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Corn Care: Plant Disease Defender

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***Abstract*— In a country like India, where a major portion of the population is involved in agriculture, it is crucial to detect plant diseases at early stages. Early disease detection is important for better yield and quality of crops. Reduction in the quality of agricultural products due to diseased plants can lead to huge economic losses for individual farmers. Various methods for detecting plant diseases have been developed as a means to ensure food security and reduce food waste through early detection. Precision farming has been developed through these technological advancements, and the application of machine learning is steadily gaining popularity in this industry as a means of solving this problem. Faster and precise prediction of plant disease could help in reducing the losses. Significant advancements and developments in deep learning have provided the opportunity to improve the performance and accuracy of detection of objects and recognition systems. This paper focuses on one of the major growing agricultural crop in India."CornCare: Plant Disease Defender" is a groundbreaking project aimed at revolutionizing agriculture, particularly in the context of maize cultivation, a vital crop worldwide. Leveraging cutting-edge Convolutional Neural Networks (CNNs) technology, the project focuses on early disease identification and categorization in corn plants. The increasing global population has heightened food security concerns, making corn, with its diverse applications in human and animal diets and various industries, a crucial resource. Although there is a wide variety of corn plant diseases, this paper covers just three major ones from the Kaggle database: Common rust, Northern leaf blight and Grey leaf spot. These diseases pose significant threats, often going unnoticed until they cause substantial crop losses and endanger food supplies. "CornCare" addresses these challenges by reducing reliance on visual inspections and the expertise of plant pathologists, thereby enhancing the efficiency and accessibility of disease identification. This project holds immense importance for the agriculture industry, ensuring early diagnosis and treatment of diseases to improve food security, stabilize markets, and promote sustainable agriculture practices. By encouraging responsible agrochemical use and reducing the environmental impact of corn farming, "CornCare" contributes to economic stability and agricultural development. To determine the model's effectiveness, it must first be trained, then validated, and ultimately tested. In testing, the proposed algorithm achieved an efficiency rate of 92%, showcasing the dataset's efficacy in accurately identifying and categorizing corn plant diseases. This result highlights the potential of the "CornCare" project to significantly improve disease management in maize crops and further support sustainable agriculture practices.**

***Index Terms*— Convolutional Neural Networks (CNN), Plant disease detection, Agriculture.**

I. INTRODUCTION

Modern-day advancements in technology have empowered humanity to provide sufficient nutrients and meals

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necessary to meet the demands of the world's expanding population. Specifically addressing India, where 70% of the population is directly or indirectly involved in agriculture, the farming sector remains paramount. However, a significant portion of farmers lack enthusiasm for improvement, leading to challenges exacerbated by pests and plant diseases. To enhance crop yield, new modern technologies such as websites and android apps have been developed.One such groundbreaking mobile application is "CornCare: Plant Disease Defender," which utilizes Convolutional Neural Networks (CNN) to transform corn disease diagnosis and control. This app offers real-time disease identification, thereby improving crop protection and global food security. Focusing on maize, a vital crop for human and animal consumption as well as various industries, "CornCare" bridges the gap between traditional farming practices and advanced technology. It facilitates early disease identification and classification, particularly for major threats like leaf rust, common rust, and northern corn leaf blight, surpassing conventional methods reliant on visual inspection. Early detection enables targeted treatments to halt disease spread and minimize crop loss. Moreover, "CornCare" promotes sustainable agriculture by reducing reliance on broad-spectrum pesticides and providing insights for enhanced crop management and sustainability. Its economic impact is substantial, shielding farmers from financial losses and bolstering market resilience. This innovation exemplifies the potential of integrating advanced technologies into agriculture, addressing food security and sustainability challenges while revolutionizing farmer education and disease management practices.

II. Related Works

[1] It presents a novel approach for the detection of plant diseases using CNN. The study was shared as part of the sustainable computing and data communication systems domain. The authors leveraged CNN technology to develop a model capable of accurately identifying plant diseases. The results of the study demonstrate the effectiveness of the CNN-based approach in detecting plant diseases, highlighting its potential for practical application in agriculture.

[2] The texture and visually striking similarities of coffee leaves can be used to detect the type of diseases they have. The focus of the study is on constructing a CNN model that processes the leaf images for disease detection using digital image processing techniques. This solution effectively identifies and classifies diseases based on features derived from the coffee leaf image samples, achieving an accuracy of 88.35%.

[3] Tomato is crucial globally, but vulnerable to diseases causing significant yield losses. Early detection is vital, prompting a deep learning-based approach using CNN for automated detection. The model was trained on a large dataset of tomato crop images, achieving over 91.66% accuracy in detecting common diseases like Early Blight, Late Blight, and Septoria Leaf Spot.

[4] The focus of this work is primarily on detecting plant diseases to reduce crop loss and increase production efficiency. The proposed method detects disease symptoms at the very early stage and classifies plant diseases based on these symptoms using a Deep Learning (DL) approach. The proposed technique employs a deep CNN, achieving an impressive accuracy of 96.50%.

[5] Automatic plant disease detection can improve monitoring and detection in large fields. A deep learning model utilizing a CNN accurately detects tomato plant diseases based on leaf data. The model achieved an average accuracy rate of 95.8% for classification.

[6] This study focuses on using a CNN to detect plant diseases using image data of infected and healthy leaves. The CNN model was trained on a database consisting of 87,848 images of 25 plant species with 58 pairs of classes [plant, disease]. The best model architecture achieved an accuracy of 99.68% in identifying the corresponding [plant, disease] pair (or healthy plant).

[7] Here Convolutional Neural Networks are utilized for high-resolution image recognition, specifically implementing the RESNET50 network to enhance effectiveness. The study uses a deep convolutional neural network algorithm to detect and classify plant diseases in grape and okra plant leaves. The dataset consists of 6 training sets containing 2500 images. The simulation results for the developed model achieved an accuracy of 95.1% in training and 91.2% in validation class tests.

[8] The study aims to identify the region of interest (ROI) in an image containing an object, proposing a method called Self-Generated Mask (SGM) to extract the ROI of objects with varied shapes, using jute leaves and stems as examples. The dataset used contains 1772 images in 10 classes of jute diseases. This study demonstrates that the manual annotation time can be significantly reduced using the SGM method.

[9] It focuses on detecting infections in Yukon Gold potatoes, specifically Alternaria, Blackleg, and Target Spot diseases, using deep Convolutional Neural Networks. The CNN is trained on 5,615 images of diseased and healthy potato leaves to distinguish between these diseases. Anomaly detection with the F-RCNN model achieved an 80%

confidence score, while infection identification using transfer learning reached 97.85% accuracy. The automated image-capturing system's effectiveness for diagnosing potato leaf diseases was determined to be 93.33%.
[10] Preprocessing, crucial for preparing plant leaf images, significantly impacts deep learning results. The proposed vision-based processes effectively identify and analyze external disease factors. Using the latest Plant Diseases Dataset, a specially trained convolutional neural network (CNN) achieves 99.29% test accuracy in classifying plant leaf images into 38 diseases.
[11] Here a flutter app is implemented which uses image location for historical weather data and offers contact with FAREI for further assistance. Image scans are stored in a Firestore Database. A CNN model trained with 3000 images achieved a 75.5% accuracy over 25 epochs. Specific diseases like Black Rot and Rust achieved accuracies of 30.0% and 60.0% respectively with a training set of 10 images per disease. Overall, the app achieved a 68.3% accuracy with a test audience of 60 people.
[12] The study emphasizes how water requirements for plants vary based on soil content, texture, and climate, necessitating tailored irrigation. It notes the significant impact of plant diseases on growth. To address these challenges, the study proposes a smart irrigation system that automates irrigation using an Android app, capturing plant leaf images sent to a cloud server for processing. These images are then compared with diseased leaf images in the database, providing users with a list of suspected diseases.

III. PROPOSED SOLUTION

The proposed solution for the "CornCare" project involves the development of a mobile application that utilizes Convolutional Neural Networks (CNNs) to accurately detect and classify corn leaf diseases. This application will allow farmers to quickly and easily identify diseases in their crops by simply capturing images of the affected leaves. The CNN model will be trained on a comprehensive dataset of corn leaf images, including various disease states and healthy leaves, to ensure robust performance. The application will provide real-time feedback on the disease status, including recommendations for treatment and management. Additionally, the app will have a user-friendly interface, making it accessible to farmers of all levels of technological proficiency. The ultimate goal of the proposed solution is to empower farmers with a tool that can significantly improve crop protection and contribute to global food security.

A. CNN Architecture

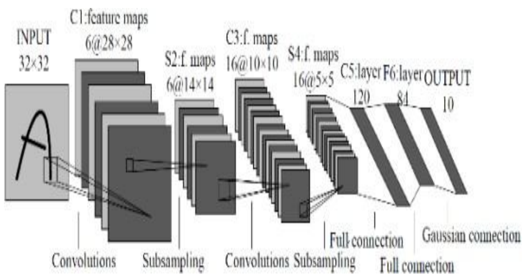

Figure 1. CNN Architecture

CNNs are fundamental in deep learning, acting as multi-layer perceptrons for input-to-output mapping. They excel in extracting information features through convolutions and pooling operations, using local connections and shared weights to streamline optimization and reduce overfitting risks. Comprising convolutional, pooling, and fully connected SoftMax layers, CNNs identify local features, extract complex correlations, and enhance pattern capture from input parameters. They excel in image recognition, natural language processing, and other tasks, revolutionizing fields by automatically learning hierarchical data representations. The convolutional layer applies filters to detect features, while the pooling layer reduces spatial dimensions to control complexity and overfitting. The fully connected layer aggregates features for classification, enabling CNNs to learn intricate patterns and relationships in data, making them highly effective in diverse applications.

B. Gadget Workflow

The key steps involved in the above workflow diagram are as follows:

- *Capture Image/Video*: Users capture an image or video of a corn plant showing signs of distress using devices equipped with cameras like smartphones, agricultural cameras, or drones.

- *Load Image/Video*: The captured media is uploaded into the core of the system - a CNN trained on a diverse dataset of corn plant images tagged with disease information.
- *Image/Video Processing*: The media undergoes pre-processing steps to optimize it for analysis, including scaling, normalization, and color space conversion.
- *Analyze and Classify Disease*: The CNN analyzes the media for patterns indicative of corn diseases, classifying the identified symptoms and providing a detailed diagnosis, including diseases like leaf rust, common rust, and Northern corn leaf blight.
- *Display Precautions and Causes*: Upon diagnosis, the application displays the name of the disease, potential causes, and recommended precautions, guiding farmers to take immediate and effective measures to protect their crops.

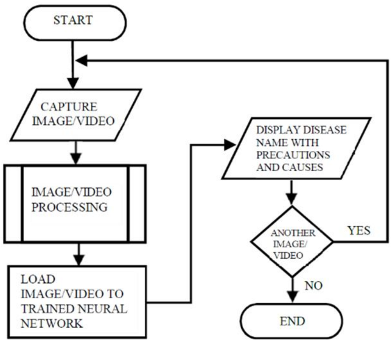

Figure 2. Workflow Diagram

C. *Architecture Diagram*

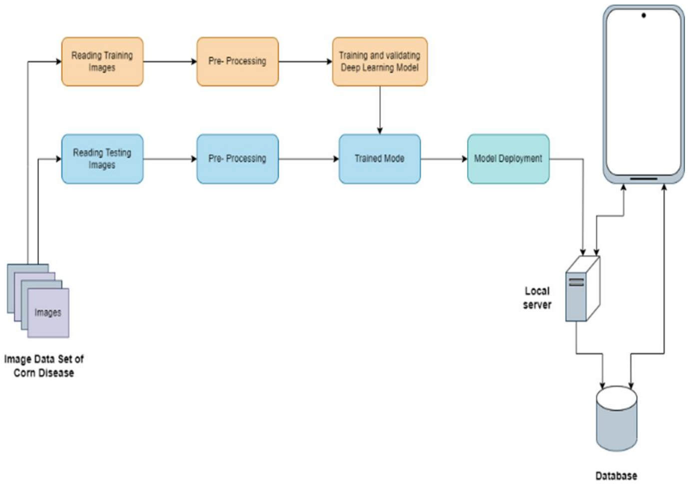

Figure 3. Architecture Diagram

The key steps involved in the above architecture diagram are as follows:

- *Reading Training Images*: Importing images for training a deep learning model to identify corn disease.
- *Pre-Processing*: Preparing training images by resizing, converting formats, and normalizing pixel values.
- *Training and Validating Deep Learning Model*: Using pre-processed training images to train the model, with a validation set to monitor performance and prevent overfitting.
- *Reading Testing Images:* This block refers to importing a set of images that will be used to test the performance of the trained model.
- *Pre-Processing*: The testing images go through the same pre-processing steps as the training images.
- *Trained Model*: The pre-processed testing images are fed through the trained deep learning model.
- *Model Deployment*: Deploying the model to a server or embedded device for real-world use.
- *Database:* Storing processed images and the trained model in a local server database, likely containing images of corn disease and associated information.

D. Sample Corn Leaf Images

Figure 4. Leaf Blight

Figure 5. Grey Leaf Spot

Figure 6. Common Rust

Figure 7. Healthy

Northern Leaf Blight, Grey Leaf Spot, and Common Rust are common corn leaf diseases that can significantly impact crop health and yield. Northern Leaf Blight, caused by the fungus 'Exserohilum turcicum', manifests as cigar-shaped lesions on leaves, starting as small, light-green spots and developing into long, brown lesions. Grey Leaf Spot, caused by 'Cercospora zeae-maydis', appears as small, circular to oval-shaped lesions with a grey center and dark-brown borders. Common Rust, caused by 'Puccinia sorghi', presents as small, circular to elongated orange to brown pustules on leaf surfaces. Effective management strategies include planting disease-resistant varieties, rotating crops, and timely fungicide applications.

IV. Results And Discussions

A. Accuracy Tables

In the training phase of the project, a dataset consisting of various plant diseases was employed. Each disease category was represented by 30 images, meticulously curated and labeled for training purposes. The algorithm exhibited promising performance during training, achieving high accuracy rates across different diseases. For instance, in the case of Northern leaf blight, out of 30 images, the model accurately detected 29 instances while misclassifying only one image, resulting in an impressive accuracy of 96%. Similar robust performance was observed across other disease categories, such as Common rust, Grey leaf spot, and Healthy plants, with accuracies of 91%, 93%, and 94%, respectively. This robust training phase laid a solid foundation for the subsequent testing phase, instilling confidence in the capabilities of the model to accurately diagnose plant diseases.

DISEASE NAME	NO. OF IMAGES	DETECTED IMAGES	UNDETECTED IMAGES	ACCURACY
Northren leaf blight	30	29	1	96
Common rust	30	27	3	91
Grey leaf spot	30	28	2	93
Healthy	30	28	2	94

Figure 8. Training Accuracy Table

DISEASE NAME	NO. OF IMAGES	DETECTED IMAGES	UNDETECTED IMAGES	ACCURACY
Northren leaf blight	30	28	2	94
Common rust	30	27	3	91
Grey leaf spot	30	27	3	89
Healthy	30	29	1	96

Figure 9. Testing Accuracy Table

During the testing phase, the performance of the trained model was rigorously evaluated on a separate dataset to assess its real-world applicability and generalization capabilities. The testing dataset mirrored the diversity and complexity of the training data, ensuring a comprehensive evaluation of the model's performance. Across various disease categories, including Northern leaf blight, Common rust, Grey leaf spot, and Healthy plants, the model demonstrated consistent and reliable performance. For instance, in the case of Northern leaf blight, the model accurately detected 28 out of 30 instances while encountering 2 undetected cases, resulting in an accuracy of 94%. Similar robustness was observed across other disease categories, with accuracies ranging from 89% to 96%. These results underscore the efficacy and reliability of the model in accurately diagnosing plant diseases, thereby showcasing its potential for practical deployment in agricultural settings.

V. Conclusions

"CornCare: Plant Disease Defender" illustrates the transformative impact of Convolutional Neural Networks (CNNs) on crop disease management. The initiative underscores the importance of meticulous data gathering and preprocessing to effectively train CNN models, underscoring the pivotal role of input data in accurate disease identification. Leveraging CNN technology, the project surpasses conventional disease diagnosis techniques, offering swift and reliable detection of corn diseases, alongside actionable insights for preventive measures. This tangible application of machine learning in agriculture highlights its potential to revolutionize farming practices.

Future enhancements for "CornCare" includes:

- Expanding the dataset to encompass a wider variety of crops and diseases.
- Integrating real-time disease monitoring and prediction features.
- Implementing the use of drones for capturing images/videos of corn plants.
- Implementing the app for iOS platforms.

These enhancements would further enhance the effectiveness and usability of the application, contributing to its potential for widespread adoption in agricultural communities.

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