A Crop Recommendation System Utilizing Machine Learning to Improve Agricultural Practices

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DECLARATION

I Dijin Dinesh hereby declare that the work contained in this dissertation, titled "A Crop Recommendation System Utilizing Machine Learning to Improve Agricultural Practices", is my original work and was conducted specifically for my studies at Dublin Business School. This work has not been submitted for any other degree or qualification at this or any other institution. All sources of information have been duly acknowledged within the text and references. Furthermore, this work has not been submitted for any other degree.

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ABSTRACT

Agriculture remains a backbone of human life, yet crop selection is often made under uncertainty. Farmers, particularly in developing regions, face challenges such as climate change, nutrient-deficient soils, and limited access to expert advice. A single poor decision can reduce yields, waste resources, and cause financial loss. This dissertation presents a machine learning–based crop recommendation system designed to provide data-driven guidance. Key agricultural factors, including nitrogen (N), phosphorus (P), potassium (K), soil pH, temperature, humidity, and rainfall, were collected from historical datasets, climate records, and Internet of Things (IOT) - enabled soil sensors. Several algorithms were evaluated, including Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), and Gradient Boosting (XGBClassifier), with Random Forest achieving the highest predictive accuracy. A web interface allows farmers to input soil and weather conditions to receive crop suggestions tailored to their context. The system reduces risk, supports sustainable agriculture, and strengthens resilience against environmental uncertainty.

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CHAPTER – 1
INTRODUCTION

Agriculture is one of the fundamental components of human life—food sources, economic stability. Therefore, it is a major contributor to GDP and an employment avenue for developing nations, where billions rely on agricultural income and ancillary efforts for financial viability and survival. Yet as the 21st century continues, agriculture faces more and more problems. From increased birth rate changes wanting more output to climate change, erratic weather patterns, and the slow erosion of soil nutrients, making agricultural decisions becomes increasingly complex (Botero-Valencia, Gómez-Gutiérrez & Rivera, 2025).

Until now, the decision-making process regarding which crops to plant occurs through anecdotal evidence. Farmers rely upon their experiences, cultural efforts, and speaking to informal networks. What worked for generations may not work effectively anymore because of the suddenly changed environment. Vastly inappropriate crop selections can lead to decreased yield through ineffective planting methods and seeds, over-fertilization, ineffective use of all resources, lost time and capital efforts, and even damaged ecosystems. Therefore, more scientifically substantiated approaches are required to assist agents in making the best sustainable planting recommendations for anticipated growth (Rejeb, 2025).

1.1 Problem Context and Justification

In the world of agriculture, there's no guarantee that just because crops are recommended for certain soil and environmental combinations across time that they will work. Agriculture is a sensitive field with much impact on crop yield where nutrients, pH, temperature, rainfall, and humidity enter a sort of world where if anything is slightly out of whack for a crop need or environmental outcome, yields fluctuate greatly. This is compounded by climate change which renders seasonality all the more unpredictable—what crops might have been planted during this time of year for decades is now up in the air (Alam et al., 2025).

Yet what's open to resolution through data and machine learning is based on somewhat recent advancements in digital farming and Agriculture 4.0. Precision agriculture offers the ability to work with excessive resolution datasets about the environment, IoT sensor networks, and machine learning (ML) algorithms that provide pinpoint solutions to planting, watering, fertilization, and harvesting needs. Especially since ML is able to decipher convoluted, non-linear relations between soil attributes and viability of crops (Agarwal et al., 2024), it is the perfect system for this endeavor.

Yet there are still gaps between research and implementation for farmers. Many systems currently available operate off fixed datasets that do not account for seasonally or regionally based changes (Vyapari, Bhosale & Parkar, 2023). For example, while the comparative studies presented Random Forest models that produced classification accuracy rates of greater than 99%, that accuracy does not apply when farmers are using the crops recommendation systems in the field with real time interactions. Thus to build trust and implement systems that are easily accessible and useable, future generations must include real time data collection and uncertainty quantification which makes findings reliable in various agricultural scenarios (Alam et al., 2025).

While this would bring a lot to the table for future endeavors, these considerations are seen as future enhancements in this dissertation as not to distract from the focus of project scope but to let future researchers know where this research could go.

1.2 Role of Machine Learning in Crop Recommendation

Just in the last couple of years, research has found machine learning (ML) capabilities to predict which crops are feasible based on soil and environmental conditions. From the most basic algorithm of Decision Trees to more complex Random Forest, Gradient Boosting and Neural Networks, successful application has occurred across multiple datasets from crop growth prediction to input-output prediction assessment (Agarwal et al., 2024; Gosai et al., 2021). The most successful application, likely, employs ensemble models. For example, Random Forest and Gradient Boosting achieve consistent accuracy in prediction through variance reduction and multiple learners with cross-validation across numerous sessions (Vyapari, Bhosale & Parkar, 2023).

Beyond precision, ML provides flexibility not possible through previous systems. Current CRS intersect soil and climate characteristics into a predictive process. For instance, characteristics of Nitrogen (N), Phosphorus (P), Potassium (K), pH, as well as temperature, humidity and rainfall, are not only critical for assessing suitability, but also for training predictive modelling as they derive from control datasets from real-life environments (Ferdib-Al-Islam et al., 2023; Balakrishnan et al., 2023).

Recent research has highlighted the importance of integrating explainable AI (XAI) into CRS to improve farmer trust and system adoption. For example, Shastri et al. (2025) demonstrated how Gradient Boosting combined with XAI techniques could identify the most influential features in crop predictions, while Shams, Gamel and Talaat (2024) showed that explainable frameworks make CRS outputs more transparent and user-friendly. Ferdib-Al-Islam et al. (2023) further emphasised interpretability by incorporating feature importance analysis into their system.

1.3 Research Gap

Despite considerable progress in crop recommendation systems (CRS) thus far, there are some gaps yet to be filled. First, generalizability remains an issue. Many models are trained and tested on specific region datasets, and while accuracy is promising under controlled conditions, it fails drastically when models are applied to different geographic and climatic settings (Gosai et al., 2021; Vyapari, Bhosale & Parkar, 2023). Second, real-time data availability poses issues in low-resource locations. For example, while the implementation of IoT-enabled soil sensors assists in deriving CRS with greater applicability, utilizing such sensors requires expensive, real-time data acquisition that is not sustainable in rural regions (Balakrishnan et al., 2023).

Third, there are still concerns with interpretability and transparency. For example, Random Forest and Gradient Boosting models exhibit overwhelmingly high degrees of accuracy; however, these models operate as “black boxes.” Unless there is some explainability, the farmers will not trust the recommendations and not implement them (Shastri et al., 2025; Shams, Gamel & Talaat, 2024). Fourth, there is a failure to provide uncertainty assessment. For example, binary recommendations are made to farmers without ascertaining how confident these recommendations may be. Thus, in a high-risk field like agriculture, where it's uncertain how likely a suggested crop will yield positive outcomes, decision-making suffers (Alam et al., 2025). Finally, some models that are champions require excessive computational powers making them infeasible for implementation in any rural or low-infrastructure scenario (Ferdib-Al-Islam et al., 2023).

This dissertation hopes to address the first two by creating a machine learning-based crop recommendation system with high accuracy and a web-based user-friendly interface for maximum accessibility. It will also be validated with a wider dataset to assess generalizability across more environmental conditions. Other considerations—real-time IoT integration, uncertainty assessments, and lightweight deployment options—are acknowledged as feasible future directions for research yet are outside the scope of this project for feasibility and focus.

1.4 Research Question

How accurately can a machine learning model recommend suitable crops based on soil properties such as Nitrogen (N), Phosphorus (P), Potassium (K), and pH, along with environmental factors such as humidity, rainfall and temperature, in order to reduce crop failure

1.5 Research Objectives

Objective 1: Development and optimisation of a machine learning–based crop recommendation system that uses soil and environmental parameters (N, P, K, pH, temperature, humidity, and rainfall) to predict the most suitable crops for cultivation.
Objective 2: To provide farmers with a practical decision-making tool by deploying the system as a lightweight and accessible application that supports sustainable agriculture, reduces the risk of crop failure, and improves yield outcomes.

1.6 Contribution and Expected Impact

This study contributes to the body of research in two ways. First, it provides a working prototype of a crop recommendation system that boasts high accuracy of machine learning algorithms with a user interface simple enough for farmers to operate. Second, it paves the way for future research that will integrate real time assessments, uncertainty detection, and easier transferability options. The expected results are accurate crop yields, reduced resource expenditure, and improved small to medium farmer accessibility to successful choices—all of which lead to sustainable farming practices and global food sustainability.

CHAPTER – 2
Literature Review

2.1 Emerging Trends and Research Landscape

Research surrounding machine learning (ML) has risen in the last decade in correlation with the technological advancements of agriculture and agriculture's subsequent boom. Recent literature reviews assess this current intrigue. Recently, Botero-Valencia, Gómez-Gutiérrez and Rivera (2025) reviewed 350+ articles to understand ML's sustainable impact on agriculture, and they found that predictive analytics, the Internet of Things (IoT), and precision agriculture are the fields making the most contributions. Similarly, Rejeb (2025) conducted a topic modelling approach to 1,100+ articles to find trending fields of support; he discovered that soil testing, yield prediction, pest/plant disease detection, and climate-change-related impact prediction are the most significant.

However, despite successful implementations, various challenges still exist. Many techniques are non-scalable; many solutions are non-human interpretable and cannot occur in low-resource settings. There remains a gap between assessing solutions via research and development and applying them in the fields. Studies show, for example, that while ML and IoT can easily integrate and provide support via mobile applications for real-time troubleshooting of agricultural needs, access is limited due to cost, availability of development/infrastructure, and usability challenges (Alam et al., 2025; Shams, Gamel & Talaat, 2024).

Interestingly, one of the fields that found solutions within smart agriculture applications that is more easily adoptable is Crop Recommendation Systems (CRS), which consistently finds the most accurate results for determining which crops should be planted based on soil/environmental conditions (Gosai et al., 2021; Vyapari, Bhosale & Parkar, 2023). Yet, similarly to other solutions, a gap exists between the accuracy achieved therein tested conditions versus what can effectively be applied in agricultural settings. Thus, this dissertation aims to test and validate that a lightweight deployable Crop Recommendation System can bridge the gap between accuracy and applicability across varying agricultural settings.

2.2 Crop Recommendation Benchmark Studies

Crop recommendation systems (CRS) tend to be benchmarked against one another as different machine learning methods are applied to the same data set and comparative results are analyzed. Multi-method studies confirm that crop recommendation systems utilize Decision Trees, Random Forest, Gradient Boosting, Support Vector Machine and Neural Networks (Agarwal et al., 2024; Gosai et al., 2021). On average, gradient boosting and neural network models yield the highest predictive accuracy, however, associated increased costs of computation limit their universal accessibility for implementation in rural areas.

Beyond the aforementioned assessments, recent CRS systems and systems benchmarking studies were created with practical assessment in mind. For instance, Balakrishnan et al. (2023) determined that Random Forest and Support Vector Machine classifiers could translate to a mobile application scenario which would take soil and weather requirements into account—as practical for end users. Ferdib-Al-Islam et al. (2023) designed Crop-RecFIS which classified the crops through Decision Tree, Random Forest and XGBoost along with assessed importance scores for each factor harnessed so that end users would know which factors were playing into the recommendations. Transparency is crucial in many aspects; without it, farmers will not trust the system.

In addition, CRS accuracy benchmarking studies bolster confidence in ensemble approaches. For example, Vyapari, Bhosale and Parkar (2023) found Random Forest reached over 99% classification accuracy during a benchmark determination test, showing it's a reliable candidate for any CRS task. Furthermore, Shariff et al. (2022) determined that XGBoosting and other gradient boosted methods maxed out at over 98% accuracy across various datasets and types of crops. Further, Shastri et al. (2025) confirmed not only high accuracy for their CRS but also integration of Explainable Ai (XAI) to show which features made the most help in making decisions. Similarly, Shams, Gamel and Talaat (2024) created an explainable CRS which found accurate results for its process but justified interpretability over justification for pure accuracy.

Finally, other recent benchmarks focus on robustness and generalizability relative to findings. Alam et al. (2025) showed that uncertainty quantification is a positive quality when predicting success; those with subsequent confidence estimates could lend themselves to positive practicality. This is a growing trend in new benchmarks to assess empirical qualities along with transparency, computational feasibilities and trustworthiness rather than relying solely on percent accuracy. The assessments above can compare what features will better predict successful efficacy versus practicality—which will be the point of this dissertation as various models will be compared against each other on the same set of data.

2.3 Real-Time and Lightweight Deployment Approaches

In recent years, the focus has also been on real-time, lightweight deployment of CRS as regions where farmers have low infrastructure need to have systems that not only operate correctly, but also function on platforms that require low computing power and low latency. For example, recent scholarship shows how machine learning can justify the embedding of deployable systems. Balakrishnan et al. (2023) deployed CRS using Random Forest and Support Vector Machines to a situation where soil and weather could be a mobile-friendly fusion, proving the use of light-weight, end-user oriented applications. Ferdib-Al-Islam et al. (2023) expand upon this, introducing their Crop-RecFIS which deployed multiple classifiers—Decision Tree, Random Forest, XGBoost—and feature importance scores to provide performance and interpretability within a framework that could be adjusted for low-resource realities.

Yet one of the greatest shortcomings from the above studies is that they are region-specific and rely upon datasets that would not function properly in regions outside their subjects. Yet as Vyapari, Bhosale and Parkar (2023) and Shariff et al. (2022) show, while accuracy is above 90% in confined datasets and controlled conditions, CRS deployed across varying regions require wider accuracy thresholds to work in heterogeneous climates. Alam et al. (2025) take this one step further to assert that CRS must induce uncertainty quantification into real-time predictions as these will bolster trustworthiness; when systems are capable of offering recommendations with confidence estimations, farmers may be more apt to trust nonhuman systems over systems with no accompanying statistic.

Thus, this dissertation mirrors these findings of the aforementioned studies relative to deployment via Streamlit for lightweight usability of CRS. Streamlit is a web interface for low-infrastructure accessibility as Streamlit allows farmers to obtain quick crop recommendations without high performance computing. While IoT-based data acquisition inclusion and uncertainty quantifications are beyond the scope of this project, this implementation is a step toward real-time CRS within adjustable situations that could translate to broader applicability for scalable agricultural decision making.

2.4 Emerging Architectures and Innovations

Whereas older CRS rely upon Decision Trees or Random Forests, more recent developments shift toward hybridization of more advanced architectures to bolster predictive accuracy and practical application. For instance, Shastri et al. (2025) hybridized Gradient Boosting with Explainable AI (XAI) techniques to allow for their CRS to assess which variables were impactful in predicting the crop recommendation. Such explainability—rare in field applications—increases trust and allows for the non-technical person to better understand and apply whatever findings stem from the system's recommendations.

Furthermore, other recent developments emphasize this need for CRS explainability. For example, Shams, Gamel and Talaat (2024) developed an explainable framework for a CRS that sought to achieve a compromise between accuracy and transparency, relying upon explainable methods which showed how specific soil and climate factors affected its predictions. Likewise, Ferdib-Al-Islam et al. (2023) advocated for an interpretable system by incorporating feature importance within the system Crop-RecFIS, making it easier for users to understand why certain crops were recommended.

Yet where hybridizing with deep learning aspects may mean greater predictive accuracy, deep learning systems are less interpretable than tree-based systems or ensemble approaches. Therefore, Alam et al. (2025) argue that the future of CRS will need to assess and communicate uncertainty as much as—if not more than—attaining high accuracy to bridge the gap between academic development and practical application. However, despite such capabilities, real world XAI-based CRS are limited, in part due to the computational load that prevents low-resourced farmers from utilizing such systems.

2.5 Synthesis and Gap Identification

Despite much of the work done to develop and broaden crop recommendation systems (CRS), several gaps exist in the literature. For example, many training and testing models use single-dataset crops from one location within geographic bounds; as such, the CRS model trained is unlikely to generalise to other climates, soils and farming practices, meaning practical reliability, when attempting to implement elsewhere, is low (Gosai et al., 2021; Vyapari, Bhosale & Parkar, 2023).

Furthermore, while research shows that ensemble models like Random Forest and XGBoost outperform the accuracy metrics—many tracks above 98% (Shariff et al., 2022; Ferdib-Al-Islam et al., 2023)–very few test them across more than one dataset to prove they can be applied at scale, which begs the question of how CRS can be executed effectively at scale. Third, while many CRS prototypes exist on mobile and web-based platforms with significant results, their evaluations focus predominantly on accuracy, not usability, ease of implementation, or accessibility for low-resource farmers (Balakrishnan et al., 2023).

Finally, few studies incorporate explainability processes and confidence estimation into their CRS. For example, in the last year, interest in related studies has emerged; Shastri et al. (2025) took an explainable artificial intelligence (XAI) approach to their CRS to show which features led to which predictions, while Alam et al. (2025) provide uncertainty quantification as a method by which to ensure automated recommendations would be accurate. Yet both of these incorporate processes complicate CRS in the real world by adding computational burden and complexities for average farmers.

Thus, these gaps coalesce to suggest that multiple accurate CRS exist, but they need to appreciate scalability, interpretability and light efforts to deploy. Thus, this dissertation will aim to solve these needs by generating an accurate machine learning–based CRS with an intuitive framework for collaboration and easy deployment via a web-based application using Streamlit.

Chapter 3 – Methodology & Research Approach (CRISP-DM Framework)

The research followed the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology, which is widely adopted for data science projects due to its structured, iterative nature. The six phases — Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment — guided the development of the crop recommendation system from conceptualisation to implementation.

3.1 Business Understanding

This study was undertaken due to the necessity of developing a Machine Learning based Crop Recommendation System that could automate crop prediction for any given site condition with necessary factors including environmental data and soil quality since it would be more reliable than traditional knowledge or peer advice or what their peers suggest based on what they have seen over time. It would serve as a detailed decision support system project outcome based on scientifically proven, data-driven results which would then allow farmers to merge this information with their own experiences to use better resource management for improved yields. In the long run, the hope is to transfer such a systematic endeavor from feel to real to provide a more sustainable, ethical and effective approach to agricultural practice than mere t raditional intuitionand more reliable analytic precision.

The research aimed to accomplish two objectives. First, to develop a functional CRS through the application of advanced supervised machine learning techniques. Second, to assess both modeling accuracy and usability from a deployment perspective. Future developments can focus on IoT integration for real-time prediction, uncertainty quantification for user peace of mind, and lightweight deployment for easy application in low-resource environments. Such considerations would increase reliability, adaptability, and usability across various agricultural environments.

3.2 Data Understanding

The information for this project came from an open source repository of agricultural databases. The file is called *Crop_recommendation.csv* and has 2200+ records with 8 differentiating input attributes that reflect necessary environmental and soil conditions.

The attributes are as follows: Nitrogen(N) - nitrogen present in the soil (ppm); Phosphorous(P) - phosphorus present in the soil (ppm); Potassium(K) - potassium present in the soil (ppm); Temperature(°C) - temperature during the growing season; Humidity(%) - humidity during the growing season; pH - pH of the soil; Rainfall(mm) - amount of rainfall; Label - crop recommended based on other inputs.
To analyze the dataset, we started with a data exploration process to review data quality and summarize any constraints. Descriptive statistics were used to measure central tendencies based on numerical existence. A box plot was used for each feature to review observation outliers, and a plot was used to assess class distribution based on Label. This was important to determine whether the feature Label was imbalanced with too many potential crops and not enough conditions or the other way around. Ultimately, the dataset was found to be clean, without any missing values, outlier situations or constraints that would challenge quality. Thus, it was clear to proceed with preprocessing and model training without the need for additional datasets. Assessments of data understanding made the proper assumptions during model building and ensured that quality of the dataset would not interrupt learning.

3.3 Data Preparation

Before modeling, several preprocessing activities took place to standardize the input and output variables while ensuring everything was machine-readable. For instance, using scikit-learn's MinMaxScaler, all numerical features converted into a range of values between 0-1. This matters because without this transformation, certain features with broader numerical value ranges—such as rainfall or potassium—could distort the distance calculations by weighting some features heavier than others. For instance, K-Nearest Neighbours (KNN) relies heavily on distance calculations, when determining whether a potato is more similar to a potato than a corn, if one feature has 5000mg nitrogen value and one has 250mg, it matters that they are both measured against one another to limit potassium as the most distinguishing feature.

The initial dataset also includes the crops as labels in string format (i.e. "rice", "wheat"), which does not work for most classifiers as they cannot interpret text like humans. Therefore, using the map() function in Python, the labels were transformed into numerical values, creating a standard readable format for machines while allowing all models to have a consistent index for labels. Lastly, using Pandas' duplicated() method, the dataset was checked for duplicate rows and discovered there were none. The data types of the features were also examined to see if they conformed to the required numerical types for the models. A class distribution analysis confirmed that the dataset was relatively balanced across crop types, allowing for unbiased learning.

Although boxplots were used to visually assess the presence of outliers in each numeric feature, no removal was performed. This decision was based on the assumption that such extreme values could represent valid, real-world edge cases. Removing them might have adversely affected the model's ability to generalise to rare but important environmental scenarios.

After these checks, the dataset was split into input features (X) and target labels (y). A 70:30 train–test split was implemented using scikit-learn's train_test_split() function with a fixed random_state=0, ensuring reproducibility across model evaluations.

3.4 Modelling

Five supervised machine learning algorithms were implemented and comparatively analysed to determine the most effective model for crop recommendation. These included K-Nearest Neighbours (KNN), configured with $k = 3$ to perform distance-based classification by identifying the most similar training instances; Support Vector Classifier (SVC), using a polynomial kernel to capture non-linear boundaries between classes; Decision Tree Classifier, which relied on the entropy criterion to generate interpretable, rule-based decision trees; Random Forest Classifier, an ensemble of decision trees using bagging and a fixed random_state=1 to improve accuracy and reproducibility; and XGBoost Classifier, a high-performance gradient boosting algorithm optimised for speed, efficiency, and overfitting control. All models were trained on the scaled training data and evaluated against the test set derived from the 70:30 split. This modelling approach ensured a fair comparison of algorithmic performance and informed the selection of the most suitable model for deployment within the crop recommendation system.

These five algorithms were selected due to their strong performance in previous agricultural machine learning studies, especially those involving structured tabular datasets. Tree-based and ensemble models like Random Forest and XGBoost are well-suited to non-linear classification tasks, while models such as SVC and KNN serve as effective benchmarks for measuring baseline performance in classification.Model selection was also informed by findings from recent studies. Vyapari, Bhosale and Parkar (2023) reported Random Forest achieving accuracy rates exceeding 99% in comparative analysis, Shariff et al. (2022) demonstrated Gradient Boosting achieving over 98% accuracy, and Ferdib-Al-Islam et al. (2023) showed how integrating ensemble learning with feature importance improved interpretability in CRS. These findings collectively support the inclusion of ensemble methods within this modelling pipeline.

3.5 Evaluation

All models were assessed with classification metrics of Accuracy, Precision, Recall, and F1-Score. These metrics would show how effective the algorithm was and where any strengths or weaknesses lied in classifying the best crop based on given environmental factors. Accuracy is a measurement of all correct guesses made overall; it does, however, present a false sense of value regarding performance, especially in multi-class classification or class imbalanced situations. Thus, metrics in addition to accuracy were used such as precision (true positive / predicted positive), recall (true positive / actual positive), and F1 score (harmonic mean of the above). These additional metrics can provide clarity as to what's really going on under the hood based on the dataset. Scikit-learn's classification_report generated these additional scores required for seamless insertion across models.

In addition, the Random Forest Classifier was the best performing algorithm out of all tested algorithms for accuracy, precision, recall, and F1-score. Random Forest had a 99.55% accuracy score which outperformed XGBoost (99.09%) and Support Vector Classifier (98.79%) with Decision Tree and KNN falling close behind. These results were compiled into a comparison table for easy readability.

The Random Forest confusion matrix was assessed via a visual output. The confusion matrix assesses prediction performance on a class level which shows if any particular crops were misclassified more frequently than others. Many of the calculations were on the diagonal which indicates good accuracy per class and good separation between crops without too much confusion. This is a good indicator that the model would work well when introduced to new data.

Assessment aided in model selection for deployment as well. In the end, Random Forest would be deployed into production because it had the best accuracy/F1-scores but it was also an explainable algorithm that executed quickly, could be easily interpreted and used in low overhead scenarios like Streamlit. As such, deployment considerations swayed toward Random Forest as the best option for the real world use case of the CRS web app.

3.6 Deployment

The final Random Forest model as well as MinMaxScaler used to fit were saved as .sav files via joblib package so that they can be read and utilized without retraining. There is also a Streamlit web application developed as a lightweight front end for real-time crop prediction. The back end is purely Python and the emphasis on this web app focuses on ease of use for non-coder farmers and agriculturalists.

The front end possessed basic numeric input fields via textbox entries for all N, P, K, temperature, humidity, ph, and rainfall. Once these values were entered, the .sav scaler would be applied and the inputs would be pushed to the trained model to yield predictions. An easy "Predict" button facilitated the crop recommendation process, while the instantaneous output of the predicted crop name was displayed almost immediately after. To further reduce cognitive load for farmers, images of each crop were uploaded into the layout as well.

Streamlit was chosen for its ease of rapid web application development through a browser host without the need for overly complicated installations. This maintained a proper realistic deployment even through potentially low system capabilities with bandwidth access limitations. Thus, it works today as a web application hosted on localhost/server, when ideally it could be deployed in the cloud on Streamlit's host. Future iterations could create a responsive mobile web application, add smart integration through sensor-based input (soil probing devices or weather-related APIs), and include multilingual services in the web app as well. This would greatly enhance usability for various farming communities.

3.7 Ethical Considerations

Ethical considerations were made at every level of the creation and implementation process. For instance, the dataset used to train the models was gathered from an open data source that anyone could access online, and no personally identifiable information was involved, thereby lending support to privacy standards. Furthermore, since the system works independently and suggests only, it offers responsible use; the user at any point in time can decline the system's proposal as not the best answer.

Furthermore, the development stage acknowledged the bias of the dataset potentially. While various crops and circumstances are utilizable, the dataset may be biased geographically/contextually that makes it non-generalizable. Thus, this ethical concern is acknowledged in the developmental stage, and the next version of this system will take more region-specific datasets to eliminate this bias. Also, no XAI efforts are made. Still, awareness that XAI is necessary for ethical alignment shows that such transparency-based efforts will be part of this decision support system in the future.

Finally, from an environmental perspective, the CRS promotes sustainable farming efforts by suggesting more sustainable crops as per specific soil and climatic conditions for different lands. Having its purpose align with larger sustainability efforts promotes ethics in agricultural technological development. For instance, suggesting not-water-intensive crops reduces farmers' efforts for overgrowth if recommended crops require fertilisation or non-drought/out-of-drought areas grow too.

Chapter 4 – Results and Findings

4.1 Introduction

This chapter seeks to justify which model for the crop recommendation system generated the best performance thus far. Understanding where predictive quality lies relative to assessment metrics and implementation efficiency based upon field experience is important. Performance will be assessed relative to Chapter 4 where data preprocessing and modeling took place, meaning this chapter continues where the last one left off as four out of five of the applied supervised learning techniques were trained and tested in the previous section.

Comparison includes KNN, SVC, Decision Tree, Random Forest and XGBoost. Each model was implemented on the training dataset created from a 70:30 train-test split (scaling applied where necessary across various datasets) and measured on the testing validation set. Classification performance was assessed based upon the quality metrics of accuracy, precision, recall and F1-score. Accuracy states how often an assessment classification is correct. Precision assesses how reliable a positive prediction is when positive predictions are made, and whether positive predictions are relevant to that crop. Recall answers whether classifiers are determining every instance of every class in the aggregate assessment to validate those models which can positively predict outcomes for each unique crop class. Thus, in multiclass assessments, these three concepts champion specific reliability across the independent crop classes as opposed to general accuracy. For example, one can be highly accurate if one always predicts wheat and never fails to do so, yet that same model could constantly misclassify the other three options. Thus, positivity must reign in multiple situations.

Furthermore, beyond tabulated results over performance metrics, the confusion matrix assessed from the best confusion matrix allows for an overall understanding of how this model predicts cross-class. The confusion matrix is a visual assessment, allowing one to see beyond qualitative metrics why this model proposed success over the others relative to accuracy with correct predictions versus classification overlap; it doesn't only show that corn was misclassified twice, but that cassava and potatoes are often confused yet two different economic prospects within agricultural systems despite having similar input values.

The chapter ends with all compiled information across models compared for performance before justifying which model should be chosen for subsequent chapters. All information within this chapter will help inform Chapter 5 of deployment considerations based on accuracy and human-centric integrations.

4.2 Model Performance Comparison

Table 4.1: Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
K-Nearest Neighbours	98.18	98.35	98.18	98.20
Support Vector Classifier	98.79	98.81	98.79	98.79
Decision Tree Classifier	97.88	97.93	97.88	97.87
Random Forest Classifier	99.55	99.55	99.55	99.55
XGBoost Classifier	99.09	99.12	99.09	99.08

To determine whether the crop recommendation system was successful, 5 supervised learning models were developed and evaluated on the agricultural data set with required preprocessing. A 70:30 train-test split was used to ensure that the generalisation of each model would be determined in a non-biased fashion. In addition, before training the chosen models, MinMaxScaler was employed to scale the inputs so that all numerical input variables would be within the same range and not skew calculations based on those attributes with larger, more significant numbers.

The models were trained in a bubble, meaning each model trained independently of one another using the same training set and evaluated on the same testing set. This ensures a comparable approach to evaluating each model against each other. Ultimately, four classification metrics would determine the effectiveness of each model: accuracy, precision, recall, and F1 score. All metrics are commonly used in multi-class classification and determine how well a model identifies the target class while avoiding false positives and false negatives.

According to Table 4.1, all the models performed better than expected and accuracy values exceeded 97%. The best performing model overall was the Random Forest Classifier with the most consistent results across the four performance measures; accuracy, precision, recall and F1-score were all at 99.55%. This is an extremely effective model that accurately predicts crop classes and does so with very few errors, making it an ideal candidate for real-world applications for which recommendations will be made.

The second most successful performance during testing came from the XGBoost Classifier with 99.09% accuracy. Its gradient boosting methodology lends this model to being a very strong ensemble learner. Furthermore, it applies very well to complex patterns discovered in the dataset. However, Random Forest remained in first place due to it's more rapid training time and less sensitivity to hyperparameter tuning when testing for performance as compared to a second run.

After this, the Support Vector Classifier (SVC) came third in performance with 98.79% accuracy. This model is known for its non-linear decision boundaries through the use of kernel functions; however, it does not scale well for larger datasets and is computationally expensive during training and prediction.

K-Nearest Neighbours (KNN) came next with an accuracy of 98.18%, demonstrating a simplicity and applicability of the algorithm to this domain. However, it is a lazy learner and places more work on prediction time when the dataset grows; additionally, it does not provide feature importance and therefore lacks transparency.

Finally, the Decision Tree Classifier had the lowest performance of the five models overall with 97.88% accuracy. Although this method is completely interpretable and very fast in processing, its tendency to overfit data without regularisation or in ensemble methods may have contributed to this lower performance finding.

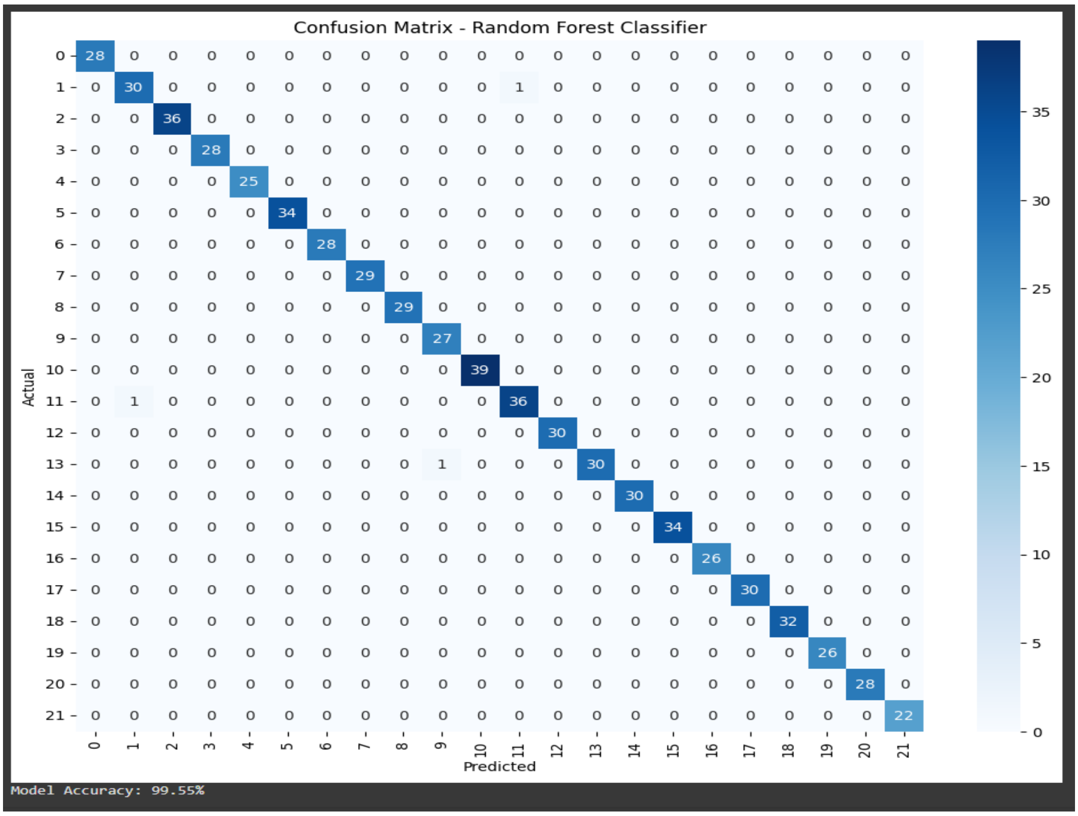
In addition to holdout testing, 5-fold cross-validation was applied to all models to confirm performance stability. Random Forest achieved the highest mean CV accuracy (99.55%), followed by XGBoost (98.83%) and SVC (98.05%). To further optimise performance, hyperparameter tuning was conducted using GridSearchCV. The best configuration for Random Forest (n_estimators=200, max_depth=None, min_samples_split=5, min_samples_leaf=1) achieved a mean CV accuracy of 99.55%, consistent with the baseline model, showing that the default parameters were already close to optimal. For SVC, tuning with C=10, kernel=rbf, and gamma=scale improved accuracy from 98.05% to 98.64%. These results confirm Random Forest as the most accurate and stable model for deployment.

Ultimately, comparisons showed that ensemble methods perform better than single trees in consistent efficiency and generalisation applicability, while Random Forest performs better than the other ensembles in training speed, interpretability and non sensitivity to overfitting. Therefore, Random Forest was chosen as the final crop recommendation system due to its robustness and ease of training thereafter.

4.3 Confusion Matrix Analysis

To further evaluate the classification capability of the best-performing model, a confusion matrix was generated for the Random Forest Classifier which was shown in Figure 4.1.

Figure 4.1: Confusion Matrix – Random Forest Classifier



Finally, the confusion matrix supports model efficacy with a visual representation of what it predicted versus crop labels. A confusion matrix represents an ideal scenario where predicted values fall into a dense diagonal pattern. Each row represents actual class, and each column represents predicted class. Therefore, ideally, all non-zero columns fall on the diagonal whereby the model predicts every occurrence correctly and none incorrectly. The Random Forest model displays this dense diagonal quite prominently, justifying its capacity to classify a multiclass model with practically no error.

Further, upon further analysis, there exists such minimal false positives and false negatives that not only can one assume great accurate aggregate accuracy levels predicted but also great accuracy at class-level accuracy because no one crop label is more erroneous than any other. This is critical because if this recommendation tool suggests the wrong crop—and often—crop will die or resources will be wasted or people will be impoverished because based on some erroneous suggestion dedicated resources to a crop that is not suitable, it's good to know that this recommendation rarely happens.

Where it did occur, it was often among crops that had similar growth characteristics and requirements. For example, if lentil and mungbean were supposed to go one way instead of the other, it was because they have similar dynamics regarding water and nutrient intake which allows for an almost blended prediction to be correct. These are the problems with multiclass classifications; often times, overlapping feature distributions are commonplace in the agricultural setting.

Moreover, the confusion matrix indicates that class dominance was not present within anything noted. Typically, within multiclass classification problems, there has historically been class dominance due to over-prediction based on majority classes. For example, it would be important to someone that they predict Class A 900 times but only predict Class C 10 times. Here, the distribution of correct predictions was relatively even with respect to no class dominance noted. This is important because it means the model is not subject to class imbalance issues which validates both the dataset used and how effective Random Forest can be for this algorithm.

Thus, the confusion matrix serves as another validation piece because what was determined high accuracy scoring through previous parts was not arbitrary, outlier behavior or overfitting, but rather consistent reliability across all crop categories making for increased recommendation system deployment factors.

4.4 Interpretation of Results

The reason the Random Forest Classifier performed better than every other model explored has to do with its ensemble nature, allowing for the sum of multiple decision trees classified via a majority vote. This occurs due to less overfitting from averaging across different decision boundaries which improves generalisation on subsequent unseen datasets. Furthermore, Random Forest has a built-in mechanism for feature importance assignment and measurement, allowing for better interpretability and distinction in which variables most influence crop recommendations—fertilizer nitrogen, rainfall, and temperature levels. Increased interpretation not only increases model trustworthiness but also allows for explainable AI capabilities down the line.

In addition, Random Forest is computationally efficient during training and predicting which is crucial for real-time advising systems. It also reliably performs with new features or excess noise because its classification threshold works despite somewhat blurred data boundaries. This is important to note in real-world agricultural settings where data collected from real world sensors or human input may not always be precise.

Another family member of ensemble learners XGBoost, was the second best performer with slightly less accuracy than Random Forest. XGBoost is a gradient boosting algorithm that builds out trees iteratively such that once the first tree builds, the second tree attempts to adjust any incorrect classifications from the first tree and so on. The resulting architecture tends to yield very strong accuracy capabilities. However, XGBoost is highly sensitive to hyperparameter adjustments and can be computationally intensive with larger datasets. Therefore, while it's a solid choice for high-performance implementation scenarios, it's challenging in rapid deployment scenarios where simplicity and stability may be preferred.

The Support Vector Classifier (SVC) was mediocre as well; kernels were used to capture non-linear relationship in the feature space however, reliance on support vectors and quadratic one-at-a-time optimisations make prediction slow in relation to scaling datasets.

Therefore, SVC is not recommended for low-latency predictions and would likely fail on low-compute devices like mobile phones or embedded devices as well.

K-Nearest Neighbours (KNN) performed reasonably but only due to its lazy learning abilities, meaning no generalised model is created during training. During prediction, KNN only computes distances to all training examples making it memory intensive and slow for prediction meaning all training data must be kept in memory during processing. This limits its usefulness for real-time systems. Also, similar to SVC, KNN has no internal relevance mechanisms rendering explainability efforts moot for interpretable systems should that be a requirement.

Finally, the Decision Tree Classifier had the statistically lowest performance relative to all other five classifiers tested in this study. Although it's highly visual and interpretable at the same time, it suffers from overfitting problems and lacks generalisation without pruning or ensemble approaches. Its lower performance relative to these results shows the advantage of combining multiple weak learners to create a more accurate predictive result in a more complex, multi-class scenario like crop classification.

Ultimately, the findings of this study corroborate much of what is found in widely used literature; ensemble models—most of all Random Forest—find the best balance between accuracy, generalisation of unseen datasets/subsequent accelerated features, interpretability efforts in both training and predicting situations, realistic implementation opportunities based on sensitivity assessed across the other classifiers. Their robustness makes them viable within practical parameters that need to be met within variations of environmental circumstances where agricultural recommendations will lie.

4.5 Summary

This chapter showcased the findings of an extensive model assessment experiment involving five supervised machine learning algorithms applied to the proposed crop recommendation system. KNN, SVC, Decision Tree, Random Forest, and XGBoost were generated from the same agricultural dataset, trained on 70% and 30% testing, and a uniformly applied feature scaling technique; all models were assessed based on accuracy, precision, recall, and F1 score—all standard classification measures.

The aggregated results indicated that the Random Forest Classifier outperformed all other models with 99.55% accuracy, precision recall, and F1 score. The model illustrated not only an effective prediction capability but generalisation without an overfitting propensity. The confusion matrix suggested trained performance was not contingent upon specific learned classes, either. The Random Forest model held steady across all crops, illustrating only a few misclassifications between comparable crops—one instance of misclassification despite many guessing opportunities.

The second-best model was XGBoost, which held a less-than-accurate percentage but greater complexity of implementation and hyperparameter tuning. SVC and KNN fell in the next tier, demonstrating over 98% accuracy and precision but rough scaling and inference times less desirable for real-time performance. Finally, although the Decision Tree model did not fare well, it demonstrated better interpretability, an anomaly for machine learning suggestive of an incorrect assumption that single learners could better facilitate less than overfitting with the correct tests, yet they could not survive multidimensional hyperparameter searching in multilabel, multi-class environments.

Thus, this chapter not only supported common conclusions found in agricultural AI research from 2020 onward but confirmed that the error-resilient real-world application problem-solving potential from similar classification endeavours was successful due to ensemble learning techniques. Therefore, the Random Forest Classifier would be the best choice to implement into the crop recommendation system, as it possessed the great balance of results performance and practically reliable usability.

Thus, the results of this chapter will contribute to Chapter 5's reasoning for implementing this work's design since the selected model is integrated into a working web-framed system. This chapter aims to substantiate artefact efficacy before real-world use as an informative decision-support system for agricultural endeavours.

Chapter 5 – Discussion

5.1 Introduction

This chapter will discuss the results in detail relative to fourth chapter findings as they stand from a technical realization and contextual perspective. Analysis of machine learning model performance will be measured against accuracy, precision, recall and F1-score as well as interpretability and deployability in the real world within an agricultural setting. Therefore, while findings of the Random Forest model performing the best will be discussed in terms of interpretability and margin of error, all other models—K-Nearest Neighbours, Support Vector Classifier, Decision Tree, and XGBoost—will be assessed with pros and cons as well.

The justification for the results will be relative to the literature review and prior studies to either validate relative success or failure compared to this research findings. In addition, this chapter will seek to validate results and relative success/failure compared to other research projects and crop recommendation systems and discuss why certain paths were taken and how successful they were relative to other findings. This chapter will also clarify any questions learned slowly throughout the process regarding the end-user experience for small to medium sized farmers who could rely upon such a system before planting in a growing season. It is hoped this will validate the need for such a system and the perceived and actual value it could bring to a region focused on socio-economic equity and sustainability efforts.

Ultimately this chapter will detail the challenges faced when finalizing the implementation of the system—even potential pitfalls of error—and provide recommendations for future development efforts such as uncertainty estimation, explainable AI, mobile deployment and IoT compatibility. Finally, this chapter will seek to position this project not just as empirically sound but also as having the potential for expansion for further socio-technical relevance.

5.2 Interpretation of Results

The distinctions between the five supervised machine learning classifiers in prediction accuracy and potential for implementation were apparent. The Random Forest Classifier was rated during testing for the best overall success across the board, including mean accuracy (99.55%) for prediction accuracy, precision, recall, and F1 score. These results are not surprising given that the Random Forest Classifier is an ensemble of decision trees, which, through the natural resampling of creating trees, provides a more reliable and less overfitted model. Its ability to understand non-linear dynamics, correctly avoid biases in high-dimensional spaces while maintaining generalisation and working with structured datasets typical in agricultural efforts makes the Random Forest approach suitable for use with this data. Its interpretability and minimal inference time—through a less complex model structure—make it the most feasible for implementation as a locally-trained and web-accessible light interface (via Streamlit).

The second-place finisher is the XGBoost Classifier, achieving similarly effective results (accuracy: 99.09%) and generalisation abilities. XGBoost provides rapid-fire classification through an effective approach, although it often requires excessive hyperparameter tuning and component interpretability is less favoured than Random Forest; yet, despite its extensive accuracy and efficacy, it was not chosen for deployment to favour the usability and transparency of the project.

The Support Vector Classifier (SVC) and K-Nearest Neighbours (KNN) both reached relatively high predictions (98.79% and 98.18%, respectively); however, the likelihoods of real-time implementation reduce their ability for time-effective predictions. The SVC predicted using a polynomial kernel, but generally, it requires excessive computational resources which reduces its scalability for extensive data investigations. On the other hand, KNN operates as a lazy learner that does not learn until prediction time; thus, excessive lag time could impede recommended results during real-time implementations. Therefore, while both classifiers possess great efficacy in non-implementation applications, they favour virtually intuitive predictability without the need for extensive resources/resources and real-time prediction needs.

The Decision Tree Classifier possessed the lowest mean performance (accuracy: 97.88%) compared to classification accuracy when operating as a single entity; it can become over-fitted based on training selections and lacks ensemble effectiveness to make it stronger. However, Decision Trees are understandable and predictable methods by themselves, but in comparison to Random Forest or XGBoost, they become weaker.

Ultimately, the findings reflected expected performances from the associated literature; ensemble classifiers provide greater classification accuracy for agricultural inquiries than singular components. Furthermore, the little variation across means demonstrated an effective dataset structured for classification suitability, supporting effective functionality from the preprocessing pipeline. Therefore, the Random Forest Classifier is the best anticipated for trading accuracy for efficiency and implementation feasibility within a crop recommendation system.

5.3 Comparison with Literature

The results of this study are consistent with the broader findings of the machine learning agricultural research community, particularly in the development of crop recommendation systems (CRS). Ensemble methods continue to dominate, with Random Forest and XGBoost regularly outperforming individual classifiers in crop classification tasks. Vyapari, Bhosale and Parkar (2023) reported Random Forest achieving accuracy rates exceeding 99% in comparative studies, while Shariff et al. (2022) and Ferdib-Al-Islam et al. (2023) highlighted the strong performance of ensemble-based systems across diverse datasets. The findings of this dissertation reconfirm that Random Forest is a reliable classifier for CRS and well-suited for deployment scenarios where efficiency, scalability, and interpretability are critical.

This study also employed XGBoost, which demonstrated competitive accuracy, in line with recent literature. Shastri et al. (2025) combined Gradient Boosting with explainable AI (XAI) to provide not only high accuracy but also interpretability, showing how model transparency can enhance user trust. Similarly, Shams, Gamel and Talaat (2024) integrated explainability into CRS frameworks to improve usability. Although the prototype presented in this dissertation does not include XAI, the success of XGBoost in this study suggests that future iterations could incorporate explainability or uncertainty quantification techniques (Alam et al., 2025) to enhance farmer trust. Nevertheless, Random Forest remained the preferred algorithm for this project due to its shorter training time, interpretability compared with boosting methods, and seamless integration with the Streamlit web framework.

In terms of deployment, the findings align with recent CRS studies that emphasise accessibility and usability for end-users. Balakrishnan et al. (2023) demonstrated the feasibility of embedding ML models in mobile-friendly interfaces, while Ferdib-Al-Islam et al. (2023) highlighted the importance of feature importance visualisation for improving usability. The Streamlit-based application in this project similarly addressed these issues by providing a user-friendly interface that delivered straightforward crop recommendations, making the system more transparent and accessible to non-expert users. This approach addresses a common limitation in prior work, where models are often presented as black-box solutions without clearly defined user interfaces.

Benchmark comparisons also validate the performance trends observed in this research. Agarwal et al. (2024) demonstrated that simpler algorithms such as K-Nearest Neighbours (KNN), Decision Trees, and Support Vector Classifiers (SVC) can achieve good accuracy but often underperform in terms of efficiency or scalability. This mirrors the results of the present study, where KNN and SVC achieved competitive test-set accuracy but proved less efficient for deployment compared with ensemble methods. Decision Trees, while interpretable, were more prone to overfitting, consistent with findings in earlier studies.

A further contribution of this dissertation is its detailed documentation of data preprocessing procedures, including MinMax scaling and categorical label encoding, which are often overlooked in published work but are essential for replicability and consistent model performance.

Ultimately, this research supports the prevailing conclusion in the literature: ensemble methods, and Random Forest in particular, are the most practical solutions for crop recommendation. Beyond achieving high predictive accuracy, this dissertation extends prior work by delivering not only a trained model but also a user-facing deployment tool. By integrating model training, web interface development, and accessibility considerations, this study contributes to bridging the gap between laboratory performance and real-world usability in low-infrastructure agricultural contexts.

5.4 Practical Implications

There are significant implications for the successful implementation and use of a machine learning-driven Crop Recommendation System (CRS) based on this research. Where developing countries are concerned, often there are only years of historical data on which to make decisions or what extension agents may be able to provide suggestions. Accomplishing assisted crop recommendation based on nitrogen, potassium and phosphorous levels, moisture, precipitation, growing temperatures and acidity levels will give these small- and medium-sized farmers greater yields from more efficient planning of effective growing execution. Therefore, for small- to medium-sized ag professionals without access to this information, at best, the crop recommendation system will prevent over fertilization and under fertilisation, off crop diagnosing and help improve resiliency to an otherwise tumultuous climate plan.

The fact that the deployed model relies upon basic environmental considerations at the low end creates assumptions that deployment and expansion is easy. No hardware, sensor networks or computational powers are needed which makes this a feasible operation in resource-poor situations. Additionally, placing the model onto a Streamlit web app makes it lightweight and smartphone browser or low-power computer front end accessible. This is in contrast to many of the complex, high-performing ML models created that exist on high-power computers and never leave the lab.

Furthermore, as those in rural environments may have trepidations working with something electronic beyond their control, the existence of such a model that creates repeatable outcomes builds trust within non-technical populations. A simple interface with a repeatable outcome will empower these farmers to accept such technology and ease the fearful response people might have when first experiencing something foreign. Reliably trusted outcomes are essential for sustainable efforts of commercial agriculture in underserved markets.

Finally, there are global consequences for commercial sustainability efforts as those most recommended will not overuse watering systems or fertilization efforts and this will put such populations on a path of guaranteed environmental responsibility. For any governmental agency, non-governmental organizations or agri-tech start up projects, something like this could be internalised into a digital decision-making framework or disbursed via digital community-based standards.

There is also the potential for deep integration into governmental/regional agricultural extension offices as a government official decision-making advisor could input this system into their infrastructure for crop determination with a region-wide accepted standard without needed input from human collaboration. It could also be used in educational settings as an example of learning.

Ultimately, throughout this research such an artefact creates not just a proof-of-concept but a ready-to-use tool that is practical, deployable, interpretable, and accurate and few systems merge all four approaches where agriculture ML projects are concerned. Therefore, continued evaluation with major localization will ensure that this CRS can extend data-driven decision-making to the populations that need it most and contribute to long term food security initiatives for the region. Language support features or voice-answer options could enhance accessibility for those in diverse communication areas or those with limited reading abilities.

5.5 Limitations

Yet there are limitations to this study. First, the crops surveyed are a relatively small sample size which does not allow for the models transferability to other regions or farming scenarios. Second, the model is based on earlier data and does not update itself with real-time temperature and other environmental changes which may render it less useful if environmental changes occur quickly within a short period of time. Finally, the list of features includes just seven environmental factors and incorporating other potentially profitable factors like soil moisture or sunlight hours could improve accuracy in the future

5.6 Future Work

Nevertheless, despite the accuracy and successful application of the CRS created to date, there's much potential for expanding functionality, usability, and flexibility in subsequent releases. For starters, one vital feature would be real-time data collection via IoT sensors and app-based entry. Currently, users are responsible for inputting soil nutrients and climate conditions; should these come up automatically via connected sensors, it would relieve challenges with input integrity and allow the CRS to expand better in field applications.

This could be further improved with Explainable AI (XAI) features. While Random Forest is a transparent model of choice for output, as it can show feature importance, this information does not get transferred to the end user. Applying SHAP or LIME to the UI could visually display how features were weighted based on environmental conditions to arrive at a particular crop recommendation.

Another major improvement comes in terms of language translation and voice output.

This is the type of tool used in countries' more rural areas, where much of the population is illiterate; localization would make such systems more omnipresent wherever agriculture exists. An offline or SMS-based version would help, too, for regions with little to no hot-spot access.

Additionally, from a modelling perspective, cross-validation and hyperparameter tuning will lead to a more generalizable model at the time of initial training; training and testing on different international datasets will lead to a more comprehensive generalizability, wherein additional features—like market demand, profitability, or prevalence of pests—can make rec recommendations more comprehensive and relevant for best decision-making purposes.

Integration or trading of APIs with external resources would help as well—regional weather services, soils and pests databases, or governmental agricultural services—wherever feasible. APIs would allow inputs to update dynamically, rather than rely on static entry, from soil-air-plant-region conditions. An API with a live pest advisory for agricultural services could help inform the CRS recommendation with real-time pests nearby.

As AI regulation grows over time, iterations may consider utilizing frameworks for ethical AI auditing or transparency standards if applying at scale. The EU AI Act—and soon to follow efforts for local-relevant guidelines—may change the recommended application in nonpersonal settings altogether.

Finally, iterations may have access to user tracking and feedback loops or usage statistics which suggest how often farmers use the tool. Over time, this could transform the CRS from a static model to an increasingly efficient decision support system aligning with current and fluid agricultural needs.

5.7 Summary

This chapter synthesized the results of the research and implementation of five ML models developed with crop prediction in mind. Of the five, the most logical to deploy was the Random Forest Classifier, which yielded an accuracy commensurate with its ease of use. The determined accuracy validates claims made by literature in the field that ensemble methods tend to yield better results than singular classifiers with agricultural data sets (Vyapari, Bhosale & Parkar, 2023; Ferdib-Al-Islam et al., 2023; Shariff et al., 2022) and that Random Forest edged out Gradient Boosting by a hair. Random Forest was also chosen with deployment intent in mind; it requires fewer calculations and can be easily interpreted and replicated within a deployment structure, lending itself to justification and explanation to end users in the real world.

Thus, while accuracy is an important aspect of machine learning legitimization, it's not the only one. For instance, this dissertation created a prototype web application on Streamlit to demonstrate how CRS established from scratch could realistically be deployed in a setting accessible to layman end users, for example, farmers. While other dissertations created web apps for their assessment purposes (Balakrishnan et al., 2023; Shams, Gamel & Talaat, 2024), none focused on resource accessibility and consequential return on investment; such findings here would imply that such logistical concerns are just as valuable—and potentially more so—than purely algorithmic feats for effectiveness and should be taken into consideration when upscaling systems.

The limitations of this project include research and reliance on static data, lack of Explainable AI integrations, and limited capabilities for real-time integration. These findings confirm earlier gaps noted by prior research on CRS (Alam et al., 2025; Shastri et al., 2025) and open the door for future research to fill such gaps. It is recommended to include uncertainty quantification, predictions for future trading data, real-time fluctuation of sensor data accompanied by Explainable AI methods of processing to validate findings further with users.

In summation, this dissertation proves that Crop Recommendation Systems are feasible not only from a technical perspective but also as a decision-making system for deployment by assessing machine learning endeavors, agricultural decision-making equity, and possible future non-technical end-user interfaces to bring this study from theoretical approaches to practical ones for possible recommendations. This outlook, interdisciplinary in nature, shows that by closing the gap between educated research and practical application on the agricultural field level, sustainable agriculture can benefit now and in future.

Chapter 6 – Conclusion and Future Work

6.1 Conclusion

The goal of this dissertation was to create, optimise, and deploy a machine learning–based crop recommendation system that provides farmers with reliable, data-driven recommendations based on soil and environmental conditions , in order to reduce crop failure. By offering an inexpensive, easily deployable solution , this dissertation project addressed shortcomings of intuitive agricultural decision-making alone.

The solution came from a stepwise approach following the stages of CRISP-DM—business understanding, deployment, data preparation—and culminated with the training of five supervised machine learning techniques on a public dataset: K-Nearest Neighbours, Support Vector Classifier, Decision Tree, Random Forest, and XGBoost. Random Forest was chosen as the optimal final model through comparative evaluation techniques holdout testing and the inclusion of cross-validation as well as hyperparameter tuning confirmed the robustness of Random Forest, ensuring that the selected model was not only accurate but also stable across folds and parameter settings, also its accuracy was 99.55% for both, it yielded positive precision/recall/F1 score averages across classes, and it was best suited for deployment based on a non-complex structure for future application.

The embedded application was created using a Streamlit framework which successfully brings the trained machine learning model into a web-facing application for farmers. Users only need to enter their soil nutrient levels and climate characteristics to receive precise recommendations based on an instantaneous response time. Accordingly, deployment considerations revolved around minimalism, easy access, low-resource use, practical naive user interface in constrained environments.

The practicality of this project provided a valuable means to apply machine learning concepts to a tangible solution to a socially-focused problem. Deployment efforts bridged the gap between a trained model and tangible realism for application in that the Random Forest was serialized into multiple files and integrated within the designated interface as a new layer of functionality above trained purposes. Often times effectively trained models fall short if they cannot be integrated into an easily understood application for their intended purpose; thus my experience focused on additional aspects after training concerning accessibility and deployment considerations feasibility. Lastly, those who seek to contribute to interdisciplinary research between artificial intelligence, sustainable agriculture and human-centred computing will value this project. Efforts to implement focused on data-efficient farming from sustainability standpoints and alternative environmental concerns and inclusive, user-centred design.

6.2 Research Contributions

This research contributes not only to academic knowledge but also directly supports farmers, aligning with the objectives of developing a system and providing a practical decision-making tool.First, it offers a functional crop recommendation system with high rate of accuracy classification in a simple interface that can be easily deployed and not only abstracts the theoretical modelling but provides the expectation of application as well.

Second, it supports the claim that ensemble methods, such as Random Forest, are transferrable to agriculture-related datasets with a decent level of confidence, adding to the growing body of literature that supports the claim. In addition, it offers a repeatable, templated process from pre-processing to deployment that future researchers can merely replicate or build upon.

Third, it champions accessibility by delivering a lightweight, web-based system that appeals to farmers operating in resource-poor settings. Very few studies cite a completed deployment pipeline in addition to testing algorithms on real-world grounds.

In addition, it acts as a project case study for student and teacher alike in the data science, sustainable agriculture and applied machine learning fields. With a completed pipeline, it acts as a pedagogical tool with real-world applications and eventual deployment to guide other similar projects.

Fourth, it relies upon open-source projects and publicly available datasets, adding to the transparency, replicability and accessibility of machine learning project creation—a move toward best practices for ethical AI studies.

Finally, this is an interdisciplinary contribution—machine learning, agriculture, sustainable efforts and digital accessibility—blended into one project. It shows what is possible when efforts to create an ethical project are applied.

6.3 Future Work

Yet even with an effective crop recommendation system and performance, there is always room for adjustments with future development iterations. Future developments could include real-time integration from IoT sensors, explainable AI components and a more trained dataset to include crops from around the world in addition to other datasets.

In addition, an improved user interface would allow for easier integration—multi-lingual capabilities, offline or mobile access. Future developments could allow for more integrations to API of other external data sources, such as local weather stations or pest alerts, to create a more holistic and informed recommendation.

As the law surrounding the governance of AI technology improves, future iterations need to be aware and compliant with laws governing data collection, storage and ethical AI use. Additionally, providing a feedback loop for users—farmers and agricultural extensions—could allow for further adjustments to the system based on what's effective in practice.

Future developments could include a localization pipeline that allows for re-training or fine-tuning on new regional datasets. Such a functionality would allow the CRS to dynamically learn about regional soil differences, changing seasonality and crop availability making it relevant in multiple geographic areas.

Finally, the academic literature goes further in suggesting the potential inclusion of market pricing, companion crops and pest resilience forecasts that would make future iterations even more thorough as decision support systems.

6.4 Final Remarks

The main research question posed throughout this dissertation was: How accurately can a machine learning model recommend suitable crops based on soil conditions such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, and environmental factors such as Temperature, Rainfall and Humidity, in order to reduce crop failure?

The findings suggest that the Random Forest was the most accurate model at 99.55% predictive accuracy, with the XGBoost model following closely behind at 99.09% accuracy. All other models employed showed high precision levels, precision, recall, and F1-scores across the multiclass levels due to varying crop types. Therefore, machine learning is a feasible solution for reasonably recommending viable crops given varying soil and environmental factors. Therefore, the research question is answered positively, and the findings support progress towards implementation in-field decision-making solutions that can provide educated crop recommendations for farmers' fleets, which should reduce crop failures. Accordingly, both research objectives were achieved, a machine learning–based crop recommendation system was successfully developed and optimised, and the system was deployed as a practical web application that can support farmers in making sustainable crop choices.

Therefore, the dissertation indicates that machine learning-based crop advisory systems are technically achievable and beneficial for small and medium farmers where the contribution potential exists and grows over time. Currently—if not into the foreseeable future—these systems encourage crop variety and better production in controlled environments without human error. Machine-processed information allows for resource management on a micro level while simultaneously aiding macro efforts in regional sustainability and food security.

The artefact produced is not a mere proof of concept; it is a scalable, transferable prototype, all the more feasible since development considered real-world application and end-user wants. As extrinsic pressures continue to plague all within the agriculture community—which can include climate change, soil depletion and varying economics—this intelligent system developed in this dissertation is but one way to enhance an otherwise challenged farming community with a more informed population.

For anyone else interested in adopting this system based on this dissertation, the trained artefact is open-source for application. Future iterations would ideally collaborate with local crop specialists, NGOs, or ag-tech startups to transition the advisory artefact into an advisory system in agriculture. The thought process applied throughout is transferrable to similar advisory systems in educational environments, healthcare or environmental conciliations.

In the end, this advisory system helps agriculture digital transformation become reality. As a baseline effort for providing open-access intelligent decision-support systems, similar efforts can be disseminated to make intelligent systems become the framework for sustainable, agricultural generations to come.

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APPENDIX

SCREENS AND DESCRIPTION OF PYTHON CODES

This appendix presents key development screens and code implementations for the Crop Recommendation System (CRS), highlighting essential stages from data preprocessing to model deployment using Streamlit.

Figure A1: Data Exploration and Preprocessing

```
import pandas as pd

d=pd.read_csv('/content/drive/MyDrive/Dissertation Dataset(DBS)/Crop_recommendation.csv')
d
```

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
...	...	...	...	...	...	...	...	...
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

2200 rows × 8 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   N            2200 non-null   int64
 1   P            2200 non-null   int64
 2   K            2200 non-null   int64
 3   temperature  2200 non-null   float64
 4   humidity     2200 non-null   float64
 5   ph           2200 non-null   float64
 6   rainfall     2200 non-null   float64
 7   label        2200 non-null   object
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB
```

```
class_counts = df['label'].value_counts()
print(class_counts)
```

```
label
rice           100
maize          100
chickpea       100
kidneybeans    100
pigeonpeas     100
mothbeans      100
mungbean       100
blackgram      100
lentil         100
pomegranate    100
banana         100
mango          100
grapes         100
watermelon     100
muskmelon      100
apple          100
orange         100
papaya         100
coconut        100
cotton         100
jute           100
coffee         100
Name: count, dtype: int64
```

```
display(df.describe())
```

	N	P	K	temperature	humidity	ph	rainfall
count	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000
mean	50.551818	53.362727	48.149091	25.616244	71.481779	6.469480	103.463655
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938	54.958389
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.211267
25%	21.000000	28.000000	20.000000	22.769375	60.261953	5.971693	64.551686
50%	37.000000	51.000000	32.000000	25.598693	80.473146	6.425045	94.867624
75%	84.250000	68.000000	49.000000	28.561654	89.948771	6.923643	124.267508
max	140.000000	145.000000	205.000000	43.675493	99.981876	9.935091	298.560117

This step involved loading the crop dataset and performing an initial exploratory analysis. The functions .info() and .describe() were used to inspect the structure and statistical distribution of the data, while .value_counts() was applied to examine the frequency of categorical values. Null checks were conducted to verify the completeness of the dataset and confirm its suitability for machine learning. Additionally, class balance was assessed, and it was found that the dataset is balanced across the target categories.

Figure A2: Label Encoding

```
df['label'].unique()
```

```
array(['rice', 'maize', 'chickpea', 'kidneybeans', 'pigeonpeas',
       'mothbeans', 'mungbean', 'blackgram', 'lentil', 'pomegranate',
       'banana', 'mango', 'grapes', 'watermelon', 'muskmelon', 'apple',
       'orange', 'papaya', 'coconut', 'cotton', 'jute', 'coffee'],
      dtype=object)
```

```
df['label']=df['label'].map({'pigeonpeas':0,'jute':1,'mothbeans':2,'mango':3,'watermelon':4,
                             'chickpea':5,'cotton':6,'mungbean':7,'coffee':8,'maize':9,
                             'papaya':10,'rice':11,'banana':12,'blackgram':13
                             ,'muskmelon':14,'orange':15,'kidneybeans':16,'grapes':17,'pomegranate':18,
                             'coconut':19,'apple':20,'lentil':21})
```

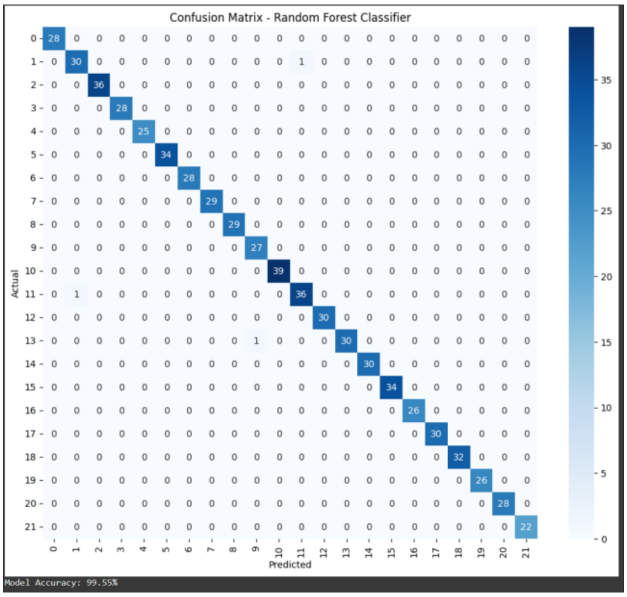
Since crop labels were in text form, they were converted into numerical format to allow supervised machine learning algorithms to interpret them correctly. The map() function was used to assign each unique crop a corresponding numeric label, ensuring compatibility with classification models.

Figure A3: Model Training Comparison

```
Model Performance Comparison:
                         Accuracy  Precision     Recall   F1 Score
KNeighborsClassifier    98.181818  98.354146  98.181818  98.195381
SVC                     98.787879  98.808784  98.787879  98.788030
DecisionTreeClassifier  97.878788  97.949220  97.878788  97.872025
RandomForestClassifier  99.545455  99.550866  99.545455  99.545590
XGBClassifier           99.090909  99.121459  99.090909  99.083965
```

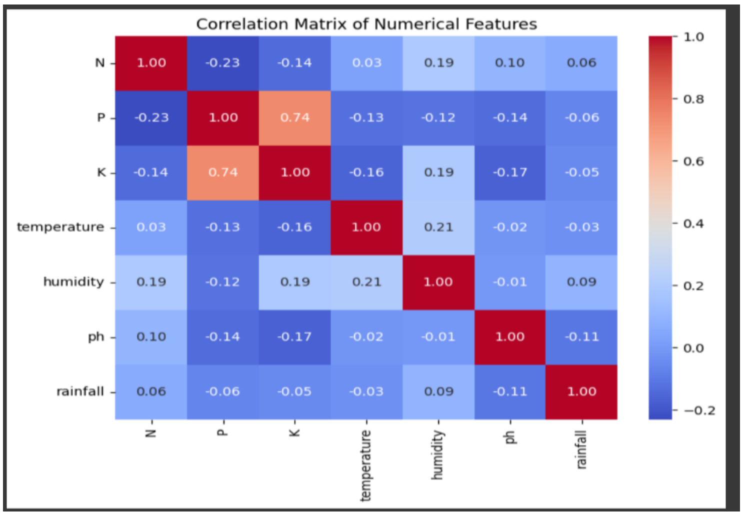
Multiple supervised learning algorithms were trained and evaluated, including KNN, SVC, Decision Tree, Random Forest, and XGBoost. Their performance was compared using standard evaluation metrics to determine the most accurate and reliable model for deployment.

Figure A4: Confusion Matrix – Random Forest



The confusion matrix for the Random Forest model illustrates how well each crop class was predicted. The matrix showed strong diagonal dominance, indicating high accuracy and minimal misclassifications. This validated the model's suitability for multi-class agricultural classification.

Figure A5: Correlation Matrix of Numerical Features (N, P, K, pH, temperature, humidity, rainfall).



This heatmap illustrates the correlation among numerical features in the dataset. Phosphorus (P) and Potassium (K) show the highest positive correlation (0.74), while most other variables exhibit weak correlations. These insights confirm that the dataset has low multicollinearity, which supports the reliability of machine learning classification.

Figure A6: Cross-validation results showing mean accuracy and standard deviation for each model.

```
#Cross-Validation
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
import numpy as np

models = {
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "KNN": KNeighborsClassifier(),
    "SVC": SVC(),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='mlogloss', random_state=42)
}

for name, model in models.items():
    scores = cross_val_score(model, X_train, y_train, cv=5, scoring='accuracy')
    print(f"{name}: Mean CV Accuracy = {np.mean(scores)*100:.2f}% (+/- {np.std(scores)*100:.2f}%)")
```

```
Decision Tree: Mean CV Accuracy = 98.25% (+/- 0.84%)
Random Forest: Mean CV Accuracy = 99.48% (+/- 0.33%)
KNN: Mean CV Accuracy = 97.73% (+/- 0.21%)
SVC: Mean CV Accuracy = 98.05% (+/- 0.98%)
XGBoost: Mean CV Accuracy = 98.83% (+/- 0.60%)
```

This code snippet demonstrates the implementation of 5-fold cross-validation for five supervised machine learning algorithms: Decision Tree, Random Forest, K-Nearest Neighbours (KNN), Support Vector Classifier (SVC), and XGBoost. The results show that Random Forest achieved the highest mean cross-validation accuracy (99.48% ± 0.33%), confirming its robustness and suitability for deployment compared to other models.

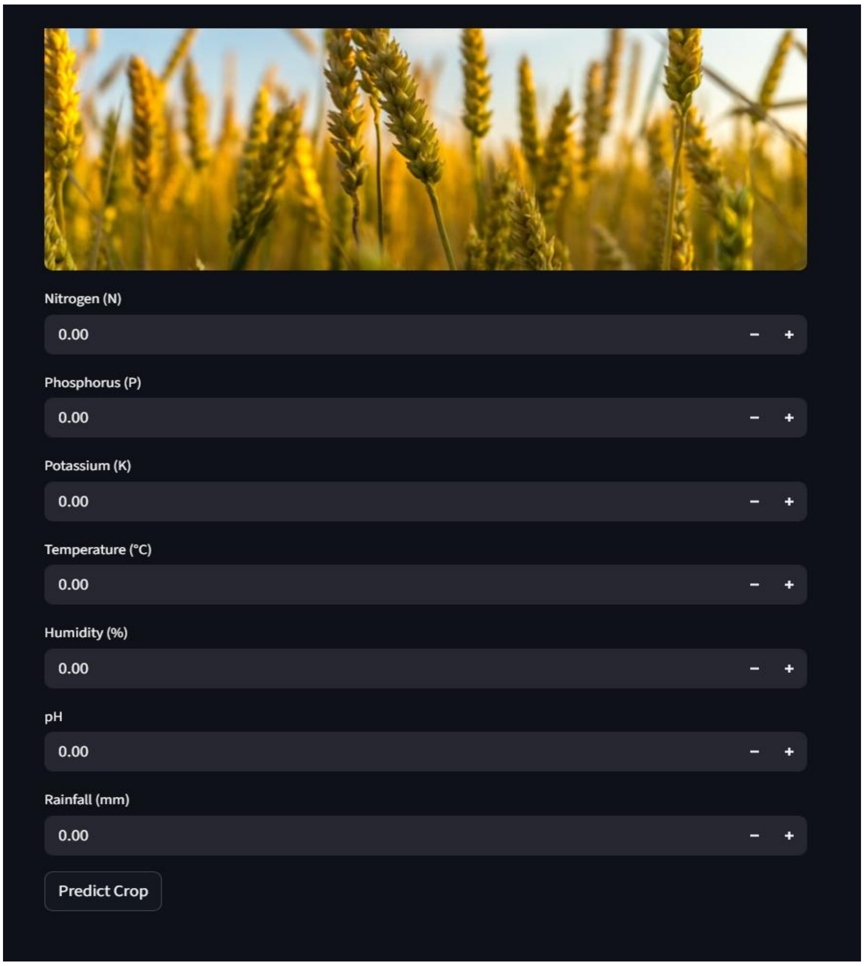
Appendix A7: Model Optimisation with GridSearchCV

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC

# Random Forest Grid Search
rf_params = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}
rf_grid = GridSearchCV(RandomForestClassifier(random_state=42),
                       rf_params, cv=5, scoring='accuracy', n_jobs=-1, verbose=1)
rf_grid.fit(X_train, y_train)
print("Best RF Params:", rf_grid.best_params_)
print("Best RF CV Accuracy:", (rf_grid.best_score_)*100)

# SVC Grid Search
svc_params = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale', 'auto']
}
svc_grid = GridSearchCV(SVC(), svc_params, cv=5, scoring='accuracy', n_jobs=-1, verbose=1)
svc_grid.fit(X_train, y_train)
print("Best SVC Params:", svc_grid.best_params_)
print("Best SVC CV Accuracy:", (svc_grid.best_score_)*100)
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
Best RF Params: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 200}
Best RF CV Accuracy: 99.54545454545453
Fitting 5 folds for each of 12 candidates, totalling 60 fits
Best SVC Params: {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}
Best SVC CV Accuracy: 98.63636363636363
```

This appendix shows the optimisation of Random Forest and Support Vector Classifier (SVC) models using GridSearchCV. These two models were chosen for fine-tuning as they are particularly sensitive to hyperparameter settings. The results shows that Random Forest achieved its best performance with 200 estimators and a cross-validation accuracy of 99.54%, while SVC achieved its best accuracy of 98.63% with an RBF kernel and C=10.

Figure A8: Streamlit Application Interface



The trained model was integrated into a user-friendly web interface using Streamlit. The interface allows users to enter soil and climate parameters, after which a crop recommendation is generated instantly. The layout was designed to be minimal and accessible for non-technical users, including farmers.

Figure A9: Saved Model Files

```
import pickle
pickle.dump(rf,open('random_forest_model.sav','wb'))

pickle.dump(scaler,open('minmaxscale.sav','wb'))
```

The final Random Forest model and the MinMaxScaler used for data preprocessing were saved as .sav files using the pickle module. This serialization process ensures that both the trained model and the scaling configuration can be easily loaded in the Streamlit web application without retraining. By storing these objects as .sav files, the deployment becomes efficient, consistent, and ready for real-time predictions.