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# ProThinNet23: A Hybrid Deep Learning Model to Detect Diseases in Potato, Tomato and Pepper

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**ABSTRACT**

Potato, tomato, and pepper are the solanaceous crops widely used across the world. These crops are rich source of vitamins, minerals, and fibers. However, many losses occur due to different diseases found in these crops. It is the need of hour to detect these diseases at early stages so that crop losses can be reduced. Conventional methods such as classification models of machine learning do not extract features from its own. On the other hand, deep learning methods are costly in terms of implementation as they require high end computational resources. In the proposed work, integration of both the techniques (machine learning and deep learning) is done. The architecture provided in this article is for a modified version of the ResNet-like neural network in conjunction with optimized Random Forest. The model is trained and tested on Plant Village Dataset consisting of healthy and diseased images of potato, tomato and pepper. This network aims to provide a lightweight yet effective convolutional neural network (CNN) architecture for the classification of images into different categories. The novelty of proposed hybrid model 'ProThinNet23' lies in its ability to provide effective feature extraction and classification while maintaining a relatively small number of parameters. This makes it suitable for scenarios where computational resources are limited, such as on edge devices or mobile applications. The proposed model strikes a balance between model size and performance, providing an alternative to more heavyweight architectures like ResNet50 or VGG16.

**Keywords:** Plant diseases, random forest, neural networks, gradient problem, neural network

## 1. INTRODUCTION

Agriculture sector plays a crucial role in the economic or financial progress of a country since it offers most of the food, we need to survive on the planet[1], [2], [3], [4], [5]. Potato, tomato, and pepper are the most cultivated solanaceous crops in India and China as they are rich source of vitamins and minerals. Various diseases (depicted in Figure 1) can degrade the quality and overall production of these crops. These diseases may occur due to biotic agents like bacteria, fungi, viruses, and abiotic agents such as temperature, pressure, humidity etc.[6][7]. Timely detection of diseases in these crops is a crucial task specially when it is done manually. Some commonly found diseases in above mentioned crops are early blight, late blight, spider mite, bacterial spot, black spot etc. It is observed that among different parts of plants such as root, shoot etc. leaves are the most prominent part from where diseases can be detected effectively and efficiently. Due to this reason, in recent years, computer vision techniques are being used by researchers to create an automated plant leaf disease detection system[8], [9], [10], [11]. Image processing, machine learning and deep learning techniques are in trend in various applications of artificial intelligence. Image processing is applied on images of diseased plant leaves to extract useful information from them. The early diagnosis of plant diseases is made possible by various image

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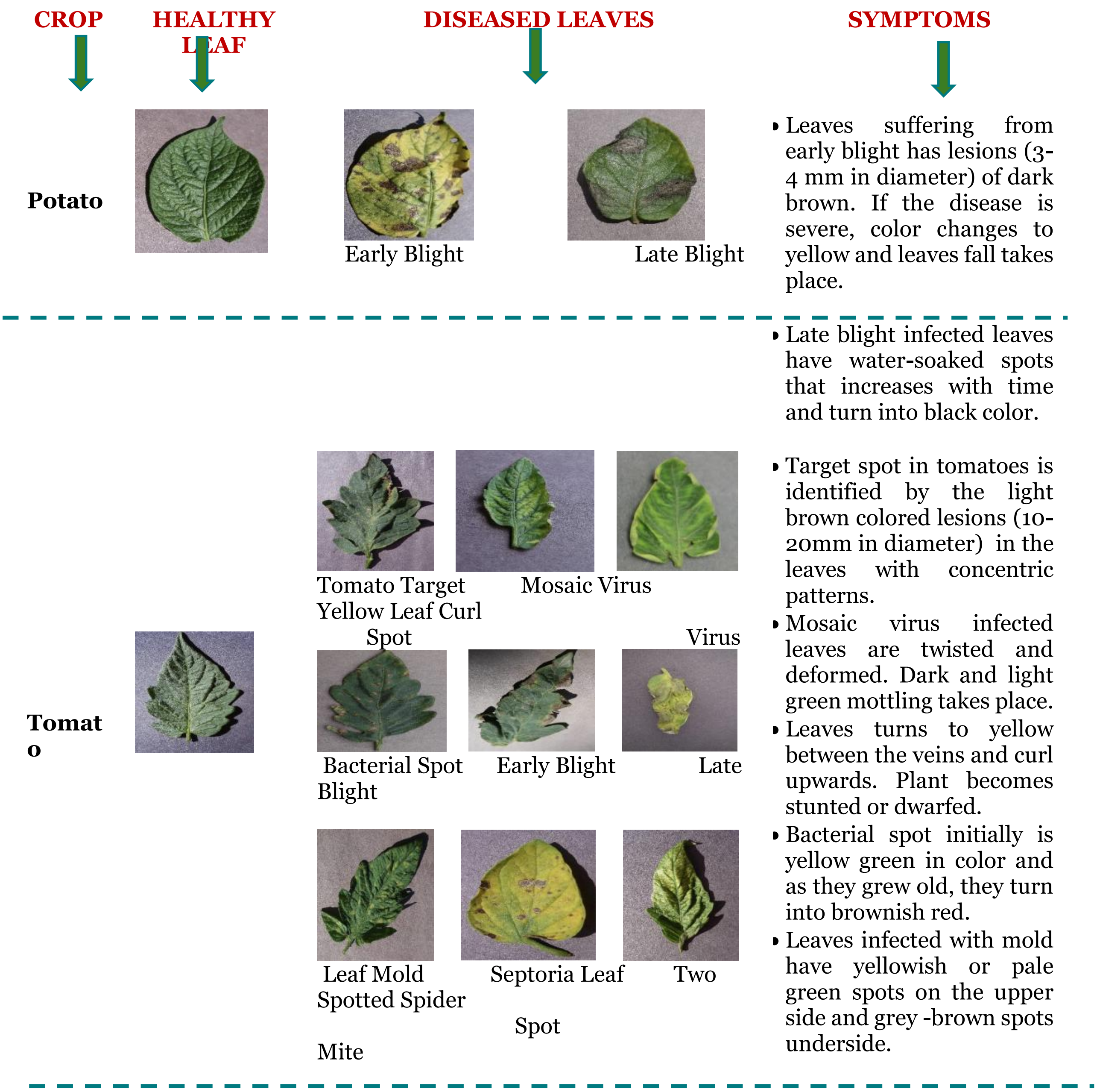
processing tools, which analyze minute variations in leaf color, texture, and form that may not be immediately noticeable to the unaided eye[12]. B. Jagtap et al. [13] used image processing for detection of plant leaf disease. They used HSI transformation for image enhancement and ANN was used for classification of three diseases: anthracnose, black spot, and red leaf blight.

The identification of plant illness is substantially supported by machine learning methods like such as SVM, Random Forest, Naive Bayes, KNN etc., which is transforming agriculture's approach to crop health issues. Machine learning methods can be applied and trained on large datasets with labelled examples of both healthy and ill plants by utilizing complex methods. These models can precisely classify new, unknown plant samples based on different aspects like leaf color, texture, and form because they are able to identify intricate patterns and correlations within the data. Such models are constantly improving and adapting to new disease strains or variants. This helps with early detection as well as speeding up the identification process, allowing farmers to take focused, timely action to stop the spread of illness.



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- In case of septoria leaf spot, many circular dark brown spots with tan to gray centers appears on the surface of leaf. Leaf turns yellow and then eventually dies.
- Speckled and dull appearance, yellowish or brownish color

Bacterial Spot

- The colour of bacterial spots changes from yellow green to brownish-red as they mature.

**Pepper**

Figure 1:Types of crops along with diseases & symptoms on which the proposed model is implemented

Deep learning methods which are subsets of machine learning, have become powerful tool for the identification of plant diseases, transforming the landscape of precision agriculture. Convolutional Neural Networks (CNNs) are one of the mostly used deep learning methods that are especially well at automatically learning hierarchical representations from unprocessed image data. These algorithms are trainable on enormous datasets of annotated images to predict complicated patterns and traits linked to various plant diseases. Deep learning methods such as VGG-16, Inception, ResNet etc. are giving promising results (represented in Table I).

Table I : Summary of research work based on deep neural networks

| **Reference** | **Year** | **Objective** | **Dataset/ Number of images** | **Model used** | **Accuracy achieved** |
|---|---|---|---|---|---|
| [14] | 2017 | Identification of rice diseases using deep convolutional | 500 natural images | CNN | 95.48% |
| [15] | 2018 | Mango leaf disease detection | 1200 | CNN | 96.67% |
| [16] | 2019 | Identification of plant leaf diseases | 54,305 | 9 layer CNN | 96.46% |
| [17] | 2019 | Plant diseases identification from lesions and spots | 46409 | CNN | Not defined |

| | | | | | |
|---|---|---|---|---|---|
| [18] | 2020 | Detection and classification of plant leaf diseases | 15,200 | ResNet34 | 99.40% |
| [19] | 2020 | Rose disease recognition | 400 images | MobileNet | 95.63% |
| [20] | 2021 | Detection and classification of leaf and spike wheat diseases | more than 10,000 images | Hybrid deep learning model | 97.88% |
| [21] | 2021 | Plant leaf disease detection and classification | 5512 | Optimal mobile network-based convolutional neural network | 98.7% |
| [22] | 2021 | Paddy leaf disease detection | 984 | Inception-ResNet-V2 | 92.68% |
| [23] | 2022 | Plant leaf disease detection | 154,500 images | ResNet197 | 99.58% |
| [24] | 2023 | Mango leaf disease detection | Mango leafBD | LeafNet | 99.55% |
| [25] | 2024 | Plant leaf disease detection | 46,672 images | CNN | 93% |

Although many other fast computing algorithms are available, but they require large computing power and a strong GPU. Considering different diseases of tomato and potato crops, [26] presented the graph cut algorithm which is an automatic method for segmentation of leaf precisely and effectively using Otsu's approach. For classification, four different methods ( SVM, KNN, ANN and RF) were used and it was observed that SVM classifier attained an accuracy of 97.4%. The researchers [27] proposed deep learning model to diagnose early blight and late blight diseases in potato and tomato crops using Resnet-9and VGG-16 models and achieved a remarkable test accuracy of 99.25%. The fundamental benefit of employing CNN is that it can process images directly, saving the trouble of reconstructing images and separating out the elements to feed into the neural network. Meanwhile, due to their superior recognition accuracy, CNNs are being used widely in fields like computer vision, where development is increasing. A modified VGG16 model was created and evaluated against three distinct deep learning (DL) architecture types—InceptionV3, VGG16, and MobileNet—in a study carried out by Agarwal et al.[28]. Ten distinct disease categories were represented by 1400 images of tomato leaves that were used to train the modified VGG16 architecture. The model was then assessed using 300 photographs in each category, each of which had a total of 100 images. In this experiment, the modified VGG16 architecture achieved an accuracy rate of 98.40%. With the introduction of smartphones and the growth of mobile applications, straightforward and user-friendly applications can be developed to offer improved agricultural infrastructure and guidance on diagnosing plant diseases[29].

The present manuscript is proposing a hybrid method, ProThinNet23, which is a lightweight version of more complex networks like ResNet and is having following advantages:

- The proposed hybrid model will provide real time disease detection, enabling data driven decision making for farmers.
- Many existing systems requires high computational resources for their implementation, this study aims to develop an optimised model for edge computing devices such that handy application can be made available for farmers.

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- The proposed model can be integrated with IoT based agricultural system using drones and mobile sensors to automate disease detection.
- The study contributes to high agricultural productivity and sustainability by improving the plant health management.

The ability of the suggested model to enable efficient feature extraction and classification with a comparatively minimal number of parameters is what makes it novel. Because of this, it can be used in situations where there are limited computational resources, like in mobile applications or on edge devices.

## 2. Dataset and Methods used

This section of manuscript describes the methods and dataset used to design the proposed model. Section 2.1 describes basic concept of random forest , ResNet and CNN to understand the defined hybrid model. 2.2 dataset used, section 2.3 preprocessing and 2.4 implementation of proposed model.

### 2.1 Basic concepts

#### *2.1.1 CNN: Convolutional neural network*

It is a deep learning technique which works on temporal and spatial features of images given as an input and classify them significantly as per requirement[30], [31]. It is composed of an input layer, set of hidden layers with activation function , different pooling layers, fully connected layers and an output layer. This technique can find the very low-level features of an image while the outer layer of the model works on complex and high-level features. Convolution can be defined as a mathematical operation that is applied on two functions (say $f(u)$ and $g(u)$) to produce a third function $f(u)*g(u)$. Mathematically, for continuous domain, it can be represented as[32]-

$$f(u)*g(u)= \int f(u).\, g(u-i)di \qquad eq.1$$

In discrete domain,

$$f(u)*g(u)=\sum_{i=-\infty}^{\infty} f(u).\, g(u-i) \qquad eq.2$$

$f(u)$ is representing the input image and $g(u)$ is the filter applied on the image. Let us assume if size of the image is $n*n$ and filter is of $i*i$ such that $i<=n$, then size of output feature map $f_m$ is given as-

$$f_m = n-i+1*n-i+1 \qquad eq.3$$

From eq 3 it can be concluded that whenever convolution operation is applied, size of $f_m$ decreases and thereby size of image also decreases. It results in accessing center features more rather than features present at the edges and corners. To deal with this problem, padding is used. Padding ensures that size of the image should not be decreased and features present at the corners and edges should not be neglected. The equation to find padding in this case is given by:

$$n+2p-f+1 => p=(f-1)/2 \qquad eq.4$$

Certain functions, known as activation functions, are used to extract nonlinear features from an image. Functions such as ReLu, sigmoid etc. are used in CNN after convolution process. Pooling layer is added after convolution operation such that most important information can be retained while spatial features (height, width) can be reduced.

#### *2.1.2 ResNet50 Model*

ResNet50 stands for residual network with 50 layers( 48 convolution layers, a maxpool layer and an average pool layer) is a deep learning model used for image classification. Residual learning was introduced to solve the vanishing gradients problem[33], [34][35]. It was found that with the increase in depth of neural network the accuracy saturates and degrades . This saturation is not caused by

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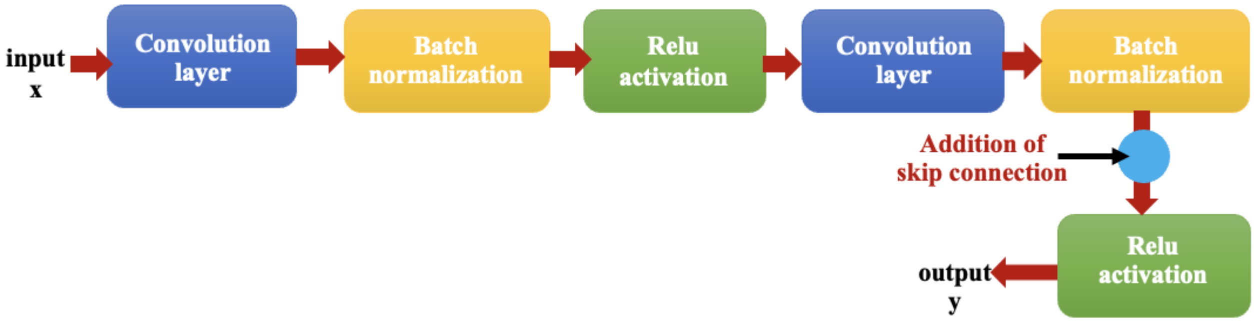
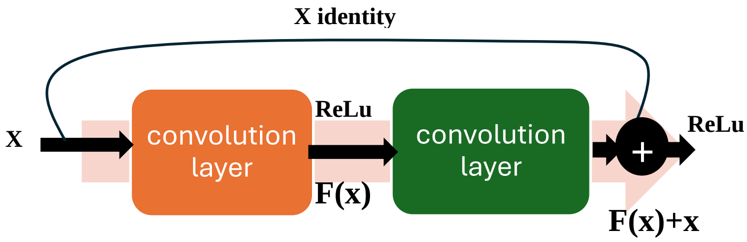
overfitting, but it is due to difficulty in optimizing deep networks. Hence making it difficult for the network to learn efficiently. The model is divided into 5 stages with each stage having a convolution layer and identity block (shown in Figure 2(a)). Each block consists of 3 convolution layers, and the number of filters also increases with each stage. The residual block can be represented as:

$$X=ReLu(\,Batchnorm(\,F(x_{in})+W_s\,x_{in}) \qquad eq.5$$

where $x_{in}$ is the input image given to the block, $F(x_{in})$ represents series of operations (convolutions, batch normalization and ReLu ) on input image, $W_s\,x_{in}$ is shortcut (skip) connection (shown in Figure 2(b)) with 1x1 convolution to match the dimensions. Average pooling layer is applied to reduce the spatial dimension after the residual block.




(a)




(b)

Figure 2: a) representing the residual block of ResNet50 and b)is showing shortcut(skip connection)

### *2.1.3 Random Forest Algorithm*

In essence, random forest is basically an ensemble learning technique which is used for classification as well as regression tasks[36]. Consider an image X, where it is converted into n vectors such that-

$$X=[X_1,X_2......X_n]$$

Multiple decision trees (say $T_1$, $T_2$....$T_m$) are created and trained. Each tree gives an output h(X), and the final prediction is obtained by majority of voting-

$$Y=mode\{h_1(X),\, h_2(X)......\, h_m(X)\}$$

*Why is Random Forest chosen for designing proposed architecture?*

After doing literature survey (shown in Table II) of several papers, it was found that SVM, Naïve Bayes, KNN and random forest are the commonly used identifiers. Initially, the dataset is passed in biased and unbiased mode to these four different classifiers to check their accuracies for prediction of diseases. In

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biased mode, all 20,639 images are passed whereas in unbiased mode, 8,219 images are passed to model. As a result, random forest gave 94.2% in biased mode, and 90.3% accuracy in unbiased mode. These results are already published in paper [7]

| Reference | Research Aim | Method Used | Images/ Dataset | Features Extracted | Accuracy |
|---|---|---|---|---|---|
| [37] | Detection of Plant Leaf Diseases Using Image Segmentation and Soft Computing Techniques | Genetic Algorithm for image segmentation and SVM for classification | 60 images for training & 46 for testing | Texture features such as local homogeneity, contrast, cluster shade | 95.71% |
| [38] | Tomato Plant Diseases Classification | SVM | Plant Village Dataset | Color & texture | 85.1% |
| [39] | Recognition and Detection of Tea Leaf's Diseases | SVM | 150 samples for training and another 50 samples for testing | Contrast, co-relation, energy, mean, SD, entropy, mean, RMS, kurtosis, skewness | 93% |
| [40] | Rice disease detection using image processing | Naïve Bayes | 60 | RGB values of the pixels | 90% |
| [41] | Rice leaf disease detection using ML | Decision tree after 10-fold cross validation | 120 images | TP Rate, FP Rate, Precision, Recall, F measure, Area under ROC | 97% |
| [42] | Detection of Rice Leaf Diseases Using Image Processing | Otsu's method for segmentation and SVM for classification | UC Irvine Machine Learning Repository | Not mentioned | 94.6% |

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| | | | | | |
|---|---|---|---|---|---|
| [43] | Potato leaf disease detection | SVM,KNN,MLP, | 4020 images | Total 9 features | MLP:98.3% |

2.2 Dataset Used

Plant village dataset consisting of images of pepper, potato and tomato is used for experimentation. The description of the dataset is given in Table II.

Table II: Total number of images present in the dataset

| Crop Name | Diseases | No. of images | | |
|---|---|---|---|---|
| | | Healthy Leaves | Diseased leaves | Total images |
| **Potato** | Early Blight, Late Blight | 153 | Early Blight:1001<br>Late Blight:1001 | 2155 |
| **Tomato** | Target Spot, Mosaic Virus, Yellow leaf curl virus, Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Two Spotted Spider Mite | 1592 | 1405<br>374<br>3210<br>2128<br>1001<br>1910<br>953<br>1772<br>1677 | 16022 |
| **Pepper** | Bacterial Spot | 1478 | 998 | 2476 |

2.3 Pre-processing

2.3.1 Image resizing

Reducing the image size, makes it more manageable for subsequent tasks, such as feature extraction or training a model. This can significantly speed up the processing time. Also, resizing an image helps in lessening the effect of noise or extraneous elements. Less significant aspects may be eliminated by scaling down to a smaller dimension, allowing the model to concentrate on more essential characteristics. For current study all images are resized to 100x100 pixels.

2.3.2 Conversion from RGB to Grayscale

All resized images are then converted to grayscale because these images are generally enough and computationally advantageous for tasks such as edge detection. In contrast to color images, which have

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extra channels for each color (Red, Green, and Blue), grayscale images just include intensity information. It makes the image data simpler, which lowers memory and computational complexity.

2.3.3 Segmentation

k-means clustering is applied to each input image to find the region of interest (ROI) that is the diseased parts. By using this technique, only the ROI will be passed to model so that it can learn relevant features of the diseased portion rather than learning other details. After this, the processed data is passed in parallel to proposed neural network and to optimized random forest method (shown in Figure 3). 70% of data is used for training and remaining 30% of data is used for testing.

## 3. ProThinNet 23: The proposed model

### *3.1 Training of proposed neural network*

The input layer accepts pre-processed images of potato, tomato and pepper crops from plant village dataset. To ensure that spatial dimension remains constant throughout the layers, 3x3 zero-padding is applied on these input images. The entire model is divided into 2 phases. The first phase which is a combination of CNN and partial ResNet and 2$^{nd}$ phase consist of optimized random forest algorithm and final model creation. The 5 stages of phase 1(shown in Figure 4) and each stage is added with a purpose which is explained below:

*Phase 1-*

**Stage 1:**

Taking reference from ResNet model, a 7x7 convolutional layer is used at stage 1 with 16 filters and a stride of 2. This helps in significant downsampling of images and extract meaningful features in the network. It also reduces the spatial dimensions of the image thereby helps the subsequent layers to work on more detailed and complex patterns. Stride of 2 is used to have a check on number of parameters and computational cost. 16 filters are chosen to provide a balance between capturing features and model's complexity in the initial layers. Batch normalization and ReLU activation help in normalization and introducing non-linearity. Consider and input image X of shape ($H, W, C_{in}$ ) and convolutional kernel K( $h, w, C_{in}, C_{out}$), the output image Y will be ($H_{out}, W_{out}, C_{out}$) where,

$$Hout= \left\lfloor\frac{H-k_H}{S}\right\rfloor+1 \qquad Wout= \left\lfloor\frac{W-k_W}{S}\right\rfloor+1 \qquad Cout=16$$

ReLu is applied on the output image using the formula

$$F(Y)=\begin{cases} 0\ for\ y < 0 \\ y\ for\ y >= 0 \end{cases}$$

A 3x3 max-pooling layer with a stride of 2 further reduces the spatial dimensions.

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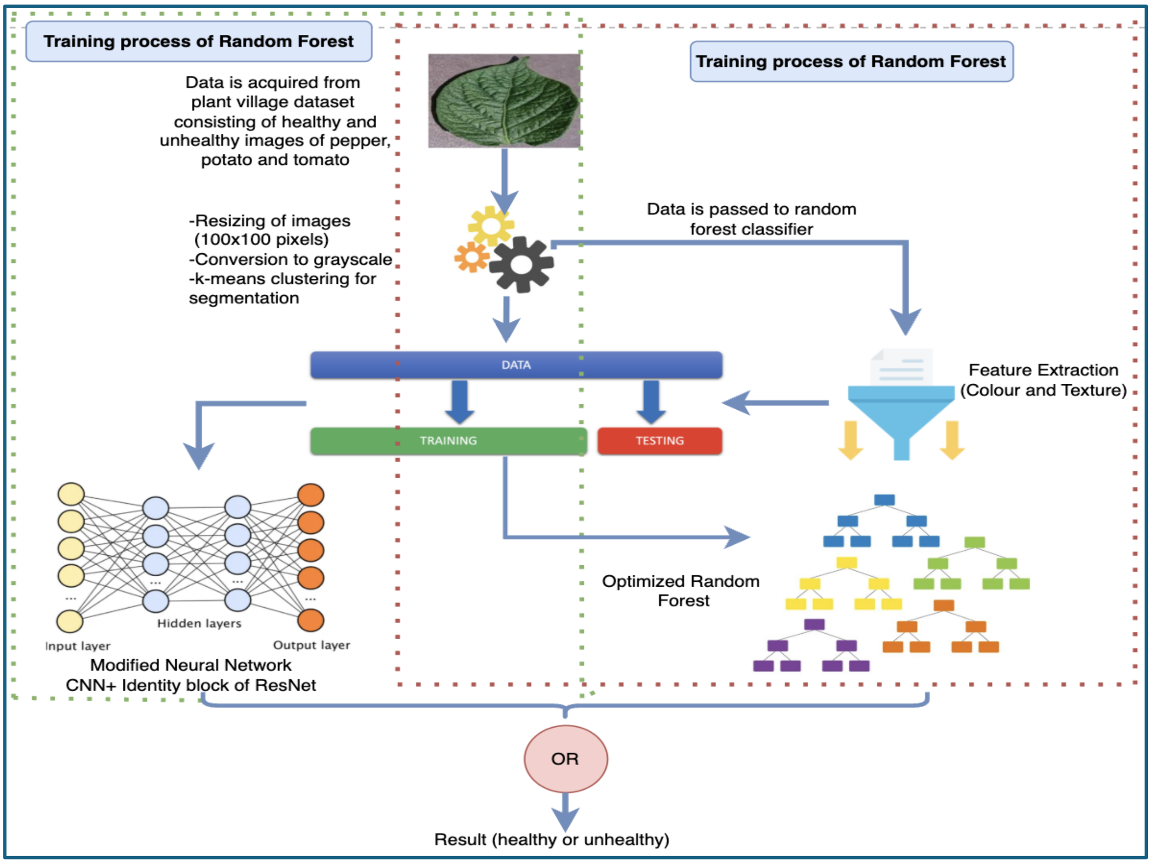


Figure 3: Architecture of ProthinNet23

**Stage 2 (Identity Block):**

In stage 2, the identity_block function is called, which represents a building block in ResNet-style networks. Two convolutional layers are used here with batch normalization and ReLU activation just like stage 1. Further, a skip connection is applied which adds the original input to the output of the second convolutional layer. This connection is used to remove the vanishing gradient problem and allows training of deep networks.

**Stages 3-5 (Identity Blocks):**

Similar to Stage 2, these stages consist of identity blocks that perform feature extraction and maintain spatial dimensions.

**Stage 6:**

This stage consists of a 3x3 convolutional layer having 128 filters and a stride of 2 to bring down the dimensions further. Followed by an identity block, it performs feature extraction. After this, global average pooling layer is applied to narrow down each feature map to a single value through averaging each value within the feature map. This helps to reduce the spatial dimensions to a manageable size before the fully connected layers.

For classification, a fully connected layer with the number of neurons matching the number of classes is applied. The softmax activation function produces class probabilities.

*3.2 Training of optimized Random Forest method*

*Phase 2-*

The architecture is assembled into a Keras model instance. In Random forest, parameters such n_estimator, max_depth, min_samples_split, min_samples_leaf are hyper tuned. Further, the random forest approach is optimised using Nelder-Mead. This approach for optimisation makes use of pattern search instead of function gradient data. This makes it appropriate for function optimisation problems where the gradient of the function is either unknown or impossible to get.

**Model Creation:**

The classification result of the modified random forest algorithm and proposed neural network are used in the model such that the proposed model gives final result on the basis of below statement-

*ProThinNet23= (Modified RF classification result) OR (CNN+ some features of ResNet)*

The final decision or output of the model depends on which one provides more accurate and confident predictions. This hybrid approach aims to utilize the strengths of machine learning models to improve the accuracy of plant leaf disease detection.

## 4. Performance metrics

Performance metrics are measurements that are used to assess a system, process, or product's efficacy, efficiency, or quality. Various metrics are used to find the effectiveness of models, algorithms, systems, or processes in a variety of sectors, including information technology, finance, healthcare, and machine learning.

Accuracy

It can be defined as ratio of number of correctly classified instances to that of total instances. It is measured using the following formula:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ Number\ of\ Predictions}$$

The model's overall correctness can be assessed by its accuracy. If one class is noticeably more numerous than the other in an unbalanced dataset, it might not be appropriate.

Precision

It can be framed as the ratio of true positives to the sum of true positives and false positives. Basically, it deals with the accuracy of positive predictions. It is the percentage of all positively projected instances that were accurately projected to be positive. When the cost of false positives is significant, precision is important.

$$Precision = \frac{True\ Positives}{True\ Positives\ +\ False}$$

Recall

The number of real positives to the total of false negatives and true positives is called recall. It assesses how well the model can capture every instance of success.

$$Recall = \frac{True\ Positives}{True\ Positives\ +\ False}$$

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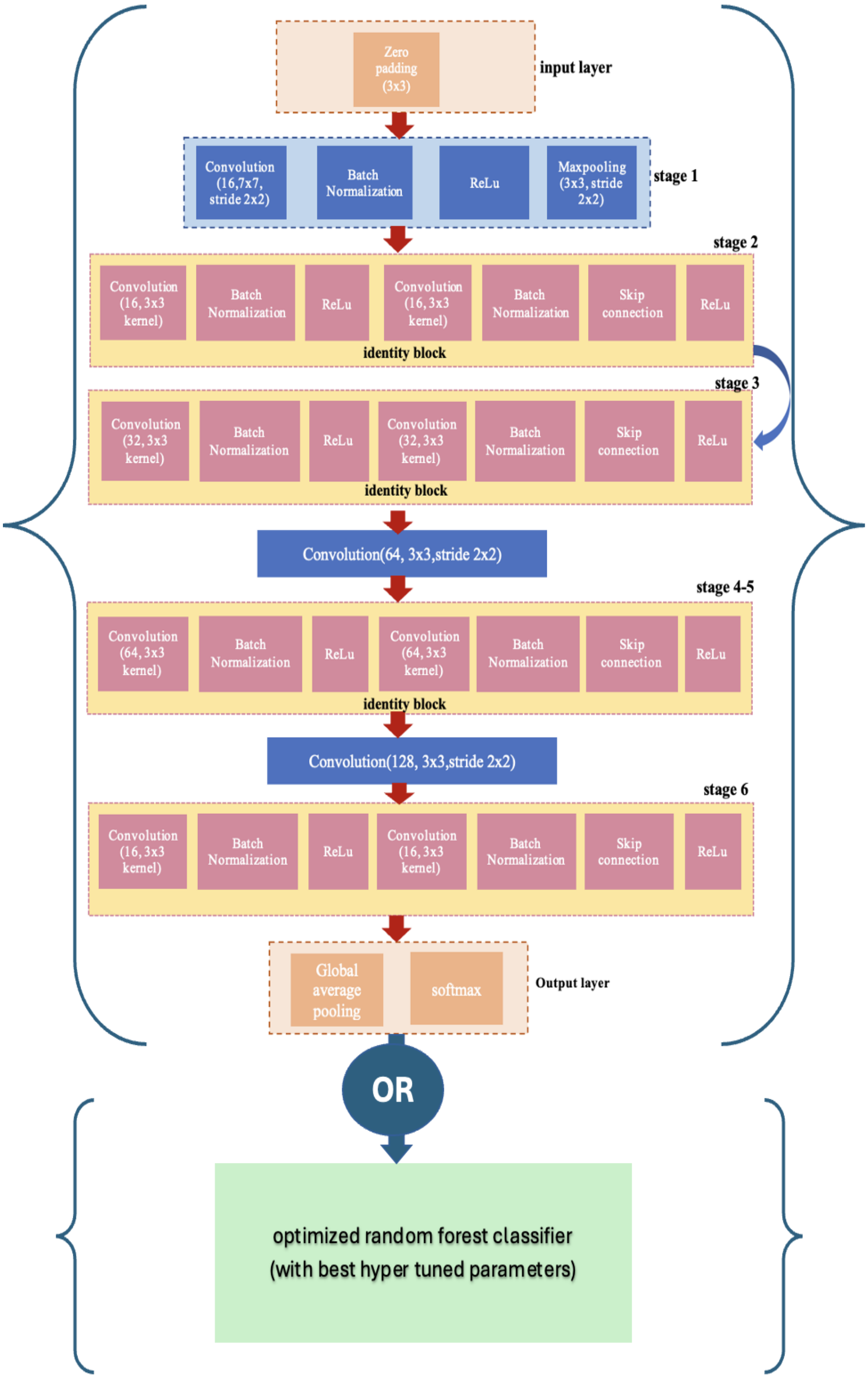


Figure 4: Architecture of proposed model showing the sequence of layers and identity blocks used in the model

F1 score

F1 score is one of the popular metrics that balances precision and recall, providing a single metric that considers both false positives and false negatives. It is particularly useful when there is imbalanced dataset or class distribution.

$$F1\ Score = 2 \times Precision \times Recall / Precision + Recall$$

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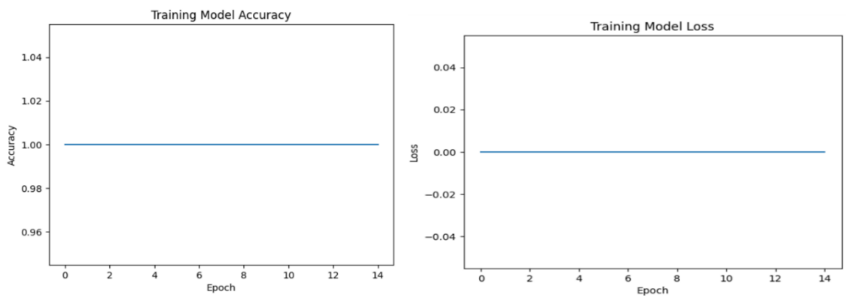
Table III: Performance metrics of proposed model

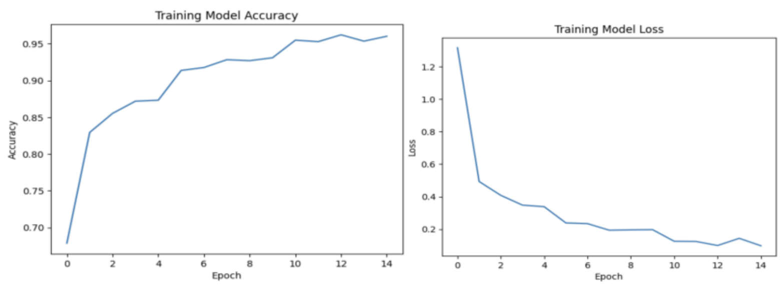
| Crop | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Pepper | 1.0 | 1.0 | 1.0 | 1.0 |
| Potato | 95.04 | 88.21 | 98.45 | 92.99 |
| Tomato | 98.56 | 98.57 | 98.56 | 98.56 |

## 5. Results

In this section, the performance evaluation of proposed plant leaf disease detection model using various metrics like accuracy, precision, recall and f1score is presented. The overall performance of the model is depicted in table III. The model was tested on the dataset depicted in Table II and it was observed that proposed method is performing exceptionally well giving 100% accuracy in predicting diseases of pepper but showed lower performance in potato leaf disease detection with F1score of 92.9%. The high precision and recall for pepper and tomato illustrates that the proposed model can differentiate healthy and diseased leaves effectively. However, the lower performance for potato may be due to similarity in visual symptoms of early blight and late blight. If a greater number of such images are added, the model could give better performance in this case also. The graphs shown in Figure 5 gives insight that how the model is learning over time and helps in identifying the potential issues during the training phase. X-axis is representing the number of epochs and y-axis is having values from 0 to 1 where 1 represents100% accuracy. Figure 5(b), potato crop, depicts that initially, the accuracy is lower, but it is increasing as the number of epochs increases. It clearly indicates that the model is learning and improving to classify the data correctly.




a) pepper




b) potato

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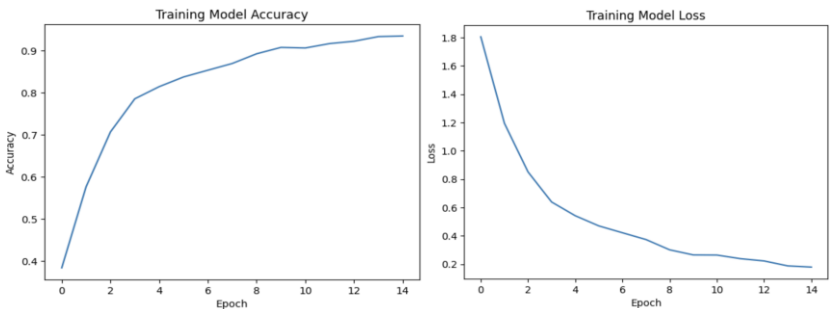


c)tomato

Figure 5: representing plots of training model vs epochs and training loss vs epochs a) pepper. B)potato c) tomato d) all crops

## 6. Discussion

The architecture's advantage over other networks of similar types is its focus on being lightweight without sacrificing too much accuracy. It leverages identity blocks to enable training of deep networks and uses global average pooling to reduce spatial dimensions before the final classification layer. This makes it suitable for tasks where computational efficiency is a priority. The choice of layers, filter sizes, and the arrangement of identity blocks contribute to its unique characteristics compared to other network designs. Unlike some lightweight networks that might sacrifice too much complexity for the sake of computational efficiency, ProThinNet23 adopts a well-considered compromise. It harnesses the power of identity blocks – a cornerstone feature of more complex networks like ResNet – to enable the training of deep networks while mitigating the vanishing gradient issue. This strategic incorporation of identity blocks ensures effective feature extraction and representation learning, contributing to the network's ability to capture intricate patterns within images.

ProThinNet23's distinctiveness lies in its global average pooling layer. By incorporating this layer before the final classification stage, the architecture skillfully reduces the spatial dimensions of the feature maps. This not only maintains vital information while drastically trimming the parameter count, but also aids in preventing overfitting, a common concern in lightweight models. This optimization is particularly valuable when deploying models in resource-constrained environments.

## 7. Conclusion

ProThinNet23 is a hybrid model which combines the predictions from random forest classifier and a deep network (CNN + identity blocks of residual network). Random forest has the ability to handle different feature sets whereas neural network works on complex features. Optimized random forest ensure the operability of this model with best hyperparameters thereby maximizing its accuracy. By embracing identity blocks for deep learning potential and optimizing through global average pooling for efficient spatial reduction, ThinNet18 manages to avoid the extremes of over-simplification and over-complexity. This recommendation extends to scenarios where resource constraints necessitate a judicious trade-off between model sophistication and real-world practicality. The logical OR operation is applied at the end of this model which aims to improve the final classification result. These results are evaluated using various metrics such as accuracy, precision, recall and F1-score. For future, ensemble methods like boosting and stacking can be used to enhance the hybrid model's performance.

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