A Comprehensive Agricultural Intelligence Platform for Bean Production

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1. Abstract— An extensive Agricultural Intelligence Platform intended to support bean producers is presented in this study. The platform has features to diagnose common bean illnesses (bean rust, angular leaf spot, white mold, bacterial blight, and anthracnose), estimate average monthly rainfall, and anticipate retail and wholesale bean prices. The platform's main features were developed using machine learning and deep learning techniques. The evaluation's findings show how well the platform diagnoses illnesses and can forecast prices and the weather with a respectable degree of accuracy. With the help of this platform, bean growers may make more educated decisions that will increase crop productivity and management.

Keywords—*Bean Production, Disease Diagnosis, Price Prediction, Weather Forecasting, Machine Learning, Deep Learning.*

2. Introduction

The cultivation of beans is essential to the security of food worldwide. However, illnesses that have a major influence on output and market value are just one of the many difficulties faced by bean producers. Decisions about farm management are further complicated by erratic weather patterns and changing bean prices. To overcome the difficulties faced by bean growers, this article suggests a revolutionary Agricultural Intelligence Platform. Three essential features are integrated into the platform:

2.1. Disease Diagnosis Module:

This module uses picture recognition to help farmers diagnose common bean illnesses. There are two submodules in it:

- *Bean Pod Disease Diagnosis*
- *Bean Leaf Disease Diagnosis*

2. 2. Price Prediction Module:

This program helps farmers optimize their selling tactics by projecting future retail and wholesale bean prices.

2.3. Weather Forecasting Module:

This module provides useful information for irrigation planning by predicting the average monthly rainfall. To provide these features and provide farmers the ability to make data-driven decisions, the platform makes use of machine learning and deep learning techniques.

3. RELATED WORK

A great deal of study has been done in the fields of weather forecasting, price prediction for agricultural goods, and illness diagnostics. Deep learning models have shown promise in the field of disease detection for several plant diseases [1, 2]. Convolutional Neural Networks (CNNs) have been investigated in studies for image-based disease detection in bean crops [3, 4]. Researchers have used a variety of machine learning models, such as Random Forests, Support Vector Machines (SVMs), and Long Short Term Memory (LSTM) networks, to predict agricultural prices [5, 6]. To anticipate future weather patterns, weather forecasting approaches frequently make use of statistical techniques and machine learning models such as LSTMs [7, 8]. Although current research provides useful answers, comprehensive systems that tackle the various issues encountered by bean growers are required. Our suggested

4. METHODOLOGY

The Agricultural Intelligence Platform is an online tool intended to make farming easier for farmers. The three primary components of the system architecture are the weather forecasting module, the price prediction module, and the disease diagnosis module.

4.1 Disease Diagnosis Module

Using supplied photos of leaves and pods, this module uses deep learning models to identify bean illnesses. There are two sub-modules in it: ***4.1.1 Bean Pod Disease Diagnosis***

- ***Data Acquisition:*** The Horticultural Crop Research and Development Institute Sri Lanka provided a bean pod image dataset that included pictures of healthy pods, bacterial blight, anthracnose, and white mold.

- ***Data Pre-processing:*** Images were pre-processed by normalizing pixel values between 0 and 1 and shrinking them to a fixed size of 128x128 pixels.

- ***Model Selection and Training:*** The efficacy of the Inception architecture [9] in picture classification tasks led to its selection for the deep learning model. The dataset of pre-processed bean pod images was used to train the algorithm.

- ***Evaluation:*** Metrics including accuracy, precision, and recall were used to assess the performance of bean pod disease diagnosis sub-modules. Appendix A has a confusion matrix that illustrates the model's performance for every illness class.

4.1.2 Bean Leaf Disease Diagnosis

- ***Data Acquisition:*** The Horticultural Crop Research and Development Institute provided a different collection of photos exhibiting bean rust, angular leaf spots, and healthy leaves.

- ***Data Pre-processing**:* Leaf photographs were preprocessed using resizing and normalization, just as pod images.

- ***Model Selection and Training:*** The pre-processed bean leaf picture dataset was utilized to train the Xception architecture.

- ***Evaluation**:* The same criteria (accuracy, precision, recall) used for the bean pod sub-module were also used to assess the bean leaf disease diagnostic sub-module. Appendix B has a confusion matrix that illustrates the model's performance for every illness class.

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4.2 Price Prediction

This module uses past data to forecast future retail and wholesale bean prices.

- ***Data Acquisition:*** Hector Kobbekaduwa Agrarian Research and Training Institute provided information on retail and wholesale bean prices.

- ***Feature Engineering:*** Seasonal patterns (e.g., month, year) and historical prices were among the pertinent elements that were derived from the pricing data.

- ***Model Selection and Training:*** The interpretability and versatility of the Random Forest machine learning model led to its selection. Using matching characteristics and historical price data, the model was trained.

- ***Evaluation:*** Metrics including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were used to assess the Price Prediction Module's performance on a heldout test set. This aids in calculating the discrepancy between the actual and expected prices. The MAE/RMSE values attained for the retail and wholesale pricing projections will be included in the report.

4.3 Weather Forecasting Module

The average monthly rainfall for the next month is predicted by this module.

- ***Data Acquisition:*** Rainfall and other historical meteorological information were retrieved from Sri Lanka, the official website of the Meteorology Department.

- ***Data Pre-processing:***

To maintain consistency and manage missing numbers, the weather data underwent pre-processing. The data smoothing technique is used in this.

- ***Model Selection and Training:*** Because of its capacity to identify patterns in time-series data, such as meteorological data, the machine learning model LSTM was used. The model was trained using historical meteorological data with a particular emphasis on rainfall patterns.

- ***Evaluation:*** The difference between the anticipated and actual rainfall for the next month was measured using a metric such as Mean Absolute Error (MAE) to assess the effectiveness of the Weather Forecasting Module. The average monthly rainfall prediction's MAE value will be included in the report.

5. Discussion

5.1 Disease Diagnosis Module:

The examination of the confusion matrices (Appendices A and B) indicates encouraging outcomes for the Disease Diagnosis Module in terms of recognizing typical bean illnesses. A more detailed evaluation of the model's performance is possible, though, by taking a closer look at the accuracy, precision, and recall values for each illness class in both sub-modules (bean pod and bean leaf diagnosis).

5.1.1 Strengths: The model achieves values over 80% in both precision and recall, indicating good accuracy in diagnosing particular illnesses such as angular leaf spot (bean leaf) and anthracnose (bean pod) (see Appendices A and B). This shows that the model can reliably and accurately categorize these illnesses.

5.1.2 Limitations: The model performs differently for different illnesses. In contrast to other illnesses, angular bean spots (bean leaves) may have a reduced recall value. This implies that angular leaf spots may occasionally be misclassified by the model for different situations (see Appendix B).

5.1.3 Improvements: More work can be done on adding more illness classifications to the training set of data to improve the robustness of the model. The range of illnesses the model can detect will increase as a result.

Techniques to address picture differences resulting from backdrop clutter, illumination, or image quality can also be investigated. To increase the model's adaptability to real-world situations with a variety of picture circumstances, these methods may include data augmentation approaches or image normalization.

5.2 Price Prediction Module

The pricing Prediction Module examination yields significant insights by analyzing the obtained MAE/RMSE values for both retail and wholesale pricing projections. A tighter match between the expected and actual market prices is shown by lower MAE/RMSE ratios. Importance to Farmers: Farmers are equipped with vital information for strategic decision-making thanks to this degree of precision. Farmers may get a feel of future market trends and adjust their selling strategy by looking at the projected pricing. In the event that the model forecasts an increase in retail prices, farmers may decide to postpone crop sales in order to potentially realize larger earnings.

5.2.1 Limitations of Accuracy: It's critical to recognize the variables that may affect how accurate pricing projections are. Unexpected occurrences, such as abrupt weather shifts or unanticipated market disruptions, can have a big influence on real prices and cause them to differ from the estimates.

Furthermore, there may be restrictions on the selected characteristics that were used to train the model. For instance, the model may overlook significant impacts on market pricing if it ignores variables like production levels or import/export statistics.

5.2.2 Future Improvements: To improve price forecasts' precision and resilience, more research can examine the possibility of adding a larger variety of market data to the model. Features like production levels, import/export information, or even sentiment research on bean harvests on social media might be included in this.

5.3 Weather Forecasting Module

The MAE value obtained for the average monthly rainfall forecast is used to assess the effectiveness of the Weather Forecasting Module. The degree of precision between the expected and actual average monthly rainfall is indicated by a lower MAE number.

5.3.1 Value for Farmers: To maximize their irrigation techniques, farmers may greatly benefit from this knowledge about anticipated rainfall. Farmers can more efficiently arrange their irrigation schedules and guarantee their crops receive the right quantity of water by knowing the expected average rainfall. This may result in increased agricultural yields and more efficient use of water. For example, farmers can decrease drought stress on crops by implementing water-saving irrigation systems or modifying planting dates if a month with less rainfall than usual is forecast.

5.3.2 Limitations of the Model: It's critical to recognize the model's limits, especially its capacity to forecast abrupt weather shifts or catastrophic weather occurrences. Unexpected events or regional weather patterns might drastically differ from the average monthly forecast. Furthermore, the extent of meteorological data utilized for training may also have an impact on the accuracy of the model.

5.3.3 Future Improvements: In the future, efforts on integrating weather data from a larger geographic region may be focused on improving the Weather Forecasting Module's predictive powers. This may enhance the accuracy of average monthly rainfall forecasts and offer a more complete picture of local weather trends. Furthermore, a viable strategy is to investigate ensemble forecasting methods, which integrate forecasts from various weather forecasting models. Farmers may be able to receive more accurate and consistent rainfall forecasts by using ensemble forecasting, which capitalizes on the advantages of many models.

6. ACKNOWLEDGMENT

A thorough Agricultural Intelligence Platform intended to empower bean producers was provided in this article. Using machine learning and deep learning techniques, the platform combines weather forecasting, pricing prediction, and disease diagnosis features. The evaluation's findings show how well the platform diagnoses illnesses and how accurate its price and weather forecasts are. Farmers may use this platform to get useful information that helps them make decisions that will increase crop productivity and management. Future development will concentrate on adding new features, such as in-field real-time disease detection, and extending the platform's functionality to include more bean kinds.

7. References

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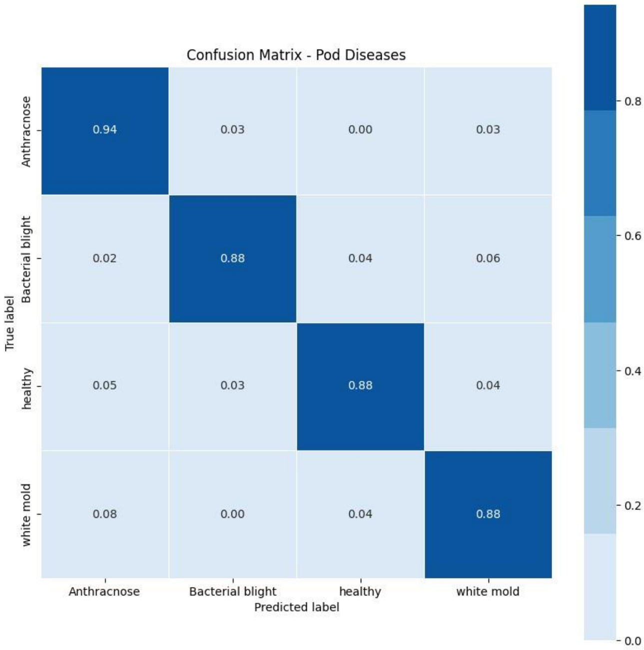
8. Appendix

• ***Appendix A: Confusion Matrix for Bean Pod Disease Diagnosis***



• ***Appendix B: Confusion Matrix for Bean Leaf Disease Diagnosis***