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Design of a Smart Management Framework for Rice Disease Control Using AI Techniques

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Abstract

In this work it has been analyse that more than half of the world's population depends on rice as a staple crop, but a variety of diseases pose a serious threat to its productivity. Conventional approaches to disease detection and management are frequently reactive, labor-intensive, and time-consuming. In order to improve the early detection, diagnosis, and control of rice diseases, this study suggests designing an intelligent, integrated management framework that makes use of Artificial Intelligence (AI) techniques. The framework combines real-time data collection via IoT sensors, intelligent decision support for suggesting suitable treatments, and image-based disease recognition using machine learning models. The system seeks to provide accurate, timely interventions to reduce crop loss and maximize resource utilization by evaluating environmental factors, crop health indicators, and historical disease data. The suggested framework provides a long-term solution for contemporary rice farming by improving disease management techniques' scalability, accuracy, and efficiency.

Keywords: Artificial Intelligence (AI), System, Security, Environment, Rice.

Introduction

Over half of the world's population eats rice, making it one of the most important staple crops. Food security depends on rice production being healthy, particularly in areas where agriculture is the main economic sector. However, a number of diseases, including blast, bacterial blight, and sheath blight, commonly pose a threat to rice crops, affecting their quality and productivity. Conventional methods of disease identification and management are ineffective and prone to mistakes since they are frequently manual, labor-intensive, and mostly dependent on human skill [1].

Artificial Intelligence (AI) has become a game-changing instrument in contemporary agriculture as a result of technological breakthroughs. Real-time disease detection, early warning systems, and optimal decision-making are made possible by AI techniques including machine learning, image processing, and data analytics. It is feasible to automate disease identification, forecast outbreaks, and recommend more precisely targeted control actions by incorporating these technologies into a smart management framework[2].

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Fig.-1 Applications of Artificial Intelligence (AI) in Agriculture

The goal of this research is to use AI-based methods to create a smart management framework for the control of rice diseases. The suggested system uses sophisticated algorithms, environmental data analysis, and picture recognition to track crop health, identify diseases early, and give farmers and other agricultural stakeholders useful information. The framework is intended to promote sustainable agricultural practices, decrease crop loss, and improve the effectiveness of disease management [3-6].

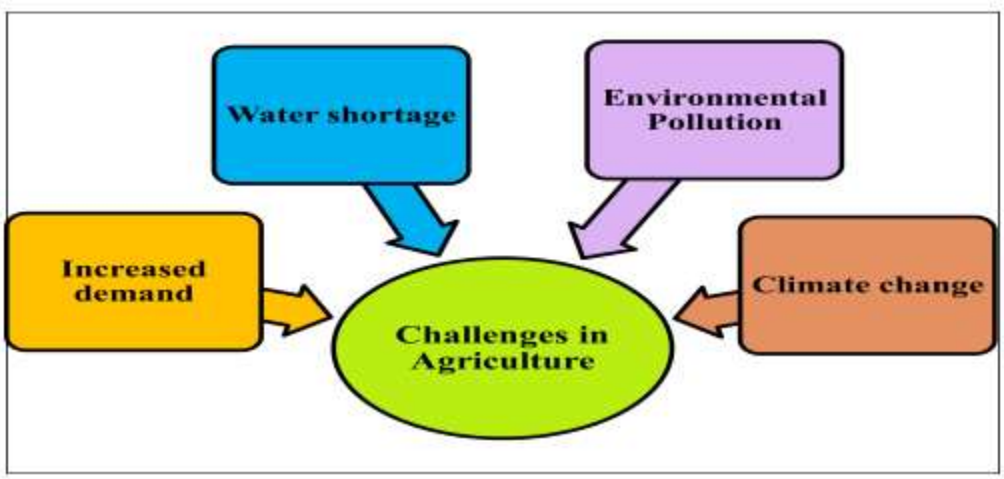

Fig.-2 Challenges in agriculture

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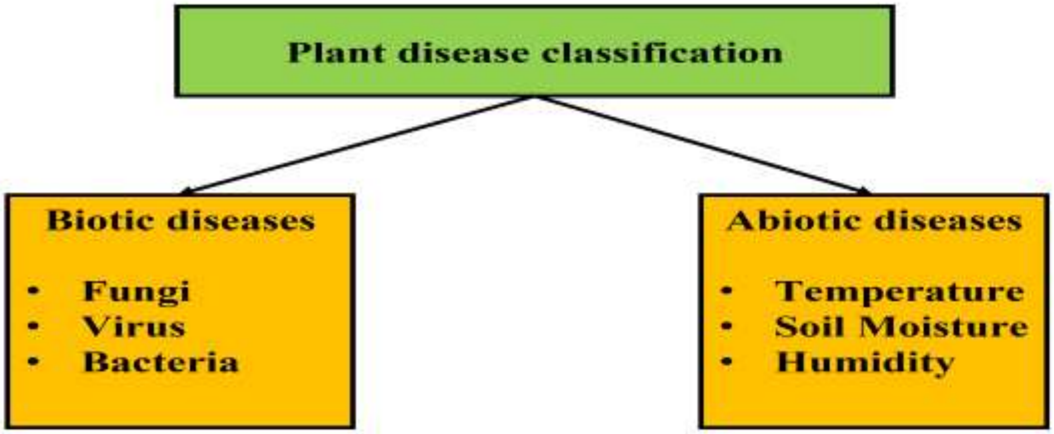

Fig.-3 Plant disease classification

Image processing is commonly used to detect and forecast crop illnesses, but accurate disease forecasts are not always possible. One approach is to correlate crop disease forecasts with weather data, using machine learning models. The model achieved high accuracy by optimizing several epochs, with 500 being the best option due to its balance between low MAE and little training time. Softmax AF-based agrometeorological regression models made accurate predictions, with the model effectively identifying every rice illness across all classes [7-10].

Fig.-4 Rice diseases

The suggested model accounts for Indian conditions and can provide farmers with precise disease predictions in advance, allowing them to take corrective and preventative action. However, it is unable to forecast fungal infections caused by bacteria. The model could be more helpful when diseases are anticipated for various geographic places well in advance. Deep learning methods like LSTM and RNN could improve the model's performance evaluation measures. Future research could use the rice leaf image dataset to forecast, identify, and classify rice diseases, incorporating an advisory message to help farmers [11-15].

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Methodology & Analysis Report

Typically, image processing—which entails supplying a model with pictures of plant leaves—is used to detect and forecast crop illnesses. Image processing is utilized to calculate the size of the affected area by estimating the color deviation of the diseased area. Identifying whether a leaf is healthy or sick depends on picture classification. The pictures serve as the basis for this. Furthermore, the severity of the condition is assessed. Unfortunately, accurate disease forecasts cannot be made well in advance using image processing approaches. Another approach is to correlate crop disease forecasts with weather data. High levels of precision and recall were produced in the analysis using ANN, a machine learning model with several activation functions. The model was applied to each of the four activation functions in each of the two examples that make up the dataset. Compared to 80–20% data split, 70–30% data split yields good overall accuracy [16-18].

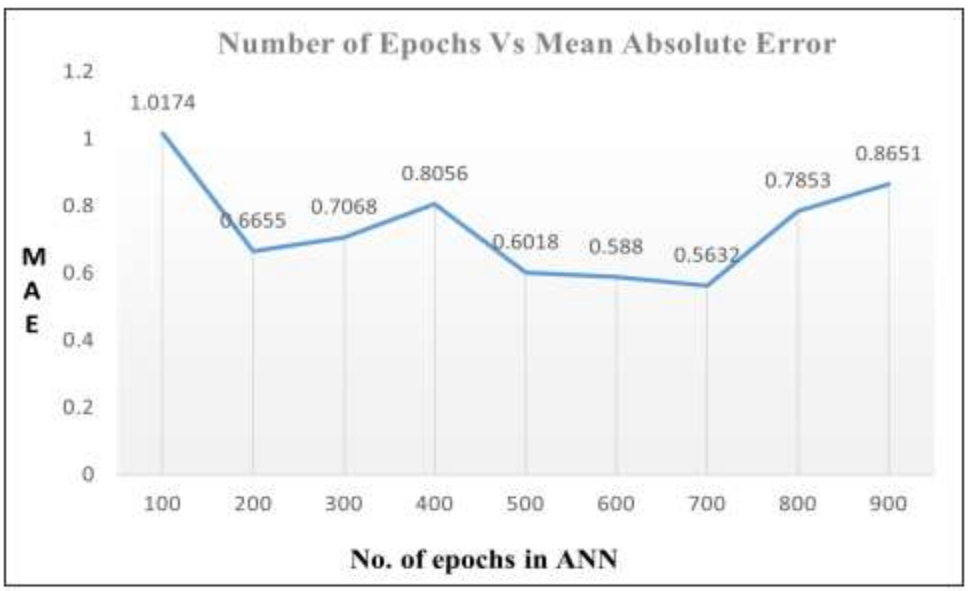

Fig.-5 Number of epochs vs Mean Absolute Error corresponding to it

Regression and classification methods are combined to create the model. It reaches our model's highest level of accuracy. This was accomplished by optimizing several epochs.

A range of epochs, from 100 to 900, have been used to run the model. While a set of 600–900 epochs yields less MAE but necessitates more training time, a set of 100–400 epochs yields greater MAE. This indicates that 500 epochs is the best option because it strikes a balance between a low MAE and little training time. A batch size of 32 is ideal since smaller batches produced a linear line that predicted the data, but larger batches led to resource exhaustion. ReLU AF-based agrometeorological regression models make accurate predictions. Softmax AF offers the best accuracy when compared to sigmoid, tanH, and ReLU. Softmax AF provides the best accurate results when classifying numerous classes [19].

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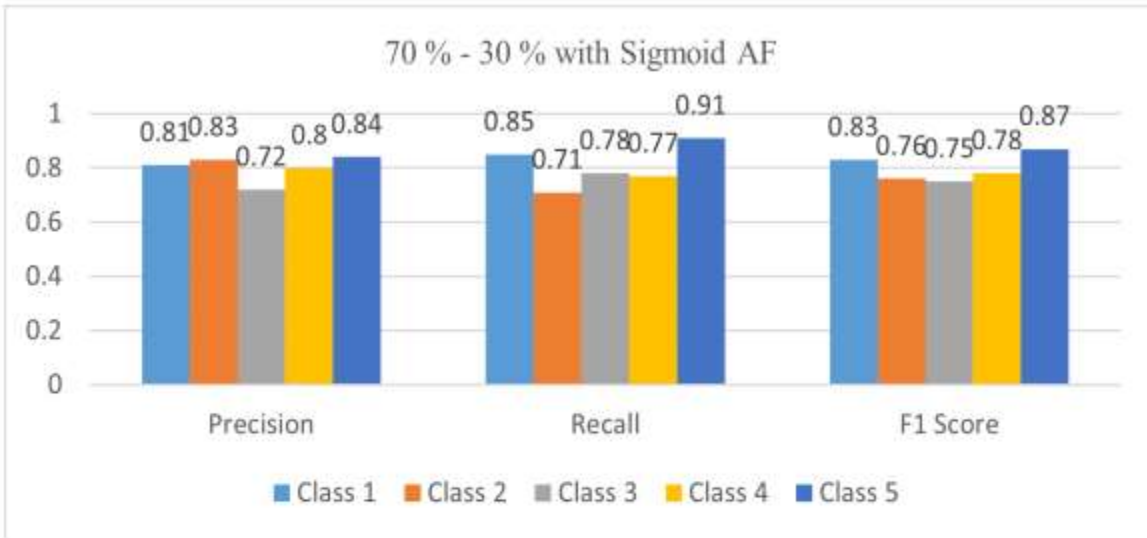

Fig.-6 Classification evaluation metrics for 70–30% data split with Sigmoid Activation Function

MAE was used to assess the regression model, whereas Precision, Recall, F1-score, and Accuracy were used for classification. When assessing our model, precision and recall are equally crucial. Therefore, it is advisable to aim for a high F1-score, which signals good precision and high recall, rather than concentrating on each parameter separately [20].

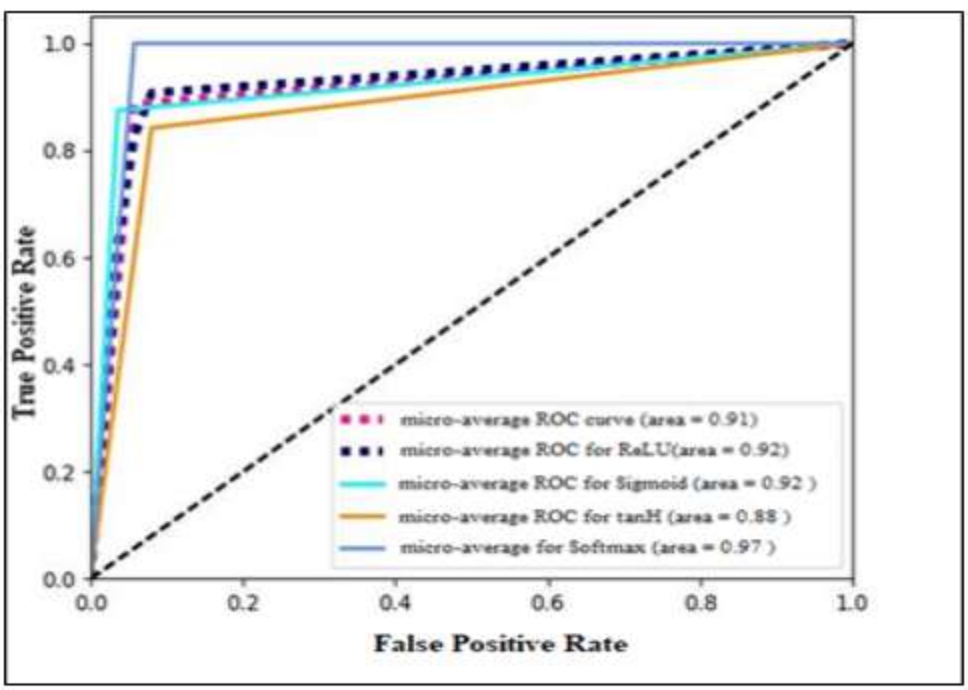

Fig.-7 The micro-average ROC curve for the activation functions for two cases of data splitting.

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The model effectively identified every rice illness across all classes using softmax. The ROC curve in TanH is skewed towards FPR, whereas in softmax AF it is slanted towards TPR. This indicates that TanH AF misclassifies more cases than softmax AF. For each of the five rice diseases examined in this study, softmax AF outperformed sigmoid, tanH, and ReLU. The softmax AF lowers the quantity of false positives and false negatives while achieving the best classification accuracy. There are numerous AI algorithms that can resolve practical issues. Radial Basis Functions, Support Vector Machines, and Multi Layer Perceptrons are the three most often used ANN approaches. These methods do, however, have a unique mix of benefits and drawbacks. One must select the appropriate network type based on the nature of the issue.

The majority of studies aim to identify plant diseases, categorize them, and assess their severity, according to a comparison of the suggested model with the systems currently in use in the literature. Predicting plant diseases, a crucial component of the suggested model, needs more attention. Fruit illnesses have been extensively studied, whereas food grain diseases have received less attention. This model examines rice-related illnesses. Using photos of leaves, the suggested model detects plant illnesses based on agro-meteorological characteristics.

Generally speaking, the majority of existing models in the literature include assumptions about foreign climates, however the suggested model accounts for Indian conditions. The techniques now in use are accurate, but not enough to be employed for actual agricultural illnesses. The suggested technologies can give farmers precise disease predictions a long time in advance, allowing them to take corrective and preventative action. This will lessen the financial losses brought on by agricultural diseases. The algorithm can accurately forecast a small number of bacterial and fungal infections for particular geographic regions. One drawback is that it is unable to forecast fungal infections caused by bacteria. The model suggested in this study might be more helpful when diseases are anticipated for various geographic places well in advance. Deep learning methods like LSTM and RNN can also be used to build the suggested model, which could improve the model's performance evaluation measures. Future research can use the rice leaf image dataset to forecast, identify, and classify rice diseases—a capability that is not yet available. In order to help the farmers, the model can also incorporate an advisory message.

Conclusion

This research proposes a novel system for controlling rice diseases, including disease prediction, diagnosis, severity quantification, and recommendation to prevent diseases. The proposed model accurately predicts four types of rice diseases based on agro-meteorological factors: healthy class, rice blast, bacterial blight, and brown spot. The regression-classification model predicts agro-meteorological parameters with a minimum mean absolute error of 0.46, with ReLU yielding a better Mean Absolute Error. The Rice-Fusion framework is an AI-based multimodal data fusion model that diagnoses rice diseases automatically, outperforming unimodal approaches like CNN and MLP architectures. The Rice-Grade system categorizes and grades the severity of rice infections through images, outperforming other severity quantification methods. The Rice-Grade model has the highest mean average precision and the highest identification results, with a 96.43% accuracy achieved. The Rice Transformer is an integrated rice disease management system based on cross attention technique, excelling at classifying rice diseases. The Rice Transformer approach has outperformed state-of-the-art methods in rice disease classification, proving the applicability of fusing information from different modalities along

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with attention techniques to improve rice disease classification. The system generates a crop advisory bulletin, which includes disease forecast in the near future, disease diagnosis, and severity grading of the disease. Based on diagnosis and severity level, the system provides pesticide recommendations. Overall, the Rice Transformer approach has outperformed state-of-the-art methods in rice disease classification. To improve crop disease management, researchers need to acquire diverse and large datasets, particularly CNN-based models with higher accuracy. Researchers should focus on developing methods to eliminate background data and factors such as disease occurrence history, geographical location, and meteorological trends to enhance disease identification systems' accuracy and reliability. Disease detection in different parts of plants, such as stems and fruits, is crucial. Implementing constraints to restrict variation in image capture conditions can overcome some limitations. To address challenges, researchers can use data augmentation techniques, such as scaling, horizontal flip, rotation, shift, and Canny edge detection, to expand the existing dataset without manually collecting new images. Multimodal datasets can be used to supplement single modality data, but there is a lack of multimodal datasets in the agricultural domain. Annotated datasets can help agricultural researchers improve their research. To tackle overfitting problems, techniques such as removing features, cross-validation, early stopping, training with more data, ensembling, and regularization can be used. These techniques can help improve prediction accuracy and reduce the need for manual data collection. Few-Shot Learning (FSL) is an innovative machine learning approach that can perform classification and regression tasks based on very few samples per class, focusing on understanding similarity and differences between objects. It is based on a meta-learning framework and is used in situations where large datasets are not available. Transfer Learning (TL) models are recommended for dealing with inadequate data, as they are highly effective in such situations.

Future research should combine genetic algorithms and neural networks to increase disease recognition rate and achieve the highest level of accuracy and speed. Advanced techniques like stratified sampling and preprocessing can help prevent noise interference in disease detection. Other actions to enhance diagnosis include optimizing feature vectors, using LSTM and RNN for plant growth estimation, and incorporating web applications with features like disease identifications from smartphone images. Electrophysiology is an emerging trend in plant disease research, focusing on real-time disease detection using electrical signals produced by plants. This approach extracts significant features like capacitance, conductivity, and impedance from electrical signals, and deploying sensors on farms can help diagnose early crop diseases and take preventive and corrective actions to control plant diseases, thereby helping farmers produce crops with good health.

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