Plant Disease Classification Using Deep Learning: A Comparative Study Using Various Machine Learning Techniques

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Abstract- Deep learning is an artificial intelligence subfield. With the advantages of automated learning and feature extraction, academic and industry circles have become increasingly interested in it in recent years. Image and video processing, speech processing, and natural language processing have all utilised it extensively. In addition, it has become a hub for agricultural plant protection research, including plant disease detection and pest range assessment, etc. The application of deep learning in plant disease detection may circumvent the drawbacks caused by the artificial selection of disease spot features, make the extraction of plant disease features more objective, and enhance the research efficiency and rate of technological transformation. This article describes the latest scientific advancements of deep learning technology in the identification of agricultural leaf diseases. In our study we have used images of healthy and diseased crop and used three CNN architectures to classify them as healthy and diseased crops.

Indexed Terms- Plant Disease, Image Classification, Agriculture, CNN, MobileNet

I. INTRODUCTION

The presence of plant diseases has a detrimental effect on agricultural production. Food insecurity will worsen if plant diseases are not detected in time[1]. Early identification is the foundation for effective disease prevention and control, and it plays a crucial role in agricultural production management and decision-making. In recent years, identifying plant diseases has been a key concern.

Typically, the leaves of plants are the primary source for identifying plant illnesses, and the majority of disease symptoms may first manifest on the leaves [2].The evolution of agriculture thousands of years ago resulted in the domestication of the majority of today's food crops and animals. Food insecurity is one of the biggest issues facing humanity today, and plant diseases are a major contributor to this problem.

One estimate places the global crop output loss attributable to plant diseases at about 16%. Fungi, fungus-like organisms, bacteria, viruses, viroids, virus-like creatures, nematodes, protozoa, algae, and parasitic plants make up the major families of plant pathogens.

Typically, the leaves, stems, flowers, and fruits of disease-infected plants have visible lesions or markings. In general, each illness or pest situation has a distinctive visual pattern that may be utilised to detect problems. Typically, the leaves of plants are the primary source for diagnosing plant illnesses, and the majority of disease symptoms may first manifest on the leaves.

Convolutional Neural Network (CNN) is a prominent deep learning approach for COVID 19 identification and is a widely used neural network architecture for a range of computer vision tasks across several areas. Researchers have deployed CNN architecture and its various versions for the categorization and detection of plant diseases.

A machine learning strategy to detect healthy and unhealthy plants using various CNN architectures such as AlexNet, GoogleNet and MobileNet. Images of plant leaves were collected, preprocessed and then classified. Our Image classifier assess and categorize healthy and unhealthy plants, depending on the images and pattern on the leaves.

Fig.1 shows the general architecture of a CNN architecture. The general process of using traditional image recognition processing technology to identify plant diseases is shown in Fig.2 [3].

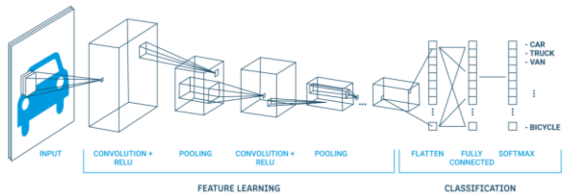

Figure [1]

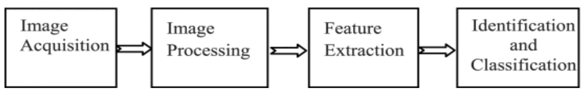

Figure [2]

Fig.3 depicts the number of images per class. The information of the number of images in each class is represented as a bar graph. The plant or diseases is represented on the x-axis while the number of plant is represented on y-axis in the bar graph.

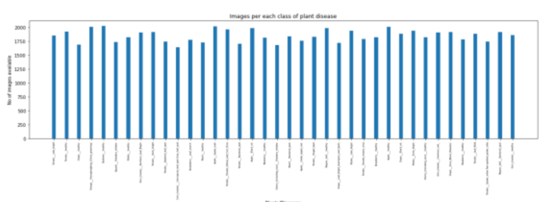

Figure [3]

II. RELATED WORK

Dubey and Jalal [4] used the K-means clustering method to segment the lesions regions, and combined the global colour histogram (GCH), colour coherence vector (CCV), local binary pattern (LBP), and completed local binary pattern (CLBP) to extract the colour and texture features of apple spots. Three types of apple diseases were detected and identified using an improved support vector machine (SVM), with a 93% classification accuracy.

Convolutional neural networks (CNN), a subset of deep learning techniques, are rapidly becoming the favoured method in recent years [5]. CNN is the most widely used classifier for image recognition, and it has demonstrated exceptional image processing and classification capabilities [6]. First introduced in plant image recognition based on leaf vein patterns were deep learning techniques [7]. They utilised three to six layers CNN identified white bean, red bean, and soybean as leguminous plant species. Mohanty and others [8]. Due to the unique characteristics of each disease site, Barbedo [9] and Lee et al.[10] advocated the use of specific lesions and patches rather than the entire leaf. The advantages of this technology include the ability to detect the presence of numerous diseases on the same leaf and the ability to enrich the data by slicing the leaf picture into multiple sub-images. The article [11] utilised the GoogLeNet model to identify 79 illnesses of 14 plant species in experimental and complicated field environments. Using a single lesion and location had a greater overall accuracy (94%) than using the entire image (82%). Lee et al.[10] proposed a new view of leaf disease detection that centred on identifying diseases disease area method (i.e., by the common name of disease rather than crops - diseases on the target category), and experiments demonstrated that regardless of crops, the model training with the common disease was more universal, especially for new data obtained in different fields or for crops that have not been observed.

III. METHODOLOGY

Dataset: Plant Disease Dataset - This dataset is recreated using offline augmentation from the original dataset. This dataset consists of about 87K rgb images of healthy and diseased crop leaves which is categorized into 38 different classes. A new directory containing 33 test images is created later for prediction purpose.

Deep learning is a form of machine learning technique that uses calculation models composed of multiple processing layers in order to learn the characteristics of the data. These deep learning architectures are trained on a subset of the ImageNet database.

A.AlexNet

The architecture is comprised of eight layers, including five convolutional layers and three fully connected layers. However, this is not what distinguishes AlexNet; the following aspects are innovative approaches to convolutional neural networks:

Nonlinearity of ReLU. AlexNet employs Rectified Linear Units (ReLU) rather than the usual tanh function at the time. The advantage of ReLU is training time. Typically, CNNs "pool" the outputs of neighbouring clusters of neurons without overlap. However, when the scientists incorporated overlap, they observed a 0.5% drop in error and discovered that models with overlapping pooling are generally more resistant to overfitting.

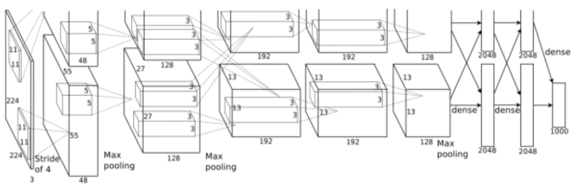

Figure [4]

It is better to use AlexNet as it will require less computations than ResNet. The architecture of AlexNet is depicted above in Fig.4 .

B.GoogleNet

The GoogLeNet design differs significantly from prior cutting-edge systems like AlexNet. Among the techniques utilised by GoogleNet:

1×1 convolution: The Inception architecture employs 11 convolution in its design. These convolutions were used to reduce the amount of architecture parameters (weights and biases).

- Global Average Pooling

In previous architectures, such as AlexNet, completely connected layers were utilised at the network's endpoint. These completely connected layers comprise the bulk of parameters in numerous systems, resulting in a rise in computation costs.

he inception module is distinct from earlier systems like AlexNet.

In this architecture, each layer's convolution size is fixed. 11, 33, 55 convolution, and 33 max pooling are conducted in parallel at the input of the Inception module, and their outputs are stacked to produce the final output. The concept that different-sized convolution filters will better manage things with multiple scales.

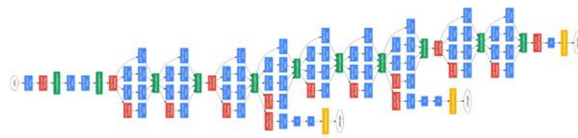

Figure [5]

The architecture of GoogleNet is depicted above in Fig.5.

- MoblieNet:

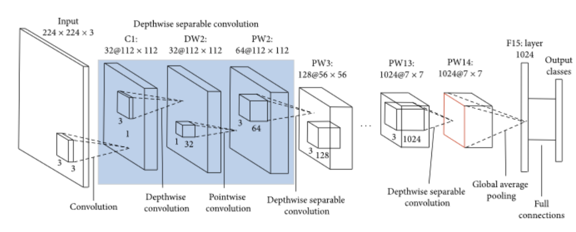

Figure [6]

The architecture of GoogleNet is depicted above in Fig.6 .

MobileNet uses depthwise separable convolutions. It reduces the number of parameters greatly when compared to networks with normal convolutions of the same depth. Thus, lightweight deep neural networks are produced. A depthwise separable convolution consists of two operations: a depthwise convolution and a pointwise convolution.

E.Experimental Setup

Mobile computing infrastructure was used throughout the whole construction of the system. A personal computer that uses the Microsoft Windows operating system and has the following specifications: an Intel i5 processor from the 8th generation, clocked at 2.1 GHz, with 3 MB of cache memory paired with 8 GB of RAM and a 1 TB hard drive (ver. 20H2, 64 bit). Google Collaboratory together with Python 3.2, Tensor Flow, NumPy, Scikit-learn, and Pandas were all part of the software configuration that came with the computer.

IV. RESULTS AND DISCUSSION

A.Evaluation Parameters

Since accuracy is insufficient for classifications in Machine Learning, we employ specific measures such as F1 score, precision, and recall. Machine learning offers a unique perspective in this industry, and to convince the field that AI can be implemented, we need a reliable assessment strategy to validate our results.

- Accuracy

Accuracy is a performance metric that represents a model's performance across all classes. When all classes receive equitable treatment, there are benefits. It is determined as the proportion of accurate forecasts to total projections, as seen below in equation (1).

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

- Precision

Precision is measured as the ratio of Positive samples correctly identified to all Positive samples classified correctly or wrongly, as stated in equation (2). Precision is a metric that indicates a model's accuracy at classifying a sample as positive.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

- Recall

The recall is calculated as the ratio of Positive samples that were properly classified as Positive to all Positive samples, as shown in equation (3). The recall value represents how well the model detects positive samples. The greater the recall, the greater the number of positive samples found.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

- F1-score

The F1 score is a statistic measuring of a model's accuracy on a given dataset. It is the harmonic mean of the model's precision and recall and is a way for combining the model's precision and recall, as illustrated by equation (4). It embodies the delicate balance of precision and recall.

$$\text{F1-score} = \frac{2 * precision \quad * recall}{precision \quad * recall} \tag{4}$$

B.Results

Python is used to determine the CNN architecture's performance on the dataset. The primary stage is learning followed by prediction. The learning stage entails training the models on the database and then classifying the plants as diseased and undiseased. The outcomes are monitored, and performance varies depending on the learning time. To avoid underfitting, we must utilise a sufficiently large dataset, which necessitates a sufficiently extensive learning phase. The model is trained on the training data before being evaluated on the test data.

In this proposal's classification, classifiers must be able to distinguish between diseased and non diseased plants. The accuracy of the three architectures were used to evaluate and compare the diseased and non diseased plants. The comparative study of the proposed proposal's metrics model utilizing evaluation metrics is provided in Fig.8. using a Bar Graph. The accuracy of MobileNet was highest with 97.2 % followed by 72.2% for AlexNet and 71.9% for GoogleNet.

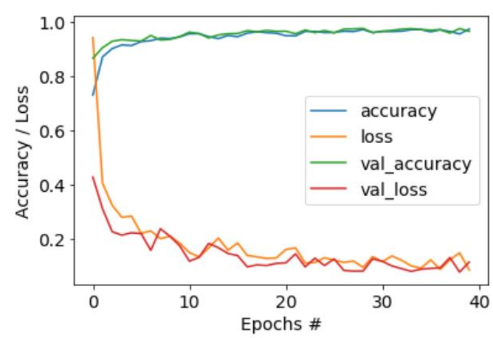

Figure [7]

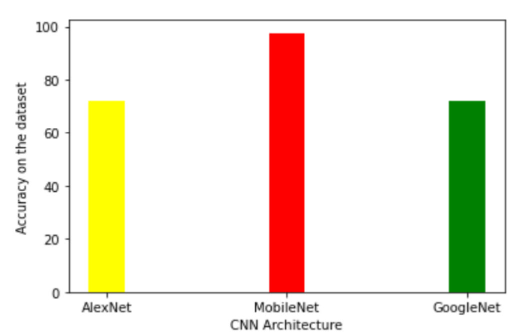

Figure [8]

The performance of different CNN architectures are depicted in Fig.8. The validation accuracy/loss and test accuracy/loss graph of MobileNet is depicted in Fig.7.

V. CONCLUSION AND FUTURE SCOPE

The aim of this study was to detect Plant disease from the analysis of images of leaf of the diseased and non diseased plants and provide a comparative analysis of three deep learning architectures for image classification. When it comes to classifying diseased and non diseased plants, experimental findings reveal that MobileNet outperforms GoogleNet and AlexNet achieved an accuracy of 97.5 %.

The future scope of the project will include the use of new deep learning architectures such as R-CNN, FAST R-CNN, FASTER R-CNN, YOLO and ViT(Visual Transformers) to the plant disease detection. Visual Transformers (Vit) has never been used on the plant disease detection in comparison to the above mentioned architectures.

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