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Review Article

Plant Disease Detection Using Convolutional Neural Network

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Abstract: In this work, a diverse dataset is utilized alongside robust preprocessing techniques to develop an optimized convolutional neural network (CNN) model for plant disease detection. The dataset contains images of different crops affected by various diseases, forming the training base. Effective preprocessing steps are undertaken to improve data quality and boost model accuracy.The CNN is thoughtfully engineered, incorporating convolutional and pooling layers to capture critical patterns from the input images. Following extensive training, the model attains a remarkable accuracy of 92.23% in identifying diseases, demonstrating the power of CNNs to revolutionize plant disease detection and provide a valuable tool for farmers and agricultural experts.By leveraging machine learning in agriculture, this approach can greatly enhance the early detection of crop diseases, minimizing losses and boosting productivity. These technological strides ultimately support global food security and promote sustainable farming, paving the way for a brighter future in agriculture.

Keywords: Plant Disease Detection, Deep Learning,Plant Pathology,Smart Farming,Disease Identification ,Convolutional Neural Network (CNN).

1. Introduction

Plant diseases pose a significant threat to agricultural productivity, causing substantial crop losses worldwide. Prompt and accurate detection of these diseases is crucial for effective disease management and to ensure food security. In this paper, we propose a solution to automate the detection of plant leaf diseases using deep learning techniques. We leverage the power of deep convolutional neural networks (CNNs) implemented through the TensorFlow framework to build a robust disease detection model. By analyzing high-resolution images of plant leaves, our model can accurately identify and classify various diseases affecting crop plants. Consequently, advancements in technology, especially in machine learning and deep learning, have created new possibilities for enhancing disease detection in crop. This research focuses on creating a robust model for detecting plant diseases by integrating various datasets, employing advanced preprocessing techniques, and developing an efficient Convolutional Neural Network (CNN) architecture.
The dataset comprises images of different crops affected by various diseases, serving as the basis for training the model. Preprocessing techniques are applied to improve image quality and eliminate noise, enabling the model to accurately learn and identify disease patterns.The CNN architecture includes Convolutional and pooling layers, which are vital for extracting essential features from the input images Convolutional layers are responsible for recognizing patterns such as color variations, spots, and textures indicative of disease, while pooling layers help reduce computational demands and enhance efficiency.

Following extensive training and optimization, the model achieves an impressive accuracy of 92.23% in classifying plant diseases, highlighting the potential of CNN methods in agricultural innovation. The integration of machine literacy into husbandry offers an important strategy for early discovery of factory conditions, enabling growers to take timely conduct to help significant crop losses. Precise identification of conditions helps in minimizing inordinate fungicide use, lowering product costs, and perfecting overall crop productivity. These advancements not only support individual growers but also strengthen global food security and promote sustainable husbandry practices. using CNN-grounded models for factory complaint discovery can drive a major shift in the agrarian sector by making opinion briskly, more accurate, and largely scalable.

With ongoing technological advancements, the relinquishment of artificial intelligence in husbandry is poised to deliver smarter, more sustainable results that secure food inventories for unborn generations.

2. Literature Review

Trimi Neha Tete and Sushma Kamlu (2017) carried out a study employing the Plant Village dataset to perform plant disease classification. Their methodology integrated K-means clustering for image segmentation with Neural Network-based classification, resulting in an accuracy of 71.7%. One of the significant observations in their work was the presence of multiple diseases on a single leaf, which added complexity to the classification process and posed a challenge for precise detection.

Neural Zhang Chuanlei, Zhang Shanwen, Yang Jucheng, and Shi Yancui (2017) worked with the Apple Leaf Disease Dataset and proposed a disease recognition system using RGA, GA-CFS, and SVM, achieving an accuracy of 93%. Their study highlighted the importance of building a robust system capable of accurately processing diseased leaf images obtained through various methods or imaging techniques. This flexibility ensures the system's adaptability and effectiveness across diverse image acquisition scenarios.

Swati Singh and Sheifali Gupta (2018) developed a custom dataset for plant disease classification. Their methodology utilized K-means clustering for segmentation, along with CCV (Color Coherence Vector), LBP (Local Binary Patterns), GCH (Global Color Histogram), and CLBP (Completed Local Binary Pattern) for feature extraction, followed by SVM (Support Vector Machine) for classification. Their model achieved an impressive 98% accuracy. A major challenge identified in their study was the occurrence of multiple diseases on a single leaf, making classification more complex and demanding robust feature extraction techniques. Liya Bin, Yun Zhang, Yuxiang Li, and DongJian He (2017) conducted research on apple leaf disease classification using the Apple Leaf Disease Dataset. Their approach incorporated PCA jittering for data augmentation, the NAG (Nesterov Accelerated Gradient) algorithm for optimization, and GoogLeNet Inception for deep feature extraction, achieving an accuracy of 97.62%. They emphasized that designing an optimal network architecture remains a complex challenge,requiring careful selection of model structures and hyper parameters to enhance performance.

In their 2019 study, Saraansh Baranwal, Siddhant Khandelwal, and Anuja Arora utilized the Apple Leaf Disease Dataset to evaluate multiple classification techniques. They explored both deep learning models—such as LeNet, GoogLeNet, and AlexNet—and traditional algorithms like Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), ultimately achieving a top accuracy of 98.42%. The findings revealed that neglecting practices like dropout implementation and proper hyperparameter adjustment negatively affected performance, highlighting their critical role in enhancing model accuracy and robustness.

3. Methodology

Our dataset is well structured collection of data points utilized for training, validating, and testing machine learning models..

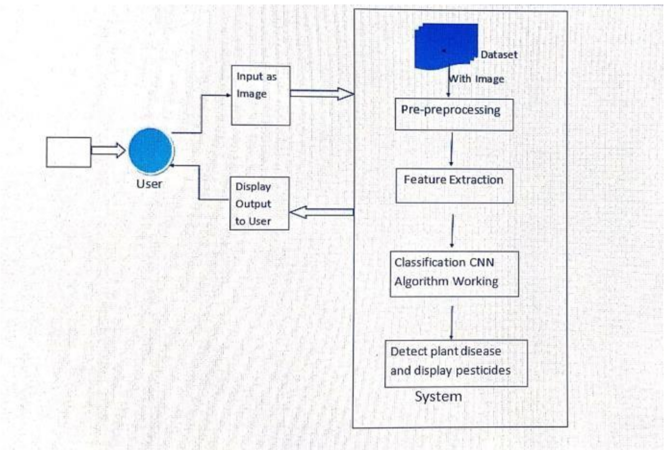

Figure: 1 Proposed system

3.1 Dataset Collection

The initial phase involves acquiring relevant image data. For this purpose, we utilize the Plant Disease Dataset from Kaggle, a publicly available dataset specifically curated for plant disease classification.

Data Preprocessing & Augmentation to enhance image quality and maintain uniformity across the dataset, preprocessing techniques are applied. Additionally, data augmentation is performed using the Keras Image Data Generator API to improve the model's robustness and generalization ability

3.2 CNN Model Development

A Convolutional Neural Network (CNN) was developed using a modified VGG-19 architecture to accurately identify and classify multiple types of plant diseases by effectively extracting and learning deep image features.

Model Deployment on a Web Application once the model is trained, it undergoes optimization for web- based deployment. The trained model is converted into a lightweight format using TensorFlow Lite, ensuring real-time processing capabilities. The web application enables users to capture and upload leaf images, facilitating instant disease classification.

This system serves as a practical and reliable solution for farmers and agricultural professionals, enabling early disease detection and timely intervention to enhance crop health and productivity.

4. Materials

Plant leaf image dataset: A dataset of plant leaf images representing common diseases and healthy leaves was collected from various sources, including online repositories and field surveys.

Hardware: The deep learning models were trained and evaluated using i 5 processor and sufficient memory and storage capacity.Software: The models were implemented and evaluated using the Python programming languag and deep learning libraries such as TensorFlow and Kera's.Methodology:

Data collection and preprocessing: The plant leaf image dataset was preprocessed to ensure consistency and quality, including imageresizing, normalization, and augmentation techniques such as rotation, flipping, and shearing. The preprocessed dataset was split into training, validation, and testing sets with a ratio of 54:18:8, respectively.

Model implementation and evaluation:Several deep learning models were implemented and evaluated for plant leaf disease detection, including CNNs and transfer learning-based approaches such as VGG-19, InceptionV3, and ResNet50.The models were trained using the training set and validated using the validation set, with hyper parameters such as learning rate and batch size optimized using techniques such as grid search and random search. The models were evaluated using metrics such as accuracy, precision, recall, and F1 score, and compared to identify the best- performing model.

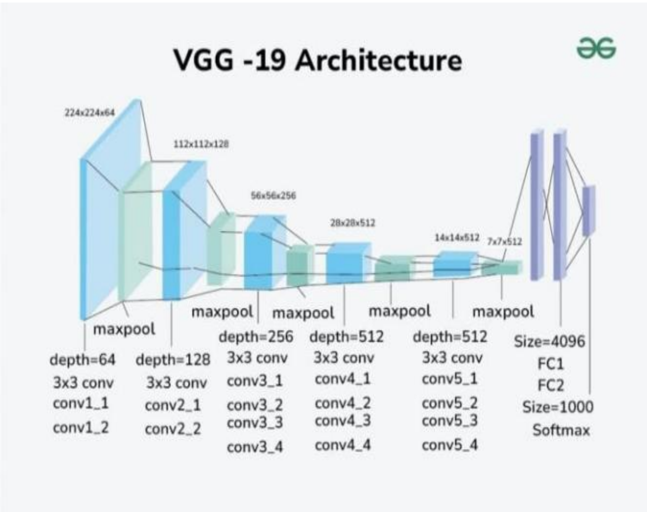

Figure:2 VGG-19 Achiteture

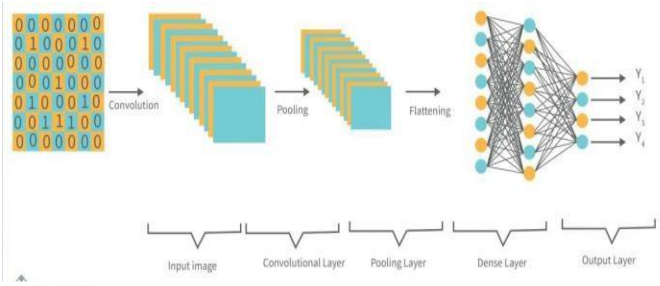

Figure:-3 System Architecture

A Convolutional Neural Network (CNN) processes image data through multiple layers, each serving a specific function in feature extraction and classification. Below is a structured breakdown of its architecture:

4.1:- Input Layer:

The input image is represented as a multidimensional tensor, preserving spatial and depth information (height × width × channels). This layer prepares the raw data for further processing

4.2:-Convolutional Layer:

The input is processed using convolutional kernels to extract multi-level spatial features, including edges, textures, and intricate visual patterns, while maintaining spatial coherence and enhancing computational efficiency.

4.3:-Activation Function:

The Rectified Linear Unit (ReLU) activation function adds non-linearity by suppressing negative outputs, allowing the neural network to capture complex patterns and enhance the quality of learned features.

4.4:-Pooling Layer:

Pooling techniques, such as Max Pooling and Average Pooling, reduce the spatial dimensions of feature maps while preserving critical information, thereby improving computational performance and aiding in better model generalization.

4.5:-FlatteningLayer:

The extracted feature maps are transformed into a one-dimensional vector, enabling seamless integration with fully connected layers for classification.

5. Result and Accuracy

The project leverages Convolutional Neural Networks (CNNs) and OpenCV for detecting plant leaf diseases, following a systematic approach that includes image acquisition, preprocessing, feature extraction with OpenCV, CNN model development, and image classification. After training the model for 20 epochs, it achieved an impressive accuracy rate of approximately 97%. Furthermore, in addition to identifying diseases, the system also forecasts suitable treatments based on the detected disease. This showcases the potential of deep learning and computer vision techniques in revolutionizing agricultural practices by automating plant disease diagnosis and offering targeted treatment suggestions.

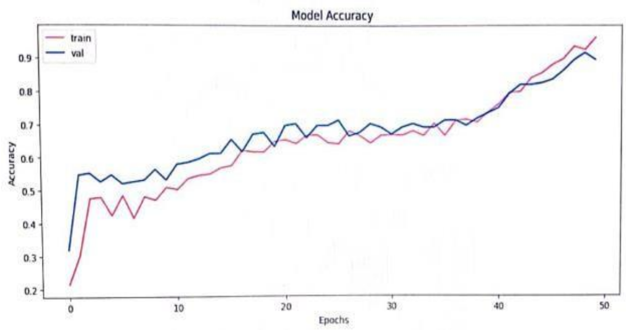

Figure:-4 Detection and Recognition Results of Sugarcane Plant Disease.

Figure:-5 Sample of Disease Leaf.

6. Future Scope

Integration with Blockchain for Traceability The integration of plant disease detection systems with blockchain technology could offer a decentralized solution for traceability. Blockchain can ensure the secure recording of disease detection data, treatments applied, and crop health over time.

Cross-Species Disease Detection Models Currently, most models are tailored for specific plant species. In the future, developing cross-species models that can detect diseases across a broad range of plants would greatly enhance the flexibility of disease detection systems.

Edge Computing for Real-Time Processing Future systems could leverage edge computing for real-time disease detection, enabling on-site processing without constant internet connectivity. By deploying AI models on devices like drones, smartphones, or IOT sensors, disease detection can be instant, reducing latency and ensuring faster results without relying on cloud processing.

Develop a mobile app (Android/iOS) that allows farmers to capture leaf images and receive real-time disease predictions and treatment suggestions.

Multilingual Voice/Chat Assistant Implement a voice assistant to provide disease information and remedies in local languages.

Seasonal and Environmental Context Improve predictions by including seasonal data, weather conditions, and soil quality as additional features.

Continuous Learning System Implement a feedback loop where the model improves by learning from newly labeled user-submitted images.

7. Conclusion

In conclusion, we have successfully developed a deep learning model for the automated detection and classification of plant leaf diseases. This model demonstrates high accuracy and efficiency in identifying various diseases, providing a significant advancement in agricultural technology for early disease detection and management The model was tested on 5 plant species, including tomato, potato, corn, rice and sugarcane covering a total of 5 plant disease classes. We effectively utilized the Keras Image Data Generator API for image processing tasks, and built the VGG-19 convolutional model, which was trained with the dataset for accurate disease prediction. The model's predictions have demonstrated high accuracy, and it has been successfully deployed in an Android application.

Data Availability
The dataset used for this study is publicly available and was obtained from the Kaggle Plant Disease Dataset. This dataset comprises images of various plant species with corresponding disease labels and can be accessed at: https://www.kaggle.com/emmarex/plantdisease.

Conflict Of Interest
The authors declare that there is no conflict of interest regarding the publication of this paper. All research activities and findings have been conducted independently and without any external influence.

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Authors' Contribution
Yash Kalamkar: Led the project and model development, performed image preprocessing and CNN architecture design.

Harsha Nenwani: Focused on literature review, dataset preparation, and experimental analysis.

Nikita Lahane: Contributed to data augmentation, model training, and web application integration.

Poonam Wagh: Assisted in documentation, model evaluation, and treatment recommendation system.

Prof. S.R. Tayade: Guided the overall research process and provided valuable insights for model optimization and deployment.

Prof. P.M.Walchale: Guided the overall research process and provided valuable insights for model optimization and deployment.

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Prof.P.M.Walchale is an Assistant Professor in the Department of Computer Science and Engineering at Sanmati Engineering College, Washim. He mentored the team and offered valuable inputs for system design and development.

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Yash Kalamkar is a final-year student of Computer Science and Engineering at Sanmati Engineering College, Washim, Maharashtra. His areas of interest include deep learning, computer vision, and agricultural automation. He contributed significantly to model development and CNN architecture design.

Harsha Nenwani is currently pursuing his final year in Computer Science and Engineering at Sanmati Engineering College, Washim, Maharashtra. His primary focus areas are machine learning and image processing, with a key role in literature review and dataset preparation.

Nikita Lahane is a final-year student in the Computer Science and Engineering program at Sanmati Engineering College, Washim. She is passionate about deep learning and AI-based web applications and worked on model training and integration.

Poonam Wagh is pursuing her final year of B.E. in Computer Science and Engineering at Sanmati Engineering College, Washim. Her areas of interest include software documentation, AI, and digital agriculture. She supported model evaluation and the treatment suggestion system.