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# An Innovative Deep Learning approach for detecting Plant Disease

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**A B S T R A C T**

The annual production of crops has increased as a result of improvements in agricultural technology, yet it is important to prevent crop loss from diseases. Plant disease issues cause farmers to experience decreased agricultural productivity. A branch of machine learning called deep learning uses cutting-edge methods to analyze images, extract features, and analyze data in order to produce promising results. By examining the leaves, it is possible to identify plant diseases at an early stage and take the required precautions, which helps to reduce the loss of agricultural products. The proposed system identifies potato and tomato plant disease by analyzing plant leaves and identifying diseases using Convolutional Neural Network (CNN) as a classification technique and Mask Region-based Convolutional Neural Network (Mask RCNN) as an object detection technique. The proposed system analyses the performance of these two models in identifying plant diseases. While CNN gives overall general classification, Mask RCNN classifies as well as emphasizes the infectious region on plant leaves.

**Keywords:** Agriculture, CNN, Deep Learning, Detection, Mask RCNN, Plant Diseases

## 1. Introduction

Agriculture is seen as a significant industry that has a significant impact on the economy and is crucial to feeding the human race. Smart agriculture is crucial to accomplishing these food security goals since addressing people's nutritional needs has become a top priority as a result of population growth. Agriculture, particularly in India, employs around 60% of the population and accounts for approximately 20% of the country's GDP. [14]. A nation's social and economic progress depends on sustainable agriculture in terms of rural employment, food security, environmentally friendly technology like soil protection, and sustainable use of natural resources. Starvation can result from agricultural losses brought on by plant diseases, especially in developing nations where access to cutting-edge disease control techniques is limited and where annual losses of 30 to 50 percent of crucial crops are not uncommon. Plant diseases have an impact on crop growth and yield and can have an adverse social, economic, and environmental impact on agriculture. Global crop yields have increased as a result of agricultural technology advancements, but preventing crop loss from disease remains a challenge. Plant diseases are typically caused by microorganisms such as fungi, bacteria, and viruses. Depending on the root cause or aetiology of the plant disease, different signs and symptoms may exist [15]. To cut down on agricultural losses, a variety of strategies, including insecticide spraying, have been used. Although this is a proactive strategy that produces positive outcomes, it is unreliable because it has a detrimental effect on farmers' health. Thus, by reaping the benefits of deep learning techniques, it is now possible to automatically identify plant diseases from raw images of respective plant leaves.

The proposed system provides an approach for detecting plant diseases by using deep learning techniques such as classification and object detection. For classification technique, Convolutional Neural Network (CNN) model is taken into consideration whereas for object detection technique Mask Region-based Convolutional Neural Network (Mask RCNN) model is considered. CNNs are one sort of neural network that are frequently used for computer vision and image recognition tasks. With its multi-layered structure, CNN can rapidly recognize and classify objects with minimal pre-processing. It is also successful in analyzing visual images and can easily separate the required features. One of the variations of a region-based convolutional neural network is the mask R-CNN. For each Region of Interest (RoI), it produces outputs like a bounding box and a class label. For every region, Mask R-CNN produces masks in addition to bounding boxes and class labels. CNN classifies plant diseases based on their respective leaves, whereas Mask RCNN highlights the infected region on plant leaves. Along with diseased leaves, healthy leaves are also rectified by these models.

## 2. Related Work

This section describes the various methodologies used in prior studies to identify and classify plant leaf diseases. Md. Khalid Rayhan Asif, et.al [1] proposes a CNN approach for detecting potato leaf diseases using image processing. The dataset used consists of images collected from Kaggle, Dataquest and some manually taken images. Priyadarshini Patil, et.al [2] presents an approach for determining if a potato plant is diseased or healthy using an 892-image dataset. The proposed approach compares three different classifier types, namely Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN). Husnul Ajra, et.al [3] proposes an approach for detecting potato and tomato leaf diseases using image processing. The dataset used consists of 4,000 images taken from Kaggle that show four different diseases, including early and late blight on tomato and potato. Two well-known CNN models, AlexNet and Resnet-50, are implemented, and their performance is compared. Piyush Juyal, et.al [4] provides a detailed analysis of the numerous diseases that affect tomato plant leaves as well as a method for identifying the disease by analysing the leaves using the Mask R-CNN technique. Melike Sardogan, et.al [5] describes a method for identifying tomato plant diseases by examining the crop's leaves. The method for detection and classification that the authors suggest combines the Convolutional Neural Network (CNN) model with the Learning Vector Quantization (LVQ) algorithm. Ketan D. Bodhe, et.al [6] presents an approach for detecting and diagnosing the diseases of the cotton plant developed using template matching techniques by utilizing a web portal which consists of client and server modules detecting four types of diseases of cotton plant. Indumathi.R, et.al [7] presents a paradigm for identifying plant diseases and suggests treatments for it. The K-medoid clustering and Random Forest algorithms form the foundation of the proposed system. Zia ur Rehman, et.al [8] proposes a deep learning approach for detecting the apple plant diseases by analyzing leaves. Plant Village dataset is used for this approach with 1200 ground truth images and 240 images for testing. The system uses Mask R CNN algorithm for detecting infectious areas using ResNet-50 as backbone architecture to train the algorithm. Murtaza Taj, et.al [9] presents a CNN architecture and a Mask RCNN-based localization and classification technique for detecting disease in a rice crop. The dataset used consists of 1700 locally obtained images of both healthy and diseased plants, separated into training and testing sets of 80% and 20% respectively. Qimei Wang, et.al [10] proposes a deep learning approach for detecting tomato disease using Faster RCNN and Mask RCNN algorithms. The dataset is composed of images gathered from the internet and divided into a training set, a validation set, and a test set in a 6:2:2 ratio. Mon Arjay Malbog, et.al [11] proposes a technique for detecting crosswalks using Mask RCNN on a dataset of 500 images, 80% of which were utilized for training and 20% for testing. Hao Su, et.al [12] proposes a system describing image sensing in military and civilian purposes using Mask RCNN utilizing NWPU VHR-10 dataset. Kirti, et.al [13] The author offers a deep learning technique based on the ResNet-50 architecture to learn different forms of fungus development on grape leaves on a dataset consisting of 1807 images.

## 3. Research Objectives

Both classification and object identification models provide an efficient solution for detecting plant diseases. There are numerous systems that use classification models like CNN to deliver results for different plant categories, however no object detection approach employing Mask RCNN model can identify diseases on more than one type of plant. This research aims to implement the Mask RCNN model in identifying diseases of more than one plant type, as well as providing performance analysis of the CNN and Mask RCNN model to assist farmers and other stakeholders in making better judgements in selecting the correct technique depending on their needs.

## 4. Proposed System & Methodology

### *4.1 Data Collection:*

The process of developing a deep learning system begins with the processing of the dataset. “New Plant Diseases Dataset" [16], a dataset from Kaggle is utilized for collecting image data. Potato and tomato plants are taken into account since they are among the most important plants and are widely used in various cuisines and cultures. Early blight and late blight diseases are taken into account for potato plant, whereas leaf mold and leaf spot infections are taken into account for tomato plant. Early blight is produced by the fungus Alternaria solani and has symptoms such as brownish patches, blackish lesions, and circular ring-like patterns, whereas late blight is caused by the microbe Phytopthora infestans de Bary and has apparent symptoms such as black lesions with a green halo and granular regions. Leaf mold is caused by the fungus Passalora fulva and its symptoms include pale green or yellowish diffuse patches on the upper leaf side, whereas Leaf spot is caused by the fungus Septoria lycopersici and its symptoms include small, round grey lesions (spots) with dark borders. Healthy leaves of these two plants are also taken into account in addition to diseased leaves. For the Mask RCNN model, the dataset annotation process is carried out using VGG Image Annotator.

### *4.2 System Block Diagram:*

The Fig.1 depicts the block diagram of the proposed system. The CNN system begins by processing leaf images of respective plants. When images are preprocessed, they are resized to a specific aspect ratio. The CNN model then performs feature extraction and provides appropriate leaf classification on a given input image. The Mask RCNN system begins by processing a leaf image of corresponding plant leaves. The image then undergoes image preprocessing, which entails scaling the image to a specific aspect ratio. The model, then extracts regions and gives respective leaf classification with a mask on infectious area of the given input image.

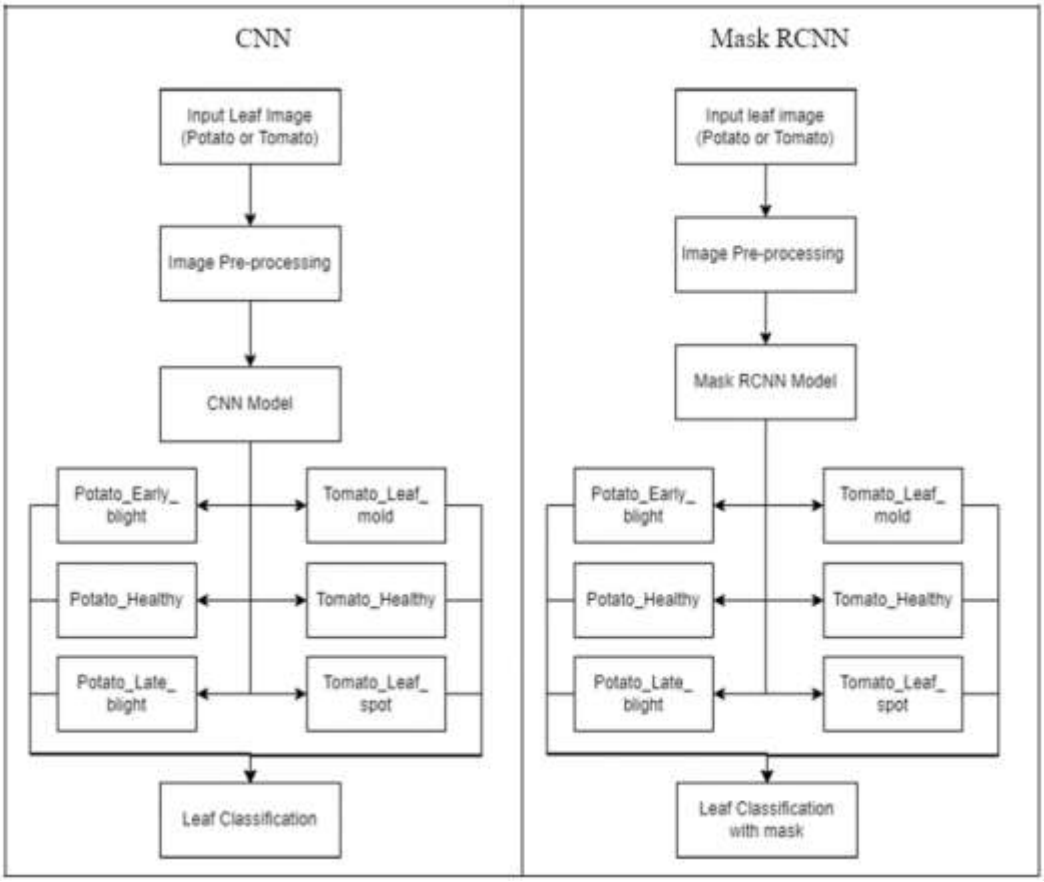


**Fig. 1 Block Diagram for CNN and Mask RCNN System**

### *4.3 Convolutional Neural Network (CNN) Architecture:*

The architecture of the CNN system is shown in Fig. 2. The proposed CNN model uses a sequential approach. In the CNN model, the leaf image is passed through a sequence of convolution layers followed by pooling layers and a fully connected layer for classification using the Softmax function for multiple class classification. Before moving on to the pooling layer, the convolution layer will extract the features by using 3x3 filters/kernels and 32, 64, and 128 channels. For faster data training, the Rectified Linear Unit (ReLU), a non-linear activation function, is used between the convolution and pooling layers. If the function takes any negative input, it returns 0, but if it receives any positive number x, it returns that value back i.e., f(x)=max (0,x). The pooling layer assists in lowering the image's parameters, which lowers the amount of processing power needed for model training. Unlike the convolutional layer, the pooling layer employs 2x2 filters. Max pooling is performed in the pooling layer by picking the greatest value from the matrix by convolutional layer and transferring this value to a new matrix. A fully connected layer, which is a network of connected neurons, is then fed the flattened matrix. By taking into account the feature that was extracted based on the classes specified, the fully connected layer enables classification of the respective leaf images.

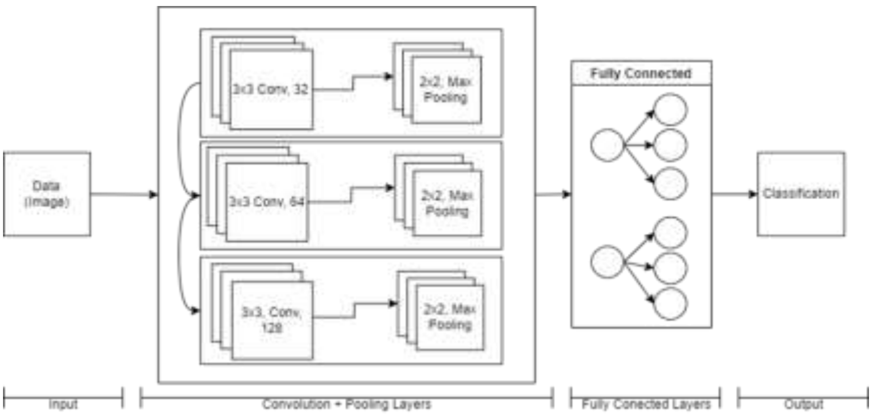


**Fig. 2 CNN Architecture**

***4.4 Mask Region-based Convolutional Neural Network (Mask RCNN) Architecture:***

The architecture of the Mask RCNN system is depicted in Fig. 3. In the Mask RCNN model, the leaf image is processed by the ResNet-101 model, which is built on a convolutional neural network architecture pre-trained on the MS COCO dataset, a sizable image dataset with 328,000 images of common objects and people. The ResNet-101 is a 101-layer deep model with associated filters/kernels and channels that extracts features from leaf images and generates feature maps. Regional Proposal Network (RPN) analyses the objects in the image and extracts the regions, which are subsequently processed by Region of Interest (ROI) Pooling layer, which structures the regions into a fixed aspect ratio. A fully connected layer then processes the feature maps and regions, producing a corresponding classification of the leaf image and a bounding box for outlining the regions, which is then followed by a mask generation phase for masking/highlighting the regions on the respective leaf image.

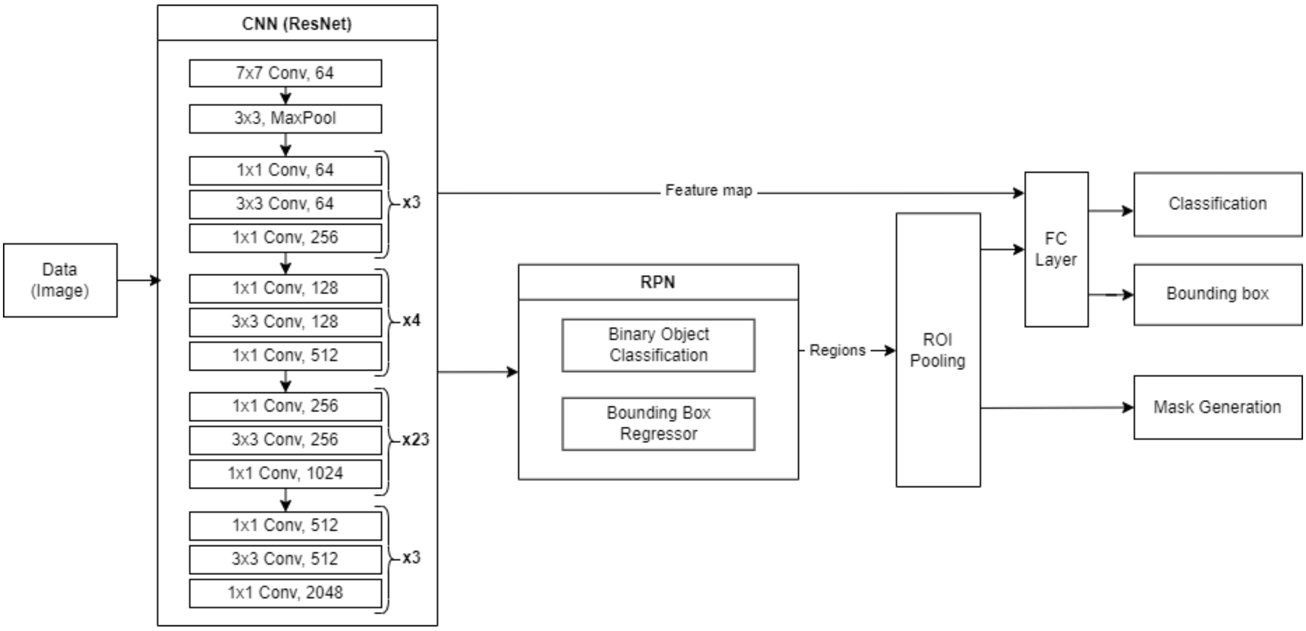


**Fig. 3 Mask RCNN Architecture**

## 5. Results & Analysis

The dataset used for performance analysis of the proposed system consists of 4116 images of which 80% images are used for training and 20% images are used for validation. The dataset considered is a collection of 6 classes namely potato early blight, potato late blight, potato healthy, tomato leaf mold, tomato leaf spot and tomato healthy. Fig. 4 depicts the appropriate classification given by CNN model on diseased and healthy leaf images of potato and tomato plants. The CNN model successfully distinguishes between each of the 6 classes.

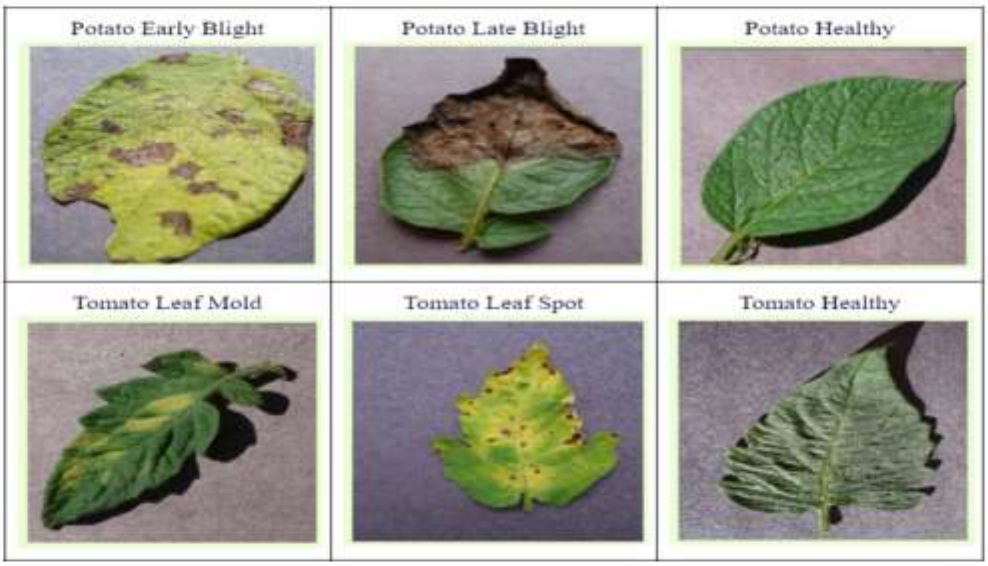


**Fig. 4 Results from CNN Model**

Fig. 5 shows the appropriate classification and region detection given by Mask RCNN model on diseased and healthy leaf images of potato and tomato plant leaves. All the 6 classes are correctly identified by the Mask RCNN model.

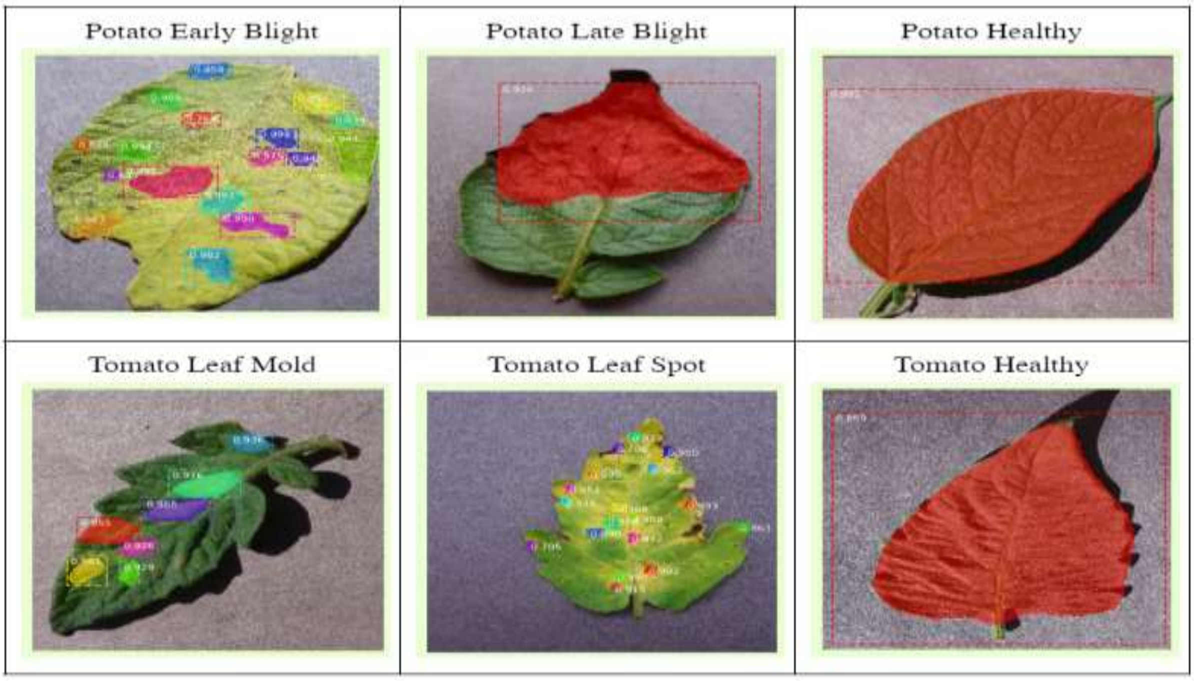


**Fig. 5 Results from Mask RCNN Model**

Table 1 depicts the loss values for CNN and Mask RCNN models. Loss is a value that symbolizes the total of the model's errors. It indicates how well (or poorly) the model is performing. CNN model is trained on 5 epochs reducing the training and validation losses to 0.011 and 0.102 respectively while Mask RCNN model is trained on 25 epochs reducing the training loss to 0.625 and validation loss to 0.748.

**Table 1 – Model Losses**

| **Model** | **Training Loss** | **Validation Loss** |
|---|---|---|
| **CNN** | 0.011 | 0.102 |
| **Mask RCNN** | 0.625 | 0.748 |

Fig. 6 shows the training and validation loss graphs of CNN model. The loss graph depicts the reduction in losses at each epoch during the model training activity. CNN model starts with a training loss of 0.378 and validation loss of 0.215 at the 1st epoch and reduces the training loss to 0.011 and validation loss to 0.102 by 5th epoch.

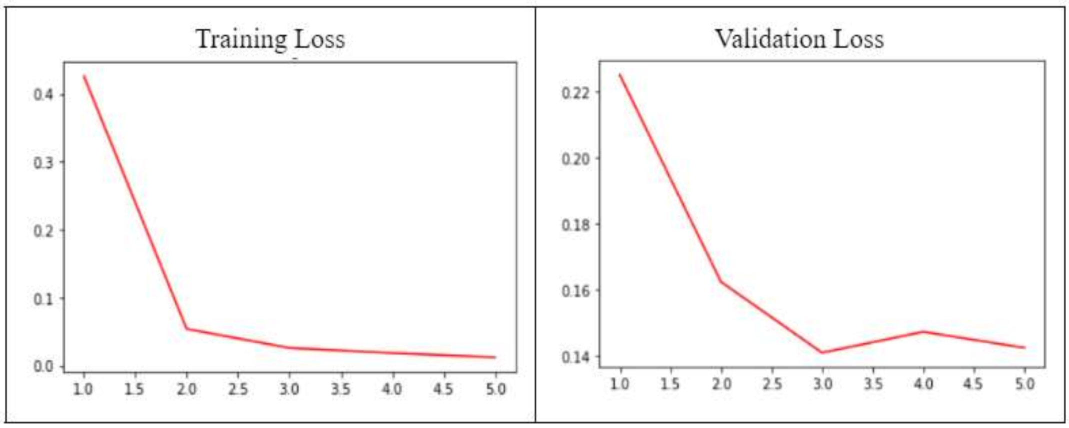


**Fig. 6 Loss graph of CNN Model**

Fig. 7 shows the training and validation loss graphs of the Mask RCNN model. Mask RCNN model starts with training loss of 2.232 and validation loss of 1.841 at the 1st epoch and reduces the training loss to 0.625 and validation loss to 0.748 by 25th epoch.

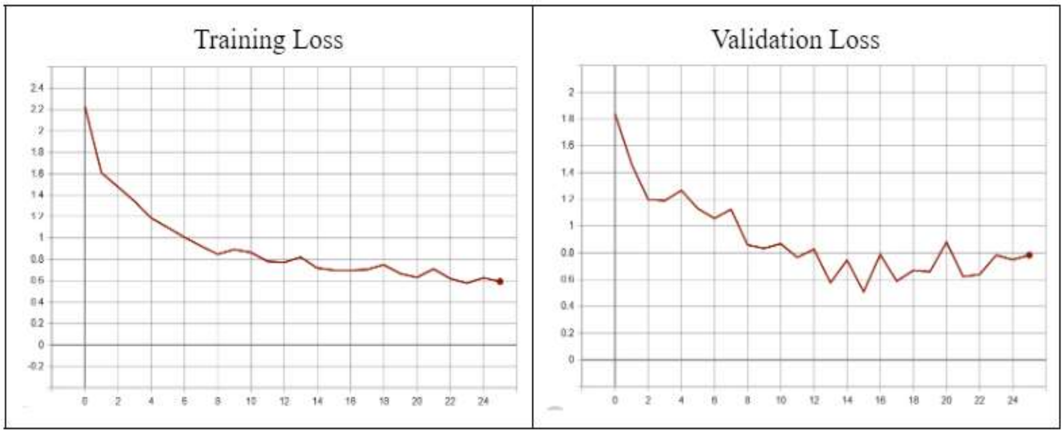


**Fig. 7 Loss graph of Mask RCNN Model**

Table 2 shows the accuracy measures of CNN and Mask RCNN models. One metric for assessing classification models is accuracy. Accuracy is the proportion of correct predictions made by the model. Accuracy for CNN model is evaluated as follows:

$$Accuracy = \frac{No.\ of\ correct\ predictions}{Total\ no.\ of\ predictions}$$

A common statistic for evaluating the accuracy of an object detection model is the Mean Average Precision (mAP). The mAP value is estimated by calculating the Average Precision (AP) for each class and then averaging over a number of classes. The mAP of Mask RCNN model is evaluated as follows:

$$mAP = \frac{1}{N}\sum_{i=1}^{n} AP$$

CNN model gives an accuracy of 0.971 whereas Mask RCNN gives an accuracy of 0.845.

The F1-score is an error metric that calculates the harmonic mean of precision and recall to evaluate model performance. It offers reliable results for both balanced and unbalanced datasets and considers the model's precision and recall capabilities. F1-score of a model is evaluated as follows:

$$F1\ Score = 2 * \frac{precision * recall}{precision + recall}$$

For object detection model F1-score can also be evaluated as follows:

$$F1\ Score = 2 * \frac{mAP * mAR}{mAP + mAR}$$

where, Mean Average Recall (mAR) is the mean of Average Recall (AR) values.

CNN model gives F1-score of 0.971 while Mask RCNN gives F1-score of 0.871.

**Table 2 – Model Accurateness**

| **Model** | **Accuracy** | **F1-score** |
|---|---|---|
| **CNN** | 0.971 | 0.971 |
| **Mask RCNN** | 0.845 | 0.871 |

Stochastic Gradient Descent Optimization is applied on both the models with a learning rate of 1e-3 to reduce the overall loss and improve the accuracy.

Table 3 shows research regarding the disease detection of potato and tomato plants based on their leaves using CNN approach. Of the various CNN model types used for disease detection, the Sequential model proves to be more effective amongst the others. Also, the proposed CNN system stands out with higher accuracy rate of 0.971.

**Table 3 – Comparison among CNN Models**

| **Sr. No.** | **Title** | **Category** | **Technique used** | **Accuracy** |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| 1 | CNN based Disease Detection Approach on Potato Leaves [1] | Plant: Potato | CNN: Sequential | CNN (Sequential): 0.97 |
| 2 | Comparison of performance of classifiers-SVM,RF, and ANN in potato blight disease detection using leaf images [2] | Plant: Potato | SVM, RF, ANN | SVM: 0.84<br>RF: 0.79<br>ANN: 0.92 |
| 3 | Disease detection of plant leaf using image processing and CNN with preventive measures [3] | Plant: Potato, Tomato | CNN: AlexNet, ResNet-50 | CNN (AlexNet): 0.953<br>CNN (ResNet-50): 0.961 |
| 4 | Plant leaf disease detection and classification based on CNN with LVQ algorithm [5] | Plant: Tomato | CNN: LVQ | CNN (LVQ): 0.86 |
| 5 | Proposed System | Plant: Potato, Tomato | CNN: Sequential | CNN (Sequential): 0.971 |

Table 4 shows the research regarding the potato and tomato plant disease detection based on respective plant leaves using Mask RCNN system. Previous research shows the implementation of the Mask RCNN system on tomato plant giving accuracy of about 0.82. The proposed system Mask RCNN system detects tomato as well as potato plant disease giving a higher accuracy rate of 0.845.

**Table 4 – Comparsion among Mask RCNN Models**

| **Sr. No.** | **Title** | **Category** | **Technique used** | **Accuracy** |
|---|---|---|---|---|
| 1 | Detecting the infectious area along with disease using deep learning in Tomato plant leaves [4] | Plant: Tomato | Mask RCNN: ResNet | Mask RCNN (ResNet): 0.82 |
| 2 | Proposed System | Plant: Potato, Tomato | Mask RCNN: ResNet-101 | Mask RCNN (ResNet-101): 0.845 |

## 6. Conclusion

This research is focused on detecting potato and tomato plant diseases by analyzing respective leaf images with the help of deep learning models namely CNN and Mask RCNN. The deep learning models were trained and validated on a dataset of 4116 images divided in a ratio of 8:2. Both the models were capable of detecting plant diseases. The models also identify healthy leaf images of both plants in addition to diseased leaf images. The performance of both the models were analyzed to determine their efficacy, and the results indicate that the CNN model performs better than the Mask RCNN model. Although the CNN model performs better than the Mask RCNN model, it does not provide the detailed results such as detecting the affected regions that Mask RCNN does. This research will assist farmers and other stakeholders in making more informed decisions in choosing the right technique based on their needs.

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