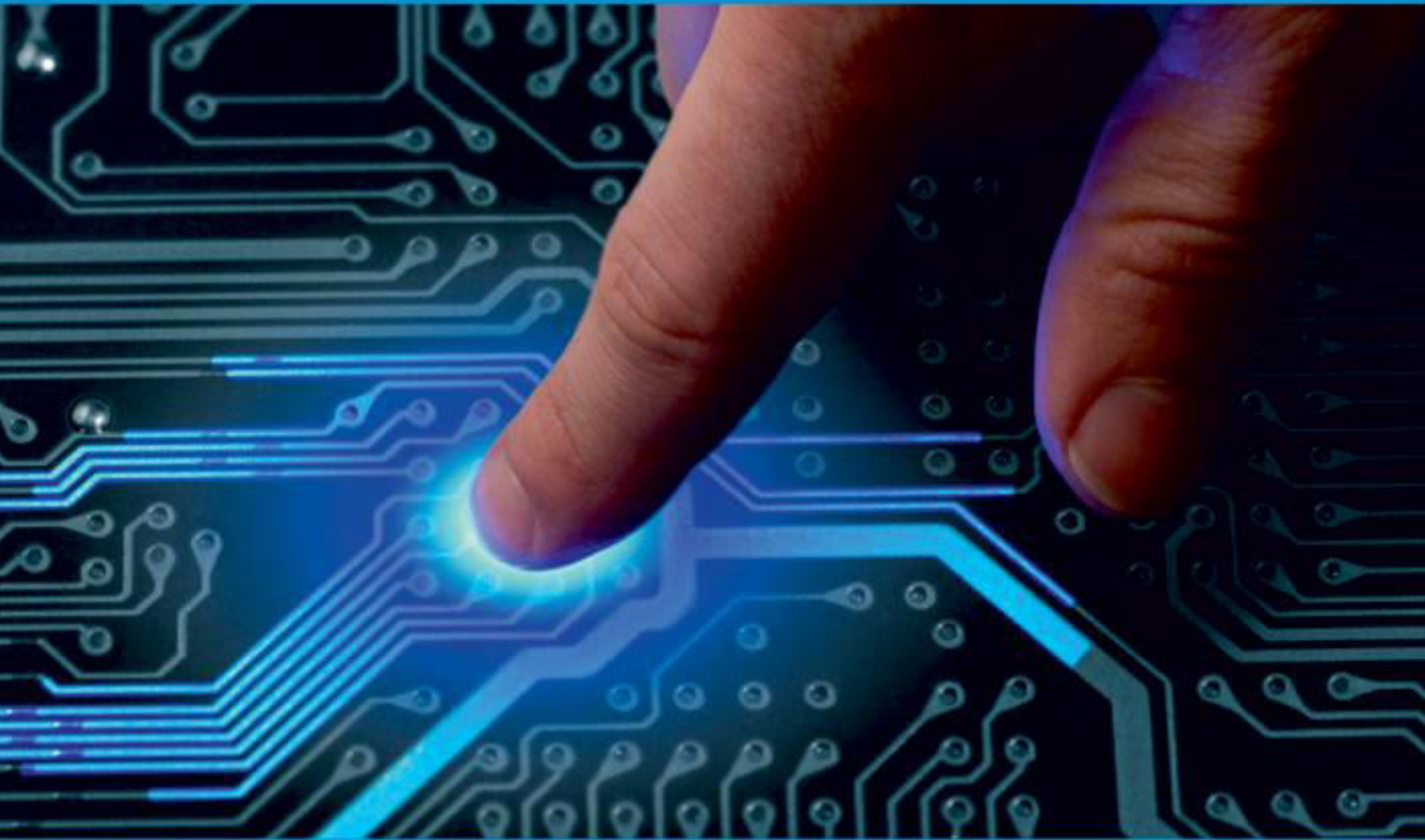
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 12, December 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.625

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

AI-Driven Crop Disease Prediction and Management with Bilingual Recommendations

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ABSTRACT: Crop diseases such as Tomato Early Blight, Potato Late Blight, and Maize Leaf Blight challenge agricultural productivity and food security around the world. In this paper, a custom Convolutional Neural Network architecture-based AI-driven web application for real-time crop disease detection is proposed. It employs latest image preprocessing techniques and assures that datasets are handled in the proposed system. It generates action recommendations in both Kannada and English bilingual mode to overcome the barriers in the language that hampers farmers in Karnataka, India. The web application links high-tech AI techniques to realistic agricultural needs. The results for experimentation have shown very high accuracy, scalably usable, and perfectly applicable for deployment in agricultural environments in rural regions.

KEYWORDS: Crop Disease Detection, AI in Agriculture, Convolutional Neural Networks, Image Processing, Bilingual Recommendations, Web Application, Tomato Diseases, Potato Diseases, Maize Diseases.

I. INTRODUCTION

A. Background

Agriculture is very significant in the global system of food security and stability in economies. Staple crops such as tomato, potato, and maize are very important factors in the global food supply. None the less, these crops are still very susceptible to diseases:

1. Tomato Early Blight: A fungal disease caused by Alternaria solani that results in yellowish discoloration of leaves, reduced photosynthesis, and considerable yield loss.
2. Potato Late Blight: Very destructive disease by Phytophthora infestans that are causing historical famines also it is causing present agriculture losses
3. Leaf Blight of Maize: In this disease, it affects the maize leaf structures which diminish the productivity and these pathogenic microbes include Exserohilum turcicum Eradication and disease management are dependent upon the time of detection.

B. Problem Description

Problems to be faced by farmers which particularly the small farmers of village

1. Limited accessibility to the experts: Majority of the small-scale farmers lack access to trained agriculture experts.
2. Labor-intensive detection: Methods utilized in the identification by human inspections are very labor-intensive and take a lot of time.
3. Subjectivity in diagnosis: Human inspections often error while providing a diagnosis, especially where symptoms overlap.
4. Language Barrier: All the available digital tools that are used for disease diagnosis are mainly written in English, hence it is inaccessible to most of the farmers who rely on such facilities like Karnataka, India.

C. Proposed Solution

The proposed solution of this study would integrate the following:

1. Custom CNN-based disease detection models for efficient and accurate classification of diseases from leaf images
2. Bilingual recommendation systems in Kannada and English, which bridge language barriers.
3. A user-friendly web application to enable real-time disease detection and management advice.

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D. Objectives

Major objectives of this research are to,

1. Design and Deploy A Specialized CNN Network Architecture Customized for Crop Disease Identification
2. Pre-processing: Collect a set of diseased leaves and disease-free leaves, continue with the pre-processing stage
3. Lightweight Web Application Development With AI-Powered Model Inclusion
4. Implementation-Based Recommendation disease management recommendations in Kannada language along with in the English language
5. Performance Analysis Testing the system for its accuracy and usability along with real world feasibility.

II. MULTILINGUAL AI SOLUTIONS FOR INCLUSIVE AGRICULTURAL DEVELOPMENT

A. Advances in AI-Based Agricultural Applications

Artificial Intelligence is revolutionizing agriculture by solving the problems of disease detection, resource management, and precision farming. AI uses machine learning and image processing techniques to enhance agricultural productivity and decision-making. Among these, CNNs have been particularly successful in crop disease detection due to their spatial pattern recognition ability in leaf images.

1. AI-Based CNN Models: CNNs is the main performance driver of the task in disease detection because of the ability to automatically process large and complex datasets in images by extracting spatial features such as shapes, textures, and patterns. They have even done better over traditional image analysis techniques.

Pretrained CNN Models:

There are models such as VGG16, DenseNet, and EfficientNet, that achieved significant accuracy levels in detecting diseases in agriculture but carried some drawbacks:

- VGG16: Suitable for low-level applications of image classification, though computationally expensive to implement in real-time.
- DenseNet & EfficientNet: This model uses dense connectivity as well as scalable feature extraction but is computer-intensive and hence not easily available in most rural communities .

2. Transfer Learning: Transfer learning is very widely used in reducing the time and computation taken in training. This is accomplished by using pre-trained models, for example, ImageNet models, and adapting them to crop disease datasets from a particular domain.

Advantages of Transfer Learning

1.Faster Training: The basic features in images, such as edges and textures, capture and increase the speed of convergence with pretraining.

2. Data Required Decreased: Transfer learning learns and predicts data and models at the desired levels by just requiring a very much smaller set of data, which achieves great accuracy rather than training on complete data.

Transfer learning is a great method for crop disease detection because it enables CNNs to identify disease patterns with fewer data and at lower computational costs . However, there is still research into developing customized CNN architectures specifically designed for agricultural image classification tasks.

B. Image Processing and Preprocessing

It preconditions the CNN models to the robust and general image data that are cleaned. It enhances convergence in the process of training, diminishes overfitting, and hence results in good models which generalize well for unseen data in varied environmental conditions.

1. Normalization: Normalization is one of the most important preprocessing techniques. The pixel values are normalized from the natural range of 0–255 to a continuous range of 0–1. It reduces the impact of changes in lighting and allows the CNNs to focus more on the spatial features rather than the changes due to brightness or exposure.

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C. Multilingual Insights in AI

The most significant hurdle to AI tool adoption among rural farmers remains language barriers, especially in places with poor English literacy. Most AI tools rely on English, meaning that non-English-speaking farmers are at a disadvantage.

1. Need for multilingual support: Success in AI comes with the ability of its output to communicate actionable insights to end-users. Insights in regional languages like Kannada, Telugu, or others are noted to increase leaps and bounds.

Important Observations

Language Localization: The ability to make insights actionable through local language translation is observed when AI outputs are in the regional language.
Contextual Adaptability: The requirement is to contextualize multilingual outputs for local agricultural practices and environmental conditions.

2. Multilingual AI Solutions: AI solutions that can interpret disease detection outputs in regional languages can eliminate the problem of literacy. Predictions and management recommendations may be translated into local languages, meaning farmers without formal English literacy will still be able to decide.

Key Benefits of Multilingual AI

1. Improving usability by overcoming the language barrier.
2. It bridges technology to the rural and urban areas.
3. Access of insights of AI by making translation of disease detection in the local languages of farmers.

These systems highlight the need for language support in agricultural AI-driven solutions for access and equitable spread of technology.

III. METHODOLOGY

A. Data preparation

1. Data collection: The dataset was obtained through the two sources for better heterogeneity and environmental variation,
Datasets Collected Through Public Datasets: From PlantVillage Dataset- https://plantvillage.psu.edu/ images with annotation details of healthy and diseased leaves.
Field Survey: Images were collected from farms in Karnataka and collected in collaboration with state agricultural agencies to mimic different real-world environmental conditions as much as possible.
Taking in both these sources gives comprehensive datasets for training and validation of the CNN model

2. Preprocessing: The images were preprocessed by standardizing the input for model performance. The methods involved are as follows.

1. Resizing: All images resized to uniformity of 128 × 128 pixels.
2. Normalization: Pixel values of all images scaled from the original range of 0 to 255 to 0 and 1 by dividing each pixel value by 255 considering variability in lighting.
3. Labeling: Each image was labeled into predefined categories, such as diseased leaves like Tomato Early Blight or Potato Late Blight, and healthy leaves.

Preprocessing reduced variability and focused on spatial features, which improved the model's learning efficiency.

B. Model Training

A customized Convolutional Neural Network was trained on the preprocessed images to classify crop diseases. It learned how to distinguish among different patterns of crop leaves as leaf disease categories such as Tomato Early Blight, Potato Late Blight, and Healthy leaves.
The training process was optimized to ensure accuracy while maintaining computational efficiency. The CNN was trained using standard hyperparameter optimization methods and validated on a separate validation dataset to check generalization and avoid overfitting.

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C. Development of Web Application

The trained CNN model was implemented in a user-friendly web application by the Django framework. This web application allowed for real-time disease detection and insights for farmers through easy interaction.

Web Application Main Features:

1. Upload Crop Leaf Images: There is an easy interface where the farmer can upload images.
2. Real-Time Disease Prediction: The CNN model analyzes the images uploaded to classify the disease status.
3. Bilingual Recommendations: The web application provides insights about the disease management in both English and Kannada so that the non-English-speaking farmers also get access to the web application. Workflow

The system workflow is described as follows:

1. A farmer uploads an image using the web interface.
2. The image is processed in advance (resized and normalized) before passing the same to the CNN model
3. The trained CNN takes that image as an input and gives output regarding the disease category.
4. Results are shown to the user with actionable recommendations both in English and Kannada.

Technology Stack:

The entire system was implemented using the tools and frameworks mentioned below.
Front-end: HTML, CSS, JavaScript to render the UI.
Back-end: The server-side processing used the Django framework for python.
Deployment of Model: TensorFlow/Keras to run the CNN predictions in real time.

IV. RESULTS AND ANALYSIS

A. Model Performance

CNN model trained and validated both on the PlantVillage dataset and the Karnataka survey data set in the field; the test performance of the reported is as per one standard measure on test sets. All the above was reported on the results as presented in Table 1.

1.Accuracy Measures: The CNN model accrued on the crop disease classes obtained below.

Disease Category	Accuracy (%)
Tomato Early Blight	92.5
Potato Late Blight	91.7
Maize Leaf Blight	90.8
Healthy Leaves	93.2

2. Analyzing the Results: In all the tested categories of the disease, the model performed exceptionally well and more than 90% accuracy was given in the classification.
On a healthy leaf, an accuracy of 93.2% was reported; thus, a difference can be considered sure with respect to diseased or non-diseased leaves.

Tomato Early Blight, with a prediction accuracy of 92.5%; Potato Late Blight, with a prediction accuracy of 91.7%, and Maize Leaf Blight, with a prediction accuracy of 90.8%, so it proves the generalization ability of the model across categories of diseases.

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This may be due to the high performance because:
1. It has used a robust and diversified dataset containing real-world environmental variations along with controlled data from PlantVillage.
2. Normalization and resizing have removed the variability generated by the external environmental change.
3. The CNN model is well optimized and has learned the effective spatial disease patterns.

These facts validate that the CNN model is accurate, generalizable and efficient for real-time crop disease classification.

B. Performance of Web Application

This CNN-trained model was used in a real-time disease detection environment application that utilized Django in order to be used within an actual web application environment. The application returned answers with relatively short response times which make its practical usage more feasible for realistic applications in agriculture.

The most critical performance of the system is as follows:
1. It returns the quick responses of the predictions after uploading the image.
2. Latency Disease Prediction, which produces fast response to the end-users.

These results support a fast system with high performance for situations of real-world applications for leaf image analysis.

V. CONCLUSION

This study proposed an AI-driven web application for real-time crop disease detection using a custom Convolutional Neural Network (CNN). The system was trained on datasets combining PlantVillage and field survey data from Karnataka to identify diseases such as Tomato Early Blight, Potato Late Blight, and Maize Leaf Blight. The CNN model achieved classification accuracy above 90% for the three types of diseases as well as healthy leaves that prove the strength and excellent generalization capability of the system. Additionally, the system includes a web interface through which farmers can upload images of their leaves and receive live predictions regarding diseases along with the actionable management information in bilingual - both in English and Kannada language.

The developed web application effectively deals with all the problems of accessibility, efficiency, and language barriers. The system provides farmers, especially in rural areas, with the opportunity to detect diseases in real time and acquire bilingual knowledge so they can take proper and timely action to deal with crop diseases. It is validated through the result in the potential of the system as a workable, user-friendly tool toward sustainable agricultural practices. Further extension of the system in detecting a wider variety of crop diseases, integration of environmental conditions, and provision of offline disease prediction capabilities will be part of future work.

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