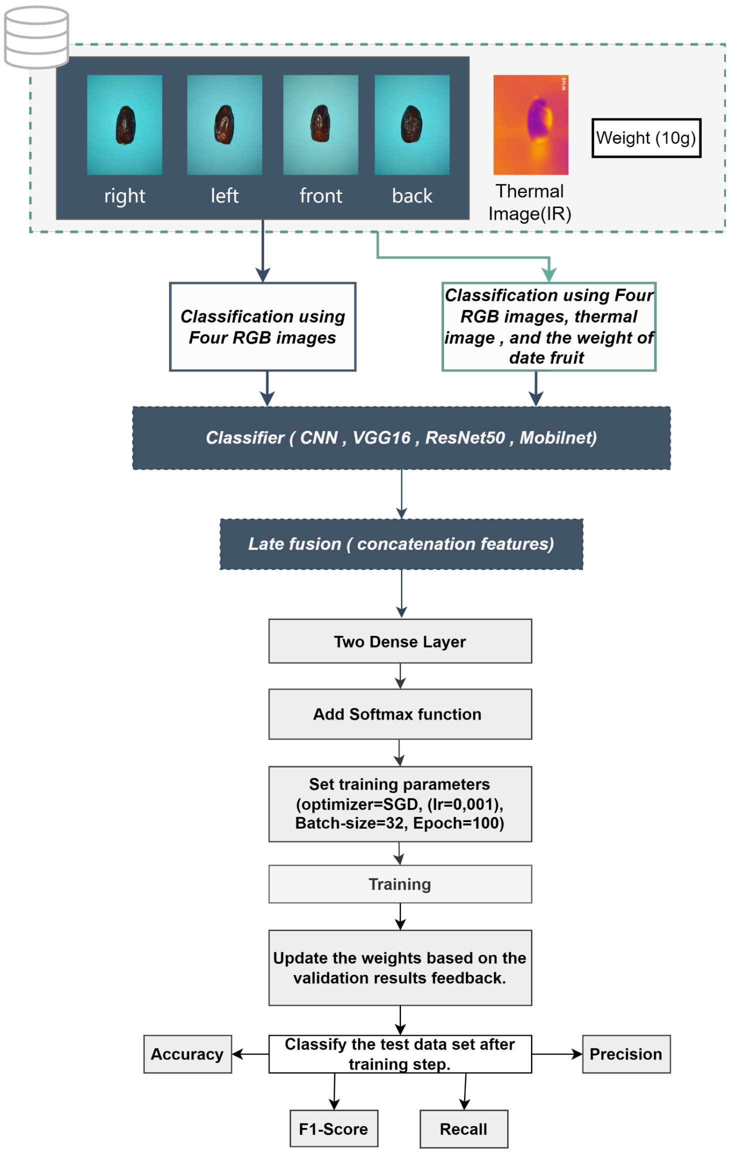


Figure 6.1: Diagram illustrates a Multimodal Fusion Architecture for Date Fruit Classification

The proposed methodology explores two distinct classification scenarios to investigate how incorporating different data modalities affects the overall classification performance.

In Scenario 1, the focus is on leveraging the visual information captured from the four acquired images. Four deep learning models are employed, one for each preprocessed image from a unique viewpoint. Each deep learning model independently analyzes its assigned image, extracting features that represent significant patterns or characteristics within the image.

Scenario 2 expands upon this by incorporating all the data modalities: multi-angle images, thermal images, and weight data. Similar to Scenario 1, four deep learning models extract features from each of the four RGB images. Additionally, a separate deep learning model likely processes the thermal image to extract features related to heat distribution patterns.

The central aspect of this contribution is how the extracted features from different modalities are combined. This methodology utilizes a late fusion strategy. After each deep learning model independently extracts features, these features are concatenated into a single feature vector. Concatenation combines all modalities' features (visual information from multiple angles, potential thermal properties, and weight) into a comprehensive representation of the date fruit sample.

This comprehensive feature vector is then used to train the final classification model. The training process involves exposing the model to a portion of the data (training set) and allowing it to learn patterns that distinguish between different fruit classes (e.g., variety, quality level). A separate validation set is used to monitor model performance and prevent overfitting. Finally, the model goes through multiple training epochs (100 epochs) to ensure it converges and achieves stability. Once trained, the performance of the classification model is evaluated using various metrics. These metrics include accuracy, precision, recall, and F1-score. These metrics provide insights into how well the model can correctly classify date fruits across different classes.

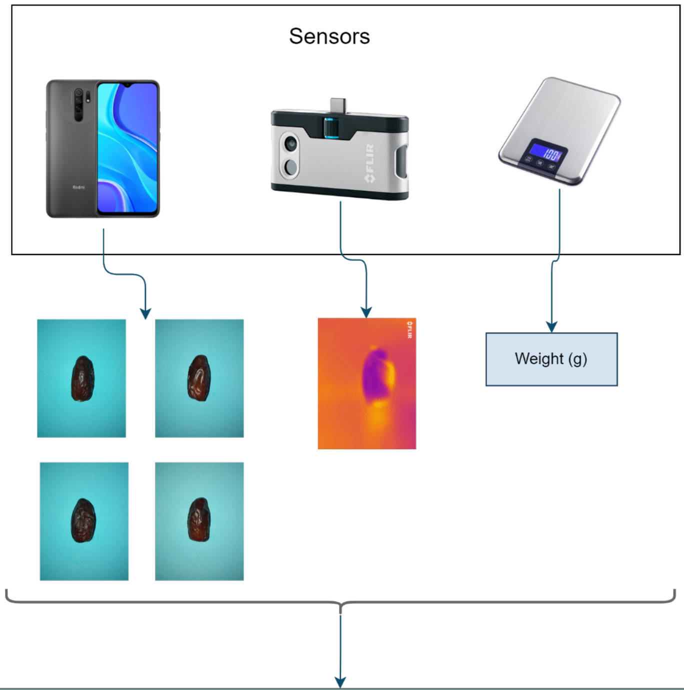
6.2.1 Data Collection

A multimodal data acquisition strategy was employed to create a comprehensive dataset for date fruit classification. This strategy encompassed 853 samples from two distinct varieties: Deglet-Noor (categorized into five quality classes) and MechDegla (categorized into three quality classes). The distribution of these samples across classes is detailed in Table 6.1. This multi-modality aimed to capture a comprehensive representation of each fruit. High-resolution RGB images were captured from four distinct angles (right, left, front, and back), thermal infrared imaging obtained with a FLIR ONE Gen 3 camera, and the weight of each fruit sample, as detailed in the previous contribution.

Variety	**Deglet Noor**					**Mech Degla**		
Grade	DN-G1	DN-G2	DN-G3	DN-G4	DN-G5	MD-G1	MD-G2	MD-G3
Number samples	109	105	69	104	80	63	120	203
Total	853							

Table 6.1: Distribution of Date Fruit Samples in our Dataset

The collected data was then organized into a comma-separated values (CSV) file for efficient storage and manipulation. Each entry within the CSV file followed a consistent structure, including unique identifiers for each fruit, designated quality class labels, file paths for the corresponding acquired images from all four angles and the thermal camera, and the recorded weight of the fruit sample. Figure 6.2 represents our dataset collection. The data was split into training, validation, and testing sets to ensure a robust training process and facilitate reliable model evaluation. This distribution allocates most of the data (80%) for training the classification model, while the remaining 20% is for validation/testing.



Dataset (.csv)

id	label	Path Face1	Path Face2	Path Face3	Path Face4	Path IR	Weight(g)
1	DN_Q1	./Face1.jpg	./Face2.jpg	./Face3.jpg	./Face4.jpg	./IR.jpg	8

Figure 6.2: Multimodal Data Acquisition for Date Fruit Classification

6.2.2 Classification Scenarios

Following data acquisition, our approach utilizes two distinct classification scenarios. The first scenario, multi-view fusion, leverages four visual representations (corresponding to four viewing angles) of each date fruit for classification. The second scenario, multimodal fusion, incorporates richer information by combining visual data (The same views used in scenario 1) with thermal image data and weight data for each date fruit. Subsequently, both scenarios leverage four deep learning models for classification: Customized Convolutional Neural Network (CNN), VGG16, ResNet50, and MobileNet.

6.2.2.1 Scenario I: Multi-View Fusion with Deep Learning Architectures

This scenario explores classifying date fruits using visual information captured from four angles (front, back, left, and right) as shown in Figure 6.3.

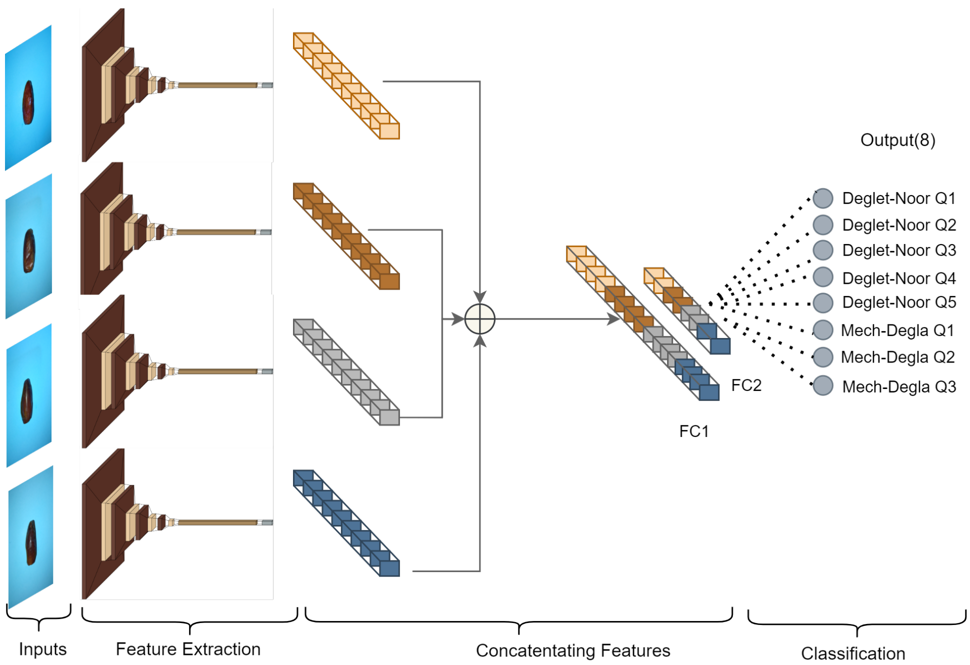


Figure 6.3: Scenario I: Multi-View Fusion with Deep Learning Architectures

We evaluate two deep learning architectures:

- **Custom CNN model Architecture:** This architecture utilizes four identical sub-networks, each dedicated to a single view. Each sub-network extracts features through convolutional layers with increasing filter complexity (64, 64, 128, 128) and ReLU activation. These layers capture spatial patterns within the images. Max pooling layers (2x2 pool size) are then applied to reduce dimensionality and capture dominant features. Finally, a flattening layer transforms the multi-dimensional outputs into one-dimensional vectors suitable for fully connected layers. Each sub-network concludes with a dense layer of 512 units and ReLU activation. The outputs from all sub-networks (representing features from each view) are then concatenated, creating a combined feature representation. This unified representation is further processed through a dense layer (FC1). Finally, a dense output layer with eight units and softmax activation makes the final classification decision, assigning each date fruit to one of eight categories.

- **Pre-trained Model Architecture:** This architecture leverages pre-trained models like VGG16, ResNet50, and MobileNet. Here, we fine-tune these pre-trained models for the specific task of date fruit classification. Like the Custom CNN model approach, the outputs from four sub-models (one for each view) are concatenated and fed into dense layers for final classification. Each sub-model utilizes a pre-trained model as its base, with its weights pre-trained on ImageNet data. These layers are then made trainable during the fine-tuning process. Global average pooling is added to the base model's output to capture overall feature information. Dropout layers are also employed to prevent overfitting during training.

6.2.2.2 Scenario II: Multimodal Fusion with Deep Learning Architectures

Building on the multi-view fusion approach, this scenario (Figure 6.4) investigates the impact of incorporating additional sensor data on classification accuracy. We enrich the dataset with thermal images alongside the four-view visual data. The classification process follows similar principles to the first scenario, employing both the Custom CNN model and pre-trained model architectures. The respective models perform feature extraction for each data modality (four visual and thermal images). The extracted features are concatenated with weight data obtained from a weight scale before final classification through dense layers. By comparing the performance of these two scenarios, we aim to assess the influence of multimodal fusion (visual, thermal, and weight data) on the effectiveness of date fruit classification.

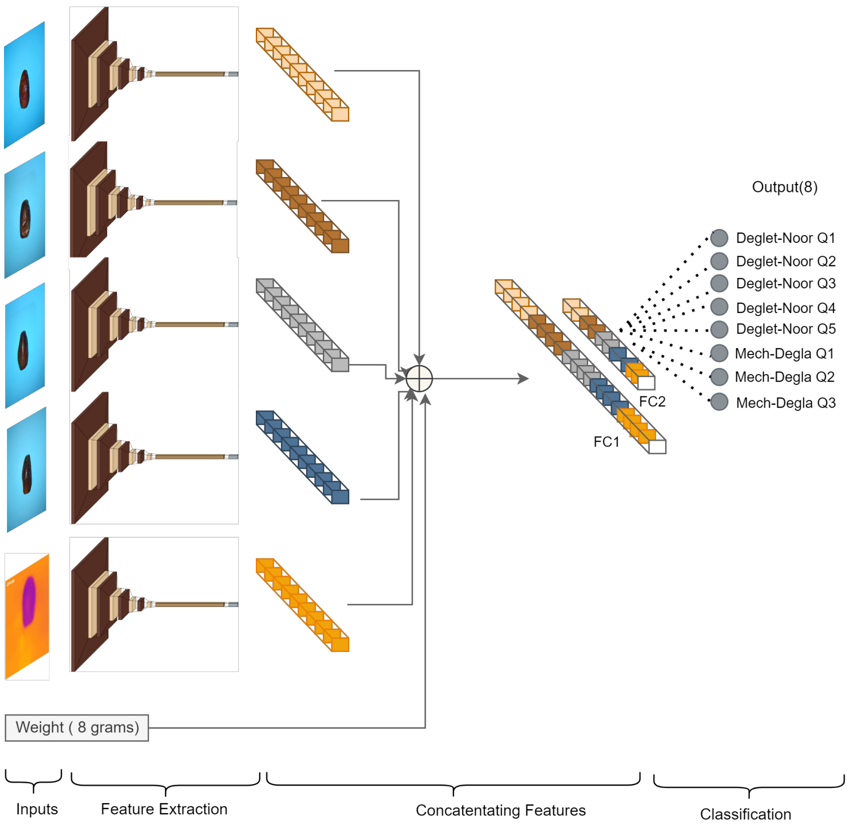


Figure 6.4: Scenario II: Multimodal Fusion with Deep Learning Architectures

6.3 Results and Discussion

We designed two scenarios with varying data complexities to comprehensively assess the adaptability of different deep-learning architectures for date fruit classification (our contribution). This section delves into the results and analysis of our experiments, where we trained and validated four models (Custom CNN model, VGG16, ResNet50, and MobileNet) on each scenario. We must note that we employed a custom dataset curated explicitly for this task, featuring images of Deglet Noor and Mech Degla date varieties. Furthermore, we optimized the training process by employing the SGD optimizer with a learning rate of 0.001, a batch size of 32, and 100 epochs. The experiments were conducted on Processeur: Intel Xeon (R) E5-2660 v3 @ de 2.60 GHz x 20, 64 GB de RAM, 2 TB HDD, RedHat Enterprise Linux Server 7.2, 64 bit.

6.3.1 Classification Results on Multi-View Data (Scenario I):

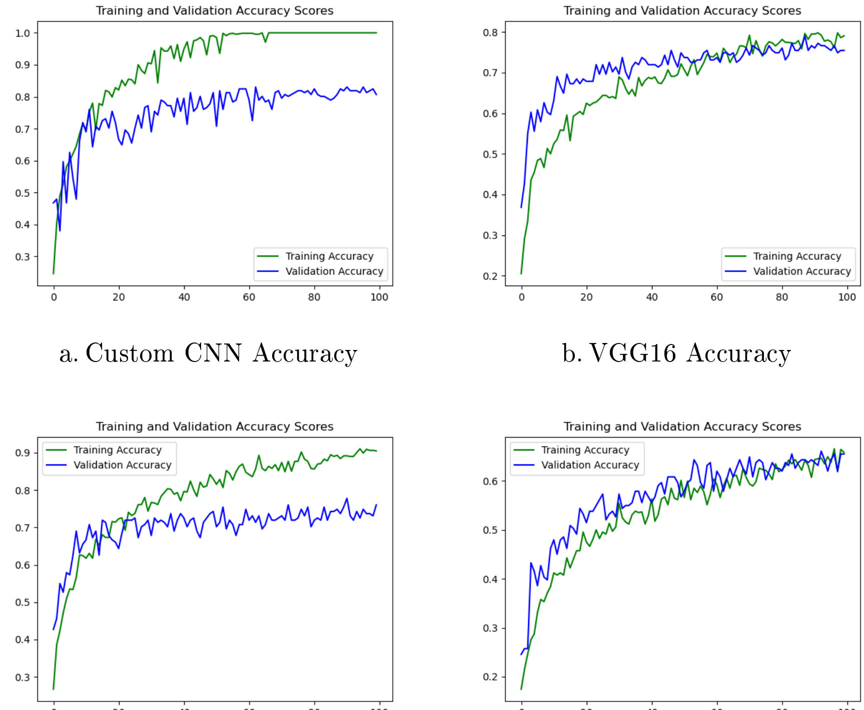
Leveraging four views of each date fruit, Scenario I explores the effectiveness of multi-view fusion for classification with deep learning models (Custom CNN , VGG16, ResNet50, and MobileNet). This subsection analyzes the performance of these models.

The Custom CNN model achieved a training accuracy of 100% and a validation accuracy of 80%, indicating that it might be overfitting the training data, memorizing specific patterns that do not necessarily generalize well to unseen examples. The overfitting phenomenon is also evident in Figure 6.5(a) and Figure 6.6(a), where we observe an increasing gap between training and validation accuracy as the number of epochs increases, eventually stabilizing after epoch 60. While a high training accuracy is desirable, the lower validation accuracy indicates a need for potential hyperparameter tuning or data augmentation to improve generalization on unseen multi-view data.

Compared to Custom CNN , VGG16 achieves a lower training accuracy (79%) but exhibits a closer gap between training and validation accuracy (75%). This trend is also evident in Figures 6.5(b) and 6.6(b), where the training and validation curves stay closer together compared to the Custom-CNN, which indicates that VGG16 is less prone to overfitting.

While MobileNet exhibits convergence between training and validation curves (accuracy and loss) in Figures 6.5(d) and 6.6(d), indicating good generalization potential, it achieves the lowest training and validation accuracy (66% and 65% respectively) among the four models. The lower performance suggests that the simpler MobileNet architecture might not be sufficient to capture the complex relationships within the multi-view data for this classification task.

Similar to VGG16, ResNet50 exhibits a moderate level of overfitting with a training accuracy of 90% and a validation accuracy of 76% (Figures 6.5(c) and 6.6(c)).



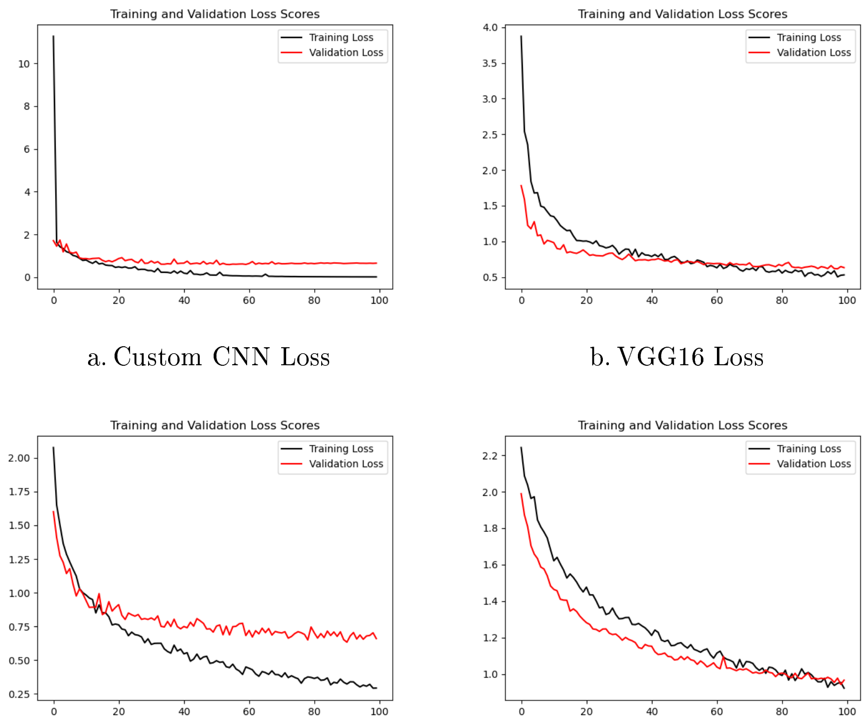
a. Custom CNN Accuracy

b. VGG16 Accuracy

c. ResNet50 Accuracy

d. MobileNet Accuracy

Figure 6.5: Accuracy Curves for the Four Models in Scenario I.



a. Custom CNN Loss

b. VGG16 Loss

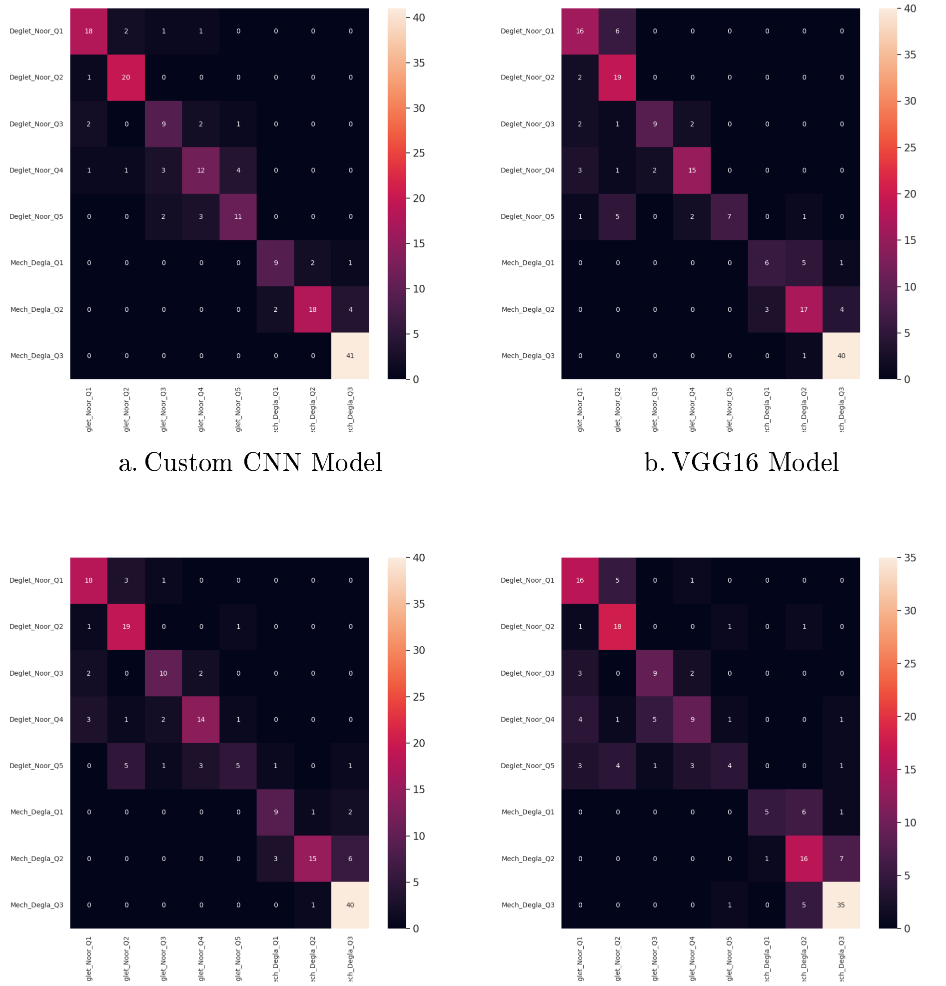
c. ResNet50 Loss

d. MobileNet Loss

Figure 6.6: Training and Validation Loss Curves for the Four Models in Scenario I.

While training and validation accuracy provide a starting point, a deeper analysis requires additional metrics like precision, recall, and F1-score. We used a 20% validation split from the original dataset to evaluate our models. Table 6.2 details the results.

Both the confusion matrix analysis (Figure 6.7) and these metrics revealed Custom CNN as the top performer in Scenario I (multi-view data). It achieved an accuracy of 80%, precision of 73%, recall of 77%, and F1-score of 80%. These values indicate minimal classification errors and a good balance between identifying accurate Deglet Noor dates and avoiding false positives.



a. Custom CNN Model

b. VGG16 Model

c. ResNet50 Model

d. MobileNet Model

Figure 6.7: Confusion Matrices for the Four Models in Scenario I (Four-View Images)

ResNet50 emerged as the second-best model, with an accuracy of 76%, precision and recall of around 70% each, and an F1-score of 76%. VGG16 followed closely, with similar performance across all metrics (around 75%). MobileNet, however, exhibited the lowest performance across all metrics (around 60% for each).

In conclusion, the analysis confirms the findings from the confusion matrix. The

Custom CNN model achieved the best overall performance in Scenario I, demonstrating high accuracy and a balanced ability to classify date fruit varieties effectively. That suggests that Custom-CNN is the most suitable choice for this scenario using multi-view data, as shown in Figure 6.8.

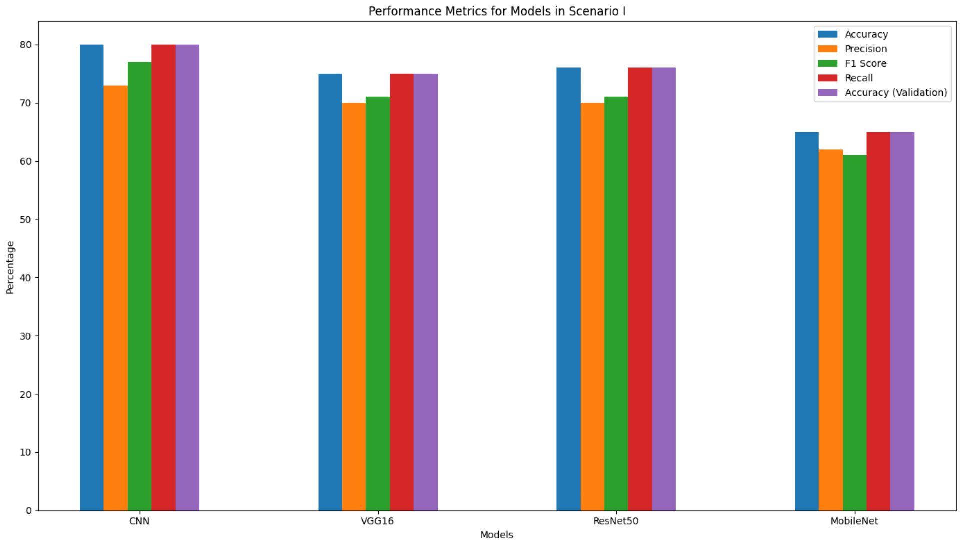


Figure 6.8: Performance Metrics for Models in Scenario I

6.3.2 Classification Results on Multimodal Data (Scenario II)

To expand upon the findings from Scenario I, this section investigates the performance of the four deep learning models (Custom-CNN, VGG16, ResNet50, and MobileNet) in Scenario II. Here, the models are evaluated on their ability to classify date fruits using multimodal data, which incorporates additional information beyond the four-view images employed in Scenario I. This multimodal data includes a thermal image and weight measurement for each fruit.

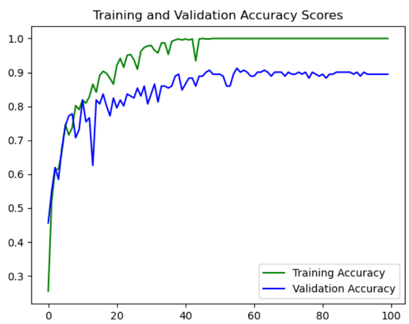
The analysis leverages a combination of performance metrics (summarized in Table 6.2 and visualized in figure 6.12) to provide a comprehensive understanding of how each model performs in this richer data environment. These metrics include accuracy, precision, recall, and confusion matrices, allowing for a detailed comparison of classification effectiveness models.

The Custom CNN model attained the highest validation accuracy (89%) in Scenario II, showing a marked improvement compared to Scenario I (80%). This indicates that combining multimodal data benefits CNN, potentially allowing it to capture more comprehensive features and improve classification performance. However, the substantial gap between training and validation accuracy (100% vs. 89%) observed in Figure 6.9(a) indicates potential overfitting. Further investigation into hyperparameter tuning or data augmentation techniques might be necessary to improve model generalizability.

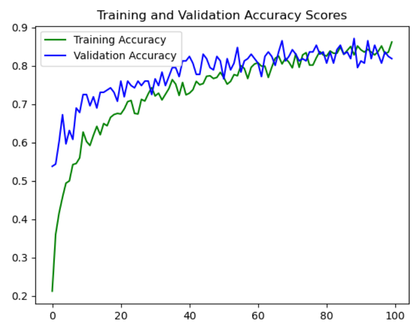
Similar to Custom CNN , VGG16 exhibited improved performance in Scenario II (82% validation accuracy) compared to Scenario I (75%) (Figure 6.9(b)). However, its overall validation accuracy remained slightly lower than Custom CNN 's in Scenario II.

ResNet50 exhibited the least improvement in validation accuracy, increasing from 76% in Scenario I to 78% in Scenario II (Figure 6.9(c)). Additionally, it displayed the lowest overall performance among the compared models, which shows that the additional sensor data in Scenario II might not be as beneficial for ResNet50's architecture as other models.

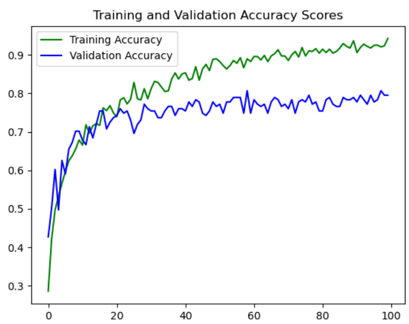
MobileNet showcased the most significant improvement in validation accuracy, rising from 65% in Scenario I to 74% in Scenario II (Figure 6.9(d)). This indicates that the additional sensor data provides valuable information for MobileNet, potentially mitigating the limitations of its simpler architecture in Scenario I. However, its overall validation accuracy remained the lowest among the models.



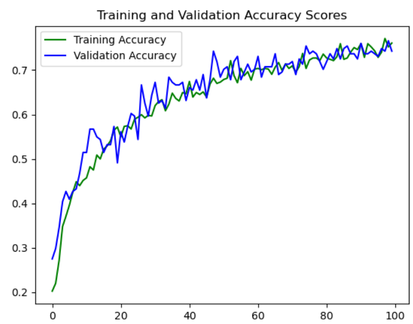
a. Custom CNN Accuracy



b. VGG16 Accuracy



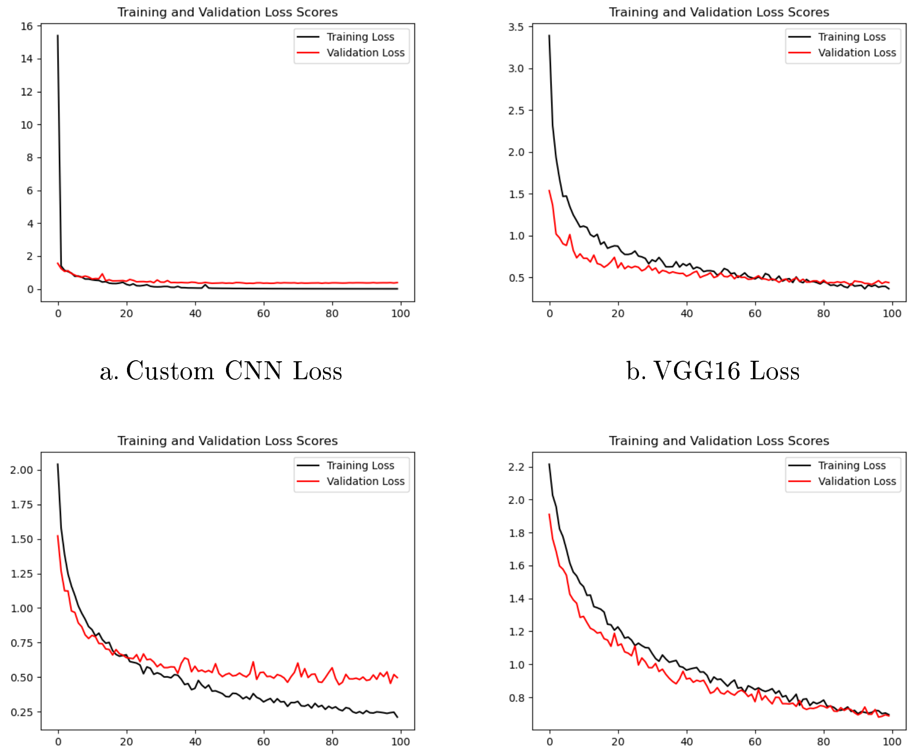
c. ResNet50 Accuracy



d. MobileNet Accuracy

Figure 6.9: Training and Validation Accuracy Curves for the Four Models in Scenario II

An analysis of precision and recall, as summarized in Table 6.2 and Figure 6.12, revealed that these metrics are lower than accuracy across all models in Scenario II. While a detailed analysis of confusion matrices (Figure 6.11) indicates acceptable error rates, with misclassified instances falling primarily within the same variety or neighbouring grade levels, further investigation might be necessary to understand potential class imbalance or



a. Custom CNN Loss

b. VGG16 Loss

c. ResNet50 Loss

d. MobileNet Loss

Figure 6.10: Training and Validation Loss Curves for the Four Models in Scenario I

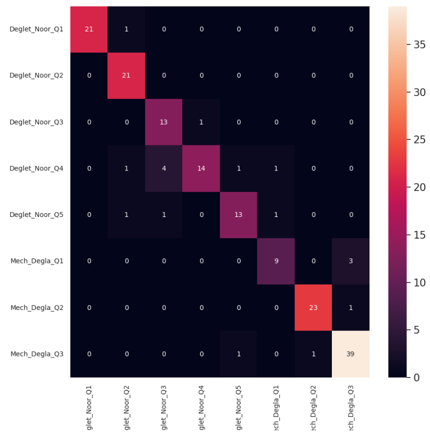
specific classification errors. Notably, the Custom CNN model demonstrated superior performance in distinguishing between grades compared to other models in Scenario II.

In conclusion, incorporating multimodal data in Scenario II led to improved performance for most models, with Custom CNN achieving the highest validation accuracy (89%). However, all models exhibit some overfitting, requiring further exploration of hyperparameter tuning or data augmentation.

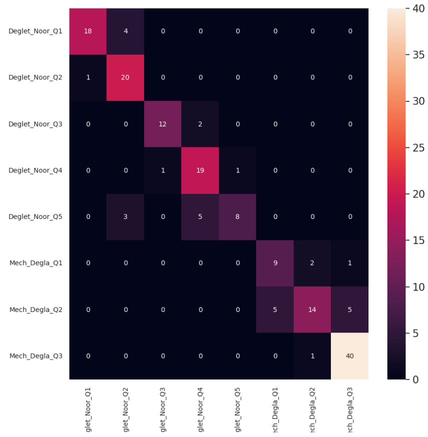
Model	Scenario	Performance Metrics (%)				
		Accuracy	Precision	F1-Score	Recall	Acc. (Train)
Custom CNN	Scenario I	80	73	77	80	100
	Scenario II	89	80	88	90	100
VGG16	Scenario I	75	70	71	75	79
	Scenario II	82	83	79	82	86
ResNet50	Scenario I	76	70	71	76	90
	Scenario II	78	67	75	78	93
MobileNet	Scenario I	65	62	61	65	66
	Scenario II	74	69	70	74	76

Note: Scenario I: Four-view images. Scenario II: Multimodal Data.

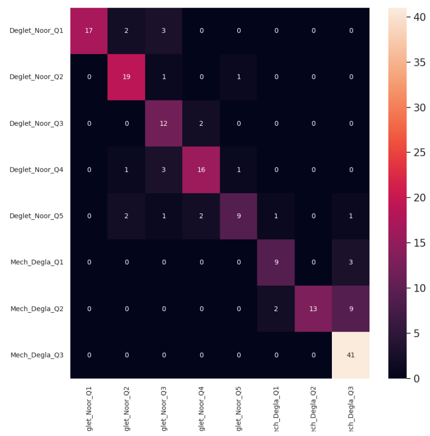
Table 6.2: Performance Metrics for Four Deep Learning Models on Multimodal Data Classification



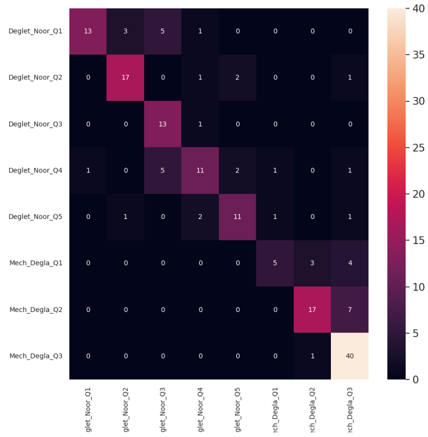
a. Custom CNN Model



b. VGG16 Model



c. ResNet50 Model



d. MobileNet Model

Figure 6.11: Confusion Matrices for the Four Models in Scenario II (Multimodal Data)

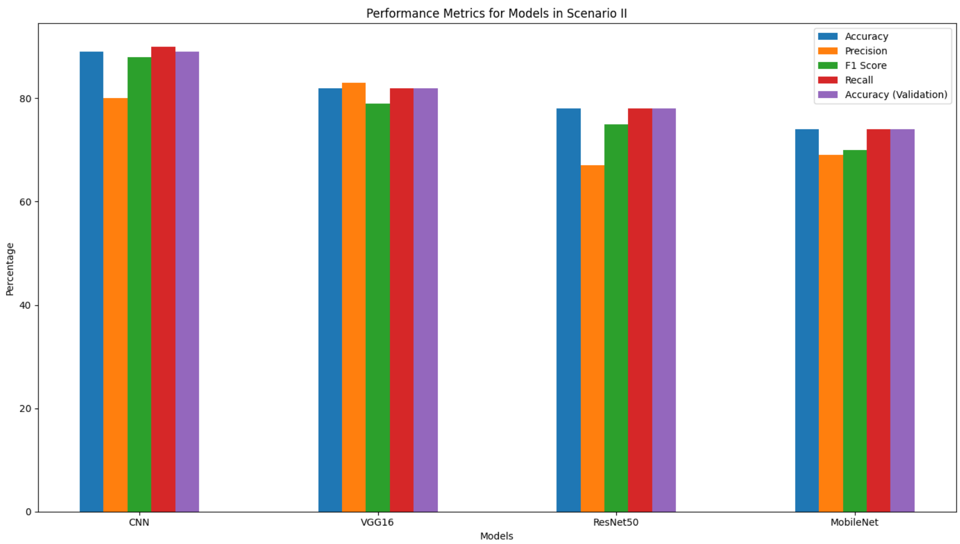


Figure 6.12: Performance Metrics for Models in Scenario II

The results reveal that different models exhibit varying success in classifying date fruits. The custom-CNN model demonstrates strong performance across both scenarios (Scenario I: four-view images; Scenario II: four-view images, thermal image, and weight).

Furthermore, incorporating additional features, such as thermal images and weight measurements in Scenario II, significantly improves CNN's classification accuracy (refer to Figure 6.13). This finding suggests that a late fusion approach, combining multimodal data before the final classification stage, can enhance model performance.

However, the results also emphasize the importance of selecting an appropriate deep-learning architecture. While Custom CNN performs well in both scenarios, other models, such as ResNet50, show limited improvement with additional data. This highlights the need for further exploration of model architectures specifically designed to leverage the combined strengths of multimodal data in the context of date fruit classification.

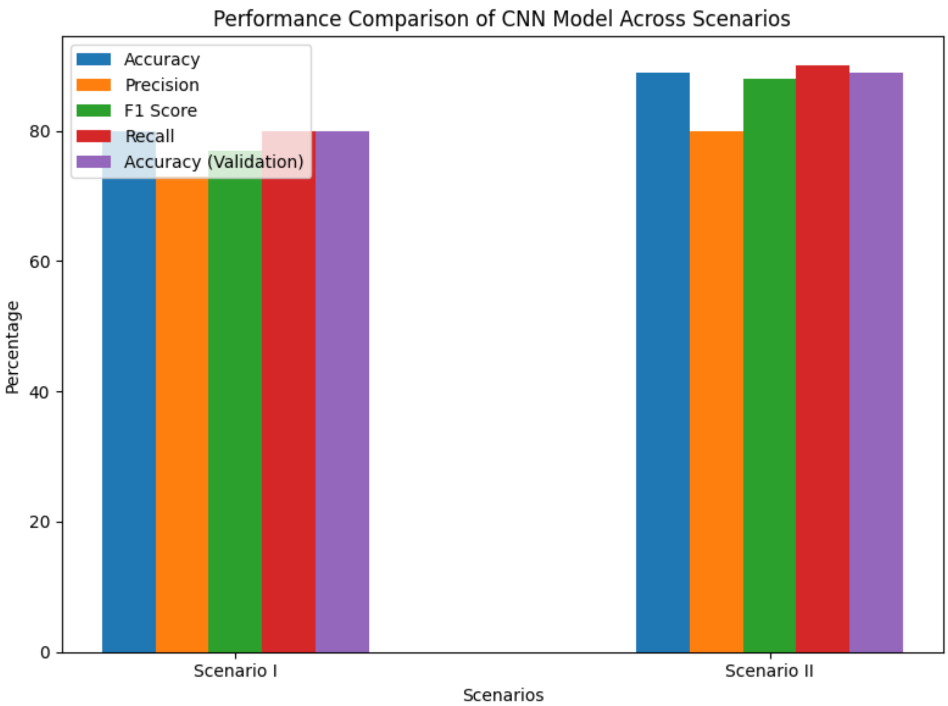


Figure 6.13: Performance Comparison of Custom CNN Model Across Scenarios

6.4 Conclusion

This contribution investigated the effectiveness of deep learning models for classifying date fruits using multimodal data. The findings demonstrate that incorporating additional information, such as thermal images and weight measurements, can significantly improve classification accuracy, particularly for Custom CNN models that achieve an accuracy of 89% using a late fusion approach.

However, the results also emphasize the importance of selecting an appropriate model architecture, as some models exhibited limited improvement with additional data. This suggests that further exploration of deep learning architectures specifically designed to leverage the strengths of multimodal data is necessary for optimal performance in date fruit classification tasks.

This contribution highlights the potential of multimodal data and late fusion techniques to enhance deep-learning model performance in date fruit classification. It also underscores the need for careful consideration of model architecture selection to maximize the benefits of this approach.

A significant limitation of this study is the relatively small dataset used. To enhance the generalFuturexpanding the dataset and exploring advanced data augmentation techniques.

to enhance the generalizability and effectiveness of multimodal and multi-view date fruit classification

Chapter 7

Optimizing Date Fruit Classification Through Multi-View Imaging and Deep Learning

7.1 Introduction

This contribution proposes an automated date fruit sorting system to address the limitations of previous studies, which encountered challenges due to inadequate and limited datasets. Specifically, this work focuses on the two most commercially significant varieties: Deglet Noor and Mech Degla, as highlighted in prior contributions.

The system leverages the power of multi-view imaging in conjunction with convolutional neural networks (CNNs) to achieve accurate classification. Four distinct facial images of each date fruit are captured, comprehensively representing its morphology. These images are then strategically merged into a single composite image, preserving data integrity and facilitating training.

A permutation function was employed to enrich the dataset further and generate variations of the multi-view images. This data augmentation technique helps improve the model's generalization ability to unseen data. The core of the classification system is a CNN architecture equipped with advanced techniques like dropout regularisation and fine-tuning.

This contribution enhances the date fruit classification system by leveraging in-depth features and examining their impact on classification precision. The subsequent sections detail our contribution: Section 7.2 describes the methodology and proposed models, while Section 7.3 presents experimental results and analysis.

7.2 Methodology

In date fruit classification, this study presents a novel methodology that uses convolutional neural networks (CNNs) to distinguish between eight distinct categories. The proposed approach, illustrated by a three-phase flowchart (Figure 7.1), emphasizes meticulous data preparation, rigorous training, and robust testing.

The initial phase involves capturing images from all four sides of each fruit, ensuring a comprehensive view of the model. Various techniques are implemented to enrich and diversify the dataset to enhance the model's ability to handle variations and prevent overfitting.

The training phase adopts a two-pronged strategy. The first approach utilizes a customized CNN architecture tailored specifically for this task. The second strategy incorporates a pre-trained VGG-16 model, previously trained on a large image dataset, for a different classification purpose. This pre-trained model provides a strong foundation, and its weights are fine-tuned for the specific challenge of date fruit classification.

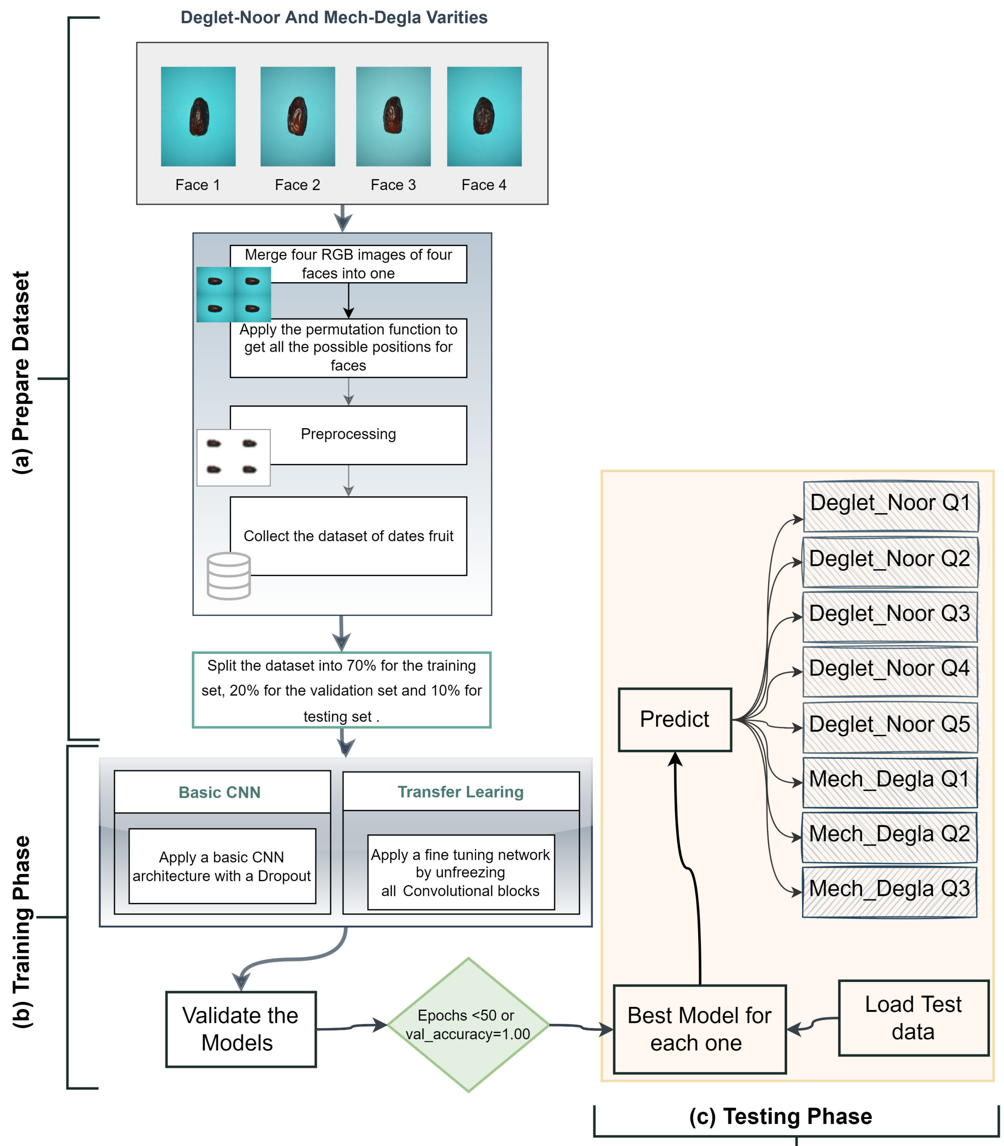


Figure 7.1: Date Fruit Classification Methodology with Four-sides Image Input

In the final testing phase, unseen data is presented to the trained models to evaluate their true capabilities. Metrics such as accuracy, precision, recall, and F1-score are used to assess the models' performance meticulously. Additionally, the research incorporates a comparative analysis, experimenting with images from one, two, and three sides of the fruit at a time, as illustrated in Figure 7.2. By capturing a more comprehensive picture by including additional date fruit faces, the study aims to demonstrate the importance of considering a more comprehensive range of date fruit attributes to optimize model performance.

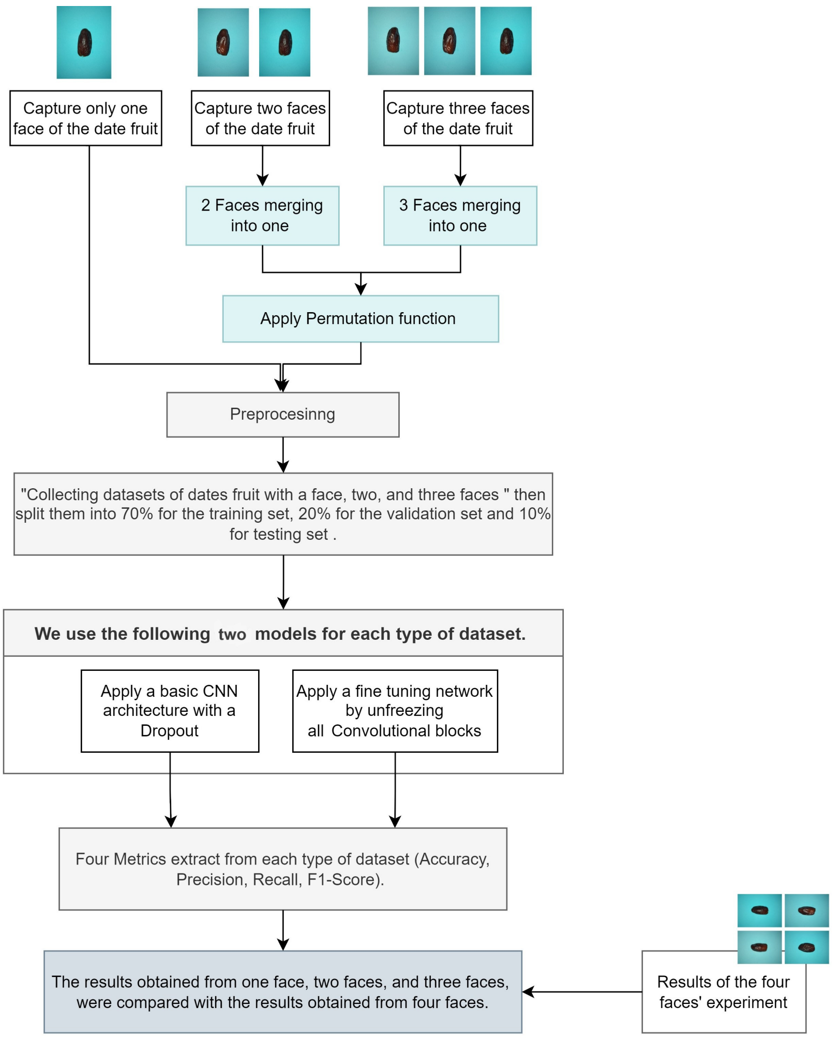


Figure 7.2: Flowchart of the Proposed Methodology for Classifying Date Fruits

7.2.1 Dataset Preparation

Our experimental of this contribution revolves around eight distinct classes of date fruit, which comprise five grades for Deglet-Noor, referred to as (DN-G1, DN-G2, DN-G3, DN-G4, DN-G5), and three grades for Mech-Degla, designated as: (MD-G1, MD-G2, MD-G3). To optimize the date fruit sorting system's performance, our approach involves capturing and extracting features from all sides of the fruit. Therefore, as mentioned and detailed in the previous contribution, we captured four images of each date, representing its four faces.

In this contribution, we created four different datasets: the first containing only one face of the date fruit, the second with two faces, the third with three faces, and the primary dataset consisting of all four faces of each date fruit, totalling approximately 3412 images.

We propose a two-step data preparation process to extract valuable information from all four sides of the date fruit and improve model performance. The first step involves merging the images from each side into a single image. The second step utilizes a permutation function to create various arrangements of these merged images.

7.2.1.1 Merging Faces Step

In our approach to classifying date fruits, a crucial step involves merging the images captured from each of the four sides into a single composite image. This merging process serves a dual purpose:

- **Data Integrity:** By combining the images, we ensure that information from each date fruit remains distinct and is not accidentally mixed with data from other fruits. This is crucial for maintaining accurate labelling and training the model effectively.
- **Model Efficiency:** Merging the images allows us to avoid separating CNN models for each face or the complex task of concatenating their fully connected layers. This streamlined approach offers several benefits:
  - **Faster Prediction:** By working with a single image, the model can make predictions more quickly than processing multiple separate images.
  - **Optimal Performance:** Our experiments demonstrate that this merging approach yields the best results for date fruit classification compared to alternative methods.

We first select the four images captured from each date fruit to implement the merging process. These images are then combined into a single composite image. The size and arrangement of this composite image depend on the number of faces available:

- **Four Faces:** For the complete dataset with images from all four sides, the merged image is a 2x2 grid (as shown in Figure 7.3(c)), referred to as "4Faces." This captures the information from each side in a clear and organized manner.
- **Two or Three Faces:** If the dataset only contains images from two or three sides of the fruit due to limitations or specific scenarios, we adapt the merging process accordingly. For two faces, the resulting image is a 1x2 grid (Figure 7.3 (a)), and

for three faces, it becomes a 1x3 grid (Figure 7.3 (b)). This maintains consistency and ensures efficient utilization of available data.

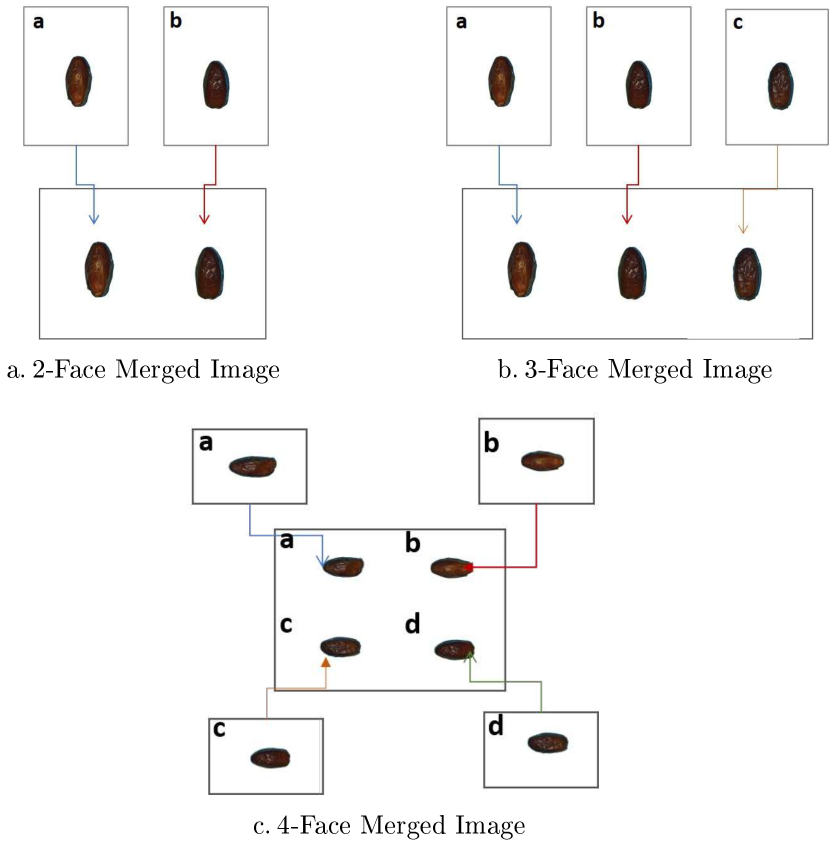


Figure 7.3: The dataset after the merging step: (a) Merged image for two faces, (b) Merged image for three faces, and (c) Merged image for four faces.

The merging process's significance extends beyond simplifying the model architecture. It also lays the foundation for the next step in our data preparation pipeline—the permutation function. This function, detailed in the following section, will further enrich the dataset by generating various arrangements of the merged images. By introducing these variations, the permutation function aims to improve the model's ability to recognize date fruits regardless of the orientation they are presented in during the classification process.

7.2.1.2 Permutation Step

Following the merging process, we introduce a crucial step called the permutation function. This function addresses a potential limitation: the model might struggle to recognize a date fruit if its orientation during classification differs from the one used during training (when the images were merged). The permutation function mathematically calculates the possible ways each face of the date fruit can be positioned within the merged image. This calculation relies on the concept of permutations, which determines the number of unique arrangements for a set of objects. The formula used to calculate the total number of permutations (P(n, r)) is provided in Equation Eq. 1:

$$P(n,r) = \frac{n!}{(n-r)!} \tag{Eq. 1}$$

Where P(n, r) represents the number of permutations, n represents the total number of faces (four in our case), and r represents the number of selected faces (also four in our case). In our study, where n and r are equal to 4 (four faces, four selected positions), the permutation function calculates 24 possible arrangements for each date fruit. This means the permutation function generates 23 additional images with different face arrangements for each merged image containing all four faces.

Figure 7.4 illustrates the concept of permutations. Figure 7.4 (c) shows an example of the complete dataset (four faces). Here, image "a" from the original merged image is moved to a different position (position 2), and all other faces are shifted accordingly, creating a new variation. Similarly, the permutation function generates different arrangements for datasets with two or three faces (Figures 7.4 (a) and 7.4 (b) respectively). This ensures the model encounters a wider variety of face orientations during training, enhancing its ability to recognize fruits regardless of their presentation during classification.

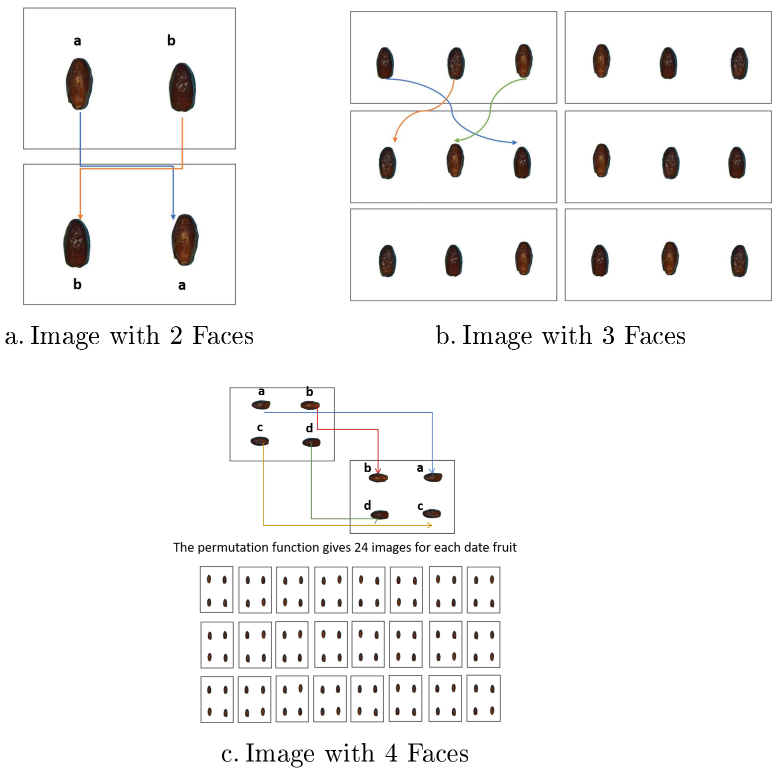


Figure 7.4: Examples of Permuted Date Fruit Images.

The merging and permutation procedures, detailed in Algorithm 1, significantly contribute to the overall effectiveness of our approach. Creating a more diverse dataset with

Algorithm 1: Permutation and Merging Algorithm for Date Fruit Images

```
Input  : List of image names
Output: Saved permutation images
Function MergeAndPermuteImages:
    nums = ['a','b','c','d'];
    y ← 0;
    foreach x in permutations(nums) do
        iteration ← 0;
        foreach e in [0, 1, 2, 3] do
            img ← chooseImg(x[e]);
            imgsPerm(iteration, img);
            iteration ← iteration + 1;
        ab ← concatenate_images_horizontally(a, b);
        cd ← concatenate_images_horizontally(c, d);
        abcd ← concatenate_images_vertically(ab, cd);
        image_name ← paths + name +' _' + str(y) +' .jpg';
        save_image(image_name, abcd);
        y ← y + 1;
Function chooseImg(img):
    switch img do
        case 'a' do
            im ← cv2.imread(file_list[i]);
        case 'b' do
            im ← cv2.imread(file_list2[i]);
        case 'c' do
            im ← cv2.imread(file_list3[i]);
        case 'd' do
            im ← cv2.imread(file_list4[i]);
    im ← cv2.resize(im, (0, 0), None, 0.25, 0.25);
    return im;
Function imgsPerm(iteration, x):
    switch iteration do
        case 0 do
            a ← chooseImg(x);
        case 1 do
            b ← chooseImg(x);
        case 2 do
            c ← chooseImg(x);
        case 3 do
            d ← chooseImg(x);
```

various face arrangements improves model generalizability by exposing the model to a broader range of scenarios, leading to better performance on unseen data. Additionally, the permutation function effectively increases the dataset size without requiring additional image acquisition, which can be particularly beneficial for datasets with limited resources.

Following the merging and permutation steps, a final preprocessing step involves removing the blue background from the date fruit images. This ensures that the model focuses on the relevant fruit features for classification.

Table 7.1 summarizes the number of samples used in our study for each Deglet Noor (DN) and Mech Deglet (MD) grade category before and after applying the merging and permutation procedures. As the table shows, these procedures substantially increase the total number of samples available for training the model.

7.2.2 Training and Testing Step

To evaluate the effectiveness of our approach, we trained and compared two distinct models: a fine-tuned VGG16 model and a custom CNN architecture specifically designed for date fruit classification. The training and testing procedures for each model, along with their detailed architecture, are illustrated in Figure 7.5 This representation offers insights into the design and implementation of our methodology.

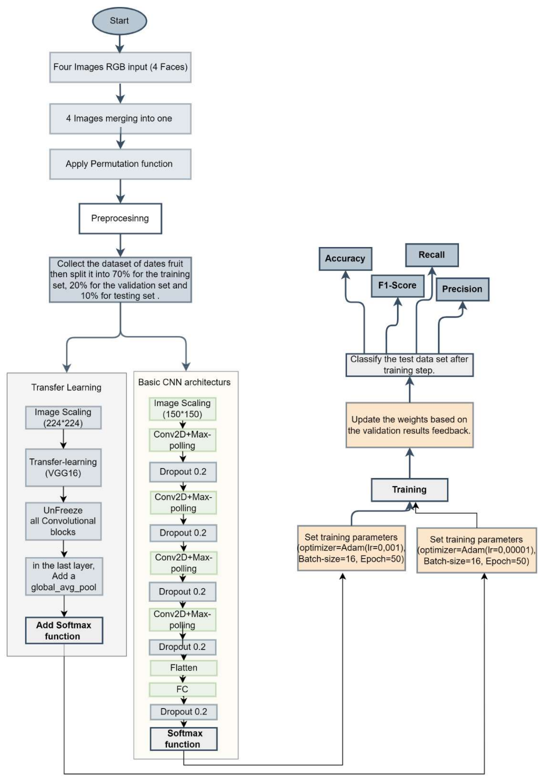


Figure 7.5: Classification Process for Date Fruits Using Proposed Architectural Models

- **Training with Pre-trained Model (VGG16):**

  Our contribution explores the application of transfer learning with a pre-trained VGG16 model for classifying date fruit images. Unlike the standard approach of freezing convolutional layers, we employ a strategy of unfreezing all layers in VGG16 during fine-tuning. This allows the model to adapt the final classification layers and the earlier feature extraction layers to the specific characteristics of date fruit images, potentially leading to improved learning of nuanced and task-specific features.

  The fine-tuning process involved training the model on a dataset containing images of the eight date fruit types. A 2D global average pooling layer was added, followed by a softmax layer with eight output nodes for classification corresponding to the eight cultivars. The detailed architecture and configuration of the pre-trained VGG16 model used for transfer learning are presented in Figure 7.6.

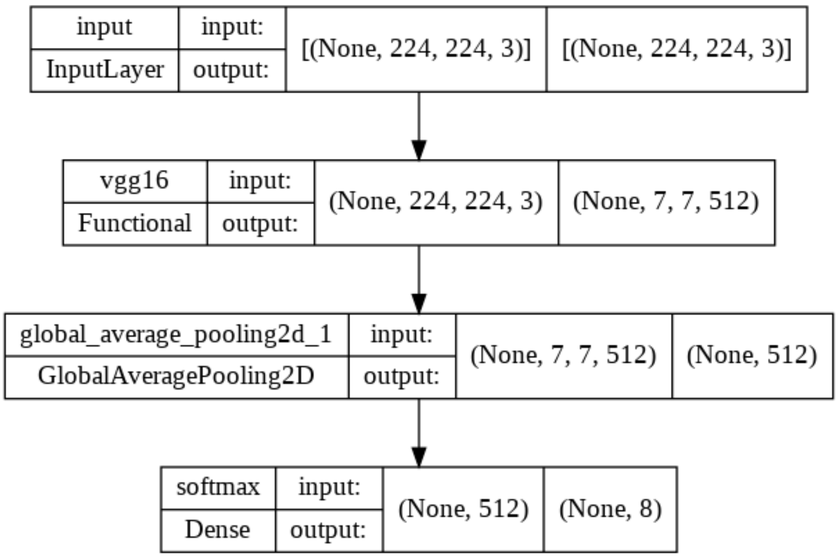


Figure 7.6: Detailed Configuration of Customized VGG16 for Date Fruit Classification.

Variety	Grade	N of samples of each type of the dataset				After Merging and Permutation		
N of faces		**One Face**	**2 Faces**	**3 Faces**	**4 Faces**	**2 faces**	**3 Faces**	**4 Faces**
Deglet Noor Variety	**DN-G1**	109	218	327	436	218	654	2 616
	DN-G2	105	210	315	420	210	630	2 520
	DN-G3	69	138	207	276	138	414	1 656
	DN-G4	104	208	312	416	208	624	2 496
	DN-G5	80	160	240	320	160	480	1 920
Mech Degla Variety	**MD-G1**	63	126	189	252	126	378	1 512
	MD-G2	120	240	360	480	240	720	2 880
	MD-G3	203	406	609	812	406	1 218	4 872
N of total samples		**853**	**1 706**	**2 559**	**3 421**	**1 706**	**5 118**	**20 472**

Table 7.1: Distribution of Samples in the Dataset by Grade and Number of Faces (Before and After Merging/Permutation)

- **Training with Custom Convolutional Neural Network (CNN)**

  This contribution proposes a convolutional neural network (CNN) architecture for classifying date fruit images. The architecture leverages convolutional layers for feature extraction, followed by fully connected layers for classification, as illustrated in Figure 7.7, which is constructed as follows:

  - Input Layer: The model accepts images with an input dimensionality of 150x150 pixels.
  - Four convolutional layers are employed to extract features from the input images. Each convolutional layer is followed by a ReLU (Rectified Linear Unit) activation function for non-linearity. Subsequently, max-pooling layers with a kernel size of 2x2 are used for dimensionality reduction and capturing dominant features.
  - To prevent overfitting, dropout layers with a rate of 0.2 are strategically incorporated after each convolutional layer. These layers randomly drop a certain percentage of activations during training, encouraging the model to learn robust features that are not overly dependent on specific data points.
  - After processing by the convolutional layers, the extracted features are flattened into a single-dimensional vector suitable for feeding into the fully-connected layer.
  - A single fully connected layer with 512 nodes is used to learn higher-level representations from the extracted features.
  - Finally, a Softmax classifier with eight output nodes and a Softmax activation function is employed for classification. This configuration allows the model to predict the probability of an input image belonging to one of eight distinct date fruit categories.

After the training phase, the model's performance is evaluated on an unseen test set. This distinction ensures an unbiased assessment of the model's generalization capability, which refers to its ability to accurately classify date fruit images it has not encountered during training. During evaluation, the model predicts class labels for each test image. These predictions are then compared to the images' true labels to calculate performance metrics that quantify the model's effectiveness. These metrics include confusion matrix, accuracy, F1-score, recall, and precision.

7.3 Experimental result and Discussion

The experiments were conducted on a Windows 10 Pro system equipped with Python (version 3.9.6), TensorFlow (version 2.6.0), and Keras (version 2.6.0). The system utilized

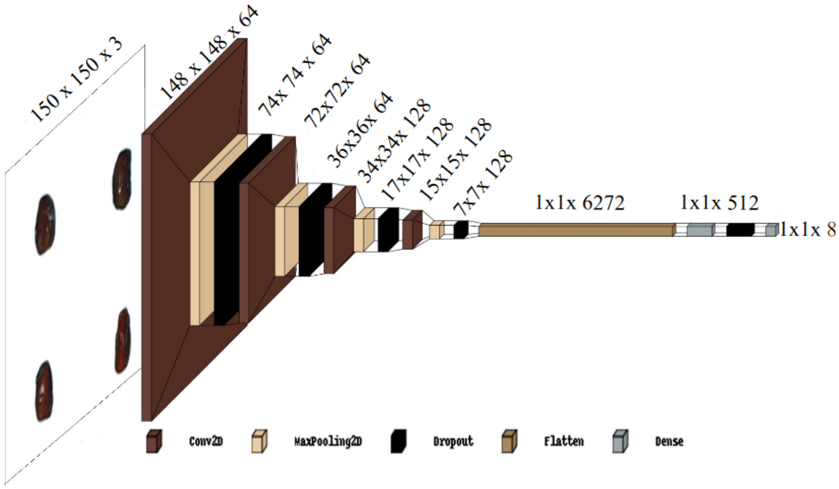
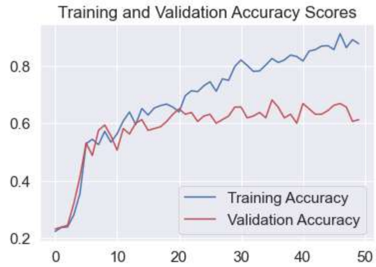


Figure 7.7: Detailed Configuration of Customized CNN for Date Fruit Classification.

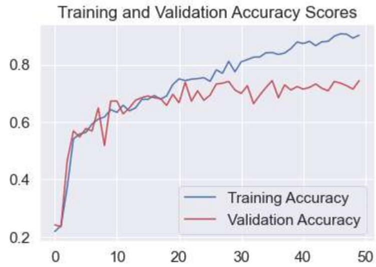
an Intel(R) Core(TM) i5-6200U CPU @ 2.30 GHz to 2.40 GHz and 4.00 GB of RAM. A consistent data preparation strategy was applied to all datasets. The data was then divided into three non-overlapping subsets: 70% for training, 20% for validation, and 10% for testing. This standard split ensures a robust evaluation methodology, allowing the model to learn from the training data, adjust its parameters based on the validation set, and ultimately be assessed on unseen data in the testing set.

This section presents a detailed analysis of the performance of the proposed CNN and fine-tuned VGG16 models for multi-face detection in date fruit images. The experiments evaluated the models' effectiveness using datasets containing varying numbers of faces (one, two, three, and four).

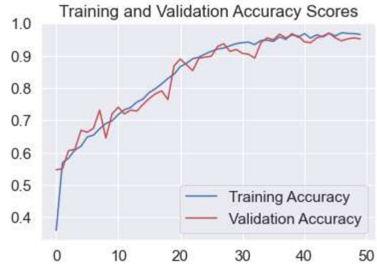
The first experiment employed a CNN from scratch model with dropout regularization (rate: 0.2) and the Adam optimizer (learning rate: 0.001). Figure 7.8 illustrates the validation accuracy curves. As observed, the validation accuracy steadily increased with the number of faces used for training. The models achieved 61% and 74.4% validation accuracies for one and two faces, respectively. The accuracy significantly improved for datasets with three and four faces, reaching 95% and 99%, respectively. The corresponding training and validation loss curves (Figure 7.9) exhibited a typical downward trend as the number of epochs increased, indicating successful model convergence.



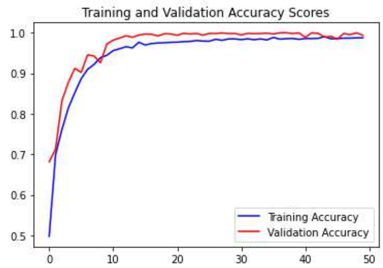
a. Using one face



b. Using two faces

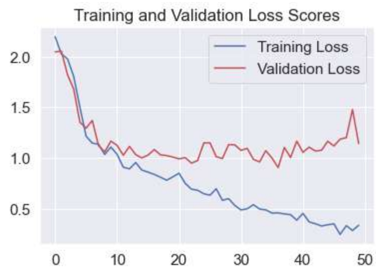


c. Using three faces

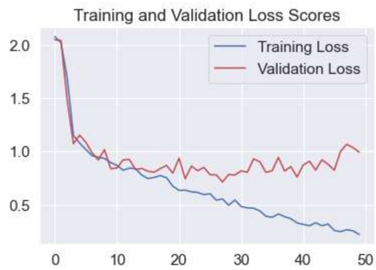


d. Using four faces

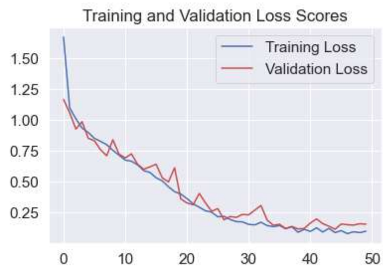
Figure 7.8: Curves of Accuracy during the model training of a CNN with dropouts



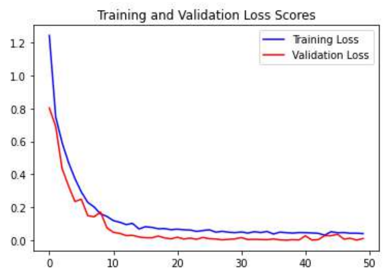
a. Using one face



b. Using two faces



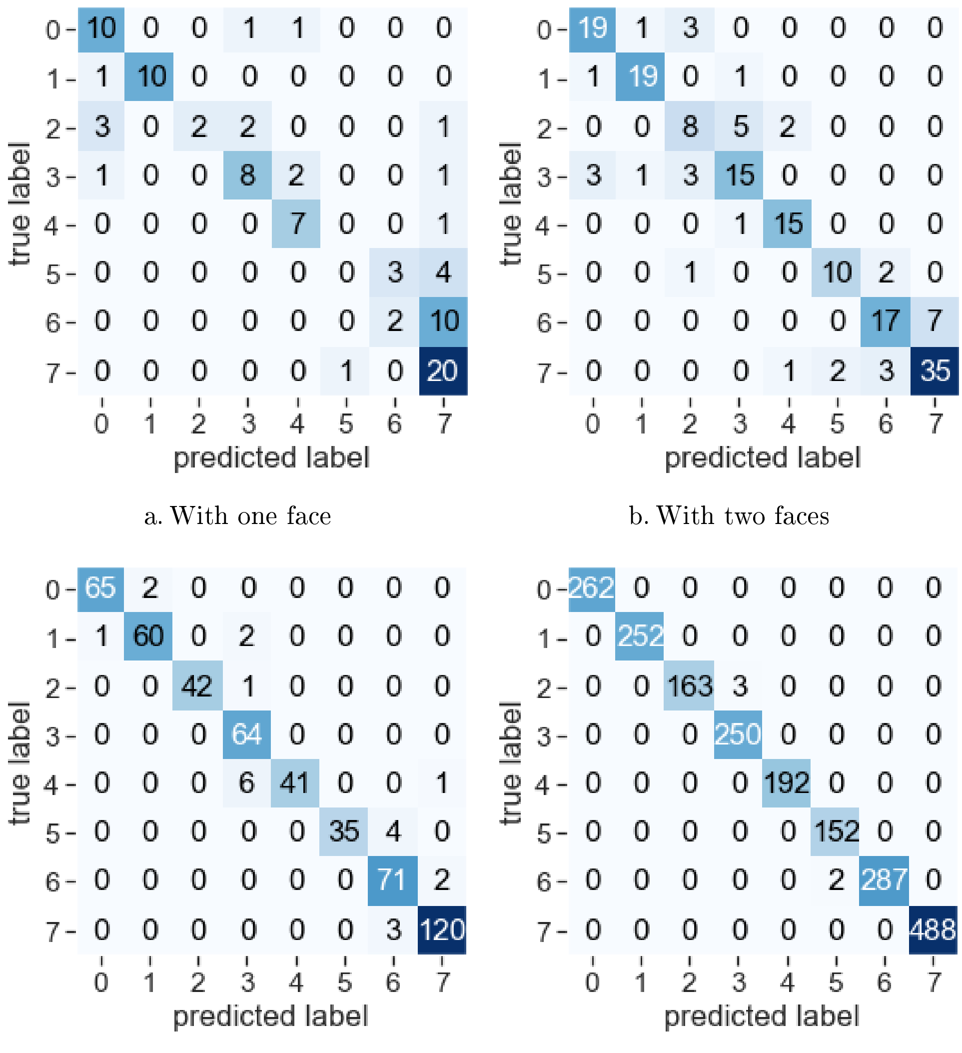
c. Using three faces



d. Using four faces

Figure 7.9: Curves of Loss during the model training of a CNN with dropouts

The effectiveness of the trained models was further evaluated on a separate test dataset not used for training. Figure 7.10 (a-d) presents the confusion matrices for each dataset configuration (one to four faces). The number of misclassified instances decreased as the number of faces used for training increased. Specifically, the model trained with one face resulted in 59 misclassifications out of 91 test images (Figure 7.10 (a)), while the model trained with four faces achieved near-perfect performance with only five misclassifications out of 2051 test images (Figure 7.10 (d)). These results demonstrate the model's improved ability to generalize to unseen data with an increasing number of training faces.



a. With one face

b. With two faces

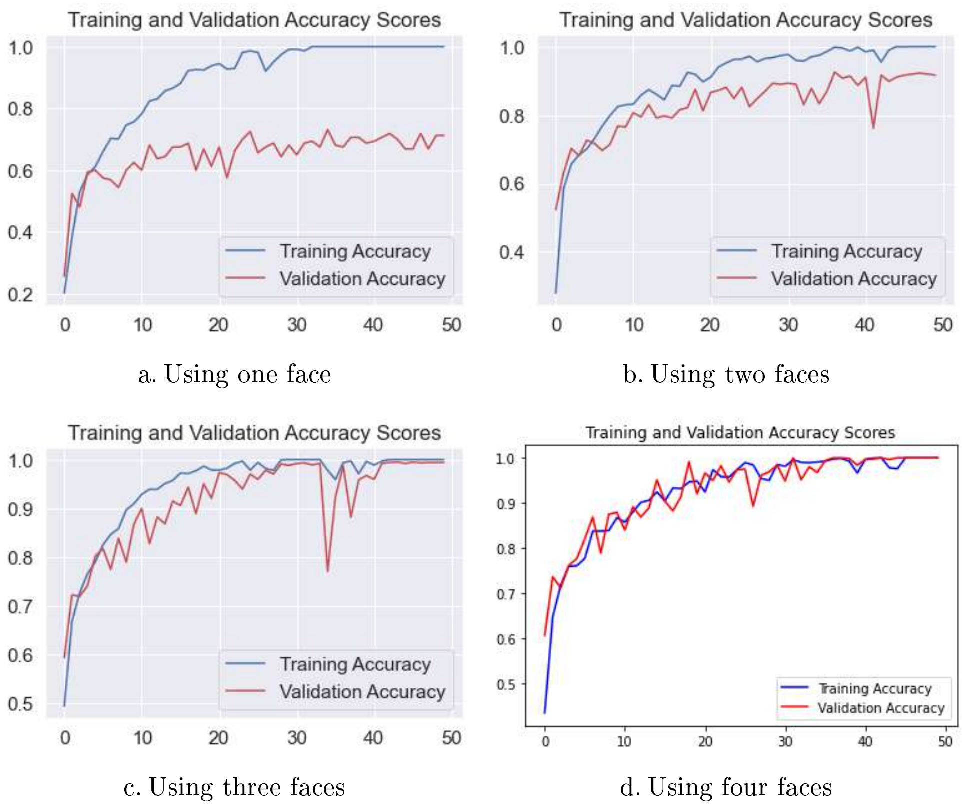
c. With three faces

d. With four faces

Figure 7.10: Confusion matrices of a CNN from scratch with a dropout

The second experiment explored the potential of a fine-tuned VGG16 model for multi-face detection. As illustrated in Figure 7.11 (a-d), the validation accuracy curves reveal a clear advantage of this approach. The model achieved exceptional validation accuracy, reaching 100% for the four-face dataset at a mere 30th epoch (Figure 7.11 (d)). This rapid convergence suggests efficient learning and optimal parameter updates. Notably, even models trained with fewer faces (71%, 91.6%, and 99.4% accuracy for one, two, and three faces, respectively) demonstrated superior performance compared to their CNN from scratch counterparts. The training and validation loss curves (Figure 7.12) further support this observation, depicting a consistent downward trend across epochs, signifying successful model optimization.

The effectiveness of the fine-tuned VGG16 model in generalizing to unseen data is further emphasized by the confusion matrices presented in Figure 7.13 (a-d). Compared to the CNN from scratch model, the number of misclassified instances in the test set significantly decreased. While the model trained with one face exhibited some misclassifications (Figure 7.13 (a)), the model trained with four faces achieved perfect classification on all test images (Figure 7.13 (d)). This remarkable performance highlights the fine-tuned VGG16 model's superior ability to learn robust representations from pre-trained features, leading to exceptional generalization capabilities, especially when trained with sufficient faces.



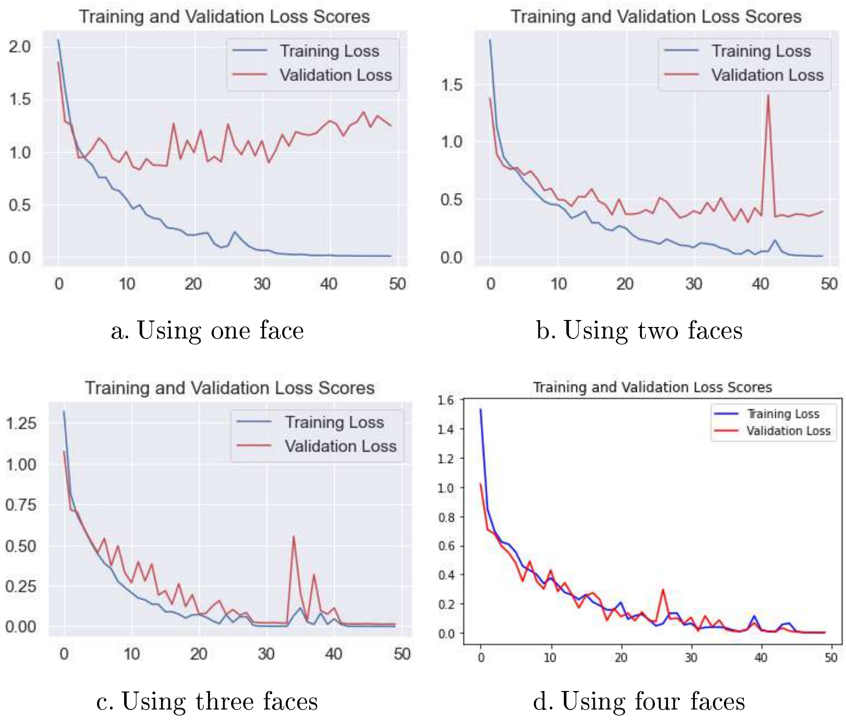
a. Using one face

b. Using two faces

c. Using three faces

d. Using four faces

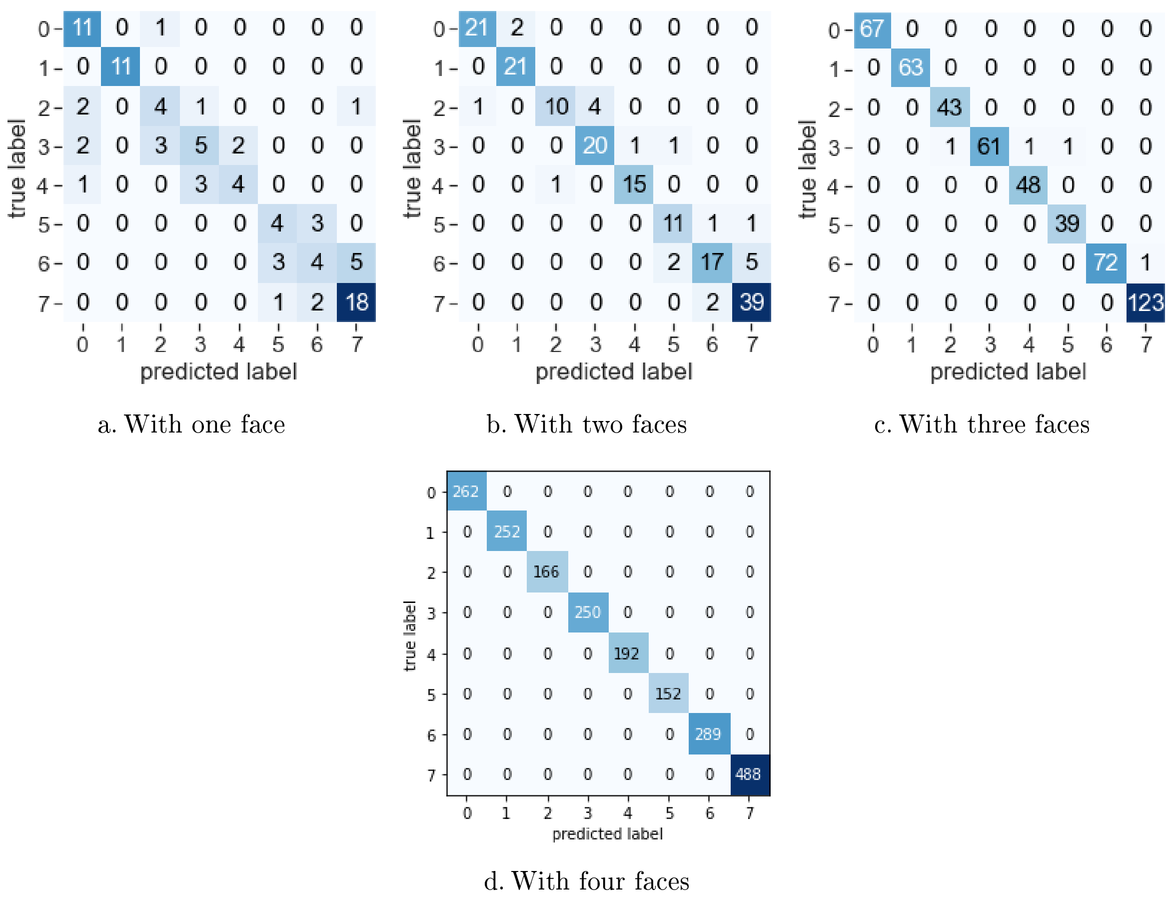
Figure 7.11: Curves of Accuracy during the model training of a fine-tuned VGG16 model



a. Using one face b. Using two faces

c. Using three faces d. Using four faces

Figure 7.12: Curves of Loss during the model training of a fine-tuned VGG16 model



a. With one face b. With two faces c. With three faces

d. With four faces

Figure 7.13: Confusion matrices of a Fine-tuned VGG16 Model

Table 7.2 summarizes the quantitative performance metrics (accuracy, precision, recall, and F1-score) for the CNN with dropout regularization and the fine-tuned VGG16 model. These metrics are evaluated on unseen data from a dedicated testing set comprising 10% of the total dataset for each dataset type (1, 2, 3, and 4 faces).

The CNN model achieved a moderate accuracy of 64.8% when trained with a single face (Table 7.2). This model demonstrated perfect precision (100%) but a lower recall (64.8%), indicating it correctly identified all detected faces but potentially missed some actual faces in the dataset. The F1-score, which balances these two aspects, was also 64.8%. During training with one face, the model achieved an accuracy of 87.7% with a loss of 0.3381, suggesting potential overfitting on the limited training data. Validation accuracy was lower at 61% with a higher loss of 1.1437, indicating the model generalizes poorly to unseen data. As the number of training faces increased, performance improved significantly. With four faces, the model achieved an accuracy of 95%, near-perfect precision (100%), and a high F1-score (99%), demonstrating its ability to accurately detect most faces with minimal errors (Table 7.2). Training and validation accuracy also increased to 98% and 99%, respectively, with lower losses (0.0407 and 0.0114), suggesting better generalization.

The fine-tuned VGG16 model displayed a similar trend of improvement with more training faces (Table 7.2). While it achieved a moderate accuracy (67%) with one face, it reached near-perfect accuracy (100%) with the four-face dataset. Precision, recall, and F1-score followed a similar pattern, reaching 100% with four faces (Table 7.2). Notably, the VGG16 model consistently surpassed the CNN model in all metrics across all training data sizes. Training accuracy for the VGG16 model remained high (often 100%) throughout, suggesting it learned effectively from the training data. Validation accuracy also generally increased with more training faces, demonstrating better generalizability than the CNN model.

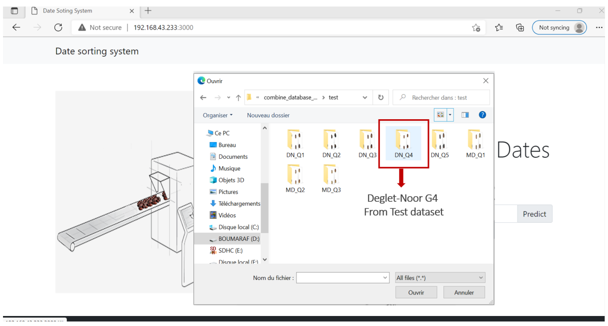
Our investigation into a multi-face classification for date fruit images revealed several key findings. First, consolidating all four faces of a date fruit into a single image (2x2 grid) and applying permutations to explore all possible face combinations significantly improved model performance (Table 7.2). This data augmentation technique mitigates overfitting by increasing training data diversity, allowing the model to learn more robust features. Furthermore, a positive correlation emerged between the number of faces used for training and classification accuracy (Table 7.2), indicating that including data from numerous faces within a single image offers a more comprehensive representation of the date fruit, resulting in more precise classifications. The study also compared the efficacy of transfer learning with a fine-tuned VGG16 model against a CNN model with dropout regularization. The results confirmed the superiority of transfer learning, with the fine-tuned VGG16 model achieving near-perfect accuracy (100%) compared to the CNN's 99% accuracy (Table 7.2).

Dataset type	**Data size**	**Model type**	**Testing results %**				**Training results**		**Validation results**	
			Accuracy	**Precision**	**Recall**	**F1-score**	**Accuracy%**	**Loss**	**Accuracy%**	**Loss**
One Face	Train: 595 val: 167 test: 91	CNN with Dropout	64.8	100	64.8	64.8	87.7	0.3381	61	1.1437
		VGG16 Fine tuning	67	75	67	67	100	0.0028	71	1.2440
Two Faces	train: 1192 val: 339 test: 175	CNN with Dropout	78.9	71.9	78.9	78.9	90	0.2210	74.4	0.9937
		VGG16 Fine tuning	88	91	88	88	100	0.0035	91.6	0.3904
Three Faces	train: 3578 val:1020 test: 520	CNN with Dropout	95.8	98.4	95.8	95.8	96.6	0.0995	95	0.1566
		VGG16 Fine tuning	99	98,9	99	99	100	0.0001564	99,4	0.0141
Four Faces	train: 16379 val: 4093 test: 2051	CNN with Dropout	95	100	99	99	98	0.0407	99	0.0114
		VGG16 Fine Tuning	**100**	**100**	**100**	**100**	**100**	**0.0012**	**100**	**0.0008**

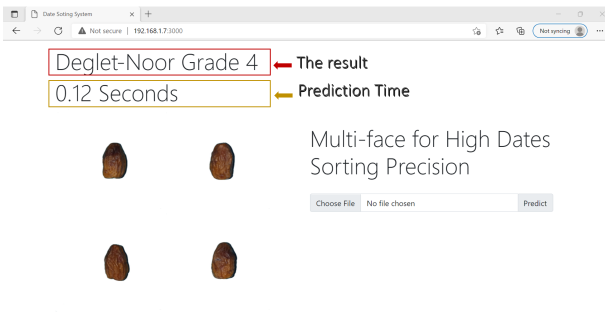
Table 7.2: The comparison among the proposed models of different datsets

The success of using pre-trained features from VGG16 for this task demonstrates its ability to learn complex representations and adapt them for multi-face detection in date fruit images. Although the custom-CNN model performed well, the substantial improvement achieved by the fine-tuned VGG16 model emphasizes the value of transfer learning for this application. Additionally, comparing with existing deep learning approaches for date fruit classification and grading highlights the competitiveness of the proposed methods (see Table 7.3). The custom CNN and the fine-tuned VGG16 model achieved excellent classification accuracy, surpassing previous works' performance, underscoring the proposed system's effectiveness for classifying different varieties of date fruits.

To demonstrate the practical applicability of the proposed approach, a user application was developed using Python and Flask (version 1.1.2) (Figure 7.14). This web-based application facilitates real-world deployment and user interaction with the multi-face classification system for date fruit. The application delivers fast and accurate predictions of date fruit classes, with a response time of only 0.12 seconds. This rapid processing speed ensures real-time functionality and minimizes user wait times. This application's successful development and implementation validate the system's effectiveness in a practical setting. Additionally, the application's fast response time suggests its potential for integration into the agricultural domain for efficient date fruit classification tasks.



a. Choosing the date fruit for classification.



b. Prediction result with processing time.

Figure 7.14: The date fruit classification process within the application interface.

	Dataset type	**Authors**	**Number of Classes**	**Model**	**Accuracy %**	**Precision %**	**F1-score %**	**Recall %**
Use One side of each date fruit	1300 dates from South of Iran's date	Nasiri et al. (2019) [4]	Four classes	VGG with modified the classifier blocks	98.49	96.63	99.05	97.33
	More than 8000 date fruit orchards	Altaheri et al. (2019) [6]	Type	VGG16	99.01	98.82	98.92	99.01
			maturity		97.25	96.17	96.71	97.25
			harvesting decision		98.59	97.46	98.02	98.59
	Date fruit bunches in Orchard	Faisal et al. (2020) [5]	Four maturity	VGG16	98.5	98.5	98.6	98.3
			Five maturity		98.3	98.9	98.6	98.24
			Seven maturity		97.7	98.8	98.1	97.9
	Saudi Arabia date fruit	Albarrak et al. (2022) [7]	8 Classes	MobileNetV2	99	99	99	99
Four faces each fruit	Algeria Date Fruit (Biskra) Self-collected	Our Proposed Systems	8 classes	CNN+Dropout	99	100	99	99
				VGG16 with fine-tuning	**100**	**100**	**100**	**100**

Table 7.3: Performance comparison between the methods using deep learning and our proposed system

7.4 Conclusion

This contribution delved into the effectiveness of utilizing multiple date fruit faces to improve classification accuracy. A self-generated dataset containing two types (Deglet-Noor and Mech-Degla) with diverse grades was utilized for training two models: a Convolutional Neural Network (CNN) and a fine-tuned VGG16 model. Our contribution was that including information from multiple faces would enhance classification accuracy.

The results confirmed this hypothesis. By merging all four faces into a single image with permutations and training on this dataset, the fine-tuned VGG16 model achieved perfect accuracy (100%). The CNN architecture with dropout also demonstrated notable results, achieving 95% accuracy on the test dataset. These findings highlight the benefits of using multiple faces over previous approaches that depend on single-face analysis.

This method significantly enhances date fruit classification accuracy compared to current techniques. Our system provides a robust and efficient solution using multiple faces and transfer learning.

Chapter 8

General Conclusion

Automated date fruit sorting is crucial for ensuring product quality and efficiency. Conventional manual sorting methods, relying on visual examination and human judgment, struggle to meet the industry's demands due to the inherent diversity of date fruit varieties and grades. This thesis tackled this challenge by investigating the potential of Convolutional Neural Networks (CNNs) for automated date fruit classification, explicitly focusing on leveraging multi-modal data from Algerian date fruits.

We proposed innovative deep learning architectures that leverage multi-modal data fusion. This approach incorporates features from multiple fruit faces alongside thermal image data and the weight measure of date fruit, providing a richer dataset for classification compared to single-face analysis. Through three distinct contributions, this thesis explored and demonstrated the effectiveness of these CNNs. The research also highlighted the importance of using multi-face and multi-modal data to achieve high-precision classification across different varieties and grades.

The first contribution explored using a multi-modal approach with CNNs [99]. This approach demonstrated the effectiveness of combining visual data from four sides of the date fruit with additional features extracted from the fruit itself to improve classification accuracy. Four models were utilized: a CNN from scratch, VGG16, ResNet50, and InceptionV3. The proposed method employed grayscaling, image averaging, and customized image channel adjustments during pre-processing to simplify and standardize the input data for the CNN models. Our experiments revealed that the VGG16 model achieved the highest performance in classifying Algerian date fruit, with a testing accuracy of 94%. While training accuracy was high at 99.6%. These findings suggest that the proposed approach has the potential to improve the efficiency and accuracy of date fruit sorting significantly.

The second contribution studied date fruit classification by incorporating multi-modal data with a late fusion technique. It employed four deep learning models, Custom-CNN, VGG16, ResNet50, and MobileNet, across two distinct scenarios. Scenario I involved classifying date fruits based on four views captured from different angles. Scenario II extended this approach by incorporating thermal images and weight measurements as additional modalities. Our results highlight the strengths of custom-CNN in both scenarios. When additional features were introduced in Scenario II, custom-CNN accuracy improved significantly, reaching 89% on the testing set (training accuracy was 100%). However, these results were within the high accuracy of the first contribution. This finding emphasizes the importance of selecting an appropriate model architecture, as some models exhibited limited improvement with additional data. Further exploration of deep learning architectures is essential. Additionally, it is imperative to investigate techniques to address the limitations of a small dataset size.

The last contribution aimed to overcome the limitations of previous studies (Section 4.3.2), which relied on classifying date fruits using only one visual image per fruit, particularly the challenge of limited dataset size in our previous contribution (5, 6). It proposed a robust solution to combine information from multiple faces to achieve high classification accuracy. The effectiveness of utilizing multiple date fruit faces was investigated by merging information from all four faces into a single image. To increase the size of the dataset, permutation functions were applied to the obtained merged faces. To evaluate the robustness of this approach, the data was evaluated using two types of models: a fine-tuned VGG16 model and a custom-CNN with dropout technique.

Additionally, data with different numbers of faces (one, two, and three) were compared. These experiments confirmed our hypothesis that incorporating information from multiple faces significantly enhances classification accuracy compared to single-face analysis. Notably, the fine-tuned VGG16 model achieved perfect accuracy (100%) with merged four faces.

In conclusion, this thesis has taken a significant step towards revolutionizing automated date fruit sorting by exploring Convolutional Neural Networks (CNNs) and in-depth analysis of multi-modal data from date fruits. While not the final answer, this research paves the way for a more efficient and accurate future for date fruit sorting.

Future research directions offer exciting possibilities for further advancement:

- Expanding the dataset size and exploring advanced data augmentation techniques like Generative Adversarial Networks (GANs): This will enhance the generalizability and effectiveness of multi-modal and multi-view date fruit classification models.

- Investigating deep learning architectures designed explicitly for multi-modal data, such as the EmbraceNet architecture: By customizing architectures to leverage the strengths of different data types.

- Developing a real prototype machine for date fruit sorting: This could involve designing a machine that utilizes embedded system technology like Raspberry Pi to benefit from the advantages of this technology.

By continuing to explore these promising avenues, we can refine and implement automated date fruit sorting systems, ultimately boosting product quality and global market competitiveness and potentially revolutionizing food sorting practices beyond the date fruit product.

Annex

DEGLET NOUR DATES

Specification

Deglet Nour dates are used in both the consumer and industrial markets in the United States. The Consumer grade dates are often referred to a B-Grade and are packed into consumer packages such as Cups, Produce Trays and Bags. The Industrial quality dates are referred to as C-Grade dates. These industrial grade dates are the dates that do not make the consumer quality and are then either grinded into a paste or chopped into pieces and sold as ingredients to bakeries and confection companies.

- **B-Grade (Consumer)**: High quality uniform Light amber dates packed in consumer packages for the retail market. (Figure 1)
- **C-Grade (Industrial)**: Low quality dates used to make paste (pate) and chopped dates for the industrial and ingredient market. (Figure 2)

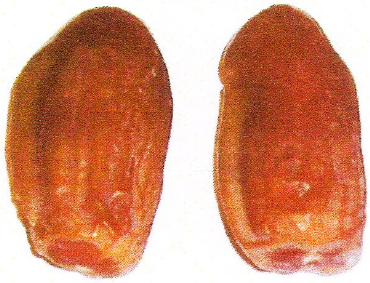
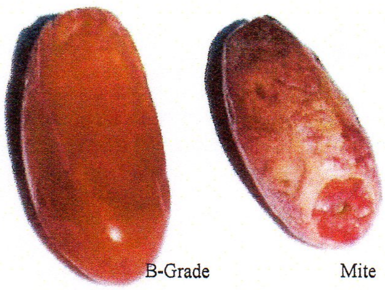
Figure 1. B-Grade Deglet Nour Dates (Consumer). Un-pitted (whole) uniform color (light brown or amber), uniform shape and few wrinkles

PROCESSING AND CLEANING FOR SHIPMENT
The dates picked from the farms are to be cleaned with a dry towel or brush, graded and sorted into B-Grade or C-Grade dates, and sometimes pitted and packed in bulk cartons without braches or stems.

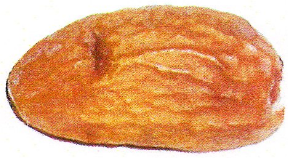
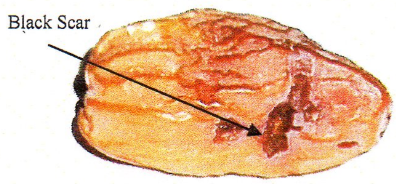
- Dates are **NOT** to be washed with water. Clean with a dry towel or brush to remove dirt or trash.
- Dates are **NOT** to be hydrated and **NOT** to be steamed.
- **Fumigation**: Methyl Bromide or Phosphine (Phoxtoxin)
- **Organic Dates are NOT to be Fumigated**

Figure 2. C-Grade Deglet Nour Dates (Industrial)
Un-pitted (whole), mixed color, variable and irregular shapes, and multiple small and deep wrinkles

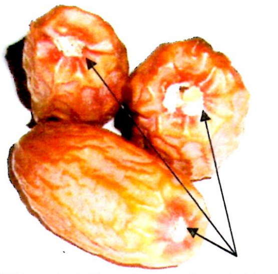
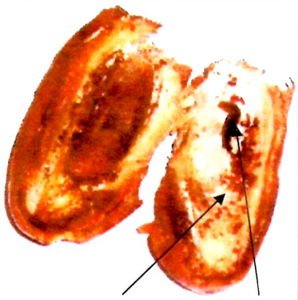
B- GRADE DEGLET NOUR VISUAL

Wrinkles	Black Scars
 Large and Few small wrinkles. B-Grade dates have a smooth texture.	 Black Scars are not allowed in B-Grade dates. For an example of a black scar, see C-Grade dates below.
Discolorations	**Mite Damage**
 Uniform Color: Light Brown or Amber.	 Mite (Not Allowed): Off Color or Greyish Color.

C- GRADE DEGLET NOUR VISUAL

Wrinkles	Black Scars
 Dry dates with lots of small wrinkles	 Black rain or water spots on Dates
Discolorations	**Mite Damage**
 Mix of Brown and dark Brown Colors is acceptable for C-Grade dates	 Mite (Allowed): Off Color or Greyish Color

REJECT DATES (CULLS) VISUAL

Dry and Shrivelled Dates	Rot or Mold	Not Ripe (Yellow or Green)
		
Extremely Woody, Dry or Shrivelled up dates	Wrinkly, shrivelled and dark dates (black) or dates with large black spots	Dates that have not been ripped are green or yellow. These dates should stay on tree longer to ripen.
Undeveloped	**Visible Infestation**	**Hidden Infestation**
		
Undeveloped dates typically don't have a pit, they are long and skinning dates that were not pollinated	White web visible on the calyx (steam) side of the date. The web is typically found in Dry dates (C-Grade)	When there is no white webbing as shown in visible infestation. Can only be determined by sampling. Can be found in B-Grade Dates by cutting them open for exam
Hidden Infestation Detail		
		
Note the Insect Excrement and the moth cocoon in the picture		

	FICHE DE CONTROLE DU PRODUIT FINI	**Réf : 4CQ13** **Version : 00** **Date:** 26/09/2016 **Page 1 sur 1**

Client : Date production : Article :

Quantité globale de la commande : Commande n° :

Paramètres	**Spécifications** **Client Maison**	**Identification des lots utilisés dans les produits finis**			
Teneur en eau					
Calibre					
Dattes infestées (%)					
Fruits aigres (fermentés), avariés (écarts) ou moisis (%)					
Dattes immatures ou non pollinisées (%)					
Dattes tâchées (%)					
Insectes vivants (nombre)					
Poids*	> poids nominal				
Emballage (ajouter n° lot emballage)*	Conforme à la commande client				
Palettisation*	-Palette propre -Palettisation conforme				
Etiquette*	- Texte lisible et conforme - Code à barre lisible				
N° de lot sur l'emballage élémentaire	Consigner le N° de lot imprimé sur l'étiquette du produit fini				
Palette N°	Indiquer N°palette du Produit Fini				
Résultats **					

* : Porter la mention : **C : Conforme / NC : Non Conforme.**
** : Porter la mention : **A : Accepté ou R : Refusé**
En cas de non-conformité n'oublier pas de remplir la fiche de non-conformité

Responsable : .... Visa :

PRODUCT SPECIFICATIONS

Property	B-Grade (Pitted)		C-Grade (Pitted)		B-Grade (Un-Pitted)		C-Grade (Un-Pitted)	
	Min	Max	Min	Max	Min	Max	Min	Max
Size (Count Per Pound)	--	70	--	100	--	60	--	90
Moisture (humidité)	14%	20%	11%	17%	14%	20%	11%	17%
Less Than 20 Wrinkles Per Date	95%	--	0%	--	95%	--	0%	--
Odor (Fermentation)	--	0%	--	0%	--	0%	--	0%
Pits: For Manual Pitted Dates or Machine pitted	--	0%	--	5%	--	100%	--	100%
Broken or Half Pitted Dates Pieces	--	1%	--	100%	--	--	--	--
Foreign Material: Rocks, Dirt, Filth, Glass, Wood, Metal, Stems, Hair or Trash, etc..	--	0%	--	0%	--	0%	--	0%
Black Scars *	--	0%	--	10%	--	0%	--	10%
Discoloration *	--	1%	--	100%	--	1%	--	100%
Mite Damage *	--	0%	--	100%	--	0%	--	100%
Hair	--	0%	--	0%	--	0%	--	0%
Hidden & Visible Dead Infestation * (Mort Insectes): Bugs, mites, worms, flies, cocoons, excrement	--	1%	--	5%	--	1%	--	5%
Live Infestation * (Vivant Insects): Bugs, mites, worms, flies, cocoons	--	0%	--	0%	--	0%	--	0%
Shriveled*	--	0%	--	0%	--	0%	--	0%
Mold or Rot*	--	0%	--	0%	--	0%	--	0%
Unripe*	--	0%	--	0%	--	0%	--	0%
Undeveloped*	--	0%	--	0%	--	0%	--	0%

*** See Visual Requirements for examples and explanations**

SAMPLING PROCEDURES

- Lot Size: 20 foot Dry Container.
- Sample Rate: A Minimum of 20 randomly selected cartons.
- Sample Size from each Carton: 25oz (708g) randomly selected dates.
  1. Count total number dates in 25oz sample and inspect.
  2. Use total count of 25oz sample and count of findings to calculate percentages.

MICROBIOLOGICAL

Property	Maximum	Units	Preferred Method
Standard Plate Count	50,000	/gram	AOAC
Coli form	100 MPN	/gram	AOAC
E.Coli	< 3 MPN	/gram	AOAC
Salmonella	Negative	per 25/gram	AOAC
Staphylococci – Coagulase Positive	<10 MPN	/gram	AOAC
Yeast	5,000	/gram	FDA-BAM
Mold	5,000	/gram	FDA-BAM

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