Potato Leaf Diseases Classification Using Deep Learning

Dr. Rashmi Asthagi, Vedant Parvekar, Omkar Rasal, Yogesh Rasal, Subodh Motbhare

Department of Computer Engineering
Vishwakarma Institute of Technology, Pune, 411037

***Abstract* - Potato (Solanum tuberosum) is a vital staple crop globally, contributing significantly to food security. However, potato cultivation is threatened by various foliar diseases, which can lead to substantial yield losses if not managed effectively. Traditional disease diagnosis methods are time-consuming and often rely on the expertise of agricultural professionals. In recent years, deep learning algorithms have emerged as powerful tools for automating disease detection in various crops. This study focuses on the application of deep learning techniques to predict and classify potato leaf diseases, specifically Late Blight (Phytophthora infestans), Early Blight (Alternaria solani) and Healthy leaves.**

The research employs a dataset comprising high-resolution images of healthy and diseased potato leaves, acquired under various environmental conditions and growth stages. Convolutional Neural Network (CNNs), a class of deep learning algorithms well-suited for image recognition tasks, are utilized to develop robust disease prediction models. The dataset is preprocessed to enhance image quality and minimize noise, including techniques such as data augmentation, normalization, and dimensionality reduction.

***Keywords* - CNN,Data Augmentation, Deep Learning, Feature Extraction, Logistic Regression**.

I.INTRODUCTION

The use of deep learning algorithms, mostly Convolutional Neural Networks (CNNs) has demonstrated impressive potential in automating crop disease detection and categorization in recent years. CNNs are a subclass of deep learning models designed to excel at image-related tasks. Their ability to learn hierarchical features from raw image data makes them well-suited for identifying patterns and anomalies in plant leaf image using Convolutional Neural Networks (CNNs) in a dataset of images of potato leaf for disease prediction involves several key steps. Below is a simplified guide on how to use CNNs in this context:

Data Collection and Preparation : Gather a dataset of potato leaf images that include various disease conditions (e.g., healthy, Early Blight, Late Blight). Ensure that the dataset is well-labeled, with each image tagged with the corresponding disease label. Make training, validation and test sets out of the dataset. A typical allocation is 15% for testing, 70% for training, and 15% for validation.

Data Preprocessing : Resize all images to a uniform size (e.g., 224x224 pixels) to ensure consistency. Normalize pixel values to a specific range (typically between 0 and 1) to facilitate model training. Augment the training data with techniques like rotation, flipping, and random cropping to increase the diversity of the dataset and improve model generalization.

Model Selection :Select a CNN architecture that is appropriate for categorizing images. Common choices include VGG, ResNet, Inception, or MobileNet. Optionally, you can use pre-trained models (e.g., pre-trained on ImageNet) as a starting point, fine-tuning them for your specific potato leaf disease dataset.

Model Training : Select an optimizer and loss function, then use the training dataset to train the CNN model. When training, keep watching the performance of model on the validation set to spot overfitting and tweak hyperparameters (such learning rate).

II. LITERATURE REVIEW

Numerous researchers have proposed different methods for identifying diseases of potato leaf in their work, and there are numerous ways to detect plant diseases. This section provides an overview of those methods.

Divyansh Tiwari et al.[1] proposed a system to identify potato illnesses including early and late blight, this study employs artificial intelligence (AI) and pre-trained models. With a high accuracy of 95.8% in identifying illnesses on the test dataset, the suggested method-especially logistic regression-offers promise to increase crop productivity for potatoes.

Javed Rashidet al.[2] proposed a system, A multi-level deep learning model for identifying diseases of potato leaf is presented in this study. It uses YOLOv5 to extract leaves and presents a novel convolutional neural network to identify diseases associated with early and late blight. The model works well on the Plant Village dataset and reaches an astonishing accuracy of above 95 on a Pakistani dataset.

Nusrat Jahan al.[3] proposed a system for training data; they used K-means clustering, segmentation, and a variety of data augmentation techniques. The models VGG16, VGG19 and ResNet50 were assessed; of them, VGG16 had the highest accuracy (96%). When examined against contemporary models with important characteristics, our suggested strategy performed better than current approaches.

Deep Kothari, al.[4] proposed a system Using the CNN approach, the authors of this study have constructed a model that can categorize potato leaf states such as late blight, early blight and healthy leaf, with a classification accuracy of almost 97%. The practice of augmenting the data makes the model more reliable.Their method can increase agricultural production and assist farmers in identifying diseases early on.

Hemant Patil, al.[5] proposed a system in which By regulating the biotic factors that lead to severe crop yield losses, deep learning algorithms greatly increase crop output and quality through the identification of plant leaf diseases.

CNN, in my opinion, performs this kind of classification object the best. This model improves its validation accuracy by 91.41%. A PLD data set was utilized by them.

Asheesh Shukla al.[6] proposed a system in which They employed the automated algorithm, which is predicated on methods for machine learning.Three categories of potato leaf disease detection are graded: early blight, healthy, and late blight. First, high-quality preprocessing is applied to images.Fuzzy C-means is used for segmentation while Gaussian is used for enhancement and noise removal. Additionally, they employed fuzzy classification and fuzzy reasoning to find the potato leaf disease. They have obtained an accuracy of 88.4.

Most. Hasna Hena al.[7] proposed a system to identify potato diseases; they have represented a convolution neural network that is based on the genuine sequential model classification technique. To attain the necessary precision, two-stage testing was also conducted and implemented. Extensive studies have been conducted on a variety of potato illnesses. Photographs of potato plants taken in the potato field are considerably numerous. A variety of algorithms were tested in order to determine the CNN architecture's maximum performance. The provided model accurately distinguishes between healthy and unhealthy plants.

Indra Adji al.[8]proposed a system for the classification of diseases of potato plant leaf is described in this work. It seems possible to examine useful characteristics for picture classification of leaf diseases using VGGNetwork (VGG16 and VGG19).

Our suggested approach can obtain an average accuracy of 91-93%, according to experiments.

Dr. Rashmi Asthagi al.[9] Neural Nets have outperformed conventional methods in pattern classification with this Supervised Hypersphere Neural Network model. The revised membership function and the suggested distance metric, which improved accuracy while addressing the drawbacks of the previous model, are the most significant features of SHNN. The model's performance on the other three benchmark datasets—Pima, Liver, and Glass Arc—was 76.17%, 71%, and 80%, respectively, whereas the accuracy of the current CSFHSNN technique was 75.5%, 68.1%, 75.9%, and 99%, on the four datasets, respectively.

In this work, an end-to-end deep learning model was trained by Dr. Rashmi Asthagi et al. [10] without the need for feature crafting or pre-processing processes. We propose an improved MobileNet with a DL model for the categorization of skin lesion photos into eight kinds of skin cancer, using the ISIC 2019 dataset. Our model used the architecture of a pre-trained MobileNet model, modified it, and used class-weighted and focal loss training procedures to reach an average accuracy of 83 percent, surpassing that of dermatologists who achieved an accuracy of 81 percent. The results demonstrated that, in comparison to earlier models, the MobileNet model generated the best outcomes.

Rashmi Asthagi and others [11] This study suggested a non-invasive method for classifying skin cancer melanoma stages. Two classification strategies are introduced here: a two-stage scheme that categorizes melanoma into two phases, called stage 1 and stage 2, and a three-stage strategy that categorizes the illness into three groups. SMTP is the loss function in an upgraded CNN neural network architecture that we use to obtain good results for test division and dataset feature learning. A sigmoid layer, loss function, activation function, convolution layer, and batch normalization layer are among the numerous local filters that are included in the model.

In order to address concerns with accuracy and automatic melanoma recognition in dermoscopy pictures, Dr. Rashmi Asthagi et al.[12] suggested a revolutionary approach.A framework utilizing CNN + SVM and CNN + XGB is suggested for the identification of benign melanoma from dermoscopic pictures. CNN performs well with training datasets, whereas SVM is used for classification due to its benefits with regard to generalization. One of SVM's main advantages is that it provides a unifying framework within which different types of machine learning models can be created by appropriately selecting portions. the SVM norm, which restricts the maximum bound of generalization mistakes. A novel CNN + SVM system is suggested after considering the features of both CNN and SVM.

III. METHODOLOGY

1.System Architecture:

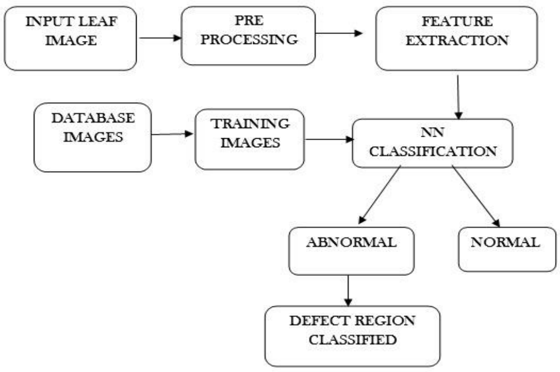


Figure 1. Block Diagram

In the above flow diagram , dataset of images are provided to model for prepossessing.After preprocessing is done , feature extraction is done on the preprocessed images. The images are forwarded for NN classification. Along with the preprocessed images, training images from the database are forwarded to the model. As the model has both input image as well as the trained images with it.By using the classification algorithm, Model will detect if the input image is normal or abnormal and accordingly it will give the output.

2. Dataset Description:

An excellent resource for research is the Plant Village Dataset [1], which is available via Kaggle, a well-known open-source repository. The collection of over 55,000 well tagged photos in this dataset includes both healthy and diseased potato plant leaves. With its extensive and diverse image pool, the Plant Village Dataset serves as a pivotal tool for researchers and data scientists seeking to explore plant health, disease detection, and related agricultural applications. The dataset's rich annotation and substantial image count make it an indispensable asset for advancing the field of plant pathology and fostering innovative solutions for crop protection and agriculture. Notably, it encompasses the inherent complexity of agricultural pathology, where each crop may exhibit multiple types of leaf diseases. To facilitate precise classification, the dataset takes a meticulous approach by treating each distinct type of leaf disease as a separate class. What sets this dataset apart is its provision of two distinct image types for every instance: one with the leaf and its natural background and another without the background. The development and assessment of machine learning and computer vision models that can precisely identify and categorize a variety of crop illnesses is made possible by this dual representation, which provides researchers with an adaptable and thorough resource. As a result, the Plant Village Dataset stands as a valuable asset for advancing our understanding of plant health and disease management in agriculture.

Figure 2: Sample image of each class

For every class, the dataset has between 152 and 1000 photos in total. This study focuses on potato photos specifically and limits its analysis to three different illness types. In order to efficiently manage imbalanced datasets, researchers must address the non-uniform distribution of data within these classes and construct classification models. This study highlights the practical difficulties in managing agricultural illnesses while also offering insights into the categorization of potato diseases. In this sense, the Plant Village Dataset is a valuable resource for furthering our knowledge of machine learning techniques for unbalanced data situations in the field of agriculture.

i.e. Images of healthy leaves, late blight, and early blight. The table displays the train-test-split data.

	Type	**Numbers**	**Training sample**	**Testing sample**
1	Early Blight	1000	787	213
2	Late Blight	1000	791	209
3	Healthy	152	122	30
Total		2152	1700	452

Table 1: Displaying the quantity of samples in our training set and testing set model

IV. EXPERIMENTAL SETUP

Using neural networks (NN) to predict potato leaf diseases usually requires putting a machine learning or deep learning model into practice. Here's a broad rundown of the tools and platforms that are frequently used for this. To increase the accuracy and dependability of the model after deployment, it's critical to keep an eye on its performance and solicit user input.

Here we have used jupyter notebook, VS Code software and python programming language for implementing the model.

A. FEATURE EXTRACTION

Feature extraction is a crucial step in the process of using Convolutional Neural Networks (CNNs) for image classification tasks such as predicting potato leaf disease. When it comes to learning hierarchical and discriminative features from images, CNNs are especially well-suited. An outline of a CNNs feature extraction procedure is provided below: CNNs apply convolution operations to the input image through a multiple convolutional layer architecture. These layers pick up different feature maps or filters that accentuate distinct textures, patterns, and shapes in the picture. These layers extract features such as corners, edges, and more intricate picture elements.

V. RESULTS AND DISCUSSION

There were 1000 photos in this subset showing late blight, 1000 photos showing early blight, and 152 photos showing healthy potato leaves. Interestingly, the dataset was carefully divided into two subsets: the training set, which makes up 70% of the total 1700 photos, and the test set, which makes up 30% of the total 452 images. This partitioning strategy adheres to best practices in machine learning model development, allowing for robust model training and evaluation. Through this comprehensive dataset selection and partitioning, the proposed model aims to effectively address the challenging task of classifying potato leaf diseases, contributing to advancements in agricultural disease management and the application of machine learning in the field.

By combining Gan for data production and Transfer Learning for increasing model correctness, we could increase the resilience of our model. Gan will assist us in improving the model's tolerance for variations in the orientation, position, and size of the object within the picture. Our ability to create a more accurate and reliable model will be aided by transfer learning.

Visualize some of the images from our dataset

```
In [6]: plt.figure(figsize=(10, 10))
        for image_batch, labels_batch in dataset.take(1):
            for i in range(12):
                ax = plt.subplot(3, 4, i + 1)
                plt.imshow(image_batch[i].numpy().astype("uint8"))
                plt.title(class_names[labels_batch[i]])
                plt.axis("off")
```

Building the Model

```
In [20]: resize_and_rescale = tf.keras.Sequential([
           layers.experimental.preprocessing.Resizing(IMAGE_SIZE, IMAGE_SIZE),
           layers.experimental.preprocessing.Rescaling(1./255),
         ])
```

Data Augmentation

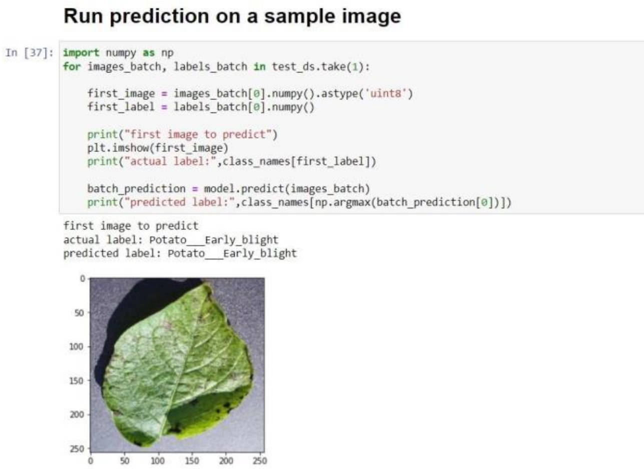
```
In [21]: data_augmentation = tf.keras.Sequential([
           layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"),
           layers.experimental.preprocessing.RandomRotation(0.2),
         ])
```

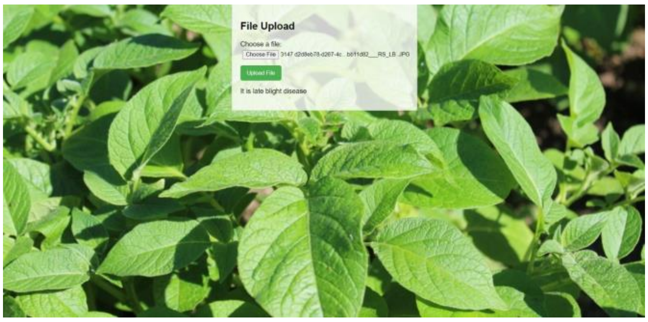
```
In [22]: train_ds = train_ds.map(
             lambda x, y: (data_augmentation(x, training=True), y)
         ).prefetch(buffer_size=tf.data.AUTOTUNE)
```

[11]

The confusion matrix is used for the evaluation model. It is represented by a table which describes the performance of a classification model on a set of test data in machine learning. Proposed work performance is assessed utilizing accuracy, recall, sensitivity, f score, specificity, and precision. Measures are calculated from:

$Accuracy= Tp+ TnTp+ Tn+Fp+ Fn$
$Sensitivity= TpTp+ Tn$
$Specificity= TnFp+ Tn$
$Precision= TpTp+Fp$
$Recall= TpTp+ Tn$
$F1= 2XPrecision\ x\ RecallPrecision+Recall$





VI. FUTURE SCOPE

These days, it's critical to identify plant diseases when they're still in the budding stage in order to improve yield quality and productivity. It would be really helpful if we could put this technology on smartphones so that farmers could snap a picture of a leaf and transmit it to the server, as disease detection requires a great deal of expertise. The disease helpful will be automatically determined and classified by the server, which will then send the results and any recommended medication back to the smartphone.

By combining Gan for data production and Transfer Learning for increasing model correctness, we could increase the resilience of our model. Gan will assist us in improving the model's tolerance for variations in the orientation, position, and size of the object within the picture. Our ability to create a more accurate and reliable model will be aided by transfer learning.

VII. CONCLUSION

In order to identify potato diseases, we have represented a convolution neural network based on the classification technique. The practice of augmenting the data makes the model more reliable. Our method can assist farmers in increasing agricultural yields and identifying diseases early on. For people involved in agriculture, we covered two types of potato leaf diseases. We created a website to make things easy for everyone. When a farmer uploads a photo of their potato leaves, the model identifies the disease and suggests necessary action to prevent more disruption. The accuracy of the model is around 97%.

VIII. REFERENCES

[1] D. Tiwari, A. Sharma, M. Ashish, N. Gangwar, S. Patel, and S. Bhardwaj, "Potato Leaf Diseases Detection Using Deep Learning", 4th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2020, pp. 461-466, doi: 10.1109/ICICCS48265.2020.9121067.

[2] Almotiri, S.H.; Rashid, J.; Khan, I.; Ali, G.; AlGhamdi, M.A.; Masood, "K. Multi-Level Deep Learning Model for Potato Leaf Disease Recognition." Electronics 10, 2064; 2021. 10.3390/electronics10172064 can be found here.

[3]https://www.sciencedirect.com/science/article/pii/S1877050922016970

[4]https://www.researchgate.net/publication/365344910_Potato_Leaf_Disease_Detection_using_Deep_Learning

[5] https://ijrpr.com/uploads/V3ISSUE5/IJRPR4071.pdf

[6]https://assets.researchsquare.com/files/rs2102065/v1/bf9e85cf-18fe-4287-a82d-16c252e06b4a.pdf?c=1667213983

[7] "CNN based Disease Detection Approach on Potato Leaves," 3rd International Conference on Intelligent Sustainable Systems (ICISS), 2020, Thoothukudi, India, 2020, pp. 428–432, doi: 10.1109/ICISS49785.2020.9316021, M. K. R. Asif, M. A. Rahman, and M. H. Hena.

[8]In 2020, Surabaya, Indonesia hosted the 2020 International Electronics Symposium (IES), with R. A. Sholihati, I. A. Sulistijono, A. Risnumawan, and E. Kusumawati presenting "Potato Leaf Disease Classification Using Deep Learning Approach," pp. 392-397, doi: 10.1109/IES50839.2020.9231784.

[9]Mane, Deepak & Moorthy; Rahul & Kumbharkar; Prashant & Upadhye; Gopal & Salunke; Dipmala & Ashtagi, Rashmi. 2022). Pattern Classification Using Supervised Hypersphere Neural Network 0. International Journal of Emerging Technology and Advanced Engineering, Volume 12, Issue 2, pages 214–222, doi: 10.46338/ijetae0822_25.

[10]Mane, D., Salunkhe, D., Upadhye, G., Ashtagi, R., Kumbharkar, P., and Kadam, S. (2022). An enhanced method of transfer learning for cancer type categorization. 39, No. 6, Traitement du Signal, pp. 2095–2101. 10.18280/ts.390622 can be found here.

[11]Machine learning technique in melanoma cancer stage identification, Rashmi Patil, Sreepathi Bellary, King Saud University - Computer and Information Sciences, Volume 34, Issue 6, Part B, 2022, ISSN 1319-1578, https://doi.org/10.1016/j.jksuci.2020.09.002.

[12]R. Patil (2021). Classifying malignant melanoma using machine learning. A VTU Publication, International Journal of Science, Technology, Engineering, and Management, 3(1), 40–46.