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NaturalCare: AI-Based Potato Leaf Disease Detection with Natural Homemade Treatment Suggestions and a Bilingual Chatbot

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Abstract:
As a staple crop, potatoes are essential to the world's food security. Thus, this effort aims to explore CNNs' potential for potato leaf disease detection. To efficiently classify different potato leaf diseases, we use a Convolutional Neural Network (CNN) technique. The CNN model uses several convolutional, pooling, and fully connected layers to extract spatial characteristics from the input images. Many academics have sought to improve the early detection of potato blight using various machine and deep learning techniques as neural networks have been included into agriculture. By learning hierarchical cues including color variations, texture, and form patterns, the network effectively differentiates between healthy and sick leaves. Additionally, the CNN model records 96.52% accuracy, 96.67% precision, 96.52% recall, and an F1 score of 96.52% for severity categorization, demonstrating its capacity to handle intricate visual patterns in agricultural disease detection.

Keywords—Machine learning, CNN, Image Processing, Crop Protection, Computer Vision

I. INTRODUCTION

Artificial intelligence (AI) has become a crucial component of many applications in the current technological era, improving accuracy and efficiency in a variety of fields. In order to protect healthy crops and ensure consistent output, I took on two difficult projects as an Artificial Intelligence Trainee at ADN DIGINET: "EDU Chatbot" and "Potato Plant Disease Detection" [1]. Plant diseases have a significant impact on both the quantity and quality of crop yield. Leaf infections are one of the most common and harmful issues that farmers deal with when growing potatoes [2]. Due to decreased yield and quality, potato leaf diseases can have a significant negative impact on farmers' livelihoods and result in significant financial losses. Effective management of these illnesses can greatly increase overall agricultural output, promoting sustainability and food supply. Bacterial and fungal infestations are especially dangerous for potato crops [3].

Given that biotic and abiotic stresses eventually limit agricultural yield, The goal of this study was to identify plant diseases using DL methods. Farmers would be able to promptly and easily detect illnesses as a result, enabling them to take the necessary treatment at an early stage. The identification of three leaf diseases and the detection of six severity levels have been the main topics of this work [4].

The device enables sustainable and economical management methods by offering natural and eco-friendly homemade therapy recommendations in addition to automated disease diagnosis [5]. The two main goals of these methods were to decrease diagnosis delay and improve classification accuracy [6]. Currently, research on artificial intelligence may be able to detect plant diseases from images. Deep learning is associated with neural network-based learning. One advantage of deep learning is its ability to automatically extract features from images. The neural network develops crucial feature extraction abilities through overtraining. CNN [7], a multi-layer feed-forward neural network, is frequently used to model deep learning.

The following are main tasks are outlined below in this research work,

i). Create a deep learning based AI system to automatically identify potato leaf illness.

ii). Application Using pre-built models such as CNN [8].

iii). Option Use ensemble learning to increase the model's performance and accuracy.

iv). Provide Natural, Handmade and eco-friendly treatments for recognized illnesses.

v). Integrate a bilingual chatbot to assist farmers with real-time results and recommendations [9].

II. RELATED WORKS

Upon The Visual Transformer network, the Visual Geometry Group 16, and the Variational Autoencoder are used to extract features from the collected photos. The Adaptive Convolutional Neural Network with Attention Mechanism is employed in this use case to classify plant leaf diseases, and the parameters are optimized using the Enhanced Gannet Optimization Algorithm technique [10]. Using federated transfer learning and feature extraction approaches, the study investigates the classification of potato leaf disease photographs. With a remarkable validation accuracy of 99%, EfficientNetB3 is proven to be the basic model for the federated learning (FL) environment [11]. The TrioConvTomatoNet, deep convolutional neural network system proposed in this study, effectively extracts and integrates information from leaf images by incorporating a three-series convolution layer beneath stage of the feature extraction topology compared to conventional CNN architectures, proving its robustness across diverse datasets [12].

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Four specific deep learning frameworks—InceptionV3, ResNet50, InceptionResNetV2, and CNN—are used in neural learning through transfer for the fine-grained classification of potato plant diseases. With a maximum validation accuracy of 87.51%, precision of 90.33%, and recall of 99.80%, ResNet50 outperforms the others in identifying and categorizing potato plant illnesses [13]. To cut down on processing time, the photo sizes must be standardized offline to 224 224-standard pixel squares before training. To increase the model's generalizability and prevent overfitting, a number of data augmentation techniques are applied to an image of each category with a predetermined chance during online model training. We have selected four data augmentation techniques for this investigation [14].

The residual-based multi-scale network (MResNet) uses crop pictures to identify several leaf diseases in maize. MResNet, which consists of two residual subnets with different scales, enables the model to detect illnesses in leaf maize pictures at numerous scales. MResNet achieves 97.45% accuracy [15]. It has been shown that the neural network architecture EfficientNetB4 can accurately detect photos with little parameters. The model was improved and altered in this endeavor to create EfficientPotatoNetB4, which is intended to identify various potato leaf diseases [16]. The suggested approach uses CNNs to classify the image and reduce overfitting problems [17]. Their performance is closely analyzed in conjunction with conventional transfer learning methods such as VGG16, Xception, ResNet50, DenseNet121, Inception ResnetV2, and Inception V3. The ability of the suggested custom VGG16 model to generalize to previously observed images was used to assess its efficacy. It exceeded the benchmarks set by the most sophisticated models currently in use with an incredible 99.94% accuracy [18].

III. Proposed Approach

This section discusses the dataset that is used for the research work, the data preprocessing involved, Data Augmentation for supplementing the smaller number of images, and an overview of CNN Models.

A. *Dataset*

Every image in the dataset was compressed to standard pixels, which is regarded as a standard 224x224 resolution, in order to create image classification models [19]. The test dataset By incorporating photos taken over the whole growing season, which spans from February to July, DiaMOS Plant seeks to produce a representative sample that includes the pear tree's primary cultural traits. Machine and deep learning techniques can be applied to the dataset to solve recognition and classification challenges. Of the 3505 images collected, 499 showed fruit and 3006 showed foliage [20]. Due to the use of a DSLR camera (Canon EOS 60D) and a smartphone (Honour 6×), two different resolutions are available: 3456 × 5184 and 2976 × 3968, respectively. Photos were taken throughout the year, from February to July 2021, to track the progression of the illness from its early symptoms. In this case, the models are taught to keep an eye on the health of the plant and make smarter decisions to boost productivity. A total of 3057 images were taken, showing both healthy and sick leaves with spots, curls, and slug damage. The five stress severity classifications were assessed using a 0–4 scale: There are five different severity percentage ranges: 0%, (6–20%) as low, (21–25%) as medium, (>50%) as high, and (1%–5%) as extremely low. Figure 4 demonstrates the classifications of images with various diseases as shown [21].

TABLE I. HEALTHY AND BIOTIC STRESS CLASS CLASSIFICATION WITH IMAGE DESCRIPTION

S.no	Category	Class	Sample Images	No of Images
1	Diseased	nematode		1000
2	Diseased	Late Blight		1000
3	Diseased	Early Blight		1000
4	Healthy	Healthy		1000

Table I The visualization of potato leaves with three distinct categories of healthy and sick leaves, along with the quantity of pictures in each category, is displayed.

TABLE II. SEVERITY CLASSES WITH NUMBER OF IMAGE DESCRIPTION

S.No	Category	No of Images
1	Potato Bacteria	1000
2	Potato Nematode	1000
3	Potato EarlyBlight	1000
4	Potato LateBlight_	1000
5	Potato Healthy	1000

The number of images in each severity category and the different severity levels—which range from 0 to 4—are listed in Table II.

B. *Data Preprocessing*

In this step, the background of the photos is removed in order to isolate the ROI. The background could introduce noise into the data, leading to an inaccurate diagnosis. For instance, the surroundings or a leaf's shadow could be mistaken for an indication of illness, skewing the results. The images are further separated into discrete classes based on different cropping techniques to increase the efficacy of model training. Overall, this process improves the trained classifier's optimal accuracy and reliability in disease detection while lowering the related calculation time [22].

C. *Enhanced Data*

In order to produce more training data from the currently available training examples, it uses the idea of augmenting the training samples by making a variety of arbitrary adjustments to create believable-looking images [23]. In this study, an image's pixels are rearranged or its brightness, contrast, rotation, or zoom level is changed using a straightforward augmentation technique to provide more training instances [24]. The following are the procedures included in the research work,Flipping in both directions, scaling, shearing, padding, sharpening, and cropping photos [25].

CNN Models

In this study, we provide a deep learning-based CNN model for precise picture classification. The suggested classifier effectively distinguishes between diseased and healthy potato leaves [26]. Through a number of layers, the sequential model is intended to extract important information from the input image. First, a 256 × 256 × 3 input image is fed into a convolutional layer. This layer uses the ReLU activation function and applies 32 3 x 3 filters [27]. The model was trained at a learning rate of 1e-3 for 20 epochs. On the validation dataset, this carefully adjusted configuration yielded an astounding 96.52% accuracy. These results emphasize the significance of including sophisticated architectural elements and carefully choosing hyperparameters [28]. The 224 × 224 × 3 input tensor for ResNet50 represents RGB images that have been scaled to 224 pixels per side. ResNet50's convolutional modules are arranged so that batch normalization and Rectified Linear Unit (ReLU) nonlinearities come right after convolutional filters. The basic architecture of ResNet50 is shown in Fig.1.
design.

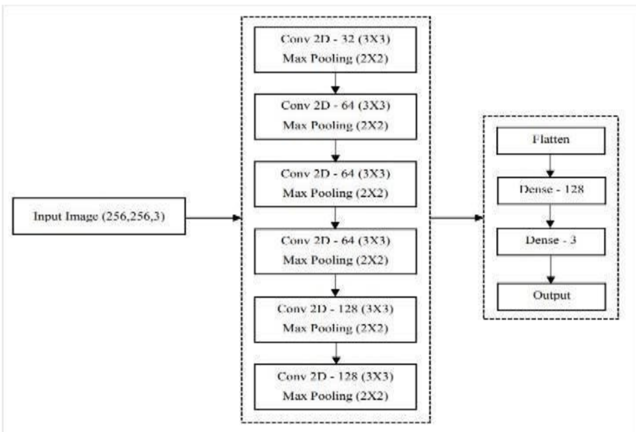

Fig. 1. Customized CNN model's Architecture

IV. METHODOLOGY

The sequence explains the pseudocode process. using the following pseudocode:

Step 1: First, load the entire dataset.
Step 2: Create train and test sets from the dataset. Step 3: Preparation
Step 4: Prepare the pictures for the test and training sets The target variables are encoded in step five.
Step 7: Describe the augmentation of data
Step 8: Putting a learned model into practice
Step 9: Build the model by combining two Step 10: Collective forecasts
Step 11: Using metrics to evaluate performance

A dataset of both healthy and diseased potato leaves is used to train the CNN model utilized in NaturalCare. Convolutional layers collect features, and the final softmax classifier predicts the disease category [29]. For image- based classification tasks, the Convolutional Neural Network (CNN) is a potent and popular deep learning model [30] Convolutional Neural Networks (CNNs) offer strong feature-learning capabilities by automatically extracting spatial patterns such as edges, textures, and disease-specific lesions from plant leaf images [31]. Convolutional Neural Networks (CNNs) provide significant advantages for plant-leaf disease classification by automatically learning hierarchical spatial features directly from image data. CNN architectures extract low-level patterns such as edges and color variations in the initial layers, while deeper layers learn complex disease-specific textures, lesion shapes, and structural distortions. These learned representations enable the model to effectively distinguish between healthy and diseased potato leaves. Prior studies in plant-disease detection highlight that a well-designed single CNN model—with optimized hyperparameters, regularization, and data augmentation—can achieve high classification accuracy and strong robustness by capturing discriminative visual patterns essential for reliable decision-making [32]. A typical CNN model includes convolutional layers for feature extraction, activation layers for introducing non-linearity, pooling layers for dimensionality reduction, and fully connected layers for final classification. This hierarchical structure enables the CNN to progressively capture simple features such as edges and textures in earlier layers, and more complex disease-specific patterns in deeper layers. The complete CNN architecture used in this study for potato leaf disease detection is illustrated in Fig. 2.

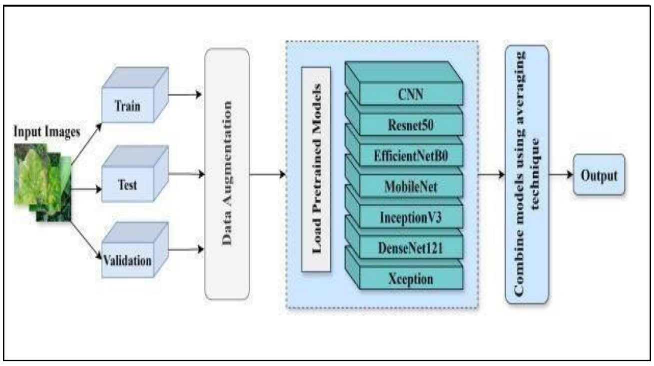

Fig. 2. A Convolutional Neural Network (CNN) architecture is employed to classify potato leaf diseases and determine their severity by learning discriminative features directly from the input images.

V. RESULTS AND DISCUSSION

A. *Hyperparameters*

Before a deep learning algorithm is applied to a dataset, hyperparameter values are specifically chosen to control the learning process. These methods are used to define the model's complexity and learning capacity. Hyperparameters are important when determining the required value for a parameter to reach its maximal value or performance. The same is displayed in Table III.

TABLEIII. HYPER PARAMETER VALUE

Hyper Parameters	Value assigned
Test_Size	0.2
Train_Size	0.8
The amount of classes	5
Batch Size	32
Input Size	128,128
Optimizer	adam
Loss Function	categorical_crossentropy
Learning rate	0.001
Epochs	20
Activation Method	Relu
Dropout	Notused
Metrics	Accuracy

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B. Performance Metrics

A confusion matrix serves as a valuable tool for measuring a classification model's effectiveness by providing a concise summary of its predictions [33].

$$Accuracy(Ac) = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision}(\text{Pr}) = \frac{TP}{\text{TP+FP}} \quad (2)$$

$$\text{Recall}(\text{Rl}) = \frac{TP}{\text{TP+FN}} \quad (3)$$

$$F1\,Score(F1Sc) = 2 * \frac{Recall*Precision}{Recall+Precision} \quad (4)$$

The outcomes of applying these pre-trained models to the classification of healthy and biotic stress are displayed in Table IV.

TABLE IV. CNN'SHEALTHY &DISEASECLASSIFICATION.

Models	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	96.52	96.67	96.52	96.52

Table V presents the class-wise performance of the CNN model for potato leaf disease detection, showing effective classification across Healthy, Early Blight, Late Blight, and Nematode-affected leaves with accuracies ranging from 95.80% to 97.10%.

TABLE V. CNN MODEL'S PERFORMANCE BY CLASS

Models	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Healthy Leaf	97.10	97.40	97.00	97.00
Early Blight	95.80	96.20	95.70	95.60
Late Blight	96.20	96.50	96.00	96.10
Nematode affected	95.90	96.10	95.80	95.80

Fig. 3 shows the CNN model's confusion matrix results for detecting potato leaf disease. The model demonstrated outstanding classification performance across Early Blight, Late Blight, and Healthy leaf categories with a high accuracy of 96.66%, precision of 96.67%, recall of 96.34%, and F1-score of 96.51%.

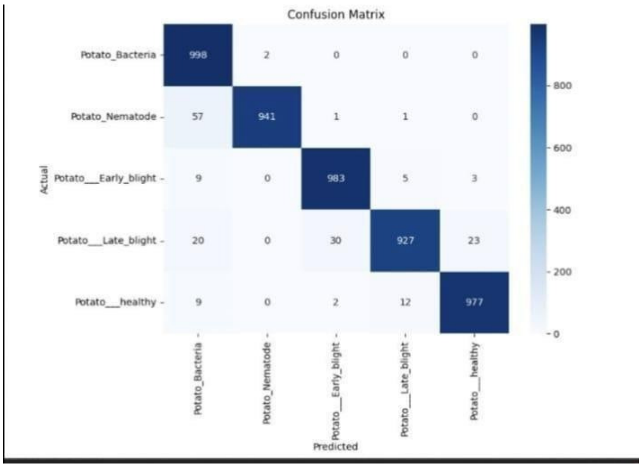


Fig. 3 CNN model's confusion matrix results

Table VI shows the CNN model's performance, achieving high accuracy for Early Blight with a precision of 96.67%, recall of 96.52%, and F1-score of 96.52%. The average

TABLE VI. HEALTHY PRECISION,RECALL, F1-SCORE OF CNN MODEL.

Performance Measures	Early Blight	Late Blight	Healthy	Average
Precision	96.67	96.20	97.10	96.66
Recall	96.52	96.50	96.00	96.34
F1-Score	96.52	96.00	97.00	96.51

According to the acquired experimental data, the suggested CNN model outperforms conventional machine learning techniques in terms of classification accuracy, precision, recall, and F1-score for the detection of potato leaf disease. Convolutional neural network models for biotic stress categorization using Ac, Pr, Rl, and F1Sc.
precision, recall, and F1-score across all classes are 62.95%, 55.47%, and 59.59%, respectively. Overall, the discussions and visualizations demonstrate the CNN model's efficacy in disease detection in potato leaves, with high accuracy rates and well-behaved accuracy and loss curves during training. In the accuracy graph, the gap between the training and validation accuracies narrows over time, suggesting that the model generalizes well to unseen data. Similarly, in the loss graph, we observe a decreasing trend in both training and validation loss over epochs, indicating that the model effectively minimizes its loss function during training, leading to improved performance. The difference between the training and the accuracy graph. These results highlight CNNs' potential as effective instruments for automated disease detection in agriculture, enabling prompt intervention and better crop management techniques.

Fig. 4 This image shows the homepage of the NaturalCare AI system, an application designed for AI-based potato leaf disease diagnosis with features like leaf analysis, weather risk assessment, and care reports

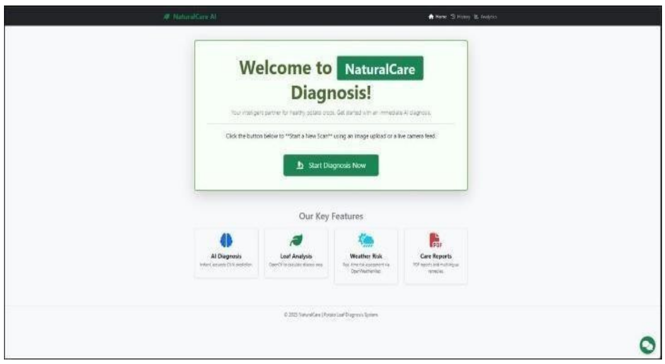
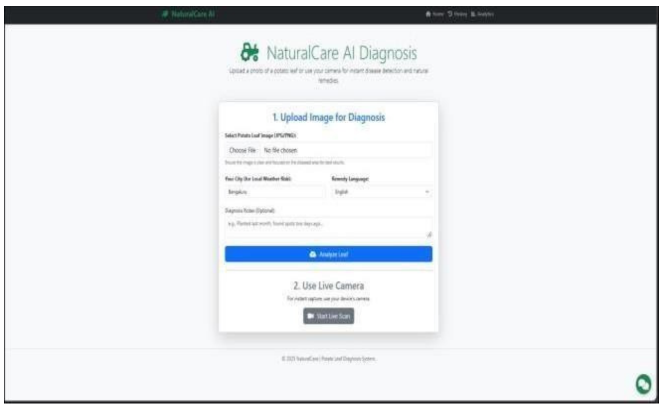


Fig. 5 The image shows the NaturalCare AI Diagnosis web interface for uploading or scanning a potato leaf to detect diseases and suggest natural remedies.



The interface has areas for choosing an image, entering the city to determine the local weather risk, selecting a remedy language, and adding optional notes. Clicking "Analyze Leaf" after entering the information initiates the AI-based diagnosis process to determine the illness and recommend natural treatments.

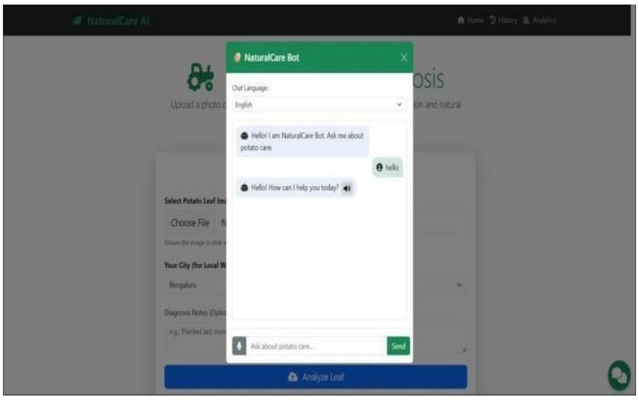


Fig. 6 The image shows the NaturalCare Bot chat interface that assists users by providing information and guidance about potato care and disease remedies.

The image shows the NaturalCare AI Diagnosis web application, which helps detect potato leaf diseases using artificial intelligence. Users can upload a clear photo of a potato leaf or use their device's live camera for instant scanning. The form allows users to enter their city for local weather risk, choose a remedy language, and add optional diagnosis notes. By clicking "Analyze Leaf," the system processes the image to identify possible diseases and suggest natural remedies.

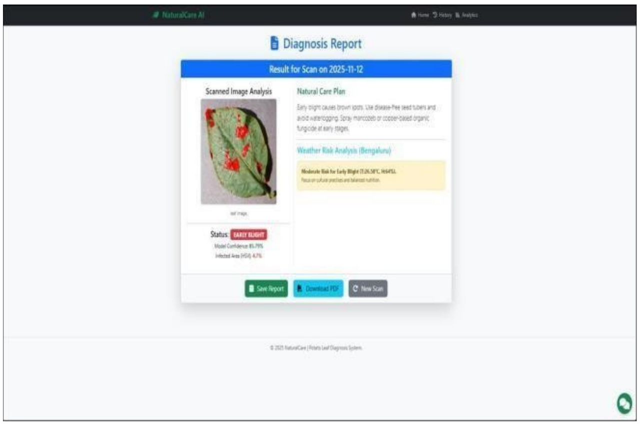


Fig. 7 The image shows a diagnosis report from NaturalCare AI detecting Early Blight on a potato leaf with 85.79% confidence.

The red plots on the leaf image represent the infected regions identified by the AI model — these are the specific areas where Early Blight symptoms (such as brown or dark spots caused by fungal infection) are detected. This image shows the Diagnosis Analytics page of the NaturalCare AI system, which provides a summary of potato leaf scan results.

Fig.8 The image shows the Diagnosis Analytics dashboard of NaturalCare AI, displaying potato leaf scan statistics, disease distribution, and model confidence levels.

It displays key metrics like total scans, average health rate, and scans done in the current month. The dashboard also includes a disease distribution chart showing the proportion of different potato diseases detected, and a model confidence graph indicating how confidently the AI classified each diagnosis.

VI CONCLUSION

To categorize plant illnesses, the TensorFlow backend system used a convolutional neural network model. The Raspberry Pi was used to implement the same for real-time data in OpenCV. The most popular activation functions and optimizers were examined. The suggested function optimizes the system with a higher accuracy of 96.52%, it may be concluded. Sensitivity and specificity were among the characteristics that were computed. Specificity and sensitivity are assumed to be more than 80%. When compared to other functions, the "Adam" and "Adamax" optimizers exhibit superior optimization. The proportion of impacted area was determined using the Kmeans clustering technique in MATLAB, and the ideal fertilizer dosage was recommended to increase crop output.

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