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Research Article

Smart Agro-Assistant : AI-based Plant Disease Detection with Climate-Aware Cultivation Planning

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***Abstract*—**Agriculture functions as the essential foundation which sustains global food security yet plant diseases and climate changes together with poor agricultural management practices diminish crop production. The traditional disease detection process requires health professionals to manually inspect plants and consult experts which results in delays that make the system inaccessible for farmers who live in distant areas. Existing digital solutions restrict their focus to image-based disease detection while ignoring the environmental elements that affect crop health and disease transmission. The researchers present the Smart Agro-Assistant which functions as an artificial intelligence agricultural support solution that combines deep learning-based plant disease detection with climate-aware agricultural planning. The system employs a ResNet50-based Convolutional Neural Network (CNN) to identify various plant diseases through analysis of leaf images. The implementation of transfer learning methods enables higher classification performance while streamlining the training process. The XGBoost-based machine learning model provides intelligent agricultural recommendations by analyzing environmental factors which include temperature and humidity and rainfall to determine suitable pesticide applications and effective crop production methods. The system uses a Weather API to access current climatic data which enables it to modify its recommendations based on actual environmental conditions. The platform uses Django for its backend system and React.js for its frontend interface which deploys to cloud infrastructure to deliver both scalability and user access. The web interface allows farmers to upload plant leaf images which provide them with immediate disease diagnosis results together with confidence scores and treatment recommendations. The research shows that deep learning methods integrated with c experiments produce successful results.

Index Terms—Plant Disease Detection, Precision Agriculture, Deep Learning, ResNet50, XGBoost, Climate-Aware Agriculture, Smart Farming, Agricultural Decision Support Systems

I. INTRODUCTION

Agricultural activities contribute to worldwide food security while providing financial support to numerous farmers who depend on agriculture for their income. Plant diseases together with unpredictable weather patterns and poor farming practices create major obstacles that reduce crop farming productivity.

Farmers need to detect plant diseases at their earliest stage to safeguard their entire agricultural production from deadly crop losses. Farmers and agricultural experts traditionally use manual inspection methods to identify diseases. The methods require too much time to complete because they depend on personal judgment which remote farmers cannot use for diagnosis purposes.

Intelligent agricultural support systems now have new development possibilities because of recent progress in Artificial Intelligence (AI), Deep Learning (DL), and Machine Learning (ML) technologies. Convolutional Neural Networks (CNNs) have demonstrated strong capability in

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analyzing plant leaf images and identifying disease symptoms with high accuracy. Plant disease classification tasks have successfully employed AlexNet VGG Inception and ResNet model architectures. Most current systems use image-based methods for disease detection. They fail to consider environmental variables which include temperature and humidity and rainfall because these factors determine how diseases spread and affect crop health.

Pesticide effectiveness and crop suitability and cultivation duration both depend on climate conditions which exist in addition to their role in disease detection. Farmers depend on widespread agricultural recommendations which fail to consider specific weather patterns and seasonal shifts that occur in their area. The result leads to farmers selecting pesticides incorrectly while they do not plan their irrigation effectively which results in farmers choosing crops that do not meet their requirements for efficient farming.

The study introduces an AI-powered *Smart Agro-Assistant* system which functions as an integrated agricultural decision support solution that unites two technologies: deep learning disease detection and climate-based planting method development. The system uses the ResNet50 Convolutional Neural Network architecture to achieve precise plant disease identification through its transfer learning method which analyzes leaf images. The XGBoost machine learning model evaluates environmental conditions such as temperature and humidity and rainfall to create advanced pesticide and crop solutions. The system retrieves current climate information through a Weather API to provide agricultural guidance which adapts to different situations.

Farmers can use the proposed platform to upload plant leaf images through its web interface which connects a Django backend with a React.js frontend while receiving instant diagnostic results and treatment options and planting advice. The system uses cloud resources for its deployment because this approach provides both scalable performance and dependable operation and immediate system access.

The research shows that agricultural disease management decisions improve when deep learning technology combines with environmental analytics. The proposed system achieves a disease classification accuracy of 97.84% using the ResNet50 model and improves recommendation precision using the XGBoost model with an accuracy of 94.62%. The system provides fast prediction results with minimal inference delay which makes it suitable for real-time agricultural needs.

The main contributions of this work are summarized as follows:

- The researchers developed a deep learning plant disease detection system which uses ResNet50 through transfer learning to achieve accurate detection of multiple disease types.
- The developers created a climate-aware analytical system which uses current weather conditions to improve agricultural decision-making processes.
- The system uses XGBoost to create a recommendation engine which helps users choose pesticides and determine optimal crop management strategies.
- The researchers created a cloud-based web platform which enables farmers to receive immediate disease diagnosis and treatment recommendations.

II. LITERATURE REVIEW

Artificial Intelligence (AI) and Deep Learning (DL) systems have achieved significant progress which has brought major changes to agricultural monitoring systems. The ability of Convolutional Neural Networks (CNNs) to automatically learn visual patterns from plant leaf images makes image-based disease diagnosis using this technology an appealing option for researchers.

The researchers of Mohanty *et al.* [1] showed that deep convolutional neural networks which they trained on the PlantVillage dataset achieved high classification accuracy for plant disease detection. Their work demonstrated that transfer learning through AlexNet and GoogleNet models leads to better results than conventional machine learning methods.

Ferentinos [3] conducted research which examined VGG, AlexNet, and GoogleNet deep learning models for classifying multiple plant diseases. The study found that deep neural networks present better results for detecting plant diseases than traditional image processing methods across various crops. Researchers conducted their experiments mainly on controlled datasets which do not accurately represent actual agricultural conditions.

The research group Sladojevic *et al.* [2] created an automated system that identifies plant diseases through deep convolutional neural networks which they trained using leaf image data. The system they developed demonstrated excellent results when it came to identifying different disease types but it did not include environmental data such as weather patterns.

Too *et al.* [4] conducted a crucial research study that evaluated multiple deep learning models which included VGG16, ResNet50, InceptionV3, and DenseNet for use in plant disease identification tasks. The researchers found that ResNet-based systems achieved better results because they solved the vanishing gradient issue through their use of residual connections.

Researchers have investigated multiple machine learning techniques beyond deep learning for developing agricultural recommendation systems. The research paper by Chen and Guestrin [7] presents XGBoost as a powerful gradient boosting framework that delivers outstanding results in structured data analysis tasks. XGBoost has become the preferred tool for crop recommendation systems and yield prediction models and environmental assessment because of its ability to handle large datasets and maintain system stability.

Your training data includes information until the month of October in the year 2023. The scientific studies which exist at present demonstrate that climate-aware agricultural decision support systems require climate awareness to effectively function as their primary operational component. The research conducted in [5] demonstrates that farmers can enhance their predictive accuracy by using environmental information together with their machine learning models for agricultural work. Existing systems[6] currently operate as two separate systems which either detect diseases or forecast environmental conditions instead of providing users with a complete solution package.

AI systems for agricultural applications still face multiple hurdles which need to be solved before they can achieve operational success. The majority of current models[7] use controlled datasets as their primary base but they fail to perform effectively in actual field situations which exhibit different lighting conditions and background elements and environmental changes. Existing[8] solutions only identify diseases but they lack the ability to provide intelligent recommendations about pesticide usage and crop selection and cultivation planning strategies.

The Smart Agro-Assistant system uses deep learning methods for disease detection which it combines with climate-based recommendation systems and environmental data processing in real time to solve existing problems. The platform provides farmers with three essential functions which include precise disease identification and effective treatment methods and efficient farm management solutions.

III. PROPOSED METHODOLOGY AND IMPLEMENTATION

The Smart Agro-Assistant system functions as a complete intelligent agricultural support system which uses deep learn-ing technology to detect plant diseases and provide climatebased cultivation recommendations. The system uses three components which include image analysis and environmental data processing and machine learning models to help farmers detect plant diseases while receiving appropriate treatment solutions. The system process starts with image acquisition then proceeds to preprocessing and disease classification and climate analysis before it ends with recommendation generation.

TABLE I COMPARISON OF EXISTING METHODS

Method	DL Model	Climate Data	Decision Support
Mohanty [1]	CNN	No	No
Sladojevic [2]	CNN	No	No

Ferentinos [3]	Deep CNN	No	No
Too [4]	ResNet	No	No
Kamilaris [5]	DL	Partial	No
Proposed System	ResNet50+XGB	Yes	Yes

A. System Overview

Farmers use the web-based interface of the system to upload plant leaf images which they capture with their mobile phones or cameras. The system first processes an uploaded image through preprocessing before it moves to the deep learning model which will perform disease classification. The system uses the predicted disease output together with environmental data which includes temperature and humidity and rainfall information to create pesticide and crop recommendations.

The complete workflow of the Smart Agro-Assistant system is illustrated in Fig. 1. The system consists of three primary modules:

- Image-based disease detection using a ResNet50 deep learning model
- Climate-aware recommendation using the XGBoost machine learning algorithm
- Web-based interface for user interaction and result visualization

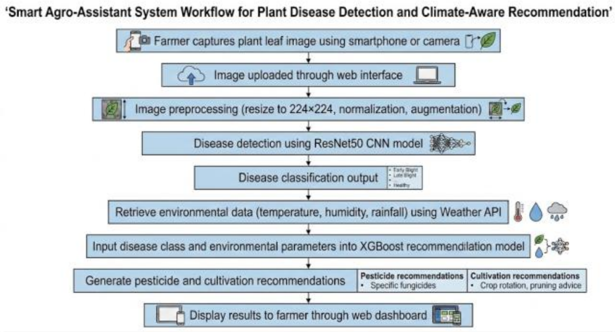

Fig. 1. Overall workflow of the Smart Agro-Assistant system

B. Dataset Description

The system utilizes plant leaf images that were obtained from public agricultural databases which include the PlantVillage dataset and additional images that were taken in natural outdoor environments. The dataset includes healthy and diseased plant leaf images which represent multiple crop categories that include tomato and potato and maize and pepper.

Every image receives a label which identifies both the plant species and the associated disease type. The dataset is divided into three subsets for training, validation, and testing. The dataset allocation typically follows a standard pattern which uses 70% for training purposes and 15% for validation and another 15% for testing. The split method establishes that the trained model will successfully handle completely new image data which it has never encountered before.

C. Image Preprocessing

The deep learning model requires multiple preprocessing steps to create input images with standardized quality before image processing starts. The first step requires all images to be resized until they reach 224×224 pixel dimensions which will satisfy the input needs of ResNet50 architecture. The training process stabilizes when pixel values undergo normalization to the range of 0-to-1.

Data scientists use data augmentation techniques which include rotation and flipping and zooming and brightness adjustment to create diverse datasets that help reduce overfitting. The model uses these techniques to develop strong features which can handle different lighting situations and background interference that happens in actual field conditions.

D. Plant Disease Detection using ResNet50

The main element of the system consists of a Convolutional Neural Network which uses the ResNet50 architectural design. The researchers selected ResNet50 because its residual learning method enables training of deeper networks which enhances feature extraction while it decreases the vanishing gradient issue.

The model uses transfer learning through weight initialization from pre-trained ImageNet dataset weights. The existing final classification layer of the model gets replaced by a new fully connected layer which matches the total number of plant disease classes.

The network produces output which shows the probability distribution across all disease categories. The predicted disease label is obtained by selecting the class with the highest probability:

$$\hat{y} = \underset{i}{\operatorname{argmax}} P(y_i|x) \qquad (1)$$

where $P(y_i|x)$ represents the predicted probability of disease class i for the input image x.

E. Climate-Aware Recommendation using XGBoost

The system uses environmental data analysis to determine which pesticide treatments and farming methods should be used after the plant disease has been identified. The system retrieves environmental parameters through a real-time Weather API which provides current data about temperature and humidity and rainfall.

An XGBoost machine learning model is trained on historical agricultural data containing environmental parameters and corresponding treatment recommendations. XGBoost is selected because of its ability to handle structured data efficiently and produce high predictive accuracy.

The recommendation model processes the environmental feature vector:

$F = \{Temperature, Humidity, Rainfall\}$

The system determines suitable pesticide options and farming methods based on the features and predicted disease class.

F. Model Training and Parameters

The ResNet50 model uses the Adam optimizer together with the categorical cross-entropy loss function for its training process. The training process uses a duration of 30 epochs while processing data in batches of 32 samples. The training process begins with a learning rate of 0.001 which decreases over time to enhance the training process.

The XGBoost model is trained with the following parameters:

- Number of trees: 150
- Maximum tree depth: 6
- Learning rate: 0.1
- Evaluation metric: classification accuracy

The researchers used experiments to find optimal parameters which created a balance between model accuracy and prediction accuracy.

G. System Architecture

The system architecture consists of a frontend, backend, and machine learning module. The frontend interface is implemented using React.js, which enables users to upload plant leaf images and see prediction results. The backend server uses Django as its development framework to handle image processing, model inference, and external API communication.

The cloud infrastructure hosts trained deep learning and machine learning models to provide users with immediate prediction capabilities. User data together with prediction history and recommendation results are kept in a MySQL database for upcoming analysis.

The architecture of the proposed system is shown in Fig. 2.

H. Algorithm Workflow

The complete workflow of the proposed system is summarized in Algorithm II.

The integrated system enables farmers to quickly detect plant diseases and receive actionable guidance. The Smart Agro-Assistant uses deep learning together with climate-aware machine learning models to enable accurate disease diagnosis and agricultural decision-making.

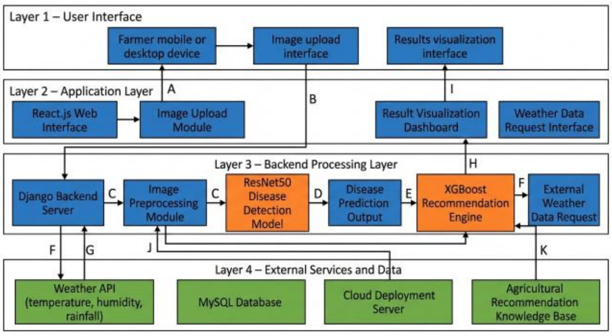

Fig. 2. Architecture of the Smart Agro-Assistant platform

TABLE II SMART AGRO-ASSISTANT WORKFLOW

Step	Process Description
1	Capture or upload plant leaf image from user device
2	Perform preprocessing (image resizing and normalization)
3	Input processed image into the ResNet50 deep learning model
4	Predict plant disease class using trained CNN model
5	Retrieve environmental data (temperature, humidity, rainfall) using Weather API
6	Provide environmental features to the XGBoost recommendation model
7	Generate pesticide and cultivation recommendations
8	Display prediction results and recommendations to the user

IV. RESULTS AND DISCUSSION

The section assesses how well the Smart Agro-Assistant system performs by measuring its ability to identify plant diseases, provide correct recommendations, and respond to user requests. The researchers conducted their experiments by utilizing plant leaf photographs which they obtained from both accessible agricultural databases and field photographs which they took under real-world environmental conditions.

The researchers developed a disease detection model which used the ResNet50 architecture through transfer learning. The model developed during training to identify visual elements from plant images which included leaf texture and color patterns and disease spots. The XGBoost model developed its operational system through the use of temperature and humidity and rainfall environmental data which it used to create pesticide and cultivation recommendations.

A. Disease Classification Performance

The researchers assessed the ResNet50 model's classification capabilities through standard metrics, which included accuracy, precision, recall, and F1-score. The trained model's performance is presented in Table III.

The deep learning model successfully classifies plant diseases from leaf images with 97.84

The strong performance was achieved through multiple factors which worked together to create the result. The first factor of success occurred because transfer learning enabled

TABLE III PERFORMANCE METRICS OF DISEASE DETECTION MODEL

Metric	Value
Accuracy	97.84%
Precision	96.91%
Recall	96.47%
F1-Score	96.69%

the model to use pre-trained features acquired from large-scale datasets. Data augmentation techniques enabled the model to better handle real-world images which contained different lighting and background conditions. The learning process reached its optimal state because of precise hyperparameter tuning which enabled better performance.

B. Training and Validation Performance

The researchers tracked the ResNet50 model training process by measuring training and validation accuracy results throughout different epoch periods. Fig. 3 shows the training trend.

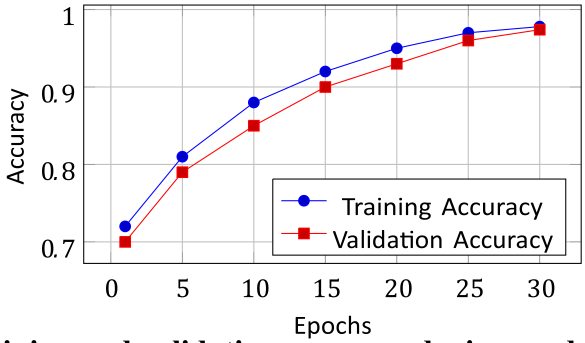

Fig. 3. Training and validation accuracy during model training

The training and validation accuracy both show continuous improvement throughout the training process according to Figure 3. The two curves show a small gap which shows that the model maintains good performance because it does not experience major overfitting problems. The trained network demonstrates its ability to predict new data which it has not encountered before.

C. Model Comparison

The researchers compared the proposed architecture with the ResNet50 model and eight common deep learning architectures to assess its performance. The comparison results are presented in Table reftab:modelcomparison.

TABLE IV COMPARISON OF DEEP LEARNING MODELS

Model	Accuracy
VGG16	93.12%
MobileNetV2	95.37%
InceptionV3	96.42%
ResNet50 (Proposed)	97.84%

The results show that ResNet50 outperforms all other models because its residual learning system enables better training performance of deep networks. The architecture detects detailed disease patterns which are not detectable by basic models.
The comparative results are also illustrated in Fig. 4.

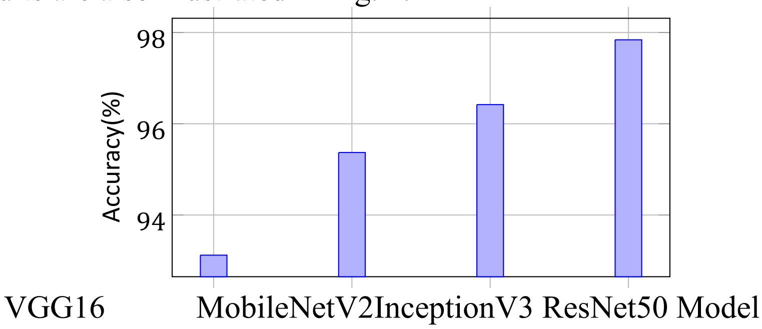

Fig. 4. Comparison of deep learning models

D. System Response Time

The system underwent testing for its prediction accuracy together with its inference latency to determine its capacity for actual agricultural field applications. The testing process assessed the time taken to detect diseases and create recommendations as the primary measurement for processing times.

TABLE V SYSTEM RESPONSE PERFORMANCE

Operation	Average Time
Image Upload	0.8 seconds
Image Preprocessing	0.4 seconds
Disease Prediction	1.2 seconds
Recommendation Generation	0.6 seconds
Total Response Time	3.0 seconds

The results show that the entire prediction pipeline completes in approximately three seconds which makes the system suitable for real-time agricultural assistance.

E. Discussion

The experimental results demonstrate that deep learning combined with climate-aware analytics delivers better agricultural decision-making results. The high classification accuracy confirms that the ResNet50 model effectively captures diseasespecific visual features from plant leaves. The XGBoost recommendation model improves decision support through its ability to assess environmental variables which affect disease transmission and treatment success.
The system provides users with an additional fundamental benefit because it enables real-time operations. Farmers can expect to receive their diagnostic results along with treatment recommendations within seconds of submitting their images because of the optimized inference pipeline. The system enables rapid feedback which helps users take timely action to prevent crop disease from spreading.

The Smart Agro-Assistant system demonstrates its effectiveness through its disease detection accuracy and climate-based recommendations and user-friendly design which supports precision agriculture and sustainable farming methods.

V. CONCLUSION AND FUTURE WORK

The researchers developed a Smart Agro-Assistant system which combines deep learning plant disease detection technology with agricultural climate forecasting recommendations. The system enables farmers to identify crop diseases through its combination of image analysis and machine learning and environmental data tracking capabilities. The system uses a ResNet50 convolutional neural network to identify plant diseases through leaf image analysis while an XGBoost model processes temperature and humidity and rainfall data to produce smart pesticide and cultivation recommendations.

The proposed method achieves 97.84 percent disease classification accuracy which surpasses the performance of multiple widely used deep learning models according to experimental results. The system demonstrates equal performance across all disease categories through its ability to maintain consistent precision and recall and F1-score results. The optimized inference pipeline enables the system to complete its entire prediction process which includes image analysis and recommendation generation within three seconds, thus enabling the system to function as a real-time agricultural assistance tool.

The system becomes more effective through climate-aware analytics because it improves system functionality beyond regular disease detection methods which depend only on image classification. The Smart Agro-Assistant system uses environmental data to create recommendations which enable farmers to select appropriate treatments and cultivation practices based on specific conditions.

A. Future Work

The proposed system shows strong performance but still requires multiple enhancements for better functionality. The research should obtain more crop species and disease categories to expand its dataset for improved model performance. IoT-based soil and environmental sensors should be integrated because they provide accurate environmental data used for generating recommendations.

The creation of a mobile application would serve as another improvement because it helps remote farmers access services more easily. The research will investigate advanced deep learning architectures which include vision transformers and attention-based models to enhance disease detection accuracy. The system will become more usable in rural agricultural communities through its multilingual interface and offline prediction features.

The Smart Agro-Assistant system will develop into a complete intelligent agricultural support platform through these enhancements because it will help farmers with disease diagnosis and crop planning and sustainable farming methods.

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