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Performance Evaluation of ProThinNet23 and State-of-the-Art Deep Learning Models in Plant Leaf Disease Identification

Madhu Bala[1]*
Research Scholar,Maharaja Agrasen University
*Corresponding Author: madhucse0105@gmail.com
Dr. Sushil Kumar Bansal
Professor, Maharaja Agrasen University
Co-author:
sk93recj@gmail.com
Computer Science and Engineering Department, MAIT,
Maharaja Agrasen University

ABSTRACT:
For sustainable development in agriculture , there is a need to develop automated systems that can identify plant leaf diseases by capturing their images directly from the field. Such systems can enhance agricultural productivity and minimize crop losses. Recent advancements in the domain of machine learning and deep learning have focused on creating powerful hybrid models for the automatic detection of plant diseases, as these approaches offer higher accuracy.

The current manuscript presents a comparative analysis of ProThinnet23, a hybrid model, against existing state of the art models in plant health monitoring. The performance of the models is compared based on accuracy, precision, re-call, and F1 score. The results demonstrate that ProThinNet23, a lightweight model leveraging the strengths of ResNet50 and an optimized Random Forest algorithm, outperforms existing models. The remarkable performance of ProThinNet23 includes an accuracy of 98.92%, precision of 98.57%, recall of 98.60% and F1-score of 93.91%. These findings underscore its potential as a highly effective solution for plant disease detection.

Keywords: Hybrid model, Agriculture, Resnet, Random Forest, Optimization, Neural Network

1. Introduction

As a cornerstone of economic advancement of a country, agricultural sector plays a significant role. Not only farmers but entire human community depends on this sector for fulfilling their food needs[1], [2], [3], [4]. It has been observed that the quality and quantity of food crops are plummeting day by day. Plant diseases (depicted in Table I) are one of the major constraints for this. These diseases are caused by biotic and abiotic factors such as viruses, bacteria, temperature, humidity etc. Early detection of these diseases is of great importance as it will be helpful in stopping the spread of such diseases in the entire field thereby minimizing the crop losses. Conventional methods of detection of plant diseases were based on manual inspection where an expert was responsible for identifying diseases among plants. This method consumes lot of time and seems impractical for large scale agricultural operations[5], [6].

Plant diseases (shown in Figure 1) can affect plants at all stages of growth and in all parts (leaf, neck, and root). Among these, the leaves are the most severely impacted[7]. Several studies [8], [9], [10] have put out machine learning algorithms and image processing strategies to recognize and classify these diseases in plants. Some researchers [11], [12], [13]have proven that the accuracy of classification tasks can be improved using machine learning algorithms, which are doing good in image processing and pattern recognition. On the other hand, it has been found that Convolutional neural networks (CNN) are being employed for object recognition and image classification by the researchers [14], [15], [16], [17], [18], [19] . Deep learning techniques have become prevalent for pattern recognition due to their effectiveness in identifying different outlines. Deep learning (DL) can automate feature extraction. Compared to traditional machine learning algorithms, DL reduces error rates and computational time, achieving high accuracy in classification tasks.

Further, hybrid models have showed up as a leading approach in terms of detecting diseases with higher accuracy. These models can detect complex patterns and extract large number of features from an image[20]. Recent transformations in machine learning and deep neural networks have altered plant leaf disease detection systems as these technologies are offering promising results in terms of accuracy, efficiency and reliability. These are much faster as they can predict number of diseases at the same time and helping in taking suitable crop management practices.

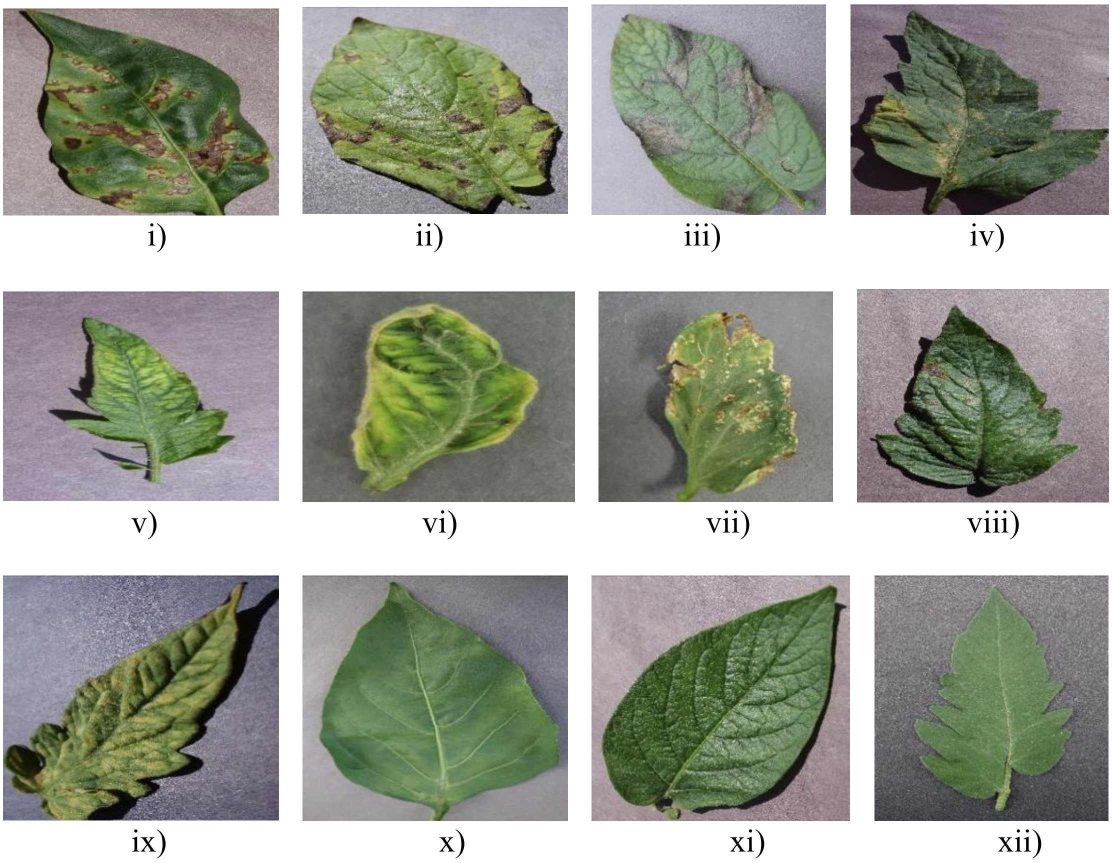

Figure 1: Sample leaf images from plant village dataset i) pepper with bacterial spot ii)potato with early blight iii) potato late blight iv) tomato target spot v) tomato mosaic virus vi) tomato yellow leaf curl virus vii) tomato bacterial spot viii) tomato early blight ix)tomato leaf mold x)pepper healthy xi)potato healthy xii) tomato healthy

The current manuscript aims to conduct a comparative analysis of ProThinNet23 with existing models in the domain of plant leaf disease detection. The comparison is done based on model performance with existing state of the art hybrid models. Also, different parameters are considered for the comparison.

Table I depicting various diseases identified in different crops

Reference	Crop	Diseases Identified
[21]	Citrus Plants	Citrus Canker, Anthracnose, Over watering, Citrus greening
[22]	Banana, beans, lemon, rose	Scorch, bacterial leaf spot, Sun burn, fungal disease
[23]	Mango	Anthracnose, Alternaria leaf spot, leaf gall, leaf webber, leaf burn
[24]	Tomato	Late blight, Leaf mold, Two-spotted Spider mite attack, Target spot, Mosaic virus,Yellow leaf curl virus disease
[25]	Rice	Brown spot, Bacterial blight, and Leaf smut
[26]	Apple	General Apple Scab, Serious Apple Scab, Apple Gray Spot, General Cedar Apple Rust, Serious Cedar Apple Rust
[27]	Several Plants	Lesions and Spots
[28]	Rice	Bacterial Leaf Blight, Rice Blast , Sheath Blight
[29]	Maize	common rust, gray leaf spot, northern leaf blight
[30]	Rice and Maize	Maize diseases: Phaeosphaeria Spot, Maize Eyespot, Gray Leaf Spot, and Goss's Bacterial wilt Rice diseases: Rice Stack burn, Smut, Rice White Tip, and Bacterial Leaf Streak, Rice Leaf Scald, Rice Leaf
[31]	Mango	Dag, Golmachi,Shutimold, Red Moricha
[32]	Wheat	Wheat Loose Smut, Tan Spot, Powdery Mildew, Leaf Rust, Healthy Wheat, Fusarium Head Blight, Crown & Root Rot, Black Chaff, Karnal Bunt, and Wheat Streak Mosaic

2. Dataset used

Plant Village dataset consisting of 20653 images of pepper, tomato and potato is taken for the experimentation purpose. This dataset contains images of diseased and healthy leaves of above-mentioned crops. It is obtained from Mohanty’s GitHub repository where 15 directories contain images of healthy and diseased leaves of potato, tomato and pepper. The details are depicted in

Table II. Reason behind choosing this dataset for current study is its popularity of being utilized by different researchers and it is clear from Figure 2 that each day this dataset is being downloaded by approximately 50 individuals.

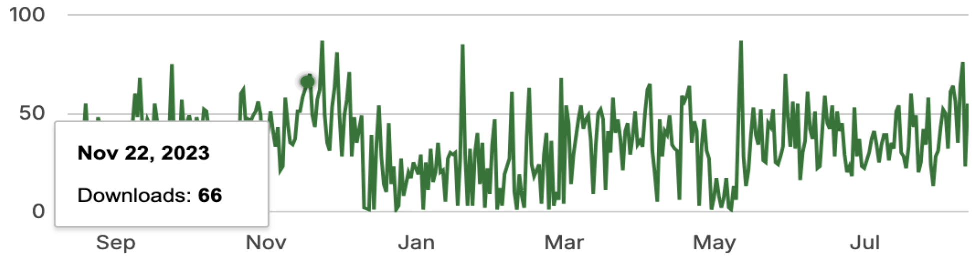

Figure 2: Plant village dataset details in past few years

Table II: Details of plant village dataset used

Crop Name	Healthy/Unhealthy images	Total images
Potato	Healthy: 153 Diseased:2002	2155
Pepper	Healthy:1478 Diseased:998	2476
Tomato	Healthy: 1592 Diseased:14430	16022
	Total images	20,653

3. Methodology

Since the objective was to create a hybrid model for edge computing devices, ProThinNet23 is formed using deep learning and machine learning approaches. The proposed model is designed using the following steps:

3.1. Finding the best performer machine learning model

The process starts with acquiring the relevant data. The dataset can be taken either from the repositories or images can be collected from the fields itself.

- For current study, plant village dataset is used. These collected images cannot be used directly to train a model as they are of different sizes and of different intensity. Hence, the dataset needs to be pre-processed to improve the quality of image.
- All images are resized to 100X100 pixels and converted into RGB format from BGR format using OpenCV library. For enhancement of image, median filtering method is used so that the noise from the image can be removed, and better edge detection can be performed on the sample data.
- To find the diseased area known as region of interest (ROI) from the given image, active contouring is applied for segmentation, so that we are left with only the focused part of the image. After this, feature extraction is done. The energy, entropy, moment of inertia, and other textural characteristics of an infected area are determined using the spatial variants of the classical grey level co-occurrence matrix (GLCM).

Appropriate classification techniques random forest, naïve bayes, support vector machine and k- nearest neighbor are applied on sampled images by training the model first and then testing is done to check how accurate is the model.

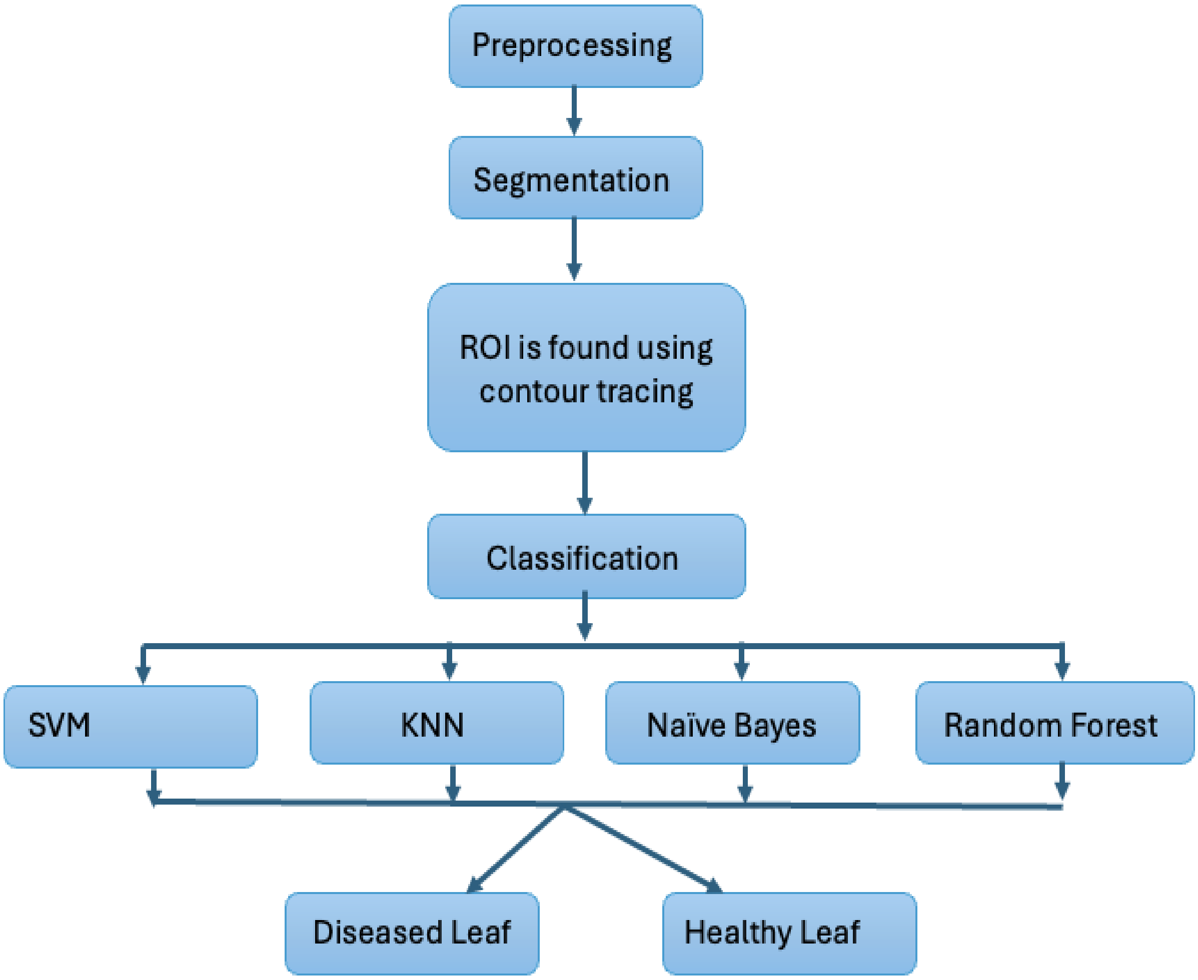

Figure 3: Steps to find the best machine learning model for identification of diseased leaf

3.2. Optimization of Random Forest

After implementing the steps depicted in Figure 3, it was found that random forest is giving best classification results. Hence, random forest algorithm along with identity blocks of ResNet50 and CNN is chosen for creating a hybrid model i.e "ProThinNet23".

Equation (1) shows the mathematical notation for random forest algorithm.

$$P' = \frac{1}{D}\sum_{d=1}^{D} P'_d\,(T) \qquad (1)$$

where, P'=prediction of final tree

D= number of decision trees in random forest, d= current decision tree and T represents training data sample.

Hyperparameter tuning of random forest classifier is done using a combination of cross-validation and Nelder-Mead optimization method. The parameters taken are n-estimators, maximum depth, minimum sample split and minimum sample leaf. The mean accuracy of 5-fold cross-validation is computed. The code snippet in Figure 4 is showing how hyper tuning parameter is performed.

```
# Define the initial set of hyperparameters
init_params = [100, 5, 2, 1]

# Define the bounds for the hyperparameters
bounds = [(50, 500), (2, 20), (2, 10), (1, 5)]

# Use the Nelder-Mead method to minimize the objective function
result = minimize(objective, init_params, method='Nelder-Mead', bounds=bounds)

# Print the best parameters and the corresponding accuracy score
print("Best Training Parameters:", result.x)
print("Best Training Accuracy:", -1.0 * result.fun)
```

Figure 4: code snippet depicting hyperparameter tuning of random forest classifier

The best hyperparameters are extracted from this optimization process and a new instance is created. The model is then trained on the reshaped training data and the corresponding labels.

3.3. Construction of deep neural network

The idea behind the construction of "ProThinNet23" is to create a lightweight network that works well on edge computing devices with minimum resource requirement. The hybrid model is created by combining convolutional neural network, identity blocks of ResNet50 and optimized random forest algorithm. Figure 5 is representing how deep neural network is constructed and is working in different stages.

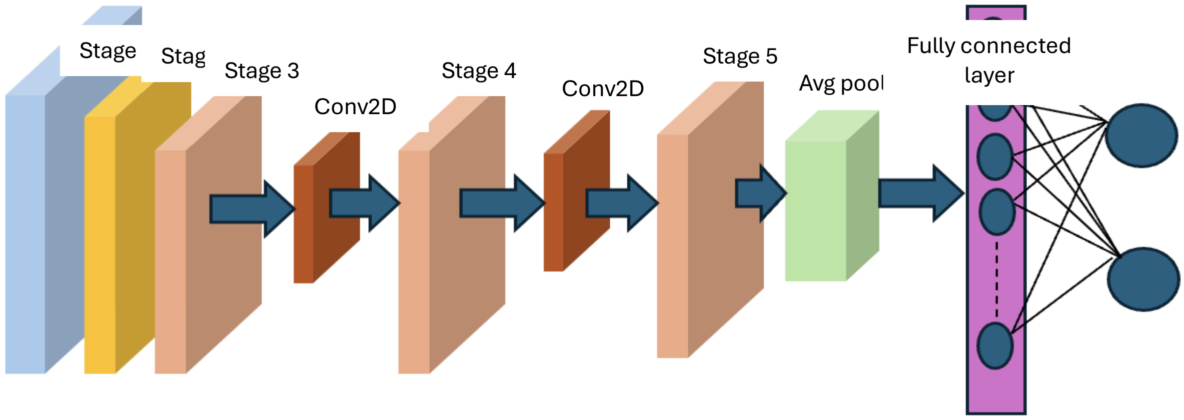

Figure 5: Deep neural architecture using CNN + identity blocks of ResNet50

ResNet50 consist of residual blocks that enables the gradients to flow better from one layer to another. Each block has several convolutional layers along with normalization and activation functions. Mathematically, a residual block is represented as-

$$s= F(r,\{W_i\})+R \quad (2)$$

where,
r is the residual block, y represents output of residual block

$F(r,\{W_i\})$ is the function representing entire residual block with convolutional layers having weight W_i
R is the identity shortcut connection

A 3x3 zero-padding is applied to the input images to ensure that the spatial dimensions remain consistent throughout the layers. The following points are describing that how different stages are constructed in the proposed model.

- **Stage 1:**A 7x7 convolutional layer with 16 filters and a stride= 2 **,**Batch normalization and ReLu activation function, 3x3 max-pooling layer, stride=2
- **Stage 2 (Identity Block):** It is composed of two convolutional layers with batch normalization and ReLu as an activation function. The original input is added to the output of the second convolutional layer via skip connection
- **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:** 3x3 convolutional layer with 128 filters and a stride=2 followed by an identity block.
- **The final layer:** A fully connected layer with the number of neurons equal to the number of classes is used for classification. The softmax activation function produces class probabilities.

For final creation of "ProThinNet23", output of both CNN and optimized random forest is combined using OR operation. The model's output will contain the value which will be higher in terms of accuracy.

2.4. Performance metrics

Accuracy, precision, recall and F1-score (depicted in Table III) are taken into consideration as the evaluation metrics to assess the performance of the suggested model. Let us consider the terms T(+ve), T(-ve), F(+ve), F(-ve) for true positive, true negative, false positive and false negative respectively. Mathematically, the metrics can be defined as-

$$\text{Accuracy}=\frac{\mathrm{T(+ve)+T(-ve)}}{\mathrm{T(+ve)+T(-ve)+F(+ve)+F(-ve)}} \tag{3}$$

$$\text{Precision}=\frac{T(+ve)}{T(+ve)+F(+ve)} \tag{4}$$

$$\text{Recall}=\frac{T(+ve)}{T(+ve)+F(-ve)} \tag{5}$$

$$\text{F1-score}=\frac{2*recall*precision}{recall+precision} \tag{6}$$

The confusion metrics (shown in Figure 6) can be used to understand the concept of true positive, true negative, false positive and false negative terms.

- True positive: Input is diseased leaf and model is predicting it as diseased leaf
- False positive: Input is healthy leaf and model is predicting it as diseased leaf
- False negative: Input is diseased leaf and model is predicting it as healthy leaf
- True negative Input is healthy leaf and model is also predicting it as healthy lea

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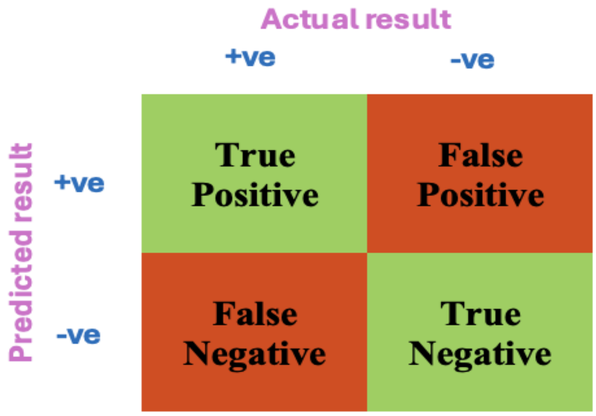

Figure 6: Confusion Matrix depicting the meaning of true positive, true negative, false positive and false negative terms

Table III: Performance of proposed model (ProThinNet23) depending on different metrics

Crops	Accuracy	Precision	Re-call	F1-Score
Pepper	100%	100%	100%	100%
Tomato	98.56%	98.57%	98.56%	98.56%
Potato	95.04%	88.21%	98.45%	92.99%
All	98.92%	98.57%	98.60%	93.91%

4. Results and Discussion

Since the dataset contains images of varied intensities and sizes, preprocessing was required. All images are converted into 100X100 and for simplification they are further converted into greyscale images. K-means clustering is applied to segment the images into two clusters shown in Figure 7 b). Each pixel is assigned to nearest centroid based on Euclidean formula. Contour tracing is done to extract region of interest and further this region of interest is passed to model.

a) b)

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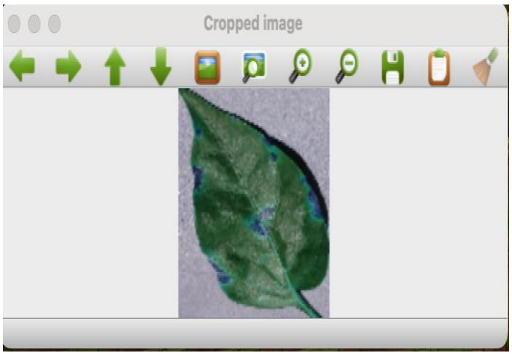


c)

Figure 7:Preprocessing and segmentation of input image where a) is representing region of interest labeled image b)clustered image after applying k-mean clustering c) cropped image

ProThinNet23 is a hybrid model, and the novel part of the model lies in the fact that it is lightweight as compared to other neural networks such as EfficientNet, ResNet50, CNN, Hybrid model of CNN and transformer. Because of its lightweight, this model can be run on machines with limited computing power and edge computing devices such as raspberry Pi. The difference between the developed model and existing models is shown in Table IV. Examining the effectiveness of ProThinNet deep learning architecture in plant leaf disease classification and contrasting its results with the literature's most advanced CNN models is the primary goal of this work.

The proposed model has the strengths of CNN and ResNet50 along with the robustness of an ensemble method i.e. optimized random forest which can improve generalization and accuracy. To train the model 20,653 images have been taken which is relatively a large dataset to train it well and improve its efficiency in detecting diseased leaves. It is working on three different crops -potato, tomato and pepper thereby providing a versatile application across these three solanaceous crops and making it outperformed as compared to moore penrose model that focus intensely on single crop. In addition to this, Moore penrose model used 120 images which could limit its generalizability. From Figure 8 it is observed that proposed model is giving significant results in terms of accuracy, precision, recall and F1-score.

The training accuracy and training loss of the model is depicted in Figure 8. Figure 8 a) is showing the accuracy 100% and loss of model is 0% with 15 epochs. This shows that the models trained well for pepper crop. Figure 8 b) is representing the same for potato crop where initially the model shows the accuracy of 64% approximately with the first epoch but when it reaches to 15^{th} epoch the accuracy achieved is 96.43%. The loss is also decreasing with increase of epochs. This again is a good sign that the model is trained well. Similarly, figure 8 c) and 8 d) are depicting that the model is giving high accuracy with each epoch and correspondingly the loss values are decreasing.

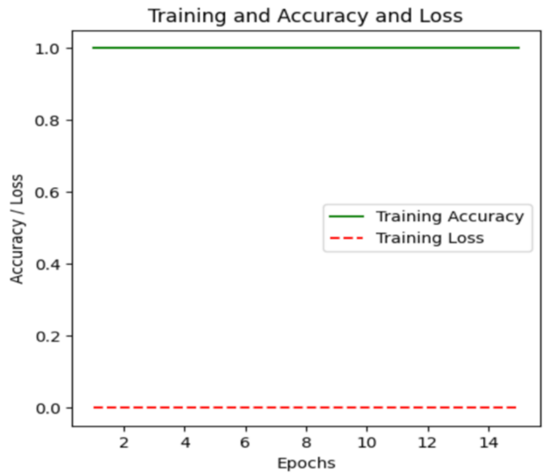
The precision value is also high which ensures fewer false positives in disease detection. In terms of predicting the number of diseases, the proposed model is covering significant number of diseases.

Table IV Comparison of ProThinNet23, EfficientNet CNN, Hybrid Model and Moore-Penrose pseudo-inverse weight-based CNN

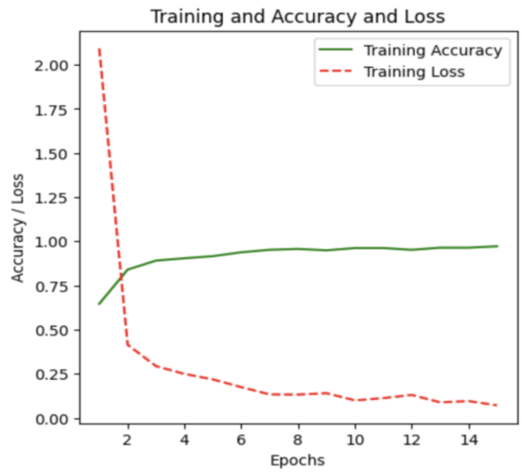
Feature	**ProThinNet 23**	**Efficient Net CNN** [33]	**Efficient Net + Random Forest** [34]	**PLDPNet** [35]	**Transformer + CNN** [36]	**Moore-Penrose pseudo-inverse weight-based CNN** [37]
Architecture	Hybrid (ResNet, CNN, Random Forest)	Deep Convolutional Network	Hybrid (Efficient Net, random forest)	PDLP (VGG19 þ Inception-V3)	Hybrid (Transformer+ CNN)	5 phases +MPW-DCNN
Dataset	20,653 images (Plant Village Dataset)	55,448 images (Plant Village Dataset)	910 images	2152 images (plant village dataset)	4072 images	120 images (UC Irvin Repository)
Crop	Potato, Tomato, Pepper	14 different plant species	Tomato	potato	Potato	Rice
No. of diseases	12	26	Early blight	Early blight, late blight	2	Bacterial leaf blight
Accuracy	98.92%	99.91%	Average accuracy 98.17%	98.66	Not determined	97.5%
Precision	98.57%	98.42%	Not determined	96.0	95.26%	95.78%
Recall	98.60%	98.31%	Not determined	96.33	95.09%	92%
F1-Score	93.91%	Not mentioned	98.17%	96.33	95.07%	93.85%
Feature Extraction	Advanced (Hybrid Approach)	Not specified	Advanced	Advanced	Not specified	6 features
Training Time	Moderate to High	High (643.3 min)	High	high	High	Moderate
Deployment Suitability	Suitable for varied environments	Suitable for high performance systems	Suitable for high-performance systems	Suitable for high-performance systems	Suitable for high-performance systems	Suitable for varied environments

Preprocessing Requirements	Low	High	High	High	High	Noise removal and normalization

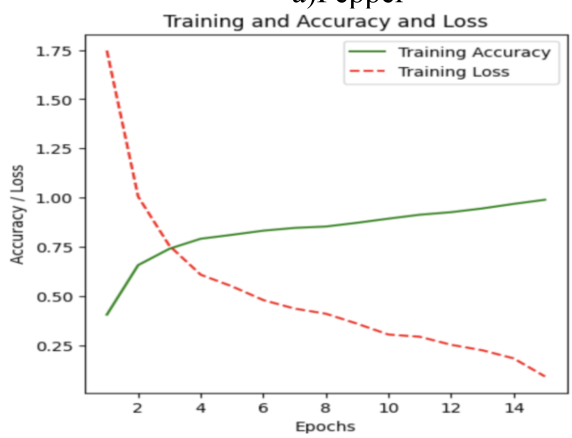
It is also observed that EfficientNet is giving accuracy of 991.91% (presented in table IV) but on the same side preprocessing requirements of this model are high and it is best suitable to be run-on high-performance system. On the other hand, due to mixed approach the proposed model's interpretability is high, and it can be run on all kind of systems i.e it is suitable for varied environments.



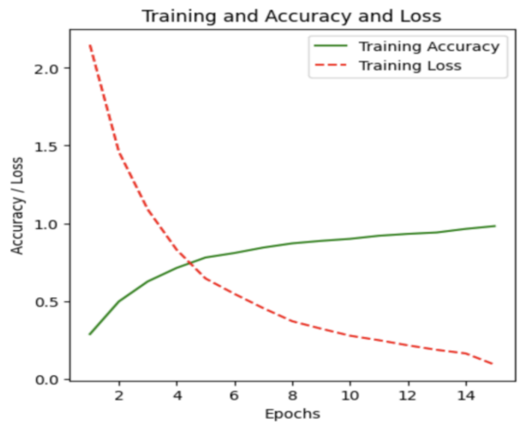
a)Pepper



b) Potato



c) Tomato



d) All crops

Figure 8: Training accuracy and training loss of proposed model ProThinNet23

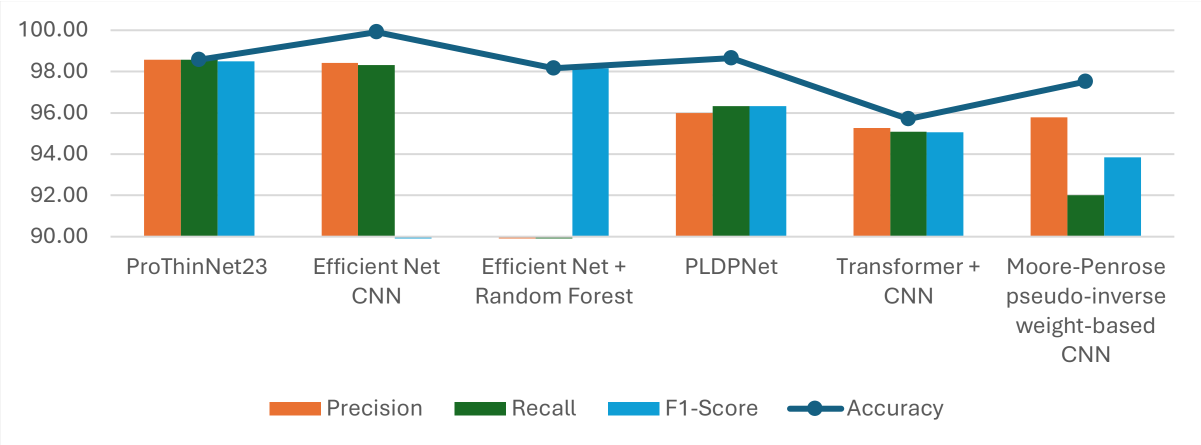


Figure 9. Performance evaluation of ProThinNet23, EfficientNet CNN, Hybrid Model and Moore-Penrose pseudo-inverse weight-based CNN

4. Conclusion

Plant disease detection system can automate the process of identifying diseases among plant leaves thereby saving economic losses. The present manuscript has presented a hybrid model which is a combination of random forest, identity blocks of ResNet and convolutional neural network. The fact that the architecture aims to be a "thin" or lightweight equivalent of more complicated networks like ResNet is perhaps where the name "ProThinNet23" comes from. 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. ProThinNet23 offers an alternative to more complex designs like ResNet50 or VGG16 by striking a compromise between model size and performance.

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