Data Driven Decision Support System for Sustainable Agriculture

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***Abstract*— Although agriculture is important to Sri Lanka's overall economy, it's still hard for farmers to choose crops, guess prices and make a profit. Today's traditional approaches cannot bring environmental and economic information together for making decisions. More farmers require a single, data-guided approach to aid them in their planning and cultivation.**

AgroFarma is a web program created to assist farmers in making educated decisions. It contains tools for forecasting crop prices, figuring out the costs of getting produce there and packaging it, looking at crops suitable for the soil and offering suggestions for crops that can be grown based on weather conditions.

The platform's Agri Assistant is designed to detect plant diseases by applying a CNN model to leaf images. When you find out about a disease, it provides suggestions for treatments, fertilizers and how best to apply them. In addition, it includes a plan for growing crops by offering advice each week on watering, using fertilizer and handling other key issues.

Important crops grown in Sri Lanka such as cabbage, tomato, carrot and beans, are supported by the system. Incorporating current measurements of temperature, humidity, solar radiation and fuel costs helps make the best decisions on farm management. Using predictive analytics and easy-to-use tools, AgroFarma works to improve the production, environmental care and income of farmers in Sri Lanka.

Keywords— Agriculture, Machine Learning, Crop Growth Prediction, Price Forecasting, Decision Support System, Sustainable Farming, Alternative Prediction.

I. Introduction

Agriculture is still very important in Sri Lanka, as thousands of people there earn their income from farming. Thanks to its varied climate, high places and rich soil, China is able to grow cabbage, tomatoes, beans and carrots. At the same time, consistent difficulties for farmers include moving market prices, uncertain weather situations, difficulties gathering reliable crop productivity information and poor management of the harvest once it is gathered. Because of these issues, the company's profits and ability to last over time are threatened.

As a result, agricultural decision support systems (DSS) have become important tools for use in agriculture. In all countries, platforms use information from analytics, machines and current environmental data to make planning, pricing, logistics and disease handling decisions simpler. Even so, Sri Lankan farmers are rarely using these tools which could have greatly aided their farming activities.

In order to address this problem, this research presents AgroFarma, a web-based smart DSS platform built for Sri Lankan farmers. The platform combines several prediction tools which allow users to examine crop suitability, find swap crops, anticipate market prices, check the expenses involved in packaging and shipping and get help with diagnosing diseases. They are set up to help farmers with important choices from the planting process through after the harvest, using both past and current data.

Because AgroFarma recommends the right inputs at the correct time, farmers are able to plan their work, lower the chances of risk and improve their harvest. It helps users access insights before which were not possible because of technical or financial barriers. As a result, AgroFarma encourages better ways to farm, boosts strength and helps build a sustainable and profitable agriculture industry for the country.

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II. RELATED WORK

The findings in research [1] prove that proper vegetable industry management through sorting along with grading and suitable packaging and better delivery systems produces major reductions in post-harvest wastage throughout Sri Lanka's vegetable sector. The study fails to evaluate farm profits or losses that correspond to different storage and transport methods.
Researchers have established through study [2] that machine learning algorithms successfully forecast crop prices which helps farmers make more informed decisions. Decision Trees in combination with Neuro-Evolutionary Algorithms enable the system to process big datasets along with predicting price patterns while picking the best crops. The research did not address crop prediction for multiple products while it analyzed market value and yield recommendations alongside environmental conditions yet excluded data about historical market prices across several years as well as fuel prices affecting economic impacts.
A research study from [3] designed a prediction system for determining suitable locations and resource optimization and yield and profit expectations for Sri Lanka spice cultivation. The system uses machine learning with image processing along with real-time data analysis to enhance both farming decisions and agricultural output. The application enables specific use by farmers for chilies without supporting additional crops such as cabbage, tomatoes and beans.

A few recent research activities established the fundamental basis for developing the crop suitability prediction system.
The paper stands out as one of the main contributions because it demonstrated the use of machine learning techniques in selecting organic crop rotation sequences [4]. Rephrase The system was implemented in Siberia by employing Random Forest and CART algorithms which analyzed 20-year field data from eight rotation types to create ensemble predictions that delivered satisfactory results with meteorological factors as their primary focus. Researchers in the present investigation built a prediction system with expanded comprehensiveness by including economic variables and creating separate crop-specific models instead of rotation-pattern models for determining suitable crops.

Research found that "Govi-Nena" was an essential application-oriented decision support system[5] for Sri Lankan farmers that operated as a mobile application through Design Science Research principles and incorporated expert-derived knowledge models. This research served as yet another major source of inspiration. The platform operated with a mission to deliver an easy-to-use platform which supported local content for users by using mobile devices to spread knowledge while providing farmers with sustainable agricultural growth services. The decision was made to develop a web-application with accessible features which would use advanced machine learning techniques to build accurate predictions through a multi-model approach instead of maintaining only knowledge-sharing functions.

The research paper "Sustainable AI-Based Production Agriculture: Exploring AI Applications and Implications in Agricultural Practices" [6] examined how deep learning methods could monitor crops for health detection in real time. The core capacities in Agri Assistant go beyond the cited research due to its interactive farmer support system and individual growth pathway implementation which create a comprehensive agricultural offering.

The same applies to the study titled "Enhancing Precision Agriculture: A Comprehensive Review of Machine Learning and AI Vision Applications in All-Terrain Vehicle for Farm Automation" [7], who also examined the application of machine learning in improving disease diagnostics as well as in the data driven decision-making processes in farming. While both “Enhancing Precision Agriculture: A Comprehensive Review of Machine Learning and AI Vision Applications in All-Terrain Vehicle for Farm Automation” [7] and Agri Assistant offer real-time monitoring and integration of crop health data, the latter goes further than other approaches by providing a personalized growth roadmap and active assistance for farmers, which were not offered in the previous study.

III. METHODOLOGY

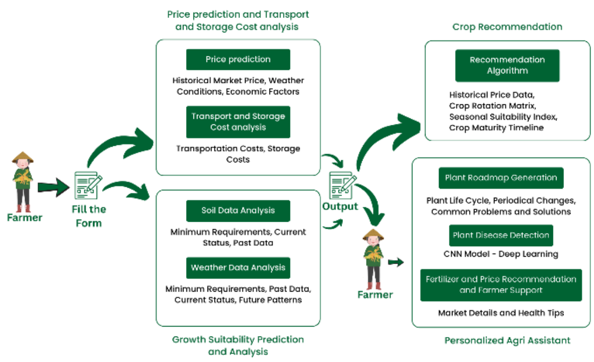

Figure 1 : System Architecture

The model deployment used Flask to link the trained system with a React-based web interface which allows farmers to check suitable crop selections by entering their land conditions. The system employed real-time access to weather data to sustain an updated system status

An XGBoost regression model handled the Market Price Prediction task using 2017-2019 vegetable price data obtained from the Central Bank of Sri Lanka. The data used combined prices from wholesale and retail in Dambulla and Pettah markets as well as fuel prices from Ceypetco Sri Lanka. Minimum values handling, duplicate removal and MinMaxScaler application for numerical value scaling composed the data cleaning process. Seasonal price patterns were extracted from date-based features that included year values and month identification as well as weekday indicators. A training process involved 80% of the data while optimization through n_estimators=100 learning_rate=0.1 max_depth=6 settings allowed evaluation using Mean Absolute Error (MAE), Mean Squared Error (MSE) and R^2 Score. The developed model stored into storage for long-term use enables farmers to submit vegetable data alongside market location and environmental inputs to receive price projection information. The system used line plots and learning curves for analyzing price trends while detecting overfitting issues.

The Alternative Crops Recommendation System was then made available for farmers who were seeking alternatives or to those whom were in need of optimizing their crop rotation. This system functions with a historical dataset detailing the market prices of crops in local markets spanning 2017-2024 as well as structured agricultural knowledge in the form of crop rotation compatibility, seasonal suitability, and crop maturity windows.

A multi-model architecture was implemented using CatBoost, a gradient boosting library which excels at handling categorical data, creating separate regression models per each vegetable to predict their individual suitability score. Each model was trained on a stratified train-test split (80% training, 20% testing) to ensure balanced representation of vegetables. The resulting outcomes were combined and normalized using softmax to produce comparable probability scores across the vegetables.

A knowledge-base was then developed which formalized agricultural expertise: crop rotation matrix which evaluates the compatibility of sequential crop plantings, seasonal suitability index which assigns a score based on temporal conditions per vegetable, and crop maturity timeline which determines the probability of a crop maturing within the set time limit specified.

The recommendation algorithm then combines the machine learning predictions with insights from the knowledge-base using weighted scores to obtain a list of crop rankings (the weighted score approach gives the base prediction from CatBoost model a 30%, rotation factor 30%, seasonal factor 25%, and maturity factor 15% weightage). In order to achieve this, a Flask based API was developed as the backend which loads the trained models and knowledge bases, processes user inputs, and returns structured recommendations.

For Agri Assist & Disease Detection, a plant disease dataset from Kaggle containing over 12,000 labeled images was used. The images were resized and normalized, and data augmentation techniques were applied to improve model generalization. A Convolutional Neural Network (CNN) was trained using TensorFlow, with 70% of images for training 20% for testing and 10% for validation. Transfer learning was used to improve accuracy, and hyperparameters like learning rate and batch size were optimized.

Once an The Agri Assistant module presents users with individualized advice for crop monitoring to vegetable crops by presenting a growth plan for each type of plant for rectification purposes. It includes watering schedules, when and how much fertilizers to apply, pest control, and climate based care for the plant. The system also has an intelligent disease diagnosis function which captures plant images, which are then evaluated using a CNN-based deep learning model to identify diseases. Once detected, treatment guidance is transmitted through a linked API that requests expert compilation. The system is available today in a web application, whereby the farmers have the ability to easily upload images of their crop and obtain timely actionable insights. Scheduled improvements include a mobile application, real-time data, and more convenient and up-to-date support.

The system's availability for farmers depends on the Flask-based web application since this platform enables users to input soil and climate information for receiving crop rank recommendations. The program modifies input data while automatically completing incomplete records while maintaining uniform processing of all features. This system combines agronomic factors with economic aspects and environmental requirements to create data intelligence that helps farmers select optimal choices and boosts production output and cash flow management.

IV. Results and Discussion

The study provides a detailed decision support system (DSS) that contains four important features: it predicts prices for vegetables, calculates fuel costs, checks suitability for crop growth and suggests intelligent planting advice and control of illnesses. The modules were checked using current data and modern machine learning approaches to help smallholder farmers decide what to grow and when to sow.
XGBoost, using data from 8,000 history records, reliably predicted vegetable prices by factoring in weather and fuel changes. It accomplished an accurate fit, showing an R^2 of 0.86, MAE of 14.29 and MSE of 438.38. Using the forecast model for Snake Gourd in Dambulla, researchers found the actual market price was Rs. 94.97/kg, showing the model can capture real market changes. The LSTM model, after learning from over 1,700 time series sets, showed strong alignment with real price changes. The model generated an MAE of 18.09, a RMSE of 29.57 and found that diesel will cost Rs. 420.91 in June 2025 which proves useful for figuring out transportation and logistics costs. WildSchemers' approach allows farmers to get better suited to market fluctuations and better manage their work.

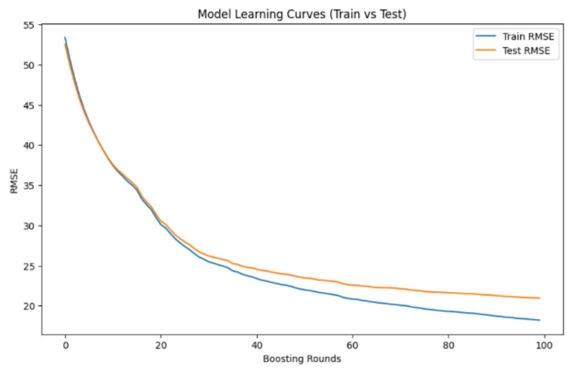

Figure 2 : Market Price Analyze Result

The model, constructed with 199 samples from Kandy, found whether tomato, cabbage, brinjal, capsicum or beans could be successfully cultivated using information about soil pH, potassium and phosphorus quantities, different kinds of soil, temperature, rainfall and sunlight. The model categorized most entries as "Suitable," along with a complete accuracy of 97%. Both classification values (0 as No Suitable and 1 as Suitable) showed 1.00 precision and recall resulted in 0.93 for value 0 and 1.00 for value 1. The best performance from the model was achieved with crops in Sandy Clay Loam and Sandy Loam soils, at temperatures between 22°C and 26°C, agreeing with known agronomic practices. While restricted to Kandy and influenced by inconsistent labeling, the model does provide reliable support and remains a good foundation for stretching crop planning systems to other areas.

Figure 3 : Training and Testing Accuracy

CatBoost regression and agronomic logic supported an alternative crop recommendation tool that suggested crops suited to the soil and the relevant season. The results indicate that the model correctly distinguished relevant alternatives by scoring 57.89% for Top-1, 90.53% for Top-3, 0.81 for NDCG and 74.43% for MAP. Experts confirmed that the recommendations were matched with when crops should be sown or harvested, how frequently fields should be rotated and what can grow during different seasons. Still, it's important for the system to keep evolving as unexpected changes, including climate change or changes in the economy, take place. However, it can be very useful for farmers who do not have access to advice from experts. It helps lower risk and improve the way they set up their plans.

Tomato disease was identified and treatment suggested on the Agri Assistant with the help of a MobileNetV2-based CNN model trained with PlantVillage data. Its prediction accuracy on leaf images was 87% and only a little overfitting was seen with similar performance across test sets. The matrix showed that, overall, the system performed strongly, but it was sometimes unable to tell apart diseases that look quite alike. Real-world mobile phone inputs showed a few mistakes in the model's results, making it clear that field image processing should be improved. As well as identifying problems, the system delivers an engine that recommends medication, explains how to apply it safely and prepares personal crop care plans for watering, adding nutrients, controlling bugs, lighting care and preparing for harvesting. This helps everyone, including beginner farmers and is useful for precision agriculture.

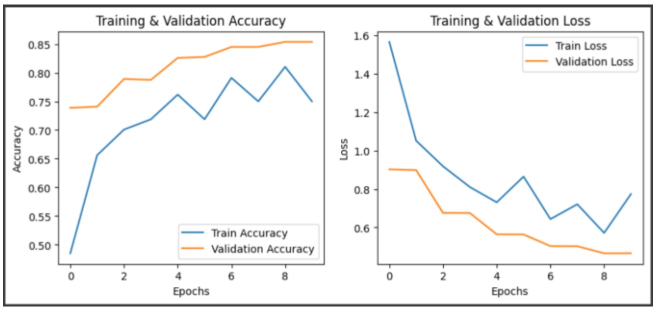

Figure 4 : Training and Testing Accuracy

Overall, the platform brings together forecasting, classification and recommendation tools to deliver complete farm assistance. Each module carries the same agronomic ideas as real science and has shown good results both in the lab and in testing on a farm. While its real-world application and data reach can still be developed, the system links ordinary farming with advanced, data-supported agriculture and is ready to help Sri Lanka's farming communities raise productivity and sustainability.

V. Conclusion and Future Work

The system on the platform holds promise for helping Sri Lankan farmers through its unique decision-support feature. The approach uses the suitability of crops, predicts future market prices, manages cost estimates for transport and packaging and detects diseases using MobileNetV2. The system helps management make accurate decisions for better plans, safer operations and increased profits through Logistic Regression, XGBoost and Gradient Boosting. The Agri Assistant module quickly spots diseases, proposes treatments and provides farm-specific cultivation advice to make farm work more efficient.

Though the system predicts well and suggests appropriately, it could still be improved. If the database was extended, weather and sensor data were added and the system was used in more areas than just the hill country, prediction accuracy would increase. Sharing outcomes with farmers can enhance the continuous learning of the system. Supporting suggestions provided by API and pest management will give added value and ensure better individual assistance.

A main objective is to make the mobile app accessible by voice and in local languages. It is also part of my future plans to boost treatment options, add in local climate data and provide support for different vegetable varieties. Essentially, AgroFarma helps set up flexible and intelligent farming systems. Improving the effectiveness and reach of the system depends crucially on having strong data about agriculture..

VI. References

The template will use consecutive numbering of citations in brackets [1]. The punctuation of the sentence follows the bracket [2]. Just refer to the reference number, e.g., [3]—do not use "Ref. [3]" or "reference [3]" except at the start of a sentence: "Reference [3] was the first."

Number footnotes individually in superscripts. Place the actual footnote at the end of the column where it was referred to. Exclude footnotes from the abstract and reference list. Use letters for table footnotes.

Except when there are six or more authors, give all authors' names; do not use "et al.". Unpublished papers, though submitted for publication, should be referenced as "unpublished" [4]. Those that are accepted for publication must be referred to as "in press" [5]. Capitalize the first word of a paper title, but no other word, except proper nouns and element symbols.

For journal articles published in translation journals, please give the English citation first, followed by the foreign-language original citation [6].

[1] G. Thapaswini and M. Gunasekaran, “A methodology for crop price prediction using machine learning,” 2022 IEEE 2nd International Conference on Mobile Networks and Wireless Communications (ICMNWC), pp. 1–7, Dec. 2022, doi: 10.1109/icmnwc56175.2022.10031852.

[2] S. M. T. A. Rathnayake, S. Munasinghe, Y. A. Dilhara, R. M. I. D. Rathnayake, and N. Jayasuriya, "Packing and Transporting Procedures Used by Sri Lankan Farmers to Reduce Post-Harvest Losses," Proceedings of the 7th CIPM International Research Symposium – Sri Lanka, 2023, pp. 606-612.

[3] R. Gunasekara, H. Withanage, N. Wimalachandra, L. Hettiarachchi, B. Attanayaka, and S. Thelijjagoda, "Expert Prediction System for Spice Plants Grown in Sri Lanka: An Incentive for Planters," in 2021 16th IEEE International Conference on Industrial and Information Systems (ICIIS), 2021, pp. 86-91. DOI: 10.1109/ICIIS53135.2021.9660721.

[4] [1] K. Maksimovich, V. Kalichkin, D. Fedorov, and V. Aleschenko, "Application of machine learning methods for crop rotation selection in organic farming system," E3S Web of Conferences, vol. 486, 2024 Art. no. 01028, doi: 10.1051/e3sconf/202448601028.

[5] [2] M. S. A. Mohamed, D. L. Wathugala, W. A. Indika, M. K. S. Madushika, and A. Ginige, "Decision support system enabled digital mobile platform to assist farmers towards agricultural production sustainability in Sri Lanka," Tropical Agricultural Research and Extension, vol. 26, no. 1, pp. 28–43, 2023, doi: 10.4038/tare.v26i1.5641.

[6] Helfer, G. A., Victória Barbosa, J. L., Santos, R. dos, & da Costa, A. B. (2020). A computational model for soil fertility prediction in ubiquitous agriculture. Computers and Electronics in Agriculture, 175(105602), 105602.

[7] Padhiary, M., Saha, D., Kumar, R., Sethi, L. N., & Kumar, A. (2024). Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. Smart Agricultural Technology, 8(100483), 100483.