

**AGRO 5.0**

Automated and Cost-Effective Monitoring of Agricultural Subsidies Using Machine Learning (CNN) and Remote Sensing.

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# **CHAPTER 1: INTRODUCTION**

## **1.1 Introduction**

This chapter establishes the foundation for the research by presenting the project background, problem statement, specific research questions, and overarching aims and objectives. It discusses the project's scope and limitations, including constraints related to time, resources, and feasibility, supported by a detailed feasibility study and proposed budget. The chapter emphasizes the project's significance in computer engineering, particularly in enhancing traditional agricultural monitoring systems through satellite imagery and machine learning, which aim to improve agricultural financing by enabling real-time monitoring, automating risk detection, and refining subsidy allocation decisions. Finally, a work plan with a timeline for project milestones is included, summarizing key points and preparing the reader for a deeper exploration of the research, as the project seeks to improve efficiency, transparency, and fairness in resource distribution to farmers, especially smallholders.

## **1.2 Background and context of the project**

Agriculture is a cornerstone of economic development, food security, and livelihood support, particularly in developing nations. According to a 2021 report by the UN Food and Agriculture Organization, global subsidies to farmers have averaged $540 billion annually from 2013 to 2018. These agricultural subsidies are government payments aimed at enhancing farm income and influencing the supply and pricing of agricultural commodities. They are essential for providing economic stability to farmers, ensuring a reliable domestic food supply, and stabilizing commodity markets (Tijun et al., 2023). However, the agricultural sector faces significant challenges, including inefficiencies in subsidy allocation, lack of transparency in financial disbursements, and dependence on outdated technologies. These issues disproportionately affect smallholder farmers, who are crucial to agricultural productivity but often struggle with inadequate resource management, delayed support, and unequal access to subsidies (Gupta 2018; Coleman 2016). Consequently, agricultural productivity remains stagnant, and many farmers encounter difficulties in accessing necessary resources.

Despite their importance, there is considerable variability in subsidy practices worldwide. Wealthier nations generally provide more substantial support, while farmers in developing countries often face higher taxes and fewer subsidies. This inequity can lead to market distortions and disadvantages for less-supported farmers. Although agricultural subsidies have historically aimed to stabilize markets and assist low-income producers, they remain a source of contention, particularly concerning trade imbalances and the competitive challenges faced by farmers in poorer regions (Omodero & Ehikioya, 2022).

The integration of modern technologies into agricultural financing is crucial for optimizing subsidy distribution and improving resource management. Among these technologies, machine learning (ML) stands out for its potential to analyze complex datasets and enhance decision-making processes. The roots of ML can be traced back to Alan Turing’s influential 1950 paper, which contemplated the potential for machines to demonstrate behaviors similar to human intelligence (Guerrero et al., 2022; Sharma et al., 2021). Over the decades, this initial concept has evolved into a prominent field within computer science, focusing on the automatic identification of patterns and rules from input data. This capability allows for accurate predictions and classifications of new data by extracting important features and creating mapping functions (Behmann et al., 2015). As a fundamental aspect of artificial intelligence, ML enables computer systems to efficiently perform a range of tasks, driving ongoing advancements in intelligent technologies (Helm et al., 2020).

ML comprises three primary components: a model, an objective function, and an optimization algorithm. These elements work together to enhance the model's predictive accuracy (Benos et al., 2021; Gao et al., 2020). It can be categorized into several types, including supervised, unsupervised, semi-supervised, and reinforcement learning. The increase in computational power and the availability of large datasets have significantly enhanced the applicability of ML, particularly within precision agriculture (PA) (Shahab et al., 2024; García et al., 2020). Innovations such as deep learning, neural networks, and data augmentation have broadened the scope of ML, presenting substantial opportunities to address challenges across various agricultural stages (Rehman 2019).

Technologies like remote sensing also play a critical role in enhancing agricultural monitoring. Remote sensing facilitates real-time assessments of crop conditions, allowing for timely and informed decision-making. By combining remote sensing with machine learning, stakeholders can better predict yields, assess risks, and optimize subsidy distribution. Furthermore, blockchain technology can enhance transparency and efficiency in financial transactions related to subsidies, addressing the inefficiencies inherent in traditional subsidy mechanisms (Gautam 2015).

Given the global population projected to increase by 68% by 2050, the demand for food will intensify, further straining agricultural systems (Gupta 2018). This context underscores the urgent need for innovative solutions in agricultural financing to enhance subsidy efficiency and effectively manage risks, particularly for smallholder farmers who are often the most vulnerable to climate-related challenges.

Historically, agricultural subsidies have been justified primarily by concerns about food security. Recent spikes in global food prices and ongoing agricultural growth challenges in regions like Africa and Asia have renewed interest in subsidy programs. Policymakers are increasingly compelled to boost rural incomes and view subsidies as a convenient mechanism for achieving this goal (Williams 2017). Given the complexity of subsidy practices and the urgent need for equitable resource distribution, an integrated approach leveraging modern technologies is essential for creating more effective subsidy systems.

This project aims to develop a web application that utilizes remote sensing, machine learning, and blockchain technologies to optimize subsidy systems and enhance agricultural monitoring. By addressing the challenges associated with subsidy distribution, the initiative seeks to improve transparency, efficiency, and fairness in managing agricultural subsidies, ultimately benefiting farmers and contributing to global food security.

## **1.3 Problem statement**

Agricultural subsidy systems, essential for supporting farmers and ensuring food security, are hindered by inefficiencies, inequities and delays, particularly affecting smallholder farmers. Traditional verification processes, outdated technologies and fragmented risk management contribute to these challenges. Remote sensing struggles with accuracy, machine learning faces scalability issues and blockchain has untapped potential in enhancing transparency and efficiency. This project aims to develop an integrated framework combining remote sensing, machine learning and blockchain to improve subsidy distribution and enhance agricultural monitoring, ultimately creating a more equitable and sustainable system for farmers.

## **1.4 Aim**

To develop a web application that utilizes remote sensing and machine learning to optimize subsidized agriculture financing.

## **1.5 Research objectives**

* To classify and verify crops for subsidy eligibility.
* To analyze data and recommend subsidy distribution.
* To monitor and track subsidy disbursements

### **1.6.1. Scope of the project**

The scope of this project encompasses the development of a web application designed to enhance agricultural financing by integrating remote sensing, machine learning, and blockchain technologies. It focuses on automating the disbursement of agricultural subsidies and monitoring farmers' compliance and progress through the analysis of satellite imagery and farm activity data. The application will evaluate farmers' eligibility for financial support based on real-time crop performance and risk insights, thereby optimizing resource allocation. A significant aspect of the project includes a farm management module that equips farmers with the necessary tools to effectively plan and manage their agricultural activities, supported by contextual data for informed decision-making. Additionally, a financial dashboard for policymakers will be created to provide real-time insights into subsidy disbursements, crop performance, and emerging agricultural risks, enabling data-driven adjustments to agricultural policies and promoting a more resilient and responsive agricultural sector.

### **1.6.2. Limitations**

Despite its potential, the project faces several limitations that could impact its implementation and effectiveness. A primary challenge is the availability and quality of data, which directly affects the accuracy of satellite-based crop monitoring; high-resolution imagery and consistent agricultural data are often scarce, potentially hindering the project's objectives. To address this issue, funding from POTRAZ has been secured to support comprehensive data collection efforts, ensuring access to the necessary information for accurate assessments. Additionally, the project may encounter technical difficulties related to processing large-scale data, which may require optimization strategies or cloud-based solutions, with support from the Zimbabwe Center for High Performance Computing providing the necessary technical resources. While blockchain technology is essential for enhancing transparency and preventing fraud, scalability issues and high transaction costs may pose barriers, particularly for smallholder farmers. Furthermore, adoption challenges stemming from limited technical literacy among farmers and resistance to new technologies underscore the need for robust training and stakeholder engagement to ensure successful implementation.

## **1.7 Delimitations**

This study is delimited to the development of a web application, despite the potential advantages of a mobile or desktop app for certain stakeholders. The focus will primarily be on the design and deployment of the application tailored to the specific needs of users in the Sub-Saharan Africa (SSA) region, although the implementation is intended to be adaptable for a global audience. The app is tailored for crop production, specifically for open-field crops since we be relying on satellite data for monitoring production. This targeted approach allows for a more nuanced understanding of the unique challenges faced by farmers in this region while providing a foundation for future expansion.

## **1.8 Assumptions**

The development and implementation of AGRO 5.0 relies on several critical assumptions for its success. Firstly, it assumes that high-quality, up-to-date satellite imagery, weather data, and historical agricultural records are readily accessible from reliable sources, which is essential for providing accurate insights. It is also crucial that stakeholders-policymakers, farmers, and financial institutions-are willing to adopt and utilize the system to enhance subsidy allocation and farm management practices. Additionally, sufficient internet connectivity and access to necessary technological infrastructure, such as smartphones and computers, are assumed for effective platform interaction, especially among rural users. The accuracy and integrity of the input data from stakeholders and external sources must also be ensured, alongside regulatory support for blockchain, AI, and remote sensing technologies. Scalability is another key consideration, requiring the system architecture to handle increasing users and data without performance issues. Lastly, stakeholder cooperation is vital, as collaboration among government agencies, financial institutions, and technology providers is necessary to support the platform’s objectives. These assumptions underpin the design and deployment of AGRO 5.0 while indicating areas for validation during implementation.

## **1.9 Feasibility Study**

### **1.9.1. Technical Feasibility**

The technical feasibility of AGRO 5.0 has been rigorously assessed, confirming that the necessary technologies and frameworks for development are both viable and compatible with existing agricultural infrastructure. Key components identified include advanced AI algorithms, blockchain protocols, and big data analytics tools, all of which are essential for optimizing data processing and decision-making within the platform. The integration of these technologies will facilitate accurate monitoring of agricultural activities, enhance transparency in subsidy allocation, and enable effective farm management.

Engagement with key stakeholders' farmers, suppliers, and financial institutions has been instrumental in validating the technical approach. A joint venture is being established with the Zimbabwe National Geospatial and Space Agency (ZINGSA), the Zimbabwe Center for High Performance Computing (ZCHPC), and the Ministry of Agriculture. This collaboration aims to consolidate resources and expertise, ensuring that the platform meets the specific needs of all stakeholders. Continuous dialogue and engagement will align the technical features of the platform with stakeholder requirements, fostering a strong foundation for the project’s success.

### **1.9.2. Economic Feasibility**

A comprehensive cost-benefit analysis has confirmed the economic viability of AGRO 5.0, demonstrating that the project is financially sound. Development and operational costs have been carefully assessed against projected savings and efficiency gains for stakeholders, resulting in a sustainable financial model. The total funding required for the project is estimated at US$ 30,000, of which US$ 25,100 has already been secured from various funding sources. This initial funding will support critical development activities, including technology implementation and stakeholder outreach.

Projected profits in the first year are anticipated to reach US$ 30,000, indicating a promising return on investment. This financial outlook not only underscores the project’s sustainability but also highlights its potential for long-term growth. By creating a shared value proposition for stakeholders, AGRO 5.0 aims to enhance productivity and profitability within the agricultural sector, ensuring that the platform remains economically viable and beneficial for all involved.

### **1.9.3. Operational Feasibility**

The operational feasibility of AGRO 5.0 has been assessed to ensure efficient implementation and maintenance within the agricultural framework. The system is designed to seamlessly fit into existing infrastructure and align with the current procedures of relevant stakeholders, minimizing disruption to established workflows. Technical experts and community liaisons, will be consulted throughout to oversee implementation and provide training and ongoing support to users. Regular training sessions will empower farmers and stakeholders to effectively utilize the platform, fostering continuous learning. Additionally, a robust support system with a helpdesk and feedback mechanisms will address technical issues and gather user insights for improvement. The project design emphasizes scalability, allowing the platform to accommodate increasing numbers of users and data without performance loss by leveraging cloud-based solutions. Overall, AGRO 5.0's operational feasibility is anchored in a strategy focused on user engagement, technical support, and scalability, ensuring effective implementation and long-term sustainability.

## **1.10 Significance and motivation for the project**

The proposed project aims to address significant inefficiencies in agricultural subsidy management by leveraging advanced technologies such as remote sensing, machine learning, and blockchain. By automating subsidy distribution and enhancing risk management, the initiative improves agricultural financing efficiency and fosters innovation in computer engineering. It integrates cutting-edge software engineering principles, demonstrating the practical use of machine learning for predictive analytics and blockchain for secure transactions, while utilizing remote sensing to analyze large agricultural datasets. The project seeks to enhance subsidy allocation, reduce fraud, and provide timely support to farmers, particularly smallholders, promoting sustainability and ensuring fair access to financial assistance. Additionally, it facilitates data-driven decision-making to improve resource allocation and policy planning, contributing to greater transparency and accountability. Ultimately, by boosting agricultural productivity and encouraging sustainable practices, the project aligns with global sustainable development goals, showcasing the transformative potential of modern engineering technologies to create positive social change in underserved areas.

## **1.11 Work plan**



*Figure 1.1: Gantt chart*

## **1.12 Chapter summary**

This project focused on developing a remote sensing monitoring system for agricultural subsidies, utilizing machine learning for real-time anomaly detection in agricultural data. The aim was to enhance the system's scalability and enable predictive analytics, thereby improving the efficiency and effectiveness of subsidy distribution within agricultural networks. By facilitating continuous monitoring of agricultural conditions, the solution ensures timely interventions and minimizes the risk of resource misallocation. Despite challenges such as algorithm complexity and the need for specialized technical expertise, the project's outcomes significantly advance modern agricultural monitoring systems and enhance operational transparency. Overall, this chapter establishes the foundation for the project and sets the stage for the subsequent chapters, which will detail the methodology and implementation.

# **CHAPTER 2: LITERATURE REVIEW**

## **2.1 Introduction**

This chapter undertakes a comprehensive review of the existing literature concerning emerging technologies relevant to agricultural subsidy systems, specifically machine learning (ML), remote sensing (RS), and blockchain. These technologies have gained considerable attention for their ability to tackle long-standing inefficiencies in subsidy systems, such as delays in fund disbursement, corruption, and mismanagement of resources. Agricultural subsidies, critical for supporting farmers, often suffer from poor targeting and inequitable distribution, necessitating innovative solutions. By exploring theoretical advancements and empirical applications, this chapter identifies the strengths and limitations of these technologies. Furthermore, it aims to highlight critical gaps in research and practice, ultimately proposing a conceptual framework that integrates ML, RS, and blockchain. This integration aims to enhance the transparency, efficiency, and sustainability of subsidy systems, aligning with the broader goal of equitable agricultural development.

**2.2. Theoretical Literature Review**

### **2.2.1. Machine Learning in Agricultural Financing**

Machine learning has emerged as a transformative tool in agricultural financing and subsidy management. It facilitates the development of sophisticated models capable of analyzing vast datasets to optimize resource allocation and predict risks. Techniques such as neural networks, Random Forest, and Gradient Boosting have demonstrated significant efficacy in credit risk assessment and market analysis (Bello, 2023). Neural networks, for instance, are particularly effective in identifying complex patterns in financial and agricultural data, improving the precision of credit scoring systems (Abdulla and Al-Alawi, 2024). Similarly, Random Forest algorithms are adept at identifying potential loan defaults, offering a robust mechanism to enhance credit risk management.

Hybrid approaches, such as combining genetic algorithms with neural networks, further enhance predictive capabilities. Wu, (2021) observed that these hybrid models outperform standalone techniques in predicting financial outcomes in agricultural contexts. Additionally, ML has enabled the integration of satellite imagery and climate models to assess creditworthiness under diverse environmental conditions. Mygdakos et al. (2024) highlight how such integration provides lenders with actionable insights, particularly in regions prone to environmental uncertainties.

However, several challenges hinder the widespread adoption of ML in agricultural financing. Limited interpretability of complex models poses a significant barrier, making it difficult for stakeholders to trust and validate predictions (Fakour et al., 2024). Moreover, poor data quality and regional variations in agricultural practices reduce the adaptability and accuracy of ML models. These limitations underscore the need for localized and interpretable solutions to maximize ML's potential in agricultural financing.

### **2.2.2. Remote Sensing in Agricultural Monitoring**

Remote sensing technologies have revolutionized agricultural monitoring by providing high-resolution, real-time data for crop mapping, health assessment, and productivity estimation. Through the integration of spectral bands and vegetation indices, platforms such as Pléiades have achieved remarkable accuracy in crop classification, with rates reaching up to 96.3% (Dimitrov 2024). These advancements are particularly beneficial for large-scale agricultural assessments, enabling policymakers to make informed decisions regarding resource allocation.

The incorporation of machine learning algorithms has further enhanced the utility of remote sensing. Automated approaches reduce labor costs and improve the reliability of image analysis, particularly in identifying crop health and predicting yields (Bereziovsky 2024). However, despite these advancements, significant barriers remain. Spectral similarities among certain crops can complicate classification efforts, leading to inaccuracies in monitoring (Schmedtmann and Campagnolo, 2015). Additionally, the high costs associated with remote sensing technologies limit their accessibility for smallholder farmers in developing regions.

Another critical limitation is the reliance on area-based assessments. While effective for large-scale monitoring, this approach often overlooks individual crop health, resulting in inequitable subsidy distribution (Rajashekar et al., 2024). Addressing these challenges requires the development of cost-effective and scalable solutions that integrate remote sensing with other technologies, such as ML, to improve individual crop assessments and ensure fair resource distribution.

### **2.2.3. Blockchain in Agricultural Subsidies**

Blockchain technology offers transformative potential for addressing issues of transparency, efficiency, and trust in agricultural subsidy systems. By enabling direct transactions between farmers and government entities, blockchain eliminates the need for intermediaries, thereby reducing corruption and accelerating the disbursement of funds (Shareef et al., 2023; Bakare et al., 2021). This is particularly valuable in subsidy systems where delays and fraud are common.

Smart contracts, a key feature of blockchain, automate the disbursement process, ensuring that payments are accurate and timely. Savita et al. (2021) emphasize that these contracts minimize human intervention, reducing errors and opportunities for fraud. Furthermore, the immutable ledger provided by blockchain enhances the auditability of transactions, facilitating better monitoring and tracking of subsidies (Kamilaris et al., 2019).

Despite these advantages, blockchain's application in agricultural financing remains underexplored. Concepts such as programmable money, which could enable conditional payments based on predefined criteria, are largely theoretical and lack empirical validation (Weber & Staples 2022). Additionally, the high costs and technical expertise required for blockchain implementation pose significant barriers, particularly for smallholder farmers in resource-constrained settings.

## **2.3. Empirical Literature Review**

### **2.3.1. Current Challenges in Subsidy Distribution**

Agricultural subsidies play a vital role in global food security and poverty alleviation, yet their distribution systems often exhibit significant inefficiencies. Research consistently identifies persistent challenges within traditional subsidy frameworks, particularly in developing nations where outdated, labor-intensive methods prevail. Issues such as delays, corruption, and resource misallocation not only hinder the effectiveness of these subsidies but also adversely affect vulnerable agricultural communities (Schmedtmann and Campagnolo, 2015).

A critical problem is the inefficiency of subsidy distribution systems, which typically rely on manual inspections and reactive assessments. As noted by Deveshwar et al. (2024), this approach leads to delayed responses to farmers' needs, resulting in misallocated subsidies. Consequently, smallholder farmers, who are already financially strained, face heightened vulnerabilities. Moreover, these inefficiencies often contribute to inequities in subsidy distribution, leaving farmers in remote or underserved regions overlooked (Deveshwar et al., 2024). Such delays have a ripple effect, diminishing the overall impact of agricultural policies aimed at enhancing food security.

Another significant challenge arises from the prevalent area-based allocation methodologies that ignore individual crop health and specific farmer needs. This one-size-fits-all approach often misallocates subsidies, as funding is based on land area instead of the unique circumstances of each farm. (Deepthi et al. (2024) emphasize how this generic strategy disproportionately affects farmers with lower yields or those facing specific environmental challenges, leaving them underserved. Tailoring subsidies to individual farm conditions is essential for alleviating financial pressures on vulnerable farmers.

Additionally, many countries rely on historical entitlements for subsidy allocation, which distorts the distribution process. (Swinnen 2009) points out that basing subsidies on past production rather than current agricultural realities leads to inefficiencies. This practice allows some farms to continue receiving financial support despite a lack of need, while more vulnerable farmers, who may not meet historical criteria, miss out on essential assistance. Such inflexibility exacerbates disparities, particularly between large-scale commercial operations and smallholder farmers (Anderson 2013).

Market distortions from trade-distorting subsidies further complicate the landscape. Hoekman and Kostecki (2010) argue that such subsidies create unfair competitive advantages, leading to overproduction and market volatility, especially in global markets. These practices disadvantage farmers in developing countries and contribute to tensions in international trade negotiations. The World Trade Organization (WTO) has highlighted these challenges, which undermine the goals of free and fair trade (Hoekman 2010).

Environmental sustainability is also a pressing concern in subsidy distribution. While initially intended to boost food production, subsidies have inadvertently caused significant environmental harm. The push for resource-intensive crops, like corn and soybeans, is linked to deforestation, soil erosion, and biodiversity loss (Tilman 2002). (Pretty et al. (2011) further note that these subsidies encourage harmful agricultural practices, including excessive use of fertilizers and pesticides, which have long-term negative effects on both the environment and agricultural productivity.

From an economic perspective, agricultural subsidies represent a considerable financial burden, particularly for developed nations. The Organisation for Economic Co-operation and Development (OECD 2020) reports that member countries allocate around $390 billion annually to agricultural support policies. This raises questions about the efficiency of these programs, especially when considering the opportunity costs associated with such large expenditures. Krueger (1997) argues that these funds could be better utilized for other development priorities, such as infrastructure, healthcare, or education, which could indirectly benefit the agricultural sector more sustainably.

Despite these well-documented challenges, agricultural subsidies remain politically entrenched due to the complex interests involved in agricultural policy. Rural communities and the agricultural sector have a strong stake in maintaining these programs, resulting in insufficient political will for reform. However, there is a growing recognition of the need for more targeted subsidy schemes. Anderson et al. (2017) suggest a shift away from blanket production-based subsidies towards market-oriented policies that promote sustainable practices and reward environmental stewardship. These reforms are crucial for ensuring that subsidies effectively contribute to rural development and sustainable agriculture.

The challenges surrounding subsidy distribution are complex and necessitate comprehensive reform. The inefficiencies inherent in area-based allocation, along with environmental, economic, and market-related issues, underscore the urgent need to modernize subsidy systems. As highlighted by Deepthi et al. (2024) and Deveshwar et al. (2024), automated, data-driven solutions present promising opportunities for improving the targeting and efficiency of subsidies. Policymakers must prioritize these innovations to create subsidy programs that are more equitable, transparent, and responsive to the actual needs of farmers.

### **2.3.2. Fragmentation in Technological Integration**

While ML, RS, and blockchain technologies have demonstrated significant promise individually, their fragmented application limits their potential in dynamic risk assessment and subsidy optimization. For instance, ML techniques such as CreditScore integrate crop growth models with satellite imagery to evaluate farmers' creditworthiness but struggle to address region-specific variations effectively (Mygdakos et al., 2024). Similarly, RS technologies face challenges related to scalability and cost-efficiency, while blockchain applications in subsidy disbursement remain largely experimental (Weber & Staples 2022; Kamilaris et al., 2019).

In the realm of environmental monitoring, the potential of Blockchain and AI remains largely untapped, as most studies focus on their individual benefits rather than their combined strengths. Few examples illustrate a scalable system that effectively integrates both technologies to enhance data integrity and monitoring capabilities (Gade 2023). As environmental monitoring increasingly relies on extensive real-time data, a unified approach becomes crucial. The ability of Blockchain to provide secure, tamper-proof records, paired with AI’s proficiency in analyzing large datasets, could significantly bolster environmental data integrity and monitoring efforts.

The lack of integration among these technologies restricts their ability to provide comprehensive solutions. A unified approach that combines the strengths of ML, RS, and blockchain is essential to address these limitations and enhance the effectiveness of agricultural subsidy systems.

### **2.3.3. Lack of Scalable and Unified Frameworks**

Existing systems often fail to cater to the diverse needs of different regions, crops, and farming practices. Remote sensing, for example, achieves only 68% accuracy in classifying certain crops, highlighting the limitations of current technologies (Schmedtmann and Campagnolo, 2015). Similarly, blockchain solutions lack tailored frameworks for agricultural applications, particularly in subsidy systems (Savita et al., 2021).

The absence of scalable and unified frameworks restricts the ability of these technologies to respond to emerging risks and ensure equitable resource distribution. Addressing this gap requires the development of integrated solutions that are adaptable to diverse agricultural contexts.

## **2.4. Gaps identified**

The literature reveals several critical gaps in current agricultural subsidy systems. Traditional systems rely heavily on post-event assessments, making them reactive and inefficient. The fragmented application of ML, RS, and blockchain technologies limits their potential for dynamic and integrated subsidy management. Existing solutions also lack scalability and adaptability, failing to address region-specific agricultural needs and diverse farming practices. Additionally, the use of blockchain in smallholder financing and conditional payments remains underexplored, with limited empirical evidence. Finally, RS technologies' reliance on area-based assessments leads to inaccuracies and uneven subsidy distribution. Addressing these gaps is essential for developing more effective and equitable subsidy systems.

| **Source** | **Insights** | **Methods Used** | **Research Gap** |
| --- | --- | --- | --- |
| Aarti, Deveshwar and Panwar, 2024(Overview of Agricultural Subsidies in India and Its Impact on Environment. *Current World Environment*) | Agricultural subsidies are financial aids provided by the government to support the agricultural sector, aimed at enhancing productivity, ensuring food security, and improving farmers' income. They can be direct or indirect and significantly impact both the economy and the environment. | Overview of agricultural subsidies and fund allocation analysis.Utilizes secondary data from government and research publications. | Mismanagement hampers subsidy effectiveness for farmers and environment.Need for improved targeting to maximize benefits and minimize consequences. |
| Schmedtmann and Campagnolo, 2015 (Reliable crop identification with satellite imagery in the context of Common Agriculture Policy subsidy control) | Remote sensing is utilized for controlling agricultural subsidies under the Common Agricultural Policy (CAP) by enabling automatic crop identification, which enhances efficiency and reduces costs. This method allows National Control and Paying Agencies to ensure proper fund allocation and compliance. | SVM classifier with 10-fold cross-validation for classification.Calibration and application steps for operational context. | Limited accuracy in crop classification at 68%.  Need for improved reliability in automatic control decisions. |
| Deepthi et al., 2024(From Pixels to Payouts A Satellite Based Solution. pp.1-5.) | Current remote sensing agriculture subsidies face limitations such as reliance on area-based approaches, inadequate weather indices, and inaccurate loss assessments, leading to unjust aid distribution and leaving deserving farmers underserved, as highlighted in the proposed PMFBY solution. | Remote sensing technology, machine learning algorithms, data analysisImage processing, segmentation, SVM, CNN for crop detection, yield estimation | Inadequate individual crop health and loss assessment.Unjust aid distribution due to area-based approach. |
| Savita et al., 2021(A Blockchain-based framework for Agriculture subsidy disbursement) | Blockchain technology can enhance agriculture subsidy disbursement by ensuring transparency, reducing fraud, and eliminating intermediaries. The proposed framework utilizes smart contracts to automate subsidy delivery, addressing issues like corruption and delays, ultimately benefiting eligible farmers directly. | Direct Cash transfer scheme under the Direct Benefit Transfer (DBT) schemeBlockchain-based smart contracts prototype model | Lack of proper auditing in subsidy disbursement process. |
| Kamilaris, Pitsillides and Karus, 2019(Blockchain technology in agriculture: A review. *Agricultural Systems*) | Existing studies on blockchain in agriculture focus primarily on traceability and supply chain management. There is limited exploration of its role in agricultural financing, particularly for smallholder farmers. |  | No platforms focusing on Agricultural Financing specifically subsidized schemes |
| Weber and Staples, 2022(Programmable money: Next-generation blockchain-based conditional payments. *Digital Finance*, 4(2), pp.109-125) | There is a notable gap in empirical studies that explore how programmable money can be effectively used to implement conditional payments tailored to the specific needs of smallholder farmers. Such payments could incentivize desired agricultural practices or ensure compliance with financing terms, but this application remains underexplored. |  | Lack of Empirical Research and implementation on Conditional Payments for Smallholder Farmers |

*Table 2.1: Gaps in similar projects or systems*

## **2.5. Conceptual Frame work**

This study presents an innovative conceptual framework aimed at enhancing agricultural subsidy systems by integrating Machine Learning (ML), Remote Sensing (RS) and Blockchain technologies. The primary goal of this framework is to improve the distribution, transparency and fairness of subsidies for smallholder farmers.

At its core, the framework focuses on two main constructs: proactive risk assessment and real-time monitoring and automated subsidy distribution via Blockchain. Leveraging ML and RS, the first construct enables the analysis of extensive agricultural datasets for risk prediction and optimal resource allocation. Remote Sensing contributes real-time, high-resolution data that enhances the monitoring of crop health, growth stages and environmental conditions. This integration allows for precise subsidy allocation tailored to the unique circumstances of individual farms, addressing the limitations of traditional area-based assessments.

The second aspect employs smart contracts to automate payment processes, ensuring accurate and transparent subsidy delivery. The immutable nature of Blockchain provides a secure record of subsidy transactions, enhancing data integrity and trust. The framework also emphasizes scalability and adaptability, allowing it to be customized to meet regional agricultural needs and various farming practices. By integrating satellite-derived biophysical data with ML techniques, the framework optimizes resource allocation based on environmental factors.

## **2.6. Chapter summary**

This chapter has provided a comprehensive review of theoretical and empirical literature on ML, RS, and blockchain technologies in agricultural subsidy systems. While these technologies offer significant potential, their fragmented application and current limitations highlight the need for an integrated approach. The proposed conceptual framework seeks to address these gaps, enhancing the transparency, efficiency, and inclusivity of subsidy management systems. The next chapter will detail the research methodology employed to implement and validate this framework.

# **CHAPTER 3: METHODOLOGY**

## **3.1 Introduction**

This chapter outlines the methodological approach for designing, developing, and implementing the AGRO 5.0 application, detailing the systematic process to achieve the project’s objectives, including data collection, preprocessing, and the integration of advanced machine learning models. It begins by describing the requirements gathering and design considerations that shaped the system's architecture, followed by an exploration of the tools and technologies used for data handling, feature engineering, and machine learning model development. The chapter also discusses validation and testing methods to ensure the application’s robustness, along with ethical considerations and potential biases to uphold principles of fairness and inclusivity. Overall, this chapter provides a comprehensive overview of the methodologies that enabled the effective development of AGRO 5.0 to enhance efficiency, transparency, and accuracy in subsidy allocation.

## **3.2 Software development process**

The methodology for this project employs a hybrid approach that combines elements of both Waterfall and Agile frameworks to enhance both efficiency and adaptability (TeamGantt, 2024). The Waterfall model provides a structured, sequential process essential for the initial phases of planning, requirements gathering, and system design. This approach ensures a clear framework for addressing the complexity of integrating technologies such as AI, blockchain, and big data, allowing for thorough documentation and planning at each stage.

In contrast, Agile principles are integrated throughout the development and implementation phases, enabling flexibility in responding to evolving stakeholder needs and facilitating iterative improvements. This dynamic aspect of the methodology allows for continuous feedback loops, where stakeholders can provide insights that inform design adjustments and prioritization of features based on their real-time needs. By employing short development sprints, the project can focus on specific components while remaining responsive to changes and new insights that emerge during the process.

This hybrid methodology strikes a balance between the discipline of Waterfall and the responsiveness of Agile, ensuring the final product not only meets initial project objectives but can also adapt to the changing landscape of agricultural technology. Ultimately, this approach aims to develop a robust and scalable agricultural monitoring system that effectively addresses the complexities of agricultural finance while remaining user-centric and aligned with stakeholder expectations.

## **3.3 Methods and techniques**

This project employs a combination of advanced technologies and software engineering practices to address inefficiencies in agricultural subsidy management. The methods and tools used were chosen to align closely with the project’s objectives of improving transparency, accuracy, and efficiency in subsidy allocation, while ensuring scalability and user accessibility.

### **3.3.1. Data Collection Methods**

The effectiveness of the platform hinges on accurate and comprehensive data. To achieve this, the project leveraged satellite imagery and geospatial data from sources such as Sentinel-2, Landsat, and ZimSat-1 for real-time crop monitoring and classification. These sources provided critical insights into crop health and environmental conditions. Weather and climate data were obtained using APIs like OpenWeatherMap, which informed predictive models used for risk assessment and yield forecasting. Historical agricultural data, sourced from agricultural databases, complemented real-time data to enhance the accuracy of machine learning models. Additionally, stakeholder input was collected through surveys and interviews with farmers and policymakers to better understand their needs, further improving the platform's design and functionality.

### **3.3.2. Software Engineering Practices**

The project was developed using Agile methodology, which allowed iterative development and regular stakeholder feedback to ensure the platform addressed real-world needs (Beck et al., 2001). Each development phase included sprints and continuous integration testing to maintain progress and quality, reflecting the iterative nature of Agile that promotes flexibility and adaptability in project management. Version control was managed using Git and GitHub, which enabled efficient collaboration and tracking of changes in the codebase, a practice that is essential for maintaining code integrity in Agile environments (Chacon & Straub, 2014) Test-Driven Development (TDD) was adopted to ensure system reliability by writing tests before the code was implemented, minimizing bugs and errors during development; this aligns with Agile's emphasis on continuous testing throughout the development process (Beck, 2022). These practices ensured the project’s robustness and adaptability throughout the development lifecycle, highlighting the benefits of Agile methodologies in delivering high-quality software efficiently.

### **3.3.3. Design Methodologies**

The platform’s architecture followed a microservices model, breaking the system into independent components for AI, blockchain, and data processing. This modular approach facilitated seamless integration, scalability, and easier maintenance of individual system parts without disrupting the entire application. A User-Centered Design (UCD) methodology was employed to create an intuitive and accessible interface for stakeholders, particularly farmers and policymakers. Regular usability testing and feedback loops during development ensured the platform’s functionality aligned with user requirements, fostering widespread adoption.

### **3.3.4. Algorithms and Data Processing**

The platform utilized advanced algorithms to deliver its core functionalities. For satellite image analysis and crop monitoring Convolutional Neural Network (CNN) model was implemented due to its ability to process complex geospatial data. Predictive analytics for risk management leveraged Gradient Boosting algorithms to forecast risks such as droughts and pest infestations. These AI-based methods enabled proactive and informed decision-making in agricultural subsidy management. Blockchain technology was employed through smart contracts written in Solidity, automating subsidy disbursement to ensure secure and tamper-proof transactions. Big data techniques were also utilized, with tools like Apache Spark employed to process and analyze large datasets efficiently, supporting optimized resource allocation (Zaharia et al., 2016).

### **3.3.5. Tools Utilized**

The platform was developed using a range of tools and technologies tailored to its multifaceted requirements. Python with the Django framework was used for backend development, enabling efficient data processing and API management. For the frontend, JavaScript with React.js provided a dynamic and interactive user experience. AI models were built using the libraries TensorFlow and Scikit-learn, while blockchain features were developed with Ethereum, Truffle, and Ganache. Data visualization was achieved using libraries Chart.js and D3.js, allowing stakeholders to access insights through intuitive and interactive dashboards.

### **3.3.6. Justification of Methods**

The selected methods and tools align with the project’s goals of enhancing agricultural subsidy systems through advanced technologies. AI models enable accurate predictions and risk assessments, while blockchain ensures transparency and security in subsidy disbursement. Remote sensing provides actionable insights into agricultural conditions, and Agile practices ensure iterative progress and responsiveness to user needs. Together, these methodologies and tools enable the development of a scalable, transparent, and user-friendly platform tailored to the complex demands of agricultural financing.

## **3.4 Data Handling and Feature Engineering**

The success of the project's machine learning components relied on effective data handling, comprehensive preprocessing, and thoughtful feature engineering. These steps ensured the development of robust models capable of delivering accurate and actionable insights for agricultural subsidy management. The data utilized spanned multiple sources, including satellite imagery, weather data, historical agricultural records, and qualitative inputs from stakeholders. Satellite imagery from platforms like Sentinel-2, Landsat, and ZimSat-1 underwent preprocessing to correct for radiometric and geometric distortions. Weather data was cleaned by addressing missing values and removing anomalies, while historical datasets were normalized for consistency across different time frames. All collected data was consolidated into a unified structure for seamless integration into machine learning workflows.

### **3.4.1. Data Cleaning**

A significant emphasis was placed on data cleaning to eliminate inconsistencies, outliers, and redundancies. Techniques such as cloud masking were applied to mitigate noise in satellite imagery caused by cloud cover. Missing weather data was imputed using interpolation methods, while outlier detection algorithms like DBSCAN identified and addressed anomalies in numerical datasets (Ester et al., 1996). This preprocessing step ensured that the data used for model training was clean, reliable, and representative of real-world conditions.

### **3.4.2. Feature Engineering**

Feature engineering focused on extracting meaningful attributes from raw datasets to enhance model performance (Digital Ag, 2025). From satellite imagery, features like vegetation indices (e.g., NDVI and EVI) were derived to quantify crop health and growth stages. Weather data contributed features such as cumulative rainfall, average temperature, and seasonal variations, which were critical for yield forecasting and risk assessment. Historical agricultural records were analyzed to create trend-based features, like multi-year yield averages and anomaly scores. Temporal features, such as time to harvest and seasonality metrics, were calculated to capture patterns over time, while spatial aggregation provided regional summaries, ensuring the models could generalize well across diverse agricultural contexts.

### **3.4.3. Model Design Considerations**

Feature selection was based on relevance to crop classification and risk management. Domain knowledge and exploratory data analysis (EDA) informed this process, with NDVI prioritized due to its correlation with crop health (Chatterjee et al., 2024). Understanding dataset characteristics was crucial for effective model design; high dimensionality in satellite imagery necessitated technique Principal Component Analysis (PCA), while temporal dependencies in weather data were addressed through time-series analysis. Imbalanced datasets, particularly in crop classification, were managed using oversampling technique SMOTE to ensure equitable representation during model training.

By implementing rigorous data handling and feature engineering processes, this project ensured that the machine learning models were trained on high-quality, meaningful data. The selected features provided a comprehensive view of the agricultural ecosystem, enabling accurate predictions and supporting effective subsidy management decisions. These efforts formed a critical foundation for achieving the project's objectives and driving innovation in agricultural financing.

## **3.5 Model development and training**

The development and training of machine learning models for this project targeted high performance, interpretability, and alignment with the goals of optimizing agricultural subsidy management. A systematic approach was adopted, encompassing model selection, architectural design, hyperparameter optimization, and rigorous validation, along with ethical considerations throughout the process.

### **3.5.1. Model Selection**

Models were carefully selected based on their suitability for specific tasks such as crop classification and risk assessment. For crop classification, Convolutional Neural Networks (CNNs) were chosen for their effectiveness in analyzing satellite imagery, excelling in feature extraction and pattern recognition. Pre-trained models ResNet and VGG16 were fine-tuned through transfer learning, significantly reducing computational overhead while enhancing performance. Ensemble models combining Random Forests and Logistic Regression were implemented for risk assessment, predicting challenges like droughts and pest infestations.



*Figure 3.1 (Cantez, Şahin and Efe, 2023)*

### **3.5.2. Architectural Design**

The architectural design incorporated multi-input systems to handle diverse data types. CNN layers analyzed satellite imagery, while fully connected layers focused on tabular features, including weather and financial data. This hybrid approach ensured effective utilization of all available data sources, providing a comprehensive view for the models.

### **3.5.3. Hyperparameter Optimization and Validation**

Hyperparameter tuning was a critical aspect of model optimization. Techniques such as Grid Search and Random Search were employed to identify optimal parameters, including the number of layers, learning rate, batch size, and tree depth. For complex models like XGBoost, Bayesian Optimization was used for iterative refinement of hyperparameters. The dataset was split into training (70%), validation (15%), and test (15%) sets to evaluate performance at different stages. K-Fold cross-validation mitigated overfitting, while regularization techniques, including L1 and L2 regularization and dropout layers, enhanced model robustness. Early stopping was also implemented, halting training when validation loss ceased to improve.

### **3.5.4. Ethical Considerations**

Recognizing potential biases and ethical implications was essential in model development. Steps were taken to ensure diverse representation in training data, employing balanced datasets and techniques like SMOTE to address class imbalances. Transparency and explainability were prioritized using Explainable AI techniques, such as SHAP (SHapley Additive exPlanations), to interpret model predictions (Kawakura et al., 2022). The models were evaluated for fairness to prevent systemic discrimination, particularly against small-scale farmers or underrepresented regions. Adhering to ethical AI practices ensured that the models supported informed decision-making without compromising user privacy or exacerbating existing inequalities.

## **3.6 Tools and technologies**

The success of this project relied on the careful selection and application of diverse tools and technologies, each chosen for its specific strengths in data handling, model development, system integration, and user experience. Together, they played a critical role in achieving the project's objectives in agricultural subsidy management.

### **3.6.1. Programming Languages**

Python was selected for its versatility and extensive ecosystem of libraries, facilitating machine learning, data analysis, and backend development. It enabled efficient implementation of AI models and streamlined data preprocessing workflows. JavaScript was essential for creating an interactive and responsive user interface, benefiting from a robust community and compatibility with modern frameworks.

### **3.6.2. Frameworks and Libraries**

For the backend, Django was chosen for its scalability, robustness, and ease of API creation, ensuring seamless integration of services, including database management. On the frontend, React delivered a user-friendly and highly interactive interface, allowing for rapid development and real-time updates. In terms of machine learning, TensorFlow and Scikit-learn played critical roles in building and training models, providing tools for feature selection, preprocessing, and evaluation. Additionally, Pandas and NumPy were utilized for efficient data manipulation and numerical computations, while Matplotlib and Seaborn helped visualize data patterns and present results intuitively.

### **3.6.3. Big Data, Analytics, and Blockchain Development**

To address the challenges of big data analytics, Apache Spark was chosen for its efficiency in processing large datasets, with distributed computing capabilities ensuring scalability and speed. Hadoop complemented this by providing a robust framework for storing and managing massive volumes of agricultural data.

In the realm of blockchain development, Ethereum and Solidity were employed to develop and deploy smart contracts, ensuring secure and transparent financial transactions. Truffle and Ganache were utilized for local testing and debugging of smart contracts before deployment, enhancing the overall reliability of the blockchain solutions.

### **3.6.4. Remote Sensing and Geospatial Analysis**

For remote sensing and geospatial analysis, Sentinel Hub and QGIS were indispensable tools for processing satellite imagery and extracting geospatial features. These tools enhanced analytical capabilities by integrating remote sensing data into machine learning workflows, allowing for more accurate insights into agricultural patterns and conditions.

### **3.6.5. Collaboration and Version Control**

Git and GitHub effectively managed collaboration and version control, enabling efficient code management and conflict resolution among team members. This facilitated a collaborative environment that was crucial for the project's success.

### **3.6.6. Justification for Tool Selection**

The tools were chosen not only for their ease of use and community support but also for their scalability and performance. Apache Spark and Hadoop were particularly suited for handling the project's large-scale data needs. Cutting-edge capabilities of TensorFlow, Ethereum, and Sentinel Hub ensured state-of-the-art functionalities in AI, blockchain, and geospatial analysis. The integration of Django and React provided a smooth connection between the backend and frontend, while blockchain tools enabled secure financial management.

## **3.7 Project requirements and design considerations**

### **3.7.1. Overview of the Requirements Gathering Process**

The requirements gathering process for this project was a comprehensive endeavor that combined stakeholder engagement, domain research, and iterative feedback. This approach was essential to ensure that the platform effectively addressed the specific needs of agricultural subsidy management while meeting both technical and usability standards.

Stakeholder engagement played a pivotal role in understanding the challenges and expectations of those directly involved in agriculture. Surveys and interviews were conducted with farmers, policymakers, and financial institutions to gather insights into their experiences and desired functionalities. Additionally, workshops involving agricultural experts and technology consultants helped align the technical capabilities of the platform with the domain-specific needs of users. This collaborative effort ensured that the project's direction was grounded in real-world requirements.

Document analysis further enriched the requirements gathering phase by reviewing existing systems and policies related to agricultural subsidies. This analysis helped identify gaps and opportunities for improvement, as well as the technical standards and legal requirements necessary for handling financial data in agriculture. Through these efforts, a comprehensive understanding of the landscape was developed, informing subsequent decisions.

### **3.7.2. Functional and Design Considerations**

The system requirements were categorized into functional and non-functional aspects. Functional requirements included the ability to process and analyze satellite imagery for crop monitoring and yield prediction, as well as the implementation of a blockchain-backed subsidy disbursement system with automated smart contracts. A user-friendly interface was essential for accessing real-time insights on crop health, financial disbursements, and risk assessments.

Non-functional requirements emphasized scalability to support a growing user base, security to ensure data privacy, performance for real-time processing, and usability to accommodate users with varying levels of technical expertise. Design considerations were crucial in shaping the platform, employing a User-Centered Design (UCD) approach to cater to stakeholders, particularly farmers with limited technical proficiency. Usability testing helped refine workflows and simplify complex tasks, such as interpreting satellite data or managing subsidies.

Security was prioritized through the use of blockchain technology for tamper-proof transactions and role-based access control (RBAC) to safeguard sensitive information. Encryption protocols, such as HTTPS and AES, were adopted to secure data during transmission and storage. Performance was enhanced using distributed computing frameworks like Apache Spark, ensuring efficient processing of large-scale data with minimal delays.

## **3.6 Chapter summary**

The methodology outlined in this chapter provides a comprehensive framework for achieving the project's objectives of developing an advanced agricultural subsidy management platform. From rigorous data collection and feature engineering to the design of machine learning models and blockchain integration, every step was carefully planned and executed to ensure accuracy, scalability, and user-centric functionality. The selection of tools, adherence to best practices in software engineering, and focus on key design considerations like usability, security, and performance ensured the robustness of the system. By aligning these methods with the project's goals, the methodology chapter establishes a solid foundation for delivering a reliable, efficient, and innovative solution to enhance agricultural subsidy management.

All these methods you are using in this chapter have been used by others so cite these text.

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