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Employing Deep Convolutional Neural Networks for Enhanced Precision in Potato and Maize Leaf Disease Detection and Classification

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Abstract

Advances in image processing and techniques in artificial intelligence have made it possible for computers to see and learn. This article introduced a technology that has utilised MobilenetV2 Deep Convolution Neural Network architecture to automatically identify and diagnose plant diseases from images. The identification and classification of plant diseases are now carried out by only human experts-crop extension agents, and farmers, expensive labour that is prone to mistakes. This study relies on dataset gathering as a technique of classifying and identifying plant diseases. It is a multistep process involving pre-process data on the raw set, mask green area of the leaf, remove green section, convert to grayscale and then obtain some characteristics, select, and classify with regard to disease management, etc. Two different types of plants, maize and potato, have been taken in consideration to show effectiveness of the outcome of the proposed model. The confusion matrix and classification performance report were used to evaluate the system. The dataset for potato and maize comprised 6228 and 6878 images, respectively, of leaves. Precise, recall, and F1-scores of 95.15%, 94.76%, and 94.93% were recorded as a cumulative performance across the datasets of potato and maize respectively. This translates to its resistance in picking most diseases for these crops, making it a resource that can be used with confidence in agriculture disease detection. The MobileNetV2 model performs well in both crops, especially for potato early blight and maize common rust. Lower performance in recognizing healthy potato leaves suggests that the feature space of healthy and diseased leaves may overlap. The MobileNetV2 model performed a robust ability in general in the detection of most diseases affecting both potato and maize leaves, but some specific areas need to be targeted for further enhancement.

1. Introduction

Plants are becoming much more important these days than only being used to feed people and animals. Plants are already used to decrease wind and soil erosion, as well as 25% of prescribed drugs originate directly or indirectly from plants [1], which enhances living circumstances for humans. Nevertheless, plants are susceptible to diseases as well. According to [2], plant infections are equivalent or very comparable to human and animal pathogens. The majority of plant diseases are caused by infectious microorganisms as well as by external factors such as excess or lack of nutrients.

Hazardous substances in the atmosphere or ground, humidity, and illumination all play a significant role. Fungi, which appear as patches on plant leaves, are the primary cause of most plant diseases. These spots significantly hinder plants' ability to carry out photosynthesis because they affect the green pigments in the leaves. This significantly influences these plants' growth and yield. An advanced stage of the fungal infection causes total covering of the leaf surface.

As explained in [3], plant diseases not only diminish crop productivity but also degrade the genetic diversity of affected plants, perhaps leading to their abandonment in cultivation. Many plant diseases result in large losses of productivity and capital. It is able to seriously damage the ecology. Insecticides, fungicides, and pesticides commonly manage plant diseases, including those affecting leaves. However, excessive use of these compounds to treat plant diseases can result in crop pollution and pose a variety of hazards to humans and animals. Because pesticides leave hazardous residues on crops, researchers have identified applying them to diseased crops as a major cause of groundwater pollution and poisoning. Overuse of pesticides by farmers raises production costs, which may lead to bigger financial deficits. Given the significant role of plants in ecosystems, it is necessary to implement an efficient disease control mechanism using a non-destructive technique at an early stage. This will effectively prevent any loss in the quality and quantity of plants in a timely and accurate manner. The effects of disease-infected plant leaves are outlined in figure 1.

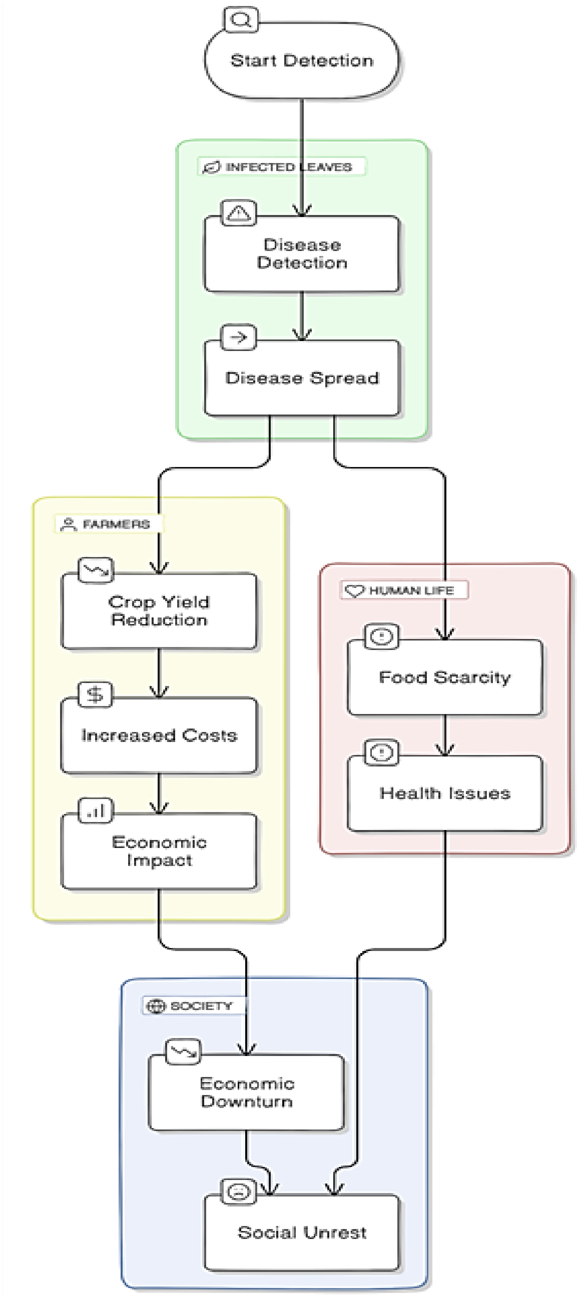


Figure 1. Effects of diseases infected leaves on farmers, human life, and society.

Plant diseases can be identified and categorized through the utilization of both manual and digitally automated procedures. As stated in reference [4], plant diseases commonly present themselves as more noticeable lesions on the vegetation. Field reconnaissance plays a fundamental role in conventional methodologies employed for the identification of diseases and the classification of diseased plants. The process is monotonous, requires a significant investment of time, and is prone to a multitude of errors and incorrect deductions.

In contrast, several diseases may not exhibit visible symptoms on the leaves, while others may manifest at a later stage, causing significant harm to the plants. In such instances, it is advisable to use automated systems as the sole method for precisely and rapidly identifying the problem. This can be achieved by applying complex algorithms and methods of analysis, preferably with the help of effective microscopes and other devices. It at times reveals the symptoms through electromagnetic means, which produce more images than can be seen by the naked eyes. A different approach at looking at the problem is provided by the RST that relies on multi-hyperspectral image captures to assess and detect plant disease [6]. Performing the approach of the RST often hinges on using the digital image processing techniques to achieve the desired results. The various studies cited above in this paper have suggested that the image-processing methods applied to research in the agriculture sector have been of diverse benefits regarding the advancement of the agricultural sector.

Identification and classification of plant diseases are always challenged through the application of the methods of image processing and machine learning. Deep learning approaches, specifically convolutional neural networks, have shown much promise in precision agriculture by learning the very complex, nonlinear relations in image data, which allows strong yield predictions and crop health assessments. CNNs combined with high resolution remote sensing data have proved quite effective at detecting subtle features in an image, thus allowing early diagnosis of disease, critical for on-time intervention in crop management. Advances of AI with particular focus in CNN architecture are still aimed at optimization of agricultural monitoring with less labored input and rapid analysis accuracy for optimal detection of diseases over vast fields [7-12]. Several different approaches using machine learning techniques along with image processing have been investigated by researchers, including CNN [13-19], ANN [20], back-propagation NN [21], and SVM [17,22] for better precision while identifying and classifying plant diseases. The next part is a concise discussion of the same on the identification and classification of diseases infecting crops of maize and potato. In this work, ANN is used to detect and classification of leaf-borne plant diseases.

Farmers need proper assistance from the agriculture specialist to improvise crop productivity and quality. This assistance is required to identify diseases in the cultivated crop and the possible solutions to overcome from this problem. Sometimes, farmers have to travel to long distances to get this assistance from the specialist. There may be cases when there are no experts available for such guidance which leads to give burden to farmers in terms of cost and time waste.

It can be identified that surveillance of small farms to identify plant diseases or deficiencies can be done quickly, efficiently, and accurately to categorize diseases and organic-based solutions to overcome from these diseases. But the same task is done for very large farms, it will face extreme challenges in monitoring, diagnosis, and classification. Delays in the proper diagnosis can lead to the spread of the pets which can't be even controlled by organic solutions. In these circumstances, farmers go for using chemical pesticides which is not a good solution in reference to human health. By providing an automated monitoring solution based on image processing and machine learning methodologies, these issues can be resolved. Researchers are continuously working on this problem of identification of classification of plant diseases. Many of the ML approaches used for classification require manual training and show poor accuracy. Also, it is required to generate a set of features for classification which must be compatible with the defined model architecture. These models are lacking in generalized characteristics because of not creating high-level properties which need to be used for the accurate classification of diseases. This fact led us to use deep learning neural networks for quick, reliable, and efficient detection and classification of plant diseases and apply the controlling solutions to stop their propagation. It will also help to improve the productivity of the crops.

This proposed system is an attempt to explain the characteristics and consequences of leaf diseases that affect potatoes and maize. The most important requirement is to choose an effective image-processing algorithm specially designed for the detection and classification of plant diseases.

Our proposed approach effectively masks and excludes the green elements from the images and simplifies the analysis process. The main focus of this paper is on designing and developing an effective deep neural network for the detection and classification of plant diseases. The network will be trained and tested on a rigorously chosen and structured dataset. We will rigorously evaluate the accuracy as well as efficiency of the proposed system through an extensive analysis and comparison with alternative methodologies. Finally, we will perform a comprehensive examination of the research results to derive significant conclusions and formulate a clearly defined plan for future progress in this critical domain of agricultural technology and research.

The proposed system is focused exclusively on identifying and categorizing two crop species, namely maize and potatoes, which are mostly used crops worldwide. We concentrated on identifying the diseases that were most prevalent in the maize and potato crops, which harmed the leaves of the plants.

2. Literature Review

The detection of diseases in plants is an issue which should be addressed. Advances in computer vision and deep learning have led to the development of CNNs as an approach for classifying and identifying plant diseases. In this field, CNN models are highly effective because they have the ability to extract and analyze crucial information from leaves images [14,23]. The CNN methods that are used for detecting plant diseases are being extensively studied. Potatoes and maize are among the most critical food entities around the world and their production can be significantly impacted by various diseases. Accurate diagnosis of diseases related to potatoes and maize using computer vision techniques and CNNs has shown promising results. The next part is a concise discussion of the same on the identification and classification of diseases infecting crops of maize and potato.

Potato crops suffer from many diseases like blight, rust, scab, rot, wilt, and scurf, which can be due to fungus, bacteria, viruses, and nutritional causes. These diseases affect the foliage and tubers that impair the quality and effectiveness of the crops. Potato crops are particularly prone to two major diseases: early blight and late blight. Alternaria solani and Alternaria tomatophila cause early blight, one of the fungal diseases that affect potatoes. It manifests as concentric rings on the foliage and can lead to premature leaf drop, which can result in a reduction of crop production. Oomycete Phytophthora infestans are the main cause of the Late blight. This disease is characterized by black, water-soaked lesions on the stems, leaves, and fruits, it quickly develops into brown necrotic patches and causes the complete collapse of the crop. These diseases show different symptoms and it's caused by different pathogens. The impact of both early and late blight on potato crops has led to the development of specific control methods, which continue to be a major focus of agricultural research [24].

Effective treatments for potato plant diseases, including blights, are resistant varieties and fungicides. While, black scurf can be mitigated by byproducts from other entities, such as Vitis vinifera. This indicates the potential of integrated insect control methods. To manage diseases and their treatment, genetic resistance, pharmacological treatments, and cultural practices are necessary. Many ongoing research are aiming at developing more effective treatments for these diseases [25,26].

The maize crop's productivity and quality can be significantly affected by various diseases. Diseases like grey leaf spot, common rust, and northern corn leaf blight (NCLB) are mostly found in maize and the primary cause of nearly all these diseases is fungi. Leaf spot is depicted by rectangular lesions on leaves that range in colour from tan to brown. The presence of tiny, brick-red blisters on the upper and lower surfaces of leaves are signs of common rust. Northern corn leaf blight displays elongated, grey-green, or brown lesions on leaves. These diseases collectively have the potential to substantially restrict maize production and also reduce photosynthetic activity in them [27,28]. These diseases can lead to substantial economic losses. Because of their severity, they have impacted maize growth and productivity. Effective disease management strategies must be implemented, as these diseases are critical for maintaining cultivation and food security [29]. Convolutional Neural Networks (CNN) with sparse detection has proved highly useful in classifying diseases in potato plants that are infected with Meloidogyne luci. The result shows that all the evaluated classification algorithms achieve accuracies above 75% even when the data is reduced to one spectral band. Such results indicate a good finding that the hyperspectral bands selected have great prospects for multispectral imaging applications as they provide a cheaper alternative to the traditional hyperspectral imaging technologies. Thus, this proves that the approach has the utility and practicality for classifying plant diseases [30].

A multi-level deep model was developed for early and late potato crop infections. This deep model produced a very high precision rate of 99.75% in the classification of diseases in the potato plants. The authors applied the core part of the model known as CNN and ResNet50 to achieve image segmentation. ResNet50 is a highly recognized architecture with the best efficiency and precision in handling deep images. The model used the integration of ResNet50 to study and segment the potato leaf images correspondingly, allowing for the accurate differentiation between the types of tissue addressed [31].

A comprehensive framework shall comprise models of segmentation, classification, and semantic instance segmentation. It worked well in identifying and classifying potato plant diseases from images whose backgrounds are complicated. In its application, the deep learning used the framework avoids the drawbacks of the traditional computer vision and pattern recognition approaches. The models that were used include Mask R-CNN, VGG16, ResNet50, InceptionV3, UNet, PSPNet, and DeepLabV3+. Together, they ensured precision and accuracy in detecting diseases. The Mask R-CNN instance segmentation model scored an average precision of 81.87% and a precision rate of 97.13%. The classification model reached an accuracy of 95.33%. These results reflect the better accuracy of deep learning over other approaches for potato disease detection while being a huge leap forward for the agricultural world. The advanced framework, thus far, is not only capable of disease identification but also exploring all possibilities of application towards agriculture [32].

The traditional machine learning approaches and pre-trained deep learning models have been used in researching on the development of disease detection systems for potato plants. The use of the combination of the VGG16 feature extractor with SVM classifier gives up to 93% accuracy. No data augmentations techniques have been employed while getting results for a very limited dataset. Pre-trained models like InceptionResNetV2 and ResNet50V2, along with traditional machine learning algorithms such as XGBoost, KNN, and Random Forest, are used in this experiment. Despite the limit on the data set, the VGG16-SVM model was shown to have acquired the highest possible efficiency towards classification of diseases in potato plants [33].

The above application was developed on the Android mobile to classify real-time potato leaf diseases using the VGG-16 model. Impressive results were reflected as 98% accuracy in the classification of potato leaves as either healthy or influenced by a disease. The VGG-16 model and transfer learning techniques of the application classified potato leaves as either healthy or affected by the disease. This novel approach was proven to be effective for the early detection and control of diseases of the potato crop. It has a lot of promise for widespread disease monitoring under practical conditions. The research also addressed the problems of manual interpretation time and small sizes of datasets within this application. The application has used the VGG-16 classification model with transfer learning, thereby greatly improving the management of the potato crop by accurately identifying the diseases [34].

A deep learning model was built in order to classify quickly the potato crop disease known as late blight. With some slight modifications following the development of a basic model that gives a high accuracy of classification on the diseases of potatoes up to 94%, more advanced developments with an additional module, reduction in the network depth, and lower utilization of 1x1 convolution reduce parameters in the range of nearly about 23% in counts while bringing about approximately the same percentage decrease in floating-point operations with respect to the entire size of the model. The improved model achieved a 0.85% increase in classification accuracy and a 25% improvement in CPU inference performance, resulting in a detection time of just 3.27 seconds. This model demonstrated outstanding accuracy and efficient performance. It proved to be highly effective for practical implementation in detecting potato late blight [35].

A framework was developed utilizing lightly supervised learning for the classification and localization of diseases in maize plants. This integrated approach combined lightweight CNNs with interpretable artificial intelligence, which achieved an outstanding level of detection accuracy. CNN architectures were used to accurately specify affected regions in maize leaves. Also, the need for manual labelling was quite reduced by using lightly supervised learning techniques. This framework achieved a mean intersection over union (mIoU) of 55.302%, enabling crop disease surveillance and improving plant protection efforts. The drawbacks of weakly supervised learning, especially its dependence on image-level annotations that limit precise localization, were also admitted. Visualization techniques were also claimed to be required to present results from deep learning models in more interpretable forms for agricultural applications, etc [36].

In the study, colour and ANN co-occurrence features were used in recognition and classification of maize diseases in Ethiopia. Through this approach with ANN and on leaf colour observation, an accuracy in recognizing 86% was attained. In this research paper, importance to the economy of Ethiopia has also been emphasized on agriculture, especially maize farming. The study, however, conceded that the accuracy rate of 86% was one limitation [37].

To identify the diseases of maize, authors developed a sparse recognition model that established an average accuracy of 88.55% classification using the Kaggle dataset. One of the features of the proposed method was the two-step method: developing the image dictionary followed by the implementation of the detection-based sparse classifiers. The two methods were shown as feasible and useful to implement in the detection of maize diseases. The research study highlights the fact that selection of feature and classifier accuracy significantly contribute to getting reliable outputs. The limitations identified in the proposed study relate to suboptimal selection of feature and classifiers. The existence of such limitations indicates that although the proposed method is beneficial, yet there exists a significant scope for further improvements in the future [38].

The proposed methodology identifies and classifies the plant diseases through transfer learning and deep convolutional neural networks (CNN). The above study used the pretrained ResNet50 model to make impressive results of 98.0% precision, 77.0% recall, 99.0% specificity, and an F1 score of 86.0% in the detection of maize diseases. The training approach resulted in a loss of 0.08 to 0.053 while the model achieved high accuracy. Application of data augmentation and segmentation preprocessing approached further improved the performance of the model. Deep transfer learning with ResNet50 has been used for achieving high accuracy results in the identification of plant diseases, mainly for maize and potato crops, but it still lacks enhancement in precision and recall metrics to improve the overall performance of the models [39].

A deep learning-based model, "MaizeNet", was designed for maize disease detection, prediction of their severity, and crop loss estimation. The MaizeNet model showed 98.50% accuracy in disease identification by using the K-Means clustering technique to select regions of interest. The authors addressed the drawbacks of prior studies by using a real-life labelled dataset to train the model and also improved the reliability and practicality of their approach. Disease severity and determining crop loss were studied in areas that were previously not adequately investigated. The proposed model was integrated into a user-friendly web application, improving its accessibility and practical use for farmers and agricultural experts [40].

3. Material and Method

Plant diseases will be classified using a structured approach. Both the training and test datasets will start with preliminary processes. The process begins with image processing to increase quality. After that, the crucial step of recognizing and separating green pixels will be performed, and those cells will be removed. This preliminary step ensures that data is analyzed after optimization. An advanced deep-learning algorithm will be used for data classification, feature extraction, and training. This method creates an effective disease classification model using well-processed training data. The training process utilizes the Keras and Tensorflow software libraries. After training, the model will be tested using the test dataset. The assessment will be improved through the removal of masked cells. The method's plant disease prediction and classification performance can be evaluated by comparing the deep learning algorithm's classification results to the test dataset. The process diagram is in figure 2. This model was trained and tested on a system equipped with an Intel Core i5 processor, 16 GB of RAM, and 512 GB of storage, using Python with TensorFlow and Keras libraries. Because MobileNetV2 is lightweight, it can be deployed on small devices and edge devices in the fields. However, training the model is still moderately computationally expensive when large datasets are used. While deployment on devices with similar specs is possible for real-time disease detection, more optimization such as model pruning and quantization could further reduce the resource demands and have a more efficient scaling, especially for use in remote or resource-poor areas.

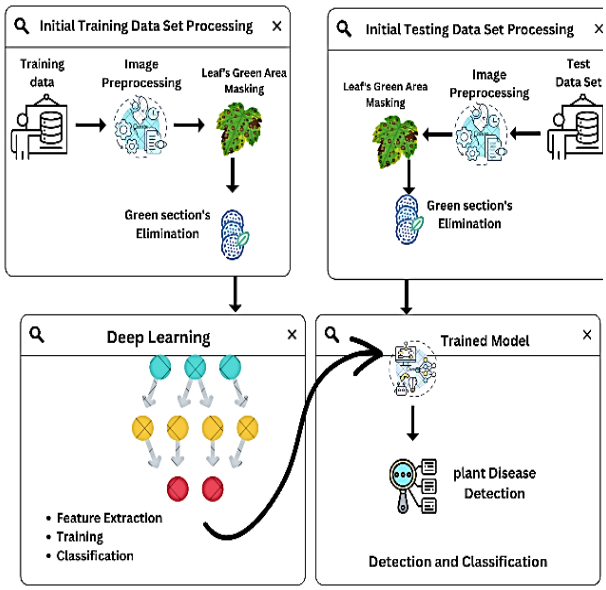


Figure 2. Block diagram of the proposed system.

3.1. Dataset

The proposed system was applied to a publicly accessible dataset consisting of 6228 and 6878 images for potato and maize leaves. This data set consists of both infected as well as healthy leaves. The sources of the data set are the website plantvillage.org [41] and the work presented in [42]. The collection consists of 1172 images illustrating the healthy leaves of potatoes. The dataset comprises 2628 images illustrating the occurrence of early blight. There are 2424 images displaying the symptoms of late blight. The collection comprises 1162 images depicting healthy maize. There are 1087 images that depict gray leaf spots. There are a total of 2498 images displaying the occurrence of common rusty. The collection also contains 2131 images depicting northern leaf blight. Table 2 presents the distribution of the initial dataset. The datasets have been partitioned into training and testing sets. 80% of each class dataset was utilized for the purpose of training and 20% for testing. The collection comprises a wide range of images, which includes images of varying resolutions, samples captured at both early and intermediate stages, and the most up-to-date documented infection status. The adjacent objects of the plant have also been collected to serve as a sufficient dataset for training and evaluating the proposed methodology. All these details of the dataset are listed in table 1 and sample images from the dataset are shown in figure 3.

Table 1. Details of Dataset for Each Classification

Crop Name	Leaf Disease Category	Initial Data Set	Data set used for Training	Data set used for Testing
Maize Leaf Dataset	Common rust	2498	1998	500
	Gray leaf spot	1087	870	217
	Healthy	1162	930	232
	Northern Leaf Blight	2131	1705	426
Potato Leaf Dataset	Early blight	2628	2102	526
	Healthy	1172	937	235
	Late blight	2424	1939	485
	Total	13102	10481	2621

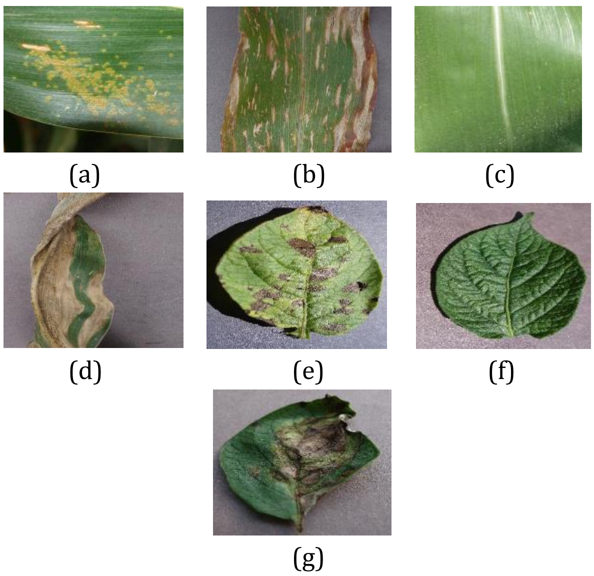


Figure 3. Samples of leaf images from the dataset (a) common rust maize leaf (b) gray leaf spot maize leaf (c) healthy maize leaf (d) northern leaf blight maize leaf (e) early blight potato leaf (f) healthy potato leaf (g) late blight potato leaf

3.2. Preprocessing

This represents the initial phase of the proposed system. The presence of distortion in an image can be characterized by fluctuations in the intensity or brightness levels [43]. The inclusion of these factors may occur while capturing of the images due to camera flash, variations in the sunlight, background disturbances, and the arteries presence within the leaf of a plant. The main intent of the preliminary processing of images is to eliminate any anomalies present in the image in order to improve the overall quality of the processed image, to achieve the utmost level of accuracy in the results, and optimize efficiency. To optimize computational resources and improve storage capacity for subsequent processing, the initial image dimensions are reduced to 128 x 128 pixels. The appropriate size of the image was rigorously determined through the experimentation of various sizes in order to ensure that the functionality of the automatic system for plant disease identification and classification is not compromised. Image resizing is crucial for achieving consistent image dimensions. The downloaded images are converted from RGB colour model to the hue, saturation, value (HSI) colour model. This conversion is based on the fact that HSI modeling is often regarded as an efficient approach to processing the images. Additionally, when we used to perceive colours, we tend to describe them in terms of their hue, saturation, and value, making the HSI model a more intuitive way to represent colours for humans. A median filter is used to eliminate several types of noise.

3.3. Green Area Masking, Elimination, and Grayscale Conversion of Leaf Images

In the second phase of the proposed methodology, the primarily green region of the input image was identified, assisting the distinction between diseased and healthy areas. After identifying the computed region for these pixels, the pixels that are predominantly green are masked as follows: the RGB components of the pixel are all set to zero if the intensity of its green component is less than that of the recognized region. This is achieved through the identification that the green pixels primarily represent the leaf's healthy regions and do not provide any significant data for the detection of diseases. Furthermore, processing time requirements are reduced significantly by this. For the purpose of masking, the OpenCV library is used in the present work. After the masking, green section has removed from the masked image. All pixels with 0 values for their RGB components, including the pixels on the outer edges of the affected section, have been completely removed. This technique is advantageous because to its ability to accurately identify and categorize diseases, leading to a substantial decrease in processing time. Subsequently, the afflicted portion undergoes a conversion from the RGB colour system to the gray colour format.

Before further processing, images need to be transformed from RGB to grayscale which solely represents intensity characteristics. Typically, this conversion is achieved by modifying the brightness of the colour image. The process of converting colour to grayscale was executed using the cvtColor module in the OpenCV package. The image in figure 4 illustrates the result of this whole process.

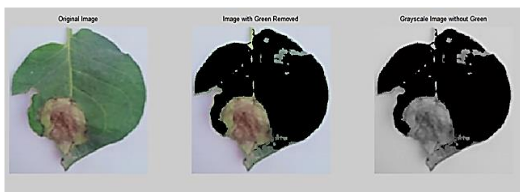


Figure 4. Result of Green Area Masking, and Grayscale Conversion of Leaf Image

3.4. Extraction of Features

After completing the process of masking and removing the green section from the input images, the subsequent step entails carrying out feature extraction. The input image is analyzed to obtain information that can be used as input for the typical machine-learning process. Feature extraction is a distinct form of minimizing dimensionality [44]. When the image supplied to an algorithm is overly vast and seems to contain a significant amount of redundant information, it becomes necessary to decrease the amount features present in the input image. Assuming that the selected features are chosen with care, it is anticipated that the set of features will successfully carry out the intended task by using the shortened representation rather than the full-scale input.

In the context of an image, a feature refers to quantitative measures that describe the attributes of a dataset. These traits are essential in the process of classification. The attributes are essential for discriminating groups from each other. The strategy must be employed to depict the elements in a manner that accentuates the significant characteristics. Therefore, in this work, texture features are chosen due to their substantial utilization in image processing and pattern recognition by other researchers for the extraction of features.

3.5. Model Architecture for Proposed System

CNN has received significant importance in the field of image processing due to its significant economic viability and high precision rate. There exist widely recognized CNN designs that have gained considerable popularity in the field of image processing and classification. These include VGG, ResNet, Inception, and MobileNet [45-47]. The convolution operation(s) play a significant role in any computer vision problem. However, the presence of extensive and intricate network architectures in models like AlexNet, VGG, Inception, ResNet, etc., leads to an increase in both processing time and cost. MobileNetV2 uses the inverse residual structure and the linear bottleneck structure to reduce the computation in convolution successfully. It is favored as an architecture for this particular system because it has a design that is not complicated in terms of the usage of the memory space.

Figure 5 illustrates the architecture of the MobilenetV2 Model that was implemented in this study. It comprises convolutional, bottleneck, and pooling layers. The expansion and normalization sub-layers include activation, addition, and 3 × 3 depth-wise convolution.

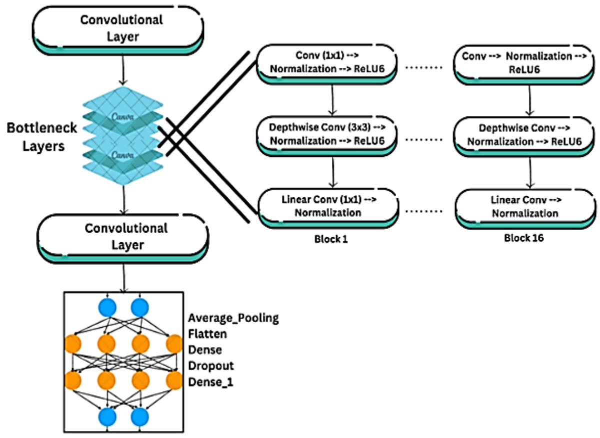


Figure 5. Mobilenetv2 architecture used for the system

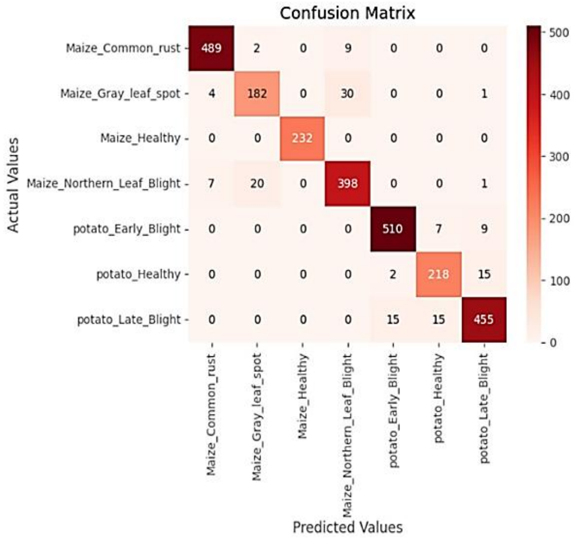
The objective of expansion operations is to increase data space. This will result in adding more channels to the input data. Reduction in the data space can be done by the projection process. The number of channels of input data are reduces by this process. The normalization process, pooling process, convolution steps, and activation layers employ the specific procedures necessary for both training as well as inference in the framework. In the model training process, a backward propagation process is performed after the data has been forwarded through the neural network. It adjusts the model weights according to the value of the loss function. Conversely, the model's inference does not involve any modification of the model's weights. Thus, the input data only needs to be transmitted via the network once. Therefore, it is claimed that inferring using a model requires less computational power and energy compared to training a model. The dimensions of the average pooling layer are defined as 7 x 7. The compressed neurons were inputted into a densely connected layer within the flattening layer, employing the Rectified Linear Unit (ReLU) activation function. Previously, the dropout layer had a probability of 0.5, and the proposed system's classification layer was augmented with an additional 7 nodes. The modifications have resulted in a revised version of the MobileNetV2 model featuring a classification layer consisting of 7 nodes.

4. Results

The present research deployed the MobilenetV2 CNN model to analyze diseases in potato and maize leaves. The evaluation was conducted using datasets obtained from sources [38,39]. The study and analytical processes are performed on a machine with a configuration of Intel (R) Core (TM) i5-5500U CPU with 4 cores. All the cores are at 2.4GHz. RAM and hard disk capacity is 16 GB and 512 GB respectively. Development IDE is Jupyter Notebook. The program is implemented using Python 3.12.2 language together with the OpenCV library and the deep-learning framework, Keras.

The dataset images of potatoes and maize were categorized into distinct groups, as listed in table 1, for potato and maize. This classification was achieved using the method under study, which underwent training for a total of 50 epochs on the potato and maize datasets respectively. Figures 6 demonstrate the confusion matrix of the model for detecting diseases in potato and maize leaves. The models' performance during training as well as validation phases, which lasted for a total of 50, respectively, is represented by these numbers.

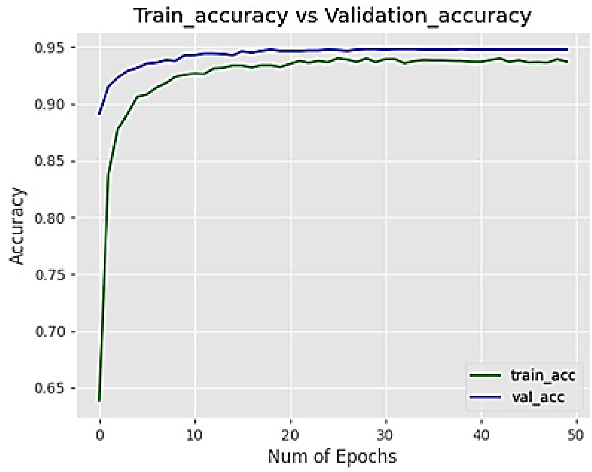
A True Positive outcome is obtained from the confusion matrix when the system correctly identifies an infected leaf as the proper disease. A False Positive result arises when the system erroneously classifies a healthy case as one of the diseased cases. A True Negative occurs when the system accurately identifies a normal case as normal, showing the absence of disease. Finally, a False



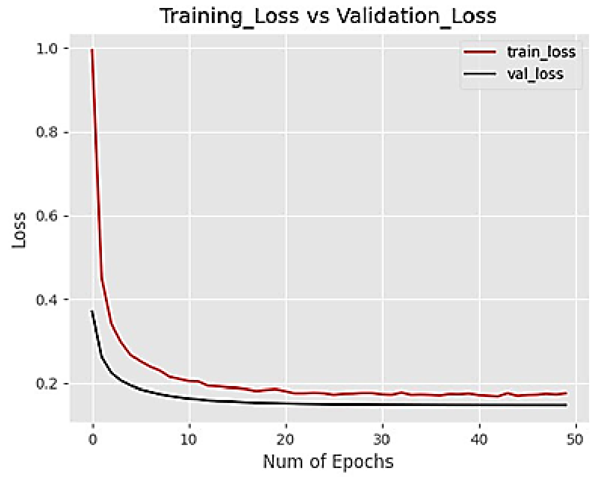
Negative result occurs when the system incorrectly categorizes an infected case as normal. The accuracy curve and the loss curves as shown in figure 7, indicate a small difference between the training and validation loss curves, indicating that the proposed models have achieved sufficient convergence. In addition, there were no signs of overfitting observed during the training and validation procedures.

Figure 6. Confusion matrix of disease detection in potato and maize leaves

Figure 7. Training v/s validation curves after 50 epochs (a) accuracy (b) loss



(a)



(b)

The model consistently demonstrates stability in its performance throughout the training and validation phase. The suggested model demonstrated excellent precision during both training and validation. The model demonstrates that it does not suffer from overfitting as visible from the training loss and validation loss curve. The improved performance from the model can be traced to the usage of effective preprocessing approaches, which facilitated superior outcomes while avoiding overfitting. Furthermore, the use of the dropout strategy enhanced the validation performance of the model by ensuring that it does not significantly diverge from its training performance.

The overall accuracy Equation 1 is calculated as the number of correctly classified instances over the total number of instances. The overall accuracy of the system for detecting potato leaf disease and maize leaf disease is 94.77. During the performance assessment of the model, precision, recall, and F1-score were some metrics that have been standard in most classification tasks in machine learning. Precision as given in Equation 2 computes the accuracy of the positive predictions by dividing true positives by the total number of predicted positives. Recall given in Equation 3 will measure the capability of the model to capture all the actual positives by the ratio of true positives to the sum of true positives and false negatives. The F1-score as given in Equation 4 is a harmonic mean that combines precision with recall to ensure an effective balance of these two features, for proper assessment of the efficacy of the model. These metrics are very useful in evaluating the model's ability to differentiate between a healthy and diseased leaf, especially when dealing with detailed classifications. Classwise performance (Precision, Recall, and F1-Score) of the proposed systems is given in table 2.

$$Accuracy = \frac{Sum\,of\;Diagonal\;Elements\,(TruePositive)}{Total\;Number\;of\;Elements} \quad \textbf{(1)}$$

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \quad \textbf{(2)}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \quad \textbf{(3)}$$

$$F - Score = \frac{2 * \;Precision * Recall}{Precision + Recall} \quad \textbf{(4)}$$

Table 2. Classwise Performance of the System

Crop Name	Disease / Healthy	Precision	Recall	F1-Score
Potato	Early Blight	96.8	96.2	96.2
	Healthy	90.8	92.7	91.7
	Late Blight	96.6	93.8	95.2
Maize	Common Rust	97.8	97.8	97.8
	Gray Leaf Spot	89.2	83.9	86.4
	Healthy	100	100	100
	Northern Leaf Blight	91.1	93.4	92.2

The model gave excellent results in the identification of early blight and late blight diseases, especially in potato leaves. Also, common rust in maize leaves and northern leaf blight in maize are successfully identified by the model. The model rarely misclassifies to healthy or other classifications of disease, as seen by the very high precision and recall scores for both of such instances. A closer analysis indicates that these errors might be due to overlapping features between healthy and diseased leaves in the dataset. Both the lower precision and the lower recall point to a larger proportion of false positives and a considerable percentage of real gray leaf spot cases not being found. Though not quite as well as for early blight, the performance in recognizing healthy potato leaves is good. This little decreased recall and precision raises the possibility that some healthy leaves could be falsely categorized as infected and vice versa. The model correctly detects healthy maize leaves; it does not produce any false positives or false negatives. This suggests the remarkable accuracy of the model in identifying healthy from infected leaves.

We have to use the weighted average methodology in order to compute the overall precision, recall, and F1-score of the MobileNetV2 model for potato and maize across each disease and healthy class. This method takes into account contributions of data from each class to make sure that the contribution of each class towards the overall metric or measure shares a relation with its representation in the dataset. Recall, F1-score and overall precision extracted from the model under question 95.15%, 94.76%, and 94.93% respectively.

5. Discussion

The proposed system uses the MobileNetV2 architecture since it has low computational requirements and memories, thus suitable to be deployed in real-time to agricultural fields where resources are limited. Its lightweight design is helpful for on-site applications in farms, because high-performance computing infrastructure may not be accessible there.

There are many factors that determine the quality of image so that its performance can be ensured on classification tasks, such as dataset diversity, lighting, and resolution, among others. For instance, an angle in which images are taken also influences the model's accuracy regarding the diagnosis of diseases in plants. The authors needed to show more adaptability, so they incorporated images of various resolutions and lighting during the training process. This achieved better robustness regarding moderate variations but may pose risks concerning extreme conditions affecting the model's accuracy. Future work can be the extension of the dataset with pictures shot with a wider variety of lighting and resolution in order to test and enhance the robustness of the model further.

It explicitly states that the model could not generalize to conditions that vary widely across different environments. The MobileNetV2 model had worked well for the dataset used, yet there are environmental features such as geographical variations, climate, and type of soil, which may influence crop health and the manifestation of diseases. Future work may be to collect and merge datasets from different regions with various conditions. Domain adaptation methods or inclusion of environmental metadata in the training process can further improve generalization capabilities.

It is also considered that the testing and fine-tuning of the model would be very crucial for wider applicability. Transfer learning strategies and powerful techniques of data augmentation might be absorbed by the proposed approach to further strengthen the robustness of the model. Integration of metadata, such as local weather or soil health parameters, would bring up a more holistic and context-aware disease detection system.

Overall, the results suggest that MobileNetV2 has great promise for precision agriculture applications: efficient and real-time identification of diseases at scale, although further refinements of datasets and model architectures are needed to achieve reliable performance in a wide range of agricultural settings.

6. Conclusion

The paper outlines an approach toward automatic identification and potato and maze leaf diseases through the application of a MobilenetV2 Deep Convolution Neural Network architecture. Excellent performance both maize and potato crops, outstandingly well-doing in maize common rust and potatoes early blight. The practical applications are almost entirely based on the almost flawless identification of healthy leaves in the maize crops. With precision, recall, and F1-score performance measure values at 95.15%, 94.76%, and 94.93% respectively, potato and maize datasets perform well overall. In this regard, the model succeeds in being a reliable tool for the identification of diseases in farms since it clearly displays its resistance to the recognition of various diseases in these crops. Refining the model or preprocessing methods could treat the rather poorer performance in classifying healthy potato leaves; this is a reasonable indication that feature spaces of healthy and infected leaves overlap. Improvement potential also exists when gray leaf spots are detected in maize. In future research, quality and quantity of the data, complexity of the model, and also how to specifically train the model will be focused upon in order to improve the recall rate on gray leaf spots. By these improvements, the model can get much better at distinguishing every occurrence of the class, which is gray leaf spots, thereby bettering the total performance of the class. As disease management is greatly helped by high precision and recall in detection, it may minimize loss for farmers. For since it saves crops from unnecessary treatments, proper identification of healthy leaves also ends up with saving on money while reducing the environmental impact of using pesticides.

Author contributions

Rituraj Jain: Conceptualization, Literature Search and Data Collection, Analysis and Interpretation of Literature, Writing – Original Draft, Writing – Review & Editing. **Simon Kasahun Bekele:** Conceptualization, Literature Search and Data Collection, Analysis and Interpretation of Literature, Writing – Original Draft, Writing – Review & Editing. **Damodharan Palaniappan:** Conceptualization, Literature Search and Data Collection, Analysis and Interpretation of Literature, Writing – Original Draft, Writing – Review & Editing. **Kumar Parmar:** Conceptualization, Literature Search and Data Collection, Analysis and Interpretation of Literature, Writing – Original Draft, Writing – Review & Editing. **Premavathi T.:** Conceptualization, Literature Search and Data Collection, Analysis and Interpretation of Literature, Writing – Original Draft, Writing – Review & Editing

Conflicts of interest

The authors declare no conflicts of interest.

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