Detecting potato plant leaf diseases with the Tuber Net model within the realm of smart agriculture

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Abstract

The detection of flaws in food crops, such as potatoes, may benefit greatly from the use of machine vision and image processing techniques. There has been an uptick in the use of image processing and AI in agriculture, particularly for the purposes of detecting and categorising plant and fruit pests and illnesses. Manual interpretation of these leaf diseases may be time-consuming and labor-intensive, but they have a significant impact on potato quality and yield due to problems like early blight and late blight. Effective and automated diagnosis of these diseases during the budding period may help improve potato crop output since it demands a very high degree of competence. Several models have been presented in the past for early detection of plant diseases. The goal of this study is to demonstrate TuberNet, a deep learning (DL) method to illness recognition in potatoes. In particular, the research employs the TuberNet in order to recognise different potato leaf diseases, hence introducing an end-to-end training-oriented strategy. To improve the approach's identification capabilities and better identify many infections, we adopt a spatial-channel attention strategy to zero in on the damaged regions. In order to deal with class-imbalanced samples and boost the network's generalisation capacity, dense layers are added to the end of the model structure to increase the feature selection power of the model, and transfer learning is used. The model is put through its paces on the open and difficult Plant Village dataset, which contains photographs captured under a wide variety of lighting and background circumstances, as well as those showing a wide range of leaf coloration. Experiments on the model's accuracy for disease classification in potato plant leaves and its ability to handle distorted data robustly have been proven. As a result, the suggested model tool may increase farmers' profits and crop yields..

Keywords: Deep Learning; TuberNet; Plant Disease Diagnosis; Transfer Learning; Potato Plant; Agriculture.

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Introduction

The agriculture sector is the world's largest provider of food, money, and employment opportunities. Typical of low- and middle-income nations, the industrial sector in India contributes 18% to GDP and employs 53.3% of the labour force [1]. Agriculture's gross value added (GVA) to India's GDP has climbed from 17.6% to 20.2% during the last three years [2], contributing to the country's burgeoning economy. It is well-known that preventative medications are ineffective for avoiding epidemic or endemic diseases [3], which might have a negative impact on agriculture and, by extension, the quality of food production. If crop diseases are monitored and identified as early as feasible, suitable crop protection measures may be put in place to assist avert production quality losses [4].

Damage to potato (Solanum tuberosum L.) crops caused by the oomycete Phytophthora infestans (henceforth P. infestans) is unprecedented. Late blight [5] is a problem for many of the potato varieties grown in Colombia since it is difficult to manage without resorting to heavy pesticide use. Percentage of diseased foliage is a common visual indicator of the severity of late blight [6]. Visual assessments of illness severity, however, involve expert (subjective) intervention and are thus time-consuming, labor-intensive, and not particularly repeatable. Accurate diagnoses may be made with the help of the different patterns left behind by infections and bug infestations [7]. Furthermore, farmers' or experts' incorrect diagnosis of plant illnesses may result in the use of treatments that are counterproductive to their intended purpose and ultimately harmful to the environment [8].

The detection issues that farmers are presently encountering have answers thanks to recent improvements in computer imaging [9]. Researchers have developed a number of methods for correctly recognising and categorising plant illnesses due to the fact that the spots indicating infection initially show as dots and patterns on the leaves. Traditional image processing is still in use [11], and it necessitates the use of manual techniques for activities like feature extraction and segmentation. Machine learning (ML) and deep learning (DL) models have been the subject of a large number of studies in the field of computer imaging since the emergence of AI [12].

CNN architectures like AlexNet, GoogLeNet, and ResNet were used as foundational models in a research [13] to identify diseases in tomato leaf data. Training and validation accuracy histograms allowed for a visual representation of the model's efficacy. The ResNet model outperformed the other CNN designs [14]. The conditional average (CA) and the F1-score [15] were used to assess the model's performance in both colour and grayscale when it was employed to detect banana leaf disease. These measures were used to colour and monochrome assessments. In [16], the architectures of five distinct CNNs—AlexNet, AlexNetOWTbn, GoogLeNet, Overfeat, and VGG—are compared and contrasted. GoogLeNet, ResNet-50, ResNet-101, Inception-v3, InceptionResNetv2, and SqueezeNet were only some of the cutting-edge DL models used in the study.

The study recommends a light DL method named TuberNet, which achieves good results in disease classification of potato plant leaves with little processing effort. TuberNet is skilled in calculating relevant and distinguishing sample attributes. The model's capacity to understand crosslinks and space-wise orientation aspects is enhanced by the inclusion of the pixel and channel attention technique in the feature computation phase, allowing for faster diagnosis of potato leaf diseases under realistic conditions. Improved accuracy in identifying diseased areas on potato leaves is achieved by the use of transfer learning and multi-class focal loss to address the issue of class imbalance and network overfitting. The research conducted extensive comparative assessments to verify the classification outcomes using a dataset of potato crop disease photos procured from a gold-standard sample repository known as PlantVillage. The proposed technique is effective in classifying potato crop diseases despite the presence of noise, distortion, uneven illumination, and differences in the form, colour, and positioning of infection signs.

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2. Related works

The improved deep learning algorithm proposed by Mahum et al. [17] uses visual features of potato leaves to categorise them into five groups: Potato Late Blight (PLB), Potato Early Blight (PEB), Potato Leaf Roll (PLR), Potato Verticillium_wilt (PVw), and Potato Healthy (PH) class. The proposed model is trained using an existing dataset (called "The Plant Village") that contains photos of potato leaves labelled as Healthy, Normal, or Infected with Early Blight (EB) or Late Blight (LB), respectively. The information for the Potato Leaf Roll (PLR), Potato

Verticillium_wilt (PVw), and Potato Healthy (PH) classes has also been acquired by hand. To successfully diagnose the potato leaf illnesses, a pre-trained Efficient DenseNet model was used, with an additional transition layer added to DenseNet-201. Since the training data is very unbalanced, our proposed technique benefits from the use of the reweighted cross-entropy loss function. Overfitting is kept to a minimum in the training of tiny training sets of potato leaves samples because to the thick connections with regularisation power. The proposed approach is the first of its kind to successfully execute disease detection and classification for four potato leaf diseases. On the test data, the algorithm achieved a 97.2% success rate in terms of accuracy. Our suggested approach has been tested and shown to be more reliable and effective than prior models for detecting and classifying illnesses in potato leaves.

Using the convolutional neural network (CNN) techniques developed by Arshaghi et al. [18], we analysed five disease categories affecting potatoes: healthy, black scurf, common scab, black leg, and pink rot. A collection of 5,000 photographs of potatoes was utilised. Our approaches for fault classification in potatoes were compared to those of Alexnet, Googlenet, VGG, R-CNN, and Transfer Learning, among others. The findings demonstrate that the suggested deep learning approach outperforms previous research in terms of accuracy. In certain courses, we achieve perfect accuracy, while in others, we achieve 99%.

Plant illness may be detected by the use of diffuse reflectance spectroscopy in the leaves, as reported by Zhou et al. [19]. To monitor the development of potato late blight disease after inoculation with the oomycete pathogen Phytophthora infestans, we gather leaf diffuse reflectance spectra in the field using a smartphone-operated, small diffused reflectance spectrophotometer. Infection may be predicted using a neural network with more than 96% accuracy within 24 hours after pathogen injection, and 9 days before visible late blight symptoms develop. Our results highlight the promise of combining handheld optical spectroscopy with machine learning analysis for early disease detection in plants.

Sadiq et al. [20] attempted to use deep learning models for precise sickness detection in potato crops, a crop with important economic implications worldwide. This study trained four distinct deep learning models on a large dataset consisting of photos of both healthy and sick potatoes: VGG16, EfficientNet B4, InceptionV3, and Inception ResNetV2. The results of these models were much better than those of more conventional visual examination techniques. The EfficientNet B4 model showed the best accuracy of all the ones we looked at, scoring a flawless 100 on our accuracy scale. After then, accuracy dropped to 99% for VGG16, 98% for Inception V3, and 94% for Inception ResNet V2. The findings show promising possibilities for improved crop management approaches, which may help cut down on economic losses caused by potato diseases by a substantial amount. The results of this research provide credence to claims that AI, and in particular deep learning models, may significantly contribute to the development of cutting-edge agricultural techniques. This is important for maintaining food security in the face of rising threats from plant diseases.

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3. Proposed system

3.1. Data collection

In the first phase, we gathered photographs of potato leaves from a publicly available dataset called Plant Village Dataset, which includes 2,152 images for Potato Leaves illnesses, including 1,000 images labelled "Late Blight," 1,000 images labelled "Early Blight," and 152 images labelled "Healthy Plants." In addition to the preexisting dataset, 1700 photographs of potato leaves with Verticillium wilt and leaf roll have been taken in different areas. Diseased potato leaf samples are shown in Figure 1 and Table 1..

3.3. Classification using TuberNet

A strong collection of picture characteristics is crucial for accurate classification since it helps to distinguish across input sample types. Recall rates for methods may be improved with the use of dense DL networks by computing a more efficient collection of features. However, the deployment of these CNN techniques is very reliant on the availability of processing power and memory, which is a computational limitation introduced by the use of deep networks. As a consequence, there is always some compromise to be made between the accuracy of an assessment and how much it costs to run. The introduction of such a framework for plant disease detection is thus urgently required, since it can provide improved classification accuracy while keeping computing cost stable. To improve model performance for identifying multiple anomalies, this research presented a lightweight and computationally robust model. The outline of the suggested model is shown in Figure 2..

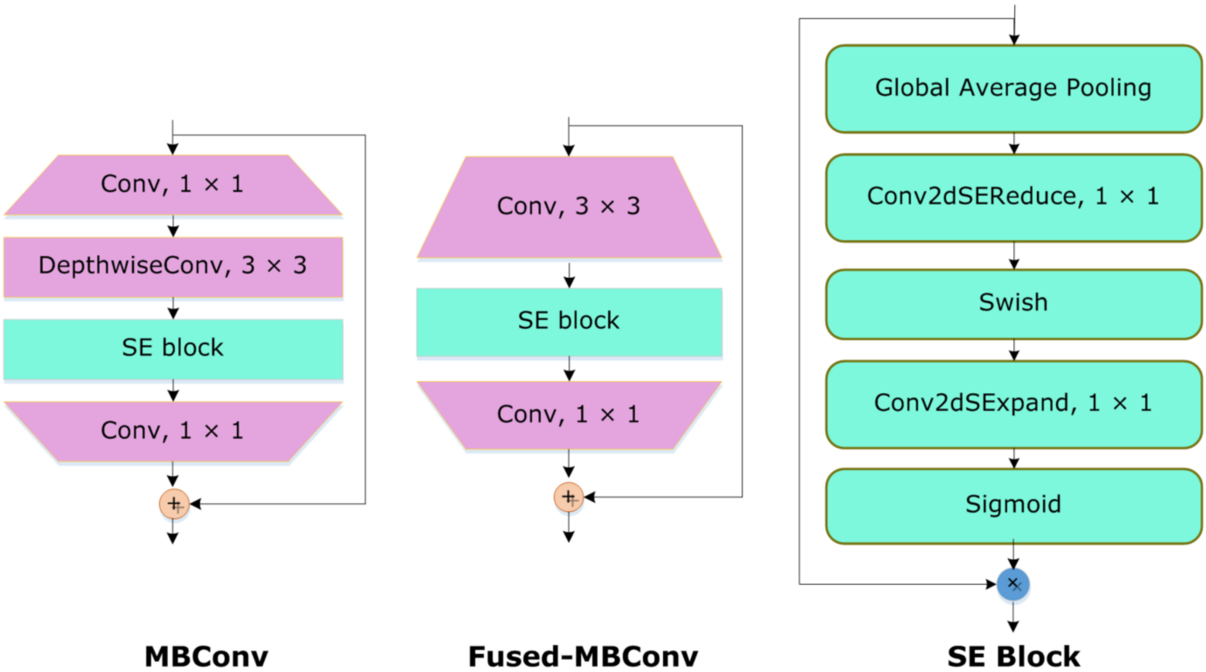

Figure 2: Visual demonstration of MBConv4, Fused-MBConv4, and SE blocks.

An enhanced version of the EfficientNetV2-B4 model was introduced in the TuberNet framework that was presented. An updated version of the original EfficientNet, called EfficientNetV2. To improve the robust recall rate while maintaining the available resources, we provide a revised version of the EfficientNetV2 model. To accommodate for varying resource restrictions without compromising the framework's efficacy, the updated EfficientNetV2 model is developed using a lightweight and competent composite scaling technique. Accordingly, the provided framework offers the best answer for both computational cost and the best choice of network structure, i.e., the number of network layers or the size of the sample feature vector. The EfficientNetV2 strategy requires few model parameters and performs the classification job accurately.

Motivated by its short inference and training time and minimal number of model parameters, the EfficientNetV2 with additive dense layers was used to the problem of categorising photos of plant diseases. The EfficientNetV2 method employs the neural architecture search (NAS) to improve classification accuracy while decreasing feature vector size and training time. In addition, EfficientNetV2's use of the FusedMBConv (FMBConv) blocks optimises operational power and makes efficient use of mobile or server accelerators. In contrast, the conventional EfficientNet method relies heavily on depth-wise convolutions and uses just MBConv blocks as its core building element. Although depth-wise convolutions reduced the amount of required arithmetic operations, they do not make full advantage of modern hardware accelerators. Both MBConv and FMBConv blocks are fully used in the EfficientNetV2 method to achieve the computational gain. Instead than using depth-based 3x3 convolution and expansion 1x1 convolution as MBConv does, FMBConv uses standard 3x3 convolution layers. By switching out some MBConv for FMBConv, we can speed up the framework's execution without sacrificing the accuracy of our classifications.

The EfficientNetV2 model built on top of a B4 base network is used to classify diseases. The B4 base was selected because it provides a good compromise between the model's classification performance and its running duration. Table 1 provides a detailed illustration of the enhanced EfficientNetV2 model. In the first layers of the enhanced EfficientNet-V2 model, we use the FMBConv blocks, and in the final layers, we employ the MBConv blocks with 3 3 and 5 5 depth-wise convolutions, squeeze-and-excitation block (SEB), and swish activation. The used MBConv blocks keep an inverted residual connection with the SEB to get the robust classification outcomes. The network is able to rank impacted regions of the input picture by using the self-learning weights, which are enhanced by the attention mechanism used by the SEBs to improve representations of critical spots. Since the ReLU activation function (ReLUAF) removes values below zero, leading to a loss of essential details in the pictures, the framework utilises the swish activation function (SAF) as an alternative. Equation (3) may be used to determine the SAF.

In addition, a Batch normalisation layer is implemented at the start of a framework to down-sample the input picture sizes. Due to the huge number of parameters required for high values of O (total output channels), only three FMBConv blocks were employed in this investigation (Table 1). Additionally, a global average pooling layer is introduced after the MBConv blocks to minimise the model parameters and prevent the issue of model over-fitting. In addition to the ReLUAF and dropout layers, the research also incorporated 2 additional inner dense layers, which help in extracting the more efficient collection of sample key-points by presenting them in a practical format. A 30% dropout rate is arbitrarily chosen to improve the performance of the model. Using a dense layer with five output neurons and the Softmax activation technique, a completely automated model for classifying plant diseases is developed.

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Validation Analysis of proposed model

Table 3: Analysis of various models on 60%-40%

Models	**PR (%)**	**RE (%)**	**SE (%)**	**SP (%)**	**AC (%)**	**F1-Score (%)**
LeNet	92.7	91.6	92.6	90.1	87.3	90.5
ResNet	93.6	92.0	93.0	90.3	88.2	91.7
AlexNet	94.3	94.5	94.5	91.2	89.5	92.3
VGGNet	95.5	95.6	94.6	93.4	90.6	93.6
GoogleNet	95.6	95.8	95.8	95.5	91.5	94.8
TuberNet	96.5	96.3	96.3	97.4	92.5	95.4

Figure 3: Graphical Comparison of various models

Table 4: Comparative Analysis of proposed model on 80%-20%

Models	**PR (%)**	**RE (%)**	**SE (%)**	**SP (%)**	**AC (%)**	**F1-Score (%)**
LeNet	96.2	96.6	96.6	96.1	96.3	96.4
ResNet	96.6	96.8	96.8	96.2	96.5	96.7
AlexNet	96.7	97.1	97.1	96.3	96.4	96.9
VGGNet	97.4	97.7	97.7	97.3	97.6	97.5
GoogleNet	97.7	97.9	98.0	97.5	97.8	97.8
TuberNet	99.5	99.3	99.3	99.4	99.5	99.4

5. Conclusion

As the rate of digitization continues to rise in every industry, now is the moment to use it in agriculture for the sake of improved crop protection. With this goal in mind, we present a model to identify and categorise potato leaves as either healthy or diseased. When potato plants are sick, farmers lose money and their yield. Early or late blight mostly attack the leaves of potatoes. It is believed that these diseases account for the vast majority of potato crop losses. Images of potato leaves were classified as either healthy, late blight, or early blight. In this research, we build a system dubbed TuberNet to recognise these types of objects. The leaves of the potato plant are classified using a DL method called TuberNet. Using the AM technique and several additional layers at the conclusion of the model structure, the research enhanced the previous EfficientNet-v2 method. By using an end-to-end learning process, the described method successfully recovers top-level indicators of infected locations and links them to relevant cohorts. Furthermore, by communicating important information about easily observable features like sick patches of plant leaves, the AM method boosts the suggested solution's recall power. We conducted extensive experiments on a complicated data set called PlantVillage to demonstrate the efficacy of our framework, and the results showed that our model is capable of recognising potato illnesses even from distorted photos, as seen by the study's performance scores. The suggested framework has an accuracy rate of 99.5 percent. However, this precision may and should be enhanced. Artificial neural networks, and in particular convolutional neural networks, may be used to expand upon the previous work. These days, researchers rely heavily on CNN methods to study pictures in an effort to improve and standardise accuracy. Convolutional neural network (CNN) designs rely heavily on activation functions, batch normalisations, convolutional layers, and fully connected layers to improve accuracy.

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