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POTATO PLANT LEAF DISEASE DETECTION USING CUSTOM CNN DEEP NET: A STEP TOWARDS SUSTAINABLE AGRICULTURE

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Session 1 – Technology, next-generation network architectures

POTATO PLANT LEAF DISEASE DETECTION USING CUSTOM CNN DEEP NET: A STEP TOWARDS SUSTAINABLE AGRICULTURE

Problem/Motivation :
Potato plants are vulnerable to various diseases, like **Early Blight** and **Late Blight**, which can significantly reduce crop yield and quality.

Solution:

- Detecting potato plant leaf diseases with Computer Vision (Using CNN) is a significant step towards sustainable agriculture.
- Early and accurate detection of diseases can help minimize crop losses, maximize yield, and reduce pesticide use *assisting farmers for a smart monitoring*

Objectives

- **Leveraging Technology:** This study aims to leverage advanced deep learning models to automate the process of identifying healthy and diseased Potato leaves.
- **Models Implemented:**

  Customised 5-layer CNN

  4-layer CNN

  Mobilenet

- **Comparative Analysis:** A comprehensive comparative analysis of these models is conducted to evaluate their performance in detecting and classifying potato leaf diseases, aiming to identify the most effective approach for enhancing agricultural practices.

Dataset (Plant Village)

- 3 categories: Early Blight, Late Blight, Healthy Leaves.
- Images used: 3000 samples for classification .
- Image dimensions: 256 x 256 x 3 pixels.

Early Blight

Late Blight

Healthy

Methodology

- Use of 3 CNN architectures: MobileNet, 4-layer CNN, 5-layer custom CNN.
- Training split: 70% training and 30% validation.
- Detection: Faster R-CNN used for detecting potato leaf diseases.

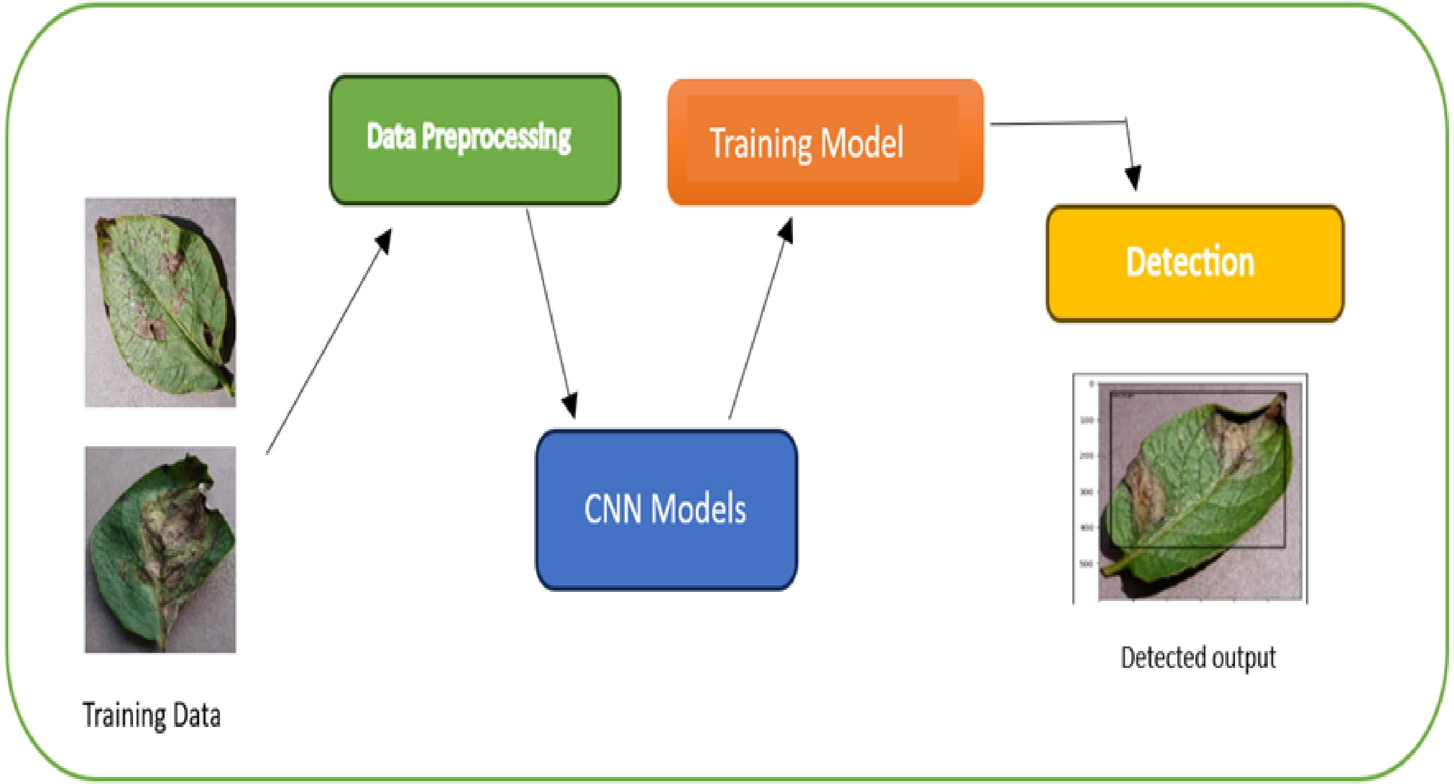


Fig.1 Workflow diagram

5 Layer CNN (Best Model)

- 5 convolutional layers with feature extraction.
- Trained for 10 epochs with Adam optimizer and learning rate of 1e-3.
- Achieved validation accuracy: 97.16%.

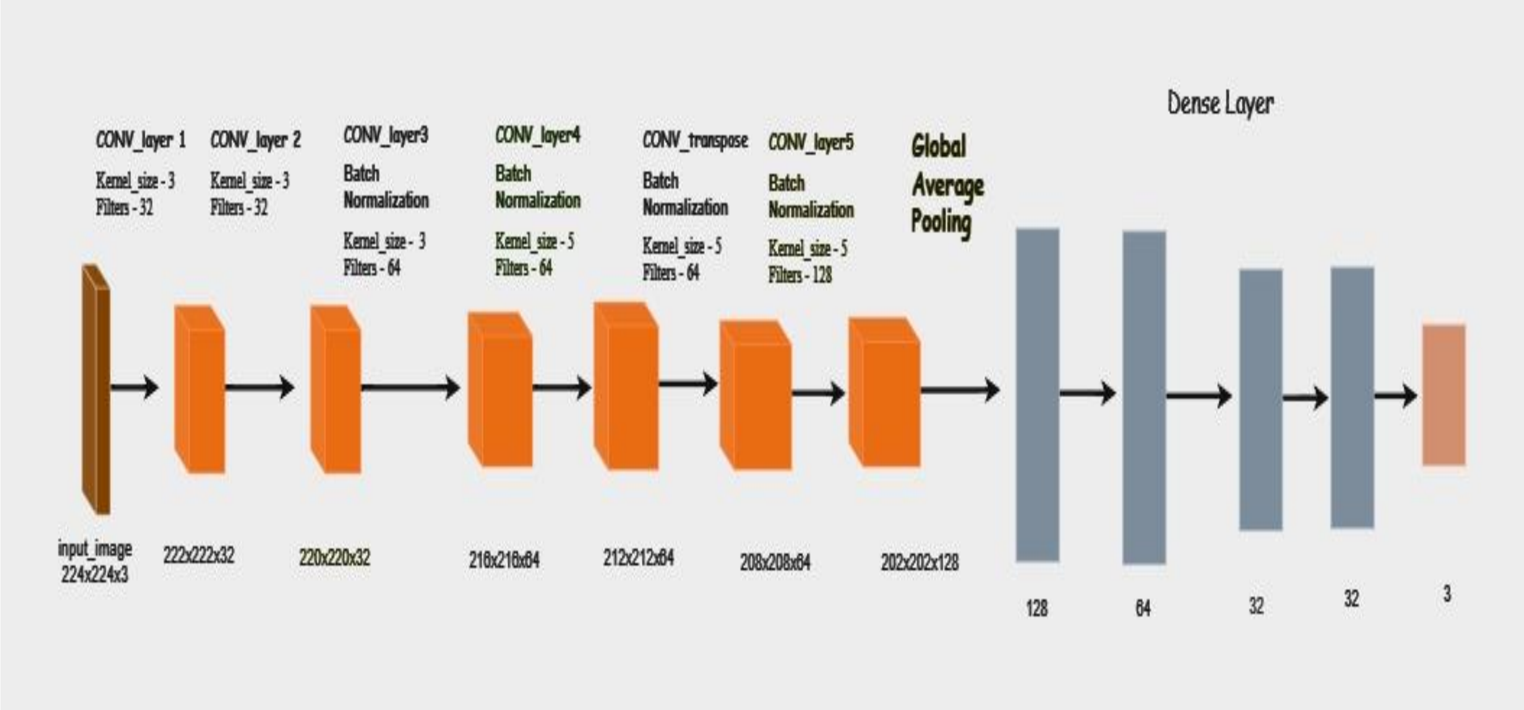


Fig.2 5-layer custom CNN

Detection Model

- **Faster R-CNN:**
  - Integrated 5-layer CNN as backbone for object detection.
  - Detected 3 categories: Early Blight, Late Blight, Healthy leaves.
  - Intersection over Union (IoU): 0.76 at 0.6 threshold.

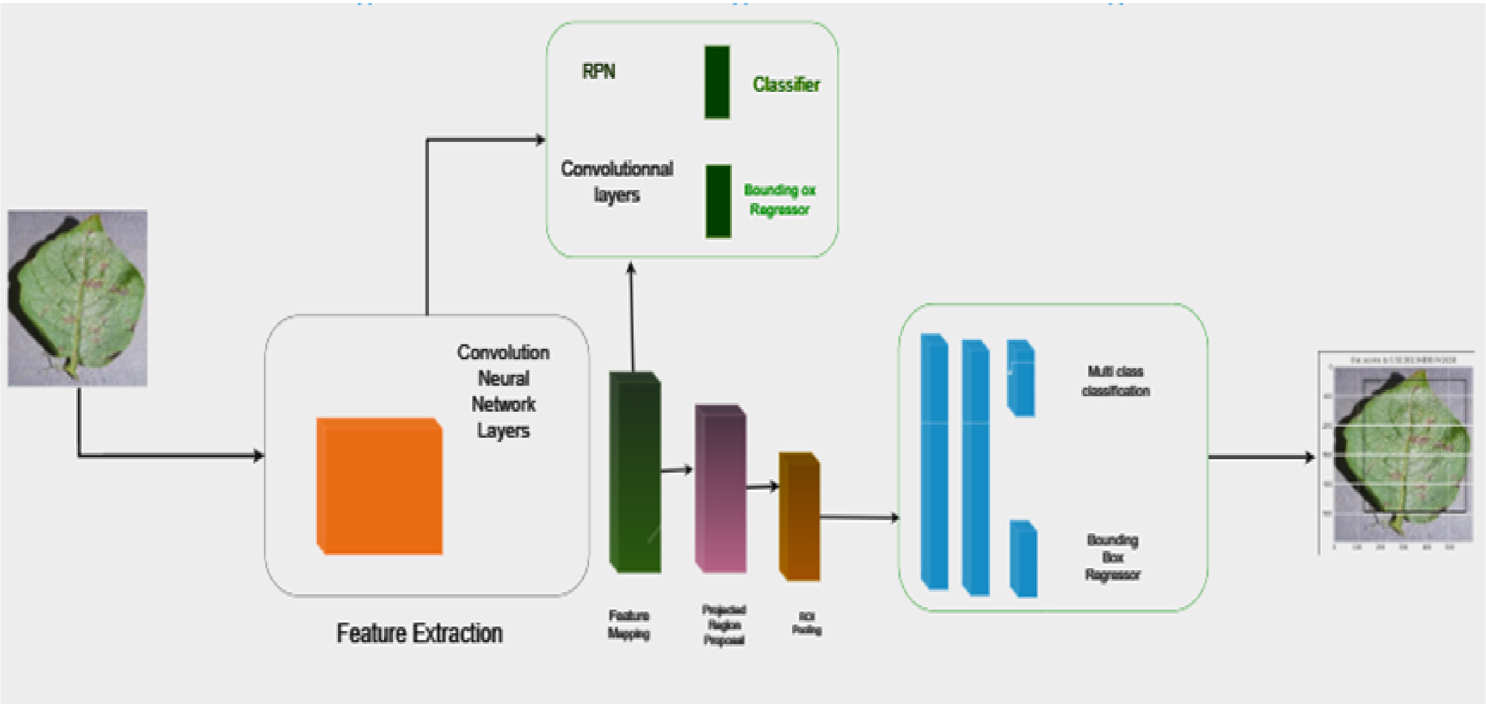


Fig.3 Architecture or FRCNN

Results

Classification:

Accuracy Comparison of 3 Models

5-layer CNN achieved a validation accuracy of **97.16%**

Mobilenet achieved a validation accuracy of **78.43%**

4-layer CNN achieved a validation accuracy of **73.21%**

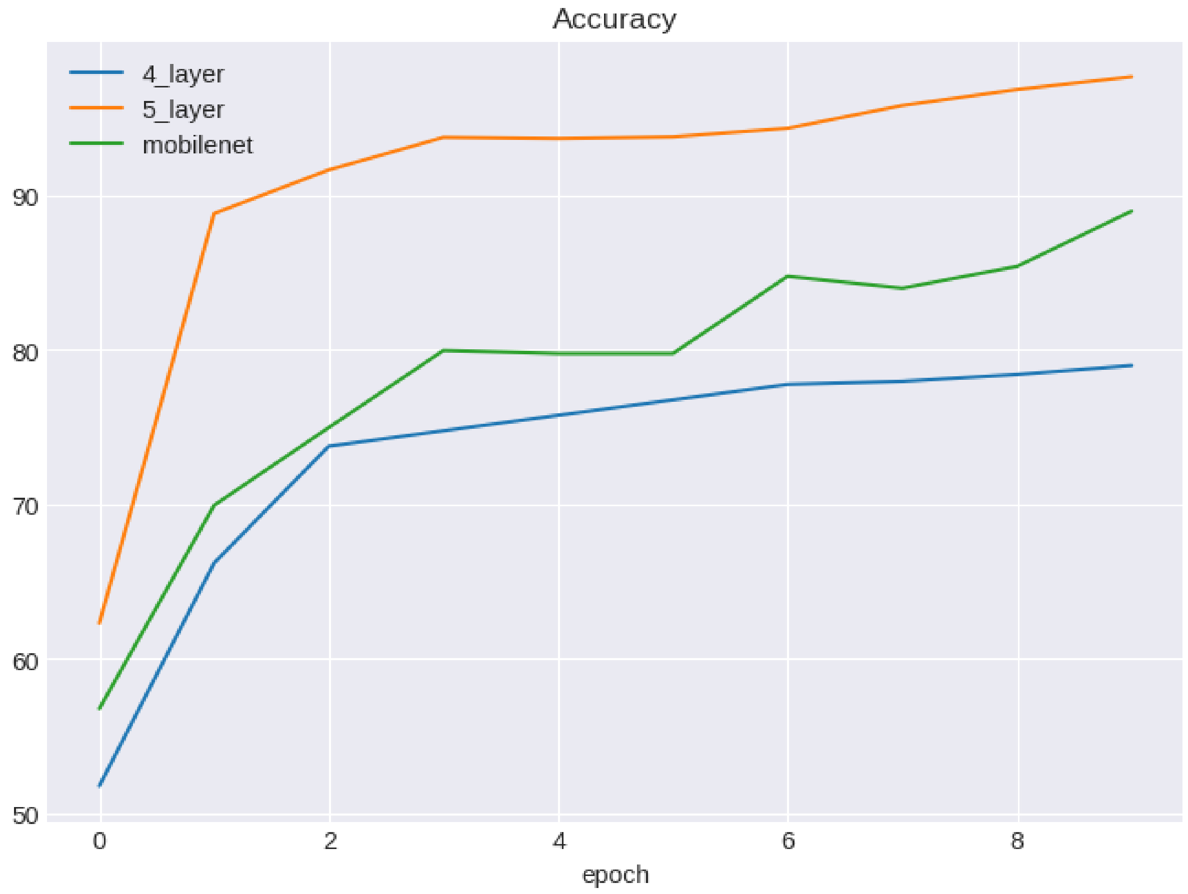


Fig.4 Accuracy Curves for the 3 Models

Results

Classification:

Accuracy(Training) of the 5-layer CNN model with different optimizers on 10 epochs.

Adadelta

Adam

AdamW

RMSProp

SGD

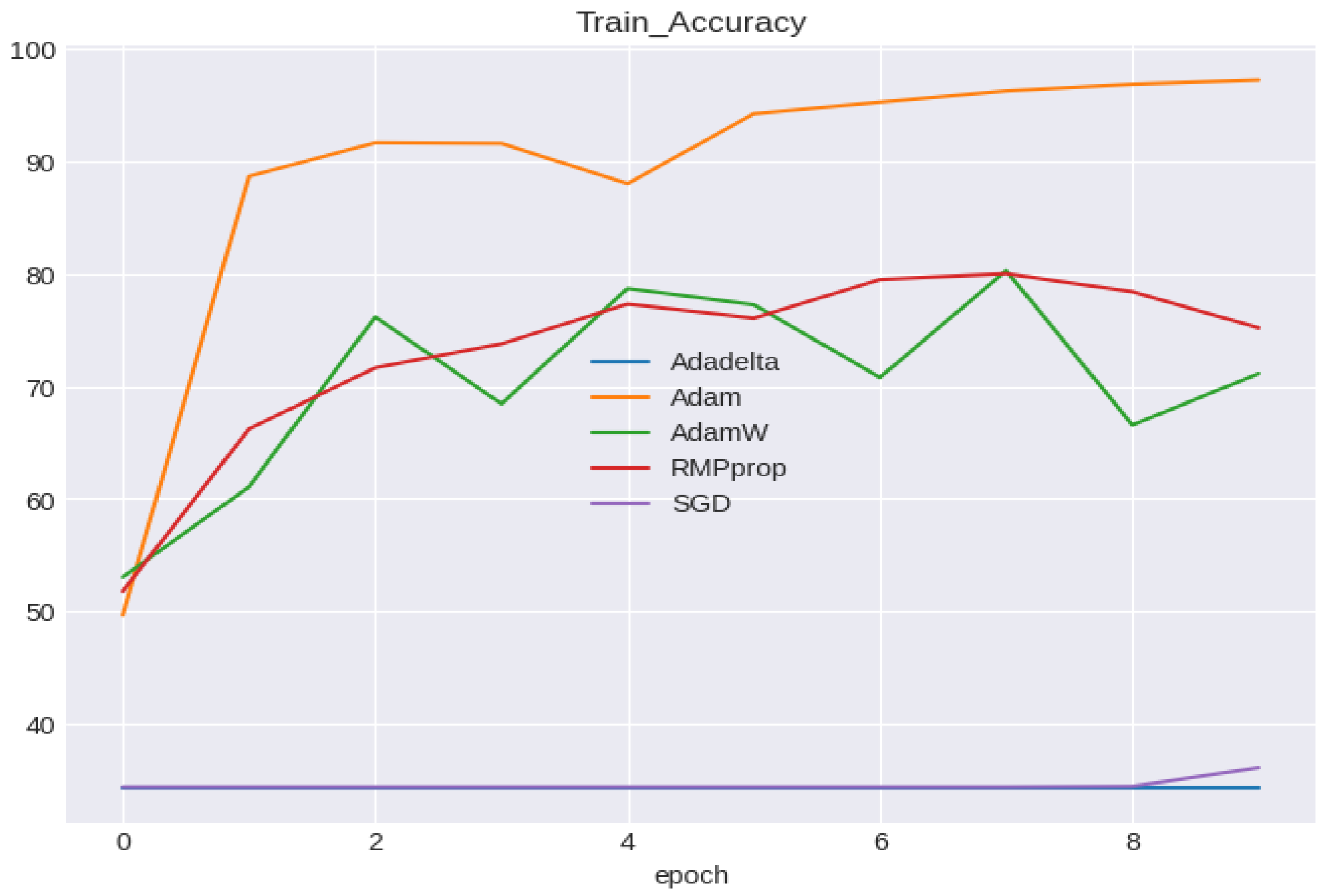


Fig.5 Training Accuracy Comparison Curves for 5 Layer CNN with different optimizers

Results

Classification:

Accuracy(Validation) Comparison of model with different optimizers

Fig.6 Validation Accuracy Comparison Curves for 5 Layer CNN with different optimizers

Results

Graph of Performance Metrics of the best model(5 layer Custom CNN) with 30 epochs.

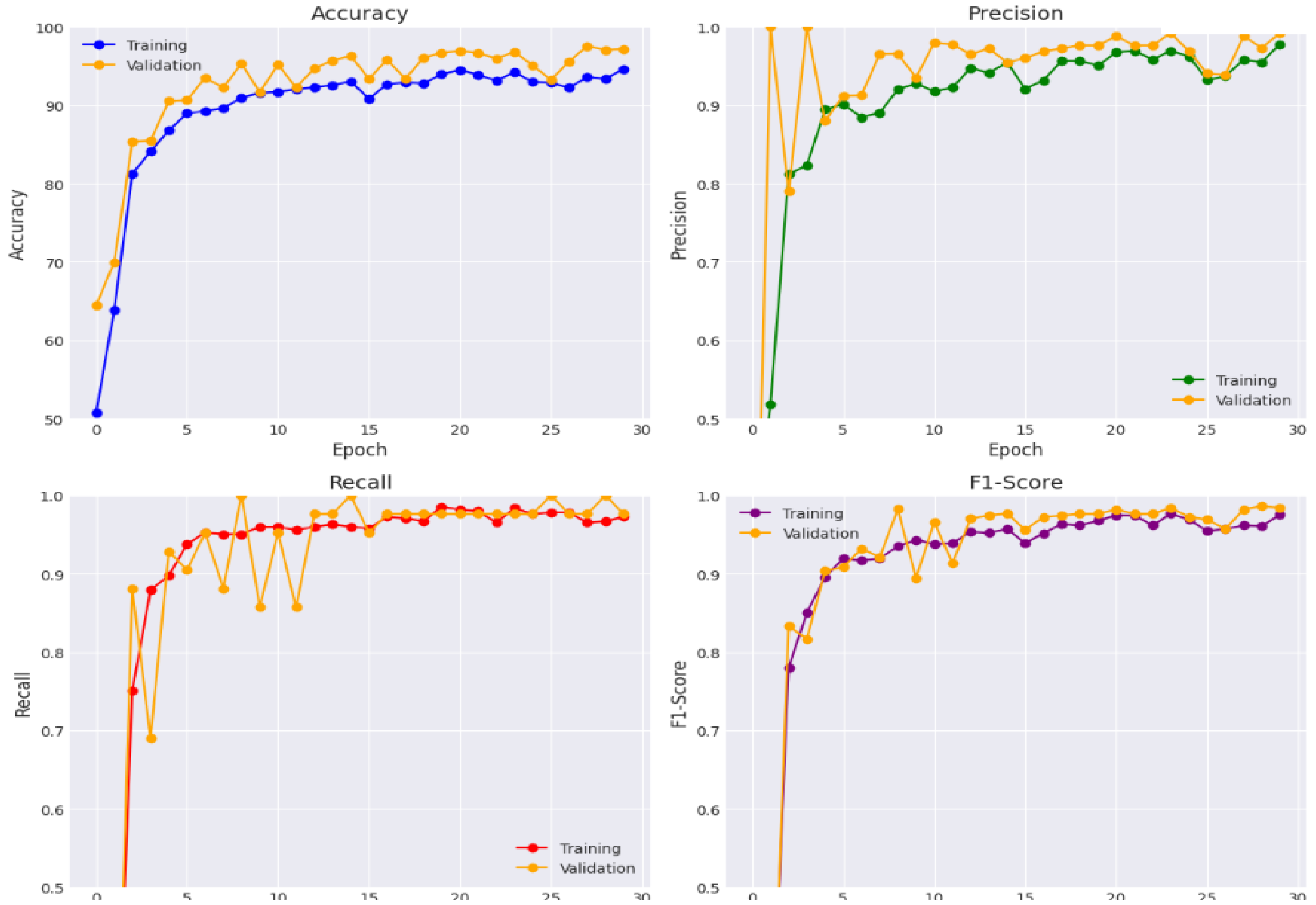


Fig.7 Performance Metric graph of the best Model

Results

Confusion Matrix of 5 Layer custom CNN on the test data set

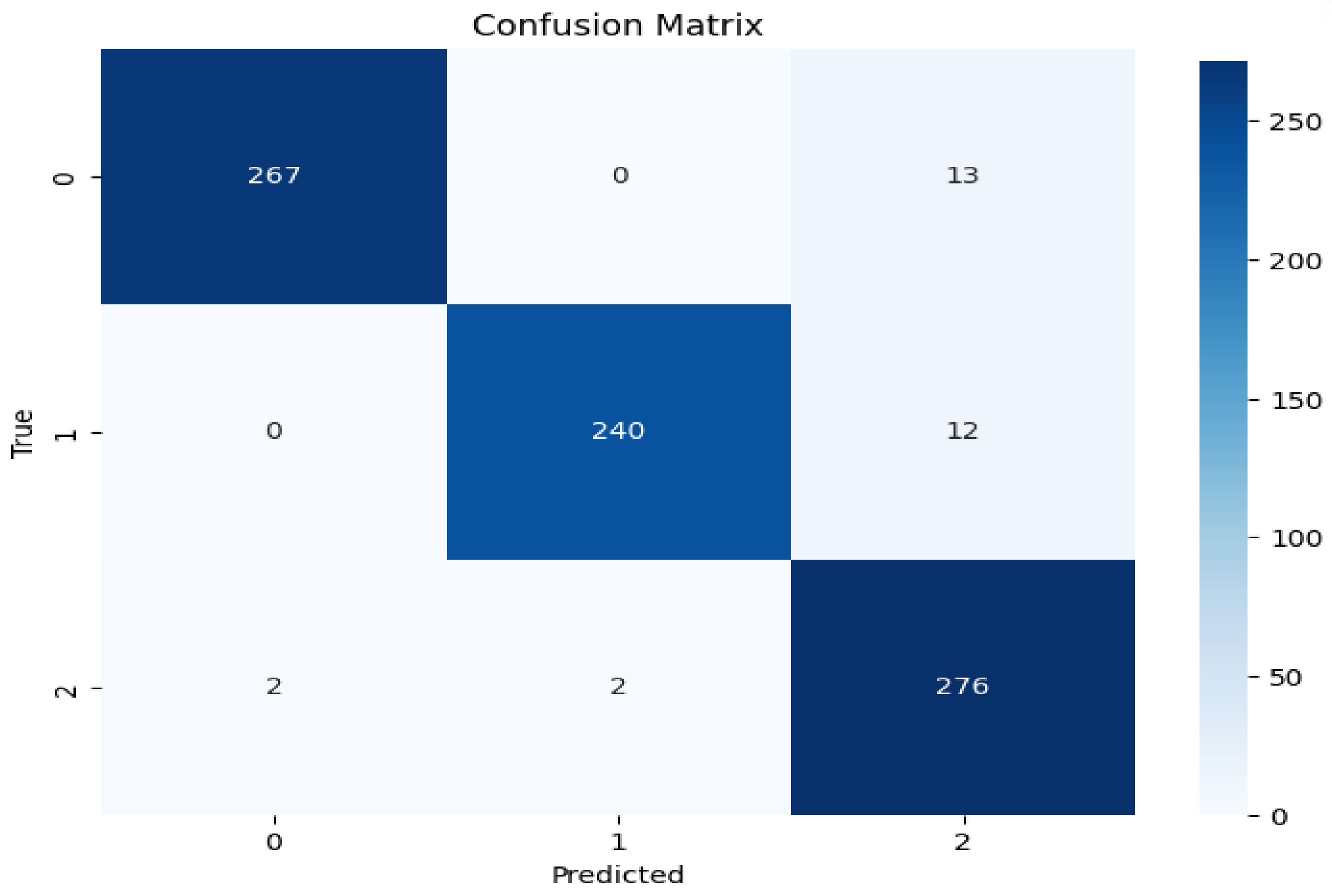


Fig.8 Confusion Matrix of 5 Layer CNN

Results

Classification Accuracy Comparison of 5 Layer CNN model with different optimizers

Table 1: Accuracy Comparison Curves for 5 Layer CNN with different optimizers

Model (with 10 epochs)	Optimizer	Training Accuracy (%)	Validation Accuracy (%)
5-layers CNN	Adadelta	35.76	35.65
	SGD	35.89	38.89
	AdamW	66.946	75.28
	RMS Prop	67.92	78.49
	Adam	**95.89 (97.16 after 30 epochs)**	**96.73 (97.17 after 30 epochs)**

Results

All Losses of the different models

- Mobilenet
- 4_layer_Conv
- 5_layer_Conv(Best Model)

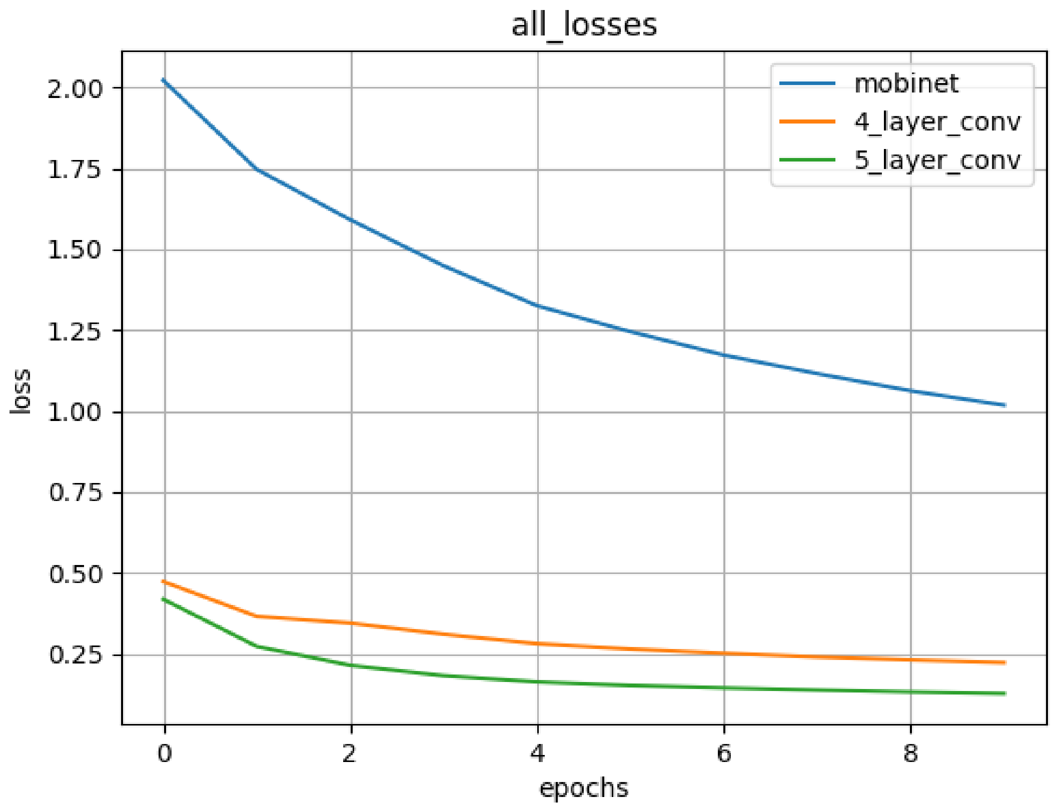


Fig.9 All Losses of the different models

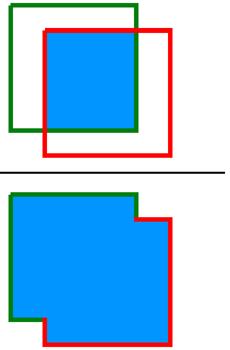
Results

Detection:

IoU(Intersection over Union) Curves of 5 Layer CNN model with different optimizers

- Best value of 0.78 with a threshold of 0.6

$$IOU = \frac{\text{area of overlap}}{\text{area of union}} =$$



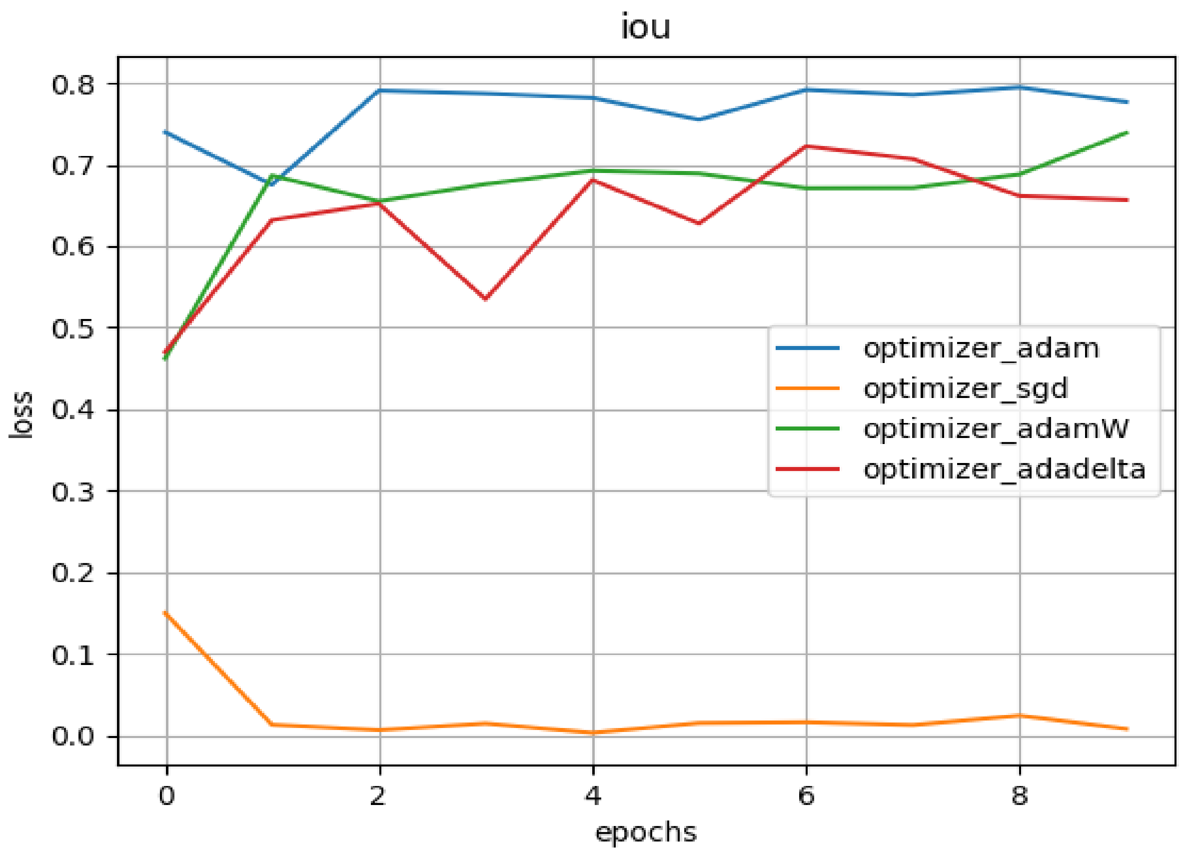
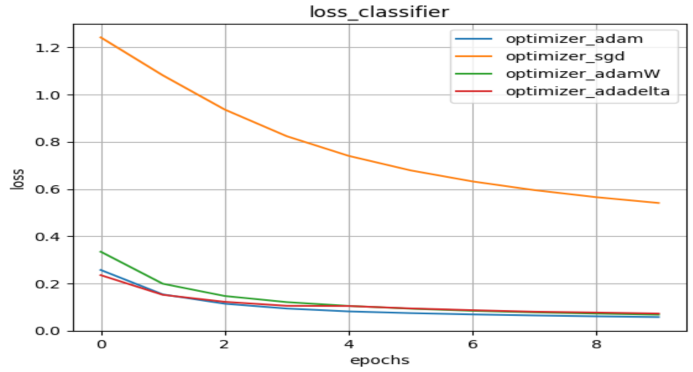


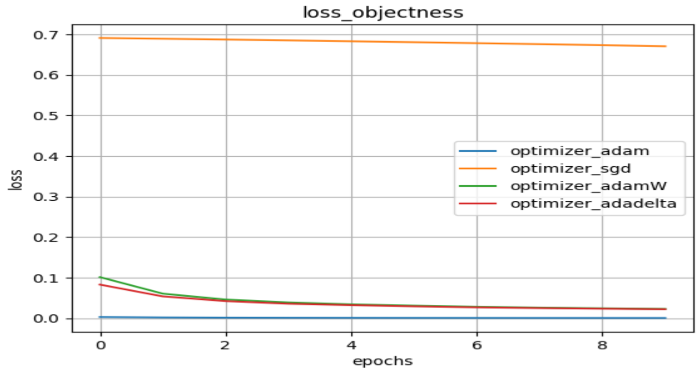
Fig. 10 IoU Curves for 5 Layer CNN with different optimizers

Results

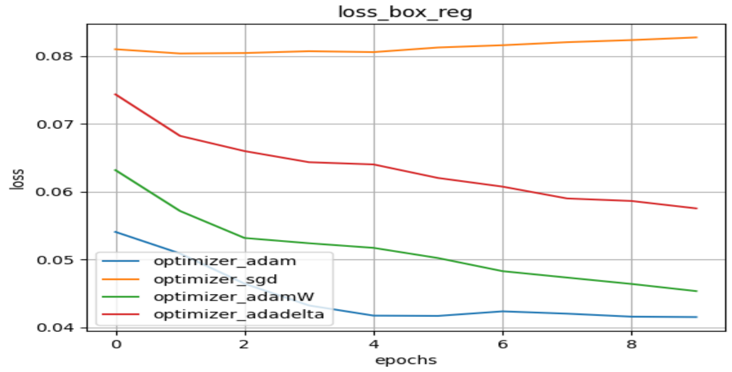
Comparison of various losses



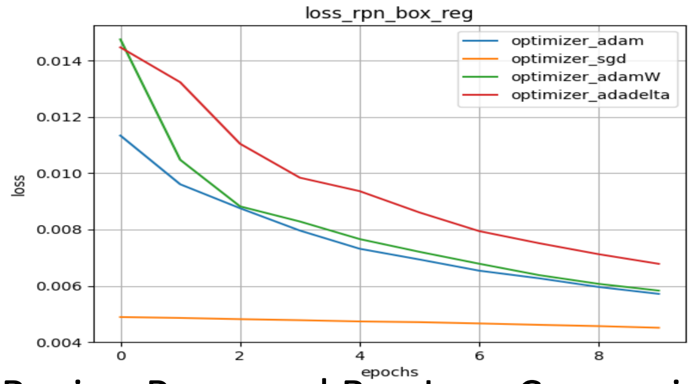
Classifier Loss Comparison



Objectness Loss Comparison



Regression Box Loss Comparison



Region Proposed Box Loss Comparison

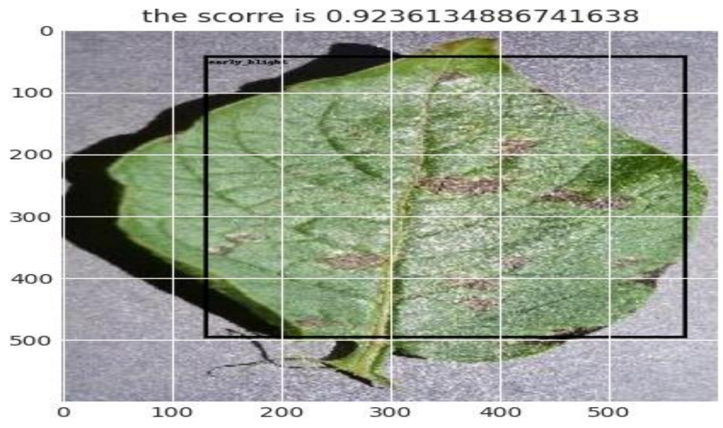
Results

Table 2: Loss and IoU Comparison of the 3 considered backbone architecture

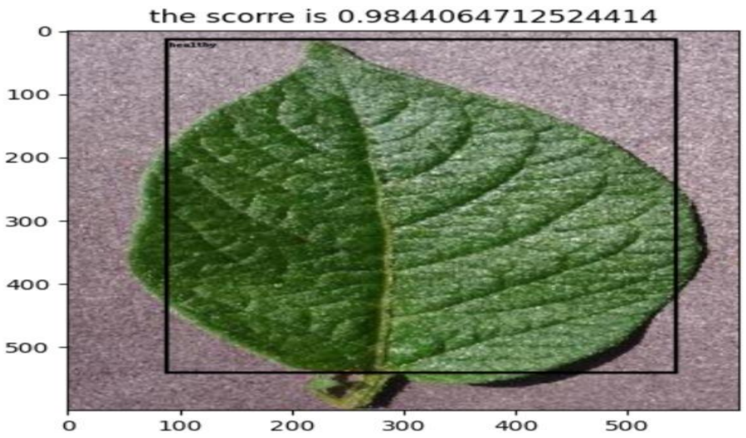
Backbone CNN Architecture	Accuracy	Loss_box_reg	Loss_Classifier	Loss_objectness	Loss_rpn_box_reg	IoU
4_layer_cnn	73.21	1.137	0.0698	0.017	0.0089	0.653
5_layer_cnn	**97.16**	**0.0415**	**0.0581**	**0.00052**	**0.0057**	**0.7845**
Mobilenet	78.43	0.924	0.0671	0.013	0.0432	0.648

Results

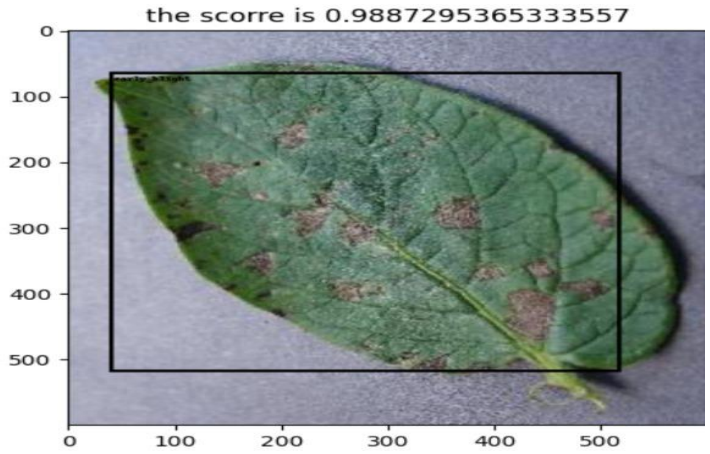
Detected Sample Output Images



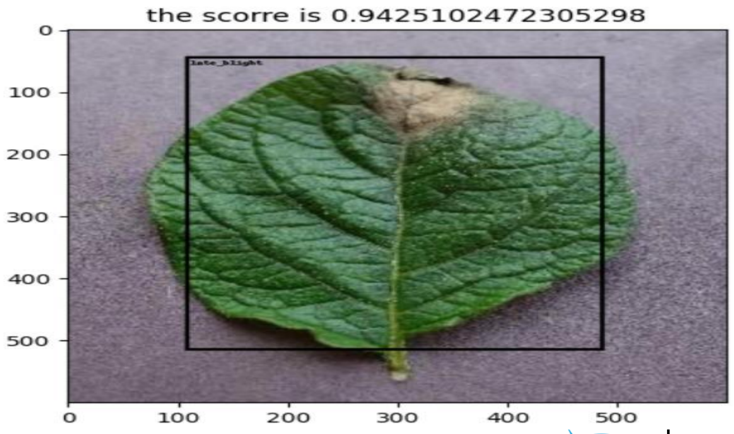
Early Blight



Healthy



Early Blight



Late Blight

Discussions

Key Findings

- **Model Performance:**
  - The 5-layer custom CNN, trained for 30 epochs, was the best-performing model and was integrated into the Faster R-CNN (FRCNN) detection model for identifying diseased potato leaves.
  - The 5-layer CNN outperformed other models in detection accuracy, and its IoU comparison across different optimizers and classifier models confirmed its superiority.
- **Impact of Data Augmentation:**
  - The use of data augmentation techniques significantly improved model performance by balancing the dataset and enhancing feature diversity.
  - Augmentation led to a more generalized model capable of better handling variations in real-world scenarios.

Societal Impacts

- **Increased Efficiency for Farmers**: Early and accurate disease detection reduces labor costs and time for farmers, enabling them to make better-informed decisions.

- **Support for Sustainable Agriculture**: The integration of AI and computer vision supports sustainable farming methods, helping conserve resources like water and soil.

- **Economic Growth in Agriculture**: Implementing advanced technologies in agriculture can drive economic growth, creating opportunities for innovation and job creation in rural areas.

- **Global Scalability**: The technology can be adapted to different crops and regions, making it a versatile tool for farmers worldwide.

Conclusions

- Highlights the potential of smart agriculture through the integration of computer vision and deep learning for automating the detection of potato leaf diseases.

- The custom 5-layer CNN model achieved a validation accuracy of **97.16%**, demonstrating its effectiveness in detecting diseased potato leaves with **Adam** optimizer.

- AI and computer vision enhance **smart agriculture** by automating crop disease detection, promoting **sustainable farming** leading to environmentally responsible practices.

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Thank you!