WHEAT YELLOW RUST INFECTION CLASSIFICATION

Using Deep learning Models

PRESENTATION OUTLINE

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ABOUT WHEAT YELLOW RUST

Yellow Rust disease appears as yellow stripes of powder or dust on leaves and leaf sheaths of the wheat crop. This yellow powder comes out on clothing or fingers when touched.

The disease can spread rapidly under congenial conditions and affects crop development, and eventually the yield.

Traditional methods for detecting and classifying wheat yellow rust are labor-intensive, time-consuming and often rely on visual inspection by experts

Developing an efficient deep learning system for wheat yellow rust classification, enables early detection and management.

IT'S IMPACT ON CROPS

The wheat yellow rust disease cycle begins when urediniospores (yellow spores) land on the wheat plant's leaves. These spores germinate and penetrate the leaf surface, leading to the development of pustules.

The pustules rupture, releasing additional spores that spread to other parts of the wheat plant and neighboring plants, perpetuating the disease cycle.

Wheat yellow rust infection can significantly hamper the crop's photosynthetic capacity due to the reduced green leaf area, thereby affecting plant growth and development.

Infected plants may experience stunted growth and early senescence, leading to reduced yields.

DISADVANTAGES

Yield losses,
Fungicide Resistance,
Crop Vulnerability

CHALLENGES

Labor-Intensive Visual Inspection

Conventional methods of detecting and classifying wheat yellow rust rely on field surveys and visual inspections by experts. These surveys are time-consuming and demand considerable labor resources, making them impractical for large-scale monitoring.

Subjectivity in Diagnosis

Visual inspections are subject to human interpretation, and the accuracy of diagnosis may vary among different experts. This subjectivity can lead to inconsistent results and misdiagnosis.

OBJECTIVES

To develop a deep learning model using convolutional neural networks (CNNs) to classify wheat leaves into healthy and yellow rust-infected categories.

To train and optimize the deep learning model using a large dataset of preprocessed wheat leaf images to achieve high accuracy in wheat yellow rust classification.

To evaluate the performance of the developed model and compare it with traditional methods and other machine learning techniques, demonstrating its superiority in accuracy and efficiency.

LITERATURE SURVEY

Authors	Topic	methodology	Results	Limitations
Qian Pan,MaofangGao, Pingbo Wu ,Jingwen Yan andShilei Li	A Deep-Learning-Based Approach for Wheat Yellow Rust Disease Recognition from Unmanned Aerial Vehicle Images	UAV images,SVM, RF, BPNN, FCN, U-Net, and PSPNet models	Training Accuracies Of respective models: SVM - 96%, RF - 73%, BPNN - 86%, FCN - 68%, U NET - 74%, PSP NET - 96%	To Improve the Wheat Rust disease Identification they will further introduce hyperspectral UAV images for deeper studies on crop diseases.
Shivani Sood and Harjeet Singh	An implementation and analysis of deep learning models for the detection of wheat rust disease usuing RESNET and VGG16	CNN(Convolution neural networks), RESNET50, VGG16	RESNET50 gave atraining accuracy of 75.76% and validation accuracy of 69.83% and VGG16 gave a training accuracy of 95.07% and validation accuracy of 94.33%	To remove the noise from the data and to detect feature that will be more generalized to the model they will extend this work further by applying various feature detection techniques.

LITERATURE SURVEY

Authors	Topic	Methodology	Results	Limitations
Togla Hayit,Hasan Erbay,Fatih Varcin	The classification of wheat yellow rust disease based on a combination of textural and deep features	Wheat Yellow Rust Infection Types,RGB IMAGES GLCM&CGLCM,DENSE NET 201,SVM,KNN Models	Training Accuracies Of respective models: under CGLCM_RGB SVM-73.1% under CNN-CGLCM_HSV SVM-92.4%	Limited Color Space,Feature Normalization,DenseNet-201 Specificity,Classifier Selection
Uferah Shafi,Rafia Mumtaz,Maryam Hafeez,Naveed Iqbal	Wheat Yellow Rust Disease Infection Type Classification Using Texture Features	GLCM,LCP,Decision Tree, Random Forest, XGBoost, LightGBM, and CatBoost	CatBoost Accuracy-92.30% on GLCM texture images Decision Tree Accuracy:-81.27% on GLCM images,74.24% on LBP texture images.	Data collection,Image quality,Data augmentation,Feature extraction,Grayscale conversion,Model selection

To develop an accurate and efficient deep learning method for early detection of wheat yellow rust disease using a large dataset of wheat leaf images

PROBLEM STATEMENT

PROPOSED SOLUTIONS

Using a deep learning model to detect and classify the intensity of Yellow rust of wheat plants. As mentioned earlier, deep learning models have been shown to be effective for image classification tasks. A deep learning model that can accurately detect and classify rice plant diseases would be a valuable tool for farmers and agricultural researchers.

Various deep learning models were already used for this type of classification, Here we have continued their journeys by removing their limitations and performed the following 3 models:

i) VGG 19 Model

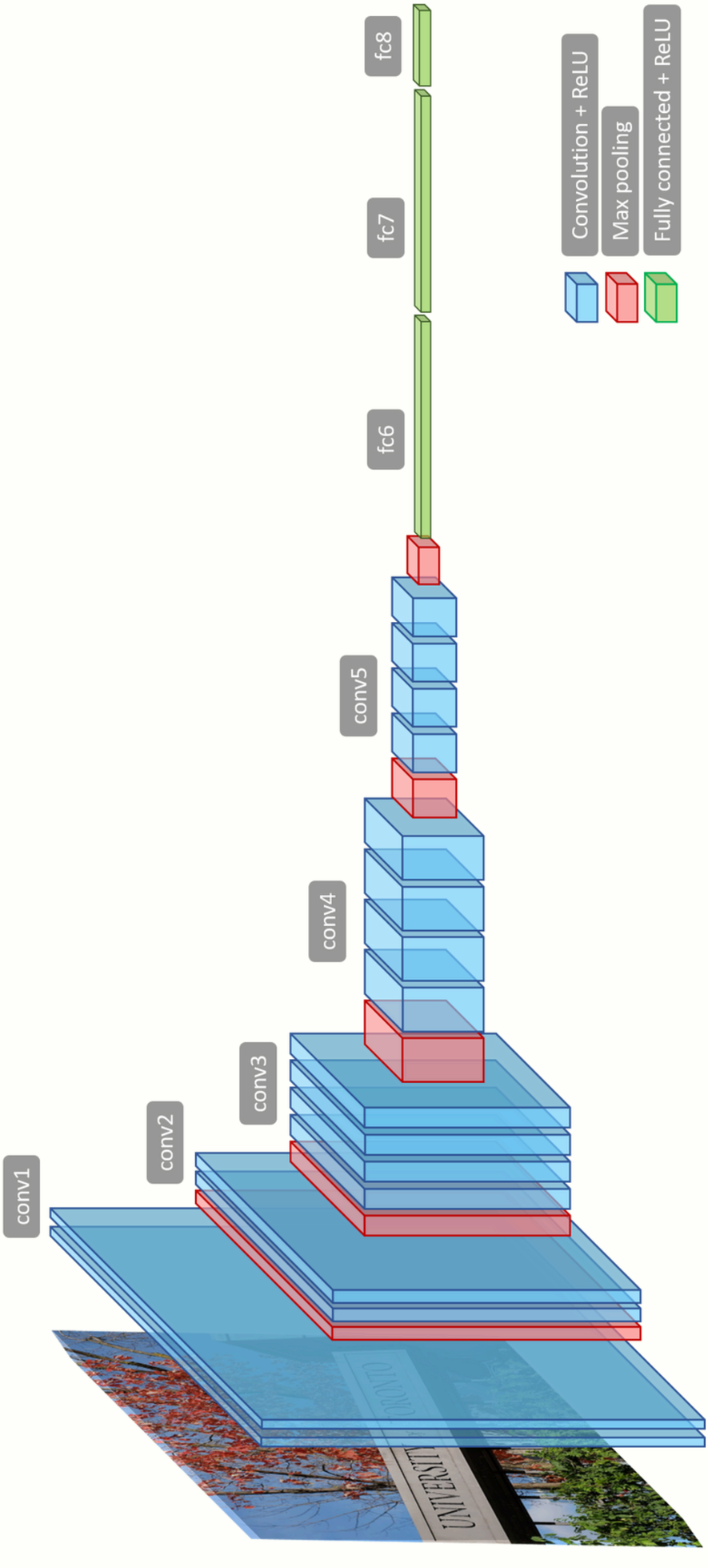
ii) Alexnet Model

iii) MobilenetV2 model

PROCEDURE

1. Collect and preprocess a dataset of images of wheat leaves with different disease intensities. The dataset should be as large as possible. The images should be pre-processed to remove noise and improve the contrast.
2. Train a model on the dataset. The model will be trained on the dataset of images of wheat leaves with different disease intensities.
3. Evaluate the performance of the model. The performance of the model will be evaluated on a held-out dataset of images of wheat leaves with disease. The accuracy of the model will be calculated as the percentage of images that the model correctly classifies.
4. Deploy the model to a production environment. Once the model is trained and evaluated, it will be deployed to a production environment so that it can be used by farmers to identify the intensity level of plant disease and take necessary measures

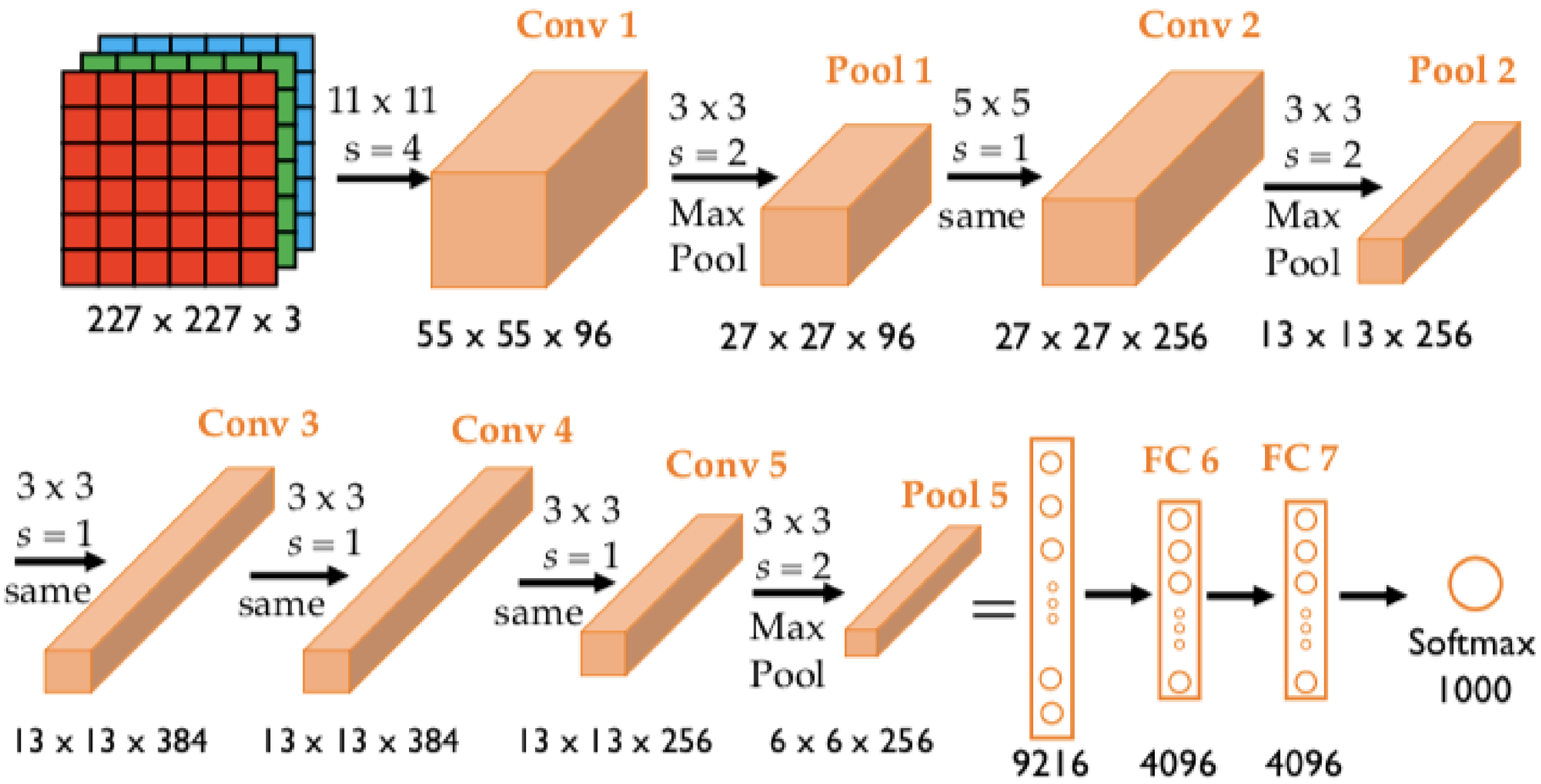
VGG 19 MODEL


fc8
fc7
fc6
conv5
conv4
conv3
conv2
conv1
Convolution + ReLU
Max pooling
Fully connected + ReLU

ALGORITM FOR VGG 19 MODEL

Step-1: Input Image
Step-2: Convolution (3x3 filters, padding)
Step-3: Activation Function (ReLU)
Step-4: Convolution Layers (Repeat) - Total 16 Convolution Layers
Step-5: Max Pooling (2x2, stride 2)
Step-6: Flatten
Step-7: Fully Connected Layers (Dense)
Step-8: Activation Function (ReLU)
Step-9: Fully Connected Layers (Dense)
Step-10: Activation Function (ReLU) Step-11: Output Layer (Softmax)
Step-12: Training the Model

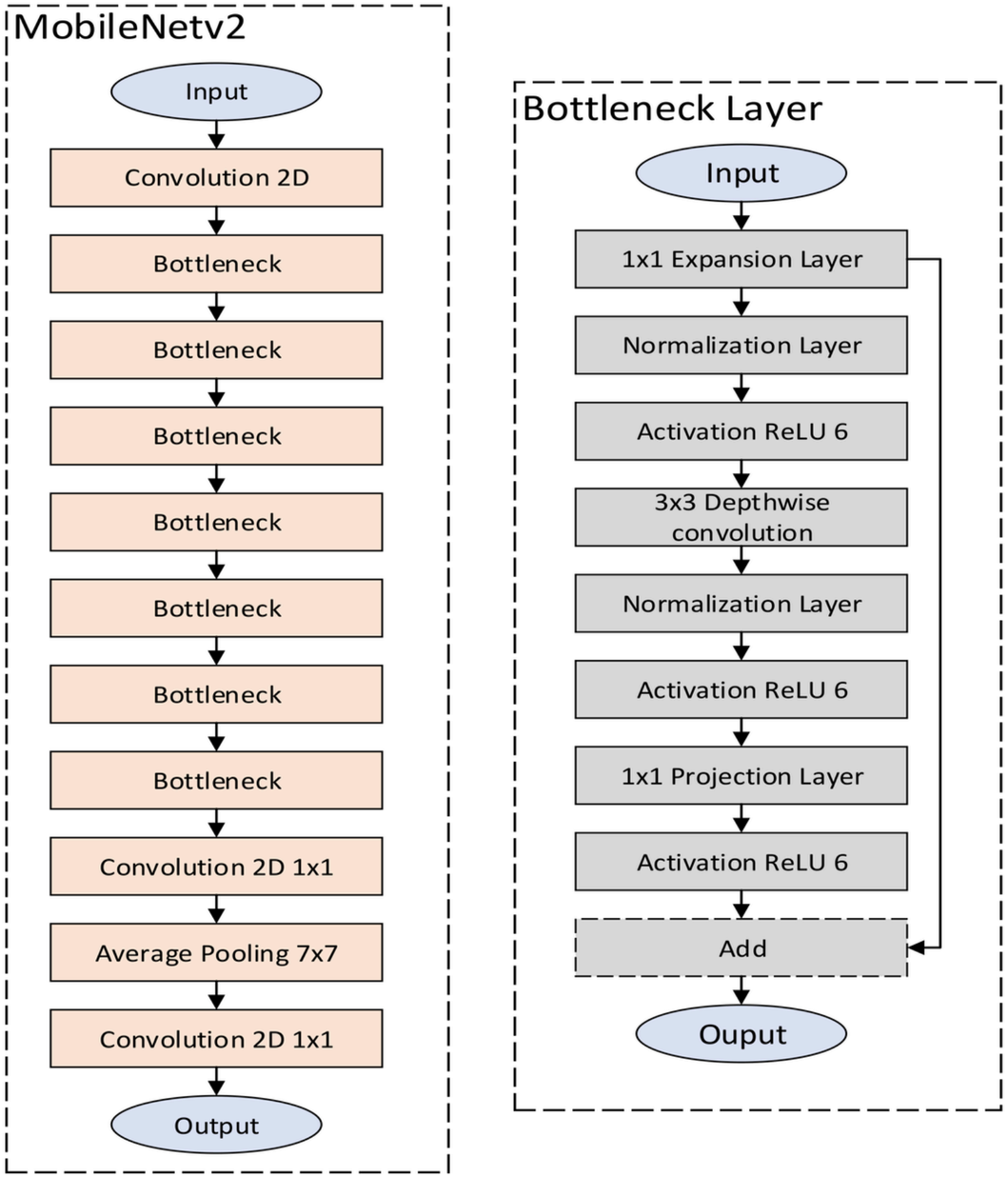
ALEXNET MODEL



ALGORITM FOR ALEXNET MODEL

1. Input Image
2. Convolution (11x11 filters, stride 4, padding) + ReLU
3. Max Pooling (3x3, stride 2)
4. Convolution (5x5 filters, padding) + ReLU
5. Max Pooling (3x3, stride 2)
6. Convolution (3x3 filters, padding) + ReLU
7. Convolution (3x3 filters, padding) + ReLU
8. Max Pooling (3x3, stride 2)
9. Flatten
10. Fully Connected Layer (Dense) + ReLU
11. Fully Connected Layer (Dense) + ReLU
12. Output Layer (Softmax)
13. Training the Model

MOBILENET V2 MODEL



ALGORITM FOR MOBILENET MODEL

Step-1: Input Image
Step-2: Convolution layer
Step-3: Activation Function (ReLU)
Step-4: Bottle Neck layer(Repeat 16 times)
Step-5: Convolution layer
Step-6: Global Average Pooling
Step-7: Fully Connected Layer (Dense)
Step-8: Dropout layer
Step-9: Output Layer (Softmax)
Step-10: Training the Model
Step-11: Inference (Classification)

INTENSITY LEVELS OF YELLOW RUST

DATASET DESCRIPTION

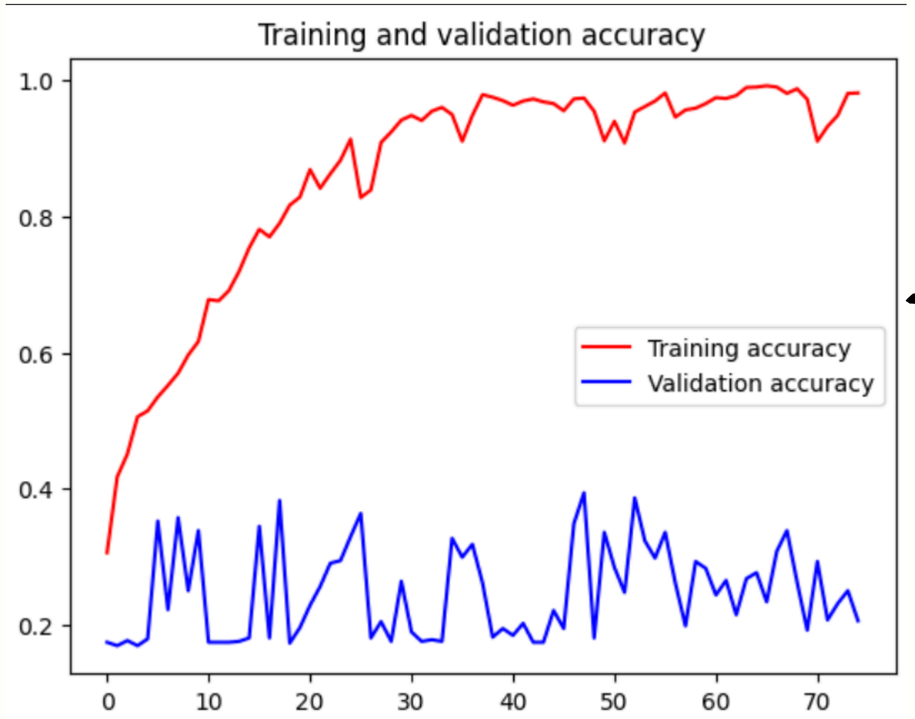
YELLOW RUST - 19 DATASET

Image type	Train data	Test data
No disease	2500	205
Resistant	2500	361
Moderately Resistant	2500	564
Moderately Resistant & Moderately Suspectible	2500	1135
Moderately Suspectible	2500	1795
Suspectible	2500	1361

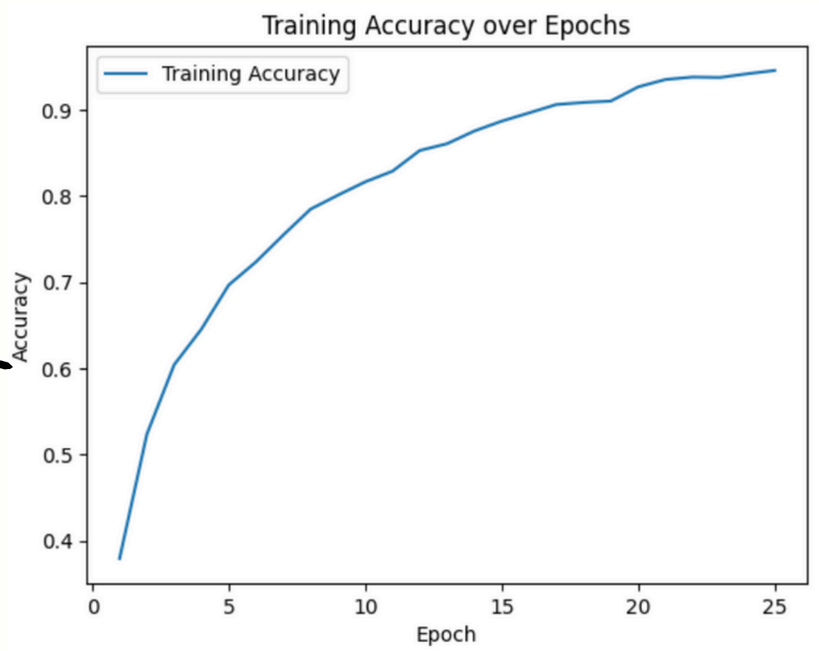
COMPARISION OF ACCURACIES OF VARIOUS MODELS

Model	Training Accuracy	Test Accuracy
VGG 19	79.11	75.56
Alexnet	98.13	65.26
Mobilenet V2	94.57	95.53

ACCURACY CURVES



Alexnet model



Mobilenet model

CONCLUSION

Wheat yellow rust is a formidable menace to global wheat production. Conventional methods for detection and classification exhibit limitations in accuracy and scalability. To overcome these challenges and achieve early detection and precise management, we harnessed the power of cutting-edge deep learning systems.

In our study, we employed three state-of-the-art models: VGG19, AlexNet, and MobileNetV2. **Notably, both MobileNetV2 and AlexNet outperformed, yielding impressive accuracies of 94% and 98% respectively.**

By embracing such advanced technologies, agriculture can effectively combat the threats posed by wheat yellow rust and bolster global food security. This approach enables precision agriculture practices and optimizes crop yields, ensuring a sustainable and resilient food supply for the future.

REFERENCES

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- Qian Pan,MaofangGao, Pingbo Wu ,Jingwen Yan andShilei Li, "A Deep-Learning-Based Approach for Wheat Yellow Rust Disease Recognition from Unmanned Aerial Vehicle Images"
- Togla Hayit,Hasan Erbay,Fatih Varcin, "The classification of wheat yellow rust disease based on a combination of textural and deep features"
- Uferah Shafi,Rafia Mumtaz,Maryam Hafeez,Naveed Iqbal, "Wheat Yellow Rust Disease Infection Type Classification Using Texture Features"

THANK YOU