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Utilizing Neural Networks for Potato Crop Disease Surveillance

Shylesh B C, Varshitha

Assistant Professor, Department of MCA, Mangalore Institute of Technology & Engineering College, Moodbidre, Karnataka, India

PG Student, Department of MCA, Mangalore Institute of Technology & Engineering College, Moodbidre, Karnataka, India

ABSTRACT: Potatoes are the most widely consumed vegetable globally. Agricultural departments are coming around to this idea more and more. Given that potatoes are a vital commodity in world agriculture, plant health has a substantial impact on food security. Potato plant infections can be identified early on, which can increase yield and reduce significant crop losses. This research presents a DL approach based on identifying potato plant diseases using leaf photos. Diseases including septoria blight, late blight, and early blight can affect potatoes. CNN are utilized in the technique to classify photos of both healthy leaves and different plant illnesses. The dataset utilized for training the algorithm consists of photos from the ”Plant Village” collection that show typical plant diseases that harm potatoes. With the dataset, which contains photos of numerous common potato plant diseases, the suggested approach shows promise for precise classification and prompt correction. In ultimately, this will help to keep potato agriculture stable and secure around the world.

KEYWORDS: Potato Disease Detection, Machine Learning, Neural Network, Image Processing.

I. INTRODUCTION

Worldwide, potatoes are a vital crop for food production in many nations. Packed with vital minerals including potassium, fiber, and vitamins C and B6, they offer a host of health advantages. Fiber promotes digestive health and can lower blood cholesterol levels, while potassium helps sustain healthy muscles and heart function. The health of the brain and the immune system depend on vitamins B6 and C. With an astounding 48.2 million tons of potatoes produced in 2021,India is the second-largest manufacturer of potatoes within theentire planet. In this business, the town of Agra, Uttar Pradesh, is referred to as the ”Potato Bowl of India” because of its substantial contribution to the nations total output of potatoes. Experts currently use antiquated methods of disease recognition, which take a lot of time and are frequently unfeasible for large-scale farming operations. As a result, there is agrowing need for automated systems that can quickly and precisely identify plant diseases. Current Progress in CNNs, a type of profound understanding, has shown promise in taskslike an image categorization, object detection, and medical imaging. This study utilizes these advancements into evolve adependable system that uses leaf photos to identify diseases in potato plants.

Although potatoes are a staple crop in every country, illnesses like Alternaria solani’s early blight and Phytophthora infestans’ late blight cause large output losses. Early disease detection is essential for putting mitigation strategies into place and reducing financial and productivity losses. Expertise visually evaluating the plants is the traditional technique of detecting disease, but this method is sometimes impracticable due to time constraints and a shortage of expertise, particularly in remote farming areas.In lately, image processing tools have emerged as an accept- able substitute for ongoing plant health monitoring and early disease diagnosis. Since diseases manifest visible symptoms on the leaves, analyzing these patterns through imaging can effectively identify the diseases. Combining imaging techniqueswith machine learning provides a robust solution to improve agricultural productivity and ensure food security. Therefore, the goal of this effort is to employ image and machine learningtechnology to develop a precise and efficient approach to plantdisease detection.

II. RELATED WORK

The utilization of DL in conjunction with ML for plant disease diagnosis has attracted a lot of interest lately. Plant diseases may now be diagnosed with remarkable success thanks to these novel approaches, which often surpass

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conventional methods with regard to of efficiency and output. With their capability to accurately detect diseases across various crops, CNNs have shown significant potential in agricultural applications. Although it's still apparent that deep learning based specialized research on potato plant diseases is lacking. The practicaluse of DL and ML in the diagnosis of plant diseases has been the subject of numerous studies. The foundations of early approaches were handwritten features and traditional classifiers. CNNs, in particular, have demonstrated greater performance in picture classification tasks, such as the identification of plant diseases, in recent deep learning breakthroughs. By employinga deep CNN model to categorize potato diseases from the Plant Village dataset, our work expands on these developments.

Tiwari, Divyansh, et al. [1] Utilized K- Means Clustering to segment potato leaf images and BPNN for categorization. Yielding a 92% accuracy rate. With a 92.5% classification Sarosh Umar3, mainly uses RFID and GSM technology. This paper presents a solution to prevent vehicle theft using RFID and GSM technology, significantly reducing transaction costs through automation. The system includes a GSM kit, RFID readers and tags, barrier gates, computers, software, and LED lights. It controls accuracy, U. Kumari et al. [6] employed Neural Network classification on tomato and cotton leaves after concentrating on picture segmentation as well as extraction of features.

M. Islam et al. [7] Achieved a 95% accuracy rate in disease classification by segmenting potato leaf images from the Plant Village dataset and utilizing a multiclass SVM. To identify and categorize fungal infections on grape leaves, C. G. Li et al. used SVM and K-Means clustering. Finally, J. Chen et al.[8] Employed SVM and MLP classifiers to categorize tea leaf images utilizing a CNN model named Leaf Net and a bag of visual words model. The strategy yielded a classification accuracy of 97.8% surpassing previous approaches by 5.8% and 2.8%It integrated feature extraction using VGG19 with classification. Asif, Md Khalid Rayhan, et al. [2] classified potato infections using a multi-class SVM, whereas Dubey et al. [9] classified apple diseases utilizing a model akin to this one. Sladojevic et al. used deep CNN to identify thirteen different illnesses in leaves of tomatoes and apples. Ferentinos et al. [10] Employedthe AlexNetOWTBn deep learning model to identify plant diseases. Through the utilizing of a CNN based model to detect diseases in potato leaves, this work improves on earlier techniques. It successfully classifies photos as healthy, early blight, or late blight with 97% accuracy.

Sholihati, Rizqi Amaliatus, and associates claim that because more advanced networks collect more semantic information, they are more accurate and robust to a wider range of circumstances. Plant disease classification has seen the approach of DL architectures such as LeNet, AlexNet, and many CNN models, which proved to function effectively on tests of visual perception. An average accuracy of 96.3% was obtained in a study that used CNN to identify diseases in five types of plants such have 13 different diseases. Also used were VGGNet designs, specifically VGG16 and VGG19, which produced a maximum accuracy of 95.83% Acharjee, Trishita, Sushanta Das, et al. [4] The related studies covered within such document center on diverse methods for deep learning based plant disease identification. For instance, Nawaz et al. achieved a 98% accuracy rate using cloud based scalable transfer learning and AWS DeepLens. With 97% accuracy, Abhishek Sharma et al. diagnosed potato leaf disease using VGG19. CNNs were used by A. Chug et al. [13] for plant disease research, and they achieved a 97% accuracyrate. SP Mohanty et al. trained a CNN with a set of 54,306 images, and they were able to reach 99% field test accuracy. In a similar vein, K.P. Ferentinos et al. [10] employing a deep learning model trained on 87,848 photos to accomplish a precision of 99%T he document states that CNNs obtained the greatest accuracy rating of 98% when processing the dataset.

III. METHODOLOGY

A number of many important components to the supervised learning process that are employed in the disease diagnosis of potato plants. The raw data set is initially enhanced employing strategies like rotation and scaling in order to increase diversity.This is done after acquiring photos from publicly accessible repositories like Plant Village and real time field collection. Image scaling, pixel value normalization, and label encoding are examples of data preparation. Because of its efficacy in image categorization, the suggested method primarily makes utilize of CNN. Either pretrained models such as VGG16 or customized CNNs with layers including dropout, convolution, pooling, and entirely linked layers are utilized in the design. Experimentation is utilized to optimize hyper parameter values which include batch size and instruction rate.Utilizing strategies like early halting and optimizers like Adam, the training process divides the data into training, validation, and test sets. To evaluate the outcome of the model, metrics such as recollection, precision, accuracy, and F1score are employed. Cross validation and hyperparameter adjustment are utilized to confirm the results. In the end, ROC curves and confusion matrices are used to assess and display the mod- els Efficacy. This ensures accurate potato recognizing plant diseases and categorization, Supporting efficient agricultural management.

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A. Data Collection

The Plant Village collection, which includes images showing normal and diseased potato plants, was utilized in this investigation. An 80-10-10 ratio was utilized to divide the dataset into training, validation, and test sets. This implies:
1.Training Set: Eighty percent of the total pictures were utilize to train the model. The algorithm was trained to identify patterns and characteristics linked to both healthy and sick potato plants using this data.
2.Validation Set: During training, 10% of the photos were reserved for the intention of validating the model. Throughout the training phase, this set provided input on the model's performance on unseen data, which helped fine-tune the model's parameters and avoid over fitting.
3.Test Set: For the purpose of validating the model during training, 10% of the photos were reserved. We refer to this as the validation set.
This group supplied feedback on the model's performance on unknown data throughout the training phase, which assisted in optimizing the model's parameters and preventing over fitting. The dataset includes the following classes: Healthy, Early Blight, Late Blight.

B. Proposed Method

Images were resized to 224x224 pixels to match the input requirements of common CNN architectures. Rotation, flipping, and zooming are a couple of methods for enhancing data that we utilized to broaden the simulated set's diversity and reduce over fitting.

1. Resizing: Every image in the dataset was resized to a standard dimension of 224 by 224 pixels. This standardization is crucial as many DL models require uniform image sizes for consistent processing.
2. Normalization: Following resizing, the image's pixel values were adjusted to fall within [0, 1]. As involvement of the normalizing procedure, the pixel values are divided by 255, themaximum pixel value, to scale them to be from zero to one. Normalization helps to stabilize and accelerate neural network training.
3. Data Augmentation: To enhance the training dataset, methods including rotation and random flipping (horizontal and/or vertical) were used. An approach called data augmentation is employed to artificially increase the number and variety of training sets by making arbitrary changes to the images. This enhances the model's capacity to generalize to new, unidentified data by exposing it to variations in the training images.

C. Model Architecture

The architecture of the CNN model, which is to categorize photos of healthy and unhealthy potato plants, is made to take information about hierarchy out of the provided images.

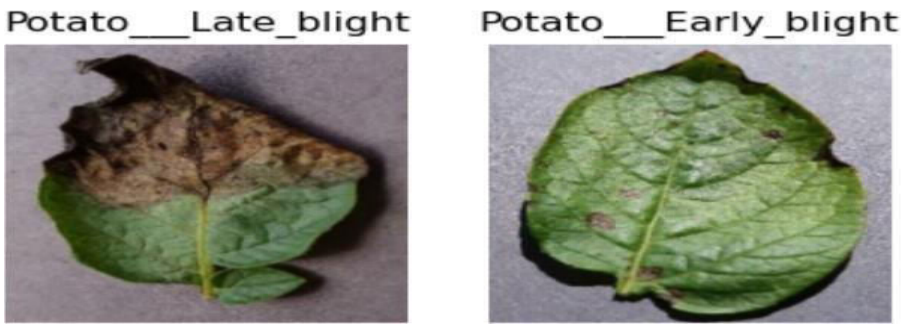

Fig. 1. **Potato Leaf Disease Classification Output Image**

The components that typically comprise such as CNN architecture are categorized as follows: that are usually present in such a CNN architecture are broken down as follows:

1. Convolutional Layers with ReLU Activation: The fundamental components of CNNs are convolutional layers. They are made up of filters, sometimes known as kernels, which glide over the input image to perform a convolution. Following each convolutional layer, the Function of ReLU Activation is frequently employed. It gives the model nonlinearity, which enables it to recognize intricate patterns in the data.
2. Max-Pooling Layers: Max-pooling layers come after certain layer configurations. They preserve the most significant characteristics while decreasing the input volume's width and height. Extraction of The most significant value obtained from every patch in the feature map produced by the convolutional stages is typically the process of max pooling.
3. Fully Connected (Dense) Layers: The texture maps are flattened employing numerous convoluted and MPL to yield a single vector. This vector is then traversed by several entirely linked layers. These layers' neurons are

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arranged similarly to those of a traditional feed- forward artificial neural network. The model can learn complex representations because every neuron in a FCL is connected to every other a covering neuron above it.

4. Softmax Output Layer: The last layer in the CNN design is called the softmax layer. Softmax activation is used for multiple classes applications. By granting a probability for each class in this case, either well as unwell potato plants it ensures that the sum of the probabilitiesfor all classes is one.

The CNN's general architecture is designed to allow it to progressively acquire hierarchical representations of the input images. While earlier layers capture low-level data like edges and textures, Higher levels capture abstraction better and complex information that is crucial for distinguishing between healthy and unhealthy potato plants. This architecture builds a comprehensive pipeline that includes preprocessing steps (resizing, normalization, and data augmentation) to prepare a trustworthy model on the Plant Village dataset.

D. Training

At a pace that allows for growth of 0.001 and categorical cross-entropy as the loss function, the model was trained utilizing the Adam optimizer. A 20% validation set and an 80% training set were separated edge of the dataset. A batch size of 32 was chosen for training across 50 epochs in order to strike a balance between memory efficiency and the efficacy of gradient updates. These decisions on regularization and optimization strategies led to the development of a robust model for precise detection of plant diseases from images.

Below is a comprehensive example of utilizing a sample dataset to train a CNN model and plot the accuracy:

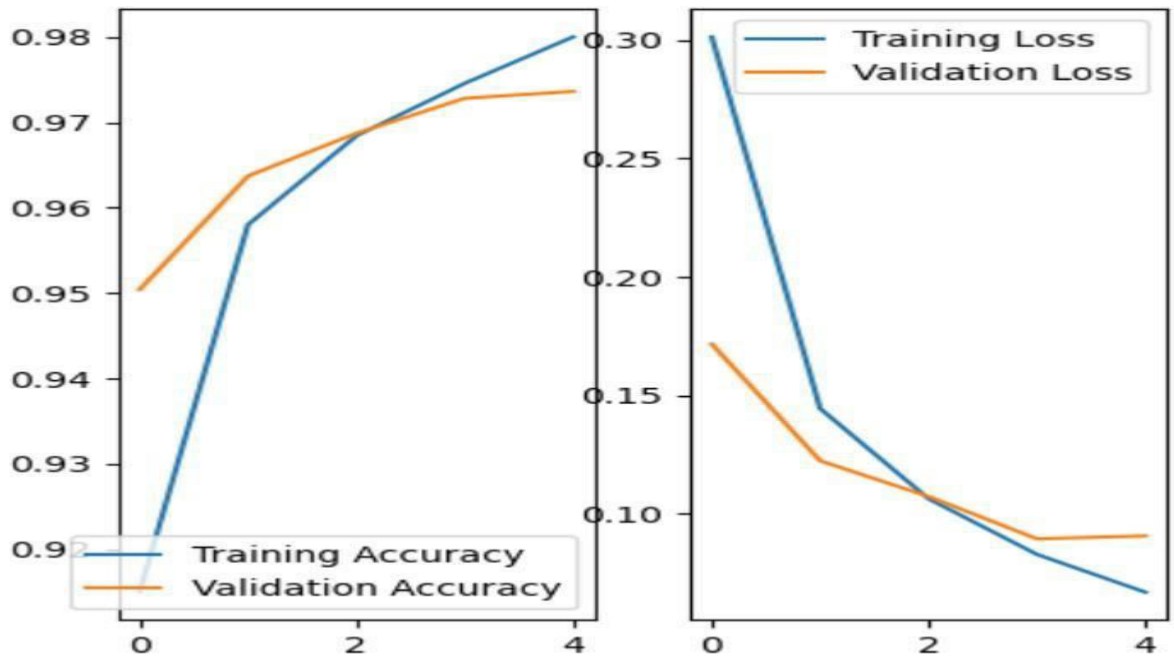

Fig. 2. Neural Network Training Process

Determining whether potato leaves are sick employing the CNN model. Trained a CNN model utilizing the 2152 image dataset.

E. Evaluation

The main criterion applied to assess the model's performance on the test set was accuracy. To evaluate the effective-ness of the method for categorizing, confusion matrices were made to display the number of actual positives, incorrectly classified true positive tests, and wrong final results for each class.

Furthermore, classification reports with comprehensive metrics including F1score, recall, and precision for every class were generated. These assessment tools provided thorough insights into the model's advantages and disadvantages, making it easier to pinpoint the places where the model works effectively and those that require more development.

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IV. RESULTS

The supplementary graphs in Figure 2 show how accuracy and loss measures change over time in relation to training and validation for a model throughout five epochs. Over the duration of the epochs, the accuracy metrics on the left graph show a constant rise in both training and validation accuracy.

The training accuracy has gradually improved by the conclusion of the fifth epoch, going from a starting point of little over 0.92 to about 0.98. The validation accuracy starts out somewhat lower than the training accuracy and increases similarly, peaking at 0.97 in the end. The model appears to be well-suited for generalization based on the little frequency observed in the training and verification runs.

The graph on the right displays the metrics for training and validation loss. In this instance, there is a discernible decrease in both losses as training increases. The training loss starts at about 0.30 and drops off quickly to less than 0.05 by the fifth epoch. The validation loss correspondingly decreases, ending at roughly 0.10, much like the training loss but at a little slower rate. Because a model can minimize error over time, this decrease in loss values shows that the model is successfully learning from the training data.

The graphs demonstrate thatthe model is generally doing well, with rising accuracy anddecreasing loss, for both the training and validation datasets.This balanced improvement shows that by accurately identifying the underlying patterns in the data, the model mayincrease forecast performance and generalize to new data with high reliability.

V. DISCUSSION

The model's excellent accuracy shows how CNNs can be used to automatically detect potato plant diseases. There are drawbacks, though, like the requirement for sizable annotated datasets and the possibility of over fitting with sparse data. The dataset will be enlarged in the future to include more complete and varied disease groups, which will strengthen the robustness of the model.The model's generalization skills will also be improved in order to guarantee that it functions properly on fresh, untested data. Advanced regularization approaches, transfer learning, as well as enhancement of data are among possible strategies. By Taking these steps, we intend to further enhance the model and make it a more dependable tool for agricultural applications Taking these steps, we intend to further enhance the model and make it a more dependable tool for agricultural applications.

VI. CONCLUSION

This work uses leaf photos to propose a deep learning-based method for identifying illnesses in potato plants. The great authority of the suggested CNN model highlights the viability of applying deep learning to agricultural applications. In the End, automated disease detection systems can help farmers diagnose and treat plant illnesses, increasing agricultural productivity and food security. Utilizing state of the creative machine learning algorithms, these systems provide a feasible means of increasing agricultural output and sustainability while assisting farmers in maintaining healthier crops and mitigating the impact various illnesses of plants.

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