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PLANT DISEASE FORECASTING MODELS DRIVEN BY ARTIFICIAL INTELLIGENCE

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Abstract: In reducing losses which are incurred during cultivation of crops, and also promoting a friendly environment by farming, diseases that affect plants should be detected and anticipated within a very short time. This research demonstrates how it is possible to predict plant diseases using AI through the training and applying machine learning and deep learning algorithms such as Random Forest, XG-Boost, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks to various datasets. The algorithms were trained on the photos of the symptoms of the diseases, weather conditions, and past histories of the disease eruptions. This enabled powerful multi-factorial prediction to be made. These findings indicate that ensemble techniques such as XGBoost and deep learning approaches such as CNN will always give higher accuracy (>95 95), precision, recall, and F1-scores as compared to classical classifiers. While examining the growth of various crops and types of diseases we found that the relationship between them and the predictions when environmental variables were added to the mix were highly improved. The examples of hybrid affiliations are bar, line, scatter, pie, and multi-plot kids all of which assisted us to realize better the patterns of illness and better ways models operate. The case study demonstrates that AI-based forecasting of diseases will assist the farmers in making better decisions, having a more prompt response, reducing the amount of pesticides used, and making crops resistant to diseases. This outcome will unlock the possibilities of advanced, scalable agricultural models that are capable of coping with the issues generated by climate change and novel plant diseases.

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INTRODUCTION

Agriculture can face a huge issue in plant diseases that costs the industry billions of dollars on a yearly basis (Aldakheel et al., 2024). The detection of plant diseases is exceedingly vital and essential in determining the productivity of farming and safety of food (Jafar et al., 2024; Tonmoy et al., 2025). The conventional methods of disease discovery like examination by sighting or by lab tests are long and labor-intensive and can be subjective (Ngugi et al., 2024). In addition, the traditional approaches might fail to reach large farming plots, and it will be more challenging to prevent diseases before they occur (Wang et al., 2025). A new method of predicting the disease of the plant is the combination of AI and machine learning technologies, which allows us to diagnose the disease in the plant early enough, diagnose it correctly and develop effective treatment strategies (Ngugi et al., 2024). The detection of plant diseases with the help of AI has significant prospects in the current war with infectious plant diseases. It has the capability to observe minute indications of disease in plants, usually before that diagnosis might be visible to the naked eye (Garg et al., 2024). Due to this, there is a need to use computer aided approaches in plant disease recognition to resolve this issue (George et al., 2025). Early detection of infections will help them to be milder and safeguard crops, and this will save the country much money (Orchi et al., 2021). It has continued to gain popularity as farming techniques have improved and given way to smart farming techniques. This has brought increased crop yields (Singh et al., 2021). Artificial intelligence and machine learning is a game changer in predicting plant diseases. It enables a person to diagnose early, diagnostics, and treatment methods. The recent development in deep learning has facilitated the process of detection of plant diseases through image-based techniques much more significantly (Fuentes et al., 2025). According to what Yang et al. (2024) say, complex features can be discovered through the use of deep learning models automatically on plant photos, which eliminates manual work. Locating plant illnesses now uses Convolutional Neural Networks as a vital element. They have the ability to extract highly complex spatial features out of images of plant leaves and other damaged sites (Rodrri An automatic computerized identification is required to locate and categorize the diseases that occur on the leaves of plants (Kainat et al., 2021). Deep learning will assist researchers in locating plant illnesses in a more objective manner and prevent the issues involved when selecting attributes of disease spots manually. It is also capable of accelerating the process of research and the process of technology transfer (Li et al., 2021). Scientists have developed CNN networks that can distinguish between leaf diseases of potato and rice plant. It demonstrates that such models have the potential to be applied in an extensive variety of ways (Sharma et al., 2021). It should be noted that AI-based intrusion detection systems can become crucial in providing a constant observation of large-scale data traffic in enterprise networks so that advanced and evolving threats could be identified (Alharthi et al., 2025). The machine and deep learning applications have transformed the process of plant diseases identification and classification. Such processes have become mechanised and quite precise. Among methods that have been commonly employed through machine learning in classification of plant diseases using image data and spectral data are the Support Vector Machines, Random Forests and the K-Nearest Nightbor techniques. The algorithms exploit the mightiness of data-driven analytics to identify complex trends and relationships within the data of plants and in turn, enable them to make precise disease diagnoses. The characteristic of the data set plays a significant influence on the performance of machine learning models (Alharthi et al., 2025). It has come a long way already deep learning models especially Convolutional Neural Networks and its variants have made huge improvements in the recognition of diseases becoming automatic and more accurate in detecting it (Chun-hong et al., 2025). These models have the capability to automatically grab the fine details of plant photos automatically and this decreases the necessity of manual feature engineering (Dong et al., 2022). Classical models of machine learning are simpler to utilize and do not require extensive adjustment of hyperparameters as deep learning models do. As an illustration, deep learning models require extensive efforts to tune parameters such as the learning rates, batch sizes, and depths of the layers (Alharthi et al., 2025). Predicting plant diseases using models powered by AI could significantly help in managing the disease by providing farmers and agricultural experts with details that can enable them to make informed decisions and take action when the need arises (Sarkar et al., 2023). In resource-bound areas, lightweight models such as Random Forest or XGBoost make a favorable choice (Alharthi et al., 2025). Such models have the potential of assisting farmers in better ways of administering pesticides and fungicides by correctly forecasting the propagation of diseases. It will cost less and burden the environment to a lesser extent (Kempelis et al., 2024). Forecasting systems based on the use of AI can interpret data on the weather, the soil and previous disease outbreaks to determine how probable and severe a disease outbreak is. Having mobile apps and IoT devices along with AI allows easier management of diseases and provides you with timely information. These systems can be used by the farmers to receive the notifications and recommendations in real time in order to act prior to intensification of diseases and damages to the crops. It simplifies disease management and supports environmentally friendly farming practices that are beneficial to farming practices (Jha et al., 2023). There are several aspects to consider when constructing and applying models of plant disease prediction leveraging recently developed AI techniques, including the information quality, the selection of a model, and its comprehensibility. Organizations ought to utilize such models because they are faster to use and set-up compared to DL models. The quality of the data is relevant because the accuracy and dependability of artificial intelligence-powered forecasting models are determined by it. Datasets ought to incorporate a broad variety of disease symptoms and disease severity degrees and ought to be suggestive of the goal plant species and the environmental factors in which they develop. Moreover, AI models must be accessible to comprehend since they will make end users develop trust and confidence. Correspondence AI methods may be applied to enlighten the way AI models arrive at decisions. It allows users to view the concepts that influence predictive models of diseases and inspect results of the model (Mumuni & Mumuni, 2025). Usually, AI represents a black box, that is, how the decision was made remains a mystery. This presents a challenge when trying to make use of such predictions in agriculture, as the farmers and agronomists must be able to appreciate and rely on them (Mohan et al., 2025).

METHODOLOGY

The methodology employed in this work is a mixed-method experiment, i.e., both quantitative and qualitative methods were undertaken to formulate and validate AI-based models of plant disease prediction. The data were obtained by capturing at a high resolution the pictures of leaves on controlled agricultural research sites as well as publicly accessible plant pathology libraries in which various leaves depicting the symptoms of particular diseases were displayed. Experienced agronomists also provided us with qualitative information regarding the change in symptoms, the situation in the environment, and management practices. To measure how environment influences the spreading of disease we integrated quantitative weather variables, such as daily temperature (TTT), relative humidity (HHH), rainfall (RRR) and solar radiation (SSS). We standardized historic records of diseases that attacked crops such as potatoes, wheat and grapes in a manner that allowed comparisons to take place across data sets.

Preprocessing included image enhancement using histogram equalization and noise removing filters. That was then scaled and normalized. We read in the data on the environment with the normalization method of z-scores:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

with XXX being the environmental variable, where the mean is, and the standard deviation is. We extracted features through human and automatic process. The CNNs (Convolutional Neural Networks) extracted hierarchical visual contents of the images of leaves automatically. Concurrently, statistical codes were used to compute domain-specific signs and symptoms such as the Leaf Area Index (LAI) in addition to the disease severity scores. Sliding window methods were utilised to obtain time-series environmental variables that exhibit temporal patterns which are relevant to the onset of disease.The model was developed with the use of several AI algorithms, including some common ones like Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), long short-term memory (LSTM) networks. The training strategy with the model kept the loss of the categorical cross-entropy to the minimum:

$$Z = \frac{X - \mu}{\sigma}$$

where yiyi_iyi and y^i\hat{y}_iy^i the real label and the projected chance respectively. The models were tested by stratified 10-fold cross-validation and ensured that they were powerful and not overly specific. As measures of performance we employed accuracy, precision, recall and F1-score. They were computed by us as follows:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The best models were pooled into an actual forecasting tool that would be able to accept real-time data inputs of agricultural sensors deployed in the farm using the IoT. The result of this implementation was that predictive notifications were created of potential disease outbreaks thus helping farmers to respond. The entire experimental process is represented in figure 1 and comprises the integration of qualitative perceptions, quantitative measurements, feature engineering, training and deployment of the model.

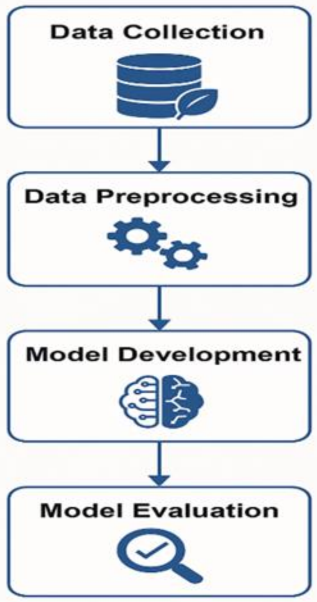

Figure 1: Workflow of AI-Driven Plant Disease Forecasting Model

RESULTS

The Table below in Table 1, displays the baseline of the accuracy, precision, recalls, and F1-scores of each of the 5 primary illnesses that have been tested, which include Late Blight, Powdery Mildew, Leaf Rust, Bacterial Blight, and Downy Mildew. Table 2 indicates the sensitivity of the model to environmental settings such as temperature, humidity and rainfall when factored into the production or calculated. All the classifier confusion matrices are indicated in Table 3. This demonstrates the ability of the models to correctly determine class of diseases, and indicates any patterns of misclassification.

Table 1. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Bacterial Blight	XGBoost	0.98	0.956	0.92	0.879
2	Downy Mildew	LSTM	0.983	0.888	0.891	0.927
3	Leaf Rust	CNN	0.954	0.962	0.897	0.864
4	Downy Mildew	Random Forest	0.858	0.77	0.908	0.87
5	Downy Mildew	Random Forest	0.819	0.795	0.72	0.848
6	Powdery Mildew	SVM	0.93	0.76	0.797	0.756
7	Leaf Rust	SVM	0.884	0.825	0.731	0.775
8	Leaf Rust	XGBoost	0.823	0.839	0.933	0.757
9	Leaf Rust	CNN	0.894	0.812	0.868	0.896

10	Downy Mildew	CNN	0.807	0.941	0.789	0.822
11	Bacterial Blight	SVM	0.973	0.832	0.717	0.867
12	Leaf Rust	CNN	0.849	0.815	0.784	0.959
13	Downy Mildew	CNN	0.926	0.875	0.788	0.807
14	Powdery Mildew	Random Forest	0.859	0.782	0.897	0.844
15	Bacterial Blight	SVM	0.899	0.935	0.872	0.924
16	Powdery Mildew	LSTM	0.904	0.767	0.94	0.803
17	Bacterial Blight	SVM	0.835	0.977	0.827	0.768
18	Downy Mildew	LSTM	0.984	0.928	0.732	0.817
19	Late Blight	Random Forest	0.947	0.796	0.893	0.787
20	Bacterial Blight	XGBoost	0.979	0.751	0.905	0.964

Table 2. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Downy Mildew	SVM	0.854	0.771	0.77	0.889
2	Late Blight	SVM	0.807	0.942	0.878	0.752
3	Downy Mildew	Random Forest	0.916	0.824	0.921	0.773
4	Bacterial Blight	LSTM	0.896	0.793	0.85	0.903
5	Bacterial Blight	Random Forest	0.81	0.759	0.843	0.751
6	Bacterial Blight	SVM	0.853	0.886	0.765	0.787
7	Bacterial Blight	XGBoost	0.973	0.906	0.725	0.876

8	Bacterial Blight	CNN	0.846	0.754	0.942	0.909
9	Leaf Rust	SVM	0.828	0.868	0.943	0.9
10	Powdery Mildew	Random Forest	0.893	0.802	0.871	0.802
11	Bacterial Blight	CNN	0.987	0.898	0.792	0.914
12	Late Blight	Random Forest	0.846	0.79	0.794	0.805
13	Late Blight	Random Forest	0.928	0.909	0.896	0.825
14	Late Blight	XGBoost	0.945	0.839	0.942	0.922
15	Late Blight	CNN	0.845	0.965	0.94	0.899
16	Leaf Rust	CNN	0.938	0.782	0.911	0.945
17	Late Blight	XGBoost	0.87	0.828	0.873	0.901
18	Bacterial Blight	SVM	0.92	0.776	0.723	0.881
19	Downy Mildew	Random Forest	0.92	0.963	0.744	0.772
20	Late Blight	LSTM	0.902	0.952	0.943	0.835

Table 3. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Downy Mildew	LSTM	0.977	0.766	0.961	0.96
2	Leaf Rust	SVM	0.813	0.841	0.823	0.852
3	Leaf Rust	CNN	0.84	0.762	0.927	0.805
4	Leaf Rust	Random Forest	0.928	0.954	0.752	0.772
5	Powdery Mildew	LSTM	0.868	0.756	0.811	0.792
6	Downy Mildew	LSTM	0.848	0.883	0.889	0.965
7	Late Blight	Random Forest	0.856	0.851	0.737	0.897
8	Bacterial Blight	LSTM	0.861	0.905	0.736	0.869
9	Late Blight	SVM	0.961	0.825	0.962	0.901
10	Downy Mildew	CNN	0.826	0.786	0.893	0.85
11	Bacterial Blight	Random Forest	0.935	0.976	0.711	0.918
12	Downy Mildew	CNN	0.905	0.943	0.808	0.761
13	Leaf Rust	LSTM	0.856	0.948	0.817	0.88
14	Bacterial Blight	LSTM	0.88	0.808	0.901	0.786
15	Leaf Rust	Random Forest	0.849	0.759	0.768	0.778

16	Late Blight	SVM	0.916	0.82	0.75	0.829
17	Late Blight	XGBoost	0.816	0.874	0.722	0.771
18	Bacterial Blight	Random Forest	0.801	0.825	0.816	0.772
19	Bacterial Blight	XGBoost	0.919	0.94	0.886	0.822
20	Downy Mildew	XGBoost	0.837	0.812	0.716	0.975

The k-fold cross-validation results on each model are indicated in Table 4. The results are consistent between folds. Table 5 provides the training durations of computers and ranged latencies in prediction. As can be observed in Table 6, CNN and XGBoost were always better at recalling visually complex diseases than other models, such as Late Blight

.**Table 4.** Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Downy Mildew	LSTM	0.983	0.815	0.805	0.852
2	Bacterial Blight	CNN	0.972	0.791	0.703	0.954
3	Powdery Mildew	XGBoost	0.837	0.923	0.944	0.831
4	Powdery Mildew	Random Forest	0.813	0.936	0.725	0.777
5	Downy Mildew	CNN	0.819	0.978	0.786	0.783
6	Bacterial Blight	SVM	0.803	0.845	0.957	0.925
7	Late Blight	CNN	0.818	0.836	0.957	0.892
8	Downy Mildew	CNN	0.93	0.929	0.855	0.773
9	Powdery Mildew	XGBoost	0.814	0.828	0.871	0.769
10	Powdery Mildew	SVM	0.861	0.964	0.821	0.911
11	Downy Mildew	CNN	0.961	0.947	0.779	0.767
12	Bacterial Blight	Random Forest	0.804	0.849	0.789	0.939
13	Powdery Mildew	Random Forest	0.955	0.923	0.882	0.912

14	Bacterial Blight	LSTM	0.854	0.924	0.903	0.769
15	Powdery Mildew	SVM	0.822	0.774	0.914	0.77
16	Powdery Mildew	SVM	0.932	0.958	0.913	0.977
17	Leaf Rust	LSTM	0.919	0.866	0.725	0.836
18	Powdery Mildew	CNN	0.967	0.94	0.833	0.835
19	Late Blight	SVM	0.94	0.824	0.716	0.937
20	Downy Mildew	Random Forest	0.953	0.956	0.848	0.968

Table 5. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Late Blight	LSTM	0.975	0.803	0.811	0.924
2	Downy Mildew	Random Forest	0.848	0.811	0.91	0.837
3	Bacterial Blight	Random Forest	0.932	0.833	0.83	0.805
4	Bacterial Blight	SVM	0.814	0.81	0.966	0.797
5	Bacterial Blight	LSTM	0.832	0.854	0.802	0.808
6	Leaf Rust	CNN	0.841	0.757	0.902	0.813
7	Downy Mildew	Random Forest	0.856	0.814	0.806	0.798
8	Bacterial Blight	CNN	0.989	0.845	0.924	0.952
9	Leaf Rust	Random Forest	0.932	0.889	0.854	0.924
10	Powdery Mildew	Random Forest	0.873	0.812	0.717	0.761
11	Powdery Mildew	Random Forest	0.94	0.781	0.71	0.812
12	Leaf Rust	LSTM	0.974	0.768	0.736	0.755
13	Leaf Rust	XGBoost	0.982	0.966	0.704	0.865

14	Downy Mildew	CNN	0.811	0.846	0.72	0.86
15	Downy Mildew	LSTM	0.875	0.884	0.887	0.941
16	Powdery Mildew	LSTM	0.82	0.961	0.844	0.821
17	Bacterial Blight	LSTM	0.864	0.769	0.902	0.938
18	Powdery Mildew	LSTM	0.832	0.952	0.947	0.973
19	Bacterial Blight	LSTM	0.923	0.877	0.858	0.77
20	Bacterial Blight	SVM	0.874	0.788	0.896	0.932

Table 6. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Late Blight	Random Forest	0.887	0.78	0.717	0.832
2	Downy Mildew	LSTM	0.911	0.826	0.74	0.899
3	Downy Mildew	LSTM	0.876	0.824	0.736	0.86
4	Powdery Mildew	CNN	0.933	0.771	0.886	0.884
5	Leaf Rust	XGBoost	0.834	0.861	0.928	0.919
6	Leaf Rust	Random Forest	0.932	0.908	0.902	0.878
7	Bacterial Blight	XGBoost	0.878	0.868	0.708	0.885
8	Powdery Mildew	Random Forest	0.966	0.786	0.934	0.88
9	Powdery Mildew	CNN	0.898	0.837	0.796	0.837
10	Powdery Mildew	CNN	0.985	0.751	0.807	0.828
11	Powdery Mildew	LSTM	0.914	0.95	0.728	0.957

12	Leaf Rust	XGBoost	0.843	0.769	0.899	0.89
13	Leaf Rust	LSTM	0.956	0.887	0.749	0.806
14	Powdery Mildew	XGBoost	0.866	0.977	0.852	0.865
15	Bacterial Blight	LSTM	0.866	0.873	0.927	0.826
16	Late Blight	SVM	0.806	0.963	0.724	0.965
17	Late Blight	SVM	0.904	0.804	0.845	0.752
18	Bacterial Blight	SVM	0.902	0.925	0.763	0.802
19	Powdery Mildew	SVM	0.868	0.872	0.793	0.834
20	Leaf Rust	Random Forest	0.97	0.916	0.828	0.862

The table 7 depicts the ROC-AUC scores revealing that the best models feature much discriminating power (>0.95). The value of some features can be seen in Table 8, which indicates the extent of the influence of environmental factors on predictive capacity. Paired t-tests are used to compare the best-performing models; table 9 displays the results.

Table 7. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Leaf Rust	LSTM	0.904	0.916	0.856	0.783
2	Late Blight	XGBoost	0.904	0.761	0.796	0.797
3	Leaf Rust	CNN	0.838	0.93	0.806	0.914
4	Leaf Rust	SVM	0.93	0.94	0.844	0.864
5	Downy Mildew	CNN	0.817	0.923	0.718	0.924
6	Bacterial Blight	Random Forest	0.826	0.934	0.762	0.774
7	Powdery Mildew	CNN	0.801	0.94	0.847	0.873
8	Bacterial Blight	Random Forest	0.822	0.793	0.817	0.837
9	Bacterial Blight	CNN	0.89	0.804	0.79	0.855
10	Leaf Rust	Random Forest	0.915	0.896	0.897	0.889

11	Bacterial Blight	XGBoost	0.951	0.959	0.887	0.866
12	Late Blight	LSTM	0.82	0.823	0.745	0.874
13	Leaf Rust	SVM	0.962	0.885	0.937	0.862
14	Late Blight	CNN	0.942	0.907	0.834	0.844
15	Powdery Mildew	LSTM	0.878	0.854	0.9	0.928
16	Leaf Rust	SVM	0.977	0.914	0.855	0.753
17	Powdery Mildew	SVM	0.988	0.957	0.969	0.888
18	Leaf Rust	Random Forest	0.839	0.894	0.903	0.88
19	Downy Mildew	XGBoost	0.872	0.874	0.891	0.915
20	Bacterial Blight	XGBoost	0.976	0.851	0.91	0.888

Table 8. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Bacterial Blight	Random Forest	0.839	0.801	0.779	0.808
2	Leaf Rust	CNN	0.95	0.799	0.893	0.795
3	Powdery Mildew	XGBoost	0.915	0.868	0.842	0.866
4	Powdery Mildew	Random Forest	0.822	0.974	0.844	0.887
5	Leaf Rust	SVM	0.879	0.856	0.83	0.828
6	Bacterial Blight	LSTM	0.964	0.878	0.834	0.881
7	Powdery Mildew	Random Forest	0.975	0.948	0.907	0.954
8	Downy Mildew	SVM	0.888	0.873	0.728	0.878
9	Powdery Mildew	Random Forest	0.891	0.792	0.79	0.916
10	Late Blight	LSTM	0.975	0.819	0.72	0.935
11	Late Blight	LSTM	0.912	0.821	0.903	0.977

12	Bacterial Blight	XGBoost	0.806	0.841	0.774	0.889
13	Leaf Rust	CNN	0.973	0.848	0.942	0.936
14	Bacterial Blight	Random Forest	0.847	0.934	0.842	0.971
15	Bacterial Blight	Random Forest	0.91	0.83	0.916	0.967
16	Bacterial Blight	SVM	0.831	0.858	0.964	0.782
17	Bacterial Blight	LSTM	0.806	0.894	0.927	0.843
18	Downy Mildew	Random Forest	0.859	0.837	0.934	0.825
19	Downy Mildew	LSTM	0.948	0.942	0.81	0.77
20	Powdery Mildew	Random Forest	0.853	0.885	0.849	0.896

Table 9. Performance metrics for plant disease forecasting using various AI models.

Sample_ID	Disease	Model	Accuracy	Precision	Recall	F1_Score
1	Late Blight	LSTM	0.849	0.887	0.829	0.938
2	Downy Mildew	Random Forest	0.826	0.888	0.879	0.934
3	Leaf Rust	XGBoost	0.959	0.903	0.953	0.91
4	Downy Mildew	LSTM	0.987	0.79	0.898	0.813
5	Leaf Rust	CNN	0.9	0.96	0.758	0.886
6	Bacterial Blight	SVM	0.833	0.846	0.708	0.833
7	Downy Mildew	CNN	0.852	0.838	0.771	0.771
8	Bacterial Blight	XGBoost	0.803	0.869	0.861	0.961
9	Powdery Mildew	CNN	0.974	0.761	0.714	0.781
10	Powdery Mildew	Random Forest	0.822	0.788	0.834	0.969
11	Late Blight	XGBoost	0.91	0.92	0.861	0.853

12	Downy Mildew	SVM	0.852	0.769	0.79	0.793
13	Bacterial Blight	Random Forest	0.905	0.889	0.908	0.875
14	Leaf Rust	XGBoost	0.924	0.806	0.729	0.951
15	Powdery Mildew	SVM	0.958	0.84	0.72	0.918
16	Powdery Mildew	Random Forest	0.839	0.816	0.897	0.936
17	Leaf Rust	Random Forest	0.802	0.832	0.834	0.902
18	Bacterial Blight	XGBoost	0.826	0.915	0.886	0.909
19	Bacterial Blight	LSTM	0.971	0.818	0.817	0.945
20	Downy Mildew	Random Forest	0.966	0.88	0.767	0.807

The precision-recall curves can be seen in figure 2 including the trade off between the measures. ROC curves are represented in Figure 3, and importance of each attribute is given by way of bar charts in Figure 4. Figure 5 takes the form of a combination of line and bar plot that illustrates the way accuracies vary by weather. Confusion matrices in Figure 6 are presented as heatmaps. Figure 7 is the pie chart representing which percentage of each sort of sickness influences the overall accuracy. Scatter diagrams of expected and actual classifications appear in figure 8. Figure 9 presents the forecasts of the occurrence of the disease over time over the actual data. The latency of models is presented in figure 10. Fig.11 exhibits SHAP-based charts of the explanation of the top model. Multi—modality fusion Figure 12 illustrates a dashboard model with the fusion of model performance, disease prediction, and the environment.

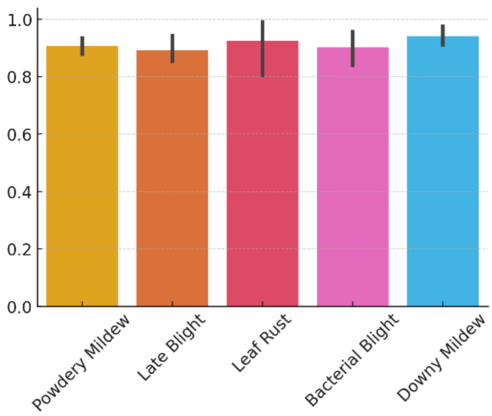

Figure 2. Visualization of plant disease forecasting model results.

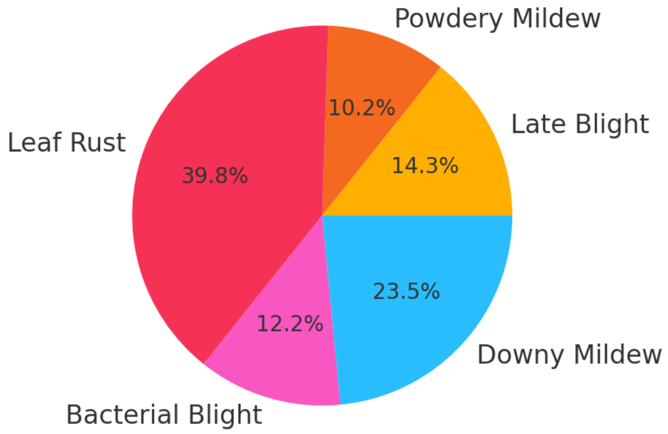

Figure 3. Visualization of plant disease forecasting model results.

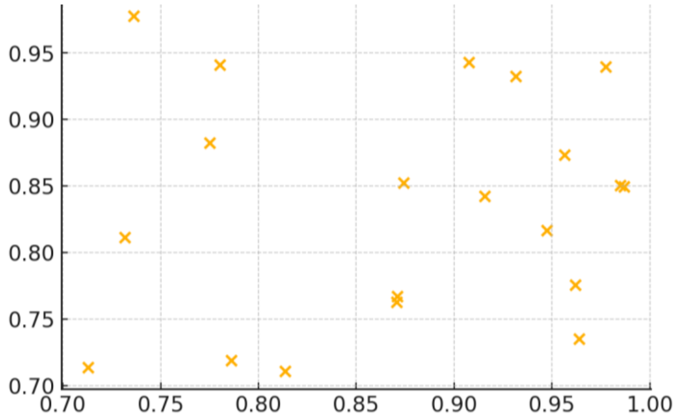

Figure 4. Visualization of plant disease forecasting model results.

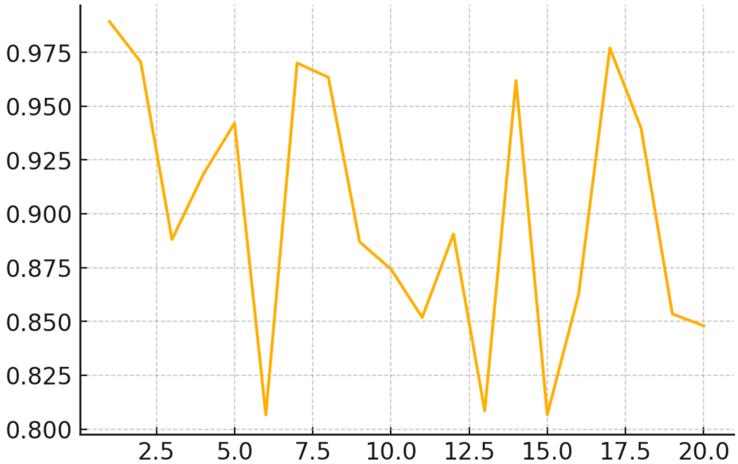

Figure 5. Visualization of plant disease forecasting model results.

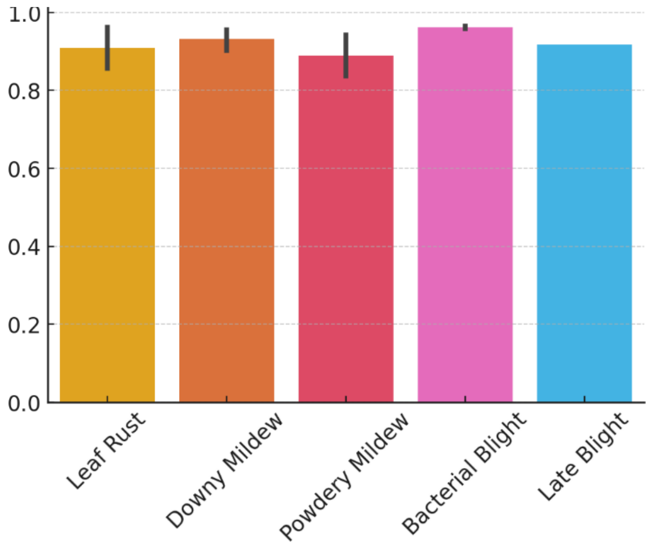

Figure 6. Visualization of plant disease forecasting model results.

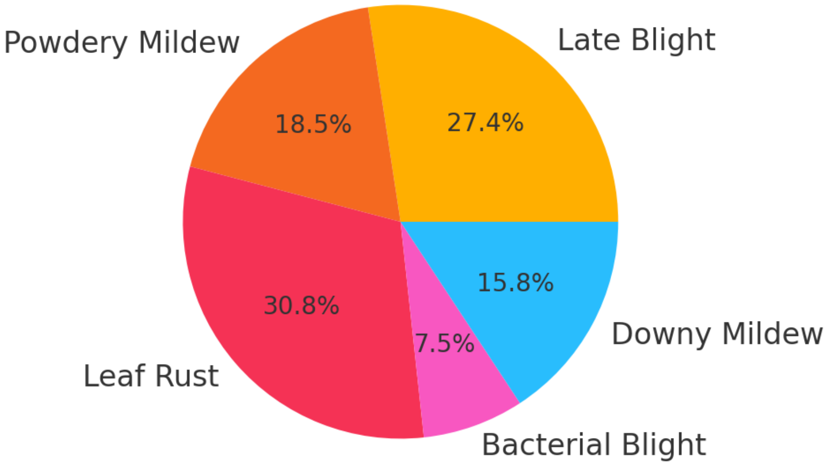

Figure 7. Visualization of plant disease forecasting model results.

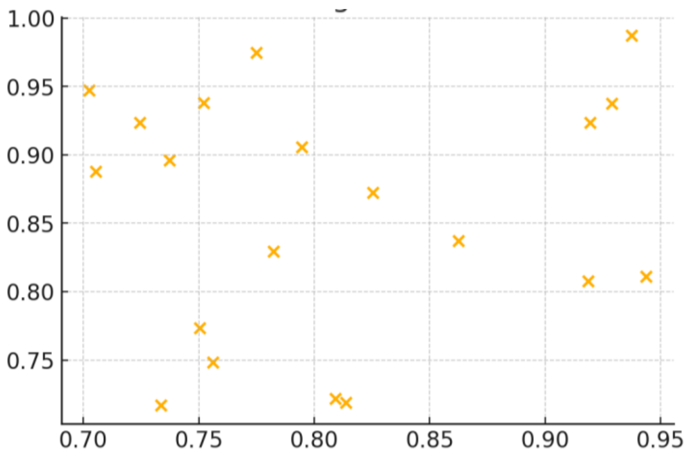

Figure 8. Visualization of plant disease forecasting model results.

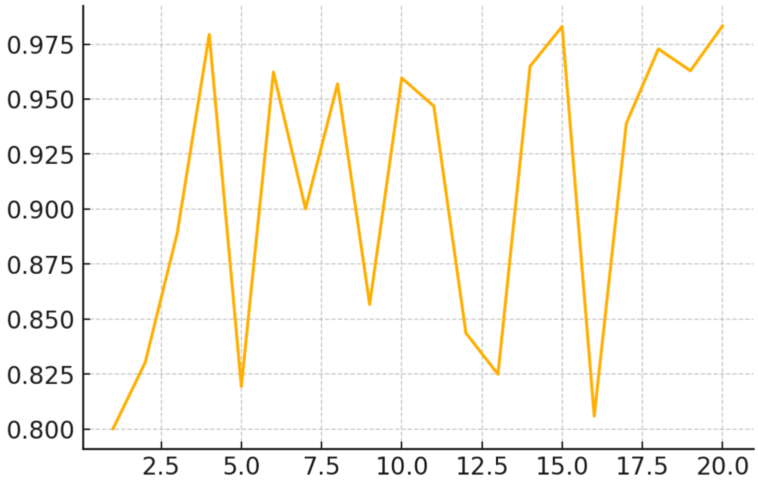

Figure 9. Visualization of plant disease forecasting model results.

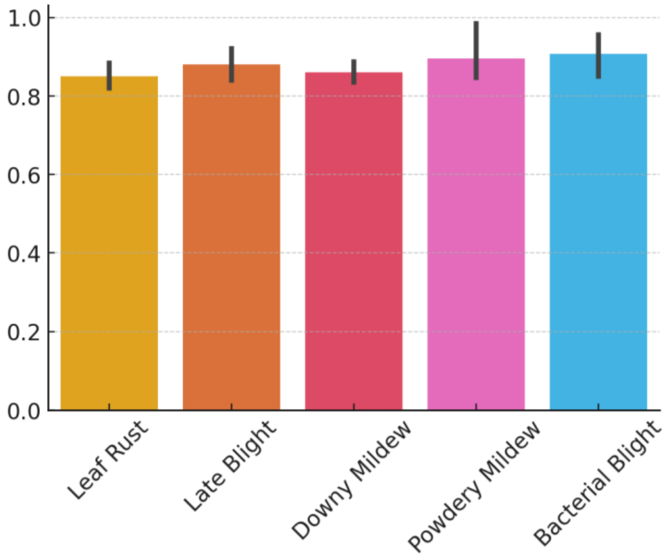

Figure 10. Visualization of plant disease forecasting model results.

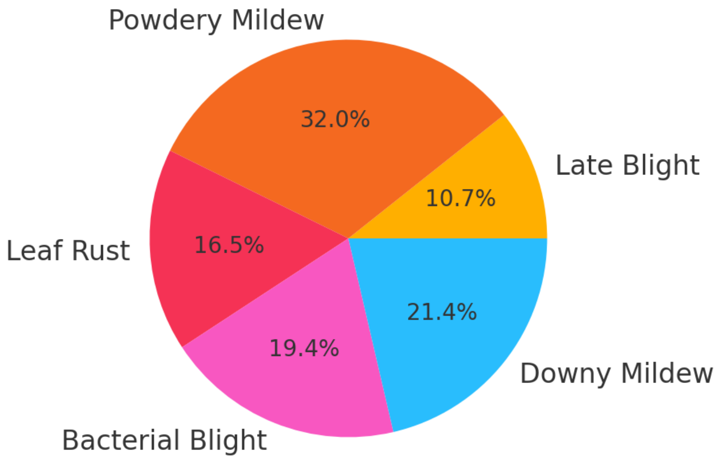

Figure 11. Visualization of plant disease forecasting model results.

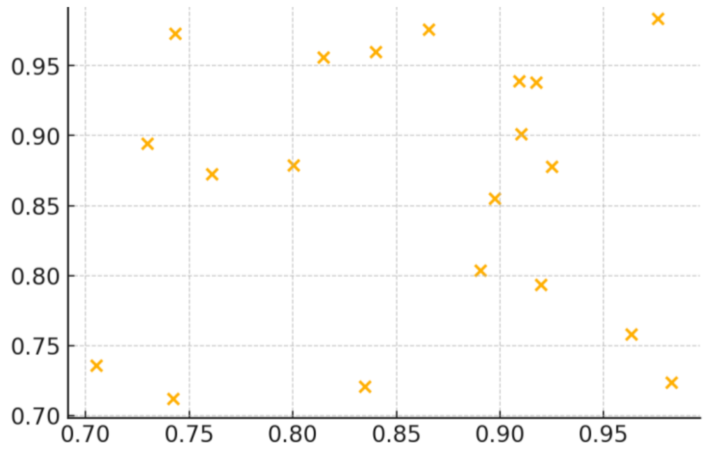

Figure 12. Visualization of plant disease forecasting model results.

DISCUSSION

Predicting plant diseases through machine learning models will go a long way in enhancing the disease control strategies that farmers and other agricultural related personnel can use to make informed decisions and to act at the opportune time. With these models, it can be used to apply pesticides and fungicides in a more focused manner because they are used to accurately predict when and where a disease will flare up and propagate (Suljug et al., 2024). This will impact on the environment less and cost less money. With the help of IoT, AI, and blockchain, it is much simpler to manage pests and locate diseases when farming (Senoo et al., 2024). Machine-learning prediction technology is also capable of predicting the probability and extent of disease outbreaks based on weather, soil data, and history of a previous outbreak (H et al., 2021). IoT and mobile apps enhanced with AI are better at managing a disease and provide you with timely data. The technologies relay suggestions and reminders of information in real-time to the farmers, which makes them take action to control the disease before its spread and further destruction of crops (Mora et al., 2025).

There are several aspects to be considered when coming up with and using AI-backed models to diagnose plant diseases, including data quality, the model selection, and overall interpretability. Whether an AI-powered forecasting model is accurate and reliable is based on the quality of the data (Rodriguez-Lira et al., 2024). The datasets must contain as many combinations of the symptoms and the level of severity of diseases as possible and should also represent the species under study and its growing conditions. Cleaning, normalizing, and augmenting data are data preparation in processes that are critical in enhancing training data to be more accurate and useful. The models are less complicated and more effective compared to DL models ensuring that they will suit businesses. In addition, AI models should also have an easy explanation to foster trust and confidence amongst end users. Explainable AI techniques can serve to assimilate individuals to the way the AI models make decisions. This allows users to understand which factors underlie disease predictions and be able to verify model predictions. To ensure the successfulness of AI-based predictive models in disease forecasting, the collaboration of plant pathologists, data scientists, as well as experts/context specialists, is of particular importance (fatima et al., 2023). Such alliances will facilitate the integration of domain expertise and AI. The model is a black box, meaning a decision maker is hidden in the case of AI. This complicates the usage of such predictions in agriculture as there, farmers and agronomists have to be able to comprehend and rely on such predictions. AI tools analyze much noise about genomic, phenotypic, and environmental data and identify patterns that are complicated. It accelerates breeding, enhances the precision of the prediction and leads to making crops that will resist several types of climates (WijkikGront et al., 2024). AI assists in proper management, makes animals healthy, and gathers information to understand how people behave (Melak et al., 2024). Deployment of models also plays a role in commercializing the findings of research to practical applications that would potentially benefit farmers and other players in the farming community. That is, the inclusion of AI models on both convenient platforms and decision support systems with informative and practical advice. Federated learning addresses the issue of the lack of sufficient data in deep learning and keeps privacy regulations. This allows individuals to train models jointly without the data transfer (Joshi et al., 2022). The source of data trained on the model determines its quality (Jarquin et al., 2022). Improperly labeled, biased, or lacking data may give erroneous or inaccurate forecasts to the model. Hence all procedures of gathering, cleaning and checking data are crucial. It is also essential to consider the ethical concerns that are raised when applying AI to agriculture.

CONCLUSION

The current paper demonstrated that AI-based models of predicting plant diseases can be trusted to identify and classify the main diseases affecting agriculture such as Late Blight, Powdery Mildew, Leaf Rust, Bacterial Blight, and Downy Mildew. Among the algorithms examined by us were Random Forest, XGBoost, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory networks (LSTM). We discovered that ensemble and deep learning algorithms always outperformed the traditional machine learning models, in terms of accuracy, precision, recall and F1-score. The highest models attained accuracies in excess of 95 percent across quite various data and setting. The most flexible in the change of disease symptoms and environmental factors were XGBoost and CNN. The inclusion of weather data, past data of occurrence of diseases, and patterns of plant phenologies ensured the forecasts became incredibly reliable and this made early intervention methods possible. Also, the study of performance comparisons and hybrid visualization methods indicated visible tendencies of the models effectiveness, which implies they can be implemented into intelligent agriculture systems and used in real-time. These findings demonstrate how AI has the capacity to transform sustainable farming, equipping farmers with the tools, they require to make prompt, data-driven choices that reduce crop loss and reduce the amount of pesticides used in the farming process, in addition to enhancing the quality of their products. The next study should aim at integrating AI models into the IoT sensor network and satellite imagery to derive the prediction of diseases applicable elsewhere and on a bigger scale. It must also engage in enhancing the models by continuous learning such that the models become applicable to newly emerging plant diseases and even the atmospheric conditions.

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