Identifying Plant Disease Using Image Processing And Deep Learning

Sriraja B[1], Suresh Rajan M[2], Thavaprakash S[3], Solasa Naga Sai Surendra Gupta[4], Rajagopal T K P[5]
[1, 2, 3, 4] Dept of Computer Science and Engineering,
[5]Assistant Professor, Dept of Computer Science and Engineering,
[1, 2, 3, 4, 5] Hindusthan College of Engineering and Technology, Coimbatore, Tamil Nadu, INDIA

Abstract- *In India's economy, agriculture plays important role. To prevent crop loss and future plants disease spread, early detection of plant infections is extremely important. The majority of plants, including apple, tomato, cherry, and grapes, exhibit obvious disease symptoms on the leaf. Farmers or plant pathologists manually inspect the plant leaf to determine the type of illness is the traditional approach. In this study a deep learning model is trained to categorise the various plant diseases.Due to the convolutional neural network (CNN) model's outstanding performance in image-based classification, it is utilised. Compared to manual plant leaf observation, the deep learning model makes predictions more quickly and accurately. Image processing techniques to avoid the model to overfitting. The ResNet model performs the best among other CNN Algorithms in terms of accuracy.*

Keywords- Plant Disease Detection, CNN, ResNet, Image processing

I. INTRODUCTION

Over 18% of India's GDP comes from agriculture, which also accounts for 60% of all employment there. In many areas of the country, climate change is currently having an impact on the yield, and it is an uncontrollable element. On the other hand, a factor that can be controlled is a decrease in yield brought on by plant diseases. Many plant diseases have an impact on agricultural productivity. Plant diseases are severely harming crops, which not only has an impact on the economy but also on the supply and quality of food.

To identify these plant diseases, numerous techniques and procedures are being implemented. Although some farmers are privileged enough even to afford laboratory and professional oversight. The majority of them lack the resources to pay for consultants and tools that would enable them to identify plant illnesses early on and stop their spread. Farmers must also transport the sample to the certified labs in order to diagnose the plant illness. These labs' setup cost a lot of money and resources, and those resources would be better invested in other projects that would increase production. Thus, we must apply digital methods to identify plant illnesses in order to make the yield profitable for customers as well as farmers in to compensate for high cost of lab and professional employees in that field.

In order to increase accuracy and reduce hardware needs, we want to further study the deep learning approaches that have been used in past attempts at solving this problemfor the purpose of reducing the expense and simplifying the process of illness identification.

II. RELATED STUDIES

The many techniques for recognising plant leaf diseases are discussed in this essay. Machine learning models have been used to classify images over time using a variety of image processing techniques. The state-of-the-art for the majority of computer vision issues has recently been advanced by the development of new deep learning architectures and methodologies. [1] CNNs have completely changed how deep learning is used in computer vision applications. CNNs use kernels with specified dimensions that serve as filters to collect spatial and temporal information from feature maps about the object.

Following that, a feedforward neural network that serves as a classifier receives these feature mappings. As kernels require significantly less space than feedforward layers to process an image of the same size, CNNs have made image processing and other jobs simpler and more effective.Using variations in the number of occurrences, the order of the convolutional layers and pooling layers, and the stride and padding parameters, multiple CNN designs are employed. Remaining links in more recent architectures enable these models to have greater depth without suffering from the drawbacks of vanishing gradients[3].These models may store enormous quantities of data and have millions of parameters. Without needing to recapture data for the network's first layers, information learned through training on one piece of data can be utilised to solve problems on another collection of data with some easy fine-tuning.The idea of transfer learning has gained popularity during the last two to three years in practically all computer vision applications.

The increased performance and accuracy of activities, particularly the identification and classification tasks, are to blame for the current increase in popularity[5]. Transfer learning has been shown to be more effective and precise than training a cutting-edge model from scratch for the diagnosis of plant diseases[6].In this research, Sharada P. Mohanty et al. show how how two state of the art models AlexNet[7] and GoogleNet[8] produce distinct results when taught using two alternative training methodologies. Compared to the pre-trained GoogleNet on which transfer learning is used and the weights that are utilised in the GoogleLeNet are taken from that of the Imagenet dataset, training the Alexnet from scratch on the Plant Disease dataset produced less accurate results[9]. In many natural language processing issues more recently, the addition of attention layers via the development of transformer neural networks has proven to be the solution[10]. Transformers were initially created to handle sequential data found in NLP tasks like text generation and abstractive summary generation. Yet, during the past few years, transformer networks have excelled in computer vision tasks and surpassed many standards set by all CNN architectures. These networks produce attention maps, which are then input to classification layers for image classification[11] and utilised to identify relationships between various components of the image.These approaches have all been demonstrated to be effective at resolving image classification issues. In this research, we examine each of these techniques for classifying and identifying plant diseases.

III. METHODOLOGY

Many diseases can affect a plant's leaves. Humidity or other environmental factors can be to cause. Virus, bacterial, and fungal diseases are among the common illnesses. Changes in colour and shape may result from this. Due of the similar patterns, it might be challenging to distinguish these variations. Consequently, loss can be avoided by early identification of these infections. This research suggests a image processing and deep learning method for categorising plant diseases.

A. Data Collection

The Google subsidiary website kaggle, which is made for data science, machine learning, and deep learning applications, is used to collect images of plant leaves from the plant village. The Plant village dataset is where the information for this study was acquired. More than 55,000 pictures from 38 classes of 14 different plant species make up the Plant Village dataset. Twelve of the 38 leaf classes are in good health, whereas 26 have sick leaves. In this study, we collected images of plant illnesses that affect 14 different types of crops, including strawberry, peach, apple, blueberry, cherry, pepper, cherry (including sour), raspberry, tomato, grape, orange, soybean, squash, potato, corn(maize), and cherry (including sour).

Fig.1 Example ofPlant village data

B. Image Processing and Data Augmentation

To categorize the plant's healthy leaves and rust disease. In image pre-processing, leaf pictures are subjected to Gaussian filters for smoothing and noise elimination They applied a log transform to the image that had been filtered by a Gaussian process to improve it. Eventually, black-and-white segmentation techniques known as binary threshold segmentation were employed to separate the image's foreground and background areas. The structural component of an image that is defined by a binary threshold has also been removed via image erosion. After completing the preceding actions, the image is now limited to the foreground and background. The segmented image's wavelet features were retrieved using the discrete wavelet transforms method.

C. Training and Validation

The entire number of images provided as input all at once for CNN forward propagation is known as the batch size. The quantity of samples that will be transmitted across the network is essentially determined by batch size.For illustration, suppose you wish to set up a batch size of 100 and you have 1050 training samples. The technique trains the network using the first 100 samples (numbered 1 through 100) from the training dataset. The network is then trained again using the subsequent 100 samples (from 101st to 200th). This process can be repeated until all samples have been distributed throughout the network.

We are going to use “ResNet”, which have been one of the major breakthrough in computer vision since they were introduced in 2015.In ResNets, unlike in traditional neural networks, each layer feeds into the next layer, we use a network with residual blocks, each layer feeds into the next layer and directly into the layers about 2–3 hops away, to avoid over-fitting (a situation when validation loss stop decreasing at a point and then keeps increasing while training loss still decreases). This also helps in preventing vanishing gradient problem and allow us to train deep neural networks.

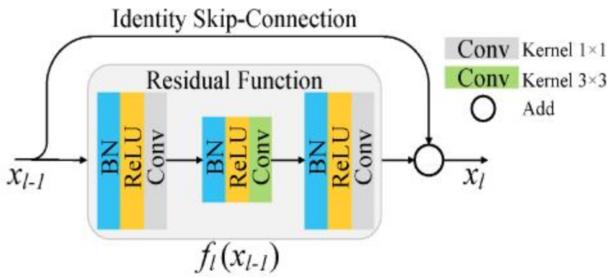

Fig.2ResNet Residual Block

Before we train the model, Let's define a utility function and evaluate function, which will perform the validation phase, and a 'fit one cycle' function which will perform the entire training process. In 'fit one cycle', we have use some techniques:

Learning Rate Scheduling: Instead of using a fixed learning rate, we will use a learning rate scheduler, which will change the learning rate after every batch of training. There are many strategies for varying the learning rate during training, and the one we'll use is called the "One Cycle Learning Rate Policy", which involves starting with a low learning rate, gradually increasing it batch-by-batch to a high learning rate for about 30% of epochs, then gradually decreasing it to a very low value for the remaining epochs.

Weight Decay: We also use weight decay, which is a regularization technique which prevents the weights from becoming too large by adding an additional term to the loss function.

Gradient Clipping: Apart from the layer weights and outputs, it also helpful to limit the values of gradients to a small range to prevent undesirable changes in parameters due to large gradient values. This simple yet effective technique is called gradient clipping.We'll also record the learning rate used for each batch.

IV. EXPERIMENTAL RESULT

ResNets perform significantly well for image classification when some of the parameters are tweaked and techniques like scheduling learning rate, gradient clipping and weight decay are applied. The model is able to predict every image in test set perfectly without any errors. ResNets Model show almost 99.2% Accuracy Score.

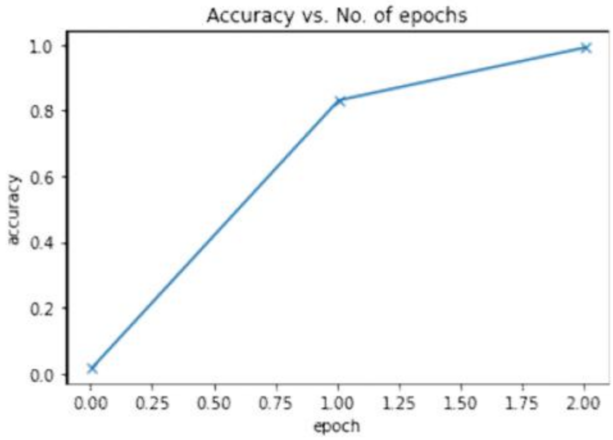

Fig.3Validation accuracy

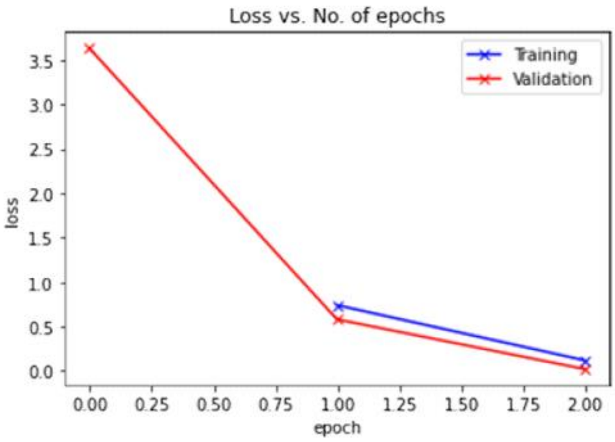

Fig.4 Validation Loss

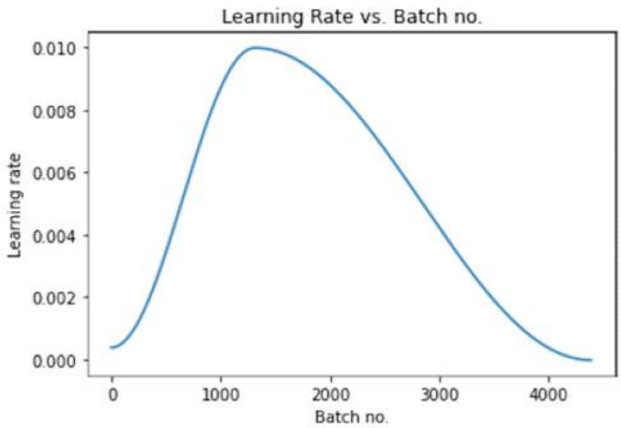

Fig.5 Learning Rate Over Time

V. CONCLUSION

In recent years, Convolutional Neural Networks have been significant for all image processing tasks, including classification, augmentation, and description. This study demonstrates how the CNN Model functions with images and to prevent Model overfitting by using several image processing techniques, such as gradient clipping, weight decay, and scheduling learning rates and trained by different CNN algorithms. For diagnosing and predicting plant diseases, ResNets Algorithm shows a higher accuracy score almost 99.30%, when compared to other Convolutional Neural Network algorithms.

REFERENCES

[1] Ashish Vaswani and Noam Shazeer and Niki Parmar and Jakob Uszkoreit and Llion Jones and Aidan N. Gomez and Lukasz Kaiser and IlliaPolosukhin, "Attention Is All You Need", 2017,https://arxiv.org/abs/1706.03762

[2] AlexNet ,Krizhevsky, Alex, Ilya Sutskever, andGeoffrey E. Hinton," ImageNet Classification with Deep ConvolutionalNeural Networks", Advances in Neural Information Processing Systems 25 (NIPS 2012)

[3] Bengio, Y. Lecun, Yann. (1997). Convolutional Networks for Images, Speech, and Time-Series.

[4] Bichen Wu and Chenfeng Xu and Xiaoliang Dai and Alvin Wan and Peizhao Zhang and Zhicheng Yan and Masayoshi Tomizuka and Joseph Gonzalez and Kurt Keutzer and Peter Vajda,"Visual Transformers: Tokenbased Image Representation and Processing for Computer Vision",2020

[5] Christian Szegedy and Wei Liu and Yangqing Jia and Pierre Sermanet and Scott Reed and Dragomir Anguelov and Dumitru Erhan and Vincent Vanhoucke and Andrew Rabinovich,"Going Deeper with Convolutions"

[6] Christian Szegedy and Vincent Vanhoucke and Sergey Ioffe and Jonathon Shlens and Zbigniew Wojna,"Rethinking the Inception Architecture for Computer Vision" in Springer

[7] J. Deng, W. Dong, R. Socher, L. Li, Kai Li and Li Fei-Fei, "ImageNet: A large-scale hierarchical image database," 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, 2009, pp. 248-255, doi: 10.1109/CVPR.2009.5206848.

[8] Kaiming He and Xiangyu Zhang and Shaoqing Ren and Jian Sun 2015 Deep Residual Learning for Image Recognition http://arxiv.org/abs/1512.03385

[9] Konstantinos P. Ferentinos, "Deep learning models for plant disease detection and diagnosis",Computers and Electronics in Agriculture,Volume 145, 2018,Pages 311-318, ISSN 0168-1699,

[10] Mohanty Sharada P., Hughes David P., Salath´eMarcel,"Using Deep Learning for Image-Based Plant Disease Detection",Frontiers in Plant Science,vol.7, 2016

[11] Pradeesh Hosea S, Ranichandra S and Rajagopal T K P, "Color Image Segmentation - An Approach" in International Journal of Scientific & Engineering Research Volume 2, Issue 3(March-2011)

[12] Rajagoapal T K P, Sakthi G, Prakash J (2021), "Convolutional Neural Networks for High Spatial Resolution Remote Sensing Image Classification" on Research Square with page[1-12] .

[13] UmitAtilaa, Murat Uçarb, Kemal Akyolc, and EmineUçar, "Plant leaf disease classification using EfficientNet deep learning model," Ecological Informatics, vol.61, Article 101182, March 2021.