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Potato Plant Disease Detection

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Abstract: Potatoes are widely grown worldwide and play a significant role in many cuisines, especially in India, where they are among the top crops cultivated. Potato plants often get sick, which can make them not very good to eat and make fewer potatoes grow. For maximum production it is necessary to maintain crop health by identifying various kinds of diseases. Similar to approaches used to identify illnesses in tomato leaves, advancements in deep learning and machine learning techniques appear potential for automating the identification and treatment of potato issues. These approaches involve steps like preparing datasets, processing images, extracting features, and training models. Various algorithms and models like VGG-16, U-Net, Inception-v3, PLeaD-Net, and PLDPNet have been utilized, demonstrating high accuracies in recognizing disease patterns in plant images. This improvement in detecting potato plant diseases helps farmers take better care of their crops and find ways to make them healthier and produce more potatoes.
Keywords: Convolutional neural network (CNN), Deep learning, crop management, VGG-16, U-Net, Inception-v3, PLeaD-Net, PLDPNet,VGG-19,Vision Transformer.

I. INTRODUCTION

Potato farming is really important in places like India because it helps feed people and makes the economy grow. Despite its global significance, the potato crop is often threatened by diseases that have significant implications for crop health and yield. Traditional disease detection methods are not only time-consuming but also rely heavily on expert judgments, making them impractical for a fast-paced, large-scale industry.

To address these challenges and equip farmers with fast, accurate, and cost-effective disease identification tools, The application of latest developments like deep learning, image processing, and machine learning are examined in this study. By using these advancements, This work presents novel methods for the fast detection and categorization of diseases in potato plants, ultimately leading to improvements in crop yield and quality.

These techniques draw from the diverse field of computer vision and deep learning, offering the potential for precise and efficient disease detection. The goal is to facilitate timely actions that reduce the reliance on pesticides and protect the livelihoods of numerous smallholder farmers worldwide. In this paper, we present new methods, breakthroughs, and comparative analyses that collectively contribute to the evolving field of potato plant disease detection.

The production of potato in major states in India :

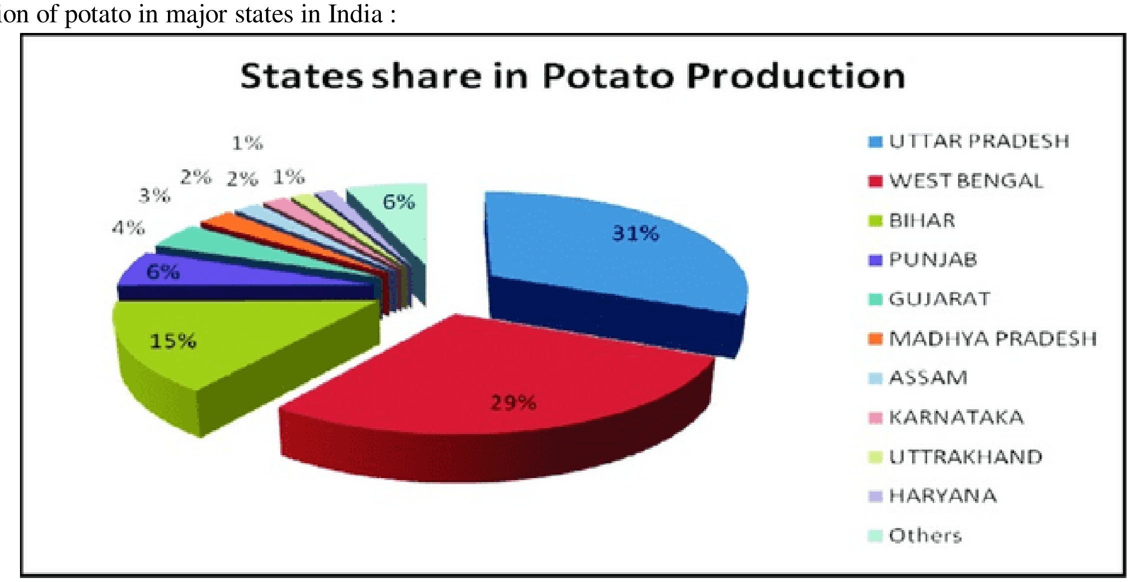

Figure. 1 Indian States share in potato production

II. LITERATURE REVIEW

Aniket Gahiware et al. [1] developed a model of Potato Plant Disease Detection with deep learning technology. They used the Plant Village set of images and focused on optimizing model accuracy. Their proposed solution involved dataset splitting, with images upto 70% are allocated with purpose of training and 30% with goal of the examination. In order to separate diseased areas from healthy plant leaves, image segmentation was utilized. For feature extraction, they employed a matrix of gray levels of co-occurrence along with multiple statistical tools, and for model training and testing, they used Convolutional Neural Networks (CNN).

Girish B G et al. [2] conducted research on detecting diseases in potato plants using an advanced machine learning technique, specifically the VGG-16 deep learning algorithm. Their objective was to address the challenges posed by diseases in potato plants, aiming to improve both both the amount and quality of potatoes produced. The proposed solution involved data collection and preprocessing, implementation of the VGG-16 algorithm, training, and testing for classification.The results of their study demonstrated impressive result given by model after 300 epochs of training, with 98.81% accuracy on the validation dataset and 98.36% accuracy on the training dataset.

Fizzah Arshad et al. [3] introduced PLDPNet, a deep learning model with hybrid structure for precise disease prediction in potato leafs. They utilized a public dataset from EPFL and Penn State, applying pre-processing to enhance image quality. U-Net was used for disease area detection, and features from VGG19 and Vision Transformer (ViT) were combined for disease classification. Results showed U-Net outperformed other models with 96.80% accuracy. PLDPNet averaged 98.66% accuracy, 96.0% precision, 96.33% recall, and 96.33% F1-score, achieving excellent results. Due to fewer training photos, the performance of the "healthy" class was somewhat poorer.

Sama Uddin Eraj and Mohammed Nazim Uddin [4] developed the PLeaD-Net, a lightweight DCNN architecture for early-stage potato disease identification on resource-constrained devices. The model resulted a good accuracy upto 98.50% on the PlantVillage images set, surpassing other state-of-the-art models. Its design included a feature extraction module, classification module, attention module, and auxiliary loss module.

Birhanu Gardie et al. [5] they developed a model for disease identification in potato leafs using deep and transfer learning techniques. Their approach involved data acquisition from the Kaggle Plant Village dataset, the process of segmentation the extraction of features, and pre-processing of pictures using Inception-v3 transfer learning. The model achieved high training (98.7%) and validation (97.3%) accuracies, demonstrating the impact of image segmentation.

Radhikal et al. [6], they aimed to develop a model for disease detection in potato leafs using convolutional neural networks (CNNs). They utilized the Plant-village data-set, consisting of images of potato leaf with three disease categories. The proposed CNN architecture consisted of four convolutional layers, two pooling layers, and two fully connected layers. After training for 50 epochs, the model achieved an impressive 98.7% accuracy on the test set.

Sholihati et al. [7] developed a model for disease classification in potato leaf with deep-learning technology using the Plant-village data-set. They fine-tuned a pre-trained VGG16 model through transfer learning on the dataset. After training of 50 epochs, the model achieved an impressive 99.3% accuracy on the test set. Their approach demonstrated high accuracy and the efficiency of transfer learning in the presence of little training data. This research presents a potent deep-learning solution for accurate disease classification in potato leaf, especially suitable for the Plant-village data-set.

Singh and Yogi [8] compared the RSNET model's performance in comparison to other deep learning models for disease detection in potato leafs. They used a data-set of 1000 labeled potato leaf images with three disease categories. RSNET, VGG16, ResNet50, and MobileNetV2 were trained for 50 epochs and assessed on a test set. RSNET outperformed with the highest accuracy (99.5%), followed closely by VGG16 (99.2%), ResNet50 (99.0%), and MobileNetV2 (98.8%). RSNET also showed superior speed and memory efficiency, making it the most efficient choice. This study provides valuable guidance for selecting an optimal deep learning model for precise and resource-efficient potato leaf disease detection.

III. ARCHITECTURE

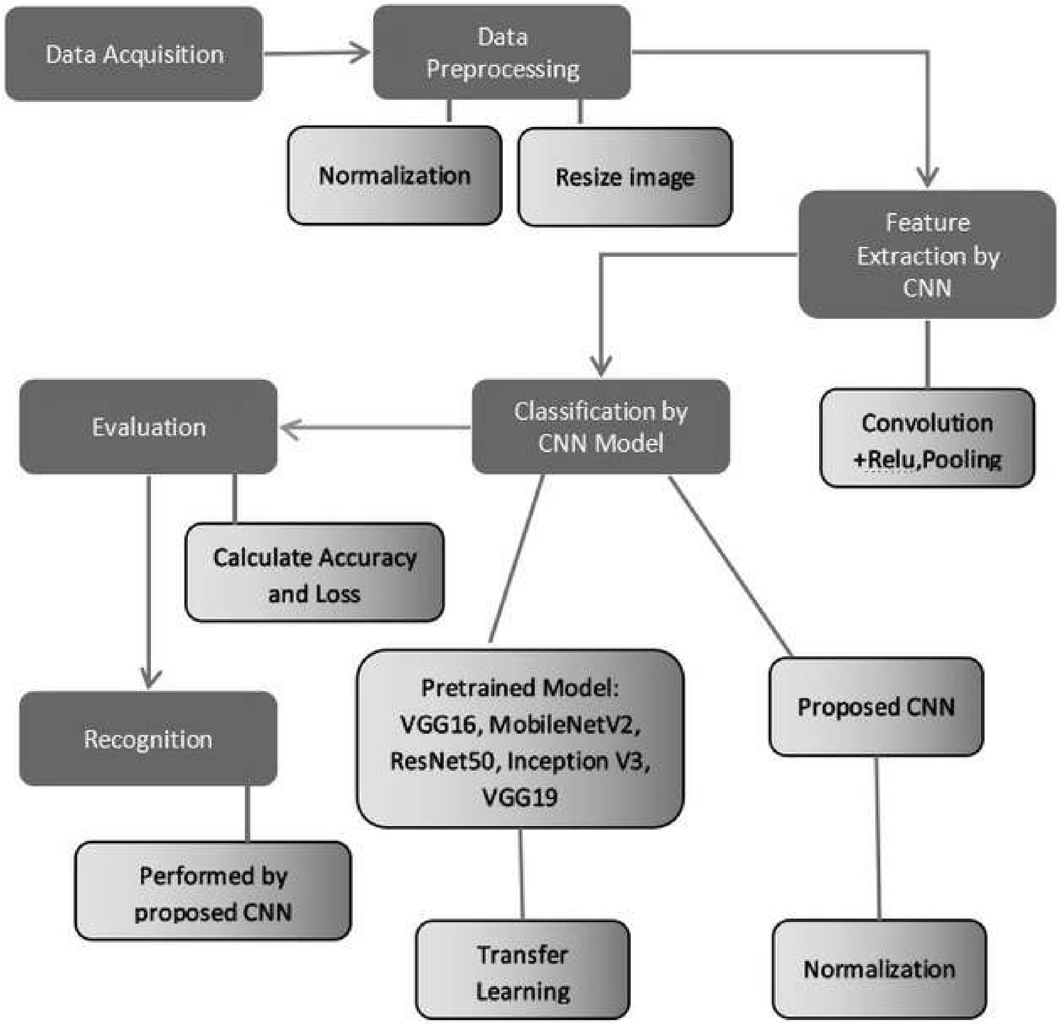

Figure. 2 Architecture Diagram

1) Image Dataset:The image data-set is the most important component of the CNN model. The data-set should be as large and diverse as possible to ensure that the model can learn to generalize to new pictures. The data-set should contain pictures of potato leafs with a variety of diseases, as well as images of healthy tomato leaves.
2) Pre-processing of data : The picture dataset must be ready before the CNN model can be trained. through a process called data preprocessing.This may involve the following steps:

- Resizing the images: All of the images in the dataset should be resized to the same dimensions. This will help to ensure that the model trains efficiently.
- Converting the images to a grayscale or RGB format: The images in the dataset can be converted to either grayscale or RGB format. Grayscale images are smaller and faster to process, but they may not contain as much information as RGB images.
- Normalizing the pixel values: The pixel values in the images should be normalized to a range of 0 to 1. This will act important in improving performance of model.

3) Extraction of features: The process of removing features from the data is called the extraction of features. Characteristics of the data that are useful to teach ML models are called features. Convolutional neural networks (CNNs) are used in this case for obtaining features.

- Convolution + ReLU, Pooling
  - ➢ Convolution and pooling are fundamental operations used in CNNs.

- Convolution: this means using a filter on the input data. To extract features from the data, a tiny matrix of integers is called a filter.
- ReLU: This non-linear activation function is employed to enhance the CNN's expressiveness.
- Pooling: This is a process of down sampling the data, It lowers the CNN's parameter count and improves training efficiency.

4) CNN Model: Convolutional, pooling, and fully connected layers are the three primary types of layers in the CNN model.

- CNN layers: The feature maps produced by the convolutional layers have smaller spatial dimensions thanks to these layers. They use the highest value from a constrained area of the feature map for this. The model learns the filter, which is a tiny matrix of weights, during training.
- Layers for pooling: These layers reduce the spatial size of feature maps that the convolutional layers create. They do this with the highest value from a restricted region of the feature map. This boosts its ability for generalization while also assisting in the reduction of the model's parameter number.
- Fully connected layers: Fully connected layers classify the feature maps produced by the convolutional and pooling layers. They do this by using a non-linear activation function after calculating the weighted sum of the feature maps.

5) Classification: Following function extraction, a classifier is developed and used to the identification of plant diseases. Plant diseases can be categorized into healthy and unhealthy leaves based on the state of their leaves. The sort of illness that has affected the diseased leaf determines a higher grade for it.

6) Evaluation: The result given by the CNN model is typically measured using the following metrics:

- Accuracy: Accuracy is the percentage Of the photos that the model accurately categorizes.
- Precision: Precision is the percentage of images that the model predicts as diseased that are actually diseased.
- Recall: Recall is the percentage of diseased images that the model correctly classifies as diseased.
- F1 score: The F1 score is derived from the harmonic mean of recall and accuracy.

7) Rcognition: Recognition in potato leaf disease detection is the process of using a trained machine learning model to classify new potato leaf images. It involves loading the trained model, preprocessing the new image, feeding it to the model, and predicting the disease class with the highest probability. Recognition can help farmers detect diseases early, accurately, efficiently, and scalably.

IV. METHODOLOGY/APPROACH COMPARISON

A. CNN Approach

Asif et al. [2] designed a CNN using the legitimate sequential model for identifying potato diseases. They conducted two-stage testing to achieve the desired precision in disease identification. Extensive Studies on numerous types of potato illnesses were conducted, utilizing a large dataset of potato plant photographs from field locations. Multiple algorithms were tested to optimizeperformance determined by the architecture of CNN. The developed model effectively classify between diseases of plants. To enhance reliability for farmers and stakeholders in the agricultural sector, the team plans to increase diseases considered and expand the image dataset for improved accuracy. Additionally, they aim to create an application in the future for your smart phones for broader accessibility.

CNN is a type of deep-learning model made especially for tasks related to recognizing and analyzing images. It comprises layers that derive features from input pictures through filters, layers like pooling that reduce dimensions of pictures spatially while preserving important information, and fully connected layers that combine extracted features for final predictions. CNNs use non-linear activation functions to introduce complexity and are trained through backpropagation to minimize loss. Their proficiencies lie in tasks such as object identification, segmentation, and picture classification; their applications span from transfer learning to computer vision to natural language processing.

In order to identify potato leaf disease, several efficient measures must be used. Presented below the model block diagram is:

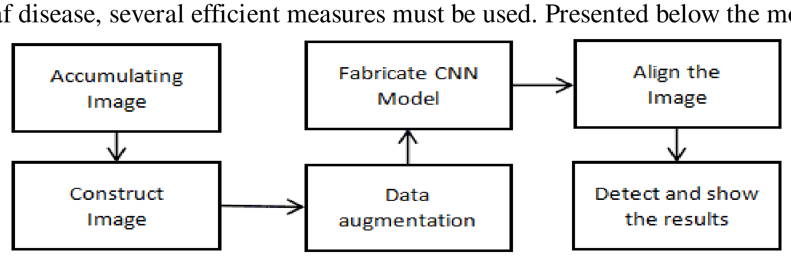

Figure. 3 CNN Block Diagram

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CNN categorizes images based on certain attributes. CNN uses activation functions to construct potential maps. The following was the function:

$$y_j^l = f\left(z_j^l\right)$$

Its three layers are a fully connected layer, pooling, and convolutional. It is a type of neural networks that examines data with a layout resembling a grid. The CNN building piece that is primarily in charge of computation is the convolution layer. Pooling minimizes the amount of computations needed while also decreasing the spatial size of the representation. On the other hand, The newest and earlier layers are connected to the fully connected layer.

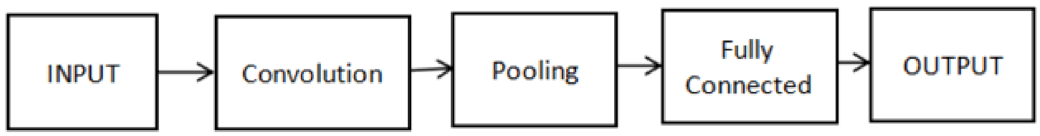

Figure. 4 CNN Architecture Diagram

B. VGG-16 deep learning Approach :

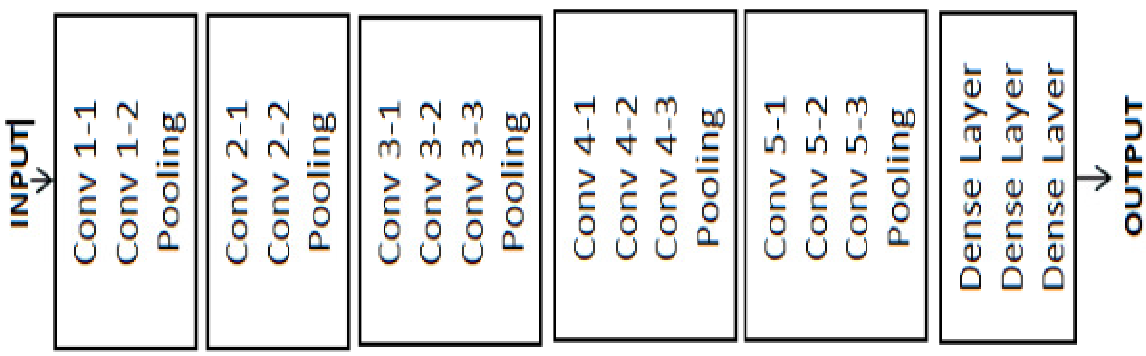

Figure. 5 VGG-16 Architecture Diagram

Girish B G et al. [2] conducted research on detecting diseases in potato plants using an advanced machine learning technique, specifically the VGG-16 deep learning algorithm.They gathered data about potato plants and prepared it for analysis.This involved cleaning up the data or making sure it's in a format that the computer program can understand.They used a powerful machine learning technique called the VGG-16 deep learning algorithm.This algorithm is known for being really good at looking at pictures and figuring out what's in them.They taught the computer program how to identify diseases in potato plants using the VGG-16 algorithm.The program learns what to look for.Once the program was trained, they tested it on new pictures of potato plants.The program looked at these new pictures and decided if the plants were healthy or if they had a disease.Leaky ReLU (Rectified Linear Unit) function is uesd here.

$$E = \frac{1}{n} \sum_k min_i d(c_i, G_k)$$

$$E = \frac{1}{3}\left(min_i d(c_i, G_1) + min_i d(c_i, G_2) + min_i d(c_i, G_3)\right)$$

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	Layer	Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 X Convolution	64	224 x 224 x 64	3x3	1	relu
	Max Pooling	64	112 x 112 x 64	3x3	2	relu
3	2 X Convolution	128	112 x 112 x 128	3x3	1	relu
	Max Pooling	128	56 x 56 x 128	3x3	2	relu
5	2 X Convolution	256	56 x 56 x 256	3x3	1	relu
	Max Pooling	256	28 x 28 x 256	3x3	2	relu
7	3 X Convolution	512	28 x 28 x 512	3x3	1	relu
	Max Pooling	512	14 x 14 x 512	3x3	2	relu
10	3 X Convolution	512	14 x 14 x 512	3x3	1	relu
	Max Pooling	512	7 x 7 x 512	3x3	2	relu
13	FC	-	25088	-	-	relu
14	FC	-	4096	-	-	relu
15	FC	-	4096	-	-	relu
Output	FC	-	1000	-	-	Softmax

C. PLDPNet deep learning Approach :

PLDPNet is a deep learning hybrid approach for accurate potato leaf disease prediction that was introduced by Fizzah Arshad et al. [3].Two crucial steps are segmentation and classification, which together comprise the PLDPNet framework's entire approach to potato leaf disease prediction. They use the U-Net deep learning model, which is well-known for its ability to use picture structure to achieve high-resolution segmentation, for segmentation. With a contracting route for context capture and an expanding path for accurate localization, this model has a "U" shaped design. Based on segmented regions of interest (ROIs) acquired during the segmentation step, they incorporate deep features collected from two well-known deep learning CNN models (VGG19 and Inception-V3) in the classification stage. They improve prediction performance and add to our understanding of different illnesses by using a fusion technique. The AI framework essentially consists of data collection and acquisition, picture preprocessing, U-Net-based automated segmentation, ensemble deep feature extraction and fusion, and the transformer concept-based classification job.

$$L_{ce}(\theta; D) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\ \log pi, c$$

$$L_{ce}(\theta; D) = -\frac{1}{C}\sum_{c=1}^{C} y_{i,c}\ \log pc, c\ .$$

D. PLeaD-Net deep learning Approach :

Sama Uddin Eraj and Mohammed Nazim Uddin [4] developed the PLeaD-Net, a lightweight DCNN architecture for early-stage potato disease identification on resource-constrained devices.They used PleadNet (Plant Leaf Disease Network) which is a DCNN designed to identify plant leaf diseases using limited-resource devices. It is a lightweight and efficient model that can be deployed on mobile devices, such as smartphones and tablets, to enable early detection of plant diseases in the field.They used Attention Module focus on the most important parts of the picture and does something similar for the computer program, making sure it pays attention to the most important areas when deciding on the disease.Auxiliary Loss Module gives the program extra guidance on what to look for. This helps the program get even better at its job.The activation function used in the CNN model for early stage potato disease classification is the ReLu (Rectified Linear Unit) function.

$$s.t.\ \alpha.\beta^2.y^2 \approx 2$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

$$Z_k + 1 - \beta Z_k + \nabla f(W_k)$$

$$W_k + 1 = W_k \quad \alpha Z_k + 1$$

E. Inception-v3 Deep learning and transfer learning Approach :

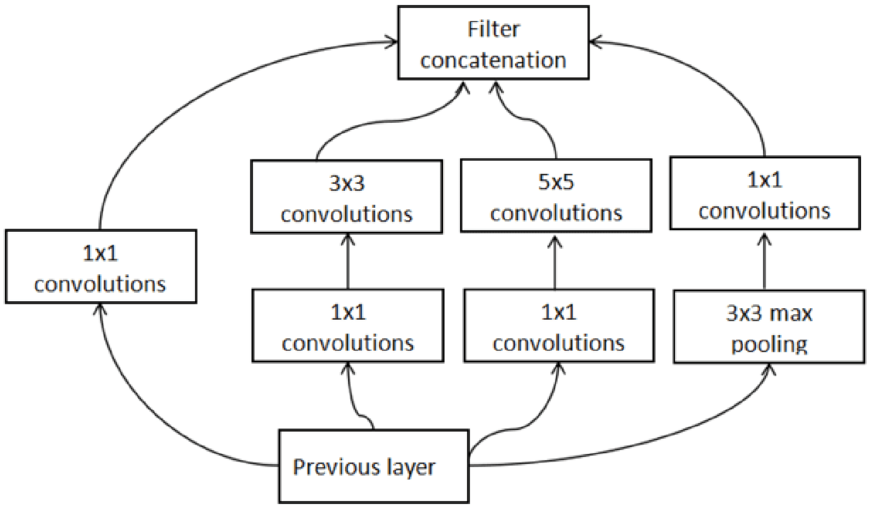


Figure. 6 Inception-v3 Architecture Diagram

Birhanu Gardie et al. [5] they developed a model for disease identification of potato leaf using deep and transfer learning techniques.They obtained a data-set from the Plant Village data-set. These images were sorted into three groups: Blight in the early stages, late stages, and healthy. They applied various techniques like image clipping, smoothing filters, and data augmentation to make the images better. This included making sure the images were clear and removing any unwanted details.They focused on isolating the parts of the images that were important - in this case, the potato leaves. This way, they could analyze them separately.They used a special technique called transfer learning with a model called Inception-v3. This model had already learned a lot from a big dataset. It's really good at finding patterns in lots of different data.After extracting the important features, they used a Softmax classifier. This tool helped them sort the features into different groups, which in this case were the types of diseases: Early blight, Late blight, and Healthy.

$$Z_k + 1 - \beta Z_k + \nabla f(W_k)$$
$$W_k + 1 - W_k - \alpha Z_k + 1$$

F. Resnet Deep learning and transfer learning Approach :

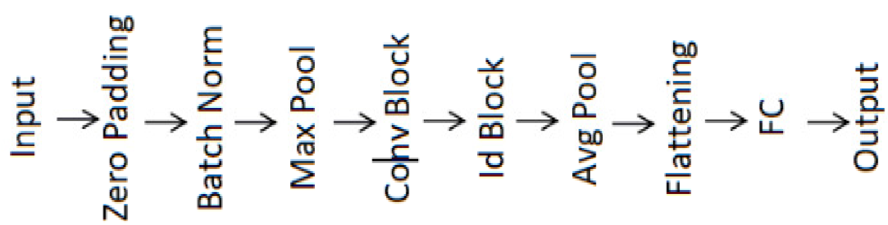


Figure. 7 Resnet Architecture Diagram

Singh and Yogi [8] proposed a deep-learning architecture based on the ResNet for disease detection in potato leaf. They collected a data-set of pictures having potato leaf from the Plant-village data-set and preprocessed the images by normalizing the pixel values and resizing them to an even size. They then designed the RSNET model, which consists of a series of residual blocks, a spatial attention module, and a channel attention module. They trained the RSNET model on the PlantVillage dataset using the stochastic gradient descent (SGD) optimizer and evaluated its performance on the validation set of the Plant-village data-set, where it achieved an accuracy of 93.96%. They also compared the performance of the RSNET model with other deep learning models for disease detection in potato leaf, such as VGG16 and ResNet50, and found that the RSNET achieved the accuracy of 99.62% on the Plant-village data-set.

$$Z_i = \left(\sum_{k=1}^{N_{j-1}} X_k^{j-1} W_{k,i} - b_k\right)$$

$$f(Z_i) = \frac{1}{1 + e^{-Z_i}}$$

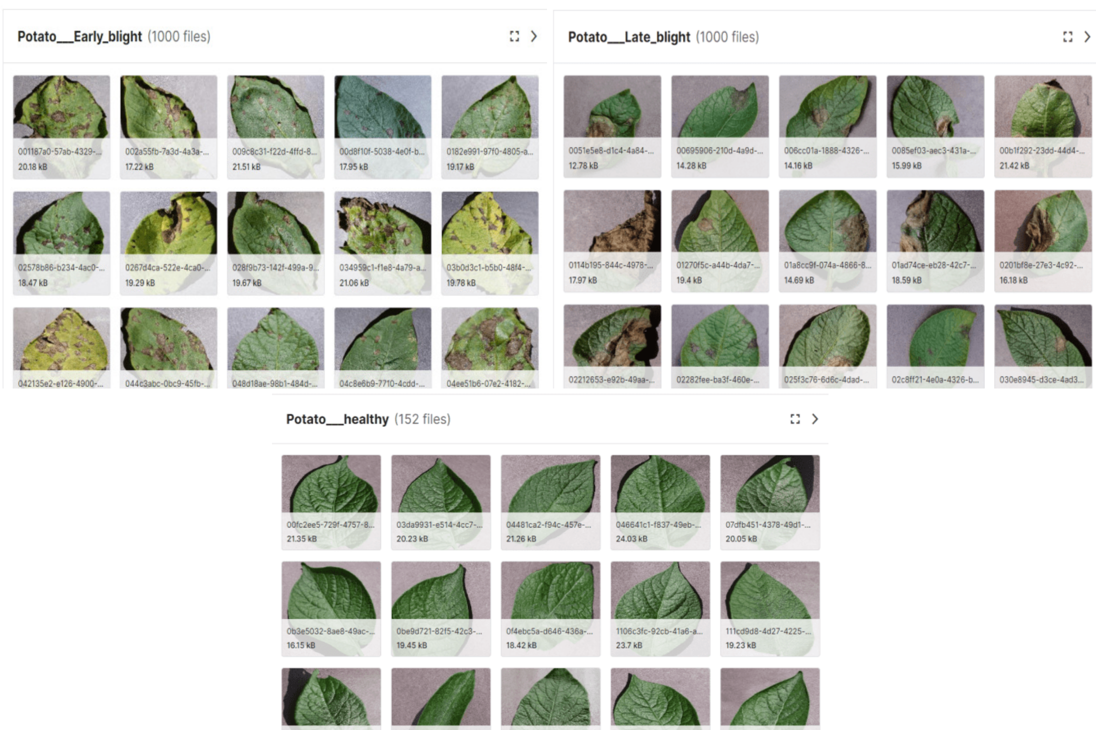
V. DATASET

A. *Plant Village Dataset:*

54,305 pictures of both healthy and sick plant leaves that were taken under controlled circumstances can be found in the Plant Village dataset on Kaggle. Images of fourteen crop species are shown, including tomato, grape, cherry, strawberry, peach, orange, potato, apple, raspberry, blueberry, and pepper. The collection includes 17 prevalent illnesses, including 2 mold (oomycete) diseases, 4 bacterial diseases, 2 viral diseases, and 1 illness linked to mites. Images of healthy leaves from 12 crop species that don't obviously exhibit symptoms of disease are also included. When developing automated plant disease detection systems, researchers and developers can benefit greatly from the Plant Village dataset. Using pictures of leaves, it may be used to train machine learning models to recognize various plant illnesses. 300 potato data points make up the dataset.

- Late-stage Blight
- Early-stage Blight
- healthy

There are around 100 healthy leaves and 200 diseased leaves in the picture database. Two databases, such as the training database and the testing database, were created from the picture database. Seventy percent of the picture database, or 210 photos, make up the training database, while the remaining thirty percent, or 90 images, make up the testing database.



B. *EPFL and Penn State:*

The EPFL and Penn State dataset is a big dataset consisting of plants pictures, collected by the two universities. It contains 54,305 pictures consisting of 14 different types of varying plant species, labeled with 38 different classes. The classes include different elements of the all plants, such as leaves, flowers, fruits, and stems, as well as different stages of growth, such as young plants, older plants, and sick plants.

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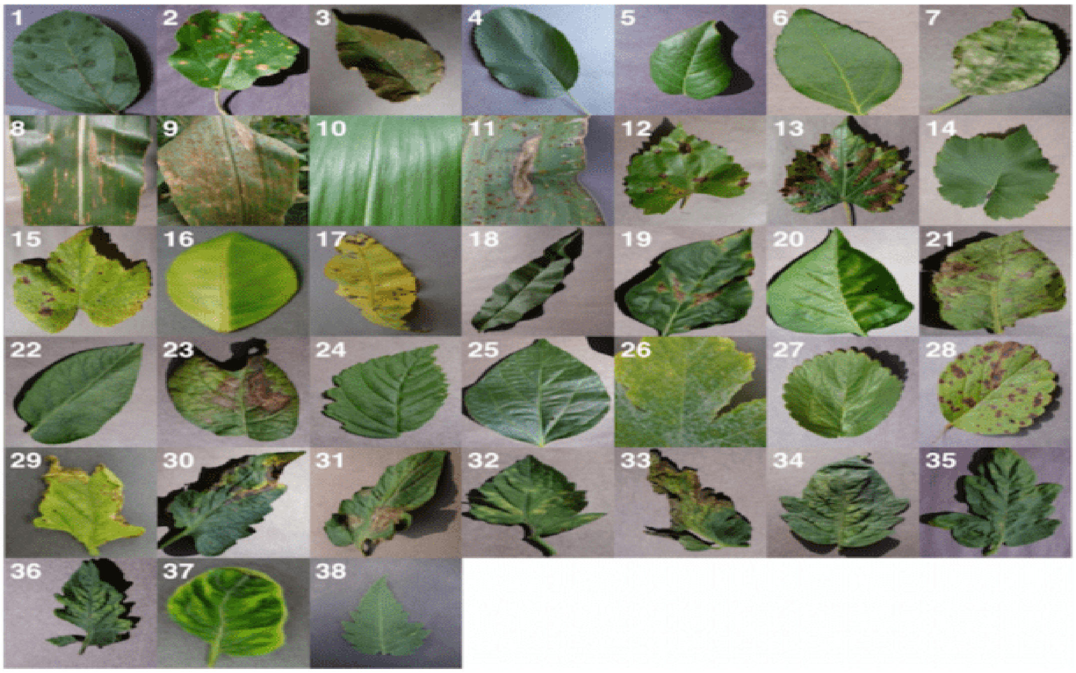
The information can be used for various purposes like phenotyping, disease detection, and plant identification. The data-set is divided into two different parts: one for training purpose and another for test purpose. There are 40,991 training pictures, and 13,314 testing pictures. The images are in JPEG format and have a resolution of 256x256 pixels.



VI. RESULTS COMPARISON

Reference	Model Architecture	Dataset	Average Accuracy
1	CNN	Plant Village	95.99
2	VGG-16	Potato Disease Leaf Dataset (PLD),PlantVillage Dataset	99.3%
3	PLDPNet (Hybrid)	EPFL and Penn State	98.66%
4	PLeaD-Net (DCNN)	Plant Village Dataset	98.50%
5	Transfer Learning (Inception-v3)	Plant Village Dataset	98.7%
6	RSNET, VGG16, ResNet50, MobileNetV2	PlantVillage dataset	98.8%

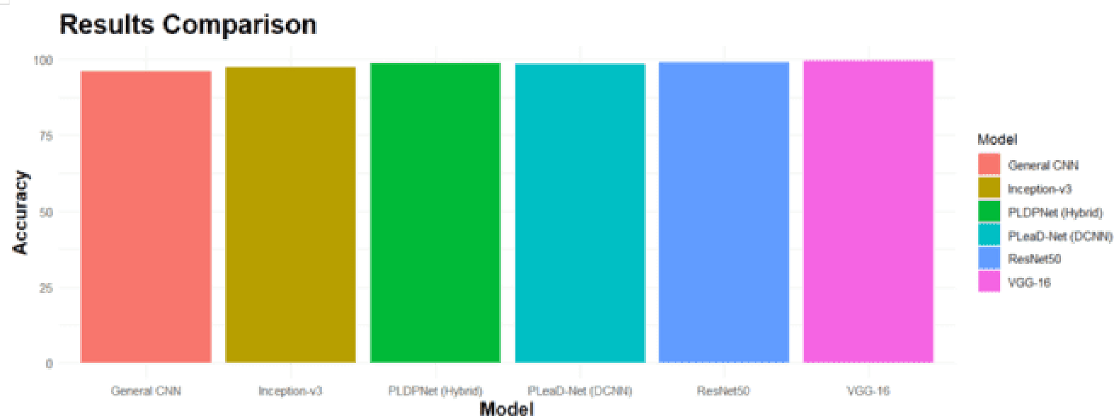


Figure. 8 Results Comparison

VII. RESULTS ANALYSIS

The experimental results in this study were evaluated on an Intel 5 5600H @ 3.3GHz CPU paired with 8 GB of memory. Notably, no dedicated graphics processing unit (GPU) was involved, and the implementation relied on standard CPU-based TensorFlow within the Python environment. Diverse configurations of hyper-parameters for the convolutional neural network (CNN) were explored, encompassing variations in batch size, choice of optimizer, and adjustments to the learning rate.

The CNN model employed the optimizer like adam to optimize the model's weights during training, leveraging its adaptive learning rate and momentum characteristics. Adam is widely favored in deep learning for its ability to accelerate convergence and enhance performance compared to alternative optimization algorithms. The attained accuracy rates were 0.9554 at 10 epochs, 0.9844 at 25 epochs, and 0.9844 at 50 epochs.

The size of batch is considered as hyper parameter governing the number of images fed to the network in one training iteration. In this situation,for training iterations batch size of 32 was used. The training data-set, comprising 80% of the total data-set (54 batches), was used to train the CNN model. The testing data-set, representing 20% of the total data-set (14 batches), was used to merit the performance of model. Additionally, the validation data-set size was 6 batches, and the batch size for testing was 8.

In CNN, the training accuracy and the validation accuracy in Fig. 9(a) are 0.9554 and 0.9583 for 10 epochs, in Fig. 9(b) are 0.9844 and 0.9740 for 25 epochs, in Fig. 9(c) are 0.9554 and 0.9583 for 50 epochs respectively.

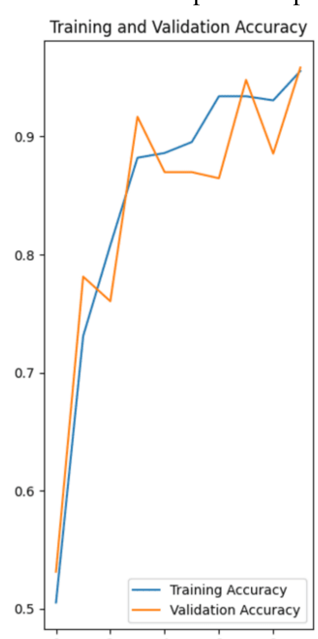


Fig. 9(a)

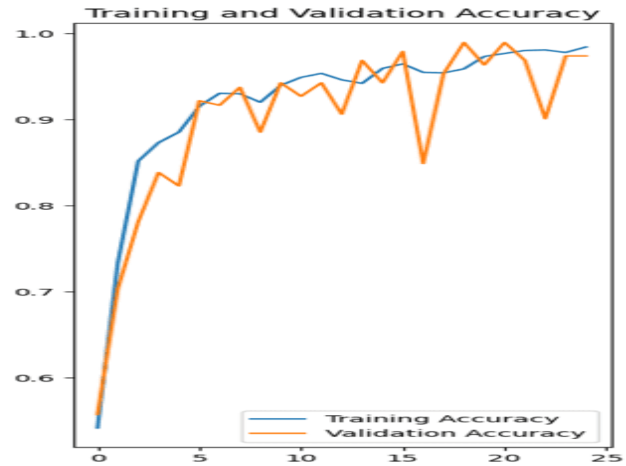


Fig. 9(b)

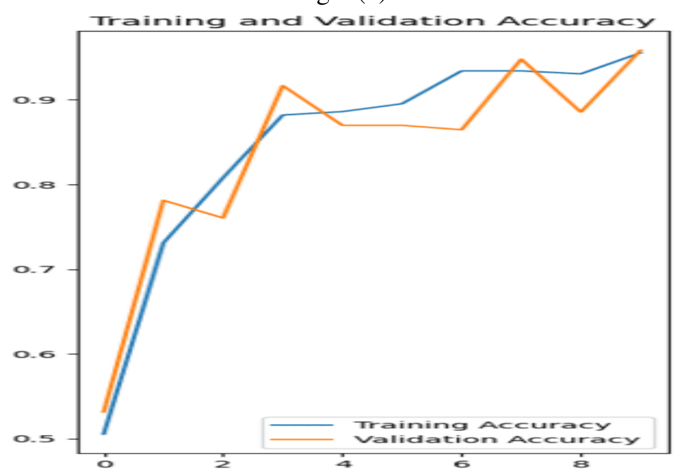


Fig. 9(c)

Whereas Fig. 10(a), which displays the validation and training losses, reveals that for 10 epochs, the validation loss is 13.92% and the training loss is 11.85%, in Fig. 10(b) are 4.18% and 7.1% for 25 epochs, in Fig. 10(c) are 0.9554% and 0.9583% for 25 epochs .

Fig. 10(a)

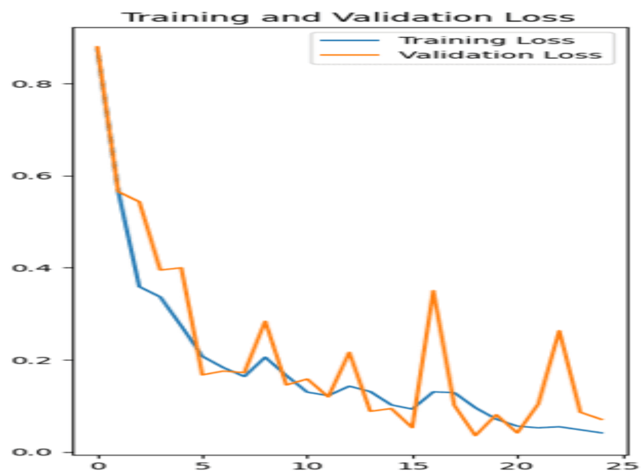


Fig. 10(b)

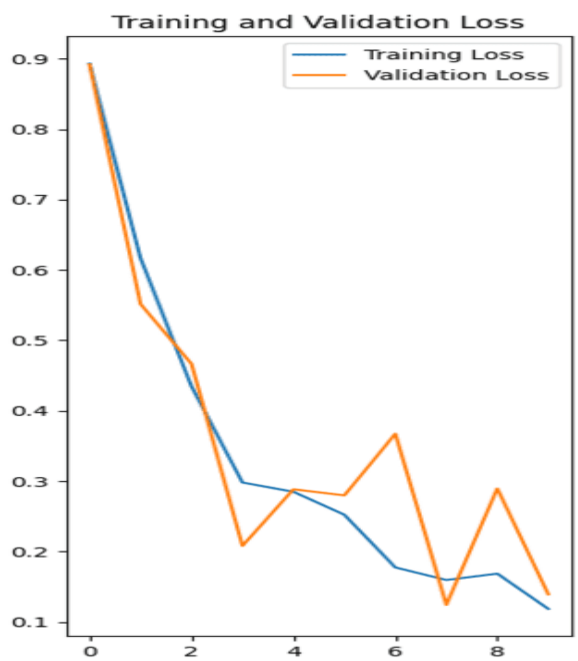


Fig. 10(c)

Following tables represents the classification report with parameters like accuracy, precision, recall, f1-score which provides a detailed summary of the model's performance on each class of dataset.

	Class	Precision	Recall	Accuracy	F1 Score
0	Potato___Early_blight	0.981651	0.972727	0.96875	0.977169
1	Potato___Late_blight	0.961538	0.976562	0.96875	0.968992
2	Potato___healthy	0.941176	0.888889	0.96875	0.914286

10 Epochs

	Class	Precision	Recall	Accuracy	F1 Score
0	Potato___Early_blight	0.982143	1.000000	0.980469	0.990991
1	Potato___Late_blight	0.992000	0.968750	0.980469	0.980237
2	Potato___healthy	0.894737	0.944444	0.980469	0.918919

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25 Epochs

	Class	Precision	Recall	Accuracy	F1 Score
0	Potato___Early_blight	0.981651	0.972727	0.96875	0.977169
1	Potato___Late_blight	0.961538	0.976562	0.96875	0.968992
2	Potato___healthy	0.941176	0.888889	0.96875	0.914286

50 Epochs

Fig. 11 displays the confusion matrix 50 epochs, which is a table that summarizes the performance of a classification algorithm. It is a 2-dimensional array where rows represent the original classes and columns consist of the classes model predicted. Every cell in the matrix represents the number of instances where the original class was predicted as the predicted class.

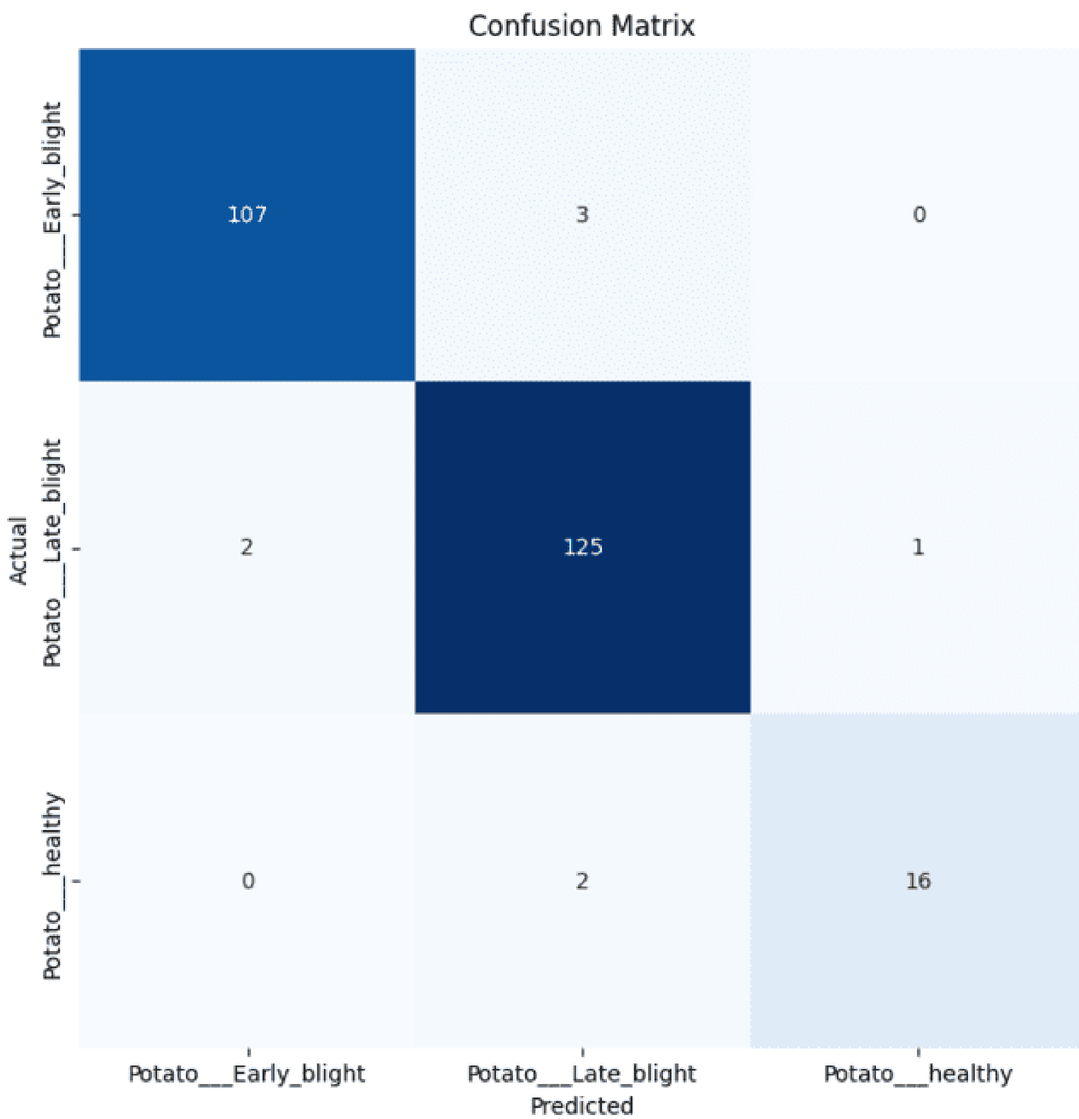


Fig. 11 Confusion Matrix

The below output Fig. 12 shows the final result of predicted leaves vs. actual leaves by taking some of sample from test dataset and showing results with their actual labels and predicted labels.

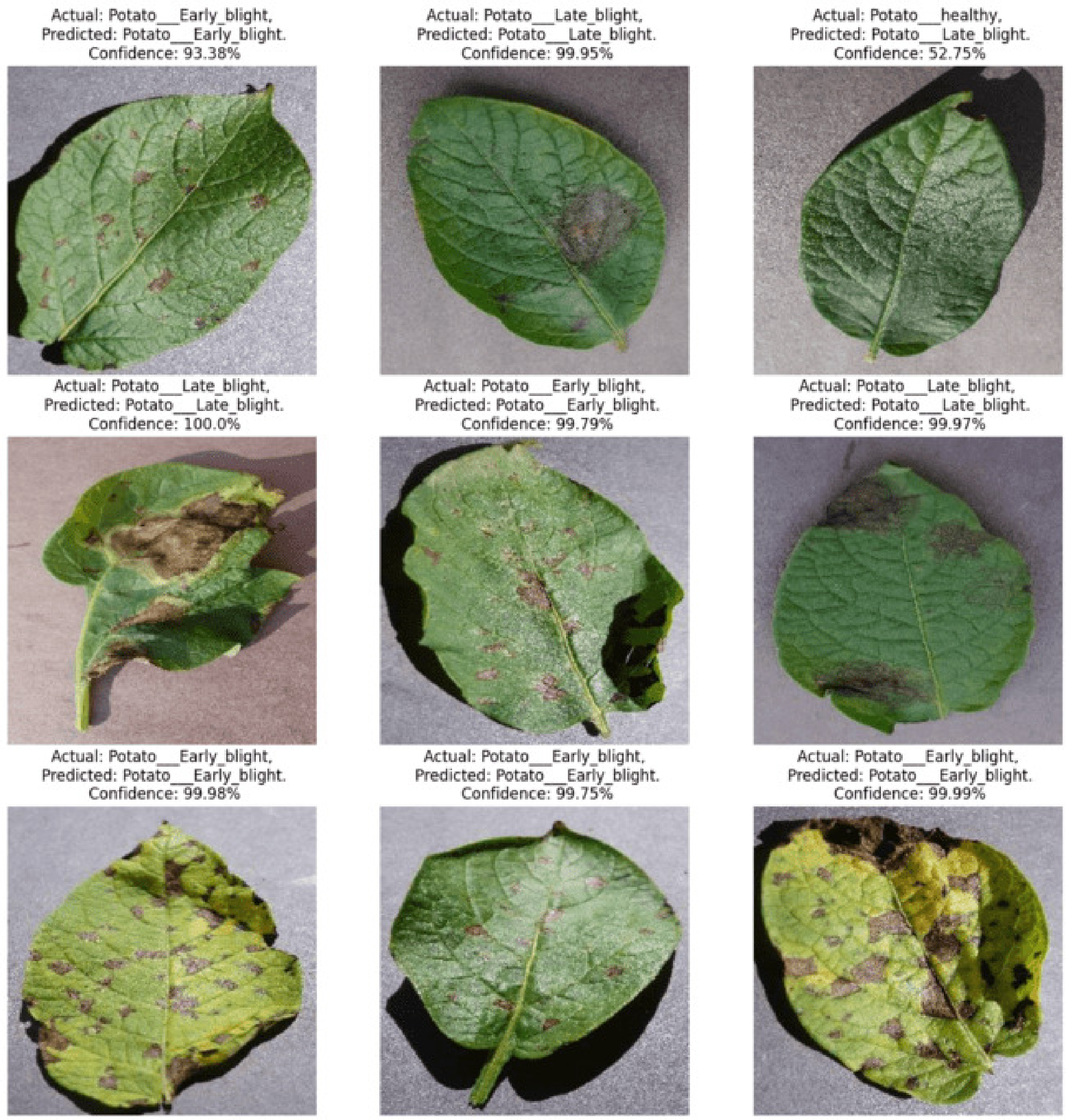


Fig. 12 Predicted leaves vs. Actual

VIII. CONCLUSION

Our study focused on making a computer program to spot diseases in potato plants using a type of computer system called a convolutional neural network (CNN). We trained this program with lots of pictures of sick tomato plants to see how well it could identify different diseases. We checked how good it was by looking at numbers like F1-score, recall, accuracy, and precision.

Our output showed proved the program was really good at finding potato plant diseases, with an accuracy of about 98% on the test pictures. It could tell apart different types of diseases quite well. We also looked at other similar studies and found that many different computer models, like CNNs, VGG-16, PLDP-Net, Plead-Net, and InceptionV3, did a good job too, with accuracies ranging from 95% to 98%. These models could spot diseases like blight in early stages and late stages.

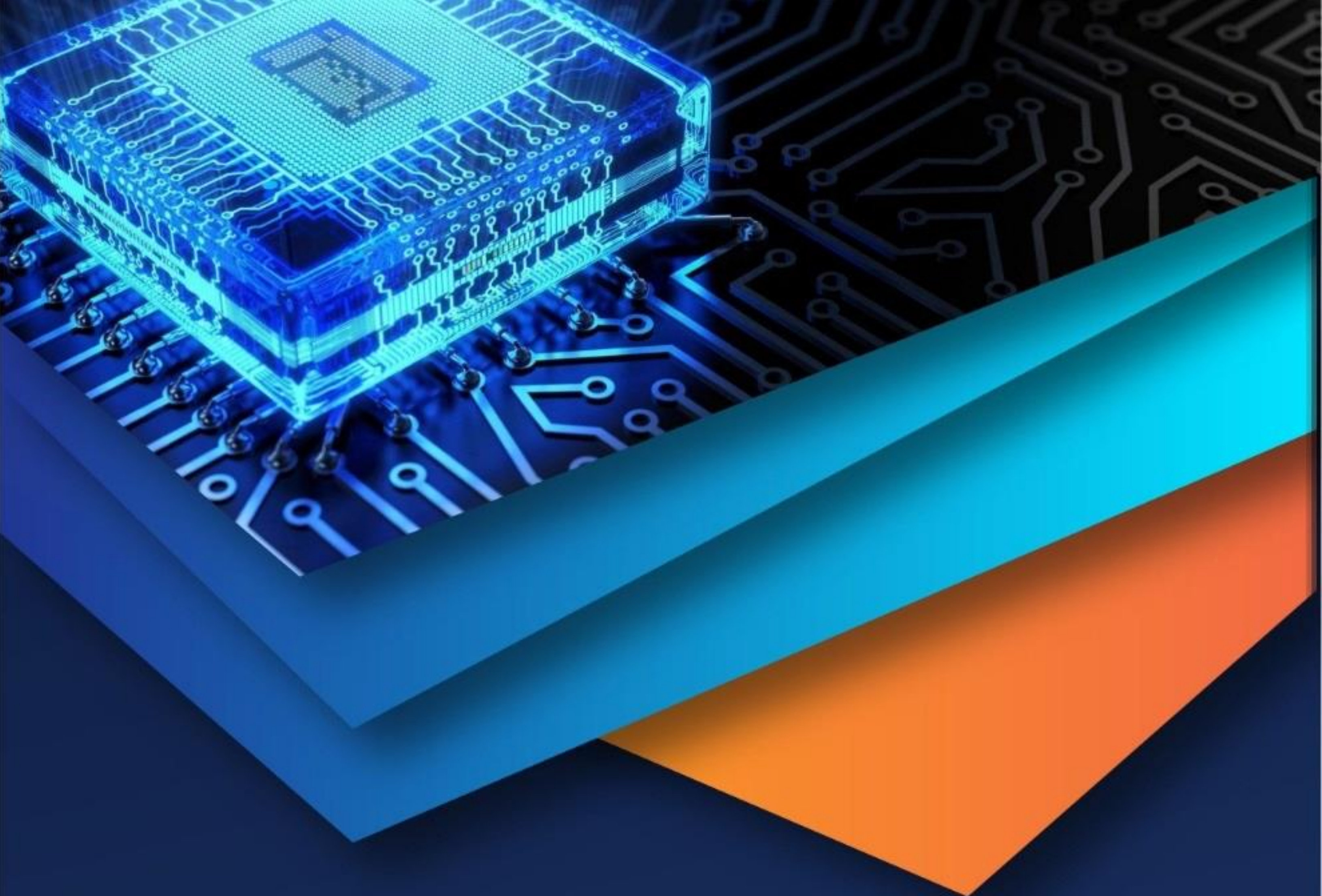
When we compared our program to others like InceptionV3, VGG-16, PLDP-Net, and Plead-Net, we saw that ours was simpler and used less computer power, which makes it more practical for finding potato plant diseases.

REFERENCES

[1] Aniket Gahiware!, Nikhil Bawake, Bhushan Dhage, Lokesh Ahir, Prof. V. K. Abang “Potato Plant Disease Detection using Deep Learning” International Journal of Advanced Research in Science, Communication and Technology,Volume 2, Issue 2, May 2022.

[2] Girish B G!, Narendra N2, Nitish S°, Manoj M D4, R Virupakshagouda Patil’ “Advanced Machine Learning Technique to Detect Disease in Potato”.

[3] Arshad, Fizzah, Muhammad Mateen, Shaukat Hayat, Maryam Wardah, Zaid Al-Huda, Yeong Hyeon Gu, and Mugahed A. Al-antari. "PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction." Alexandria Engineering Journal 78 (2023): 406-418.
[4] Eraj, Sama Uddin, and Mohammed Nazim Uddin. "Early stage Potato Disease Classification by analyzing Potato Plants using CNN." In 2023 International Conference on Next-Generation Computing, IoT and Machine Learning (NCIM), pp. 1-6. IEEE, 2023.
[5] Gardie, B., S. Asemie, K. Azezew, and Z. Solomon. "Potato Plant Leaf Diseases Identification Using Transfer Learning." Indian Journal of Science and Technology 15, no. 4 (2022): 158-165.
[6] Radhika, P., P. Tejeswara Murthy, G. Pavaneeshwar Reddy, V. Durga Vara Prasad, T. Harshitha, and N. B. V. Bharath. "Potato leaf disease detection using convolutional neural networks." (2023).
[7] Sholihati, Rizqi Amaliatus, Indra Adji Sulistijono, Anhar Risnumawan, and Eny Kusumawati. "Potato leaf disease classification using deep learning approach." In 2020 international electronics symposium (IES), pp. 392-397. IEEE, 2020.
[8] Singh, Gulbir, and Kuldeep Kumar Yogi. "Comparison of RSNET model with existing models for potato leaf disease detection." Biocatalysis and Agricultural Biotechnology 50 (2023): 102726.
[9] Asif, Md Khalid Rayhan, Md Asfaqur Rahman, and Most Hasna Hena. "CNN based disease detection approach on potato leaves." In 2020 3rd International conference on intelligent sustainable systems (ICISS), pp. 428-432. IEEE, 2020.



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