International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Plant Disease Detection Using Convolutional Neural Networks (CNNs)

Kuldeep Dillliwar[1], Subham Mandal[2], Nagesh Sahu[3], Manish Kumar Shriwas[4], Rajeshri Lanjewar[5]

[1,2,3,4,5]Department of Computer Science Shri Shankaracharya Technical Campus
Bhilai, Chhattisgarh, India
[1]kuldeepdilliwar@gmail.com, [2]subhamkvc25@gmail.com, [3]nageshsahu1020@gmail.com
[4]mkshriwas2782003@gmail.com,[5]rajeshri21@gmail.com

Abstract

Plant disease detection is crucial for ensuring agri- cultural productivity and food security. However, accurately identifying diseases across various crops remains a challenge, particularly in resource-constrained regions. This study addresses this issue by developing a single convolutional neural network (CNN) model capable of identifying diseases across multiple crop types. Using a comprehensive dataset containing labelled images of healthy and diseased leaves from various crops: including apples, potatoes, and bell peppers, the model was trained to recognize both the crop type and the specific disease. The CNN architecture was optimized for performance, leveraging techniques such as data augmentation and transfer learning to improve generalization. The model achieved an accuracy of 98.53% on the training set, with high precision and recall for most disease categories. These results highlight the potential of deep learning for scalable plant disease diagnosis. Integrating this model into a Node.js-based web application further extends its accessibility, enabling real-time disease identification via user- uploaded images. This approach could empower farmers and agricultural workers worldwide, reducing dependency on expert diagnosis and facilitating timely disease management.

Index Terms: Plant Disease Detection (PDD), Convolutional Neural Network (CNN)

1. Introduction

Agriculture forms the bedrock of the global economy, with billions of people relying on it for food production and their livelihoods. Even though food production and access have improved, factors such as the decline of pollinators and plant diseases threaten food security. Reports indicate that more than 50% of crop yields in the developing world are lost to pests and diseases, and smallholder farmers, who produce more than 80% of agricultural production, bear the greatest burden of these losses.

Traditional PDD techniques rely on human observation, which is time-consuming, prone to error, and relies on ex- pertise. In remote or underdeveloped areas, access to such expertise is scarce, resulting in delayed or wrong diagnoses.

Similar symptoms often appear for various diseases, which complicates correct identification.
The proliferation of smartphones—expected to reach around 6 billion devices by 2050—offers immense potential for lever- aging their built-in capabilities for disease detection. Despite this potential, existing automated solutions face several chal- lenges, including:

- Class imbalance in datasets that affects model accuracy
- Overfitting of models during training, reducing general- izability
- Lack of robustness in real-world conditions, limiting usability

This research develops a web-based application using CNN to make this vision come into action. The work is motivated by the creation of an accessible, reliable, and scalable tool for PDD to empower farmers to manage crop health, contributing towards sustainable agricultural practices.

2. Literature Review

The study on plant leaf disease detection begins with image capturing, where color data such as HSV features are extracted and an artificial neural network (ANN) is trained to discriminate between healthy and diseased samples [1].
Ishak utilized MLP and RBF networks for leaf disease classification, demonstrating that RBF networks outperformed MLP in accuracy when combined with image preprocessing techniques for feature extraction [2].
Sladojevic introduced a CNN-based method for crop disease recognition using the Caffe framework, achieving 91-98% precision across different classes and establishing CNNs as powerful tools for PDD [3].
Cortes combined CNNs with Generative Adversarial Net- works to address imbalanced datasets in plant disease clas- sification, achieving over 80% accuracy in under five epochs while demonstrating the importance of data augmentation [4].

Ferentinos developed CNN models for crop disease identi- fication using a dataset of 87,848 photos, with the best model achieving 99.53% accuracy, highlighting CNNs' potential as early detection tools for various crops and diseases [5].
Wallelign applied LeNet architecture to soybean disease identification using the PlantVillage dataset, achieving 99.32% accuracy on images captured in natural environments, proving CNNs' effectiveness in real-world conditions [6].
Fuentes evaluated three deep learning architectures inte- grated with feature extractors like VGGNet and ResNet for real-time tomato PDD, showing promising performance across challenging images with varying infection status [7].
Shrestha's team identified 12 plant diseases with 88.80% accuracy using a CNN on 3,000 RGB images, but achieved a low F1 score of 0.12, revealing a significant gap between precision and recall in disease classification [8].
Nishant et al. demonstrated CNNs' superiority over tradi- tional algorithms for PDD while highlighting challenges in data preprocessing and the need for extensive training datasets to prevent overfitting [9].

International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

3. Methodology

This project focuses on identifying plant diseases us- ing a CNN model trained on the PlantVillage Dataset, a popular open-source resource for agricultural research. The dataset comprises 38 classes, including both healthy and diseased leaves of crops such as apples, bell peppers, potatoes, and tomatoes. Images are categorized into three sets: training, validation, and testing. The training and validation sets are organized in folders named as <PlantName>_<DiseaseName>, ensuring clarity in class labeling. Preprocessing steps involved resizing all images to 256×256 pixels and normalizing pixel values to the range [0, 1] using TensorFlow's Rescaling layer.

The CNN architecture was designed to efficiently capture image features and patterns associated with different plant diseases. It consists of four convolutional blocks, each con- taining two convolutional layers. These layers use increasing numbers of filters (32 to 256), with kernel sizes of 3×3 in the initial layers and 5×5 in deeper layers. ReLU is used as the activation function, and 'same' padding maintains consistent dimensions. Each convolutional block is followed by a MaxPooling layer (2×2 kernel) to reduce feature map dimensions while preserving important information.

The fully connected section begins with a Flatten layer, followed by a Dense layer with 1024 neurons activated by ReLU. A Dropout layer with a rate of 0.5 helps prevent overfitting by randomly deactivating neurons during training. The final output layer is a Dense layer with 38 neurons and a Softmax activation function to generate class probabilities.

Training was performed using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. The model was trained over 12 epochs, with early stopping implemented to halt training if no improvement in validation accuracy was observed for 3 consecutive epochs. Data augmentation techniques including random rotation, horizontal flipping, and slight zoom variations were applied to increase the diversity of the training data. These strategies helped ensure optimal train- ing efficiency and prevented overfitting. The model achieved an impressive training accuracy of 98.53% and test accuracy of 96.99%. Precision, recall, and F1-score were all consistently high at approximately 97%, demonstrating the model's ability to generalize well across various plant diseases. A 38×38 confusion matrix further highlighted accurate classification, with most misclassifications occurring between diseases with similar visual symptoms.

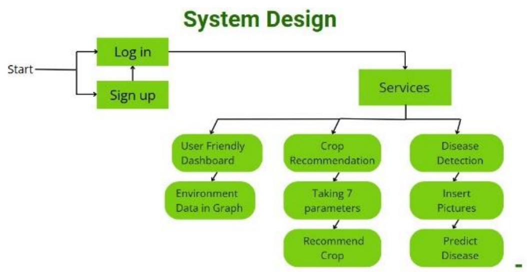

Fig 3.1: System design for our web app.

For deployment, the trained Keras model was converted to TensorFlow.js format and integrated into a web application. On the backend, Node.js with @tensorflow/tfjs-node handles server-side inference, while the React.js frontend allows users to upload plant leaf images. Upon submission, the app displays the detected disease, confidence score, and recommended so- lutions. This system ensures a fast, accurate, and user-friendly solution for real-time plant disease diagnosis, enabling farmers and agricultural professionals to take prompt and informed action in the field.

4. Results

Our CNN model's performance metrics surpass those of existing methods in the literature for PDD:

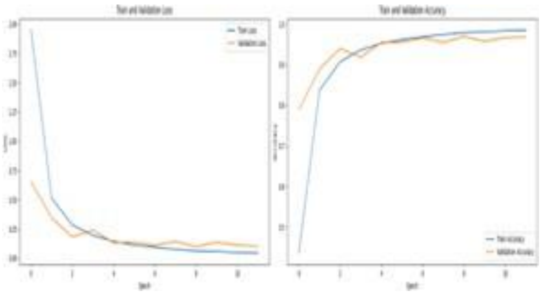

Fig 4.1: Training and validation accuracy and loss curves over epochs.

Models with simpler architectures often achieve accuracies in the range of 85–92%, whereas our model reaches a test ac- curacy of 96.99%. The use of data augmentation, dropout, and early stopping contributed significantly to this improvement.

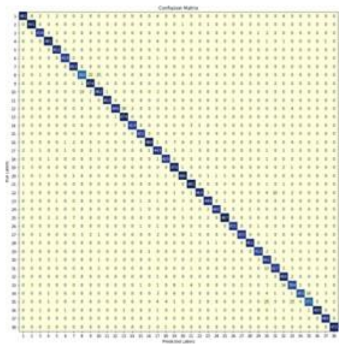

Fig 4.2: Confusion matrix for the 38-class classification task.

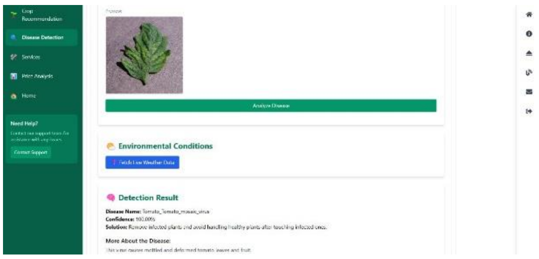

Fig 4.3: Examples of correctly predicted diseased and healthy leaf images with model confidence scores.

5. Conclusions & Future Scopes

Our CNN model achieved outstanding performance in clas- sifying plant diseases with high accuracy across all metrics. The confusion matrix confirmed minimal misclassification, with most errors occurring in visually similar classes. Integra- tion of techniques like data augmentation, dropout, and early stopping contributed to reducing overfitting and improving model generalization.

We have successfully developed a PDD system using a deep learning model built with CNNs capable of accurately classifying various plant diseases across multiple crops. By utilizing TensorFlow and integrating the model into a Node.js web application, we provide real-time disease detection that can support farmers and agricultural experts in early disease identification, potentially preventing crop loss and improving productivity.

References

1. M. Ranjan et al., "Detection and classification of leaf disease using artificial neural network," International Journal of Technical Research and Applications, vol. 3, no. 3, pp. 331-333, 2015.
2. S. Ishak et al., "Leaf disease classification using artificial neural net- work," Jurnal Teknologi, vol. 77, no. 17, 2015.
3. S. Sladojevic et al., "Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience, vol. 2016, 2016.
4. E. Cortes, "Plant disease classification using convolutional networks and generative adversarial networks," 2017.
5. K. P. Ferentinos, "Deep learning models for PDD and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311-318, 2018.
6. S. Wallelign, M. Polceanu, and C. Buche, "Soybean plant disease identification using CNN," in The Thirty-First International FLAIRS Conference, 2018.
7. A.Fuentes et al., "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," Sensors, vol. 17, no. 9, p. 2022, 2017.
8. G. Shrestha and M. Deepsikha, "Das, and N. Dey," PDD Using CNN," in 2020 IEEE Applied Signal Processing Conference (ASPCON), 2020.
9. Nishant, Suraj, Shubham et al., "PDD Using CNN," 2022.