PLANT LEAF DISEASE RECOGNITION USING CNN

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Abstract**—** Farming output plays a crucial part in India's economic landscape, yet it faces significant setbacks from pests and crop illnesses. Over the last twenty years, neural networks have represented a significant leap in addressing these issues. Yet, the current infrastructures are resource-intensive and expensive to deploy. These activities also typically necessitate a collection of leaf photographs that mimic actual environmental conditions, a resource that is difficult to procure. Hence, the aim of this study is to address these challenges through the development of a cost-effective and streamlined deep learning structure utilizing the suggested CNN model. By employing 46,800 photos for validation and 60,000 images for training, this method divides the collection of leaf images known as "PlantDoc" into 38 classes.An independent dataset is reserved exclusively for evaluating model efficacy on unseen data. The CNN framework is utilized for its rapid processing capabilities, straightforward process, and distinct data purification features. In summary, a classification precision of 94% is attained.

***Keywords* — Convolutional neural network (CNN), deep learning, VGG16, CNN, image classification, PlantDoc's, transfer learning**

I. INTRODUCTION

The requirement for farm produce is increased by the annual 1.7% rise in Earth's population. Thus, it is essential to safeguard the plants from infections. Growing plants and crops is important, especially in India where the agricultural sector accounts for the majority of the country's GDP. India is the world's greatest producer of important spices like ginger and chilli pepper, as well as a variety of fresh fruits and vegetables like chickpeas, okra, guava, and papaya. Presently, it holds the second position globally in the production of various dry fruits, agriculturally derived textile raw materials, farmed coconut, sugarcane, and a wide variety of vegetables. Regardless of the weather, when these plants are afflicted with illnesses, it is detrimental to the agricultural industry.

These days, illnesses can spread over the world and emerge in previously unidentified areas, making it more challenging for medical professionals to treat them. This could be caused by a number of factors, one of which is ignorance about the illness or an incapacity to devise a treatment.Among the leaf spot that can be brought on by viruses, bacteria, fungi, oomycetes, phytoplasmas, and other agents. For farmers, identifying plant diseases has never been an easy chore. As a result, the farmers call the helpline or other farmers for advice. It is necessary for someone to be able to recognise plant diseases. It is quite expensive to diagnose plant diseases using a team of professionals. Therefore, it is just as important to empower farmers to diagnose and treat plant diseases on their own, providing wider protection for plants and crops, as it is to grow the agricultural sector of the Indian economy through programmes like farmer-focused crop insurance, data-driven supply chain management, intelligent irrigation, and so forth.

Regarding the resolution of this issue, we have been a lot of developments during the previous 20 years. The majority of the research has been conducted using approaches for localization and picture feature extraction. Using multiple linear regression to segment histograms is a significant feature extraction method. It shows a strong ability to recognise images with great precision, dependability, and power. Bayes classifier, K-means algorithm, genetic algorithms, and Support Vector Machine (SVM) are a few segmentation techniques that can be used to divide the illness section. Other methods for identifying plant disease spots involve comparing data with several colour spaces, including YCbCr, CIELAB, and HSI[11]. Compared to other traditional filters, hybrid filters are superior for improving image quality and removing noise. To improve leaf photos and isolate individual spots, image processing techniques such as contour extraction, region-expansion algorithms, and image morphology approaches can be applied.

The suggested model in this research will identify or categorise plant illnesses using the PlantDoc data set [15] when photos of the leaves are captured and used as input for the DenseNet-121 transfer learning algorithm network. In contrast to most previous work in this area, our research aims at creating a flexible network model that runs quickly and produces comparable results.For the practical implementation, we utilised the CNN framework[5] in this case to help us with the endeavour. In addition to offering quicker computation than competitors like Tensorflow and keras ,additionally, CNN provides special data cleaning features that come in handy when preparing images from actual events.

II. Literature Survey

It has been clear over the last few years that the deep neural network (CNN) approach to picture categorization performs significantly better than any conventional machine learning strategy. A significant portion of research in the area of classifying plant leaf diseases has been conducted on PlantVillage, an open-access platform offered by SP at http://www.PlantVillage.org. Numerous researchers have also conducted independent studies using data gathered from actual labs and field settings. An overview of some noteworthy recent research in this area may be seen below.

A. Review of literature

In the research by Saguna Kailas et al [12] outlined and contrasted three techniques for classifying leaf images: genetic algorithms (GA), Probabilistics Neural Networks (PNN), and K--Nearest Neighbour classifiers (KNN). These are all essentially ways for recognising patterns. The authors gave a comprehensive overview of the three approaches' potential for classifying leaf photos for the purpose of disease recognition by discussing the benefits and drawbacks of each one.

While the early stages of picture classification were largely successful with pattern recognition approaches, convolutional neural networks greatly improved classification performance and efficiency. In order to achieve higher accuracy, CNNs were also used in addition to traditional machine learning and pattern recognition techniques.

Liang et al [6], presented a novel method for recognition of rice blast, which serves as a good illustration of that methodology. For the purpose of testing and training their CNN model, they gathered 2902 negative and 2906 positive data samples. Their institution's website hosted the data they had gathered. The authors compared how CNNs performed significantly better than other algorithms, including Haar-WT (Wavelet Transform) and local binary histogram (LBPH). They also demonstrated that CNN in conjunction with Softmax and SVM produced strong ROC curves, high accuracies, and big AUCs.

In a similar vein, further writers focused on picture categorization with CNNs. Chen et al.[3] created a special deep CNN model named "LeafNet" to recognise different kinds of tea plant diseases Beautiful photographs of leaves taken in their natural habitats from the Chibi and Yichang regions of the Chinese province of Hubei, taken with a Cannon PowerShot G12 camera.

In order to extract visual features autonomously, the model was built using feature extractor filters of different sizes. Furthermore, support vector machines (SVM) and multi-layer perceptron (MLP) classifiers were used to build a BOVW model for disease classification utilising the retrieved DSIFT characteristics. The MLP and SVM models had classification accuracy of 70.77% and 60.62%, respectively, while the LeafNet model had an average accuracy of 90.16%.

The leaves of ladies finger plants were gathered from farms in several villages located in the Tiruvannamalai(D) district of Tamil Nadu(TN), India were classified by the Selvam et al [13]. The picture dataset included 1088 samples of photos of the leaves of ladies finger plants, of which 457 showed healthy (i.e., pest-free) leaves, 509 showed disease and pest infected leaves, and 122 images showed burned leaves from overfertilization. The researchers employed a novel CNN model architecture that combined multiple data augmentations and drop-out features to classify pictures of leaves as healthy, burned, or diseased. The overall classification accuracy of their suggested custom model was 96%.

Deep learning techniques were utilised in the publication by Bharali P et al [2] to determine whether a plant is unhealthy by using training images of plant leaves. The 1400 picture dataset that was used was assembled from Google Images. They employed a straightforward CNN model that was created from the bottom up without using any transfer learning frameworks that were already in place. They used TensorFlow and Keras to build the network, adding various data augmentation techniques like rotation and photo flipping, among others.Their accuracy with the final model was 99.6%.

To produce a comprehensive dataset, Chohan et al [4] combined the PlantVillage dataset with their own dataset that they had personally collected from real-time settings. For picture categorization, they used CNNs with different augmentations and pooling layers. Fifteen percent of the PlantVillage dataset was used as test data in order to evaluate the efficacy of their suggested model.They obtained 98.3% classification accuracy on the test set. The authors also proposed a potential extension of this study, namely the integration of the classification system with drones for real-time disease detection and timely reporting of results.

A multi convolutional neural network (MCNN) was developed by Uday Pratap Singh et al [16] as a novel method of differentiating between mango leaves that are healthy and those that have the fungal disease anthracnose.There were also additional feed-forward and pooling layers in the suggested MCNN model.The dataset included a set of 1070 photographs of mango leaves from Shri Mata Vaishno Devi University in Katra, J&K, India.Their suggested model remarkably outperformed previous state-of-the-art methods, with an accuracy rate of 97.13%.

After seeing CNNs' success, researchers began experimenting with transfer learning models, which are essentially CNN models with a lot of pre-trained data. Using transfer learning models has the benefit of saving training time because they do not require initial training. Researchers started looking into frameworks for transfer learning, which are basically CNN models modified.While classifying plant species based on floral photos, Mohammad Abbas et al. [1] employed a VGG16 transfer learning model, without explicitly addressing the problem of plant leaf disease recognition. The flower utilised in the study was made up of 2800 photos from 4 different classes of floral species. In addition, they employed dropout and data augmentation strategies to prevent the model from becoming overfit. Additionally, they improved upon several model architectural layers. The VGG16 model produced precision, recall, and an F1 score of 0.90 during the course of 29 training epochs.It is obvious that the authors of this work produced results using simpler CNN models that are far better than those of the earlier works we reviewed, and in fewer epochs.

In the research "An Enhanced Plant Disease Classifier Model Based on Deep Learning Techniques," Madallah Alruwaili et al [8] utilized the PlantVillage dataset. They suggested using the PlantVillage dataset's photos to identify images using the AlexNet transfer learning model. They also applied various data augmentation techniques, including geometric shifts and density shifts, to handle uneven targets, reduce image size to save computational resources, and remove noise from the data. With an overall accuracy of 99%, the suggested model produced outcomes with a precision of 99.11%, a recall rate of 99.49%, and an F1 score of 99.29%.

Using CNNs, Bayesian optimised SVM, and random forest classifiers, this research by SVN Sreenivasu et al. [14] uses AI and computer vision to identify diseases in the leaves of crops like tomatoes and apples. It leverages the PlantVillage dataset and focuses on binary particle swarm optimisation and hybrid features for early identification with the goal of improving agricultural productivity worldwide.

Maeda-Gutie´rrez et al [9] suggested utilising the PlantVillage dataset to analyse other CNN designs, including AlexNet, GoogleNet, Inception V3, ResNet18, and ResNet50. Their main goal was to classify tomato leaf illnesses through a thorough analysis of the tomato leaves in the dataset.It is clear that the authors of this work achieved better outcomes in fewer epochs with simpler CNN models than those of the previous publications we studied. To the best of their abilities, they focused primarily on all of the transfer learning models already described. Multiclass statistical analysis measures including F-Score, AUC, ROC curve, sensitivity, specificity, accuracy, and precision were used in the assessment. The model with the highest performance was GoogleNet, which obtained an AUC of 99.72% and a sensitivity rate of 99.12%.

Liu et al [7] study, focused on grape photos from the whole PlantVillage collection. They presented a number of cutting- edge techniques for integrating transfer learning models, including InceptionV3, VGG16, and VGG19, using classifiers like SVM, logistic regression, neural networks, and KNN.At 99.4%, the combination of logistic regression with InceptionV3 produced the best results in terms of classification accuracy, AUC, precision, recall, and F1 score.

In research by Vijayakumar et al.[17] specially trained dragon fruit photos using RESNET152 and VGG16/19 deep learning networks via many epochs, based on Keras and Tensorflow. They found that RESNET152 offered significantly higher accuracy than VGGNET models, which showed the opposite behaviour. This tendency persisted throughout 500 training epochs. They used 80% of their image collection for training and the remaining 20% for testing. Additionally, using RESNET152, they arrived at AUROC of 1.0.

Using a condensed version of DenseNets, Wenyan Pan et al [10] demonstrated that classification accuracy exceeded 88% on an image dataset with six distinct types of citrus leaf diseases, in addition to a considerable reduction in training time. By removing certain convolutional layers from the architecture and replacing them with extra pooling layers, the more straightforward DenseNet model was created. The researchers of this study have also developed a mini-program for WeChat that allows people to instantaneously take pictures with their smartphones and submit them for examination.

A. *Comparison between the reviewed surveys and our approach*

When it comes to leaf image classification, selecting an image classification architecture and selecting a dataset are the two most crucial decisions to make.

Researchers have either collected photos on their own in a real-time context or used the publicly accessible PlantVillage dataset in the majority of the existing work that we evaluated. However, we used the relatively fresh PlantDoc dataset [15] in our research. This dataset was chosen because it includes actual-life photos of plants, often including full plants with all the background noise found in the real world, rather than simply single leaves. Consequently, testing our training model on real-world photos would greatly improve its performance.

In the majority of the research that has already been done, massive CNN architectures that were trained from scratch—sometimes taking hundreds of epochs—have been utilised for classification. Even in cases where transfer learning models were employed, they continued to function using computationally slow frameworks like Keras and Tensorflow. We focused on using the DenseNet-121 transfer learning architecture to develop a lightweight and quick deep learning network model. For the actual code execution, we employed the latest version of the CNN framework. Our CNN trained more quickly when we used DenseNet, and computation became more effective due to DenseNets' reduced storage requirements. Conversely, CNN offered the advantage of obtaining high accuracy with fewer epochs, which reduced training time. As a result, we were able to attain a classification accuracy of almost 92% after 10 training epochs.

For classification tasks, large-scale CNN frameworks that frequently required hundreds of epochs of initialization were used in much of the previous research. Even in cases when transfer learning techniques were used, they were dependent on platforms with high computational overhead, such as Tensorflow and Keras. Our strategy focused on using the DenseNet-121 transfer learning model to build a deep learning network that is quicker and more effective. We utilised the most recent CNN framework version to execute the real code. DenseNet accelerated the training rate of our CNN and boosted its computational efficiency by reducing the amount of storage it required.

III. MODULES

A. *Data set used*

Most individuals use the Plant Village data collection, which is supplied by SP Mohanty, to identify plant diseases. However, an issue appears when models trained on the Plant Village dataset are unable to function well when applied to real-world photo datasets. This is as a result of the photos in this data collection having previously been cropped to certain leaves.

Unlike photos taken in a real-time setting, they are often free of background noise and tainted data. In response to this issue, a group of researchers from IIT Gandhinagar developed a different data dubbed "PlantDoc: "A Visual Plant Disease Detection Dataset" includes 2,598 data points from 13 different plant species and as many as 17 different disease categories.

Although there are fewer samples and much more background clutter in the photos, the same species of plants are featured as in the PlantVillage collection.

Fig. 1. Sample of PlantDoc dataset

There were two versions released: one for object detection and the other for image categorization. The train and test datasets are provided by the authors to aid in picture classification. Using the training data, we implement an 80/20 split, designating 80% for training the model and 20% for validation. This validation set aids in our evaluation of the model's training performance. Importantly, the test folder is used just for the last stage of model validation and is completely unaltered during the training phase.

B .Training Architecture

Over a long time, age classification problems were one of the main applications of the K-Nearest Neighbours (KNN) method. Suitable for both regression and classification problems, KNN is a supervised machine learning technique. The underlying idea is to use distance measurements to determine which objects are closest to one another on a geometric plane. To categorise the data, labels are applied to these clusters according to their distances from one another. Use well-known formulas, such as the Manhattan or Euclidean distance, to determine the distance between any two places.

For several years now, it has been clear that Deep Neural Nets outperform conventional machine learning algorithms when it comes to the actual model implementations used today for the purpose of classifying images. The conventional techniques that were utilised especially for feature extraction and picture purposes—K-nearest neighbours, support vector machines, etc.—have become outdated on their own these days. Improved features for more efficient completion of the same tasks are offered by neural networks. Consequently, a growing number of agricultural AI researchers are focusing on deep learning models, which provide them superior performance across several domains.

Any CNN model can be vastly altered by using various augmentations and activation functions, such as Softmax and ReLU. All they are are feed forward neural networks that are sequential and have many hidden layers. They also use activation functions. CNNs are capable of recognising intricate patterns like gradients, circles, lines, and more in any given image. You can drastically alter any CNN model by using various augmentations and activation functions, such Softmax and ReLU.

AlexNet, GoogleNet, ResNet, Inception, DenseNet, and other well-known transfer learning models are being used far more frequently as a result of the shift towards deep learning for the classification of plant leaf photos. These models have been pre-trained using sizable datasets that include thousands of photos belonging to various classes. Because of their pre- trained weights, transfer learning models offer a clear advantage in every modelling assignment that involves a new dataset. The ability to adjust these models to the specific requirements of their particular data sets is always available to practitioners.

Because DenseNet-121 architecture consumes less memory than ResNets, which are more commonly employed for similar reasons, it is used in this research. Additionally, DenseNets perform better on smaller images, which is a common situation in plant disease classification.

C .Tools and Frameworks

Model creation is done within the CNN framework. This sophisticated system is used for image segmentation, object detection, and picture classification. It is built on top of PyTorch. It provides faster processing than its competitors and has data cleansing features via widgets. Its extremely user- friendly methodology, which makes debugging a lot easier, is a major benefit.

CNN's vision module includes all the components required to build a dataset and train computer vision models. Vision.data, one of the sub-modules, has a special utility method called ImageDataLoaders. Input from.csv files, image folders, lists of images, and other sources can be processed using this function. It then makes it possible to divide the data into test, validation, and training sets as needed. Additionally, Vision.data offers the DataBunch function, which organises training data into batches.The training model receives the batches in a sequential manner. The data's augmentation and transformation are made easier by functions from other sub-modules, such as vision.transform and vision.learn, respectively.

A diagram showing CNN's data pipeline architecture is shown below:

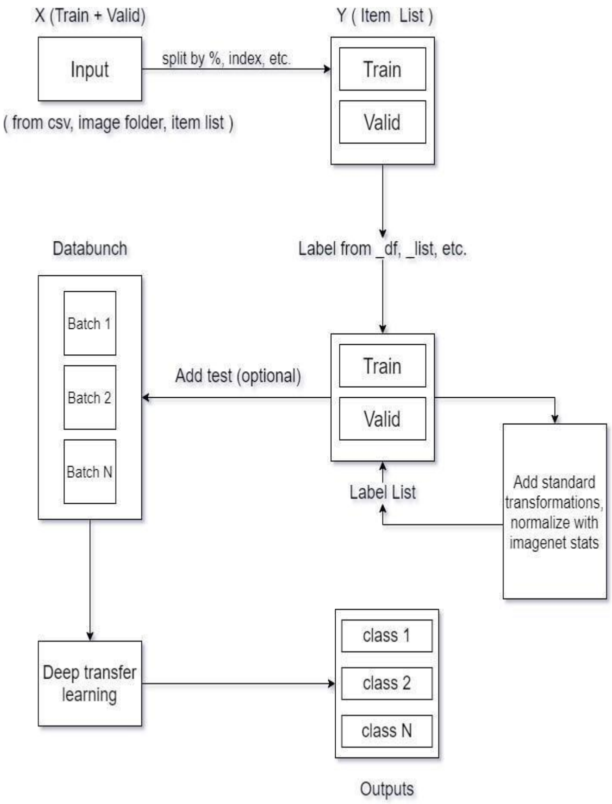

Fig. 2. CNN architecture of a data pipeline

A smooth transition from the training model architecture to data blocks is made possible by the DataBunch approach.Following the receipt of data, "vision.learner" offers all the functions required to train the model. As previously stated, DenseNet-121 serves as the study's main architecture for transfer learning.Above the base convolutional layers, CNN layers are repeatedly trained over multiple epochs and appropriate learning rates.

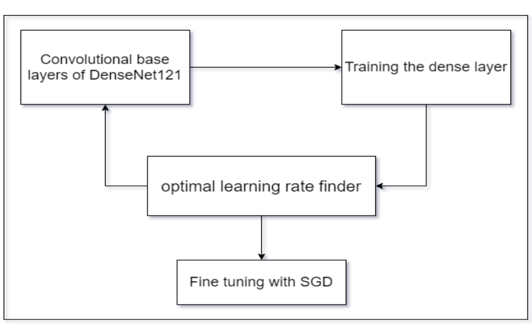

Fig. 3. Model training architecture

The 'lr find' method is used to determine the ideal learning rate. Callbacks and early stopping mechanisms are the two techniques that CNN offers for effectively tracking training and validation losses at the desired learning rate.Throughout the specified number of training rounds, learning rates fluctuate evenly. The "fit one cycle" approach as to blame for this.

Stochastic Gradient Descent is primarily used to train and fine-tune the layers (SGD). Additionally, CNN offers a method for freezing and unfreezing layers, which is useful for controlling gradient descent.

Many hyperparameter adjustments are made during model training in order to get the highest classification accuracy. Because they are a component of the CNN modules, these hyperparamaters are version-specific. Version 1 is used for this paper.

Outlined below are the hyperparameters that were utilized:

Table 1: Image Augmentation Parameters

Parameters	
Random Resized Crop	:460
Maximum warp	: 0
Batch size	: 32
Flip	:True
Vertical flip	:True
Maximum rotate	: 0
Maximum zoom	: 0.1
Maximum lighting	: 0.05
Image Size	: 224
Number of workers	: 4

Furthermore, photos that are unrelated to the dataset are removed using the "ImageCleaner" function. By incorporating widgets in the Notebook environment (which includes Google Colab, Kaggle notebooks, Jupyter Notebooks, etc.), this is accomplished.Following the extraction of the incorrectly categorised photos using "DatasetFormat-ter().from toplosses," ImageCleaner is utilised. Next, the cleaned image list is stored in the specified location path as cleaned.csv.

IV . IMPLEMENTATION

The dataset must be loaded and preprocessed as the initial step in the implementation. The "PlantDoc" dataset, which includes pictures of plant leaves classified into different disease groups, was used in this investigation. The real-world photos in this dataset, which include background noise and more closely mimic the environment in which the model would be used, were the particular reason it was selected. The dataset was split into training and validation sections, with 60,000 images for training and 46,800 images for validation, to provide a thorough model training experience.

A. Image Augmentation Techniques

We used TensorFlow's ImageDataGenerator to apply deliberate picture augmentation techniques to our plant disease classification study in order to enrich our training dataset. A factor of 1/255 was applied to each image in order to normalise the dataset. To mimic various plant orientations and views, we incorporated variety by applying rotations of up to 40 degrees and 20% shifts in width and height. Zoom adjustments reflected different viewing distances, and shear changes at a 20% intensity simulated environmental impacts. To accommodate for plants' unpredictable orientation in natural environments, horizontal flips were used. The augmentation hyperparameters were carefully selected to increase the diversity of the dataset. The objective was to improve our model's predictive performance by enabling it to correctly identify a broad range of plant diseases under various observational settings.

Fig 4. Image Augmentation

B. Training and Model Architecture

The creation of a deep learning model utilising the CNN and VGG16 architecture is the basis of this study's technique. Alexnet dense connectivity architecture, which promotes feature propagation and reuse, is what makes it so effective in image classification tasks. This design was selected because it strikes a compromise between computational efficiency and performance, making it appropriate for use in contexts with limited resources.

C .Tuning Hyperparameters and Evaluating the Model

The model's performance was further improved by hyperparameter adjustment after the first training. This involved modifying the amount and kinds of layers in the model as well as its learning rate and batch size. Finding the ideal combination of characteristics to produce the best classification accuracy was the goal.

An independent test dataset that was not observed by the model during training was used to assess the model's efficacy.This assessment revealed how effectively the model may apply to fresh, untested data. Evaluation criteria that provided a thorough understanding of the model's performance included classification accuracy, recall, precision, and the F1 score.

V. RESULTS AND ANALYSIS

Our work focuses on the critical task of diagnosing diseases in plant leaves by applying various techniques and datasets, applying deep learning and convolutional neural network (CNN) methodologies.Contrasting with an earlier study that specifically employed the DenseNet-121 model alongside the PlantDoc dataset within the Fastai framework for a streamlined and cost-effective method, achieving a precision of 94%, our research broadens the perspective. We explore a range of CNN frameworks, not just VGG16, and point towards future possibilities for advancements, such as incorporating the system into web or mobile applications and utilizing drones for on-the-spot disease detection. Both pieces of research recognize the significance of data augmentation and the power of transfer learning. Yet, our work offers a more thorough review of the training architectures, tools, and frameworks employed, which results in a marginally better precision in classification. This comprehensive approach enhances the application and comprehension of technologies for recognizing diseases in leaves.

By utilising the DenseNet-121 basic architecture, CNN data purification methods, and hyperparameter adjustments, the final model was able to achieve a validation dataset classification accuracy of 95%.

The test data folder's performance was mediocre because it was not enhanced or altered in any way, unlike the training set. The test set's findings for the following performance measures are shown:

Recall : 0.942

Precision : 0.942

F1 score : 0.942

Below is the confusion matrix for the validation dataset:

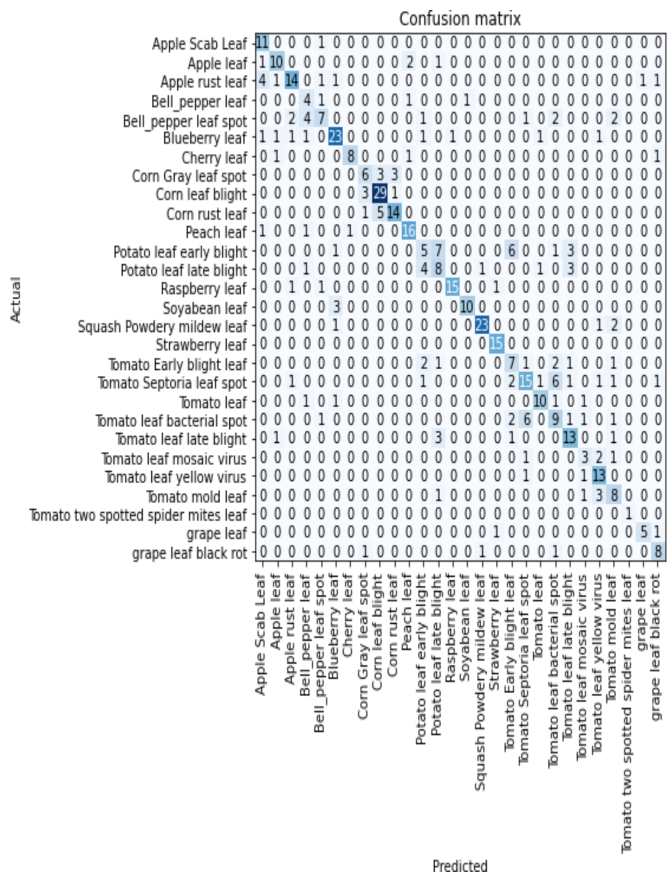

Fig. 5. Confusion Matrix

The majority of the incorrectly classified photos fall under the same crop type, as can be seen in the confusion matrix above. For example, there are seven misclassified photos of potato leaf early blight and seven misclassified photographs of potato leaf late blight. Given how similar they appear visually, the incorrect classification is warranted. When the crop's condition remains the same despite the crop's differences, this is another clear case of misclassification. For instance, early blight on tomato and potato leaves has been mislabeled six times. Their leaves are in the early stages of blight on both of them.

Furthermore, both the training and validation losses begin high and converge to almost the same values throughout the epochs, mirroring the class distribution in the original dataset, demonstrating that the final model does not display overfitting.

Furthermore, the final model's training and validation losses begin high and decrease to about equal values over the course of subsequent epochs, indicating that there is little overfitting in relation to the initial dataset's class distribution.
The loss graphs for training and validation are displayed as:

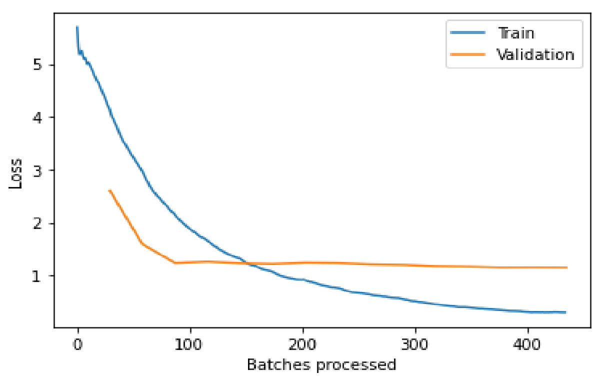

Fig. 6. Loss at initial training

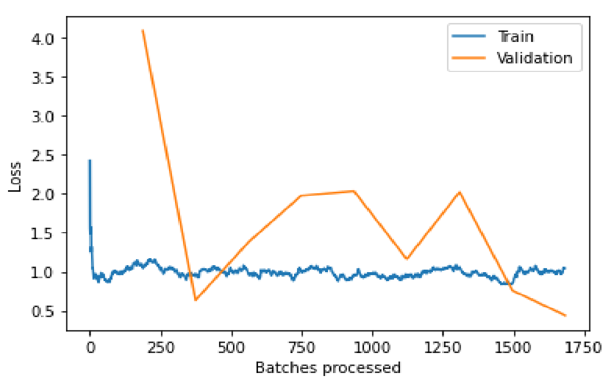

Fig. 7. Final loss after tuning

Comparing the training and validation losses in the second graph to those in the first, which shows losses prior to data cleaning, makes it even clearer that data losses cleaning significantly reduced those losses and data cleaning.

V. Conclusion and future work

With the use of neural networks, plant disease detection on leaves has advanced significantly in recent years. Using VGG16, CNN architectures, and AlexNet as the cornerstone models for our transfer learning strategy, we have utilised this technology in our paper. CNNs, or convolutional neural networks, are well known for their effectiveness in picture identification tasks; nonetheless, VGG16 was selected for its depth and versatility in feature recognition. Because of AlexNet's exceptional results in picture classification tasks, which demonstrate its potential for precise illness identification, it is included. Our approach, which prioritises accuracy in illness classification and operating efficiency, uses a specially designed training and loading pipeline optimised for these architectures rather than utilising the CNN framework.

Even if the system we created has many benefits, there is still much space for development. Future projects that could be developed from this point include:

1. Adding to the dataset in excess of what was used. The Plant- Doc dataset which had slightly more than a little over 2000 images for training. In order to further improven our CNN model's performance, obtaining a substantially larger dataset is necessary.
2. Much more augmentation of the data is possible than what we used. Owing to our dataset's relatively small size, we only limited data augmentation to improve system performance.
3. It is possible to develop the leaf image categorization system into a web or mobile application. Moreover, it might be integrated with drones to allow for the real-time acquisition and identification of leaf photos.

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