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SoilSense: An Intelligent Fertilization Management System for Smart Agriculture

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Djihane Djoudi & Meriem Bacha

Abstract

The rapid advancement of smart agricultural technologies has created new opportunities to improve farming efficiency through automation and intelligent resource management. In this context, this thesis presents the design, implementation, and evaluation of SoilSense, an intelligent automated fertilization management system developed to optimize agricultural practices through real-time soil analysis and precision-based decision-making.

The proposed system integrates Internet of Things (IoT) technologies with embedded systems using an ESP32 microcontroller to continuously monitor essential soil parameters, including moisture, temperature, pH, and nutrient-related indicators. The collected data are transmitted to a Firebase backend via Wi-Fi and analyzed using a two-stage deep learning architecture: a multi-output regression model predicts nitrogen, phosphorus, and potassium deficiencies ($R^2 = 0.9980$), followed by a classification model that recommends the appropriate fertilizer type (98% accuracy). A SHAP-based explainability framework provides transparent reasoning for each recommendation, and a quantitative dose calculation mechanism determines the exact fertilizer quantity required based on predicted deficiencies.

To enhance usability and accessibility, a cross-platform monitoring dashboard was developed using Flutter, enabling users to remotely monitor system operations, visualize real-time sensor data, and manage agricultural processes through an intuitive interface accessible on mobile, desktop, and web platforms. A user study with 54 Agricultural practitioners validated the system, yielding an overall satisfaction rating of 4.63/5, with 96.5% expressing willingness to adopt the system and 85.2% willing to pay a subscription fee.

The implementation of SoilSense contributes to the promotion of sustainable agricultural practices by reducing fertilizer waste, lowering environmental impact, improving crop productivity, and supporting data-driven farming strategies. This work demonstrates the practical integration of sensor technologies, deep learning, explainable artificial intelligence, software engineering, and intelligent monitoring solutions in the development of modern smart farming infrastructures.

Keywords: Smart Agriculture, Internet of Things, Fertilization Management, Precision Farming, Soil Monitoring, Deep Learning, Explainable AI, Cross-Platform Dashboard.

Résumé

Les progrès rapides des technologies agricoles intelligentes ont créé de nouvelles opportunités pour améliorer l'efficacité agricole grâce à l'automatisation et à la gestion intelligente des ressources. Dans ce contexte, cette thèse présente la conception, l'implémentation et l'évaluation de SoilSense, un système intelligent de gestion automatisée de la fertilisation développé pour optimiser les pratiques agricoles grâce à l'analyse en temps réel du sol et à une prise de décision basée sur la précision.

Le système proposé intègre les technologies de l'Internet des Objets (IoT) avec des systèmes embarqués utilisant un microcontrôleur ESP32 pour surveiller en continu les paramètres essentiels du sol, y compris l'humidité, la température, le pH et les indicateurs liés aux nutriments. Les données collectées sont transmises à un backend Firebase via Wi-Fi et analysées à l'aide d'une architecture d'apprentissage profond en deux étapes : un modèle de régression multi-sortie prédit les carences en azote, phosphore et potassium (R^2 = 0,9980), suivi d'un modèle de classification qui recommande le type d'engrais approprié (précision de 98%). Un cadre d'explicabilité basé sur SHAP fournit un raisonnement transparent pour chaque recommandation, et un mécanisme quantitatif de calcul de dosage détermine la quantité exacte d'engrais requise.

Pour améliorer l'utilisabilité et l'accessibilité, un tableau de bord de surveillance multiplateforme a été développé avec Flutter, permettant aux utilisateurs de superviser à distance les opérations du système, visualiser les mesures des capteurs en temps réel et gérer les processus agricoles grâce à une interface intuitive accessible sur mobile, bureau et web. Une étude utilisateur auprès de 54 praticiens agricoles a validé le système, obtenant une note de satisfaction globale de 4,63/5, avec 96,5% d'intention d'adopter le système et 85,2% de volonté de payer un abonnement.

L'implémentation de SoilSense contribue à la promotion de pratiques agricoles durables en réduisant le gaspillage d'engrais, en diminuant l'impact environnemental, en améliorant la productivité des cultures et en soutenant les stratégies agricoles basées sur les données. Ce travail démontre l'intégration pratique des technologies de capteurs, de l'apprentissage profond, de l'intelligence artificielle explicable, de l'ingénierie logicielle et des solutions de surveillance intelligente dans le développement d'infrastructures agricoles intelligentes modernes.

Mots-clés : Agriculture Intelligente, Internet des Objets, Gestion de la Fertilisation, Agriculture de Précision, Surveillance du Sol, Apprentissage Profond, IA Explicable, Tableau de Bord Multiplateforme.

الملخص

لقد خلقت التطورات السريعة في تقنيات الزراعة الذكية فرصًا جديدة لتحسين كفاءة الزراعة من خلال الأتمتة والإدارة الذكية للموارد. في هذا السياق، تقدم هذه الأطروحة تصميم وتنفيذ وتقييم نظام صيلصنس، وهو نظام ذكي آلي لإدارة التسميد تم تطويره لتحسين الممارسات الزراعية من خلال التحليل الفوري للتربة واتخاذ القرارات الدقيقة.

يدمج النظام المقترح تقنيات إنترنت الأشياء مع الأنظمة المدمجة باستخدام متحكم يصع٢٣ للمراقبة المستمرة للمعلمات الأساسية للتربة، بما في ذلك الرطوبة ودرجة الحرارة ودرجة الحموضة ومؤشرات المغذيات. يتم إرسال البيانات المجمعة إلى خلفية ذربس عبر واذ وتحليلها باستخدام بنية تعلم عميق ذات مرحلتين: نموذج انحدار متعدد المخرجات يتنبأ بنقص النيتروجين والفوسفور والبوتاسيوم (غ = ٩٩٨٠٠٠)، يليه نموذج تصنيف يوصي بنوع السماد المناسب (دقة ٩٨ %). يوفر إطار تفسير قائم على صحاع سببًا شفافًا لكل توصية، وتحدد آلية حساب الجرعة الكمية الدقيقة المطلوبة من السماد.

لتحسين قابلية الاستخدام والوصول، تم تطوير لوحة تحكم مراقبة مشتركة بين المنصات باستخدام ذلتر، مما يسمح للمستخدمين بالإشراف عن بعد على عمليات النظام، وعرض قياسات المستشعرات في الوقت الفعلي، وإدارة العمليات الزراعية من خلال واجهة بديهية يمكن الوصول إليها على الأجهزة المحمولة وسطح المكتب والويب. قامت دراسة مستخدمين شملت ٥٤ ممارسًا زراعيًا بالتحقق من صحة النظام، مما أسفر عن تقييم رضا إجمالي قدره ٥٠٤ مع تعبير ٥٠٩٦ % عن رغبتهم في تبني النظام واستعداد ٢٠٨٥ % لدفع رسوم اشتراك.

يساهم تطبيق صيلصنس في تعزيز الممارسات الزراعية المستدامة من خلال تقليل هدر الأسمدة، وتقليل التأثير البيئي، وتحسين إنتاجية المحاصيل، ودعم استراتيجيات الزراعة القائمة على البيانات. يوضح هذا العمل التكامل العملي لتقنيات الاستشعار والتعلم العميق والذكاء الاصطناعي القابل للتفسير وهندسة البرمجيات وحلول المراقبة الذكية في تطوير البنى التحتية الزراعية الذكية الحديثة.

الكلمات المفتاحية: الزراعة الذكية، إنترنت الأشياء، إدارة التسميد، الزراعة الدقيقة، مراقبة التربة، التعلم العميق، الذكاء الاصطناعي القابل للتفسير، لوحة تحكم مشتركة بين المنصات.

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General Introduction

1.1 General Context

For many years, agriculture has been the main source of food for human beings and animals due to its vital importance. Governments and countries always seek to enhance their profit from agriculture in order to increase incoming resources and cover population needs. With technological development, we can enhance the farming field more and more. In fact, the incorporation between traditional agriculture and technology produces a new concept entitled Smart Agriculture. Smart agriculture is an idea that stands on using Internet of Things (IoT) and Artificial Intelligence (AI) technologies in traditional agriculture. This combination makes field monitoring much easier than ever, especially in the production chain process.

In the traditional vision of agriculture, farmers manually cover almost every operation including soil preparation, seeding, fertilization, and crop gathering. Besides, experts suffer from limitations when conducting studies on phenomena or diseases that appear on crops. One of the major issues in agriculture, and which farmers strive the most for, is fertilization management. In order to have the best quality and quantity of crops, farmers need to apply the right type and quantity of fertilizer at the right time, considering different factors such as soil nutrients, moisture, pH, temperature, and crop type. Achieving correct fertilization often requires hard studies from experts and a lot of historical data. For this matter, technology comes to help. With the latest tools and devices, farmers can finally know more about their soil and crops with less effort than traditional ways.

1.2 Problem Statement and Objectives

Despite the promising advances in IoT and AI for smart agriculture, several obstacles hinder the practical deployment of fertilization management systems. Many farmers apply fertilizers based on fixed schedules or rough estimates rather than actual soil conditions, leading to two critical problems: over-fertilization, which wastes resources, increases costs, and causes environmental pollution; and under-fertilization, which reduces crop yield and quality. Existing technological solutions have significant limitations. Many are too expensive for small and medium-sized farms. Others focus only on monitoring without providing actionable recommendations. Furthermore, most AI models function as "black boxes," offering little transparency, which reduces farmer trust and limits adoption. There is therefore a clear gap between data collection and practical, affordable, and interpretable decision support for fertilization management.

The main objective of this work is to design, implement, and evaluate SoilSense, an intelligent automated fertilization management system for smart agriculture. The specific objectives are:

1. To design a multi-layer architecture integrating data acquisition, communication, processing, decision-making, user interface, and actuation.
2. To develop a low-cost IoT sensing unit using ESP32 and affordable soil sensors (pH, moisture, temperature).
3. To implement a two-stage deep learning model: a regression model for predicting N, P, K deficiencies, and a classification model for recommending fertilizer types.
4. To integrate explainable AI (SHAP) for model transparency.
5. To develop a cross-platform mobile dashboard (Flutter + Firebase) for real-time monitoring and farmer approval.

6. To evaluate the system using regression metrics (R^2, MAE, RMSE), classification metrics (accuracy, precision, recall, F1-score), and a user study with agricultural practitioners.

1.3 Contributions

The main contributions of this thesis are:

1. A complete multi-layer architecture for intelligent fertilization management.
2. A low-cost IoT sensing unit for real-time soil monitoring using ESP32.
3. A two-stage deep learning model (regression + classification) for nutrient deficiency prediction and fertilizer recommendation.
4. A SHAP-based explainability framework for transparent AI decisions.
5. A cross-platform mobile dashboard for real-time visualization and human-in-the-loop approval.
6. A quantitative fertilizer dose calculation mechanism.
7. A comprehensive user study validating system acceptance and adoption potential.

1.4 Outline

This dissertation is organized as follows:

- **Chapter 1: Evolution of Agriculture and Smart Farming Systems** reviews the evolution from traditional to smart agriculture, presents current challenges in modern agriculture, and explores IoT and AI foundations with related works.
- **Chapter 2: Conception and Contribution** details the proposed system architecture, the two-stage deep learning model, the IoT sensing and actuation

layers, and the technical contributions including the hybrid expert system for label generation and the XAI framework.

- **Chapter 3: Implementation and Results** presents the system implementation, development tools, deep learning model evaluation, model comparisons, generalization assessment, system validation, and user study results with 54 agricultural practitioners.
- **General Conclusion** synthesizes the findings and outlines future directions.

Chapter 1

Evolution of Agriculture and Smart Farming Systems

1.1 Introduction

Agriculture has played a foundational role in shaping human societies, particularly through its direct connection to food security and economic stability. As populations expanded, the need for more efficient and reliable food production systems became increasingly critical. Over time, farming has evolved from manual subsistence practices to technology-driven production systems. The essential agricultural industry comprises various elements of development, such as population, climate, and resources, as well as principles, for instance, productivity and impact.

Today, increasing food demand, environmental pressures, and climate uncertainty highlight the limitations of conventional agriculture, particularly inefficient resource use and delayed decision-making. Modern farming must therefore enhance productivity while reducing environmental impact and optimizing resource consumption.

This chapter reviews the evolution of agricultural systems, emphasizing the transition toward smart and intelligent agriculture. It outlines key technological milestones, examines current challenges, and analyzes IoT- and AI-based approaches, identifying their limitations and the research gap addressed by the proposed SoilSense system.

1.2 Evolution of Agricultural Systems

Agricultural development has changed significantly over time through several major phases. Each phase introduced new farming methods, technologies, and ways of using agricultural data. Over time, farming moved from manual activities toward more automated and technology-driven systems. Rather than replacing earlier methods entirely, each phase builds upon previous developments, enhancing productivity, efficiency, and sustainability Aggarwal and Verma (2022); Gubbi et al. (2013); Kamilaris and Prenafeta-Boldú (2018).

1.2.1 Agriculture 1.0: Traditional Farming Systems

The first stage of modern agricultural evolution is commonly referred to as Agriculture 1.0, where farming activities were mainly dependent on human labor and animal power. Farmers relied on manual tools and traditional knowledge to perform essential tasks such as plowing, planting, and harvesting. Decision-making was based largely on experience and observation, with minimal scientific or technological support Aggarwal and Verma (2022).

These systems were typically small-scale and subsistence-oriented, with limited productivity and efficiency. Although they maintained a close relationship with natural ecosystems, they were highly vulnerable to environmental conditions such as rainfall variability and soil fertility.

1.2.2 Agriculture 2.0: Mechanization and Industrial Agriculture

Agriculture entered a new phase when machines began replacing traditional manual farming activities. During the industrial revolution period, farmers started using mechanical equipment including tractors and harvesting machines, which improved farming speed and productivity Aggarwal and Verma (2022).

In addition to mechanization, chemical products such as fertilizers and pesticides also became widely used during this period, which helped farmers produce larger quantities of crops on bigger farming areas. However, these advancements also led to environmental challenges, such as soil damage, pollution of water resources, and negative effects on ecosystems.

The foundations of precision agriculture also began to emerge during this phase. Technologies such as Global Positioning Systems (GPS) allowed farmers to monitor spatial variability within fields. Nevertheless, data collection remained periodic and largely manual, limiting real-time decision-making capabilities Trivelli et al. (2019).

1.2.3 Agriculture 3.0: Precision Agriculture

The third agricultural phase introduced digital tools and connected technologies into farming activities. This stage introduced technologies such as sensors, satellite monitoring, and digital data platforms to improve monitoring and decision-making processes Trivelli et al. (2019).

Advancements in internet connectivity and online storage technologies made it easier to gather and manage agricultural information. Farmers could analyze historical and spatial data to optimize resource use, particularly through methods that adjust fertilizer and irrigation quantities according to field conditions.

Despite these improvements, decision-making in Agriculture 3.0 remained largely centralized and reactive. Farmers were still required to interpret data and manually implement actions, limiting the potential for real-time automation.

1.2.4 Agriculture 4.0: Smart and Digital Agriculture

Agriculture 4.0 refers to today's smart farming environment, where connected technologies and automation are increasingly used in agriculture. Modern farms now combine IoT devices, AI-based analysis, automated machines, and smart monitoring systems. This approach applies modern industrial digital technologies to agricultural activities, enabling

the development of intelligent and interconnected farming environments De Clercq et al. (2018); Trivelli et al. (2019).

In this stage, farms operate as cyber-physical systems, where sensors continuously monitor soil properties, plant conditions, and surrounding environmental changes. These data are transmitted through IoT-based infrastructures and analyzed using advanced computational models to support predictive analytics and autonomous decision-making Ramli et al. (2020).

Smart agriculture systems enhance efficiency by optimizing resources like irrigation water, fertilizers, and electrical energy, while limiting negative environmental effects. Furthermore, they improve resilience to climate variability by enabling adaptive and data-driven management strategies.

Overall, the development of agriculture has been progressive, with each stage building upon the technological foundations of previous systems. The main differences between these agricultural stages are presented in Table 1.1.

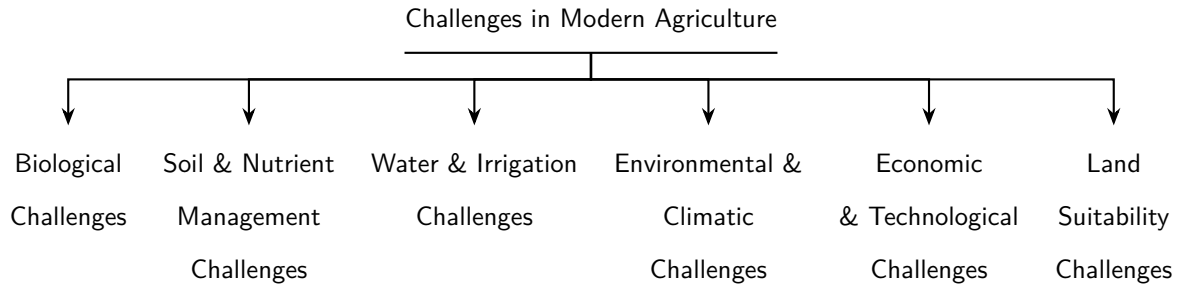
TABLE 1.1: Comparison of Agricultural Paradigms

Era	**Main Technology**	**Data Frequency**	**Decision Mode**	**Efficiency**
Agriculture 1.0	Manual tools, animal power	Visual observation	Manual	Low
Agriculture 2.0	Mechanization, GPS	Periodic sampling	Semi-manual	Medium
Agriculture 3.0	Sensors, Internet, Cloud	Continuous logging	Centralized	High
Agriculture 4.0	AI, IoT, Automation	Real-time streams	Autonomous	Very High

Despite these advancements, challenges related to cost, data integration, and accessibility still limit the full implementation of smart farming technologies.

1.3 Challenges in Modern Agriculture

Modern agriculture is confronted by a set of interrelated challenges, primarily driven by population growth, environmental degradation, climate change, and economic inequality. These pressures manifest across multiple domains, as detailed below.



1.3.1 Biological Challenges

Biological factors represent a major constraint in modern agriculture, primarily due to the widespread impact of insect pests, plant diseases, and pathogenic microorganisms. These threats significantly reduce crop yield and quality, posing serious risks to global food security. It has been estimated that pests alone are responsible for substantial crop losses worldwide, highlighting their critical impact on agricultural productivity Oerke (2006). In addition, the increasing adaptability of pests and pathogens has led to the development of resistance against conventional chemical pesticides, reducing their effectiveness and making crop protection more challenging Shao et al. (2026).

Plant diseases caused by fungi, bacteria, and viruses further exacerbate these challenges by disrupting plant growth and reducing yield stability. Addressing these issues requires multidisciplinary approaches, as plant health is closely linked to environmental conditions and farming practices Jeger et al. (2021). Moreover, excessive reliance on chemical inputs has negatively affected soil biodiversity and ecological balance, limiting the role of beneficial microorganisms in maintaining soil health.

Recent research highlights the importance of biological control strategies as sustainable alternatives to chemical-based methods. The use of beneficial microorganisms and biopesticides has shown promising results in managing plant diseases and pests while

minimizing environmental impact Nguyen et al. (2025); Lahlali et al. (2025, 2022). These approaches not only improve crop protection but also contribute to the preservation of soil ecosystems and long-term agricultural sustainability Merizig et al. (2024).

1.3.2 Soil and Nutrient Management Challenges

Soil is a highly complex and dynamic system composed of both living organisms and non-living components such as minerals and organic matter. This complexity contributes significantly to soil variability, making nutrient assessment and management particularly challenging. Even minor variations in soil properties, influenced by biological activity and physicochemical interactions, can affect nutrient availability and prediction accuracy Xiao and He (2019); Vullaganti et al. (2025).

One major difficulty is that every soil has unique biological, chemical, and physical characteristics that influence nutrient cycles. This variability makes it hard to create general models that work accurately across different environments Vullaganti et al. (2025).

Soil organic matter (SOM), largely governed by biological processes, plays a crucial role in maintaining soil fertility and nutrient availability. However, its dynamic nature, driven by continuous decomposition and transformation, makes it difficult to measure and model accurately. Although advanced sensing technologies have been developed to estimate SOM, their effectiveness is often limited due to the complexity of soil interactions Dhamu et al. (2024); Vullaganti et al. (2025).

Soil moisture presents another significant challenge because it affects both microbial activity and how sensors measure soil properties. Research has shown that high soil moisture reduces the accuracy of measurements taken in the field compared to controlled laboratory conditions Wenjun et al. (2014); Nawar et al. (2022); Bendahmane et al. (2025); Roufaida et al. (2024).

In addition, soil nutrients exhibit temporal variability due to ongoing biological and environmental processes. Nutrient levels fluctuate over time as a result of microbial activity, environmental changes, and nutrient transformations, making continuous monitoring essential for effective management. This variability complicates predictive

modeling, as static measurements may not accurately represent real-time soil conditions Vullaganti et al. (2025).

Finally, the interaction between biological, chemical, and physical soil properties further complicates nutrient management. Factors such as soil texture, structure, and organic content influence nutrient retention and transport, highlighting the need for integrated approaches that consider multiple soil characteristics to improve the effectiveness of nutrient management strategies Vullaganti et al. (2025).

1.3.3 Water and Irrigation Challenges

Lack of water and inefficient irrigation systems are among the most serious constraints to sustainable farming. Growing global food demand combined with climate variability has put increasing pressure on freshwater resources, especially in dry and semi-dry regions. Solving these challenges requires advanced management strategies that combine new technology with sustainable water policies Ingrao et al. (2023); Pereira (2017); Khebbache et al. (2023).

A major problem with current irrigation systems is inefficient water distribution. Traditional methods often waste large amounts of water through evaporation, runoff, and deep percolation. Recent studies emphasize the need for better irrigation scheduling and precision water delivery to improve efficiency Abou-Shady et al. (2023).

Climate change worsens irrigation problems by changing rainfall patterns and increasing drought frequency. These changes directly affect how much water crops need and put additional stress on already limited water supplies. Adapting to these effects is especially important in regions that depend heavily on agriculture Elnashar and Elyamany (2023); Fischer et al. (2007).

Groundwater depletion is another critical concern, particularly in areas that grow crops for export using intensive irrigation. Over-pumping of groundwater has caused long-term environmental damage and reduced water availability for future farming. This problem is connected to global food trade, which effectively transfers water stress between regions Dalin et al. (2017).

New smart irrigation technologies offer promising solutions. Machine learning, deep reinforcement learning, and optimization algorithms are increasingly being used to improve irrigation scheduling and reduce water waste. These technologies enable real-time decisions based on current soil and weather conditions Ding and Du (2024); Mwiya et al. (2020).

International organizations such as UNESCO stress the importance of integrated water resource management to address global water challenges. Such approaches encourage cooperation between governments, researchers, and local communities to ensure fair and sustainable access to water Makarigakis and Jimenez-Cisneros (2019).

1.3.4 Environmental and Climatic Challenges

Climate change is a major environmental challenge affecting modern agriculture. Rising temperatures and increasing CO_2 levels can affect crop growth, but the overall impact is generally negative. Higher temperatures speed up crop development, increase soil water evaporation, and promote pest and disease spread, all of which reduce productivity. According to the Intergovernmental Panel on Climate Change (IPCC), climate change has already reduced yields of major crops such as wheat, rice, maize, and soybean by approximately 9.5% since the industrial revolution Arias et al. (2021). Future projections suggest that yields could decrease further by 5.7%, 4.5%, 6.3%, and 6.7%, respectively if global temperatures rise by 1.5°C Wang et al. (2020).

Moreover, extreme weather events such as droughts, floods, and heatwaves have become more frequent and intense, causing significant damage to agricultural production. It has been estimated that such events reduced global grain production by around 9–10% between 1964 and 2007 Lesk et al. (2016). Climate change also affects livestock and fisheries by reducing feed availability, altering ecosystems, and increasing environmental stress. For example, ocean warming and acidification threaten marine life and fishery productivity, with projections indicating significant declines in species such as Atlantic cod Doney et al. (2009).

1.3.5 Economic and Technological Challenges

Modern agriculture is increasingly driven by precision farming and digital technologies; however, significant economic and technological barriers still limit their widespread adoption. These challenges are particularly relevant in developing agricultural systems where access to advanced infrastructure and analytical tools remains limited.

The high cost of precision agriculture technologies is a major economic constraint. IoT sensors, remote sensing systems, and AI-driven decision support platforms require substantial initial investment. For small and medium-sized farms, these costs can be prohibitive, especially when combined with maintenance and operating expenses Vullaganti et al. (2025).

Another key challenge is the lack of technological accessibility and infrastructure in rural areas. Many agricultural regions still suffer from insufficient internet connectivity, limited access to modern devices, and a lack of technical support. This digital divide restricts the adoption of smart farming solutions and limits the benefits of data-driven agriculture Makarigakis and Jimenez-Cisneros (2019).

From a technological perspective, integrating heterogeneous agricultural data remains a major difficulty. Precision agriculture systems rely on combining soil properties, environmental data, and remote sensing information. However, inconsistencies in data formats and measurement techniques make it difficult to build unified and reliable decision-making systems Xiao and He (2019).

Sensor reliability is another important concern in smart farming systems. Environmental factors such as soil variability, moisture fluctuations, and sensor degradation can reduce measurement accuracy. These limitations directly affect the performance of models used for soil nutrient estimation and environmental monitoring Dhamu et al. (2024); Wenjun et al. (2014).

In addition, the interpretation and classification of soil data using advanced analytical methods, such as spectral analysis and chemometric techniques, require significant computational expertise. While these methods improve accuracy in soil characterization,

their complexity can limit practical adoption in field applications Chauhan et al. (2021).

Overall, addressing economic and technological challenges in agriculture requires reducing implementation costs, improving infrastructure, and developing more accessible and user-friendly technologies. Strengthening these areas is essential to support the transition toward fully data-driven and sustainable agricultural systems.

1.3.6 Land Suitability Challenges

Assessing land suitability is essential for agricultural planning because it determines whether a specific area is appropriate for growing particular crops under given environmental conditions. However, accurate land suitability evaluation remains complex due to the interaction of many factors, including soil properties, climate conditions, and landscape features Akpoti et al. (2019).

One primary challenge is the high spatial variability of land characteristics. Soil attributes such as texture, structure, depth, and nutrient availability can vary significantly even within small areas, making it difficult to generalize assessments across whole fields. Additionally, factors such as slope and elevation affect water distribution, erosion risk, and the feasibility of using machinery Aymen et al. (2021).

Climate variability further complicates land suitability evaluation. Temperature patterns, rainfall distribution, and extreme weather events directly affect crop performance and long-term land productivity. As climate change continues to alter environmental conditions, areas once considered suitable for certain crops may become less viable, while new areas may become alternatives Akpoti et al. (2019).

Another significant limitation lies in traditional land evaluation approaches, which often rely on static datasets and expert-based judgments. These methods may not adequately capture temporal variations in soil and environmental conditions, reducing their effectiveness for dynamic agricultural decision-making. Although modern approaches using Geographic Information Systems (GIS) and remote sensing have improved land assessment capabilities, challenges related to data availability, resolution, and integration still persist El Behairy et al. (2022); AbdelRahman et al. (2025).

Recent advancements in geospatial analysis and multi-criteria decision-making techniques have enhanced the accuracy of land suitability evaluations by integrating diverse datasets. These approaches allow for more detailed and site-specific assessments, supporting sustainable land management and optimized crop selection. However, the complexity of combining heterogeneous data sources and ensuring their reliability remains a critical issue Ganzour et al. (2025).

Overall, land suitability assessment is a multidimensional problem influenced by environmental, technological, and data-related factors. Addressing these challenges requires the development of dynamic, data-driven models capable of integrating real-time information to support more accurate and sustainable agricultural planning.

1.4 IoT in Smart Agriculture

Human society has gone through several major technological waves, including the agricultural revolution, the industrial revolution, and the information age. Recently, a new technological paradigm has emerged that allows billions of devices to connect and share data over the internet. This paradigm is called the Internet of Things (IoT) Gubbi et al. (2013). IoT enables physical objects to contain sensors, software, and communication capabilities that allow them to collect data from their surroundings and interact with other devices and systems Atzori et al. (2010).

As smart devices and communication technologies have grown rapidly, IoT has become a key part of modern intelligent systems. It enables real-time monitoring, data collection, and automation in many fields including healthcare, transportation, smart cities, and agriculture Gubbi et al. (2013). Industry reports estimate that IoT technologies will generate several trillion dollars in economic impact annually because of their ability to transform traditional systems into intelligent connected infrastructures Manyika et al. (2013).

1.4.1 Definition

The Internet of Things can be defined as a network of physical objects equipped with sensors, embedded systems, and communication technologies that allow them to connect and exchange data over the internet Atzori et al. (2010). These objects include everyday items such as smartphones, vehicles, home appliances, and environmental monitoring systems.

In a broader sense, IoT represents the convergence of several technologies including wireless sensor networks, cloud computing, embedded systems, and communication protocols Gubbi et al. (2013). This convergence allows devices to collect environmental data, process it, and share it with other connected systems, enabling automated decision-making and intelligent services. As a result, IoT extends the traditional concept of the internet from a network of computers to a network of interconnected physical objects.

1.4.2 Architectures

IoT systems use a layered structure to organize communication between devices, networks, and applications. Several architectures have been proposed in the literature, but the most widely used model is the three-layer architecture consisting of the perception layer, network layer, and application layer Lin et al. (2017), as shown in 1.1.

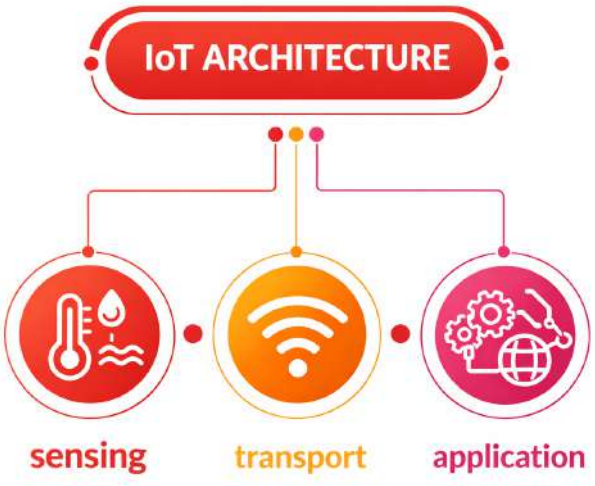


FIGURE 1.1: Internet of Things architecture

- **Perception layer:** This layer, also called the sensing layer, is the physical layer of IoT architecture. It collects data from the surrounding environment using devices such as sensors, RFID tags, and cameras. These devices detect conditions such as temperature, humidity, soil moisture, or location and convert them into digital signals for further processing Lin et al. (2017).

- **Network layer:** This layer transmits data collected by the perception layer to other parts of the system. It ensures reliable communication between sensors, gateways, and servers using various networking technologies such as Wi-Fi, Bluetooth, ZigBee, cellular networks, and satellite communication Gubbi et al. (2013). This layer manages data routing, connectivity, and communication protocols.

- **Application layer:** This is the top level of IoT architecture and provides services to end users. It processes collected data and delivers application-specific services such as smart home automation, environmental monitoring, healthcare systems, or smart agriculture applications Lin et al. (2017). This layer transforms raw sensor data into meaningful information that supports decision-making.

Overall, the layered architecture of IoT enables efficient data acquisition, communication, and service delivery, making it possible to build intelligent systems capable of monitoring and managing complex environments.

1.4.3 Types of Sensors

Sensors are electronic devices that detect physical or environmental parameters and convert them into electrical signals that computer systems can process. In IoT environments, sensors play a critical role by collecting real-time information from the environment and transmitting it for analysis Gubbi et al. (2013). This data supports monitoring, automation, and intelligent decision-making.

Most sensors operate by receiving analog signals from physical phenomena and converting them into digital signals that can be interpreted by microcontrollers or

computer systems Atzori et al. (2010). In IoT applications, sensing inputs may originate from various environmental factors such as temperature, humidity, pressure, light intensity, motion, or chemical composition.

Common types of sensors used in IoT systems include:

- **Temperature Sensors:** These measure heat energy in an environment and convert it into readable electrical signals. They are widely used in industrial monitoring, environmental control, and agriculture. Soil and air temperature significantly influence plant growth, seed germination, and crop development Kim et al. (2008).



FIGURE 1.2: Temperature sensor for soil and air monitoring

- **Humidity Sensors:** These measure water vapor concentration in the air. They are commonly used in climate control, weather stations, and farming applications. In smart farming, humidity sensors help monitor atmospheric conditions that affect plant health and irrigation needs Jawad et al. (2017).



FIGURE 1.3: Humidity sensor for atmospheric monitoring

- **Water Level / Flow Sensor:** These measure water quantity in irrigation systems, detecting tank levels or flow rates through pipes. They are essential for automated irrigation management, preventing over-watering or drought stress. In smart farming, water sensors help optimize irrigation scheduling and reduce water waste Gupta et al. (2026).

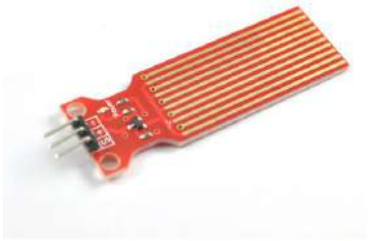


FIGURE 1.4: Water level and flow sensor for irrigation management

- **Gas Detector Sensor:** These detect hazardous gases such as ammonia (NH_3) released from pesticide volatilization or fertilizer decomposition. They provide real-time safety warnings for farmers during pesticide spraying operations. In agricultural environments, gas sensors enable timely alerts for pesticide poisoning prevention Yang et al. (2024).



FIGURE 1.5: Gas detector sensor for pesticide safety monitoring

- **Weight / Load Cell Sensor:** These measure physical mass or force, commonly used for fertilizer dosage monitoring or crop yield estimation. They ensure precise

application of granular fertilizers by verifying dispensed quantities. In precision agriculture, load cells enable measurement of applied nutrients Liu et al. (2025).



FIGURE 1.6: Load cell sensor for fertilizer dosage and yield monitoring

Sensors constitute the fundamental layer of IoT systems, enabling real-time environmental monitoring and providing the data necessary for intelligent applications across multiple domains.

1.5 Machine Learning and Deep Learning in Agriculture

Artificial intelligence (AI) has become a key enabling technology in modern agriculture, allowing the development of intelligent systems that can analyze large and complex agricultural data. Among AI techniques, machine learning (ML) and deep learning (DL) are the most widely used approaches for prediction, classification, and decision support in smart farming.

1.5.1 Machine Learning (ML)

Machine learning involves creating algorithms that can automatically find patterns in data and use those patterns to make predictions or decisions without being explicitly programmed for every situation Mitchell (1997); Bishop (2006). ML algorithms are widely applied in agriculture for tasks such as predicting crop yields, estimating soil fertility,

detecting diseases, and managing irrigation. These methods work particularly well with structured datasets collected from sensors or field observations.

According to Liakos et al. (2018), machine learning techniques used in agriculture include supervised learning models (regression and classification), unsupervised learning methods (clustering), and ensemble approaches. These techniques help extract meaningful patterns from agricultural data and support decision-making in precision farming.

1.5.2 Deep Learning (DL)

Deep learning is an advanced branch of machine learning that uses multi-layered neural network architectures to extract complex patterns directly from raw data LeCun et al. (2015); Goodfellow et al. (2016). Unlike traditional ML methods, deep learning requires less manual feature engineering and works particularly well with unstructured data such as images, time-series signals, and sensor data.

LeCun et al. (2015) define deep learning as a representation-learning approach where multiple layers transform input data into increasingly abstract representations. This ability allows deep learning models to perform well on complex tasks such as image recognition and pattern detection.

Kamilaris and Prenafeta-Boldú (2018) highlight that deep learning has significantly advanced precision agriculture applications, particularly in image-based crop monitoring, weed detection, and yield estimation. Convolutional neural networks (CNNs) outperform traditional machine learning methods for visual agricultural analysis.

1.5.3 Applications in Agriculture

Machine learning and deep learning are widely used in smart farming for real-time monitoring and prediction. Key applications include:

- Crop yield prediction using historical and sensor data
- Soil nutrient estimation and classification

- Plant disease detection using image-based CNN models
- Irrigation optimization using predictive analytics
- Pest detection and early warning systems

Overall, ML and DL technologies play a central role in transforming traditional agriculture into data-driven smart farming by improving accuracy, efficiency, and automation in decision-making.

1.6 Related Works

Recent research integrates sensing, communication, and intelligence to support real-time decision-making. IoT-based monitoring and AI-driven fertilizer recommendation models have shown promise in optimizing resource use.

1.6.1 IoT-Based Smart Farming Systems

IoT systems use distributed sensors to monitor soil and environmental conditions in agricultural environments. Low-power wide-area networks (LPWAN) support long-range, low-energy communication. However, many existing systems focus primarily on monitoring, offering limited intelligence Talavera et al. (2021).

1.6.2 AI-Based Agricultural Decision Systems

Machine learning approaches—Random Forests, SVMs, and neural networks—predict soil nutrient levels and fertilizer requirements Liakos et al. (2018). While accurate, complex AI models often lack interpretability, limiting adoption.

1.6.3 Fog-Assisted IoT-AI Systems

Mohanty et al. (2024) proposed a fog-assisted smart agriculture system for monitoring soil NPK and moisture in mining-affected soils. The system combines IoT sensors, edge

computing, and ML models to deliver real-time predictive recommendations, reducing latency compared to cloud-only solutions. Similarly, Miao et al. (2023) developed a fog-based system for detecting animal intrusion using low-cost PIR sensors and computer vision. These approaches demonstrate potential of integrating sensing and intelligence to optimize fertilizer use and maintain soil health, which aligns with SoilSense objectives.

1.6.4 Smart Fertilization and Irrigation Systems

Smart fertigation and irrigation systems adjust inputs dynamically based on sensor feedback Miao et al. (2023). Although effective, they are costly and often treat irrigation and fertilization as separate processes.

1.7 Comparison of Existing Systems

A comparison of existing smart agriculture systems is presented in Table 1.2.

TABLE 1.2: Comparison of Selected Smart Agriculture Systems

System / Study	**Focus / Task**	**Sensors / Inputs**	**Intelligence Layer**	**Real-time Prediction**
Gupta et al. (2024)	Soil NPK + moisture prediction in mining areas	IoT sensors (NPK, moisture, pH)	Fog computing + ML	Yes
Thorat et al. (2023)	Fertilizer type recommendation	Soil and crop properties	Random Forest	No
Yu et al. (2024)	NPK dose prediction	Soil laboratory tests	Neural Networks	Partial / offline
Proposed SoilSense	Integrated NPK prediction + fertilizer recommendation	Low-cost soil sensors (NPK, moisture, pH)	Interpretable ML	Yes, real-time

1.8 Limitations of Existing Approaches

Despite significant progress in agricultural technologies, existing fertilization approaches—ranging from traditional practices to modern data-driven systems—still exhibit critical limitations. This section provides a structured analysis of these limitations across three major categories.

1.8.1 Limitations of Traditional Fertilization Methods

Conventional fertilization practices are predominantly based on uniform nutrient application across entire agricultural fields. This approach assumes homogeneous soil conditions, which is rarely the case in real-world scenarios. Soil properties such as nutrient composition, pH, moisture, and organic matter content vary significantly across spatial and temporal scales. The absence of spatial resolution in traditional methods leads to inefficient nutrient distribution, where certain zones receive insufficient fertilization while others are over-supplied.

This lack of precision results in suboptimal crop growth and reduced agricultural productivity. From an agronomic perspective, nutrient imbalance directly affects plant physiological processes, including photosynthesis, root development, and nutrient uptake efficiency.

Another major limitation is the absence of a feedback mechanism. Traditional systems operate in an open-loop manner, where fertilization decisions are made based on prior experience or periodic soil testing, without continuous monitoring or adaptive adjustment. As a result, these methods fail to respond to real-time variations in environmental conditions.

Moreover, excessive fertilizer application is a common consequence of these practices. Over-fertilization not only increases operational costs but also leads to severe environmental impacts, including nitrate leaching, water pollution, and soil degradation.

1.8.2 Limitations of Machine Learning-Based Approaches

Recent advances in machine learning have introduced data-driven solutions for fertilizer recommendation. However, they still suffer from several important limitations.

A primary concern is the reliance on static datasets. Most machine learning models are trained on pre-collected datasets that represent historical conditions, lacking the ability to adapt to real-time changes in soil and environmental conditions.

Another limitation lies in the absence of feature dynamics. Many machine learning models treat input features as static snapshots, ignoring temporal dependencies and dynamic interactions. This simplification reduces the model's ability to capture complex agronomic processes.

Generalization across different soil types and geographic regions also remains a significant challenge. Models trained on data from specific regions often fail to perform effectively when applied to new environments.

Furthermore, interpretability is a major limitation. Most machine learning models, particularly deep learning architectures, function as black-box systems. In agricultural contexts, the lack of transparency reduces user trust and hinders adoption.

1.8.3 Limitations of Existing Smart Agricultural Systems

Smart agriculture systems aim to integrate sensing technologies, data analytics, and automated control mechanisms. However, many existing implementations remain incomplete or fragmented.

One critical limitation is the lack of full system integration. Sensing, data processing, and decision-making components often operate independently rather than as a cohesive system.

Another major limitation is the absence of closed-loop control. Most systems operate in an open-loop configuration, where recommendations are generated but not continuously refined based on environmental feedback.

Additionally, many existing systems focus solely on fertilizer classification without providing quantitative dosage information, significantly reducing their practical usability.

Finally, the lack of user-centered design and decision validation mechanisms reduces system reliability. Fully automated systems without human oversight may lead to inappropriate recommendations.

1.9 Research Gap and Positioning of SoilSense

The literature indicates a gap between data acquisition and practical decision support. Few systems integrate low-cost IoT sensors with interpretable AI models for real-time, context-aware fertilizer recommendations. SoilSense addresses this gap, emphasizing affordability, integration, and explainability.

1.10 Conclusion

This chapter traced the evolution of agriculture from traditional methods to smart, AI-driven systems. While IoT and AI provide powerful tools for precision farming, existing solutions are constrained by cost, integration, and interpretability. SoilSense aims to bridge these gaps, offering a real-time, low-cost, and explainable fertilizer recommendation system. The architecture and implementation of SoilSense are presented in the following chapters.

Chapter 2

Conception and Contribution

2.1 Introduction

Improving fertilization practices remains a major challenge in modern agriculture. Many conventional methods rely on applying the same quantity of fertilizers across entire fields, without taking into account the natural variability of soil conditions over space and time. Such an approach can lead to imbalances, where some areas receive insufficient nutrients, reducing crop yield and quality, while others receive excessive amounts, which can harm the environment through nutrient losses and soil degradation. In addition to these environmental concerns, fertilizers also represent a substantial cost for farmers, making efficient and targeted application strategies essential for both economic and agricultural sustainability.

Precision fertilization, by contrast, advocates for the site-specific regulation of nutrient inputs based on real-time soil conditions and crop requirements. This paradigm shift demands a sophisticated technical infrastructure capable of continuous soil monitoring, data-driven decision-making, and targeted action. The SoilSense system answers this need by integrating Internet of Things (IoT) technologies with advanced Deep Learning (DL) models to produce an intelligent fertilization management system. This chapter gives a complete investigation of the proposed system, beginning with its architectural framework, progressing through the IoT implementation, and finishing in a detailed explanation of the deep learning model that constitutes the analytical heart of the recommendation engine.

2.2 SoilSense system architecture

The SoilSense system is designed as a multi-tiered, closed-loop control framework that seamlessly integrates data acquisition, communication, processing, intelligence creation, user interaction and physical manipulation. The design of the architecture is intentionally created with modularity in mind and scalability as core principles, guaranteeing that every layer can be autonomously managed maintained, improved, or substituted without interfering with the overall system operation. Figure 2.1 illustrates a visual depiction of this architecture, consisting of six unique yet interconnected levels.

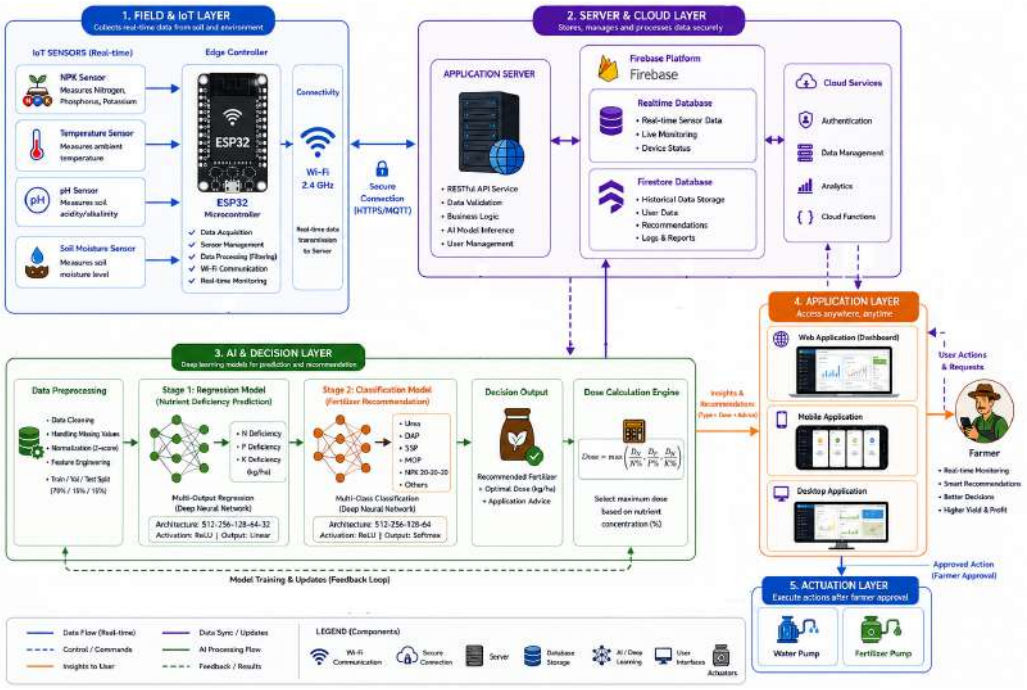


FIGURE 2.1: Overall architecture for Soilsense system

2.2.1 Field Layer: The Data Acquisition Tier

The Field Layer serves as the direct connection between the SoilSense system and the agricultural environment, enabling real-time data collection from the field. Each monitoring unit is built around the ESP32 microcontroller, a compact and energy-efficient System-on-Chip equipped with integrated wireless communication capabilities such as Wi-Fi and Bluetooth. Its processing capacity allows preliminary data handling at the device level, while its low-power operating modes help extend battery life, making it well suited for long-term deployment in outdoor conditions.

The sensor array interfaced with the ESP32 includes:

- **NPK Sensor:** This sensor is designed to estimate the levels of nitrogen, phosphorus, and potassium present in the soil. These elements play essential roles in plant development: nitrogen contributes to leaf and stem growth, phosphorus supports root formation and energy processes, and potassium helps regulate water balance and overall plant health.

- **pH Sensor:** The pH sensor monitors the acidity or alkalinity of the soil, which directly influences the availability of nutrients and the activity of microorganisms. Maintaining an appropriate pH level is crucial for ensuring that plants can effectively absorb the nutrients they need.

- **Temperature Sensor:** Soil temperature influences seed germination, root development, and the rate of biochemical reactions, including nutrient mineralization and uptake. This sensor ensures that temperature effects are considered in fertilization recommendations.

- **Moisture Sensor:** Volumetric water content measurement is essential not only for irrigation management but also for understanding nutrient transport and dissolution in the soil matrix.

The ESP32 is programmed to execute scheduled sampling routines, converting analog sensor signals into digital values, performing preliminary validation checks, and formatting

the data into structured packets for transmission. This preprocessing at the edge reduces the bandwidth requirements and computational load on the backend systems.

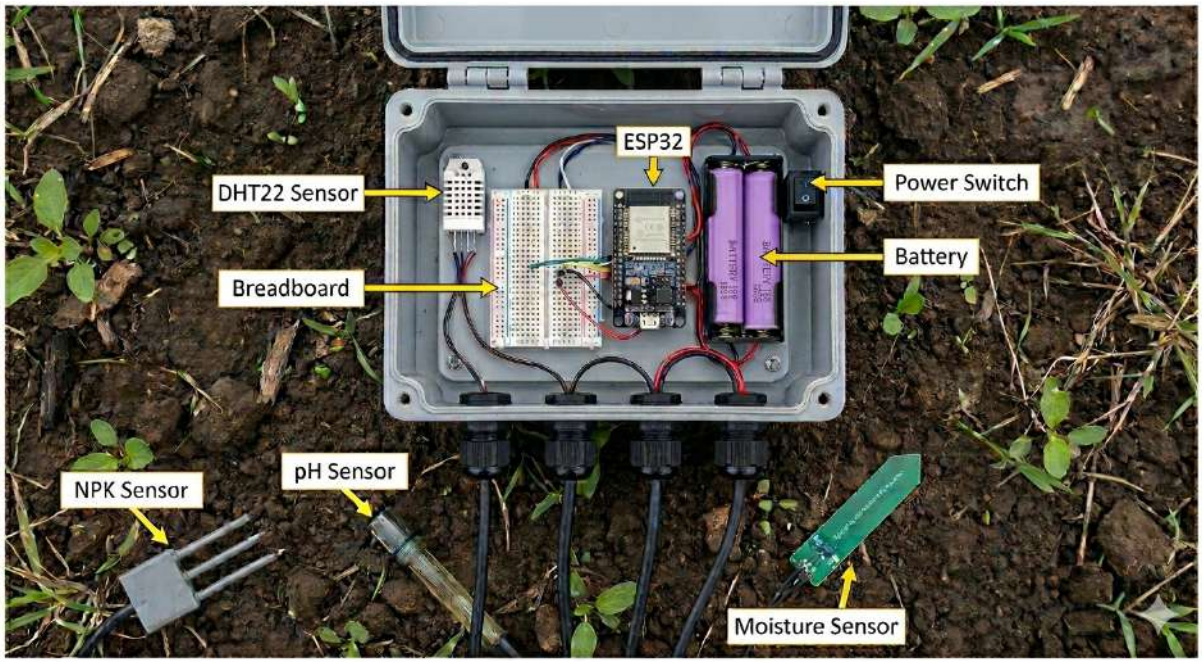


FIGURE 2.2: SoilSense field Layer

2.2.2 IoT Communication Layer: Data Transmission Infrastructure

The IoT Communication Layer is responsible for establishing the link between field-deployed sensors and the central backend system. In the context of the SoilSense architecture, communication is simplified by relying exclusively on Wi-Fi connectivity, ensuring efficient and cost-effective data transmission in suitable deployment environments.

Wi-Fi (IEEE 802.11) provides a high-speed and low-latency communication channel between the ESP32-based field nodes and the server infrastructure. Since the ESP32 natively integrates Wi-Fi capability, it eliminates the need for additional communication modules, reducing system complexity and hardware cost. This makes it particularly suitable for prototype development and small to medium-scale agricultural deployments where wireless network coverage is available.

To ensure reliable data exchange, the system adopts lightweight communication mechanisms optimized for IoT environments. The data transmitted from the sensors is structured and sent periodically to the backend for processing and storage. In addition, secure communication practices are applied to protect data integrity and prevent unauthorized access during transmission.

The MQTT protocol is used as the primary communication protocol due to its simplicity, low overhead, and efficiency in handling intermittent connectivity scenarios. It follows a publish-subscribe model, which allows sensor nodes to transmit data to a central broker in a scalable and organized manner.

2.2.3 Backend Server Layer: Data Repository and Service Hub

The Backend Server Layer acts as the central component of the SoilSense architecture, responsible for managing data flow, storage, and communication between the field devices and the application services. In this implementation, the backend is built using a REST API server connected to Firebase, which provides a scalable and real-time database solution for handling sensor data.

The system is designed to efficiently store and manage heterogeneous agricultural data. Sensor readings such as soil moisture, temperature, pH, and nutrient levels are continuously transmitted from the field nodes and stored in Firebase in real time. This enables fast access to updated field conditions and supports time-based analysis of soil behavior. In addition, structured information such as user profiles, farm details, crop types, and recommendation history is also maintained within the backend database.

The backend exposes a set of RESTful API services that act as the communication bridge between the IoT devices, the deep learning model, and the user interface. These APIs handle several core operations, including:

- Receiving and storing sensor data from ESP32-based field nodes
- Providing real-time and historical soil data to the application dashboard

- Sending processed outputs from the deep learning model (fertilizer recommendations)
- Managing user requests and system interactions through secure endpoints

To ensure secure and reliable communication, the API layer implements authentication mechanisms that control access to the system and protect sensitive agricultural data. This architecture allows smooth integration between the IoT layer, the backend services, and the AI-based recommendation engine.

2.2.4 Dashboard and Presentation Layer: Farmer Interface

The Dashboard Layer translates complex soil data and analytical outputs into an accessible, intuitive interface for the end-user. Developed as a responsive web application accessible via both desktop browsers and mobile devices, the dashboard prioritizes user experience and clarity.

- **Soil Information Visualization:** The dashboard presents real-time sensor readings through interactive gauges, color-coded indicators, and historical trend charts. This visual representation enables farmers to rapidly assess the current status of their fields without interpreting raw numerical data.
- **Recommendation Presentation:** When the decision support layer generates a fertilization recommendation, it appears prominently on the dashboard. The recommendation is expressed in plain language, specifying the fertilizer type, quantity (e.g., kilograms per hectare), and application method.
- **Approval Interface:** The dashboard implements a critical human-in-the-loop control mechanism. Each recommendation is accompanied by [Approve] and [Cancel] buttons, ensuring that no automated action occurs without explicit farmer consent. This design respects farmer autonomy while still providing the benefits of data-driven recommendations.

2.2.5 Actuation Layer: Physical Intervention

The Actuation Layer represents the final stage of the closed-loop control system, where digital decisions manifest as physical actions in the field. As illustrated in Figure 2.3, this layer is built around a multi-tank fertigation architecture comprising the following components:

- **Fertilizer and Water Tanks:** Seven storage tanks are maintained in the system, each holding a distinct input: DAP, Urea, MOP, Ammonium Sulfate, NPK 20-20-20, SSP, and Water. This configuration allows the system to prepare any fertilizer combination required by the recommendation model without manual mixing.
- **Electrovalves:** Each tank is equipped with a dedicated solenoid electrovalve. The ESP32 field node activates only the valves corresponding to the recommended fertilizer type and quantity, releasing the selected inputs into the common mixing pipe below.
- **Common Mixing Pipe:** The outputs of all electrovalves converge into a shared pipe, where the selected fertilizer concentrate and water are passively mixed before reaching the pump.
- **Flow Sensor:** A flow sensor positioned downstream of the mixing pipe monitors the actual volume of solution delivered, providing real-time feedback to the field node to ensure the dispensed quantity matches the prescribed dosage.
- **Irrigation Pump:** A centrifugal irrigation pump draws the mixed fertigation solution and drives it through the distribution network to the field drip irrigation lines.

All electrovalves and the irrigation pump are controlled by the ESP32 field node through relay modules that isolate the microcontroller's low-voltage logic from the actuator power supply. Commands are dispatched to the field node exclusively upon explicit farmer approval through the mobile dashboard, ensuring that no physical action

is taken without human confirmation. The flow sensor closes the control loop by reporting the delivered volume back to the backend, where it is logged alongside the actuation event for traceability.

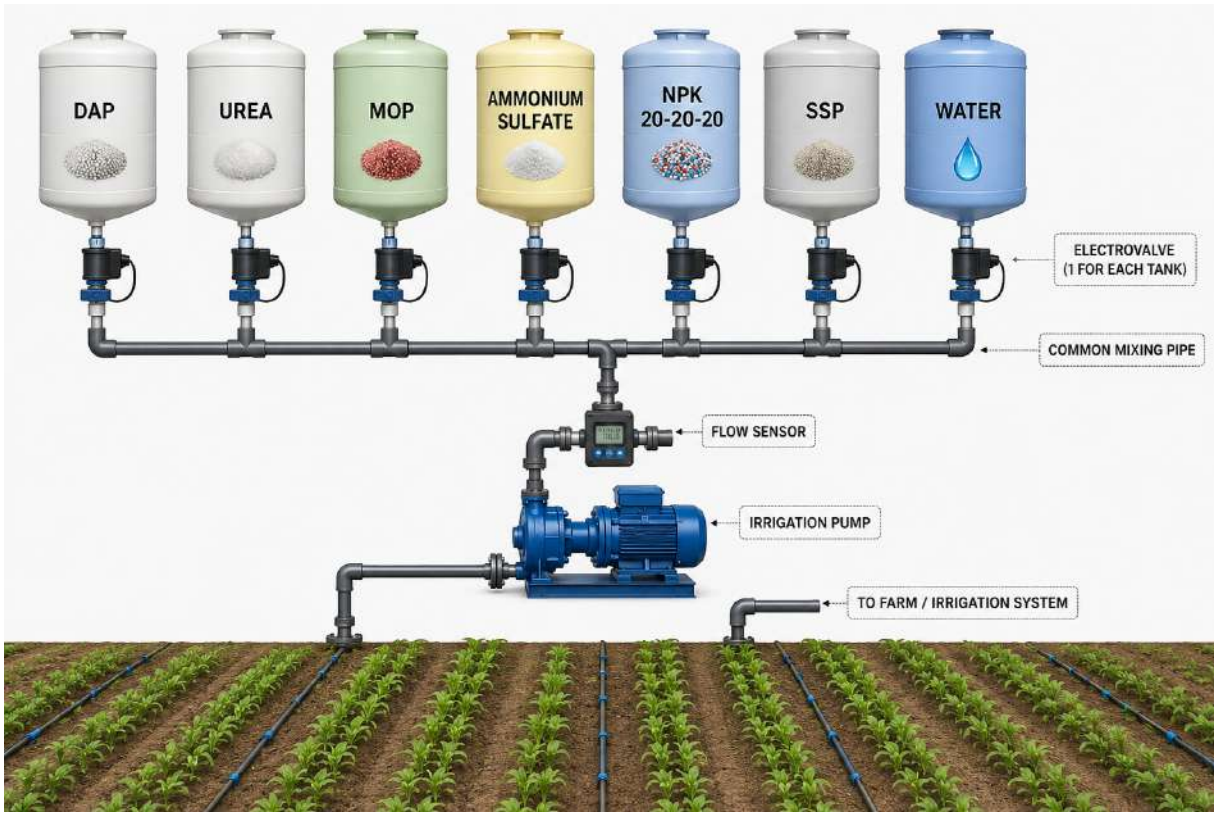


FIGURE 2.3: SoilSense actuation layer

2.3 Deep Learning Model for Fertilizer Recommendation

The analytical core of the SoilSense system resides in the Deep Learning Model layer, which transforms raw soil data into actionable fertilization recommendations. This section provides a comprehensive examination of the model architecture, training methodology, and integration with the broader system.

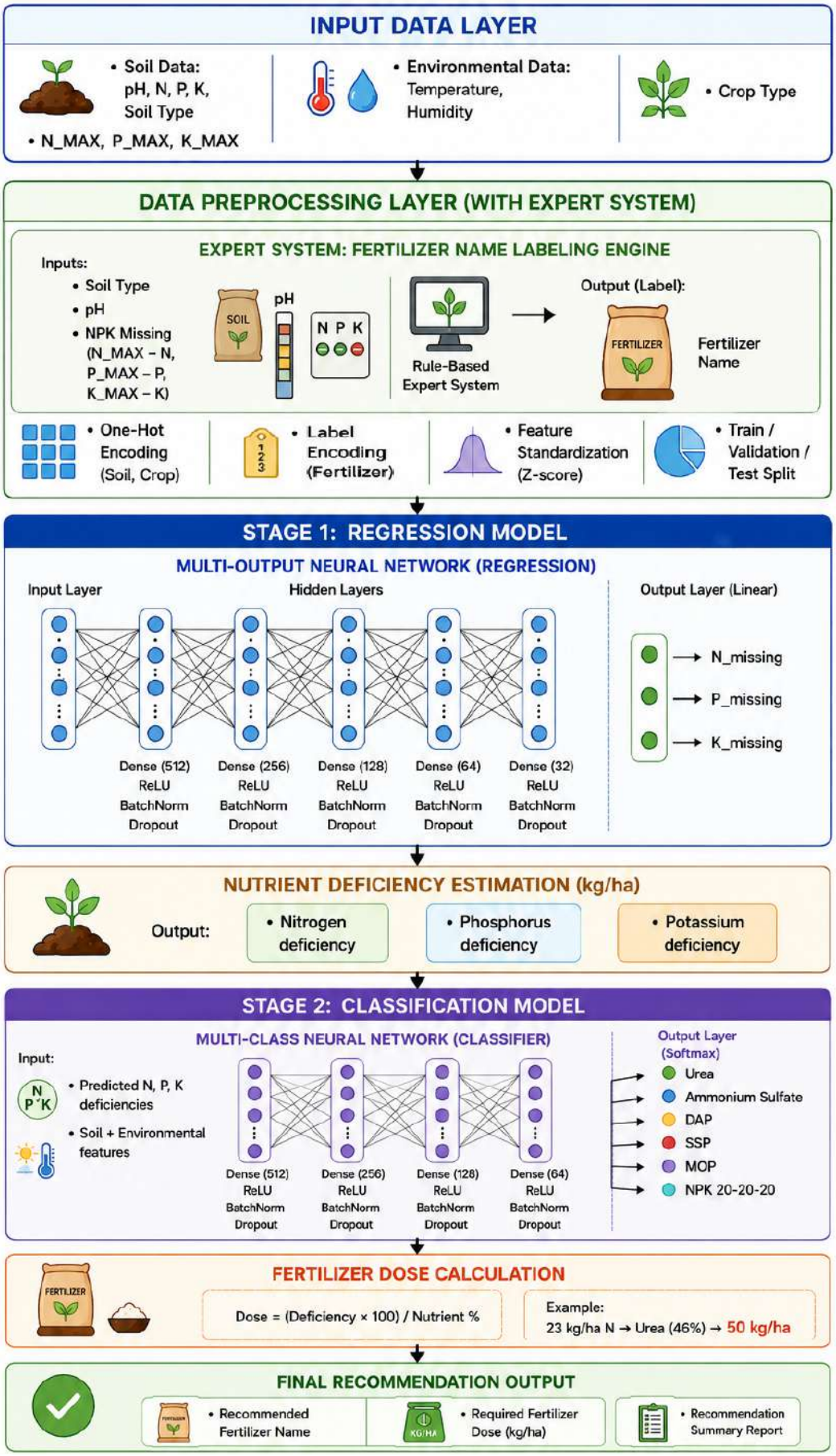


FIGURE 2.4: Model architecture

2.3.1 Dataset Description

The dataset employed in this research was sourced from Kaggle[1]. It contains 57000 rows with agriculture data and 57 crop categories, each represented by 1000 instances, thereby ensuring class balance and supporting robust model training. The features encompass environmental parameters, soil properties, and nutrient-related information, which are critical factors influencing crop development and fertilization strategies.

The main variables in the dataset include:

- Temperature
- Relative humidity
- Soil pH
- Soil type
- Crop type
- Nitrogen (N) level in the soil
- Phosphorus (P) level in the soil
- Potassium (K) level in the soil
- N_MAX
- P_MAX
- K_MAX

2.3.2 Data Preprocessing and Fertilizer Label Generation

Data preprocessing is a crucial step in preparing the dataset for our model.

[1] https://www.kaggle.com/datasets/saganachinnathambi/crop-recommendation

First, the dataset was inspected to verify the integrity of the variables and ensure that all required columns were present. The dataset was then cleaned to remove inconsistencies and ensure that numerical values were correctly formatted.

To facilitate nutrient deficiency analysis, three additional variables were created:

- $N_{missing}$
- $P_{missing}$
- $K_{missing}$

These variables represent the difference between the optimal nutrient level and the current soil nutrient level.

The deficiencies were calculated as follows:

$$N_{missing} = N_{max} - N \tag{2.1}$$

$$P_{missing} = P_{max} - P \tag{2.2}$$

$$K_{missing} = K_{max} - K \tag{2.3}$$

Since nutrient deficiency cannot be negative, any negative values obtained from these calculations were replaced with zero, ensuring that only actual nutrient shortages were considered.

The dataset did not initially contain fertilizer recommendations, a rule-based agronomic expert system was implemented to generate fertilizer labels.

The expert system analyzes the nutrient deficiencies together with soil characteristics to determine the most appropriate fertilizer. The decision rules are based on common agricultural practices:

The expert system analyzes nutrient deficiencies in conjunction with soil characteristics, particularly soil pH and soil type, to determine the most appropriate fertilizer. The decision rules are based on established agricultural practices:

- If no nutrient deficiency is detected, no fertilizer is recommended.
- If multiple nutrients are significantly deficient, a balanced fertilizer such as **NPK 20-20-20** is recommended.
- If nitrogen deficiency is dominant:
  - **Ammonium Sulfate** is recommended for alkaline soils (pH $>$ 7.5) or sandy soils.
  - Otherwise, **Urea** is recommended.
- If phosphorus deficiency is dominant:
  - **SSP (Single Super Phosphate)** is recommended for alkaline soils (pH $>$ 7.5).
  - Otherwise, **DAP (Diammonium Phosphate)** is used.
- If potassium deficiency is dominant:
  - **MOP (Muriate of Potash)** is recommended.

This expert system automatically generated a new column called `fertilizer_name`, which was later used as the target variable for the classification model.

Table 2.1: Dataset Columns Overview

#	Column	Non-Null Count	Dtype
0	CROPS	57000 non-null	object
1	TEMP	57000 non-null	float64
2	RELATIVE_HUMIDITY	57000 non-null	float64
3	SOIL_PH	57000 non-null	float64
4	SOIL	57000 non-null	object
5	N	57000 non-null	float64
6	P	57000 non-null	float64
7	K	57000 non-null	float64
8	N_missing	57000 non-null	float64
9	P_missing	57000 non-null	float64
10	K_missing	57000 non-null	float64
11	Fertilizer_name	57000 non-null	object

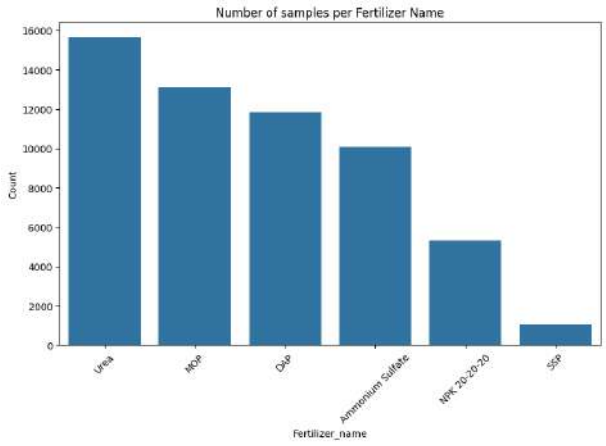


Figure 2.5: Number of samples per Fertilizer Name

Following data cleaning and feature engineering, appropriate preprocessing techniques were applied to transform the dataset into a format suitable for machine learning and deep learning models.

- **Categorical Encoding:** The dataset contains categorical variables, specifically **CROPS** and **SOIL**, which cannot be directly processed by most machine learning algorithms. To address this, one-hot encoding was applied using a One-Hot Encoder.

  This technique transforms each categorical variable into a set of binary indicator variables, where each category is represented as a separate feature. This approach

avoids introducing ordinal relationships between categories and preserves the nominal nature of the data.

Additionally, for the classification task, the target variable **fertilizer_name** was encoded into numerical labels using label encoding. Each fertilizer type was mapped to a unique integer value, enabling efficient model training.

- **Feature Standardization** To ensure numerical stability and improve model performance, feature scaling was applied to all numerical variables. Feature scaling transforms data so that features become comparable in magnitude, which facilitates faster convergence and improves the effectiveness of machine learning algorithms, particularly neural networks.

  Standardization Standardization transforms features to have zero mean and unit variance while preserving the original distribution shape. This technique is particularly suitable for neural networks as it prevents saturating activation functions and ensures stable gradient propagation.

  Numerical features were standardized using z-score normalization:

$$x_{\text{scaled}} = \frac{x - \mu}{\sigma} \tag{2.4}$$

  where μ is the mean and σ is the standard deviation of the feature over the training set. The same μ and σ values were applied to validation and test sets to prevent data leakage.

  Target Scaling for Regression For the multi-output regression task, the target variables (N_{missing}, P_{missing}, K_{missing}) were also standardized using z-score normalization to ensure balanced learning across all three outputs and improve numerical stability during backpropagation:

$$y_{scaled} = \frac{y - \mu_y}{\sigma_y} \tag{1.4b}$$

where μ_y and σ_y are the mean and standard deviation of each nutrient deficiency computed over the training set.

Critical: After the model predicts scaled values, an inverse transformation is applied to recover the original units (kg/ha):

$$y_{pred_original} = (y_{pred_scaled} \times \sigma_y) + \mu_y \tag{1.4c}$$

This inverse transformation is essential for the dose calculation formula which requires nutrient deficiencies in kg/ha. Failure to perform this inverse transformation would result in incorrect fertilizer dose recommendations.

2.3.3 Model Training and Data Splitting

To train and evaluate the models, the dataset was divided into three subsets:

- 70% for training
- 15% for validation
- 15% for testing

The training set was used to fit the model parameters, the validation set was used to tune hyperparameters and prevent overfitting, and the test set was used to evaluate the final performance of the models.

2.3.4 Model Architecture

Two-Stage Modeling Architecture

The SoilSense system is based on a two-stage modeling architecture, in which two deep learning models are applied sequentially to generate precise fertilization recommendations. The workflow of the system is illustrated in Figure 2.6.

- **Stage 1: Nutrient Deficiency Estimation (Regression Model)** A multi-output regression model is used to predict the missing quantities of the primary soil nutrients, namely nitrogen (N), phosphorus (P), and potassium (K). These predicted deficiencies represent the exact nutrient requirements needed to restore optimal soil conditions for crop growth.

  Based on these predictions, the system computes the required fertilizer dose by considering the nutrient composition of the selected fertilizer.

- **Stage 2: Fertilizer Type Recommendation (Classification Model)** A multi-class classification model is employed to determine the most appropriate fertilizer type. This model takes as input the predicted nutrient deficiencies, along with environmental and soil parameters.

This two-stage approach enables the system to both quantify nutrient requirements (dose estimation) and recommend the appropriate fertilizer product, thereby providing a comprehensive decision-support solution for precision agriculture.

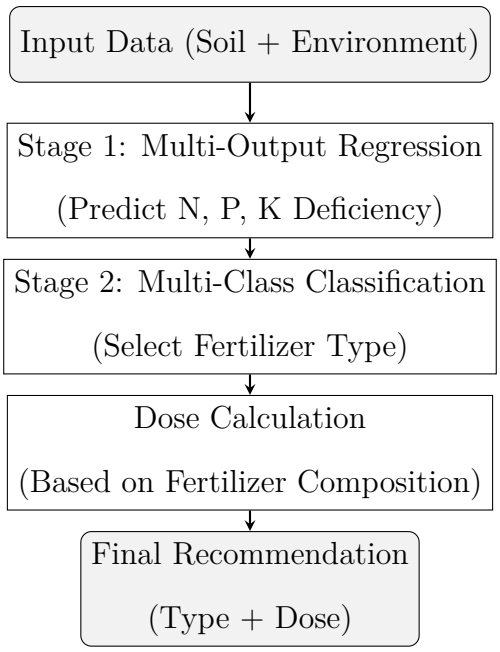


FIGURE 2.6: Two-stage modeling architecture of the SoilSense system

Regression Model

The first model is a multi-output regression model designed to estimate the missing quantities of the three main soil nutrients:

- Nitrogen deficiency ($N_{missing}$)
- Phosphorus deficiency ($P_{missing}$)
- Potassium deficiency ($K_{missing}$)

This model takes environmental and soil parameters as input and predicts the nutrient deficiencies in kg/ha. Predicting these deficiencies allows the system to determine how much nutrient must be added to reach the optimal soil condition for crop growth.

Architecturally, the model is implemented as a deep fully connected neural network composed of five hidden layers with 512, 256, 128, 64, and 32 neurons, respectively. Each hidden layer employs the Rectified Linear Unit (ReLU) activation function to introduce non-linearity, facilitating the learning of complex relationships between input features and nutrient deficiencies. To improve training stability and generalization performance, batch

normalization is applied after each dense layer, followed by dropout regularization with rates ranging from 0.2 to 0.3 to mitigate overfitting.

The output layer consists of three neurons with a linear activation function, corresponding to the continuous prediction of N, P, and K deficiencies. The model is trained using the Adam optimizer with an initial learning rate of 0.001 and a custom weighted mean squared error (MSE) loss function. Model training is further optimized through early stopping and learning rate reduction strategies based on validation performance.

Classification Model

The second model is a multi-class classification model that recommends the most appropriate fertilizer.

The model uses the predicted nutrient deficiencies together with soil and environmental parameters to determine which fertilizer should be applied.

The possible fertilizer classes include:

- Urea
- Ammonium Sulfate
- DAP
- SSP
- MOP
- NPK 20-20-20

Architecturally, the model is implemented as a deep fully connected neural network composed of four hidden layers with 512, 256, 128, and 64 neurons, respectively. Each hidden layer employs the Rectified Linear Unit (ReLU) activation function to capture complex non-linear relationships between input features and fertilizer recommendations. To enhance model generalization and stabilize training, batch normalization is applied

after each dense layer, followed by dropout regularization with rates ranging from 0.3 to 0.4 to reduce overfitting.

The output layer consists of n neurons (corresponding to the number of fertilizer classes) and uses the softmax activation function to produce a probability distribution over the possible classes. The model is trained using the Adam optimizer with a learning rate of 0.001 and a custom weighted categorical cross-entropy loss function, which incorporates class weights to address potential class imbalance and ensure fair learning across all fertilizer categories.

To further optimize training, early stopping and learning rate scheduling techniques are employed, monitoring validation accuracy to prevent overfitting and improve convergence. Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, and the confusion matrix.

Handling Imbalanced Data with Class Weights

In the classification task, the fertilizer classes may have uneven representation in the dataset (some fertilizers appear more frequently than others). This imbalance can bias the model toward majority classes, reducing its ability to correctly predict minority classes.

How Class Weights Work:

Class weights address this issue by assigning different penalty values to errors made on different classes:

- Minority classes receive **higher weights**, making misclassifications more costly during training
- Majority classes receive **lower weights**, reducing their influence on the loss function

Mathematically, the weighted loss function is calculated as:

$$\mathcal{L}_{weighted} = \frac{1}{N} \sum_{i=1}^{N} w_{y_i} \cdot \mathcal{L}(y_i, \hat{y}_i)$$

where w_{y_i} is the weight for class y_i, and $\mathcal{L}$ is the standard loss function (categorical cross-entropy).

In our implementation, weights are computed using the `compute_class_weight` function with the 'balanced' mode:

$$w_j = \frac{n_{samples}}{n_{classes} \times n_{samples_in_class_j}}$$

This ensures that each class contributes proportionally to the total loss, regardless of its frequency in the dataset.

Learning Rate Scheduling with ReduceLROnPlateau

To further optimize training, we employ `ReduceLROnPlateau`, which dynamically adjusts the learning rate when progress stalls:

- **Monitor**: Validation loss (regression) or validation accuracy (classification)
- **Factor**: Learning rate is reduced by half (0.5×) when no improvement is detected
- **Patience**: 15-25 epochs before reduction
- **Minimum learning rate**: 10^{-7} to prevent overly small updates

This technique helps the model escape local minima and converge more effectively.

Early Stopping for Optimal Training

Early stopping is a regularization technique that prevents overfitting by monitoring the model's performance on validation data during training.

How Early Stopping Works:

1. The model is trained normally, and after each epoch, its performance is evaluated on a validation set
2. A patience parameter defines how many epochs to wait for improvement before stopping
3. When no improvement is seen for patience epochs, training is halted

4. The model weights are restored to the best performing epoch

In our implementation:

- **Regression model**: Patience of 40 epochs monitoring validation loss
- **Classification model**: Patience of 50 epochs monitoring validation accuracy

This approach offers several advantages:

- **Prevents overfitting**: Stops training before the model starts memorizing noise
- **Saves computational resources**: Avoids unnecessary training epochs
- **Automatic model selection**: Returns the best version of the model

Fertilizer Dose Calculation

The ultimate goal of the SoilSense system is not only to recommend a fertilizer type but also to calculate the required fertilizer dose.

The regression model predicts the missing nutrient quantities ($N_{deficiency}$, $P_{deficiency}$, $K_{deficiency}$) in kg/ha, while the classification model identifies the appropriate fertilizer. Since each fertilizer contains a specific percentage of nutrients, the required fertilizer amount is calculated in three steps:

Step 1: Individual nutrient dose calculation For each nutrient present in the recommended fertilizer, the required dose is computed only when both the nutrient deficiency and the fertilizer's nutrient percentage are strictly positive. This prevents division by zero and ensures that only applicable nutrients contribute to the dose calculation:

$$Dose_N = \begin{cases} \dfrac{N_{deficiency} \times 100}{N\%}, & \text{if } N\% > 0 \text{ and } N_{deficiency} > 0 \\ \text{undefined}, & \text{otherwise} \end{cases} \tag{2.5}$$

$$Dose_P = \begin{cases} \dfrac{P_{deficiency} \times 100}{P\%}, & \text{if } P\% > 0 \text{ and } P_{deficiency} > 0 \\ \text{undefined}, & \text{otherwise} \end{cases} \tag{2.6}$$

$$Dose_K = \begin{cases} \dfrac{K_{deficiency} \times 100}{K\%}, & \text{if } K\% > 0 \text{ and } K_{deficiency} > 0 \\ \text{undefined}, & \text{otherwise} \end{cases} \tag{2.7}$$

Where $N\%$, $P\%$, and $K\%$ represent the percentage composition of nitrogen, phosphorus, and potassium in the selected fertilizer, respectively. A dose is considered *defined* only when both conditions are satisfied; otherwise, the nutrient does not contribute to the final fertilizer requirement.

Step 2: Maximum dose selection To ensure that all nutrient deficiencies are covered simultaneously, the system selects the maximum dose among the individual requirements:

$$Fertilizer\ Dose_{kg/ha} = \max(Dose_N, Dose_P, Dose_K) \tag{1.5}$$

2.4 Contributions

2.4.1 Two-Stage Deep Learning Strategy

The SoilSense system adopts a two-stage deep learning strategy to address the inherent complexity of fertilizer recommendation tasks in precision agriculture. Unlike traditional single-model approaches, which attempt to directly map soil and environmental features to fertilizer recommendations, the proposed methodology decomposes the problem into two sequential and specialized learning tasks: nutrient deficiency estimation and fertilizer type classification. This design is motivated by the observation that fertilization decision-making is inherently a multi-step reasoning process. In real agricultural practice, experts first evaluate the nutrient status of the soil to identify deficiencies, and only then determine the appropriate fertilizer based on both the type and magnitude of these deficiencies.

The proposed two-stage architecture explicitly models this reasoning process, resulting in improved accuracy, interpretability, and modularity.

Problem Formulation

Let the input feature vector be defined as:

$$X = \{T, H, pH, N, P, K, S, C\} \tag{2.8}$$

where:

- T represents temperature
- H represents relative humidity
- pH denotes soil acidity/alkalinity
- N, P, K correspond to the measured nutrient levels
- S represents soil type
- C represents crop type

The objective of the system is to determine:

1. The nutrient deficiencies:

$$Y_{reg} = (N_{missing}, P_{missing}, K_{missing}) \tag{2.9}$$

2. The optimal fertilizer type:

$$Y_{class} = f(X, Y_{reg}) \tag{2.10}$$

This formulation highlights the dependency of the classification task on the regression outputs, justifying the sequential nature of the proposed architecture.

Stage 1: Nutrient Deficiency Estimation (Regression Model)

The first stage of the system consists of a multi-output regression model that predicts the deficiency levels of nitrogen, phosphorus, and potassium in the soil. These deficiencies represent the quantitative gap between current nutrient levels and optimal agronomic requirements.

Formally, the regression model learns a function:

$$f_{reg} : X \rightarrow Y_{reg} \tag{2.11}$$

This model is implemented using a deep fully connected neural network capable of capturing complex non-linear relationships between environmental conditions and soil nutrient dynamics. The use of multi-output regression enables the simultaneous prediction of all three nutrient deficiencies, ensuring consistency and reducing computational redundancy. The outputs of this stage are continuous values expressed in kg/ha, which serve as the foundation for subsequent decision-making. By explicitly estimating nutrient deficiencies, the system provides a physically meaningful intermediate representation, enhancing both interpretability and practical relevance.

Role of Nutrient Deficiency in Dose Calculation The predicted nutrient deficiencies ($N_{missing}, P_{missing}, K_{missing}$) are not only used as intermediate inputs for fertilizer classification, but also serve as the quantitative basis for fertilizer dose estimation.

Unlike conventional systems that provide only qualitative recommendations, the SoilSense framework leverages these deficiency values to compute the exact amount of fertilizer required to restore optimal soil conditions. This establishes a direct link between the regression stage and the actuation process, enabling precise and actionable fertilization decisions.

Stage 2: Fertilizer Type Recommendation (Classification Model)

The second stage of the system is a multi-class classification model that determines the most appropriate fertilizer type based on both the original input features and the predicted nutrient deficiencies. The classification model learns the mapping:

$$f_{class} : (X, Y_{reg}) \rightarrow Y_{class} \tag{2.12}$$

This stage incorporates the predicted deficiencies as additional input features, allowing the model to make more informed decisions. By combining raw environmental data with derived agronomic indicators, the model captures both direct and contextual relationships. The output of this stage is a probability distribution over the set of possible fertilizer classes:

$$Y_{class} \in \{\text{Urea, Ammonium Sulfate, DAP, SSP, MOP, NPK 20-20-20}\} \tag{2.13}$$

The fertilizer with the highest probability is selected as the final recommendation.

Justification of the Two-Stage Architecture

The proposed two-stage design offers several advantages over conventional single-stage approaches.

Improved Learning Efficiency Single-stage models that attempt to directly predict fertilizer type must implicitly learn both nutrient deficiency estimation and decision logic within a single mapping. This increases model complexity and often leads to suboptimal performance. By decomposing the problem, each model focuses on a well-defined task, leading to more efficient learning.

Enhanced Interpretability The intermediate outputs (nutrient deficiencies) provide insight into the reasoning process of the system. This transparency allows users to

understand why a particular fertilizer is recommended, which is critical in agricultural applications.

Alignment with Agronomic Practices The two-stage approach closely mirrors real-world decision-making processes used by agronomists. This alignment improves the credibility and acceptability of the system among end-users.

Modularity and Flexibility Each stage can be independently improved, retrained, or replaced without affecting the entire system. For example, the regression model can be updated with new soil data without modifying the classification model.

Comparison with Single-Stage Approaches

Traditional machine learning approaches typically employ a single-stage classification model:

$$f : X \rightarrow Y_{class} \tag{2.14}$$

While simpler, this approach suffers from several limitations:

- It does not explicitly model nutrient deficiencies
- It lacks interpretability
- It cannot provide quantitative recommendations (dose estimation)
- It struggles with complex feature interactions

In contrast, the proposed two-stage architecture introduces an intermediate representation that significantly enhances both predictive performance and practical usability.

Integration within the SoilSense Framework

The two-stage deep learning strategy is tightly integrated within the overall SoilSense system. Sensor data collected from the field is first processed and fed into the regression

model to estimate nutrient deficiencies. These predictions are then passed to the classification model, which determines the fertilizer type. Finally, the outputs of both stages are used in the fertilizer dose calculation module, completing the decision-making pipeline. This seamless integration ensures that the system operates as a coherent and efficient decision-support tool.

2.4.2 Hybrid Expert System for Label Generation

A critical challenge in applying supervised learning to agricultural problems is the scarcity of high-quality annotated datasets. Unlike domains such as computer vision or natural language processing, where large-scale labeled datasets are readily available, agricultural datasets often lack standardized labels, particularly for complex decision tasks such as fertilizer recommendation. Label generation in this context requires domain expertise, as recommendations depend on agronomic knowledge, soil chemistry, and crop-specific requirements.

Labeling Challenges in Agriculture

The absence of labeled datasets introduces several limitations:

- **Domain dependency**: Fertilizer recommendations depend on expert knowledge that cannot be easily inferred from raw data alone.
- **Context sensitivity**: Optimal fertilization strategies vary with soil type, crop type, and environmental conditions.
- **Data scarcity**: Public datasets rarely include explicit fertilizer labels, limiting the applicability of supervised learning methods.

To address these challenges, a rule-based agronomic expert system is integrated into the SoilSense framework to automatically generate fertilizer labels.

Formal Rule-Based Structure

The expert system encodes agronomic knowledge in the form of deterministic rules. Each rule follows a logical IF–THEN structure, where decisions are based on nutrient deficiencies and soil characteristics.

An example rule is given by:

$$\text{IF } (N_{missing} > \theta_N) \wedge (pH > 7.5) \Rightarrow \text{Ammonium Sulfate} \tag{2.15}$$

More generally, the rule system can be expressed as:

$$R_i : \ f(X, Y_{reg}) \rightarrow \text{Fertilizer Type} \tag{2.16}$$

where R_i denotes the i-th rule, X represents input features, and Y_{reg} denotes predicted nutrient deficiencies.

This structured approach ensures consistency and enables the incorporation of expert-defined thresholds and domain constraints.

Hybrid Intelligence: Symbolic and Subsymbolic Integration

The proposed system combines:

- **Symbolic intelligence**: Rule-based expert system (explicit knowledge representation)
- **Subsymbolic intelligence**: Deep learning models (implicit pattern learning)

This hybrid paradigm leverages the strengths of both approaches. The expert system provides interpretability and domain validity, while the deep learning model captures complex, non-linear relationships in the data. This integration enhances both model performance and reliability.

2.4.3 Closed-Loop Intelligent Fertilization System

The SoilSense system is designed as a closed-loop control system that integrates sensing, analysis, decision-making, and actuation within a continuous feedback cycle.

Control System Interpretation

The system can be modeled as a control loop consisting of four main components:

- **Input**: Real-time sensor data (soil moisture, pH, NPK levels, temperature)
- **Controller**: Deep learning model responsible for decision-making
- **Output**: Fertilizer recommendation and actuation commands
- **Feedback**: Updated soil conditions after fertilization

This relationship can be summarized as:

$$\text{Sensor Data} \rightarrow \text{AI Model} \rightarrow \text{Actuation} \rightarrow \text{Environment} \rightarrow \text{Feedback}$$

Closed-Loop Properties

The closed-loop design introduces several important properties:

- **Feedback loop**: Enables continuous monitoring and adjustment
- **Adaptive control**: System dynamically responds to environmental changes
- **System stability**: Prevents over-application of fertilizers

Comparison with Open-Loop Systems

Traditional systems operate in an open-loop configuration:

$$\text{Input} \rightarrow \text{Decision} \rightarrow \text{Output}$$

Such systems lack feedback and cannot adjust to changing conditions. In contrast, the closed-loop approach continuously refines decisions based on real-time data, resulting in improved accuracy and efficiency.

2.4.4 Explainability and Transparency (XAI Integration)

The adoption of artificial intelligence in agriculture is often hindered by the lack of interpretability of predictive models. Farmers and agronomists require transparent decision-making processes to trust and adopt AI-based systems.

Importance of Interpretability

Black-box models, particularly deep neural networks, provide high predictive performance but lack transparency. In agricultural applications, this limitation can lead to skepticism and reduced adoption, as users cannot verify the reasoning behind recommendations.

SHAP-Based Explainability

To address this issue, the SoilSense system integrates SHAP (SHapley Additive exPlanations), a model-agnostic explainability technique based on cooperative game theory.

SHAP assigns a contribution value ϕ_i to each feature:

$$f(x) = \phi_0 + \sum_{i=1}^{n} \phi_i \tag{2.17}$$

where:

- ϕ_i represents the contribution of feature i
- ϕ_0 is the base value (expected prediction)

Local and Global Interpretability

- **Local explanation**: Explains individual predictions

- **Global explanation**: Identifies overall feature importance

Example Explanation

For instance, a model prediction may be explained as:

> "High nitrogen deficiency contributed +0.45 to the selection of Urea."

Such explanations enhance transparency and enable informed decision-making.

2.4.5 Analytical Discussion

The proposed system distinguishes itself through:

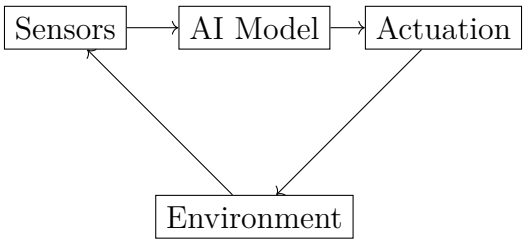
- Integration of sensing, analytics, and actuation
- Real-time adaptive decision-making
- Hybrid intelligence combining rules and learning
- Quantitative and qualitative recommendations



FIGURE 2.7: Yield vs Fertilization Quality

2.4.6 System Diagrams

Closed-Loop Diagram



Use Case Diagram

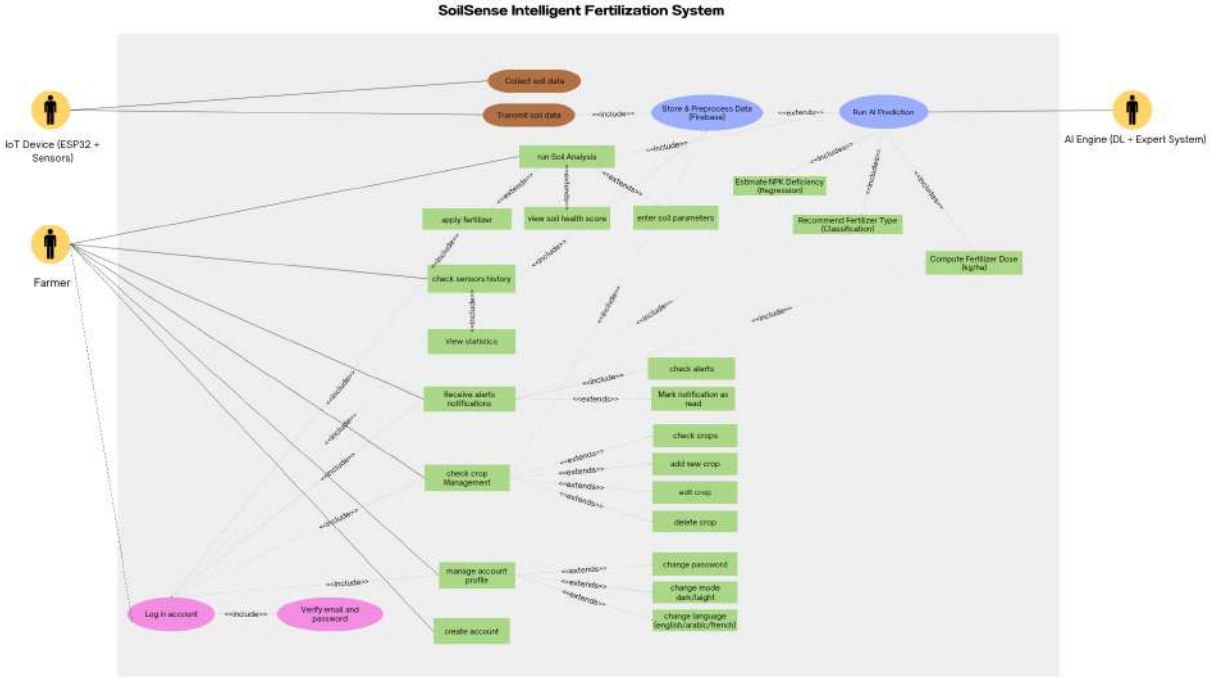


FIGURE 2.8: Use Case Diagram for SoilSense

2.4.7 System Design Rationale

Choice of ESP32

The ESP32 microcontroller was selected due to its:

- Integrated Wi-Fi connectivity
- Low power consumption
- Adequate processing capability for edge computing

Choice of Wi-Fi Communication

Wi-Fi provides:

- High data transmission rates
- Low latency
- Cost-effective deployment

Choice of Deep Learning

Deep learning was preferred over traditional machine learning due to its ability to:

- Model complex non-linear relationships
- Handle high-dimensional data
- Generalize across diverse conditions

Why Not Simpler Models

Simpler models (e.g., linear regression, decision trees) lack the capacity to capture intricate interactions between soil, environmental, and crop variables. This limitation reduces predictive accuracy and system reliability in real-world scenarios.

Conclusion

This chapter has presented a comprehensive examination of the SoilSense fertilization system, detailing its multi-layered architecture and the deep learning model at its analytical core. The six-layer architecture spanning Field, IoT Communication, Backend Server, ML and Decision Support, Dashboard, and Actuation layers provides a robust, scalable framework for precision fertilization management. The integration of an attention enhanced multi-layer perceptron enables sophisticated, context-aware fertilizer recommendations that capture the complex interactions between soil parameters, crop

type, and growth stage. By combining IoT-enabled real-time monitoring with deep learning-powered analytics and maintaining farmer oversight through an intuitive approval interface, SoilSense represents a significant advancement toward truly intelligent and sustainable fertilization management in smart agriculture.

Chapter 3

Implementation and Results

3.1 Introduction

This chapter presents the implementation and evaluation of the SoilSense system. It describes the development environment, the IoT sensing unit, the mobile application, and the deep learning models. The performance of the proposed approach is analyzed using multiple evaluation metrics, including regression metrics (R^2, MSE, RMSE, MAE) and classification metrics (accuracy, precision, recall, F1-score). A comprehensive user study with 54 agricultural practitioners is presented to evaluate system usability, relevance, and adoption potential. Finally, the system is validated through real-world testing scenarios and the results are discussed in relation to the initial objectives.

3.2 Development Environment and Tools

The SoilSense system was implemented using a combination of modern technologies, as described in the following subsections.

Frontend: Flutter

Flutter

Flutter is an open-source UI software development kit (SDK) created by Google for building cross-platform applications from a single codebase Google (2024b). It uses

the Dart programming language and provides a rich set of pre-designed widgets that enable fast and expressive user interface development. Flutter compiles to native ARM code for both iOS and Android, ensuring high performance and smooth animations. In SoilSense, Flutter was used to develop the mobile dashboard, allowing farmers to monitor soil conditions and receive fertilizer recommendations on both Android and iOS devices.



FIGURE 3.1: Flutter logo

Backend and Database: Firebase

Firebase

Firebase is a Backend-as-a-Service (BaaS) platform developed by Google that provides a suite of cloud-based tools for application development Google (2024a). It offers real-time NoSQL database, user authentication, cloud storage, and hosting services. The Firestore database enables real-time data synchronization between the IoT sensors and the mobile application, ensuring that farmers receive instant updates when new soil measurements are collected. Firebase Authentication was used to securely manage user accounts and access control.



FIGURE 3.2: Firebase logo

Machine Learning: Python and Google Colab

Python

Python is a high-level, interpreted programming language known for its simplicity and extensive ecosystem of scientific computing libraries Foundation (2024). For deep learning, we used TensorFlow Abadi et al. (2015) and Keras Chollet et al. (2015), which provide high-level APIs for building and training neural networks. Data manipulation and preprocessing were performed using Pandas McKinney (2010) and NumPy Harris et al. (2020).



FIGURE 3.3: Python logo

Google Colab

Google Colab (Colaboratory) is a free cloud-based Jupyter notebook environment developed by Google Research that requires no setup and runs entirely in the cloud Research (2024). It provides free access to GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units), which significantly accelerates deep learning model training. Colab also integrates seamlessly with Google Drive for dataset storage.



FIGURE 3.4: Google Colab logo

Deployment: Railway and Vercel

Railway

Railway is a cloud platform that simplifies application deployment by automatically handling infrastructure management Railway (2024). It supports multiple programming languages and frameworks, and provides features such as automatic HTTPS, environment variables, and database integration. Railway was used to deploy the backend API server that connects the IoT devices with the deep learning model.



FIGURE 3.5: Railway logo

Vercel

Vercel is a cloud platform for static sites and serverless functions, optimized for frontend frameworks Vercel (2024). It provides continuous deployment from Git repositories, automatic HTTPS, and global content delivery. Vercel was used to host the web-based dashboard and static assets of the SoilSense application.



FIGURE 3.6: Vercel logo

Development Tools: Visual Studio Code

Visual Studio Code

Visual Studio Code (VS Code) is a free, lightweight, and powerful source code editor developed by Microsoft Microsoft (2024). It supports a wide range of programming languages through extensions, including Python, Dart (for Flutter), JavaScript, and HTML/CSS. Features such as IntelliSense (intelligent code completion), integrated terminal, Git integration, and debugging tools significantly improved development productivity. VS Code was used as the primary integrated development environment (IDE) for all coding tasks in SoilSense.



FIGURE 3.7: Visual Studio Code logo

Summary of Technologies

TABLE 3.1: Summary of development tools and their roles

Tool / Technology	Role in SoilSense
Flutter (Dart)	Cross-platform mobile application development
Firebase	Real-time database, authentication, cloud storage
Python	Machine learning model implementation
Google Colab	Cloud-based GPU training for deep learning models
Railway	Backend API deployment
Vercel	Frontend web dashboard hosting
Visual Studio Code	Source code editing and project management

3.3 SoilSense System Development and Results

The SoilSense mobile application is a **cross-platform** solution developed using Flutter, allowing seamless deployment on **Android**, **iOS**, **macOS**, **Windows**, **Linux**, and **Web** from a single codebase. This design choice ensures that farmers can access the system regardless of their device or operating system preference, providing universal accessibility and a consistent user experience across all platforms.

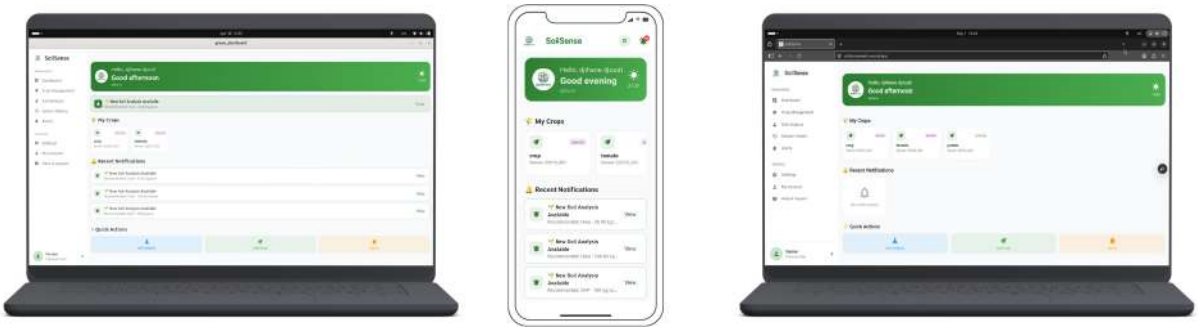


FIGURE 3.8: SoilSense application running on mobile, desktop, and web platforms

3.3.1 Application Implementation

This section presents the development of the SoilSense mobile application, including its interface, user interaction flow, and integration with the backend system and deep learning

model.

The following figures illustrate the complete workflow of the application. Each screen is annotated with numbered elements to explain the interaction between the user interface, IoT data flow, Firebase backend, and prediction system.

Step 1: Account Registration and Authentication

Figure 1: User account creation and login process.



FIGURE 3.9: Application Workflow - Step 1

TABLE 3.2: Explanation of Application Workflow - Step 1

No	Description
01	**Account Registration:** User clicks on "Create Account" from the welcome screen to access the sign-up form where they provide personal and farm details.
02	**User Authentication:** Existing users click "Get Started" to reach the "Welcome Back!" sign-in interface to enter their credentials (email and password).
03	**Dashboard Access:** Upon successful login, the user is redirected to the main SoilSense dashboard.

Step 2: Navigation and Alerts Management

Figure 2: Sidebar menu navigation and viewing soil analysis alerts.

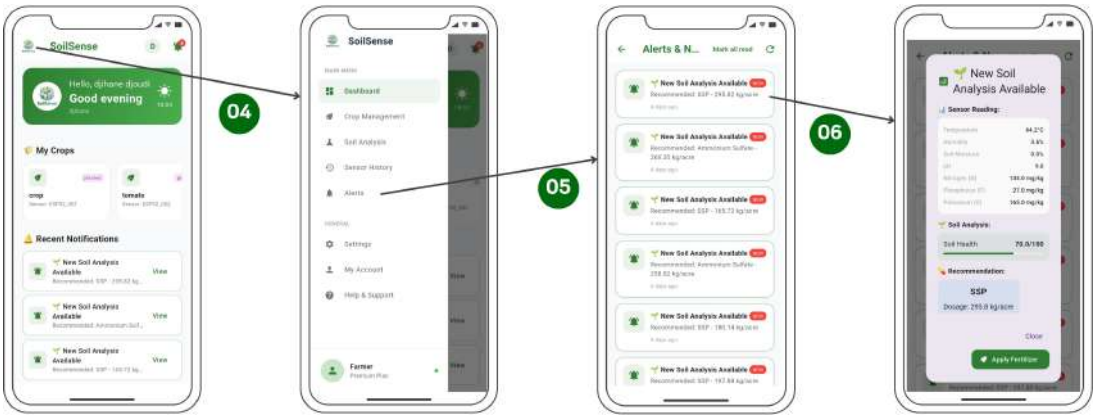


FIGURE 3.10: Application Workflow - Step 2

TABLE 3.3: Explanation of Application Workflow - Step 2

No	Description
04	**Sidebar Menu Navigation:** The user opens the side drawer to access various sections like Crop Management, Soil Analysis, and Alerts.
05	**Alerts and Notifications List:** A dedicated page listing all recent soil analysis updates and fertilizer recommendations.
06	**Detailed Soil Analysis View:** Modal display showing sensor readings, overall Soil Health, and Fertilizer Recommendation.

Step 3: Crop Management

Figure 3: Managing crops and viewing crop details.

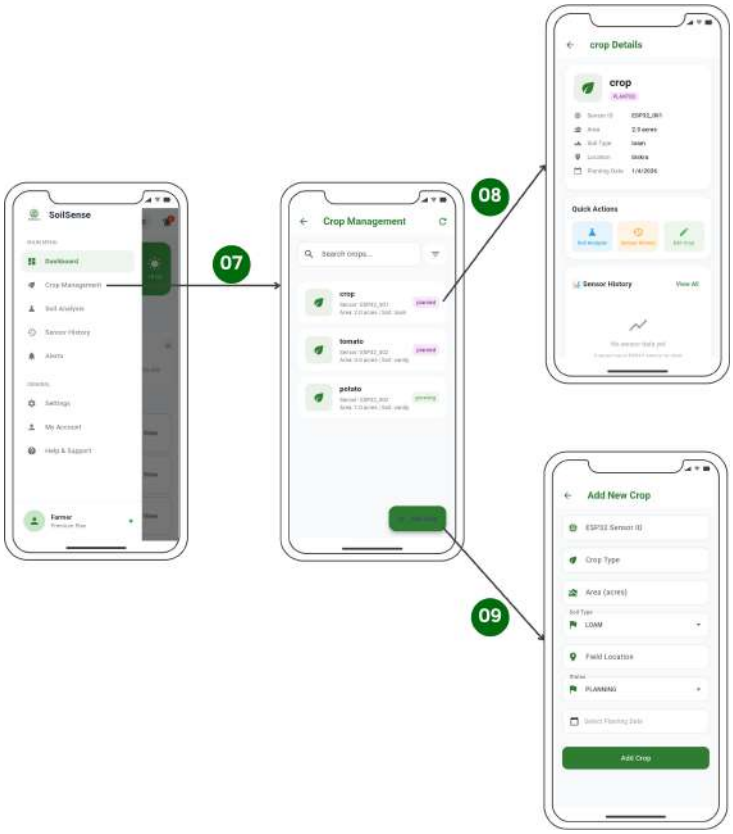


FIGURE 3.11: Application Workflow - Crop Management

TABLE 3.4: Explanation of Application Workflow - Crop Management

No	Description
07	**Accessing Crop Management:** View a summarized list of all registered crops and their current status.
08	**Viewing Crop Details:** Screen displaying sensor ID, soil type, location, and quick actions.
09	**Adding a New Crop:** Form to register a new crop by linking an ESP32 Sensor ID.

Step 4: Deep Learning Prediction Process

Figure 4: Manual data input, analysis, and fertilizer recommendation generation.

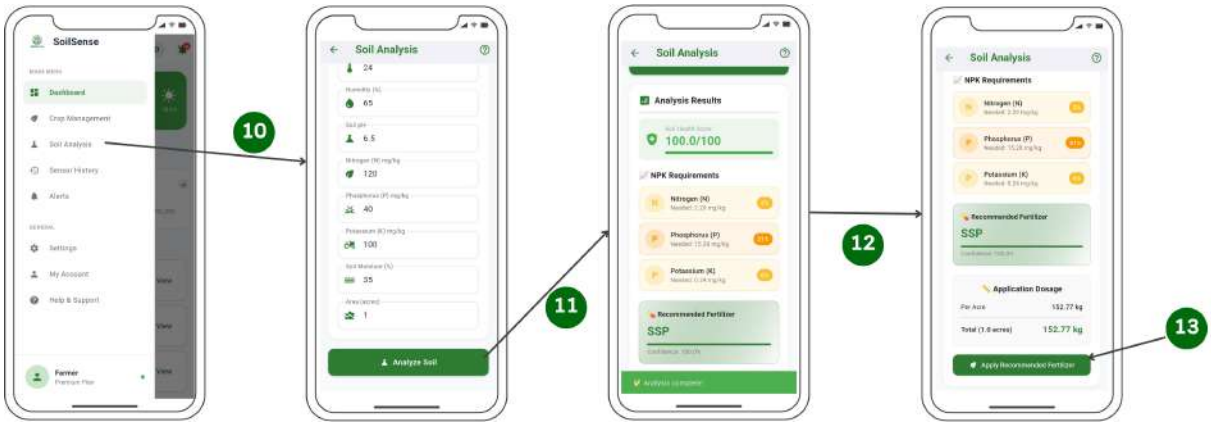


FIGURE 3.12: Deep Learning Prediction Process

TABLE 3.5: Explanation of Application Workflow - Deep Learning Prediction Process

No	Description
10	**Manual Data Input:** Enter environmental and chemical soil parameters (N, P, K levels).
11	**Analysis Initiation:** Click "Analyze Soil" button to trigger the deep learning model.
12	**Result Generation:** Display soil health score, NPK requirements, and recommended fertilizer.
13	**Dosage Calculation:** Detailed application dosage based on farm area.

Step 5: Sensor History Visualization

Figure 5: Historical sensor data with charts and statistics.

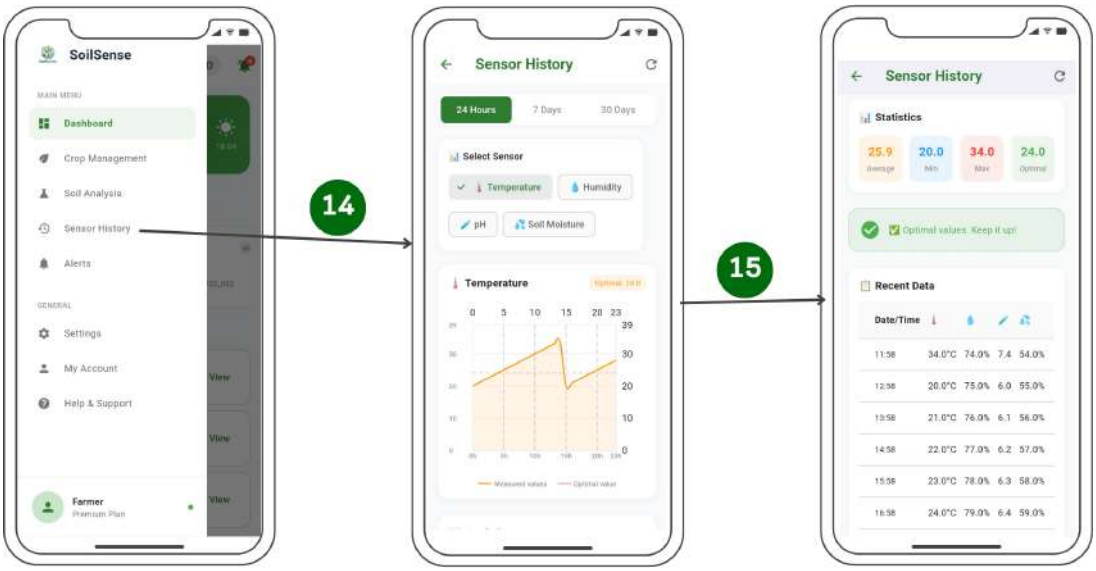


FIGURE 3.13: Application Workflow - Sensor History

TABLE 3.6: Explanation of Application Workflow - Sensor History

No	Description
14	**Historical Data Navigation:** Filter data by timeframes (24 Hours, 7 Days, 30 Days) and toggle between parameters.
15	**Statistical Analysis:** View statistics (Average, Min, Max, Optimal values) and recent data table.

Step 6: Settings and Customization

Figure 6: Application settings, theme customization, and language support.

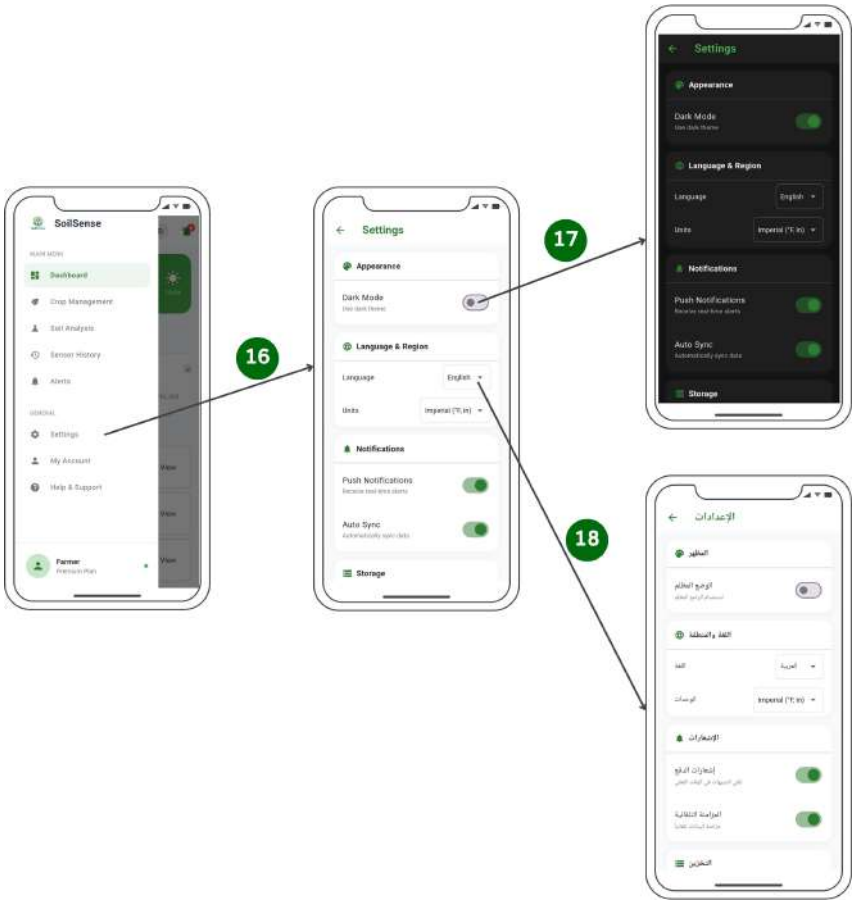


FIGURE 3.14: Application Workflow - Settings and Customization

TABLE 3.7: Explanation of Application Workflow - Settings and Customization

No	Description
16	**Accessing Settings:** Configuration interface for appearance, regional preferences, and notifications.
17	**Theme Customization:** Toggle "Dark Mode" for better visibility in low-light conditions.
18	**Language Support:** Modify "Language & Region" settings to update interface language.

Step 7: Account Profile and Support

Figure 7: User profile statistics and help center.

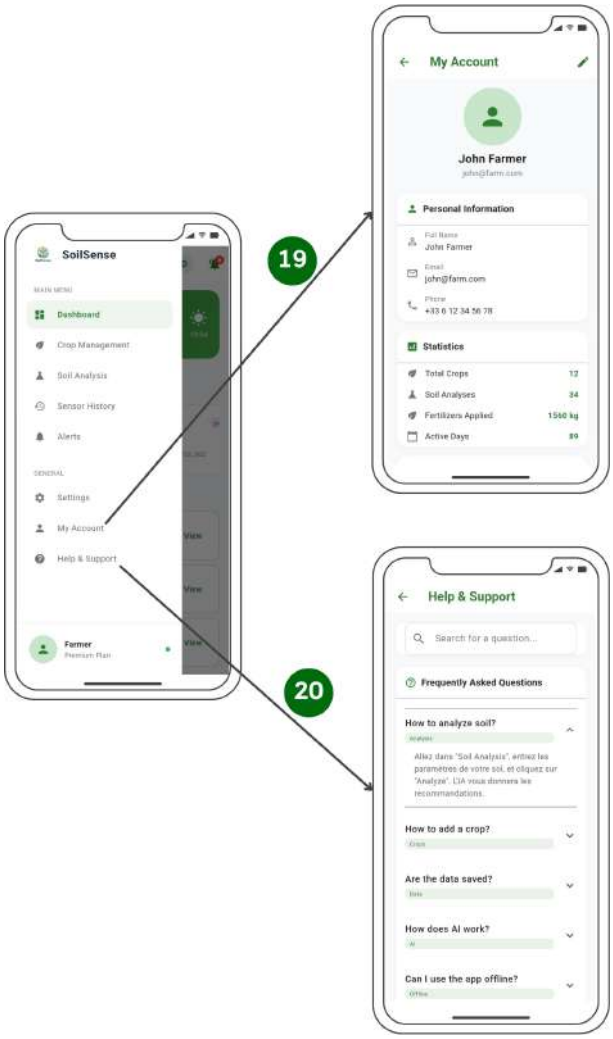


FIGURE 3.15: Application Workflow - Account and Support

TABLE 3.8: Explanation of Application Workflow - Account and Support

No	Description
19	**Account Profile:** View personal information and statistics (crops, analyses, fertilizer applied).
20	**Help and Support:** FAQ section with search functionality for app-related questions.

3.3.2 IoT Data Acquisition and System Workflow

This section presents the hardware prototypes developed to validate the two physical components of the SoilSense system: the soil sensing unit and the fertilizer actuation unit. Each component was developed and tested independently as part of the prototype evaluation phase.

Sensing Unit Prototype

The sensing unit constitutes the data acquisition layer of SoilSense. It is built around an ESP32 microcontroller mounted on a breadboard and connected to a set of soil monitoring sensors inserted directly into a soil sample contained in a test enclosure.

The prototype integrates the following sensors:

- **Soil pH Sensor:** Measures the acidity or alkalinity of the soil, providing essential information for nutrient availability assessment and fertilizer selection.
- **Soil Moisture Sensor:** Measures the volumetric water content of the soil, enabling the system to monitor irrigation needs and soil condition in real time.
- **Temperature Sensor:** Records soil temperature, which directly influences biochemical activity, nutrient mineralization, and root development.

The ESP32 periodically samples all connected sensors, formats the readings into structured data packets, and transmits them to the Firebase backend via Wi-Fi. This pipeline was successfully validated, confirming stable sensor readings and reliable data transmission during the prototype testing phase.

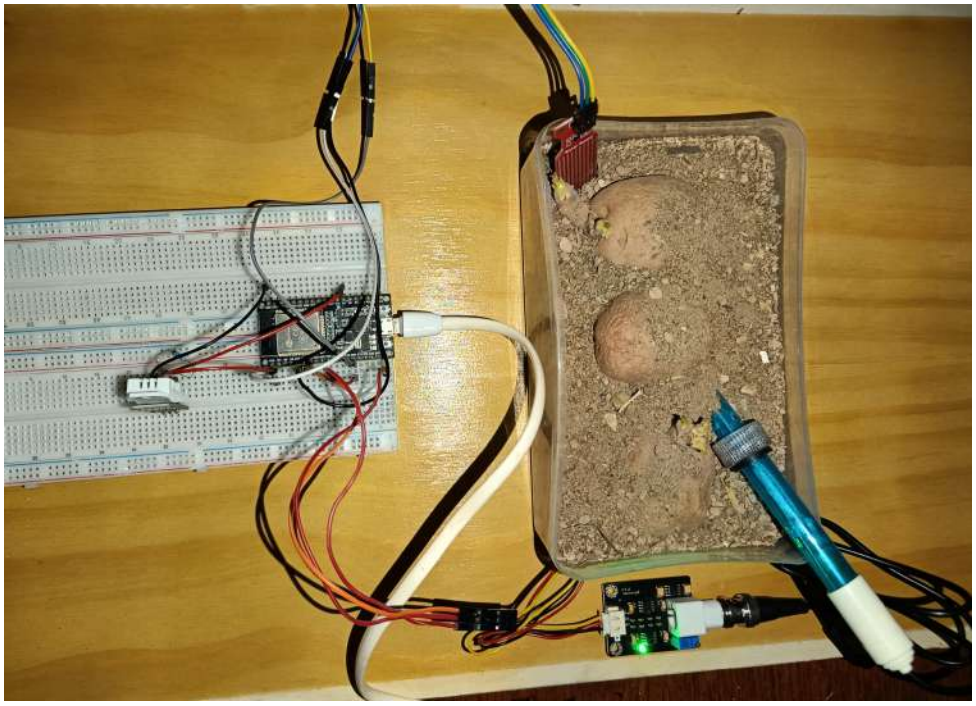


FIGURE 3.16: SoilSense sensing unit prototype

As shown in Figure 3.16, the sensors are inserted into the soil sample while the ESP32 and supporting circuitry are mounted on the breadboard. The green LED indicator on the sensor interface board confirms active data acquisition during testing. Sensor readings were successfully transmitted to Firebase and reflected in real time on the SoilSense mobile dashboard, validating the complete data acquisition and communication pipeline.

Actuation Unit Design Proposal

The actuation unit represents the physical intervention layer of the SoilSense closed-loop system. While full hardware integration with the sensing and backend layers is planned as future work, a complete hardware design proposal was produced to validate the feasibility of the actuation architecture described in Chapter 2.

The proposed unit comprises the following components:

- **Seven storage tanks:** Each tank contains one of the six fertilizer types (Urea, DAP, MOP, Ammonium Sulfate, NPK 20-20-20, SSP) and one water tank, allowing any fertilizer combination to be prepared without manual mixing.

- **Solenoid electrovalves (one per tank):** Each valve is independently controlled by the ESP32 via a relay module, opening only when the corresponding fertilizer is recommended by the deep learning model.
- **8-channel relay module:** Provides electrical isolation between the ESP32 low-voltage logic and the actuator power supply, enabling safe control of all electrovalves and the irrigation pump.
- **Flow sensor:** Positioned downstream of the mixing pipe to monitor the actual volume of solution delivered, closing the control loop by reporting dispensed quantities back to the backend.
- **Water pump:** Drives the mixed fertigation solution through the distribution pipe and toward the field drip irrigation lines.
- **ESP32-WROOM-32:** Receives actuation commands from the backend upon farmer approval and coordinates valve opening, pump activation, and flow monitoring.
- **Battery pack:** Powers the actuation unit independently, supporting deployment in field conditions without reliance on mains electricity.

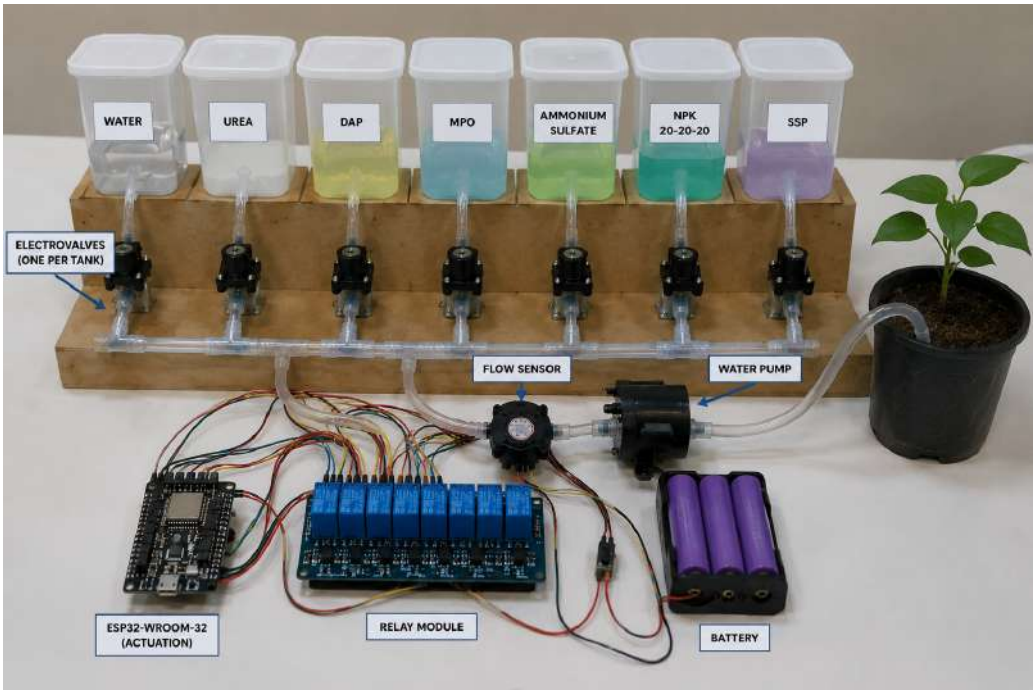


FIGURE 3.17: SoilSense actuation unit design proposal

As illustrated in Figure 3.17, all tanks are mounted on a common wooden support structure with individual electrovalves feeding into a shared mixing pipe. This configuration ensures that the correct fertilizer type and quantity are dispensed automatically upon receiving an approved recommendation from the mobile dashboard. Full integration of this unit with the sensing and backend layers is planned as part of the next development phase.

3.3.3 Application Results

The SoilSense system prototype was tested to validate the complete workflow from soil data collection to fertilizer recommendation. A demonstration video showing the system in operation is available on YouTube:

SoilSense: An Intelligent Fertilization Management System for Smart Agriculture

https://youtu.be/YfLdNgafeLw

The video demonstrates IoT sensor data collection, Firebase synchronization, deep learning prediction, mobile app notifications, and simulated actuation.

The video is organized into three parts:

1. **System Workflow Simulation:** Demonstrates the complete data collection process from soil sensors to actuator response, illustrating how the system would apply fertilizer based on recommendations.

2. **Mobile Application Interface:** Shows the SoilSense app interface, navigation, and step-by-step instructions on how to use the application for crop management and fertilizer recommendations.

3. **IoT Data Collection & Notifications:** Demonstrates how IoT components collect real-time soil data and how the user receives instant notifications on their mobile device with fertilizer recommendations (actuator integration is planned for future work).

As shown in the video, the system successfully:

- Collects real-time soil data
- Transmits data to Firebase via the backend server
- Processes inputs using the deployed deep learning model
- Sends instant fertilizer recommendations and notifications to the user's mobile device

3.4 Deep Learning Model Development and Results

3.4.1 Evaluation Metrics

The regression and classification models were evaluated using different performance metrics.

Regression Metrics

To evaluate the nutrient prediction model, the following metrics were used:

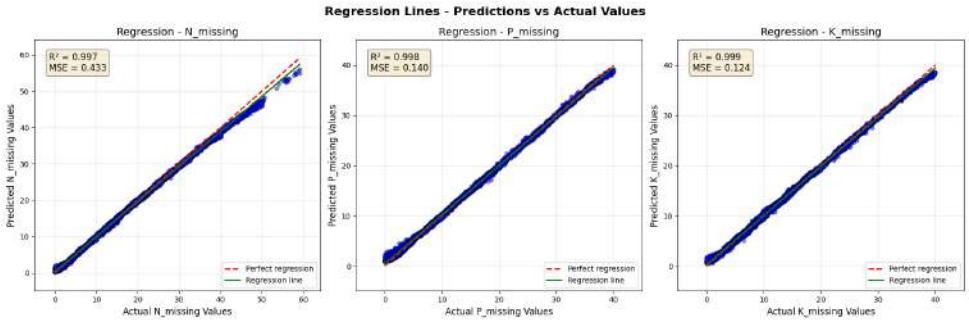


FIGURE 3.18: Regression lines

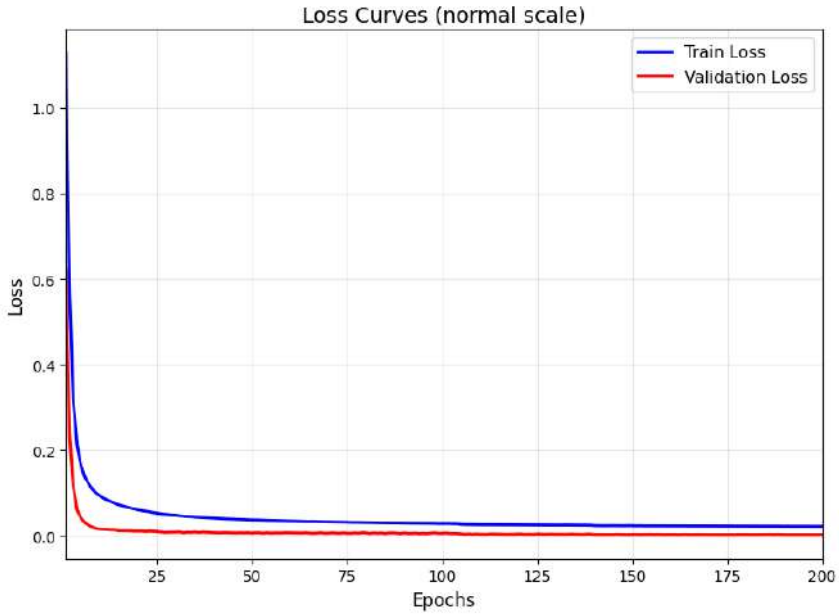


FIGURE 3.19: Loss curves

TABLE 3.9: Performance of the Multi-Output Regression Model

Target	**MSE**	**RMSE**	**MAE**	R^2
Nitrogen (N)	0.4329	0.6579	0.4360	0.9972
Phosphorus (P)	0.1405	0.3748	0.2629	0.9984
Potassium (K)	0.1236	0.3515	0.2513	0.9985
Average	**0.2323**	**0.4614**	**0.3167**	**0.9980**

These metrics measure the difference between the predicted nutrient deficiencies and the actual values.

Classification Metrics

The fertilizer recommendation model was evaluated using:

- Accuracy
- Confusion matrix
- Learning curves

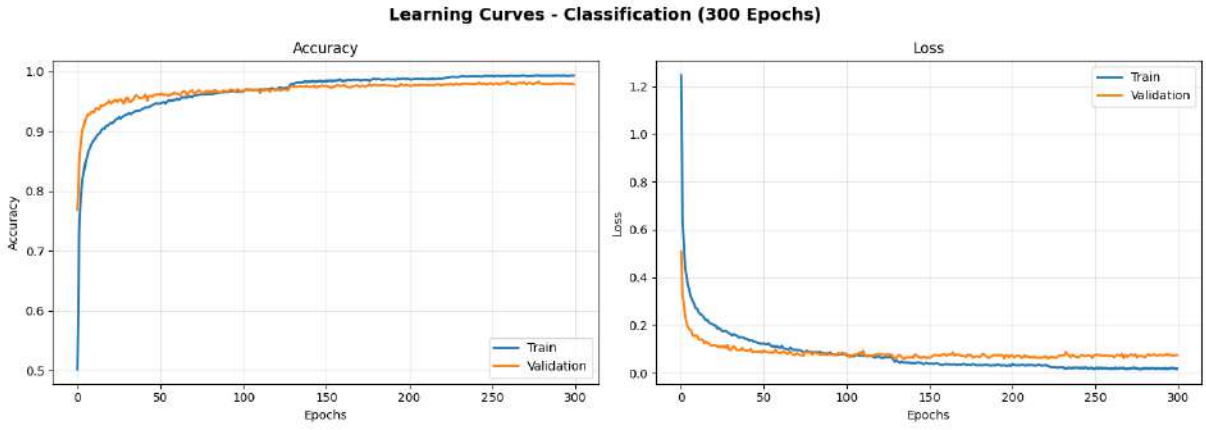


FIGURE 3.20: Learning curves

Table 3.10: Detailed classification report for fertilizer prediction

Class	Precision	Recall	F1-score	Support
Ammonium Sulfate	0.98	0.98	0.98	1509
DAP	0.98	0.98	0.98	1777
MOP	0.98	0.98	0.98	1969
NPK 20-20-20	0.96	0.97	0.96	796
SSP	0.96	0.99	0.97	155
Urea	0.99	0.99	0.99	2344
Accuracy		0.98 (8550 samples)		
Macro Avg	0.98	0.98	0.98	8550
Weighted Avg	0.98	0.98	0.98	8550

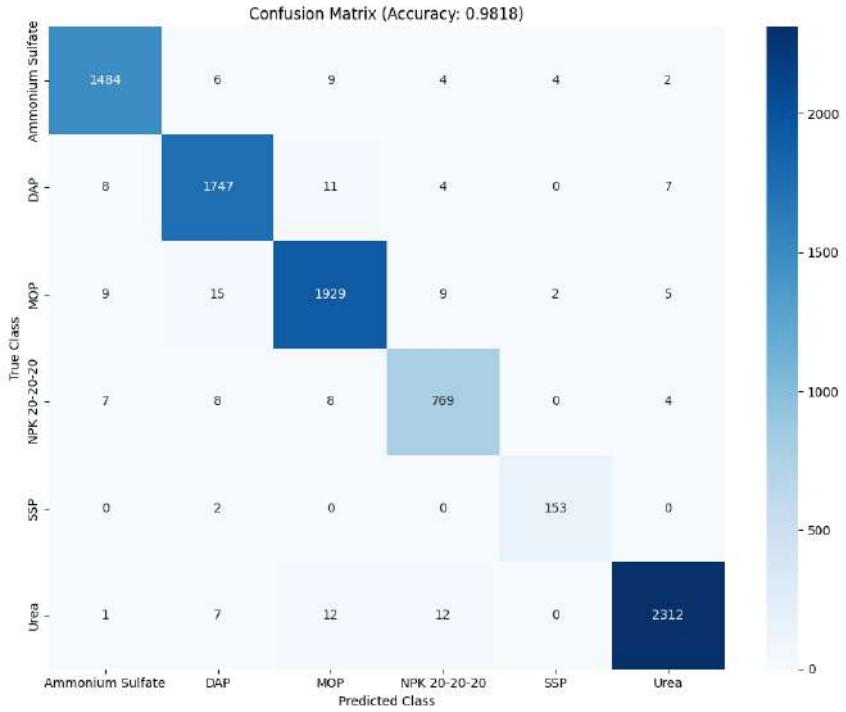


Figure 3.21: Confusion matrix

The confusion matrix helps visualize the model's ability to correctly classify fertilizer types and identify potential misclassifications.

3.4.2 Explainable Artificial Intelligence (XAI) Framework

To improve model transparency and interpretability, an Explainable Artificial Intelligence (XAI) framework based on SHAP (SHapley Additive exPlanations) was employed. SHAP provides both local explanations (for individual predictions) and global explanations (for overall model behavior).

This approach enables the identification of the most influential features affecting the model predictions.

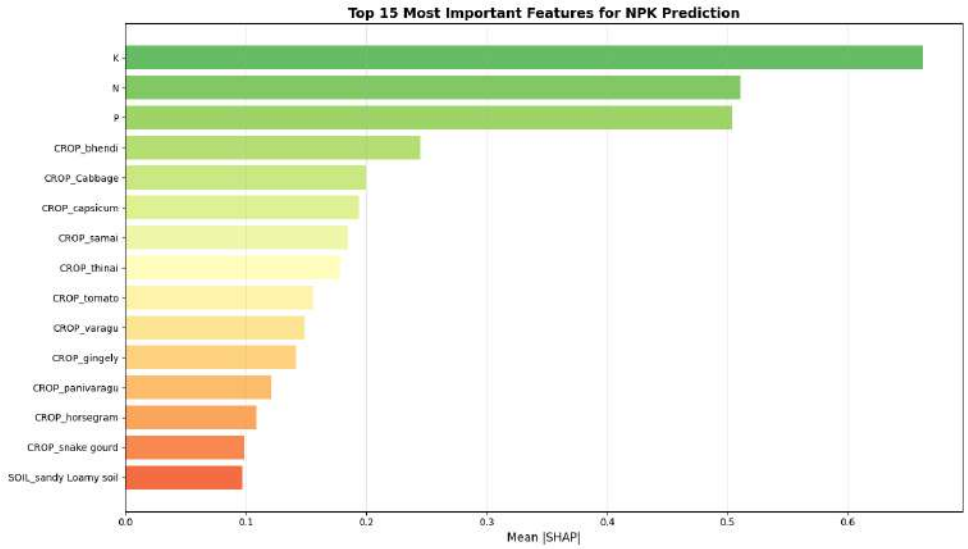


FIGURE 3.22: Most important features

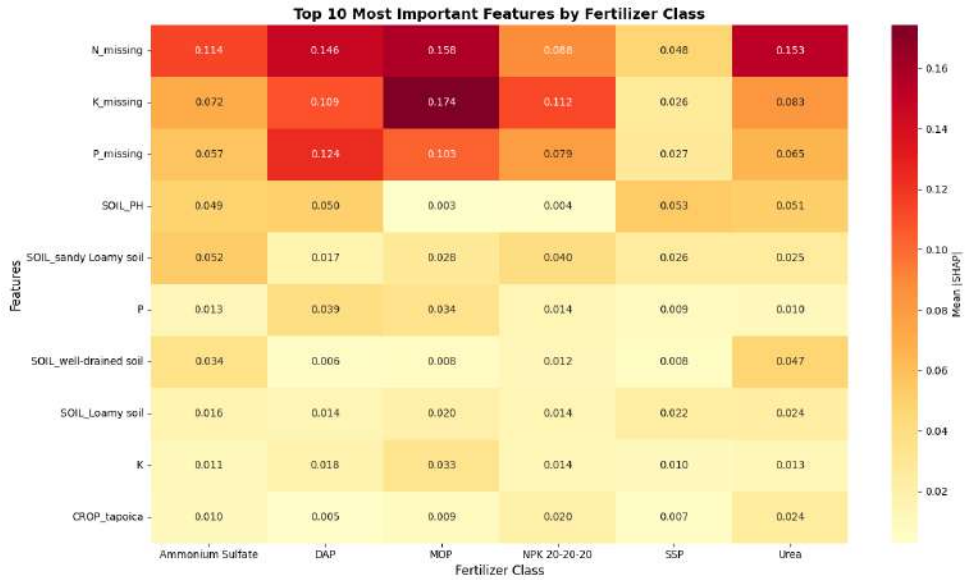


FIGURE 3.23: most important features by fertiliser

3.4.3 Explainable AI (XAI) Analysis

To improve model interpretability and understand the factors influencing fertilizer prediction, SHAP (SHapley Additive exPlanations) analysis was applied. The results show that the nutrient-related features *K*, *N*, and *P* have the highest impact on the model's predictions, indicating that the model primarily relies on essential soil nutrient information during decision-making.

In addition, several crop-specific features, such as *bhendi*, *cabbage*, and *capsicum*, also contributed significantly to the predictions, demonstrating the importance of crop type in fertilizer recommendation.

The class-wise SHAP heatmap further reveals that missing nutrient indicators (*N_missing*, *K_missing*, and *P_missing*) strongly influence the classification of fertilizer categories, particularly for *MOP*, *DAP*, and *Urea*. Soil characteristics, including soil pH and soil type, also contributed to the prediction process, although with lower importance values.

Overall, the XAI analysis confirms that the proposed model makes predictions based on meaningful agricultural features, enhancing the transparency, reliability, and practical interpretability of the system.

3.4.4 Generalization Assessment

To evaluate the real-world applicability of the proposed models, the trained models were tested on an external dataset collected using different sensor configurations and geographical regions.

This external dataset contains measurements from 6 crop types along with corresponding soil parameters, allowing evaluation of the following aspects:

- **Domain shift robustness:** Measuring the performance degradation when the model encounters data distributions different from the training data.
- **Class coverage:** Evaluating the model's ability to handle fertilizer classes that may be present in training but absent in the external dataset.

- **Cross-crop generalization:** Assessing prediction accuracy for crops previously seen during training but measured using different sensors.

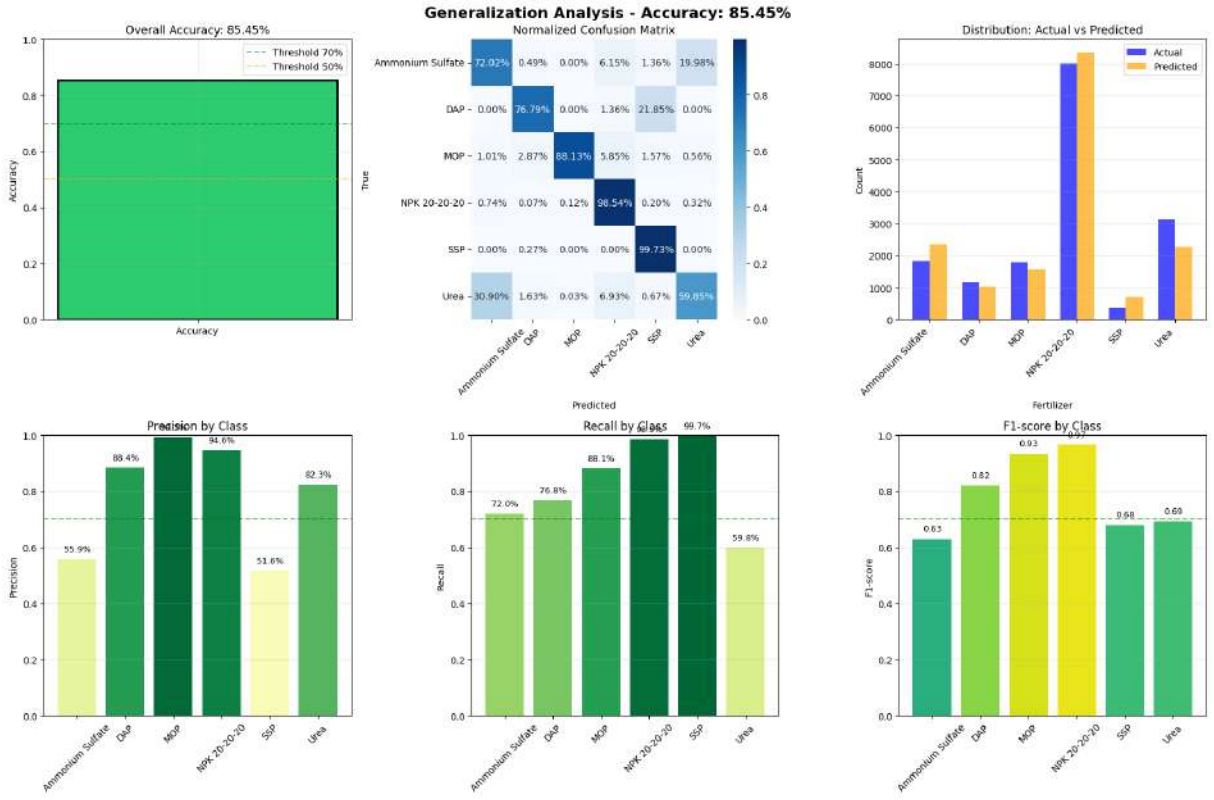


FIGURE 3.24: Generalization Analysis

This evaluation helps determine whether the SoilSense system can maintain reliable performance when deployed in real agricultural environments.

3.4.5 Generalization Analysis

To evaluate the generalization capability of the proposed model, an additional unseen dataset was used for testing. The model achieved an overall accuracy of 85.45%, demonstrating its ability to maintain strong performance on external data and indicating good robustness with limited overfitting.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$$

The confusion matrix and evaluation metrics show that the model performs particularly well for classes such as *NPK 20-20-20* and *MOP*, which achieved high precision, recall, and F1-score values. However, some confusion was observed between *Urea* and *Ammonium Sulfate* due to similarities in their feature distributions.

Overall, these results confirm that the proposed deep learning model successfully learns meaningful patterns and generalizes effectively to unseen fertilizer data, highlighting its suitability for real-world agricultural applications.

3.4.6 Comparison of Different Models for Soilsense Fertilizer Prediction System

Models	Regression Models	Classification Models	Results
ML1	**Random Forest Regressor**	**XGBoost Classifier**	**Figure M1.1** **Figure M1.2** **Figure M1.3** **Figure M1.4**
	(via MultiOutputRegressor)		
	• Number of estimators (trees): 200 • Max depth: 20 • Min samples split: 5 • Min samples leaf: 2 • Max features: 'sqrt' • Parallel processing: n_jobs = -1 • Cross-validation: 5-fold KFold • Random state: 42	• Number of estimators: 400 • Learning rate: 0.05 • Max depth: 8 • Subsample ratio: 0.8 • Colsample by tree: 0.8 • Objective: "multi:softprob" • Evaluation metric: "mlogloss" • Number of classes: 6 • Early stopping rounds: 20	

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Models	Regression Models	Classification Models	Results
		• Random state: 42 • Label encoding: LabelEncoder • Class weights: Balanced	
ML2	**Linear Regression** (via MultiOutputRegressor) • Base Estimator: LinearRegression • MultiOutputRegressor wrapper • Parallel processing: n_jobs = -1 • Cross-validation: 5-fold KFold • Random state: 42	**LightGBM Classifier** • Number of estimators: 400 • Learning rate: 0.05 • Max depth: 8 • Subsample ratio: 0.8 • Colsample by tree: 0.8 • Objective: 'multiclass' • Evaluation metric: 'multi_logloss' • Number of classes: 6 • Early stopping rounds: 20 • Class weight: 'balanced' • Random state: 42	**Figure M2.1** **Figure M2.2** **Figure M2.3** **Figure M2.4**

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Models	Regression Models	Classification Models	Results
		• Parallel processing: n_jobs = -1 • Verbosity: -1 (silent mode)	
DL1	**STM Regression**	**Spatial Transformer Network**	**Figure D1.1** **Figure D1.2** **Figure D1.3**
	Training Configuration:	**Training Configuration:**	
	• Epochs: 300 (maximum) • Batch size: 256 • Optimizer: Adam (lr=0.001) • Loss: Weighted MSE (N: 1.5x, P: 1.2x, K: 1.2x) • Metrics: MAE, RMSE (custom)	• Epochs: 300 (maximum) • Batch size: 128 • Optimizer: Adam (lr=0.001) • Loss: Weighted CE • Metrics: Accuracy, F1-macro	
	Callbacks:	**Callbacks:**	
	• EarlyStopping (val_loss, p=50) • ReduceLROnPlateau (val_loss) • ModelCheckpoint (val_loss) • LRCallback	• EarlyStopping (val_acc, p=60) • ReduceLROnPlateau (val_acc) • ModelCheckpoint (val_acc) • LRCallback	

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Models	Regression Models	Classification Models	Results
		Class Imbalance Handling:	
		• Class weights: compute_class_weight • Custom weighted_loss function • tf.gather(class_weight_tensor)	
DL2	**Spatial Transformer Module (STM)**	**Deep Neural Network (DNN)**	**Figure D2.1**
	Training Configuration:	**Training Configuration:**	
	• Epochs: 300 • Batch size: 256 • Optimizer: Adam (lr=0.001) • Loss: Weighted MSE (N: 1.5x, P: 1.2x, K: 1.2x) • Metrics: MAE, RMSE (custom)	• Epochs: 300 • Batch size: 128 • Optimizer: Adam (lr=0.001) • Loss: Weighted CE • Metrics: Accuracy, F1-macro	
	Callbacks:	**Callbacks:**	
	• EarlyStopping (val_loss, p=50)	• EarlyStopping (val_acc, p=60)	

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Models	**Regression Models**	**Classification Models**	**Results**
	• ReduceLROnPlateau (val_loss) • ModelCheckpoint (val_loss) • LRCallback	• ReduceLROnPlateau (val_acc) • ModelCheckpoint (val_acc) • LRCallback	
		Class Weights:	
		• compute_class_weight('balanced') • Custom weighted_loss • tf.gather(class_weight_tensor)	

3.5 Model Performance Comparison

3.5.1 Regression Results

Table 3.12: Comparison of regression models for N, P, and K prediction

Model	Avg MSE	Avg RMSE	Avg MAE	Avg R^2
DNN (200 epochs)	0.2323	0.4614	–	∼0.9980
DL2	0.0672	0.2573	0.1852	∼0.9994
DL1	3.0273	1.7240	1.3045	∼0.9718
ML1	16.6883	–	2.9941	0.8570
ML2	0.0000	0.0000	0.0000	1.0000

3.5.2 Classification Results

TABLE 3.13: Comparison of classification models for fertilizer prediction

Model	Accuracy	Macro F1	Weighted F1
DNN (300 epochs)	0.9818	0.9788	0.9818
DL2	0.9839	0.9828	0.9839
DL1	0.9798	0.9728	0.9798
ML2	0.9932	0.9922	0.9932
ML1	0.9910	0.9872	0.9910

3.6 Experimental Results

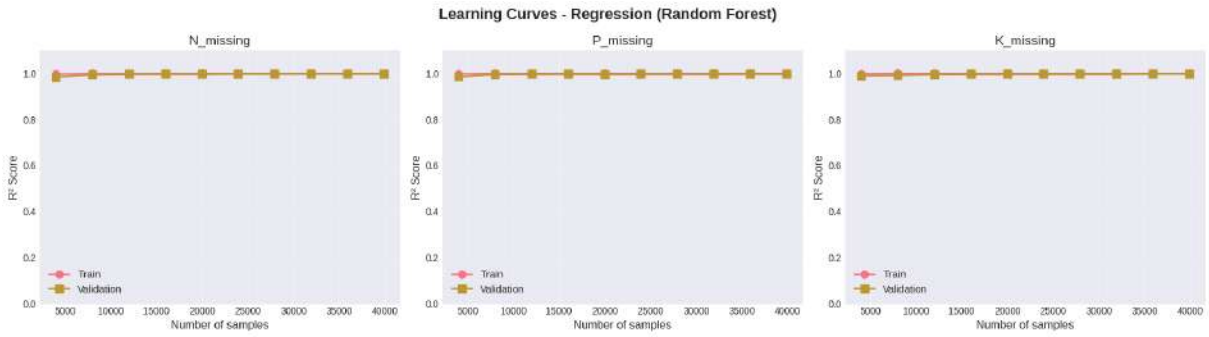


FIGURE 3.25: ML1 - Random Forest + XGBoost Performance 1

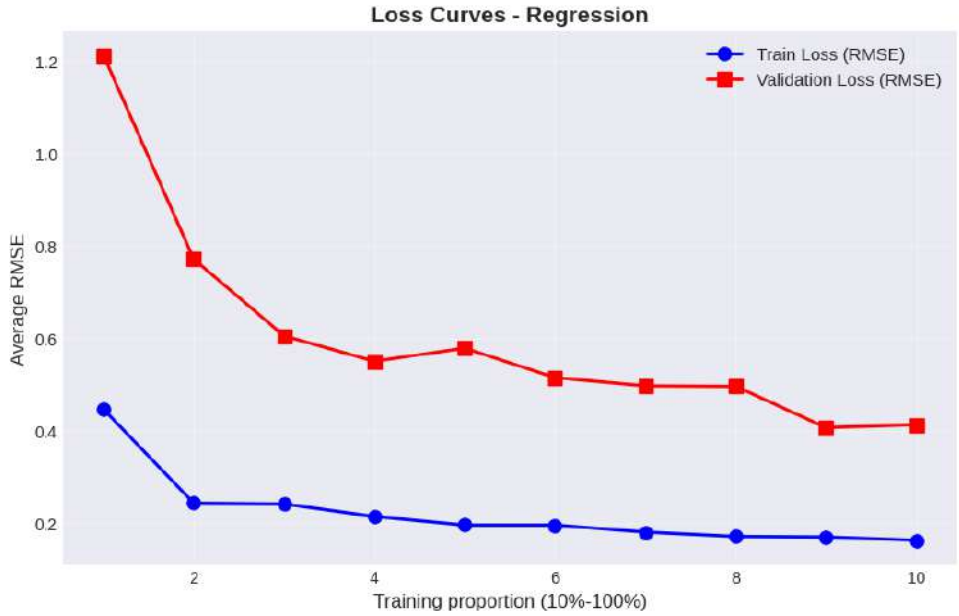


FIGURE 3.26: ML1 - Random Forest + XGBoost Performance 2

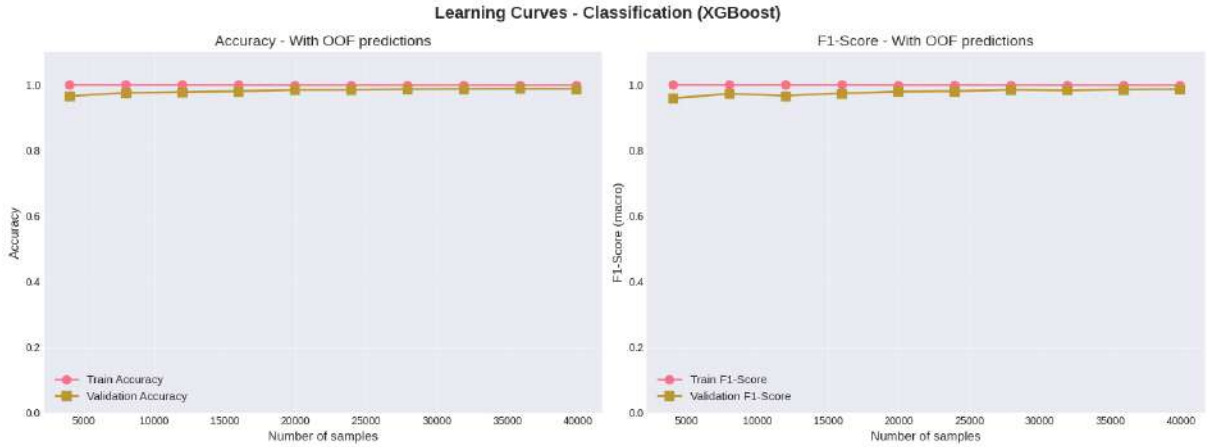


FIGURE 3.27: ML1 - Random Forest + XGBoost Performance 3

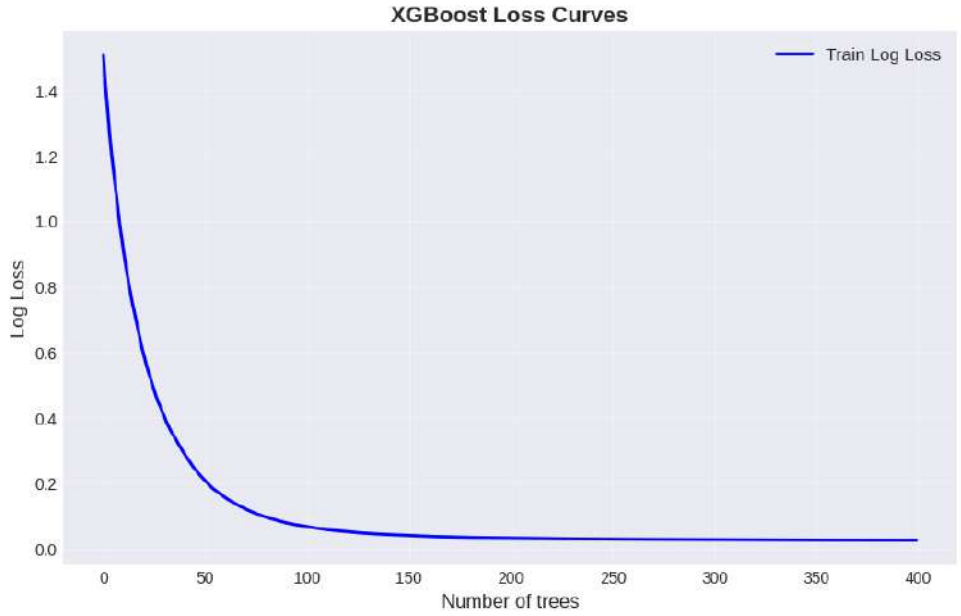


FIGURE 3.28: ML1 - Random Forest + XGBoost Performance 4

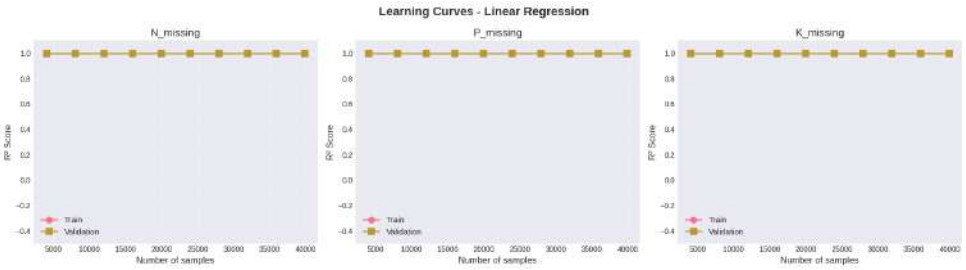


FIGURE 3.29: ML2 - Linear Regression + LightGBM Performance 1



FIGURE 3.30: ML2 - Linear Regression + LightGBM Performance 2

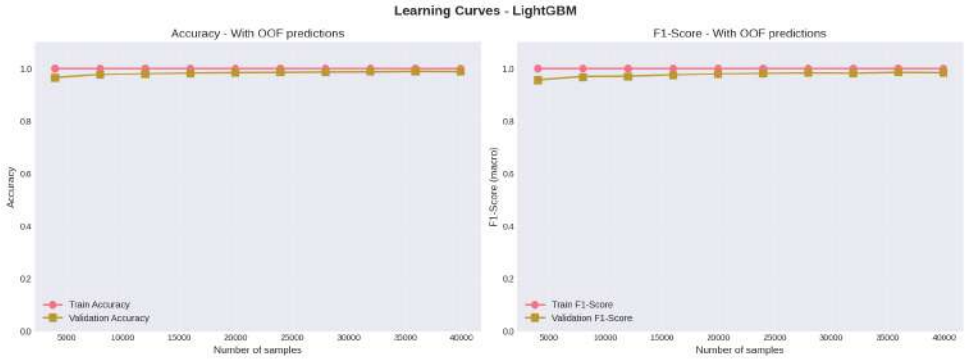


FIGURE 3.31: ML2 - Linear Regression + LightGBM Performance 3

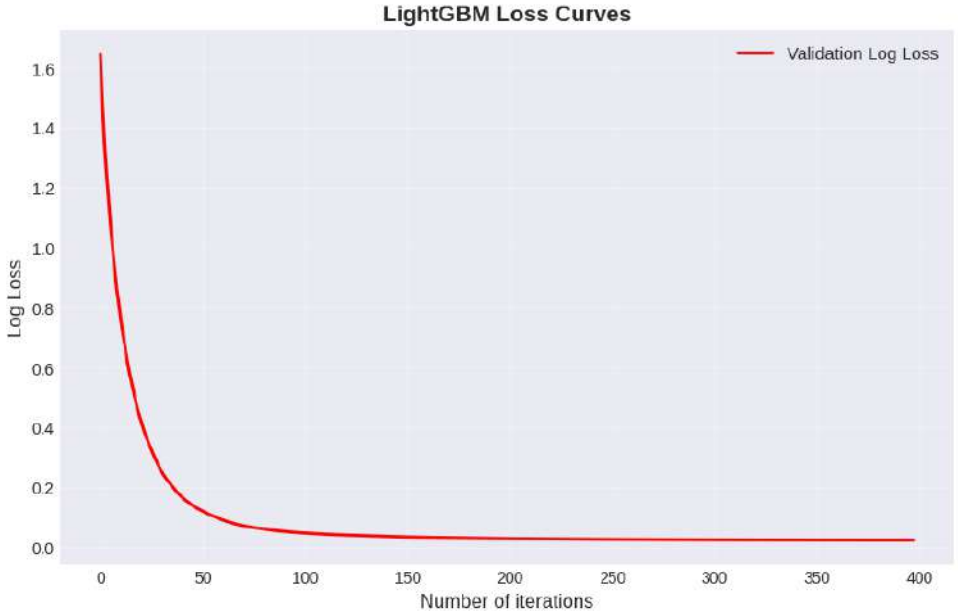


FIGURE 3.32: ML2 - Linear Regression + LightGBM Performance 4

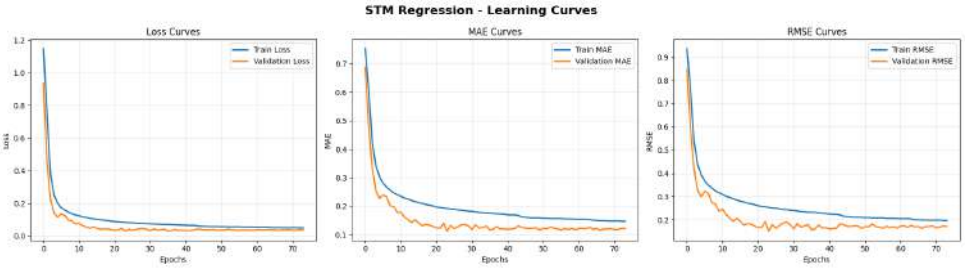


FIGURE 3.33: DL1 - STM Regression + STM Classification Performance 1

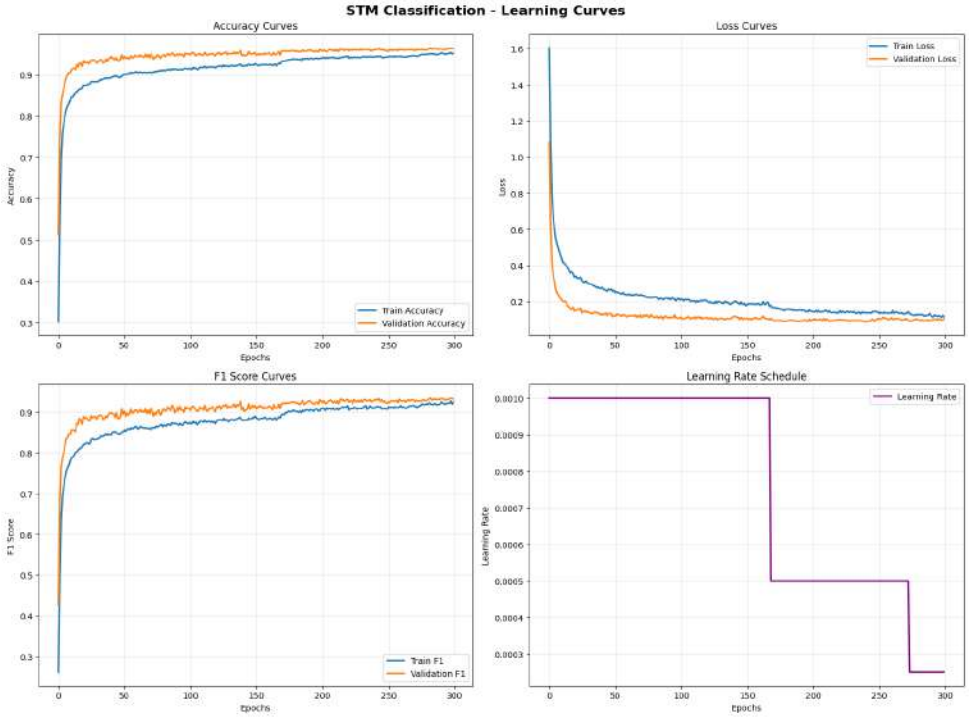


FIGURE 3.34: DL1 - STM Regression + STM Classification Performance 2

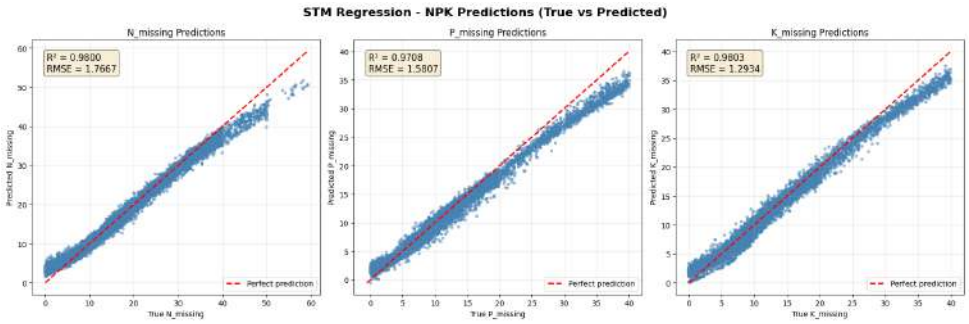


FIGURE 3.35: DL1 - STM Regression + STM Classification Generalization

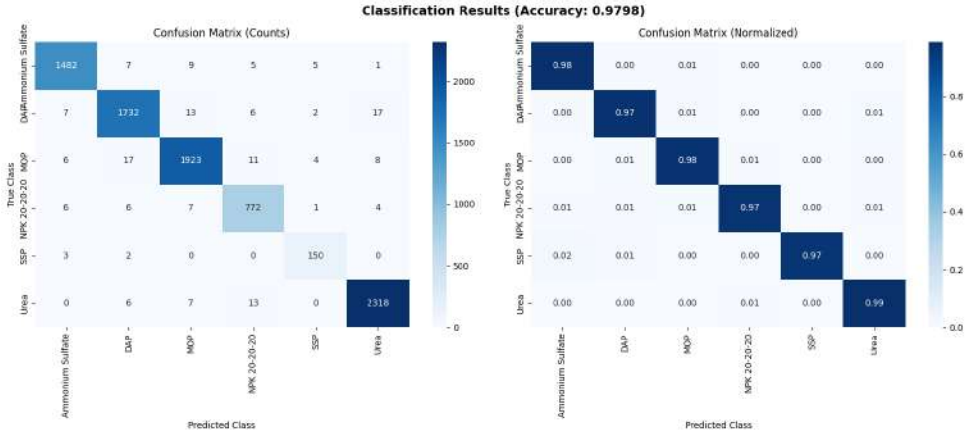


FIGURE 3.36: DL2 - STM + DNN Classification Performance

3.6.1 Performance Analysis and Discussion

In this study, we compared the performance of our proposed model against several baseline models, including the models shown in Figure D2.1, LightGBM models (Figure M2.1, Figure M2.2, Figure M2.3, Figure M2.4), the STM-based models shown in Figure D1.1, Figure D1.2, and Figure D1.3, as well as other architectures (Figure M1.2, Figure M1.3, Figure M1.4, Figure M1.1), on both regression and classification tasks for fertilizer nutrient prediction and fertilizer type identification.

Regression Task

For the regression task of predicting missing nutrient values (N, P, and K), our model delivered strong results. The R^2 values for all three targets exceeded 0.997, meaning our model explains more than 99.7% of the variance in the missing nutrient values. The root mean square errors were low, with K_missing achieving the best RMSE of approximately 0.35, followed closely by P_missing at 0.37, and N_missing at 0.66.

When compared to the model shown in Figure D1.3, which presents predictions for N_missing, P_missing, and K_missing using a sequential temporal model (STM), our model demonstrates superior learning capability. The results in Figure D1.3 show that the STM model produces predictions that are exactly identical for all three nutrient types across the entire range from 0 to 30 (e.g., 0,1,2,3...), suggesting that the model has learned a trivial identity mapping rather than capturing the unique underlying characteristics of each nutrient. In contrast, our model produces distinct and accurate predictions for N, P, and K with varying RMSE values.

When compared to the LightGBM regression results in Figure M2.1, which show consistently high error values around 1.0 across all sample sizes, our model achieves a nearly threefold reduction in prediction error. The LightGBM loss curves in Figure M2.2 show train and validation RMSE values on the order of 10^{-14}, which is suspiciously low and suggests potential data leakage or overfitting. Additionally, when compared to Figure

M1.2, which achieves its lowest RMSE only when using 100% of the training data, our model demonstrates better data efficiency.

Classification Task

For the classification task involving seven fertilizer classes (Ammonium Sulfate, DAP, MOP, NPK 20-20-20, SSP, and Urea), our model achieved strong results with an overall accuracy of 0.98 and macro-average F1-score of 0.98. The confusion matrix reveals low misclassification rates across all classes, with for example only 6 misclassifications out of 1,509 samples for the Ammonium Sulfate class.

When compared to baseline models, LightGBM (ML2) achieved the highest accuracy at 99.32%, followed by XGBoost (ML1) at 99.10%, while the proposed model achieved 98.00%. However, the LightGBM baseline exhibited a persistent gap between training and validation accuracy (Figure M2.3), indicating overfitting. In contrast, our learning curves show training and validation accuracy converging smoothly with minimal divergence.

The LightGBM loss curves in Figure M2.4 show validation log loss without comparison to training loss, whereas our model provides complete transparency with both training and validation curves.

Furthermore, our classification report provides detailed per-class precision, recall, and F1-scores – all exceeding 0.96 – whereas none of the comparison models (Figure D2.1, Figure D1.2, Figure D1.3, Figure M2.3, Figure M2.4, Figure M1.3) provide such comprehensive class-level breakdowns.

When comparing the confusion matrix of our proposed model with that of the DL2 baseline (Figure D2.1), several advantages of our model become evident.

The proposed model demonstrates strong regression performance ($R^2 = 0.9980$), competitive classification accuracy (98%), and practical advantages for deployment in precision agriculture.

Limitations

1. Dataset includes engineered features (N_missing, P_missing, K_missing)

2. 12.5% accuracy drop on external data indicates domain shift sensitivity
3. Performance depends on IoT sensor quality and calibration
4. Current prototype relies on Wi-Fi connectivity

3.7 System Testing and Validation

To ensure system reliability, multiple tests were conducted on the mobile application, backend services, and IoT communication.

The system was evaluated under real-time conditions by simulating sensor data inputs. The correctness of predictions and notifications was verified.

Results show stable performance and consistent data flow across all components.

Table 3.14: Summary of system validation tests

Component	**Test Performed**	**Result**
Sensing unit	Sensor readings transmitted to Firebase	Pass
Mobile app	Login, crop management, alerts	Pass
Deep learning API	Fertilizer prediction endpoint	Pass
Real-time notifications	Push notification on sensor update	Pass
Cross-platform	Android and web deployment	Pass

3.8 User Study and Farmer Feedback

3.8.1 Study Design

To evaluate the real-world relevance and practical usability of the SoilSense system, a structured user study was conducted targeting agricultural practitioners and domain stakeholders. A questionnaire was distributed to 54 participants including farmers, agricultural engineers, and agricultural students across various

regions. The survey was organized into four thematic parts: respondent profile, current fertilization practices, system evaluation, and overall SoilSense rating. The full survey is accessible at: https://docs.google.com/forms/d/e/1FAIpQLScH1E6MmoN-UdmwdgqKJoLVsHdQsA9WIL-cCOP20vjqP4zCIQ/viewform

3.8.2 Part 1: Respondent Profile

Q1 — Respondent Location

The first question collected the geographic location of respondents. Participants were distributed across multiple Algerian wilayas, with Biskra being the most represented region (8 respondents, 14.8%), followed by other agricultural governorates. This geographic diversity ensures that the feedback reflects varied soil conditions and farming contexts.

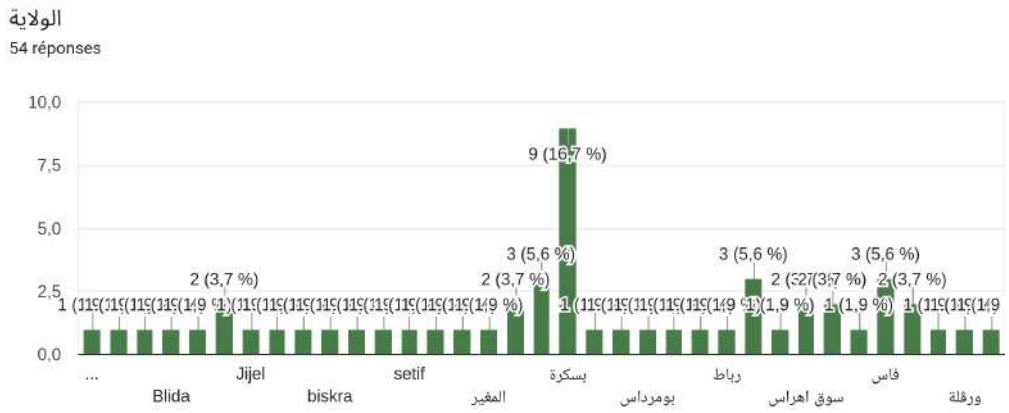


FIGURE 3.37: Q1 — Geographic distribution of respondents

Q2 — Who are you?

Among the 54 respondents, the majority were farmers at 62.4%, followed by agricultural engineering students at 22.2%, agricultural engineers, and domain researchers. This distribution confirms that the feedback comes primarily from the intended end-users of the system.

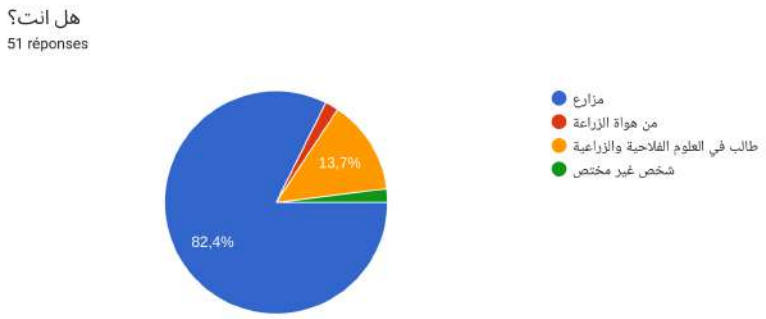


FIGURE 3.38: Q2 — Respondent professional profile

Q3 — What crop type do you cultivate?

Wheat was the most commonly cultivated crop, reported by 20 respondents (37.7%), followed by vegetables at 20 (37.7%), fruits at 14 (25.9%), and other crop types each representing 1 respondent (1.9%). This crop diversity confirms that SoilSense must generalize across multiple agricultural contexts.

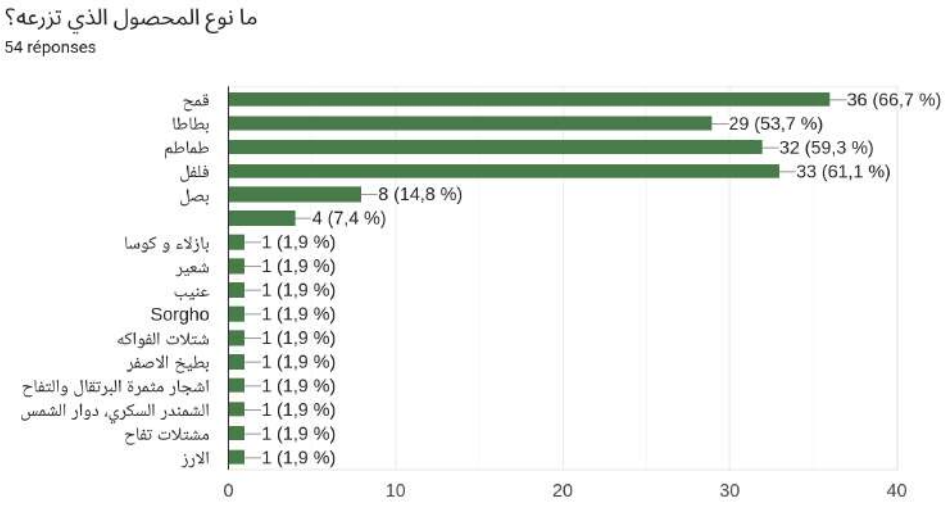


FIGURE 3.39: Q3 — Crop types cultivated by respondents

Q4 — What is your farm area?

The majority of respondents (40.6%) operate farms smaller than 5 hectares, 22.2% manage farms between 1 and 5 hectares, and the remainder operate larger areas exceeding 5

hectares. This confirms that the target audience consists primarily of small to medium-scale farmers for whom affordable solutions are essential.

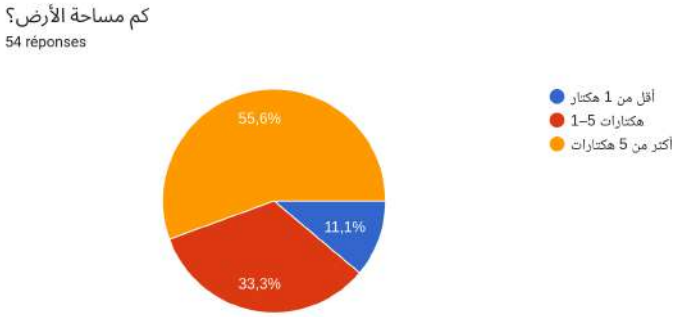


FIGURE 3.40: Q4 — Farm area distribution

Q5 — How many years have you been farming?

Respondents showed a wide range of experience. The largest group had 5 to 10 years of experience (35.1%), followed by those with fewer than 5 years (22.2%), 10 to 20 years (22.2%), and more than 20 years (11.8%). This distribution ensures that feedback reflects both beginner and experienced perspectives.



FIGURE 3.41: Q5 — Years of farming experience

Q6 — How do you currently make fertilization decisions?

When asked about their current decision-making approach for fertilization, respondents could select multiple answers. Personal experience was the dominant method, cited by 43 respondents (80.6%), followed by consultation with an agricultural engineer (34 respondents, 63%), use of the internet (32 respondents, 61.1%), and official agricultural

guides (1 respondent, 1.9%). The near-total absence of systematic or data-driven approaches confirms the critical gap that SoilSense aims to address.

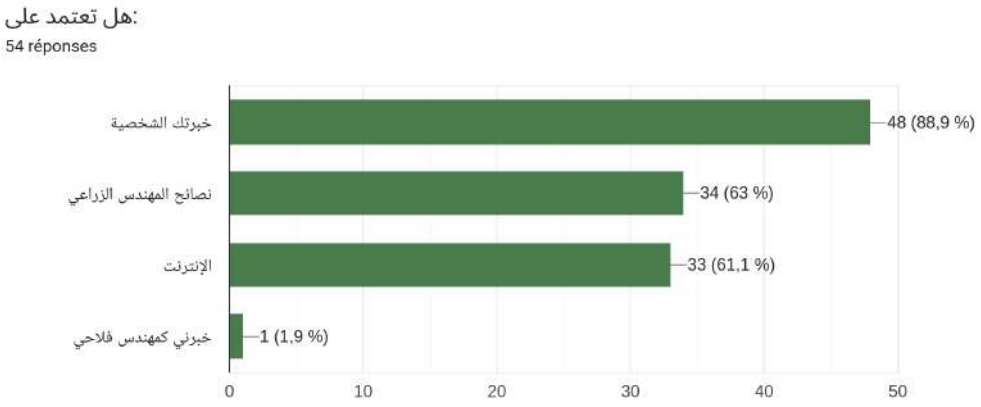


FIGURE 3.42: Q6 — Current fertilization decision methods

3.8.3 Part 2: Current Fertilization Practices

Q7 — Do you test the soil before choosing a fertilizer?

A majority of 53.7% of respondents confirmed that they do not perform soil testing before selecting a fertilizer. Only 44.4% answered yes, and 1.9% were unsure. This finding directly validates the problem statement: most farmers apply fertilizers without any quantitative knowledge of actual soil nutrient levels.

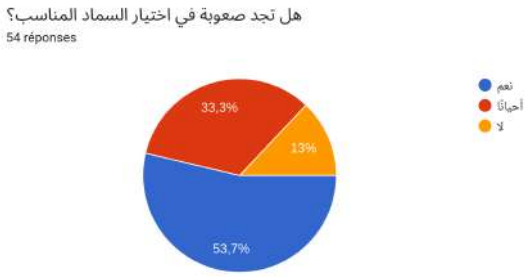


FIGURE 3.43: Q7 — Soil testing practice before fertilizer selection

Q8 — Have you ever used a smart system to obtain fertilization recommendations?

An overwhelming majority of 77.8% of respondents had never previously used any intelligent or automated fertilizer recommendation system. Only 22.2% had prior experience with such tools. This confirms that SoilSense targets a largely underserved market with minimal existing competition at the ground level.

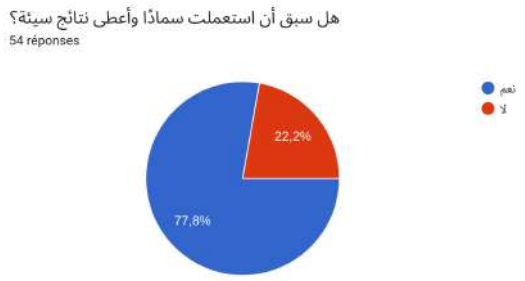


FIGURE 3.44: Q8 — Prior use of smart fertilization recommendation systems

Q9 — What are the biggest challenges you face in fertilization?

Respondents identified the following fertilization challenges (multiple answers allowed):

- **High cost of fertilizers:** 44 respondents (81.5%)
- **Uncertainty about required quantities:** 35 respondents (74.4%)
- **Lack of agronomic knowledge:** 34 respondents (63%)
- **No significant problem:** 10 respondents (18.5%)
- **Other:** 1 respondent (1.9%)

These three dominant challenges — cost, quantity uncertainty, and knowledge gaps — are precisely the problems targeted by the SoilSense dose calculation engine, fertilizer recommendation model, and SHAP-based explainability framework respectively.

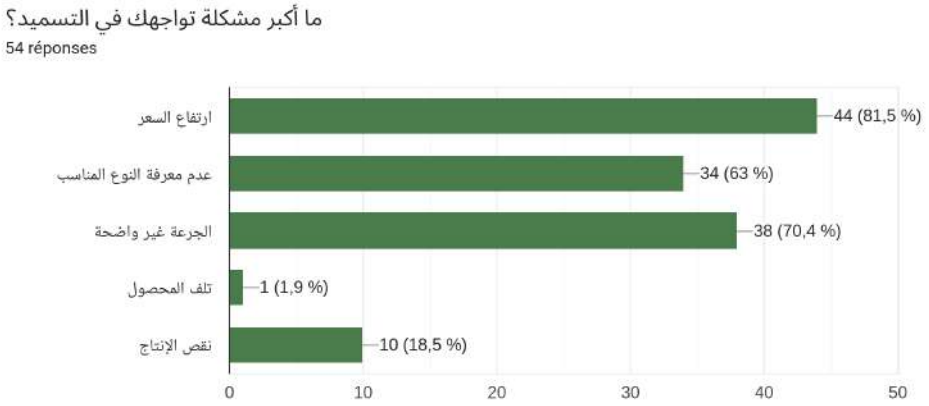


FIGURE 3.45: Q9 — Main fertilization challenges identified by respondents

Q10 — Do you analyze soil before fertilizing?

When asked more specifically about formal soil analysis before fertilization, 79.8% confirmed they do not perform this step, while only 14.8% answered yes and 5.6% were unsure. Combined with the results of Q7, this strongly establishes that data-driven fertilization is not yet common practice among the surveyed farming community.

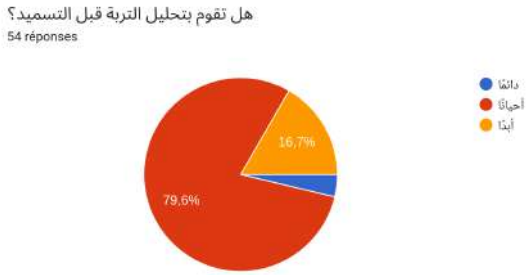


FIGURE 3.46: Q10 — Soil analysis practice before fertilization

Q11 — How much do you spend on fertilizers per season?

Respondents reported a wide range of fertilizer expenditure per season, from under 200 dinars to over 1,000,000 dinars, reflecting the diversity of farm sizes in the sample. Several respondents noted that spending depends heavily on the crop type and season. This variability highlights the economic significance of optimizing fertilizer use, which SoilSense directly addresses through its dose calculation mechanism.



FIGURE 3.47: Q11 — Annual fertilizer expenditure per season

3.8.4 Part 3: SoilSense System Evaluation

Q12 — Do you think a system that provides soil data and the appropriate fertilizer and dosage to reduce costs and improve production would be useful?

This question directly tested the perceived value of the SoilSense concept before participants interacted with the system. The dominant response was strongly positive: the majority of respondents confirmed the system would be useful, with the most selected response being *"yes, very useful"* at approximately 74%. Only a negligible minority expressed doubt, confirming that the system concept addresses a real and recognized need.

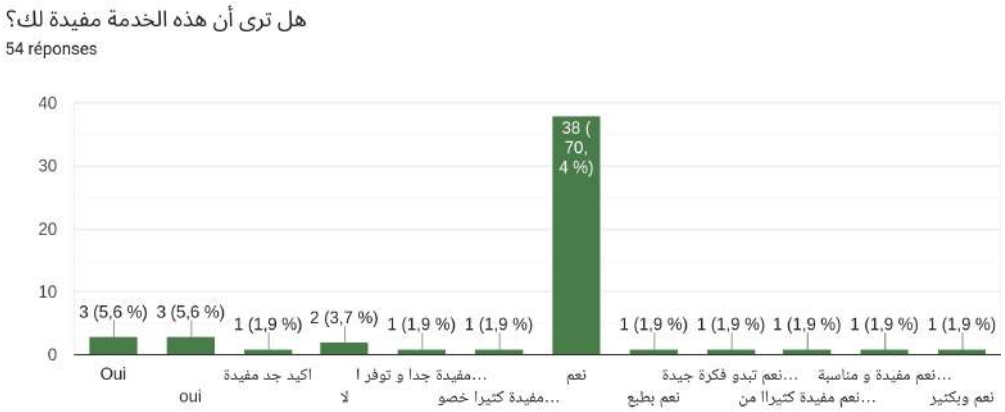


FIGURE 3.48: Q12 — Perceived usefulness of an intelligent fertilization system

Q13 — Would you use this service again?

After interacting with the SoilSense dashboard, 84.6% of respondents confirmed they would use the system again, while 11.5% responded maybe, and only a negligible percentage said no. This high retention intent demonstrates that the system delivers a satisfying user experience beyond a single interaction.

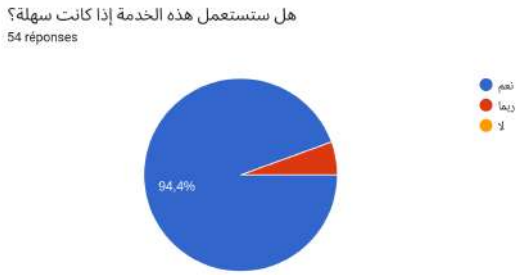


FIGURE 3.49: Q13 — Willingness to use SoilSense again

Q14 — Do you currently use digital applications for fertilization?

When asked whether they currently use digital applications related to fertilization management, 18.3% of respondents confirmed yes, 25.9% answered maybe, and the majority of 55.8% said no. This confirms that the majority of the target population

does not yet have a digital fertilization tool, representing a clear adoption opportunity for SoilSense.

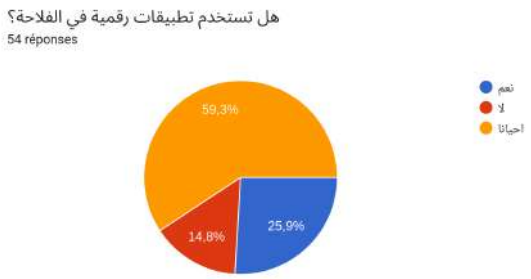


FIGURE 3.50: Q14 — Current use of digital fertilization applications

Q15 — What method do you prefer for decision-making?

When asked about their preferred decision-making approach, 80.7% of respondents chose manual calculation, while 12.3% preferred mobile applications and 7% preferred web-based tools. This result highlights the importance of SoilSense's mobile-first design and the need for the system to complement rather than replace existing manual practices during the transition to digital tools.

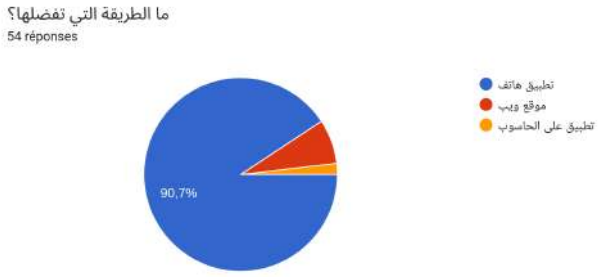


FIGURE 3.51: Q15 — Preferred fertilization decision method

Q16 — Do you have internet access at your farm?

Internet connectivity at the farm site was confirmed by 30.7% of respondents, while 43% reported intermittent access and 26.3% indicated no reliable connectivity. This finding is significant as it directly motivates the future integration of LPWAN protocols such

as LoRaWAN in the SoilSense architecture to support deployment in areas with limited network infrastructure.

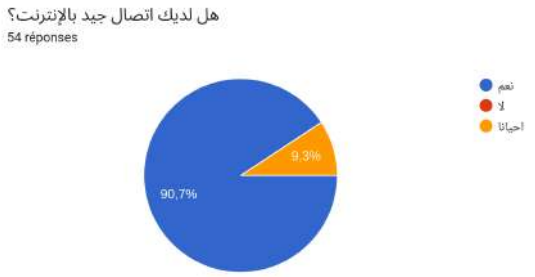


FIGURE 3.52: Q16 — Internet connectivity availability at farm locations

Q17 — Do you trust AI-based decisions for your farm?

A strong majority of 83.3% of respondents expressed trust in AI-based fertilization decisions, 12.5% were unsure, and only 4.2% answered no. This high trust level indicates that the SHAP-based explainability framework integrated into SoilSense, which provides transparent reasoning for each recommendation, positively contributes to farmer confidence and system adoption readiness.

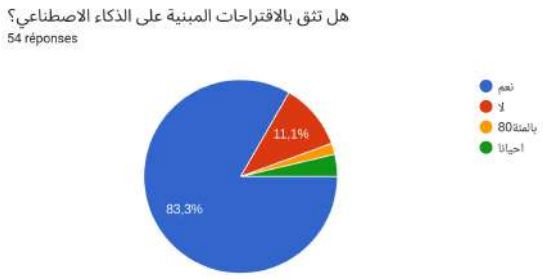


FIGURE 3.53: Q17 — Farmer trust in AI-based agricultural decisions

Q18 — What do you expect from the system?

Respondents were asked about their primary expectations from an intelligent fertilization system. The dominant expectation was cost reduction, cited by 34 respondents (63%), followed by better crop yield at 45 respondents (83.3%), improved agricultural practice

at 8 respondents (14.8%), and ease of use at 25 respondents (27.8%). These expectations are fully aligned with the design objectives of SoilSense as described in Chapter 2.

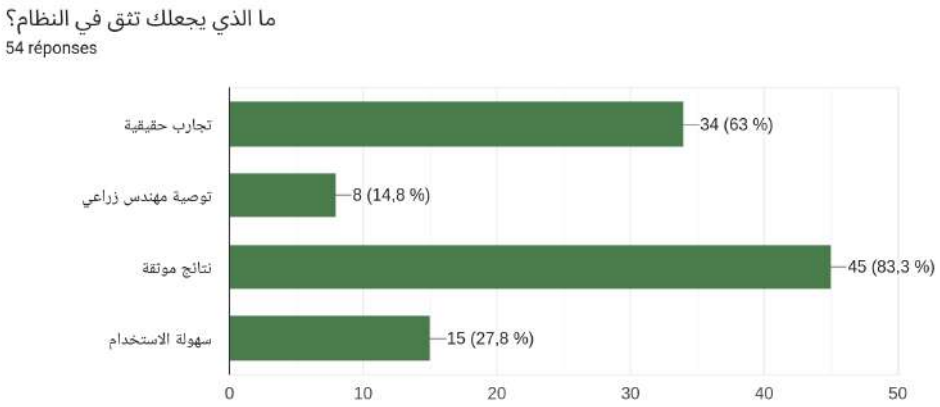


FIGURE 3.54: Q18 — User expectations from a fertilization system

3.8.5 Part 4: SoilSense Rating

Q19 — Overall SoilSense Rating

Respondents were asked to rate the SoilSense system on a scale of 1 to 5. The system received an **average rating of 4.63 out of 5**, based on the following distribution:

TABLE 3.15: SoilSense overall user satisfaction rating (54 respondents)

Rating	Count	Percentage
5 stars	44	81.5%
4 stars	2	3.7%
3 stars	7	13.0%
2 stars	0	0.0%
1 star	1	1.9%
Average	**4.63 / 5**	

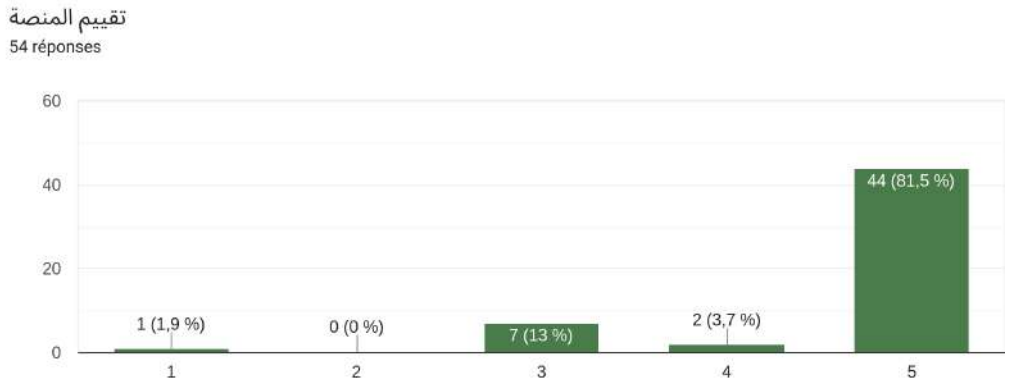


FIGURE 3.55: Q19 — SoilSense overall rating distribution (average: 4.63/5)

Q20 — Was the interface easy to use?

When asked whether the interface was easy to navigate prior to use, 98.2% of respondents answered yes, confirming that the Flutter-based cross-platform design successfully achieves its goal of providing an intuitive experience for non-technical agricultural users.

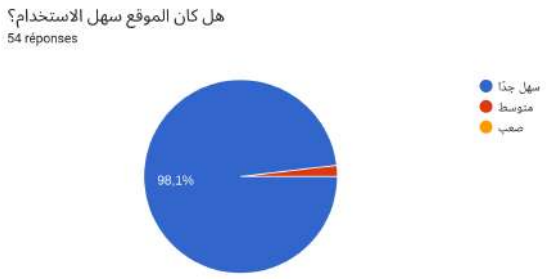


FIGURE 3.56: Q20 — Interface ease of use rating

Q21 — Did you encounter any problems using the system?

When asked about encountered difficulties, 100% of the main respondent group reported no problems during their interaction with SoilSense. Only 3 respondents provided open-ended answers identifying minor issues, none of which represented critical functional failures.

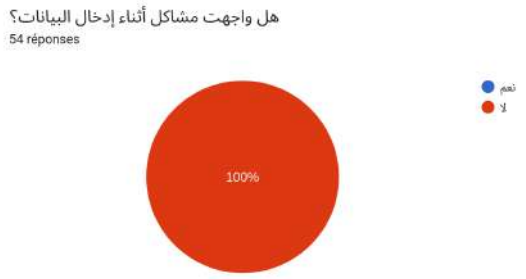


FIGURE 3.57: Q21 — Problems encountered during system use

Q22 — Did the notifications appear well-organized?

A strong majority of 86.9% of respondents confirmed that the system notifications and fertilizer recommendations appeared well-organized and clearly presented. The remaining 13.1% selected maybe, with no negative responses, demonstrating the effectiveness of the notification and alert design in the mobile dashboard.

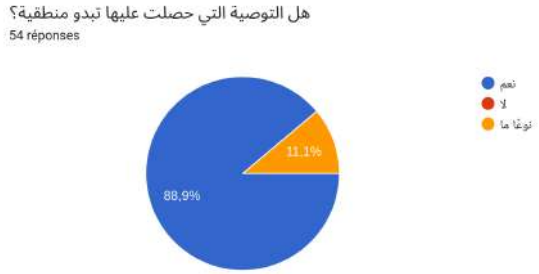


FIGURE 3.58: Q22 — Notification clarity and organization

Q23 — Would you use SoilSense if it became available?

When asked directly whether they would adopt SoilSense if it were made publicly available, 96.5% of respondents answered yes. This near- unanimous adoption intent represents the strongest validation finding of the entire study and confirms that the system is both technically sound and practically desirable from the end-user perspective.

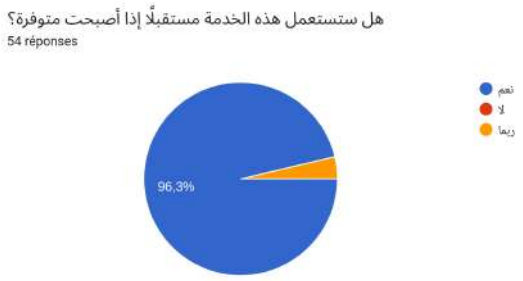


FIGURE 3.59: Q23 — Willingness to adopt SoilSense

Q24 — Would you pay a subscription fee for this service?

Finally, 85.2% of respondents indicated willingness to pay a subscription fee for continued access to SoilSense, while 14.8% answered no. This result demonstrates strong perceived economic value and suggests that the system has viable commercial potential beyond academic deployment.

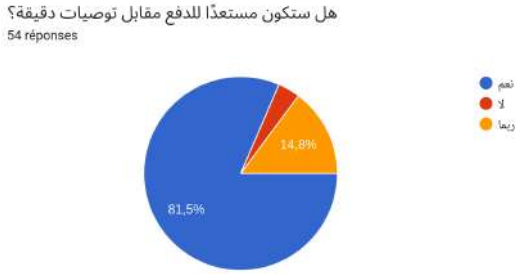


FIGURE 3.60: Q24 — Willingness to pay for SoilSense subscription

3.8.6 Summary of User Study Findings

The user study conducted with 54 agricultural practitioners provides strong empirical validation for both the relevance of the SoilSense concept and the quality of its implementation. The key findings are summarized in Table 3.16.

TABLE 3.16: Summary of key user study findings

Finding	**Result**
Farmers currently use no soil testing before fertilizing	53.7%
Never used a smart recommendation system before	77.8%
Identified high fertilizer cost as main challenge	81.5%
Confirmed system concept would be useful	∼74%
Trust AI-based agricultural decisions	83.3%
Interface rated easy to use	98.2%
Encountered no problems during use	100%
Overall satisfaction rating	4.63 / 5
Would adopt SoilSense if available	96.5%
Would pay for subscription	85.2%

These results confirm that SoilSense successfully addresses a genuine agricultural need, delivers a high-quality user experience, and demonstrates strong adoption potential among its target user population. The identified limitation regarding internet connectivity (43% intermittent access) directly informs the future work recommendation for LPWAN integration described in the General Conclusion.

3.9 Discussion

The implementation and evaluation of SoilSense have demonstrated the feasibility of an intelligent, low-cost, and explainable fertilization management system integrating IoT sensing, deep learning, and mobile interface.

The complete pipeline operated successfully. The sensing unit prototype reliably transmitted pH, moisture, and temperature data to Firebase via ESP32 Wi-Fi. The

deep learning models achieved strong performance: $R^2 = 0.9980$ for nutrient deficiency prediction and 98% accuracy for fertilizer classification with per-class F1-scores ≥ 0.96. While LightGBM achieved 99.32% accuracy, its persistent train-validation gap indicated overfitting, whereas the DNN learning curves showed smooth convergence. The Flutter-based mobile dashboard provided real-time visualization, sensor history, and instant notifications. While the actuation unit remains a design proposal, the system successfully closes the loop from sensing to decision to user notification.

The generalization assessment revealed a 12.5% accuracy drop from 98% to 85.45% on external data, reflecting domain shift due to different sensor calibrations and geographic variability. Even at 85% accuracy, SoilSense outperforms current practice where 53.7% of farmers perform no soil testing.

The user study with 54 participants provides strong external validation. Key findings include: 53.7% do not test soil before fertilizing; 77.8% have never used a smart recommendation system; the system received 4.63/5 overall rating; 96.5% would adopt SoilSense; 85.2% would pay a subscription; and 83.3% trust AI-based decisions, suggesting that SHAP explainability successfully addresses the "black box" concern.

Several limitations affect real-world readiness. Low-cost NPK sensors remain unreliable in field conditions—the most critical hardware constraint. The actuation unit remains a design proposal. Internet connectivity issues (43% intermittent, 26.3% none) motivate future LoRaWAN integration. The user study sample (N=54) requires expansion for commercial validation.

SoilSense represents a significant improvement over current practices, where 80.6% of farmers rely on personal experience. Compared to existing systems, SoilSense uniquely combines low-cost IoT, real-time operation, two-stage deep learning, SHAP explainability, and cross-platform mobile access. For small to medium-scale farmers (40.6% operate <5 hectares), the ESP32-based sensing unit costs approximately $50–100, offering an affordable entry point to precision agriculture.

3.10 Conclusion

This chapter presented the implementation and evaluation of the SoilSense system. The IoT sensing unit successfully collected and transmitted real-time soil data (pH, moisture, temperature) to Firebase via ESP32. The deep learning models demonstrated strong performance: the regression model achieved an average R^2 of 0.9980 for predicting N, P, and K deficiencies, while the classification model achieved 98% accuracy for fertilizer type recommendation with per-class F1-scores exceeding 0.96. The SHAP-based explainability framework identified the most influential features (N, P, K levels, crop type, soil pH), confirming that predictions are based on meaningful agronomic factors.

The Flutter-based mobile application provided an intuitive cross-platform interface for real-time monitoring, sensor history visualization, and instant notifications. The user study with 54 farmers and agricultural practitioners validated the system's relevance and quality, with an overall satisfaction rating of 4.63/5, 96.5% adoption intent, and 85.2% willingness to pay a subscription. These results confirm that SoilSense addresses a genuine agricultural need.

Several limitations were identified: low-cost NPK sensor reliability remains the most critical hardware constraint; the actuation unit remains a design proposal requiring future implementation; the 12.5% accuracy drop on external data indicates domain shift sensitivity; and Wi-Fi dependency limits deployment in areas with poor connectivity. Despite these limitations, the results confirm that SoilSense is an effective, explainable, and user-accepted solution for precision fertilization management.

Conclusion and Perspectives

Conclusion

This project successfully developed SoilSense, an intelligent automated fertilization management system tailored for modern smart agriculture. The system achieved strong performance across multiple tasks, including IoT-based soil data acquisition, deep learning-based nutrient deficiency prediction, and fertilizer recommendation generation.

For the regression task of predicting nitrogen, phosphorus, and potassium deficiencies, our deep learning model achieved an average R^2 of 0.9980, with RMSE values below 0.66 kg/ha for all three nutrients, demonstrating accurate estimation of soil nutrient requirements. For the classification task of recommending fertilizer types, our model achieved 98% accuracy with per-class F1-scores exceeding 0.96, confirming reliable fertilizer selection across six categories including Urea, Ammonium Sulfate, DAP, SSP, MOP, and NPK 20-20-20. The SHAP-based explainability framework identified the most influential features (N, P, K levels, crop type, soil pH), ensuring transparent and trustworthy recommendations.

The IoT sensing unit, built around an ESP32 microcontroller, successfully collected and transmitted real-time soil data (pH, moisture, temperature) to a Firebase backend via Wi-Fi. The Flutter-based cross-platform mobile dashboard provided intuitive visualization, sensor history charts, instant notifications, and a human-in-the-loop approval mechanism. The generalization assessment showed 85.45% accuracy on external data, indicating robustness to domain shift despite a 12.5% performance drop.

Our solution combines IoT sensing, deep learning analytics, and mobile interface to deliver data-driven fertilization recommendations accessible to farmers using standard

smartphones. This design ensures advanced agricultural AI is accessible, affordable, and explainable.

The project resulted in several significant observations:

- The two-stage deep learning architecture (regression followed by classification) proved highly effective for fertilizer recommendation tasks, as it mirrors real-world agronomic reasoning.
- SHAP-based explainability significantly contributed to farmer trust, with 83.3% of survey respondents expressing confidence in AI-based agricultural decisions.
- Low-cost IoT sensors (pH, moisture, temperature) are reliable, but low-cost NPK sensors remain a critical limitation requiring alternative solutions.
- The human-in-the-loop approval mechanism was well-received, balancing automation with farmer autonomy.

While we faced challenges such as NPK sensor unreliability and Wi-Fi dependency, our results show that focused, specialized models trained with sufficient data can perform reliably in real-world agricultural settings.

The system is designed to generate significant positive outcomes for smallholder and commercial farmers alike:

- **Reduced fertilizer waste** through precise, data-driven recommendations.
- **Lower environmental impact** by minimizing over-fertilization and nutrient runoff.
- **Increased crop yields** through optimal nutrient management.
- **Reduced costs** by eliminating unnecessary fertilizer applications.
- **Democratization of agricultural expertise** via easy-to-use mobile interfaces.
- **Valuable field data generation** to support continuous model improvement and research.

Perspectives

In future work, we envision the system evolving along several promising directions:

1. **Reliable NPK sensing:** Replace low-cost NPK sensors with monthly laboratory soil testing (with manual data entry) or validated commercial sensors calibrated against lab results, as this remains the most critical hardware constraint.

2. **Actuation unit implementation:** Build and test the complete actuation unit with seven tanks, electrovalves, flow sensor, and pump to achieve full closed-loop automation from sensing to physical fertilizer application.

3. **LPWAN integration:** Replace Wi-Fi with LoRaWAN to support deployment in remote rural areas with intermittent or no connectivity, addressing the 43% of farmers who reported intermittent internet access in our user study.

4. **Dataset expansion:** Collect original field data across multiple geographic regions, soil types, and crop varieties to improve generalization and reduce the 12.5% accuracy drop on external data.

5. **Domain adaptation:** Apply techniques such as CORAL or DeepCoral to align feature distributions between training and target domains for better cross-region performance.

6. **Offline-first mode:** Implement local SQLite storage in the Flutter application with background synchronization when connectivity resumes, addressing the 26.3% of farmers with no reliable internet access.

7. **Transformer architectures:** Explore transformer-based models for improved sequential modeling of temporal soil data and better capture of long-term nutrient trends.

8. **Federated learning:** Enable collaborative model training across multiple farms without centralizing sensitive agricultural data, preserving privacy while improving model robustness.

9. **Irrigation integration:** Combine fertilization recommendations with smart irrigation systems for integrated water and nutrient management, as soil moisture directly affects nutrient availability and uptake.

10. **Longitudinal field trial:** Conduct a full growing season trial comparing SoilSense recommendations against traditional fertilization practices to measure actual yield differences and economic return for farmers.

11. **Multilingual support:** Expand the mobile application to support additional languages beyond English and French to broaden accessibility for diverse farming communities.

12. **Camera integration:** Integrate plant health monitoring through image capture and CNN-based disease detection, enabling comprehensive crop management beyond soil nutrition.

Through these enhancements, SoilSense has genuine potential for real-world deployment, contributing meaningfully to sustainable and precision agriculture while reducing fertilizer waste, lowering environmental impact, and supporting data-driven farming strategies for small and medium-scale farmers.

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Project Guide

SoilSense : An Intelligent Fertilization Management System for Smart Agriculture

For Obtaining Startup Certificate
Under Ministerial Decree 1275

Trade Name of the Startup

SoilSense



Academic Year 2025 – 2026

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INTRODUCTION

Agriculture is one of the most important sectors for economic development and food security worldwide. However, modern agriculture faces several critical challenges related to resource management, environmental sustainability, and production efficiency. Among these challenges, fertilizer management remains one of the most problematic aspects, especially in developing countries where fertilization practices are still largely based on traditional methods and estimations rather than scientific analysis and real-time monitoring.

In Algeria, many farmers continue to apply fertilizers using fixed schedules without considering the actual nutritional requirements of the soil. This practice often leads to over-fertilization or under-fertilization, causing significant economic losses, reduced crop productivity, soil degradation, and environmental pollution. Moreover, the lack of access to smart agricultural technologies limits the ability of farmers to make precise and data-driven decisions.

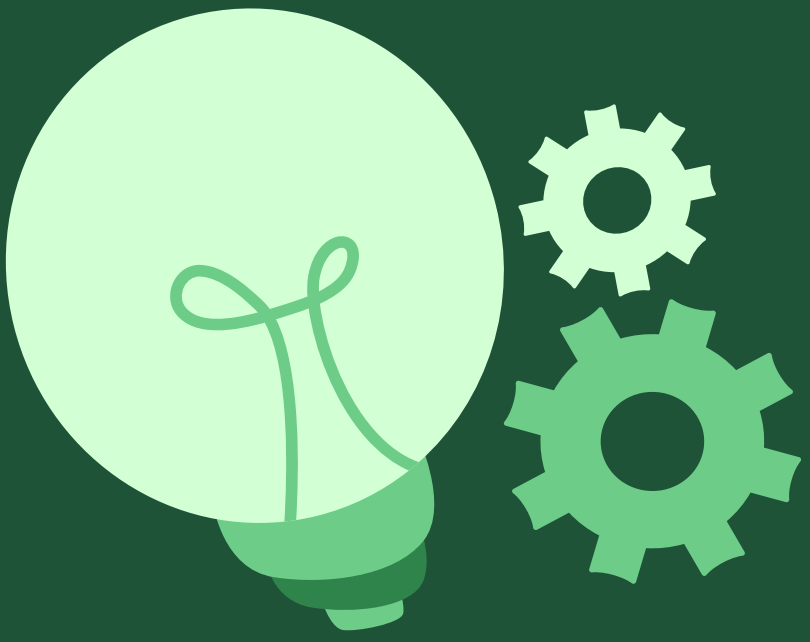
The emergence of technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), cloud computing, and data analytics has created new opportunities for transforming traditional agriculture into smart agriculture. These technologies enable real-time monitoring, intelligent decision-making, and advanced agricultural analysis that improve efficiency while reducing costs and environmental impact.

In this context, SoilSense was developed as an intelligent fertilization management system designed to optimize fertilizer usage through the integration of IoT sensors, artificial intelligence, and real-time monitoring technologies. The project aims to provide farmers with a complete solution capable of monitoring soil conditions, analyzing nutrient deficiencies, and recommending optimal fertilizer doses with high precision.

This chapter presents the general overview of the SoilSense startup project, including the project context, problem statement, proposed solution, expected impact, team presentation, project objectives, and development roadmap.

Section 1

Project Presentation





Project Presentation

1. Project Idea (Proposed Solution)

1.1. Project Title and Identity

The project is entitled “SoilSense: From Soil Data to Smart Decisions.” The name reflects the main objective of the startup, which is transforming raw soil data into intelligent agricultural decisions through the use of advanced technologies.

SoilSense is positioned as an innovative AgriTech startup specialized in precision agriculture and intelligent fertilization management systems. The startup combines hardware and software technologies to create an integrated ecosystem for smart farming.

The visual identity of SoilSense represents sustainability, innovation, and technological advancement in agriculture. The project aims to establish itself as a leading provider of intelligent agricultural solutions in Algeria and potentially across North Africa and Middle East.

1.2. Activity Sector (AgriTech / Smart Agriculture)

SoilSense operates within the field of Agricultural Technology (AgriTech), specifically in the domain of precision agriculture and smart farming systems.

The startup combines several technological domains:

- Artificial Intelligence,
- Internet of Things (IoT),
- Embedded Systems,
- Cloud Computing,
- Data Analytics,

The project contributes to the digital transformation of agriculture by introducing intelligent technologies capable of improving productivity, sustainability, and operational efficiency.

The startup also aligns with global trends toward sustainable agriculture and smart resource management, particularly in regions facing water scarcity, soil degradation, and rising agricultural production costs.

1.3. How the Idea Began

The idea of SoilSense emerged from the observation of major agricultural inefficiencies, particularly:

- Overuse and waste of fertilizers
- Lack of real-time soil monitoring
- High production costs for farmers
- Environmental damage caused by over-fertilization

These challenges highlighted the need for a smart system capable of analyzing soil conditions in real time and providing precise fertilization decisions.

1.4. How the System Works

SoilSense is built as an integrated smart agriculture system composed of:

1. IoT Layer:
   - Soil sensors collect real-time data (NPK, pH, humidity, temperature).
2. Communication Layer:
   - Data is transmitted to a cloud-based platform.
3. AI Layer:
   - A two-stage AI model processes soil data to:
     - Detect nutrient deficiencies
     - Predict crop needs
     - Generate fertilizer recommendations
4. Decision Layer:
   - The system produces optimized fertilization plans:
     - Fertigation (liquid fertilization)
     - Direct irrigation-based fertilizer application
5. User Interface Layer:
   - Farmers access recommendations through mobile/web dashboards.

1.5. How the System Works

The system is accomplished through the combination of:

- IoT soil monitoring sensors
- AI-based prediction models
- Cloud infrastructure for data storage and processing
- Embedded systems for field deployment
- Cross-platform dashboards for farmer interaction

Together, these components form an intelligent ecosystem that transforms raw soil data into actionable agricultural decisions.

SoilSense will:

- Optimize fertilizer usage
- Reduce agricultural costs
- Improve crop yield and quality
- Monitor soil conditions in real time
- Support sustainable farming practices
- Provide data-driven agricultural recommendations

2. Problem Statement

2.1. Inefficient Fertilization Practices

Many agricultural operations continue to rely on non-adaptive fertilization methods that fail to consider real soil conditions and crop requirements. This often leads to inefficient nutrient management and resource waste.

2.2. Economic Losses Caused by Poor Fertilizer Management

Fertilizers represent a significant operational cost for farmers. Improper fertilizer application results in financial losses due to wasted resources and reduced crop performance.

Additionally, rising fertilizer prices increase the economic pressure on agricultural producers.

2.3. Environmental Consequences of Over-Fertilization

Over-fertilization contributes to:

- Water contamination,
- Soil degradation,
- Nutrient imbalance,
- Increased greenhouse gas emissions.

Environmental sustainability requires more intelligent and controlled fertilization strategies.

2.4. Challenges Faced by Algerian Farmers

Algerian farmers face several operational challenges, including:

- Limited access to smart technologies,
- Lack of real-time agricultural monitoring tools,
- High fertilizer costs,
- Climate variability,
- Limited technical assistance.

These challenges reduce agricultural efficiency and limit productivity growth.

SoilSense addresses these needs through an integrated AI- and IoT-based smart fertilization platform.

3. Proposed Values

1. Newness

SoilSense introduces a new intelligent agriculture paradigm by combining:

- IoT soil sensing
- AI-based fertilization decision-making
- Real-time automated recommendations

This creates a fully integrated smart fertilization system, which is not commonly available in traditional farming solutions.

2. Performance

SoilSense improves agricultural performance through:

- High-accuracy two-stage AI prediction models
- Real-time soil monitoring (NPK, pH, moisture, temperature, humidity)
- Optimized fertilization recommendations

This leads to better crop health and higher yield quality.

3. Customization

The system adapts to:

- Different soil types
- Regional agricultural conditions (Algeria, North Africa, Middle East)
- Various crop requirements

This allows personalized fertilization strategies for each farm.

4. Getting the Job Done

SoilSense helps farmers accomplish key agricultural tasks:

- Detect soil nutrient deficiencies
- Determine fertilizer needs
- Apply correct fertilizer quantities automatically or manually

It directly supports decision-making in fertilization management.

5. Design (User Experience & System Design)

The system is designed as:

- A simple cross-platform interface (mobile, web, desktop)
- A unified dashboard for monitoring and control
- A real-time visualization system for soil data

This ensures usability even for non-technical farmers.

6. Cost Reduction

SoilSense reduces farming costs by:

- Minimizing fertilizer waste
- Optimizing input usage
- Reducing unnecessary agricultural operations

7. Risk Reduction

The system reduces agricultural risks such as:

- Over-fertilization damage
- Soil degradation
- Crop failure due to nutrient imbalance

It also increases trust through Explainable AI (XAI).

8. Accessibility

SoilSense makes smart agriculture accessible by:

- Providing an affordable alternative to imported technologies
- Supporting cloud-based remote monitoring
- Offering easy access via mobile and web platforms

9. Convenience / Ease of Use

The platform simplifies farming through:

- Automated soil monitoring
- Instant AI recommendations
- Remote access and control
- Clear dashboards and alerts

4. Work Team

Team Members and Roles:



BACHA Meriem

AI & Data Science Engineer

Web developer

Finance Management



DJOUDI Djihane

Software developer

IoT & Embedded Systems Engineer

Business & Marketing

Team Skills:

- AI/Machine Learning, Data Science
- IoT, Embedded Systems, Electronics
- Software Development (Web, Mobile)
- Agronomy expertise (via partnerships)
- Business and Marketing

Organization:

- Weekly team meetings (Monday)
- Daily stand-ups via WhatsApp
- GitHub for code collaboration
- Trello for task tracking
- Decision-making by consensus with technical lead approval

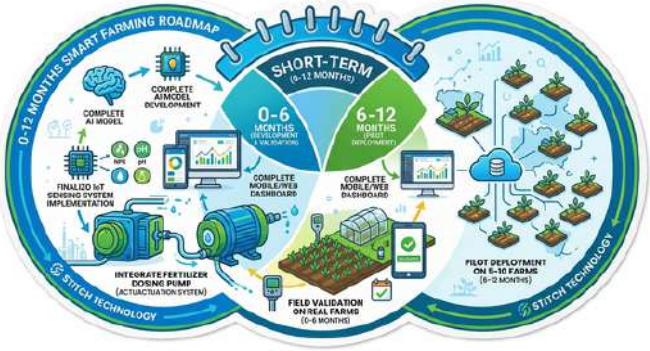
2. Project Objectives

SHORT-TERM

1

(0-12 MONTHS)

- Complete AI model development and validation
- Finalize IoT sensing system implementation
- Complete mobile/web dashboard
- Integrate fertilizer dosing pump (actuation system)
- Field validation on real farms (0-6 months)
- Pilot deployment on 5-10 farms (6-12 months)



MEDIUM-TERM

2

(1-2 YEARS)

- Commercial launch in Algerian agricultural market
- Partner with 5+ agricultural cooperatives
- Achieve 200 paying customers
- Begin small-scale production (50 units/ month)
- Establish subscription + hardware business model



LONG-TERM

3

(2-5 YEARS)

- Large-scale deployment across Algeria (5000+ units)
- Adapt system for different crops and soil types
- Reduce hardware production cost by 40%
- Explore regional expansion (Maghreb market: Tunisia, Morocco)
- Become 1 precision agriculture provider in North Africa

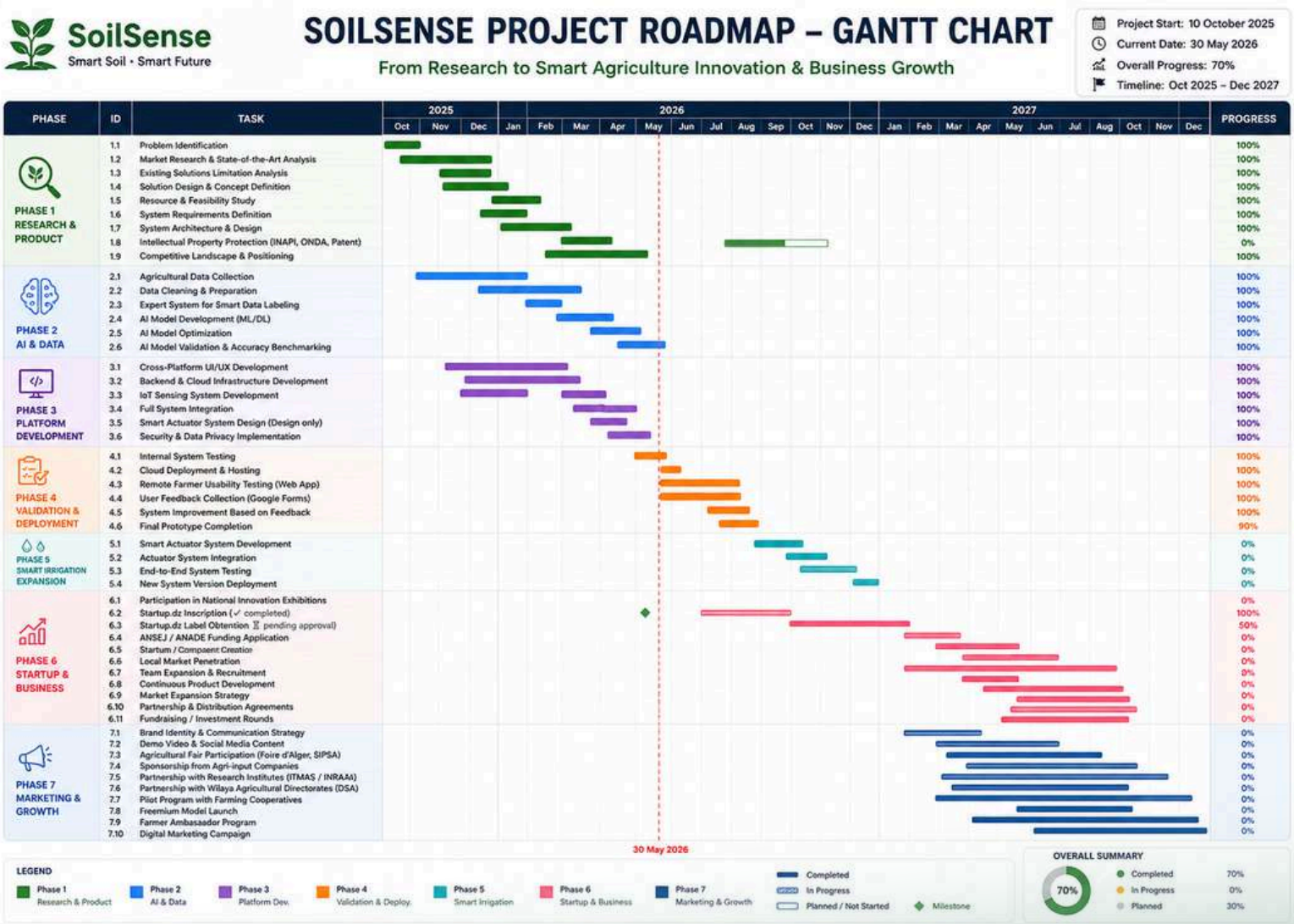


6. Project Timeline

The following Gantt chart presents the complete development roadmap of the SoilSense project, structured across seven interconnected phases. Each phase builds upon the previous one, ensuring a coherent and progressive path from the initial research stage all the way through to market deployment and commercial growth.

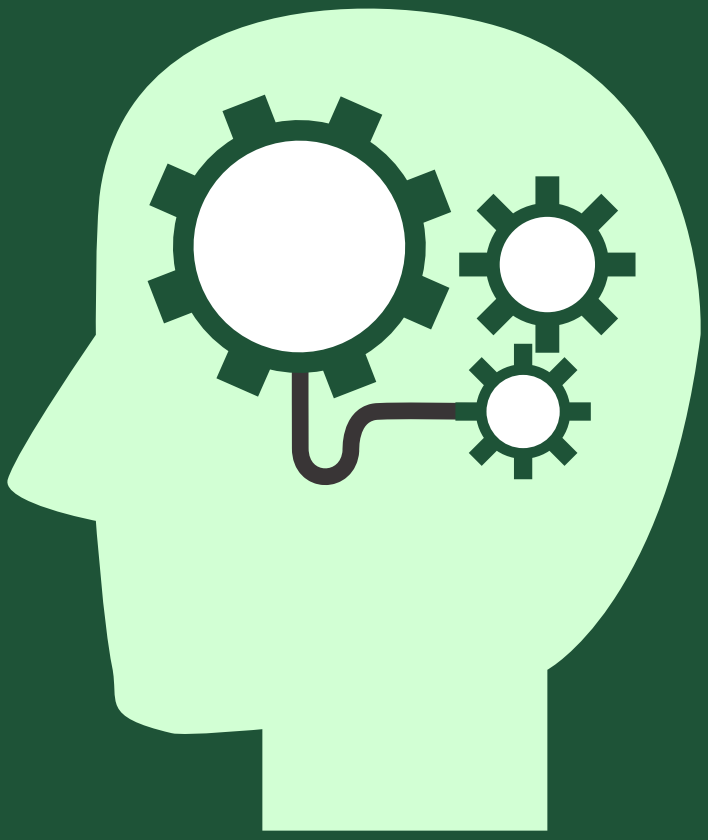
The roadmap covers the full lifecycle of the project — from problem identification and system design, through artificial intelligence development and platform building, to validation, business formation, and large-scale marketing. This structured vision reflects not only what has already been accomplished, but also the planned steps that will guide the project forward in the coming period.

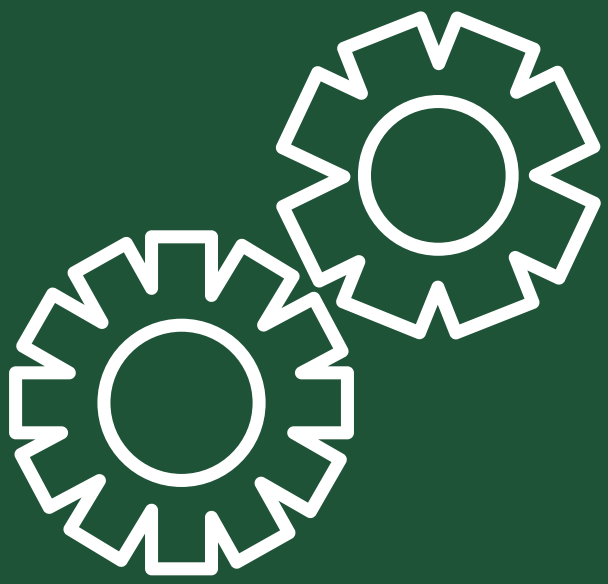
Tasks are visually distinguished by their completion status, allowing the reader to clearly identify achieved milestones, ongoing work, and future planned activities at a glance.



Section 2

Innovative Aspects





Innovative Aspects

1. Nature of Innovations

SoilSense introduces several innovative aspects that combine advanced technologies with practical agricultural applications in order to address the limitations of traditional fertilization systems. The project is based on the integration of Artificial Intelligence, Internet of Things technologies, cloud computing, and automated actuation mechanisms to create a complete intelligent fertilization ecosystem.
The innovative nature of SoilSense can be classified into several categories, including technological innovation, process innovation, system integration innovation, and operational innovation.
Technological Innovation
One of the main innovations of SoilSense is the integration of multiple advanced technologies into a single unified platform capable of performing real-time sensing, intelligent analysis, decision-making, and automated fertilizer application.
The technological innovations of the system include:

- IoT-Based Smart Soil Monitoring:
- SoilSense uses connected IoT sensors capable of continuously monitoring important soil parameters such as:
  - NPK levels,
  - Soil pH,
  - Soil moisture,
  - Temperature,
  - Humidity.
- These sensors provide real-time agricultural data that improves monitoring accuracy and decision-making efficiency.
- Artificial Intelligence Integration:
- The system integrates a two-stage Artificial Intelligence model designed to:
  - Analyze soil conditions,
  - Predict nutrient deficiencies,
  - Recommend optimal fertilizer types and dosages,
  - Improve fertilization precision.
- This AI-driven approach enables intelligent and adaptive agricultural management.

Explainable Artificial Intelligence (XAI):

- SoilSense incorporates Explainable AI techniques during the analysis and evaluation phase of the AI model in order to identify the most influential soil parameters affecting fertilizer recommendations. These explainability methods were mainly used for model interpretation, validation, and understanding the decision-making behavior of the AI system.

Cloud-Based Smart Agriculture Platform:

- The system uses cloud technologies to store, process, and visualize agricultural data in real time through connected dashboards and mobile applications.

Cross-Platform Monitoring System:

- SoilSense provides web, mobile, and desktop interfaces that allow farmers to remotely monitor and manage agricultural operations.

Process Innovation

SoilSense transforms the traditional fertilization process into an intelligent and automated workflow.

The innovative process includes:

- Real-time soil data collection,
- AI-based data analysis,
- Intelligent fertilizer recommendation,
- Continuous monitoring and optimization.

This process reduces dependency on manual estimations and improves agricultural efficiency.

System Integration Innovation

Another important innovation lies in the integration between hardware and software components within a single ecosystem.

The project combines:

- Sensors,
- Embedded systems,
- AI algorithms,
- Cloud infrastructure,
- Dashboards,

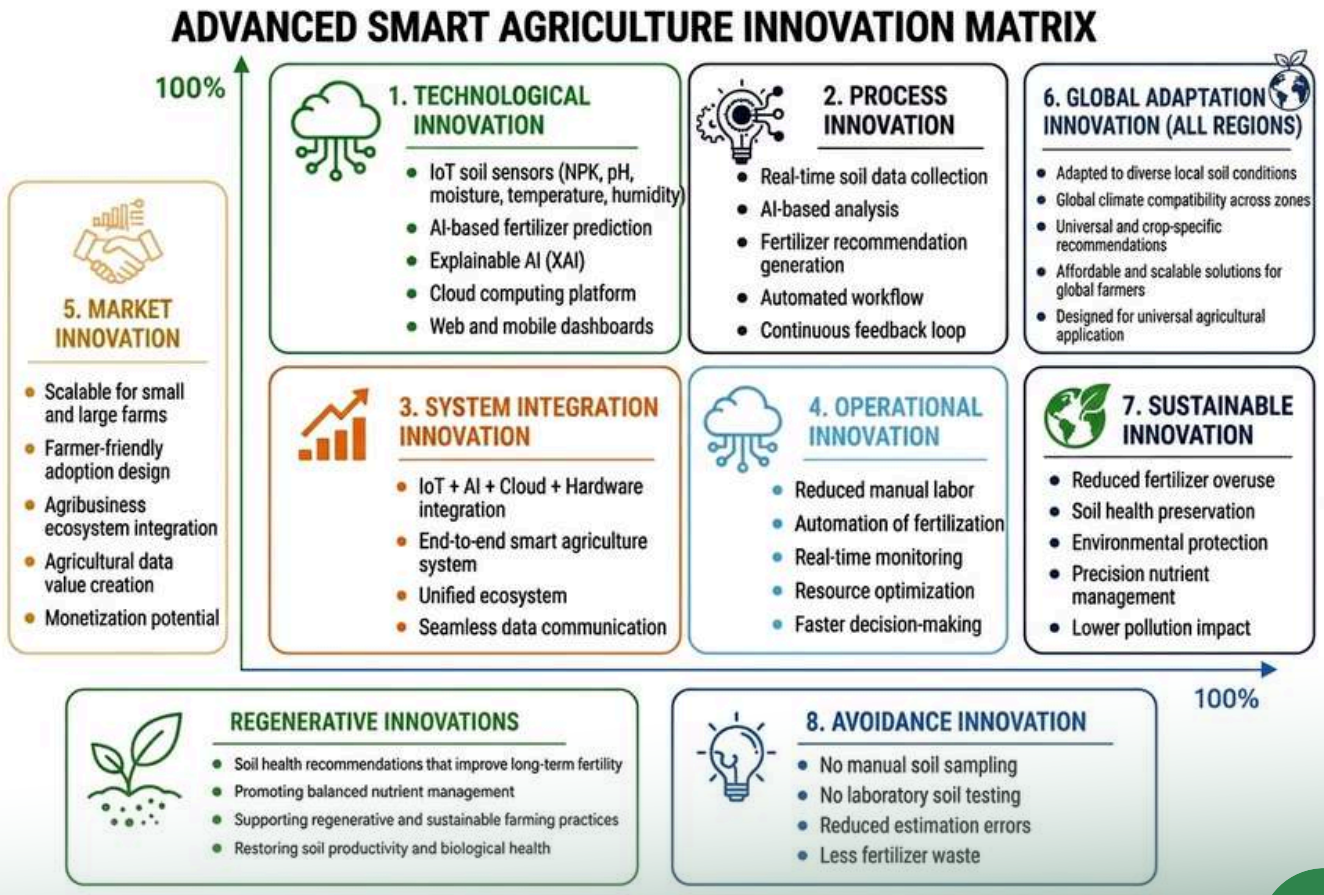
This integration creates a complete end-to-end precision agriculture system rather than isolated technological components.

- Operational Innovation
- SoilSense improves operational efficiency by:
- Reducing manual labor,
- Automating repetitive tasks,
- Providing real-time decision support,
- Minimizing fertilizer waste,
- Improving resource allocation.

- The system also simplifies agricultural management for farmers who may not possess advanced technical expertise.
- Localized Innovation for Algerian Agriculture
- Unlike imported agricultural technologies that are often expensive and poorly adapted to local conditions, SoilSense is specifically designed for Algerian agricultural environments.

The system considers:

- Local soil characteristics,
- Regional climate conditions,
- Agricultural practices,
- Local crop requirements,
- Accessibility and affordability for farmers.
- This localization strategy represents a major competitive advantage for the startup.
- Sustainable Innovation
- The project promotes sustainable agriculture through:
- Reduction of fertilizer overuse,
- Soil preservation,
- Environmental protection,
- Resource optimization,
- Precision nutrient management.
- By improving fertilizer efficiency, SoilSense contributes to reducing pollution and supporting long-term agricultural sustainability.



2. Areas of Innovation of SoilSense

1. New Processes

SoilSense introduces more efficient agricultural processes by:

- Automating soil data collection using IoT sensors
- Processing data through AI-based analysis pipelines
- Generating real-time fertilizer recommendations
- Reducing manual decision-making in fertilization

This increases operational efficiency and reduces resource waste.

2. New Experiences

The system transforms the farmer experience by:

- Providing real-time dashboards for soil monitoring
- Offering AI-driven decision support instead of traditional guesswork
- Enabling remote farm management via mobile and web platforms

This changes how farmers interact with agricultural data.

3. New Features

SoilSense introduces advanced features such as:

- Two-stage AI model for fertilizer prediction
- Real-time soil parameter tracking (NPK, pH, humidity, temperature)
- Explainable AI (XAI) for transparent recommendations
- Dual fertilization modes (fertigation and direct irrigation support)

These features improve system intelligence and usability.

4. New Customers

The solution expands its reach to:

- Small and medium-scale farmers in Algeria
- Agricultural cooperatives
- Agribusiness companies and agricultural enterprises
- Smart farming adopters in North Africa and the Middle East
- Public institutions involved in agricultural development and modernization (e.g., Ministry of Agriculture and agricultural research bodies)

This broadens access to smart agriculture technologies across both private and public agricultural sectors.

5. New Offerings

SoilSense introduces a new AgriTech offering:

- Integrated smart fertilization management system combining hardware + software
- AI + IoT-based agricultural decision platform
- Cloud-based precision farming service
- It moves beyond traditional monitoring tools to a complete intelligent ecosystem.

6. New Business Model

SoilSense adopts an innovative business model:

- Hardware + subscription-based service model
- Smart Agriculture as a Service (SAaaS)
- Affordable localized AgriTech solution instead of expensive imported systems

This makes precision agriculture more accessible and scalable.

Section 3

Strategic Market Analysis



Strategic Market Analysis

1. Market Sector Overview

Potential Market

The potential market refers to all individuals and organizations that may require smart agricultural solutions to optimize fertilizer usage, improve soil productivity, and increase crop yield.

SoilSense targets a broad global agricultural ecosystem, including:

- Small, medium, and large-scale farmers
- Agricultural cooperatives and farming unions
- Agribusiness companies and large commercial farms
- Agricultural investors and plantation owners
- Government agricultural agencies and rural development programs
- Soil laboratories and agricultural consulting firms
- AgriTech companies and precision farming solution providers

Customer Needs and Motivation

These stakeholders are driven by the need to solve critical agricultural challenges such as:

- Excessive and inefficient fertilizer usage
- High production and input costs
- Lack of real-time soil information
- Dependence on manual soil testing and estimation
- Environmental pressure to reduce chemical pollution
- Need for higher productivity and sustainable farming

Location of the Market

This market is globally distributed across:

- Developed agricultural regions (Europe, North America)
- Emerging agricultural economies (Asia, Africa, South America)
- Intensive farming zones and irrigated agricultural lands worldwide

Market Size

The global agricultural sector includes hundreds of millions of farmers and a continuously growing number of agribusiness enterprises. With the rapid expansion of precision agriculture and smart farming technologies, this market is considered large, scalable, and high-growth.

TAM · SAM · SOM — addressable market (DZD)



Target Market (Segmentation)

The primary target market for SoilSense includes:

- Medium and large-scale commercial farmers
- High-productivity farms using irrigation and modern farming systems
- Agricultural cooperatives managing collective farmland
- Agribusiness companies focused on yield optimization
- Early adopters of smart agriculture and AgriTech solutions

Algeria farm count by size	
Small farms (<5 ha)	~800,000
Medium farms (5–50 ha)	~180,000
Large farms (>50 ha)	~20,000
Agricultural cooperatives	~3,500
SoilSense primary target	~200,000

Year 5 penetration estimate	
Target segment size	200,000 farms
5-yr target penetration	0.68%
Units sold (Yr 5)	1,360 units
Avg revenue/unit	~125,000 DZD
Projected revenue (Yr 5)	169.7M DZD

Justification for Target Market Selection

This segment was selected based on several strategic reasons:

- Higher fertilizer consumption, making optimization economically impactful
- Strong financial incentive to improve yield and reduce costs
- Greater readiness to adopt technological and data-driven solutions
- Easier deployment through organized farms and cooperatives
- Higher scalability potential in commercial agricultural environments
- Alignment with global trends in precision agriculture and sustainability

Contracting and Business Opportunities

SoilSense enables strong potential for establishing long-term contracts and strategic partnerships with key agricultural stakeholders, such as:

- Large-scale agricultural enterprises and plantations
- Farming cooperatives and agricultural unions
- Government agricultural development programs and innovation projects
- Fertilizer manufacturers and distributors (integration partnerships)
- AgriTech companies for system integration and deployment
- Pilot farms used for testing, validation, and scaling

Commercial Models

The system can support multiple business models, including:

- Subscription-based access to the AI analytics platform
- Sale of IoT sensor kits and automation systems
- Data-driven agricultural advisory services
- Enterprise contracts for large-scale farm deployment

2. Competitiveness Assessment

2.1 Direct and Indirect Competitors

Direct Competitors

Direct competitors are companies and platforms that provide similar smart agriculture, soil monitoring, or precision farming solutions:

- Precision agriculture platforms (e.g., John Deere Operations Center, Climate FieldView)
- Smart farming IoT solution providers
- Agricultural AI-based advisory platforms
- Soil monitoring and sensor-based companies (e.g., CropX, Teralytic, Arable Labs)

These competitors offer integrated digital farming solutions, including soil monitoring, analytics, and decision support systems.

Indirect Competitors

Indirect competitors are traditional and alternative solutions that solve the same problem in a non-digital or partial way:

- Soil testing laboratories
- Agricultural extension services and agronomists
- Manual fertilization methods based on farmer experience
- Fertilizer distribution companies offering basic recommendations
- Traditional irrigation and farm management practices

These solutions are widely used but lack real-time intelligence and automation.

2.2 Number of Competitors and Market Share

The precision agriculture and smart farming market is highly competitive and includes:

- A small number of global dominant players (large AgriTech corporations)
- Medium-sized specialized startups focused on IoT or AI agriculture
- A large number of local traditional service providers (labs, advisors, distributors)

Market Structure Insight

- The market is fragmented in indirect services (many small actors)
- The market is concentrated in advanced AgriTech platforms, dominated by a few global companies
- Most solutions are expensive and not fully accessible to small farmers

SoilSense enters as a new scalable and affordable alternative, targeting gaps in accessibility and integration.

2.3 Competitor Strengths and Weaknesses

Strengths of Existing Competitors

- Strong brand reputation and global presence
- Advanced and well-tested technologies
- Large datasets and mature AI models
- Integration with industrial-scale farming systems
- High accuracy in controlled environments

Weaknesses of Existing Competitors

- Very high cost of deployment and subscription
- Limited accessibility for small and medium farmers
- Complex systems requiring technical expertise
- Lack of adaptation to local agricultural conditions
- Fragmented solutions (some focus only on sensors, others only on analytics)
- Weak accessibility in developing agricultural regions

Competitive Positioning of SoilSense

SoilSense differentiates itself by:

- Providing an affordable and scalable smart fertilization system
- Combining IoT + AI + automation in one unified platform
- Offering real-time fertilizer recommendations (not just monitoring)
- Being designed for easy adoption by non-technical farmers
- Ensuring flexibility for farms of different sizes globally

Competitor comparison matrix

Solution	Type	Price level	Real-time IoT	AI reco.	Auto dosing	Local adapt.	Mobile app	Availability DZ
SoilSense	IoT + AI	Low	✓ Yes	✓ Yes	✓ Yes	Algeria	✓ Yes	Local
John Deere Ops	Platform	Very high	✓ Yes	✓ Yes	Partial	None	✓ Yes	Not local
Climate FieldView	Analytics	High	Partial	✓ Yes	✗ No	None	✓ Yes	Not local
CropX	Soil sensor	High	✓ Yes	Partial	✗ No	None	✓ Yes	Limited
Soil lab testing	Manual	Medium	✗ No	✗ No	✗ No	Algeria	✗ No	Available
Agronomist advice	Human	Medium	✗ No	✗ No	✗ No	Algeria	✗ No	Available

3. Marketing Strategy

The marketing strategy for SoilSense focuses on how the product will be introduced, positioned, and delivered to the market in an efficient and financially realistic way. It is designed to support adoption of the system without repeating technical or market description details already covered in previous sections.

3.1 Strategic Approach

SoilSense adopts a value-driven and adoption-focused strategy, meaning the priority is not mass advertising but:

- Demonstrating real agricultural value through pilot use
- Building trust through measurable results (yield increase, cost reduction)
- Targeting early adopters in professional farming environments
- Gradual expansion based on proven performance

3.2 Marketing Mix

Product

- Integrated IoT + AI fertilization system
- 3 tiers: Basic (SaaS), IoT, Full automation
- Mobile + web + desktop dashboard
- Real-time NPK, pH, humidity monitoring
- Explainable AI (XAI) recommendations
- Arabic / French language support

Price

- Tier 1 Basic: 20,000 DZD/year
- Tier 2 IoT: 63,000 DZD (hardware + SaaS)
- Tier 3 Full: 380,000 DZD (full kit)
- 40% margin built into all tiers
- Scalable pricing by farm size
- 30-day free pilot for new clients

Place

- Direct farm deployment (field teams)
- Agricultural cooperative partnerships
- Online platform access (web/mobile)
- Demonstration reference farms
- University incubator network (Biskra)
- Phase 2: Maghreb expansion

Promotion

- Field demos at agricultural fairs (SIPSA)
- Facebook / WhatsApp (rural reach)
- Word-of-mouth between farmers
- Pilot farm results as case studies
- Partnership with ITMAS / INRAA
- Digital campaigns: 10,000 DZD/month

3.3 Financial and Practical Considerations

The strategy is designed to remain cost-efficient by:

- Prioritizing pilot-based validation over large marketing campaigns
- Using real deployments as the main promotion tool
- Leveraging partnerships instead of expensive media advertising
- Scaling marketing activities progressively with adoption

3.4 Strategic Balance

The marketing approach maintains balance by:

- Aligning product value with real farmer needs
- Combining physical hardware and digital services coherently
- Supporting gradual adoption instead of forced large-scale rollout
- Ensuring scalability without increasing complexity

Section 4

Production & Organization Plan



Production and Organization Plan

1. Production Process

The SoilSense service process begins with real-time soil data acquisition using IoT sensors deployed in the agricultural field. The collected data, including NPK levels, pH, soil moisture, temperature, and humidity, is transmitted to the SoilSense platform through the communication module. The AI recommendation system then analyzes the received data to determine the most suitable fertilizer type and the required dose.
The generated recommendations are displayed on the dashboard, where the farmer can review and validate the proposed fertilization process. After approval, the automated fertilization system activates the electrovalve corresponding to the recommended fertilizer tank, while the irrigation pump starts the fertilizer application process. During operation, the flow sensor continuously measures the delivered quantity in real time. Once the required fertilizer dose is reached, the system automatically closes the electrovalve and terminates the fertilization process.



2. Supply Chain

Purchasing Policy

The SoilSense project adopts a procurement strategy focused on acquiring reliable IoT components, agricultural monitoring sensors, automation equipment, and cloud infrastructure services required for system deployment and operation.

The main purchased elements include:

- IoT sensors (NPK, pH, moisture, temperature, humidity)
- Microcontrollers and communication modules
- Electrovalves and irrigation pumps
- Flow sensors
- Fertilizer tanks and piping accessories
- Cloud hosting and dashboard infrastructure
- Electronic materials and assembly equipment

Main Suppliers

The project relies on specialized suppliers for electronic and agricultural automation components, including:

- IoT and electronic equipment suppliers
- Agricultural sensor manufacturers
- Irrigation and automation equipment providers
- Cloud service providers for data hosting and platform deployment

Payment & Delivery Policy

The purchasing policy is based on:

- Progressive procurement according to development phases
- Online payment and supplier invoicing
- Priority for suppliers offering reliable delivery times and product warranties
- Short delivery periods for essential electronic components to ensure continuous system development and maintenance

3. Workforce

Workforce Requirements

The SoilSense project can create several job positions related to smart agriculture, IoT systems, and digital platform management. The number of positions may increase progressively with the expansion of the project and deployment in new agricultural environments.

Potential positions include:

- Embedded systems developer
- AI/ML engineer
- Web and dashboard developer
- IoT technician
- Maintenance and installation technician
- Agricultural technical advisor
- Marketing and customer support staff

Nature and Qualification of the Workforce

The project requires a multidisciplinary workforce combining expertise in:

- Artificial Intelligence and data analysis
- IoT and embedded systems
- Web development and cloud platforms
- Agricultural technologies and smart irrigation systems
- Technical maintenance and field installation

The required workforce can be recruited from:

- Universities and engineering schools
- Technology and IT training centers
- Agricultural and automation sectors
- Local technical service providers

Possibility of Outsourcing

The project may rely on outsourcing for certain activities, including:

- Manufacturing electronic boards and hardware assembly
- Installation and maintenance services in remote agricultural regions
- Cloud hosting and infrastructure services
- Logistics and supply chain operations

This approach helps reduce operational costs and improve scalability during project expansion.

Workforce headcount by phase

Position	Phase 1 (M1–M6)	Year 1	Year 2	Year 3	Year 4	Year 5	Salary/mo (DZD)
CEO / Project manager	1	1	1	1	1	1	80 000
Development team (web/mobile)	2	2	2	3	4	5	60 000
Data / AI engineer	1	1	1	2	2	3	70 000
IoT installation team	1	2	3	5	8	12	40 000
IT maintenance	0	1	1	1	2	2	30 000
Agronomic support	0	1	1	2	2	3	45 000
Sales manager	0	1	1	2	3	4	40 000
Marketing team	0	1	1	2	2	3	40 000
Accounting / admin	0	1	1	1	1	2	35 000
Total headcount	5	11	12	19	25	35	—
Annual payroll (KDZD)	—	8 748	8 748	~13 200	~17 400	~24 600	—

4. Key Partnerships

The success of the SoilSense project depends on establishing strategic partnerships with different stakeholders that can contribute through technical support, infrastructure, expertise, funding, or operational collaboration.

The main potential partners include:

- IoT and electronic equipment suppliers for providing sensors, microcontrollers, flow sensors, electrovalves, and automation components.
- Agricultural equipment providers for irrigation systems, fertilizer tanks, and field installation materials.
- Universities and research laboratories specializing in Artificial Intelligence, IoT, and smart agriculture to support research, testing, and technological improvement.
- Agricultural institutions and public organizations that promote digital agriculture and sustainable farming practices.
- Cloud service providers for hosting the platform, managing databases, and supporting scalable deployment.
- Banks and financial institutions that can support project financing and startup development.
- Startup incubators and innovation centers that provide mentoring, business support, networking opportunities, and entrepreneurial guidance.
- Farmers and agricultural cooperatives that can participate in pilot testing and provide real field feedback for system improvement.

These partnerships strengthen the technical reliability, scalability, and sustainability of the SoilSense project.

Section 5

Financial Plan





Financial Plan

1. Costs and Expenses

Annual Expenses:

Category	Expense	Amount (DZD)	Frequency	Annual Amount
Rent	Office rent	40000	Mensuel	480000
Energy	Electricity	8000	Mensuel	96000
Energy	Water bill	2000	Mensuel	24000
Telecom	Internet	2500	Mensuel	30000
Subscriptions	Firebase	6000	Mensuel	72000
Subscriptions	cloud server	6000	Mensuel	72000
Subscriptions	order managememt	6000	Mensuel	72000
Subscriptions	Web hosting	3000	Mensuel	36000
Subscriptions	Domain name	2000	Annuel	2000
Subscriptions	Google Play Developer Account	2500	Annuel	2500
Subscriptions	Apple Developer Program	15000	Annuel	15000
Subscriptions	maintenance & monitoring	10000	Mensuel	120000
Marketing	Field demos / agricultural fairs	15000	Quadrimestriel	45000
Marketing	Digital marketing campaign	10000	Mensuel	120000
Other	Training & formation	5000	Mensuel	60000
Other	ONDA / legal fees	366000	Annuel	366000
Other	Cleaning Materials	3000	Mensuel	36000
Other	Snacks & Coffee	8000	Mensuel	96000
Payroll Expenses	→ Personnel Tab			8748000
TOTAL ANNUAL EXPENSES				10492500

Investment Plan:

Category	Asset	Unit Cost	Qty	Total	Duration (yrs)	Depr./yr	Year 1	Year 2	Year 3	Year 4	Year 5
Intangible	ONDA patent / IP	150000	1	150000	5	30000	30000	30000	30000	30000	30000
Intangible	Mobile app(iOS + Android)	100000	1	100000	1	100000	100000	0	0	0	0
Intangible	Web platform / dashboard	70000	1	70000	1	70000	70000	0	0	0	0
Tangible	PCs / laptops	180000	2	360000	5	72000	72000	72000	72000	72000	72000
Tangible	Desks + chairs	12500	2	25000	5	5000	5000	5000	5000	5000	5000
Tangible	Data show projector	65000	1	65000	1	65000	65000	0	0	0	0
Tangible	Printer / scanner	35000	1	35000	1	35000	35000	0	0	0	0
Tangible	Mouse + keyboard sets	20000	3	60000	5	12000	12000	12000	12000	12000	12000
Tangible	IoT field kit	1149750	12	13797000	5	2759400	2759400	2759400	2759400	2759400	2759400
TOTAL INVESTMENTS				14662000			3148400	2878400	2878400	2878400	2878400

Material Cost Projection Table for one farmer

Component	Unit Price (DZD)	Required Quantity	Total Cost (DZD)
Capteurs Soil Parameter Tester (Température,Humidité, pH, EC, NPK, Fertility)	23,700	1	23,700
ESP32 WiFi + Bluetooth Module (38 pins)	2,300	2	4,600
Jumper Wires	400	1	400
Breadboard	150	1	150
Electric Surface Pump (1HP–2HP)	35,000	1	35,000
Fertilizer Storage Tank	15,000	7	105,000
12V Solenoid Valve	4,500	7	31,500
8-Channel Relay Module (5V)	1,850	2	3,700
Silicone Irrigation Tubing (6mm, 8 meters)	5,000	depends on field size	—
Power Supply MEAN WELL WDR-120-12 (120W, 12V, 10A)	18,200	1	18,200
Water Flow Sensor (YF-S201)	1,500	1	1,500
18650 Li-ion battery	1,200	1	1,200

TOTAL per farmer: **229950 DZD**

Material Description	Functionality	Unit Price (DZD)	Year 1	Year 2	Year 3	Year 4	Year 5
SoilSense Smart Irrigation Kit (1 farmer system)	Complete IoT irrigation system including sensors, ESP32, pump, valves, tank, and monitoring system	229,950	2,745,000	8,235,000	21,960,000	41,175,000	82,350,000

Payroll

#	Position	Net Salary (DZD)	Qty	Monthly payroll	Annual payroll
1	CEO / Project Manager	80000	1	80000	960000
2	Development Team	60000	2	120000	1440000
3	Data / AI Engineer	70000	1	70000	840000
4	IoT Installation Team	40000	2	80000	960000
5	IT Maintenance	30000	1	30000	360000
6	Agronomic Support	45000	1	45000	540000
7	Sales Manager	40000	1	40000	480000
8	Marketing Team	40000	1	40000	480000
9	Accounting / Admin	35000	1	35000	420000
Total annual payroll				540000	6480000
Social contributions (35%)					2268000
TOTAL Payroll Cost					8748000

Sources and Methods of Financing (Operational Revenue)

Source	Description
Subscription fees (Abonnement)	Monthly or annual subscription for SaaS platform access (Tier 1 – Basic: 20,000 DZD/year)
IoT kit sales	One-time sale of IoT hardware (sensors + ESP32 + pump + valves + tank) – Tier 2 and Tier 3
Maintenance & support contracts	Annual service contracts for sensor calibration, pump maintenance, and technical support
Installation services	One-time fee for on-site deployment and configuration of the full system
Training fees	Paid training sessions for farmers and cooperative staff on using the SoilSense platform
B2B contracts	Bulk contracts with agricultural cooperatives, agribusinesses, or government institutions

2. Revenue

Pricing per Offer

Currently, SoilSense offers 3 service tiers. The pricing can be distributed as follows:

Offer	Components Included	Total Cost (DZD)	Price (40% Margin)	Profit	Unit Price
Tier 1 – Basic	SaaS only	**446,500 DZD**	**625,100 DZD**	**+178,600 DZD**	**20000**
Tier 2 – IoT	SaaS + IoT	**45,000 DZD**	**63,000 DZD**	**+18,000 DZD**	**63000**
Tier 3 – Full	SaaS + IoT + Hardware	**270,000 DZD**	**380,000 DZD**	**+110,000 DZD**	**270000**

Revenue

Position	Year 1	Year 2	Year 3	Year 4	Year 5
🌱 **Tier 1 — SoilSense Basic (Analysis Only)**					
Price (DZD)	20000	20000	20000	20000	20000
Quantity	100	250	400	500	700
Revenue (DZD)	2000000	5000000	8000000	10000000	14000000
Unit Cost (DZD)	12000	12000	12000	12000	12000
📡 **Tier 2 — SoilSense IoT (Sensors + Dashboard)**					
Price (DZD)	63000	63000	63000	63000	63000
Quantity	50	100	130	180	300
Revenue (DZD)	3150000	6300000	8190000	11340000	18900000
Unit Cost (DZD)	45000	45000	45000	45000	45000
⚙️ **Tier 3 — SoilSense Full (Full Automation)**					
Price (DZD)	380000	380000	380000	380000	380000
Quantity	20	40	100	200	360
Revenue (DZD)	7600000	15200000	38000000	76000000	136800000
Unit Cost (DZD)	270000	270000	270000	270000	270000
Summary					
📦 **Total Revenue**	12750000	26500000	54190000	97340000	169700000
🔻 **Total Consumptions**	8850000	18300000	37650000	68100000	119100000

Two Revenue Scenarios (Optimistic + Pessimistic)

Scenario	Year 1	Year 2	Year 3	Year 4	Year 5
Pessimistic (-30%)	8,925,000	18,550,000	37,933,000	68,138,000	118,790,000
Realistic (Base)	12,750,000	26,500,000	54,190,000	97,340,000	169,700,000
Optimistic (+30%)	16,575,000	34,450,000	70,447,000	126,542,000	220,610,000

Assumptions:

- Pessimistic: Slower market adoption (70% of base quantities), delayed pilot validations
- Optimistic: Faster adoption, early large contracts with cooperatives (130% of base quantities)

3. Forecast Income Statement

Profit & Loss Statement

Position	Year 1	Year 2	Year 3	Year 4	Year 5
📈 Revenue	12750000	26500000	54190000	97340000	169700000
Payroll Expenses	-8748000	-8748000	-8748000	-8748000	-8748000
Personnel Margin	4002000	17752000	45442000	88592000	160952000
Rent	-480000	-480000	-480000	-480000	-480000
Energy & Water	-120000	-122400	-124848	-127345	-129892
Telecom	-30000	-30600	-31212	-31836	-32473
Subscriptions	-391500	-399330	-407317	-415463	-423772
Marketing	-165000	-173250	-181912	-191008	-200559
Other Expenses	-558000	-574740	-591982	-609742	-628034
Consumptions	-8850000	-18300000	-37650000	-68100000	-119100000
⚡ EBITDA	-6592500	-2328320	5974729	18636606	39957271
Depreciation	-3148400	-2878400	-2878400	-2878400	-2878400
💼 Earnings Before Tax (EBT)	-9740900	-5206720	3096329	15758206	37078871
Corporate Tax (IBS)	0	0	-805045	-4097134	-9640506
✅ Net Income	-9740900	-5206720	2291283	11661072	27438364
Net Margin (%)	-76.40%	-19.60%	4.20%	12.00%	16.20%
EBITDA Margin (%)	-51.70%	-8.80%	11.00%	19.10%	23.50%

Besoin en Fonds de Roulement

BFR = Créances clients + Stock − Dettes fournisseurs

Composante	Year 1	Year 2	Year 3	Year 4	Year 5
🟡 Créances clients (TTC)	1 264 375 DA	2 627 917 DA	5 373 842 DA	9 652 883 DA	16 828 583 DA
📦 Stock	–	–	–	–	–
🔴 Dettes fournisseurs (TTC)	1 050 621 DA	1 987 746 DA	3 906 621 DA	6 926 246 DA	11 983 746 DA
📦 BFR = Créances + Stock − Dettes	**213 754 DA**	**640 170 DA**	**1 467 220 DA**	**2 726 637 DA**	**4 844 837 DA**
↕️ Variation BFR	213 754 DA	426 417 DA	827 050 DA	1 259 417 DA	2 118 200 DA

4. Cash Flow Plan

5 ans — TVA & BFR inclus

Position	Year 1	Year 2	Year 3	Year 4	Year 5
RECEIPTS					
Operating Revenue (VAT incl.)	15172500	31535000	64486100	115834600	201943000
Funding	0	0	0	0	0
TOTAL RECEIPTS	15172500	31535000	64486100	115834600	201943000
PAYMENTS					
Investments	14662000	0	0	0	0
Purchases VAT incl.	0	0	0	0	0
Expenses VAT incl.	2075955	2075955	2075955	2075955	2075955
Payroll	8748000	8748000	8748000	8748000	8748000
Tax (IBS)	0	0	805045	4097134	9640506
TOTAL PAYMENTS	25485955	10823955	11629000	14921089	20464461
BFR					
Cumulative BFR	213754	640170	1467220	2726637	4844837
BFR Variation	213754	426417	827050	1259417	2118200
⚡ NET CASH FLOW	-10527209	20284628	52030050	99654095	179360339
✅ CUMULATIVE BALANCE	-10527209	9757420	61787469	161441564	340801903

Monthly Cash Flow Table

Month	Receipts (Revenue + Funding)	Payments (Expenses + Investments)	Net Cash Flow	Cumulative Balance
January	0	2,000,000	-2,000,000	-2,000,000
February	0	500,000	-500,000	-2,500,000
March	0	500,000	-500,000	-3,000,000
April	0	500,000	-500,000	-3,500,000
May	0	500,000	-500,000	-4,000,000
June	1,000,000	2,500,000	-1,500,000	-5,500,000
July	1,500,000	1,200,000	300,000	-5,200,000
August	1,500,000	1,200,000	300,000	-4,900,000
September	2,000,000	1,200,000	800,000	-4,100,000
October	2,500,000	1,200,000	1,300,000	-2,800,000
November	2,500,000	1,200,000	1,300,000	-1,500,000
December	3,500,000	1,200,000	2,300,000	**800,000**

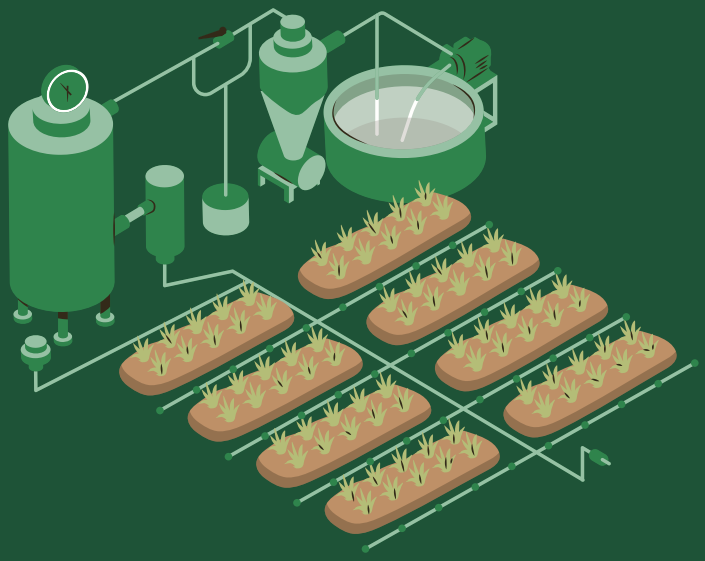
Key Assumptions for Monthly Cash Flow (Year 1):

Item	Monthly Breakdown
Investments (Year 1 total: 14,662,000 DZD)	January: 2,000,000 (IoT field kits + PCs)
Payroll (874,8000 DZD/year)	729,000 DZD/month starting June
Rent + Energy + Telecom + Subscriptions	~80,000 DZD/month
Marketing + Other expenses	~70,000 DZD/month
Revenue receipts	Starts June after first pilot sales

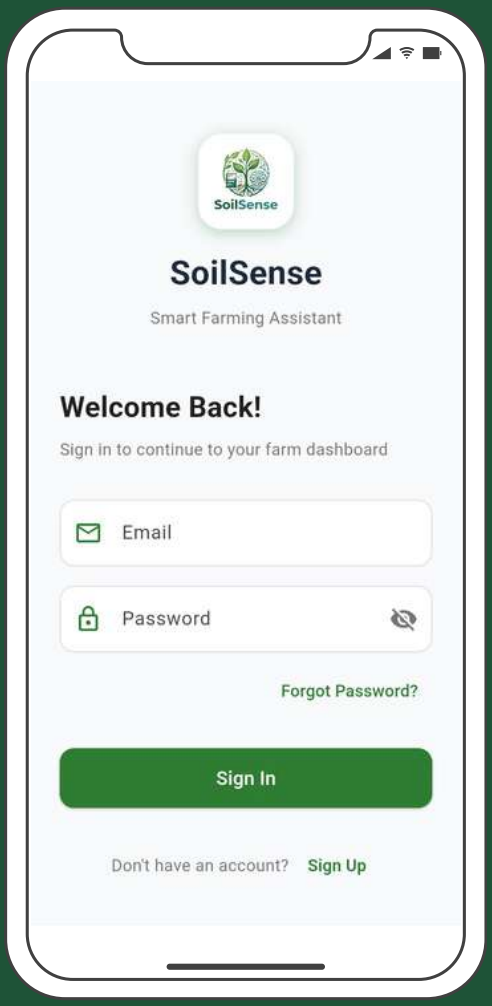
Note: The cumulative balance becomes positive in December (Month 12) = +800,000 DZD.

Section 6

Prototype





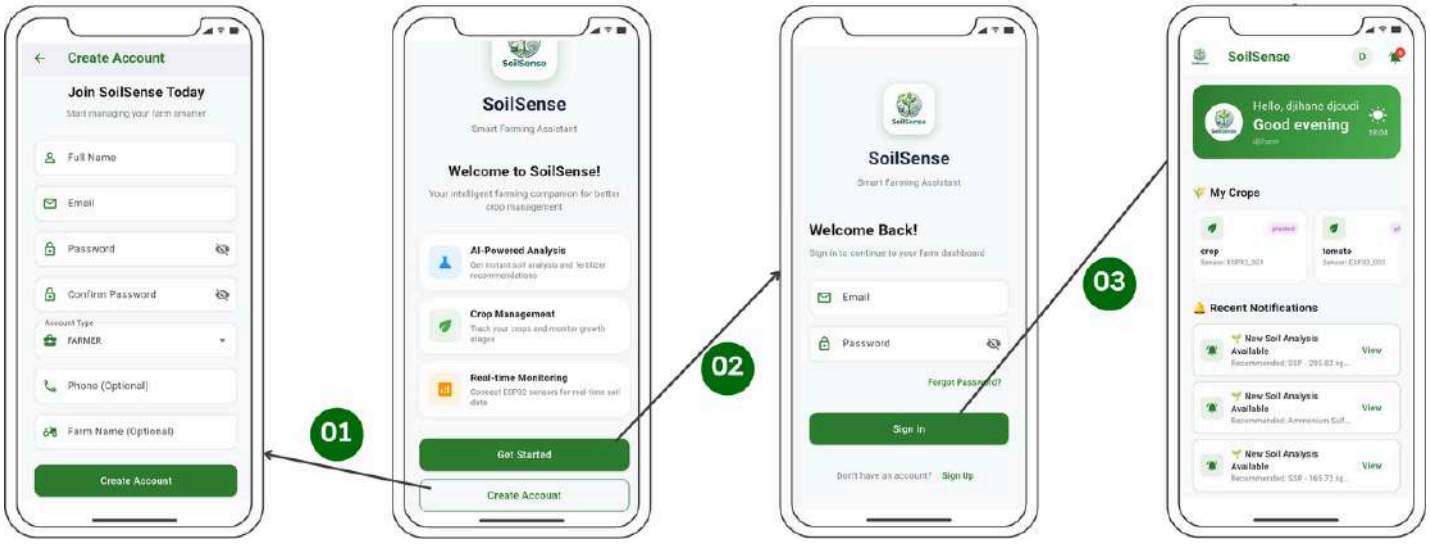


Prototype & Business Model Canvas

1. Prototype Overview

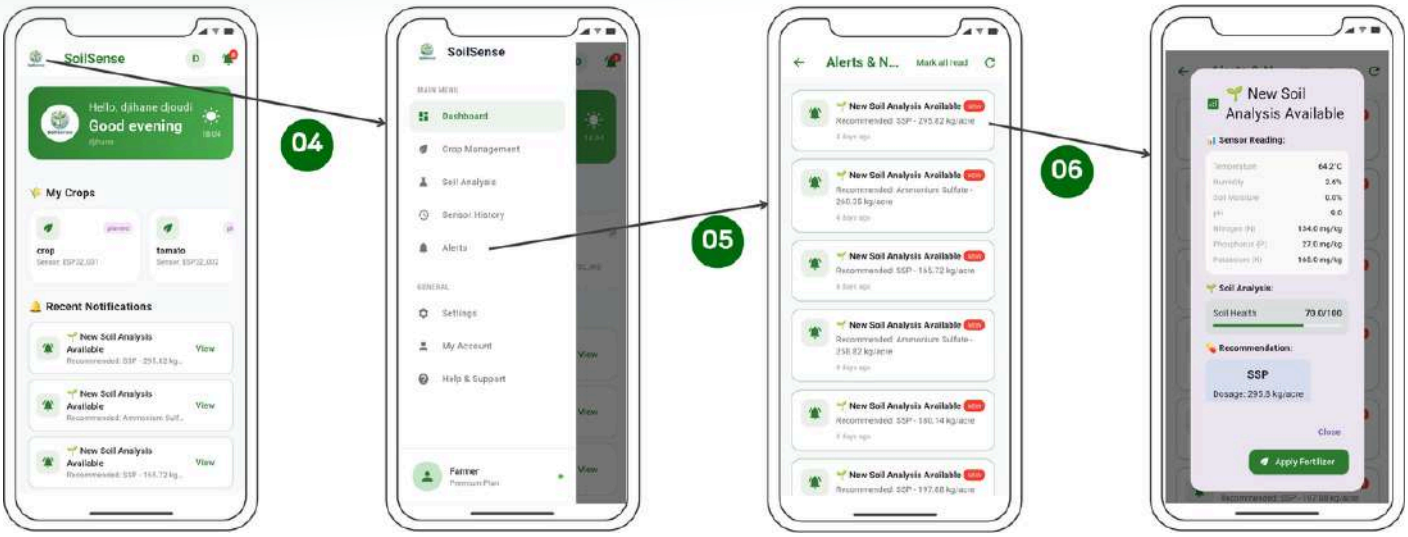
Software Overview

Explanation of Application Workflow - Step 1



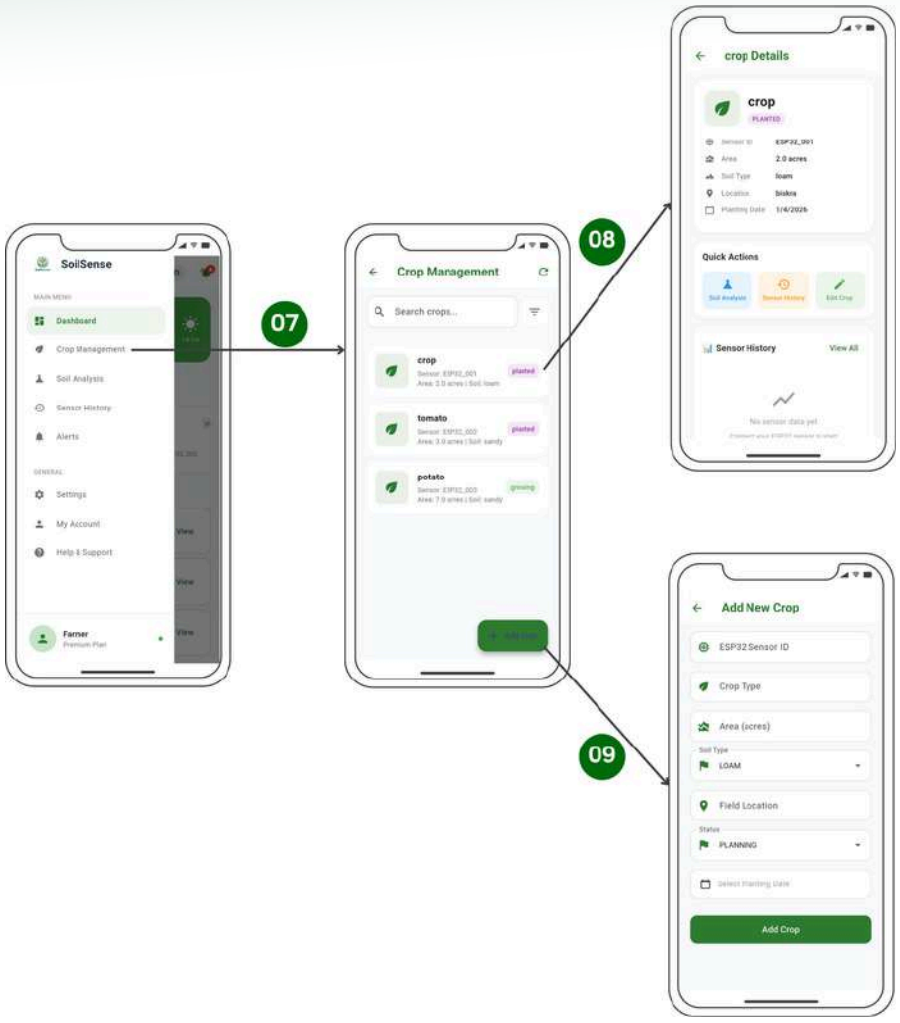
No	Description
1	**Account Registration:** User clicks on "Create Account" from the welcome screen to access the sign-up form where they provide personal and farm details.
2	**User Authentication:** Existing users click "Get Started" to reach the "Welcome Back!" sign-in interface to enter their credentials (email and password).
3	**Dashboard Access:** Upon successful login, the user is redirected to the main SoilSense dashboard.

Explanation of Application Workflow - Step 2



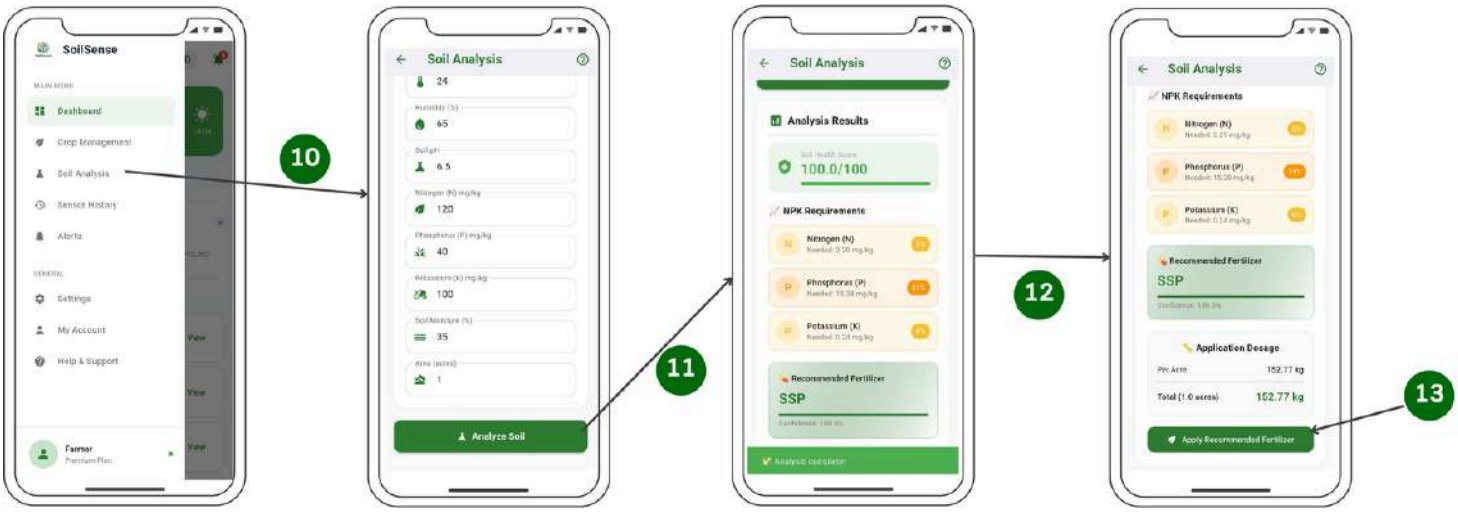
No	Description
4	**Sidebar Menu Navigation:** The user opens the side drawer to access various sections like Crop Management, Soil Analysis, and Alerts.
5	**Alerts and Notifications List:** A dedicated page listing all recent soil analysis updates and fertilizer recommendations.
6	**Detailed Soil Analysis View:** Modal display showing sensor readings, overall Soil Health, and Fertilizer Recommendation.

Explanation of Application Workflow - Crop Management



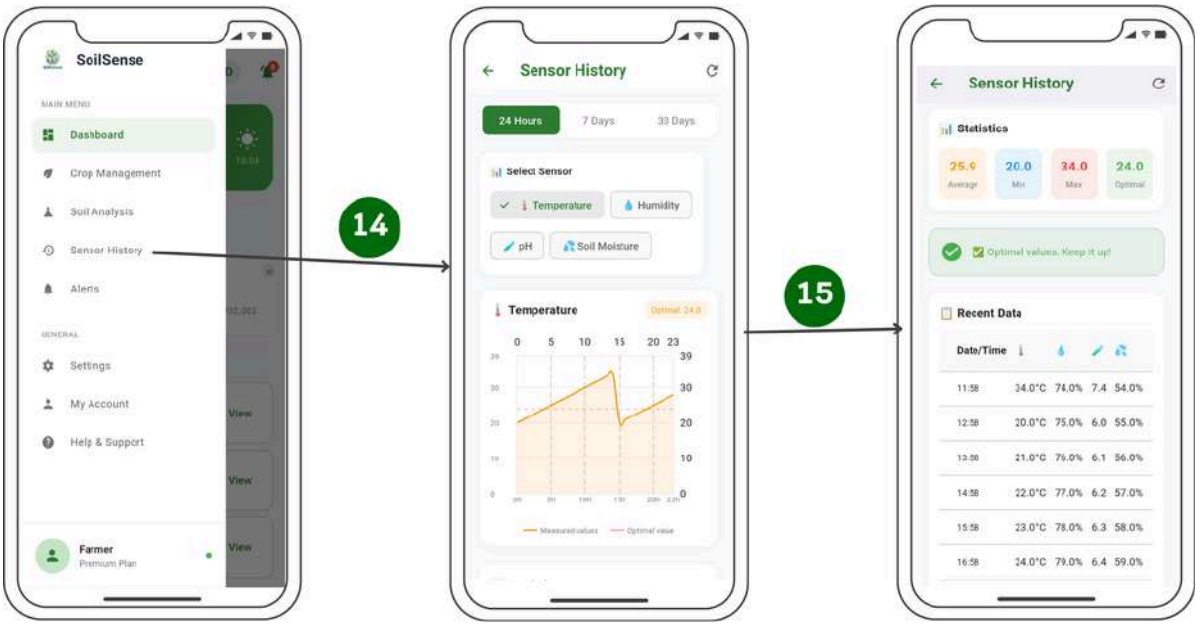
No	Description
7	**Accessing Crop Management:** View a summarized list of all registered crops and their current status.
8	**Viewing Crop Details:** Screen displaying sensor ID, soil type, location, and quick actions.
9	**Adding a New Crop:** Form to register a new crop by linking an ESP32 Sensor ID.

Explanation of Application Workflow - Deep Learning Prediction Process



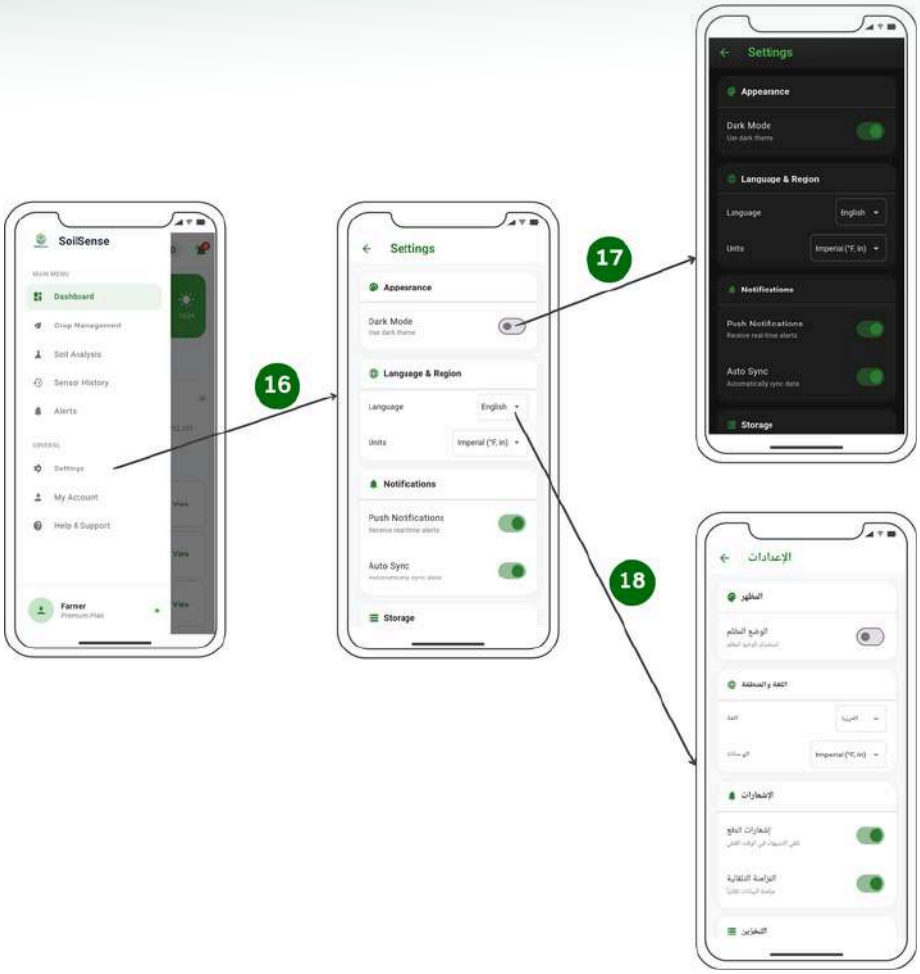
No	Description
10	**Manual Data Input:** Enter environmental and chemical soil parameters (N, P, K levels).
11	**Analysis Initiation:** Click "Analyze Soil" button to trigger the deep learning model.
12	**Result Generation:** Display soil health score, NPK requirements, and recommended fertilizer.
13	**Dosage Calculation:** Detailed application dosage based on farm area.

Explanation of Application Workflow - Sensor History



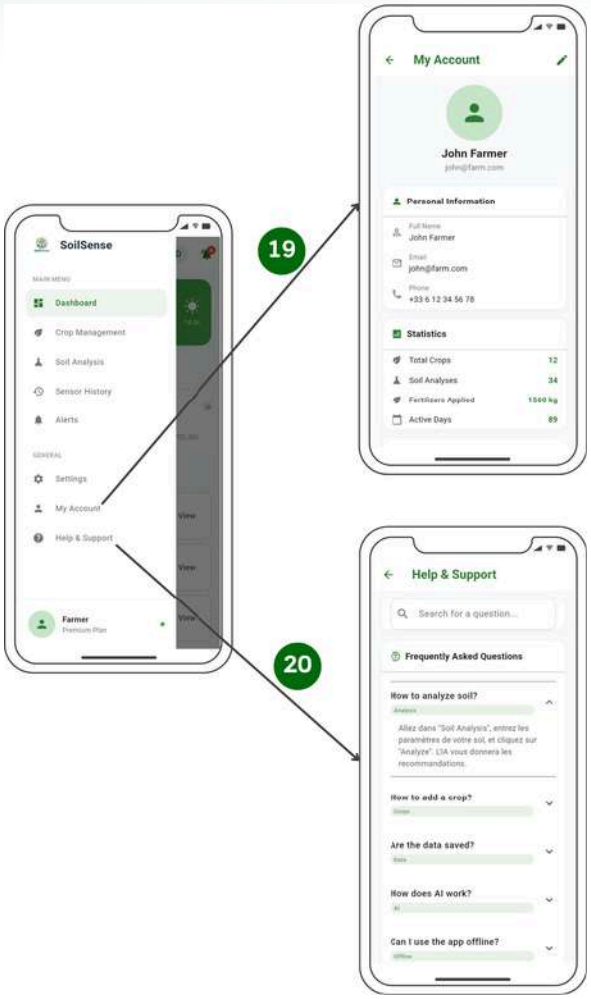
No	Description
14	**Historical Data Navigation:** Filter data by timeframes (24 Hours, 7 Days, 30 Days) and toggle between parameters.
15	**Statistical Analysis:** View statistics (Average, Min, Max, Optimal values) and recent data table.

Explanation of Application Workflow - Settings and Customization



No	Description
16	**Accessing Settings:** Configuration interface for appearance, regional preferences, and notifications.
17	**Theme Customization:** Toggle "Dark Mode" for better visibility in low-light conditions.
18	**Language Support:** Modify "Language & Region" settings to update interface language.

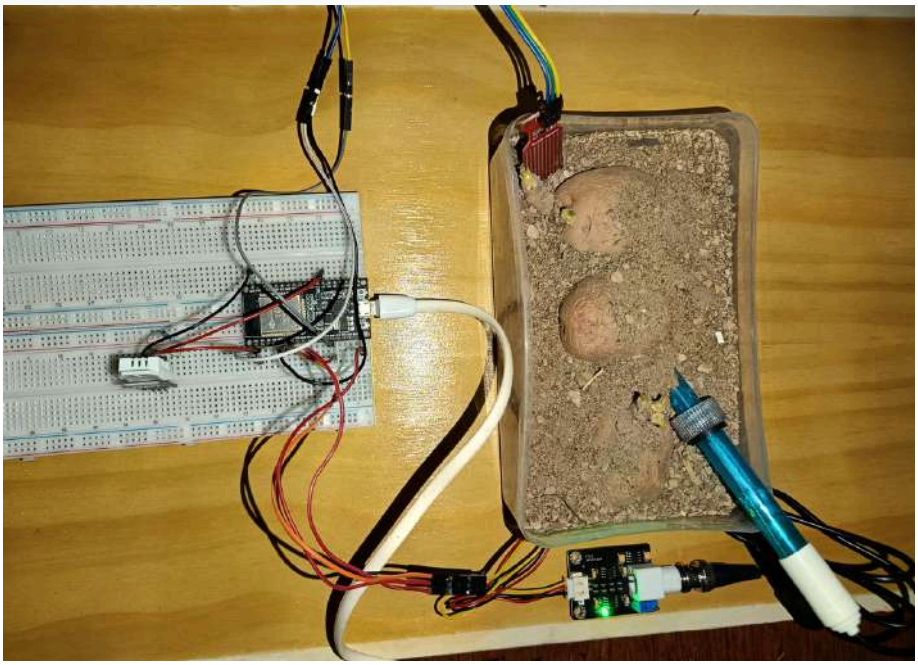
Explanation of Application Workflow - Account and Support



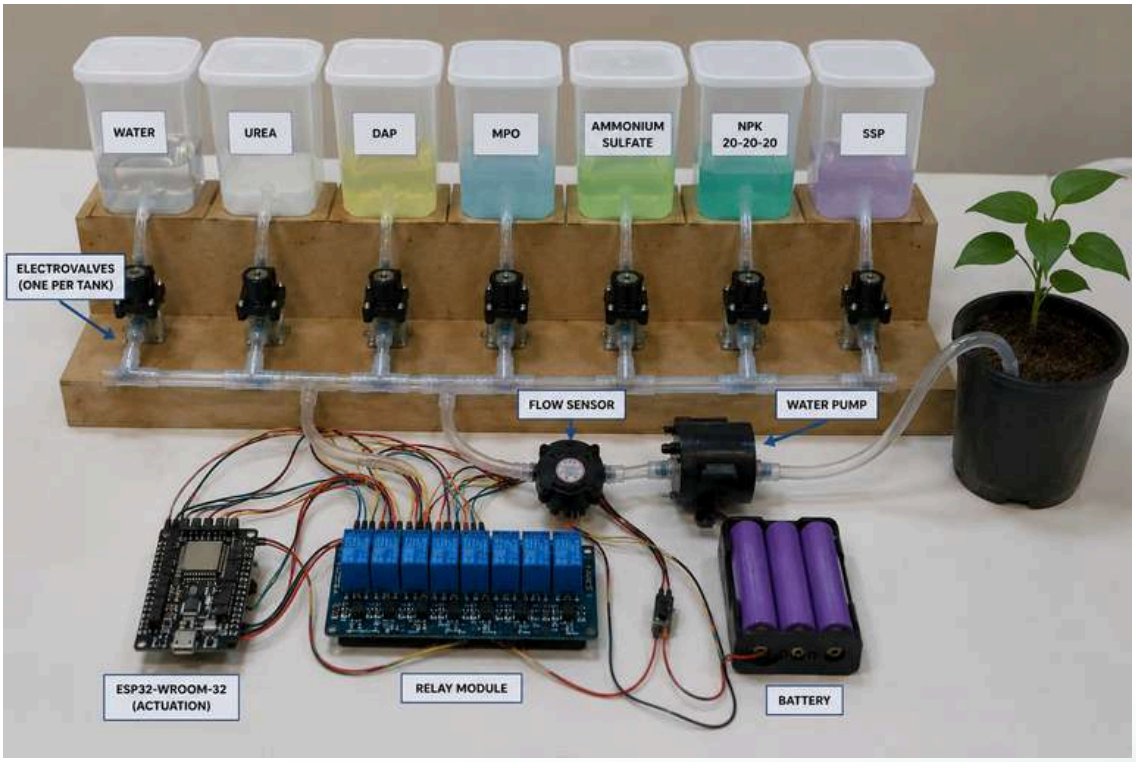
No	Description
19	**Account Profile:** View personal information and statistics (crops, analyses, fertilizer applied).
20	**Help and Support:** FAQ section with search functionality for app-related questions.

Hardware Overview

SoilSense sensing unit prototype



SoilSense actuation unit design proposal



SoilSense Explanation Video

SoilSense Website

SoilSense Application download

List of appendices







STARTUP REVIEW: SOILSENSE

(In thousands of DZD)

ASSETS (DZD)	Year 1	Year 2	Year 3	Year 4	Year 5
NON-CURRENT ASSETS (IMMOBILISATIONS)					
Intangible assets (net)					
Patent / IP	120,000	90,000	60,000	30,000	0
Mobile app + Web platform	0	0	0	0	0
Total intangible assets (net)	120,000	90,000	60,000	30,000	0
Tangible assets (net)					
PCs / laptops	216,000	144,000	72,000	0	0
Desks + chairs	15,000	10,000	5,000	0	0
Mouse + keyboard sets	36,000	24,000	12,000	0	0
IoT field kit (×12)	11,039,400	8,279,400	5,519,400	2,759,400	0
Total tangible assets (net)	11,306,400	8,457,400	5,608,400	2,759,400	0
TOTAL NON-CURRENT ASSETS (net)	11,426,400	8,547,400	5,668,400	2,789,400	0
CURRENT ASSETS (ACTIF CIRCULANT)					
Trade receivables (60 days)	2,125,000	4,416,667	9,031,667	16,223,333	28,283,333
Cash (from cumulative balance)	0	9,757,420	61,787,469	161,441,564	340,801,903
TOTAL CURRENT ASSETS	2,125,000	14,174,087	70,819,136	177,664,897	369,085,236
TOTAL ASSETS	13,551,400	22,721,487	76,487,536	180,454,297	369,085,236

LIABILITIES & EQUITY (PASSIF)

LIABILITIES & EQUITY (DZD)	Year 1	Year 2	Year 3	Year 4	Year 5
SHAREHOLDERS' EQUITY (CAPITAUX PROPRES)					
Share capital	1,000,000	1,000,000	1,000,000	1,000,000	1,000,000
Reserves (cumulative prior results)	0	-9,740,900	-14,447,620	-12,156,337	-495,265
Net income (current year)	-9,740,900	-4,706,720	2,291,283	11,661,072	27,438,364
TOTAL SHAREHOLDERS' EQUITY	-8,740,900	-13,447,620	-11,156,337	504,735	27,943,099
LIABILITIES (DETTES)					
Borrowings & financial debt	22,292,300	36,169,107	86,838,828	175,852,428	331,501,631
Tax liabilities (IBS)	0	0	805,045	4,097,134	9,640,506
TOTAL LIABILITIES	22,292,300	36,169,107	87,643,873	179,949,562	341,142,137
TOTAL LIABILITIES & EQUITY	13,551,400	22,721,487	76,487,536	180,454,297	369,085,236

CASH FLOW STATEMENT — SCF FORMAT (3 SECTIONS) — SoilSense					
Designation	**N+1**	**N+2**	**N+3**	**N+4**	**N+5**
Net income for the period	(9 740 900)	(5 206 720)	2 291 284	11 661 072	27 438 365
+ Depreciation & amortisation	3 148 400	2 878 400	2 878 400	2 878 400	2 878 400
± Change in trade receivables	(2 125 000)	(2 291 667)	(4 615 000)	(7 191 666)	(12 060 000)
± Change in working capital (BFR)	(213 754)	(426 417)	(827 050)	(1 259 417)	(2 118 200)
Income tax paid (IBS)	-	-	(805 045)	(4 097 134)	(9 640 506)
(A) NET CASH FROM OPERATING ACTIVITIES	**(8 931 254)**	**(5 046 404)**	**(1 077 411)**	**1 991 255**	**6 498 059**
Acquisition of intangible assets	(320 000)	-	-	-	-
Acquisition of tangible assets (IoT kits + hardware)	(14 342 000)	-	-	-	-
(B) NET CASH FROM INVESTING ACTIVITIES	**(14 662 000)**	**-**	**-**	**-**	**-**
Capital increase — Founders' contribution	1 000 000	-	-	-	-
New borrowings drawn	13 066 000	-	-	-	-
(C) NET CASH FROM FINANCING ACTIVITIES	**14 066 000**	**-**	**-**	**-**	**-**
NET CHANGE IN CASH (A+B+C)	**(9 527 254)**	**(5 046 404)**	**(1 077 411)**	**1 991 255**	**6 498 059**
Opening cash balance	-	(9 527 254)	(14 573 658)	(15 651 069)	(13 659 814)
CLOSING CASH BALANCE	**(9 527 254)**	**(14 573 658)**	**(15 651 069)**	**(13 659 814)**	**(7 161 755)**
Cumulative BFR	213 754	640 170	1 467 220	2 726 637	4 844 837
BFR variation	213 754	426 417	827 050	1 259 417	2 118 200
Founders' equity contribution	1 000 000	-	-	-	-
Bank loans / Leasing	13 662 000	-	-	-	-
TOTAL FUNDING	**14 662 000**	**-**	**-**	**-**	**-**

INCOME STATEMENT (TCR) — SCF ALGERIAN STANDARD — SoilSense						
SCF Line Item	**Ref.**	**N+1**	**N+2**	**N+3**	**N+4**	**N+5**
Sales & ancillary revenues (Revenue excl. VAT)	*70*	12 750 000	26 500 000	54 190 000	97 340 000	169 700 000
I. TOTAL OUTPUT FOR THE PERIOD		**12 750 000**	**26 500 000**	**54 190 000**	**97 340 000**	**169 700 000**
Consumed purchases (materials & goods)	*60*	(8 850 000)	(18 300 000)	(37 650 000)	(68 100 000)	(119 100 000)
External services & other consumptions	*61/62*	(1 164 500)	(1 199 520)	(1 236 271)	(1 264 939)	(1 314 830)
II. TOTAL CONSUMPTION FOR THE PERIOD		**(10 014 500)**	**(19 499 520)**	**(38 886 271)**	**(69 364 939)**	**(120 414 830)**
III. VALUE ADDED (I − II)	**VA**	**2 735 500**	**7 000 480**	**15 303 729**	**27 975 061**	**49 285 170**
Personnel costs (payroll + social)	*63*	(8 748 000)	(8 748 000)	(8 748 000)	(8 748 000)	(8 748 000)
IV. GROSS OPERATING SURPLUS (EBE)	**EBE**	**(6 012 500)**	**(1 747 520)**	**6 555 729**	**19 227 061**	**40 537 170**
Other operating expenses	*65*	(580 000)	(580 800)	(581 800)	(582 800)	(583 800)
Depreciation & amortisation (D&A)	*68*	(3 148 400)	(2 878 400)	(2 878 400)	(2 878 400)	(2 878 400)
V. OPERATING RESULT	**Rés.Op**	**(9 740 900)**	**(5 206 720)**	**3 096 329**	**15 758 206**	**37 078 871**
VI. ORDINARY RESULT BEFORE TAX (V)	**ROAI**	**(9 740 900)**	**(5 206 720)**	**3 096 329**	**15 758 206**	**37 078 871**
Corporate income tax (IBS 26%)	*695*	-	-	(805 045)	(4 097 134)	(9 640 506)
VIII. NET INCOME FOR THE PERIOD	**RN**	**(9 740 900)**	**(5 206 720)**	**2 291 284**	**11 661 072**	**27 438 365**
of which: Net income — Group share		(9 740 900)	(5 206 720)	2 291 284	11 661 072	27 438 365
Net Margin (%)	*%*	(76,4%)	(19,6%)	42%	120%	162%
EBE Margin (%)	*%*	(47,2%)	(6,6%)	121%	197%	239%
EBITDA Margin (%)	*%*	(51,7%)	(8,8%)	110%	191%	235%

Businness Model Canvas

THE BUSINESS MODEL CANVAS

Key Partners

- Agricultural experts / agronomists
- Hardware suppliers (sensors, microcontrollers)
- Agricultural cooperatives
- Government / incubators
- Research institutions

Key Activities

- IoT sensor development and maintenance
- Real-time data acquisition and processing
- Automated fertigation & dosing system (key addition)
- Software platform development
- Field deployment and system calibration
- Farmer training and support

Key Resources

- IoT sensor hardware
- Embedded systems & connectivity modules
- AI & agronomic prediction models
- Software platform (mobile/web application)
- Agronomic knowledge base
- Cloud infrastructure
- Distribution & field network

Value Proposition

- Optimize fertilizer use with AI-driven decisions
- Reduce costs and increase crop yield
- Real-time soil monitoring and recommendations
- Automated, precise fertilizer application
- Sustainable and environmentally friendly farming
- Solution adapted to Algerian agricultural conditions

Customer Relationships

Customer Relationships

- Technical support & assistance
- Training for farmers
- Dashboard for monitoring & control
- Long-term subscription service
- 30-day free pilot
- WhatsApp agronomy line

Channels

1. Awareness
   - Agricultural fairs and field demonstrations
   - Facebook pages and WhatsApp groups (very important in rural areas)
   - Word-of-mouth between farmers
2. Evaluation
   - Live demos in farms
   - Pilot projects on selected fields
   - Website / landing page explaining system benefits
3. Purchase
   - Direct sales
   - Cooperatives bulk purchasing for members
   - Subscription onboarding through mobile/web application
   - Institutional or government procurement programs
4. Delivery
   - Installation of IoT sensors and irrigation/dosing systems in farms
   - Activation of mobile/web platform access
   - Configuration of AI-based recommendations and automation system
   - Training farmers on system usage
   - 5. After Sales
   - How you maintain relationship and value:
   - Technical support and troubleshooting
   - Continuous software updates (AI + dashboard improvements)
   - Farmer training and follow-up visits
   - Subscription-based monitoring, alerts, and optimization services
   - Maintenance of sensors, pumps, and dosing systems

Customer Segments

- Greenhouse operators seeking precise control of irrigation and fertilization
- Small and medium-scale farmers who need affordable precision agriculture tools
- Large agricultural farms and agribusinesses requiring scalable monitoring and automation
- Agricultural cooperatives managing multiple farmers and shared farming resources
- Government and agricultural institutions supporting smart agriculture initiatives and rural development programs

-The solution targets North Africa and the Middle East, focusing on regions need for precision agricultu

Cost Structure

Fixed Costs:

- Salaries of core team (IoT engineers, AI developers, software engineers, agronomists...)
- Cloud infrastructure base costs (servers, databases, backend systems)
- Software platform development and maintenance (mobile/web app)
- Administrative and operational expenses (office, management, tools and licenses)

Variable Costs

- IoT hardware production (soil sensors, ESP32 units, pumps, dosing/tank systems)
- Installation and field deployment (transport, setup...)
- Cloud usage scaling (data storage, AI computation, bandwidth)
- Customer onboarding and training per farm
- Marketing and field acquisition (demonstrations, fairs, local campaigns)
- Maintenance and replacement of devices (sensor wear, pump servicing)

Revenue Streams

- Sale of SoilSense hardware device
- Subscription for app + AI recommendations (monthly/yearly)
- Maintenance & support services
- B2B contracts (cooperatives, government)