HYBRID DEEP LEARNING AND MACHINE LEARNING MODELS FOR SMARTER PREDICTIONS

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INTRODUCTION

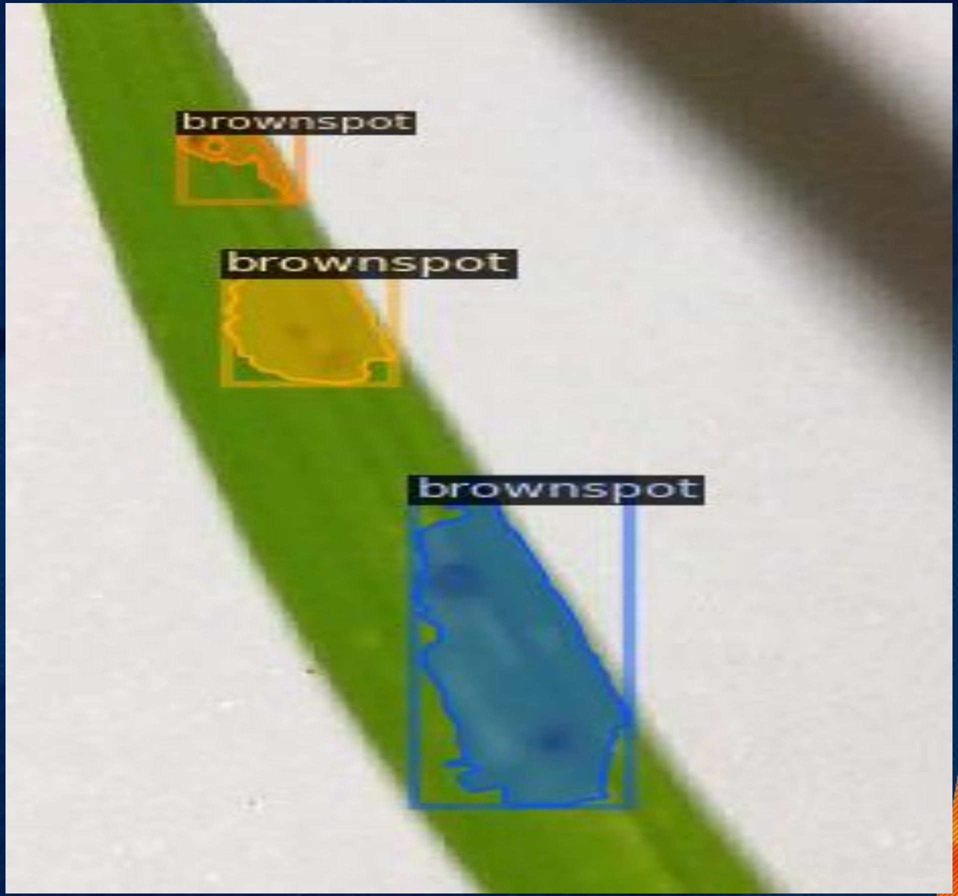
The agricultural sector plays a pivotal role in global food security, yet it faces constant threats from plant diseases that can severely reduce crop yields. Traditional methods of disease detection, which rely heavily on manual inspection by experts, are time-consuming, subjective, and unsuitable for large-scale monitoring. In recent years, deep learning—especially Convolutional Neural Networks (CNNs)—has shown remarkable potential in automating plant disease diagnosis through image analysis. However, standalone deep learning models are often computationally intensive, making them impractical for deployment on low-power or edge devices commonly used in agricultural settings. To overcome these limitations, we introduce SmartLeafNet, a hybrid deep learning and machine learning pipeline designed for efficient and scalable crop disease detection. This system utilizes pre-trained CNN architectures such as EfficientNetB0 and ResNet50 for feature extraction, capturing high-level image representations from leaf samples. These features are then fused and passed to an XGBoost classifier, a gradient-boosted decision tree model known for its speed and accuracy, to perform the final classification. To improve generalization and reduce overfitting, the system integrates data augmentation techniques (e.g., rotation, zoom, flipping), PCA for dimensionality reduction, and SMOTE to address class imbalance. Further, we use Optuna, an automated hyperparameter optimization framework, to fine-tune the XGBoost model for enhanced performance. By combining the strengths of deep learning in representation learning with the interpretability and speed of machine learning classifiers, SmartLeafNet delivers a robust, accurate, and deployment-ready solution for real-world agricultural disease detection applications.

NEED OF STUDY

- Crop productivity and Quality: Plant diseases can drastically lower crop productivity and have an impact on the caliber of harvested goods.
- Economic Impact: Farmers and the agriculture sector as a whole may suffer significant financial losses as a result of plant diseases.(As per the LR China, Brazil, USA are affect mass)
- Food Security: Ensuring food security is crucial given the expanding world population.
- Stop Spreading : Certain plant diseases can quickly spread and harm entire crops or even entire ecosystems.
- Precision Agriculture: Farmers can implement precision agriculture approaches by employing technology for disease detection.

PROBLEM STATEMENT

- In agriculture the leaf was affect by the diseases which lead to decreased crop yields, impacting farmers' income and food production.
- Human eye can’t identify the diseases correctly though image it can detect
- The toughest part is images because we need accurate image ,some image contains lots of leaves but the disease spotted in small amount.
- Sometimes the images have small colour of disease like (brown spot or mild rust)



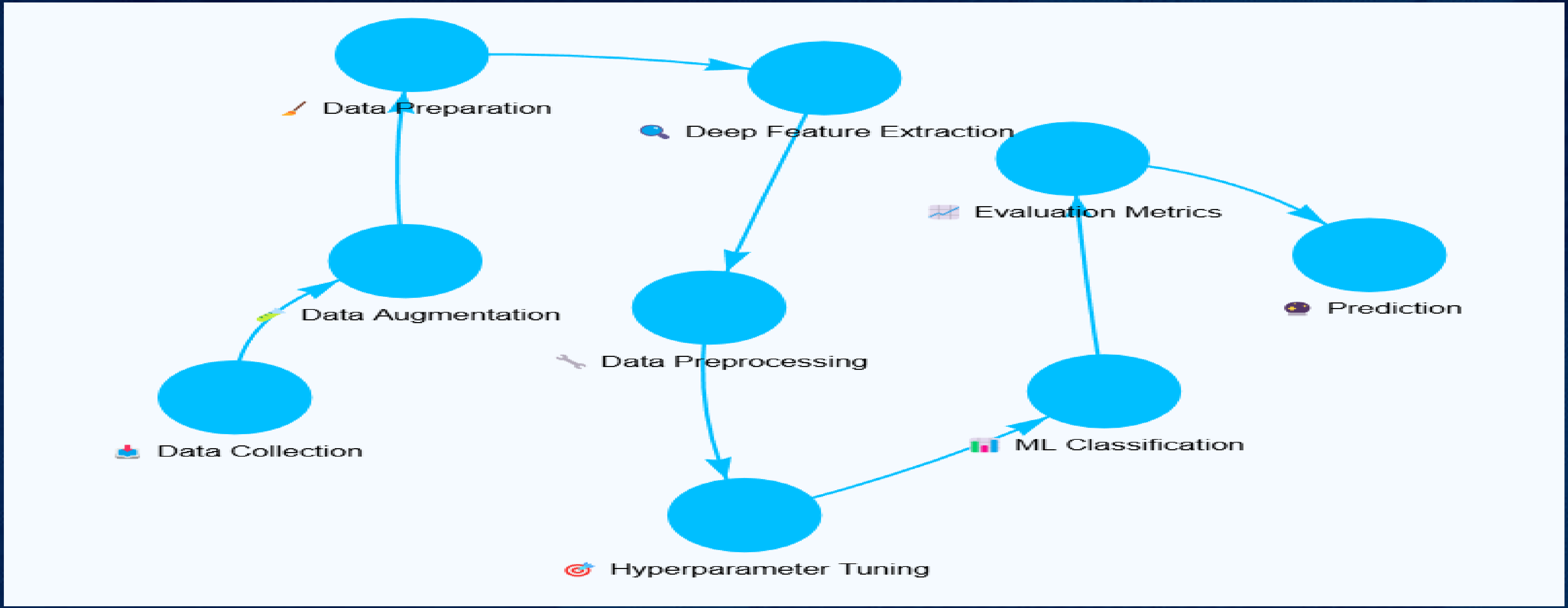
RELATED WORK

BASE PAPER:

The related work of this Project, which taken from the **A Cutting-Edge Deep Learning Models for Paddy Leaf Disease Detection and Classification (IEEE Publication).** In this paper they used Detectron 2 as the base model and also compare the performance of the Other Algorithms.

MODEL	ACCURACY FOR 25 EPOCHS (%)	ACCURACY FOR 50 EPOCHS (%)
CNN	89	92
VGG 16	57	76
MobileNetV2	65	91
ResNet 50	32	50
Inception V3	85	80
Densenet121	84	92
Xception	76	92
Densenet& XCeption	88	91
Efficient b3	19	32

METHODOLOGY



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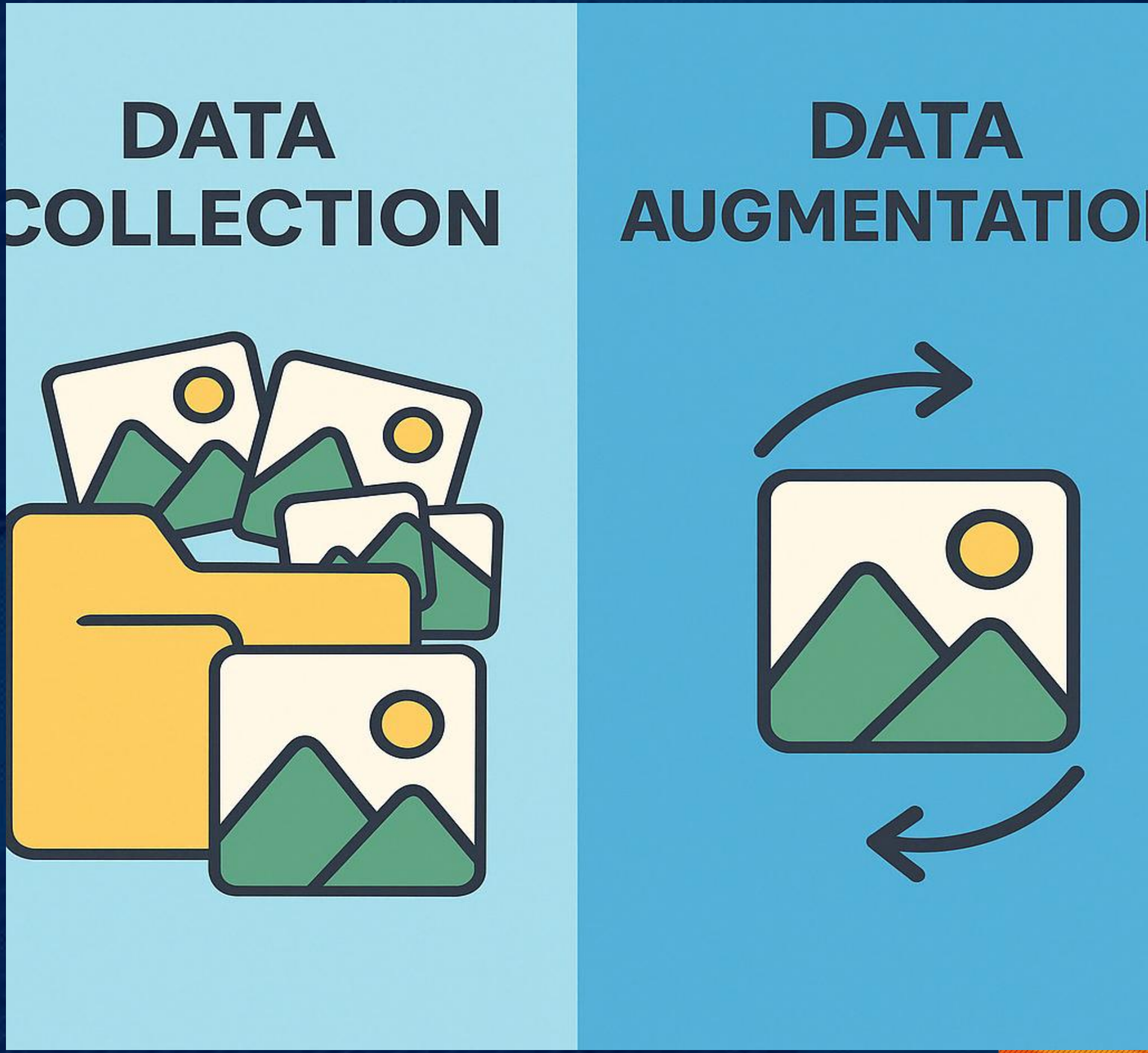
DATA COLLECTION AND DATA AUGMENTATION

- Data collection is the major step. We are taking the dataset from the Kaggle (Leaf Disease).
- Data Augmentation is what we did to expand the dataset, because the existing paper get very low accuracy and feels hard to detect the disease.
- With the help of the Data Augmentation we change 2000 images into 22000 images.

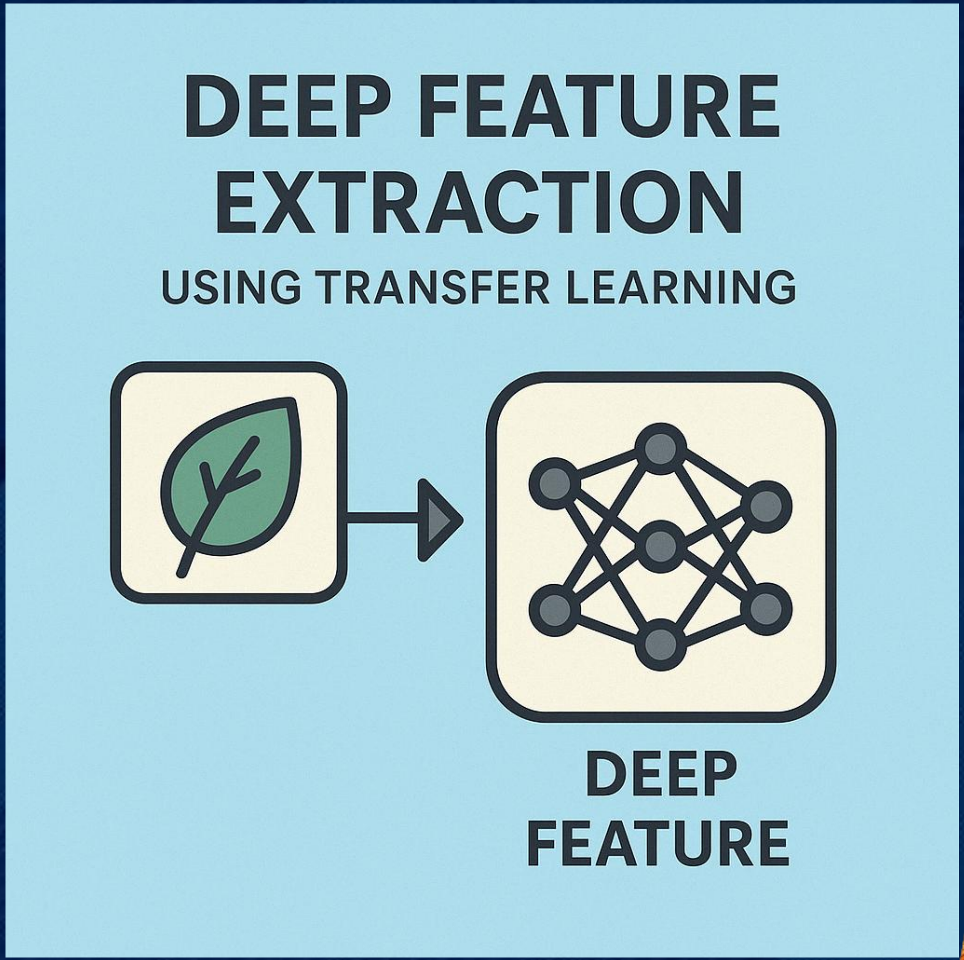


DATA PREPARATION

Leaf images were organized into training and validation folders. An ImageDataGenerator was employed to perform real-time augmentation on the training set, including rescaling, rotations, shifts, shear, zoom, and horizontal flips to enhance model generalization. The validation set was rescaled but not augmented. Image dimensions were standardized to 224×224 pixels, and a batch size of 8 was used.

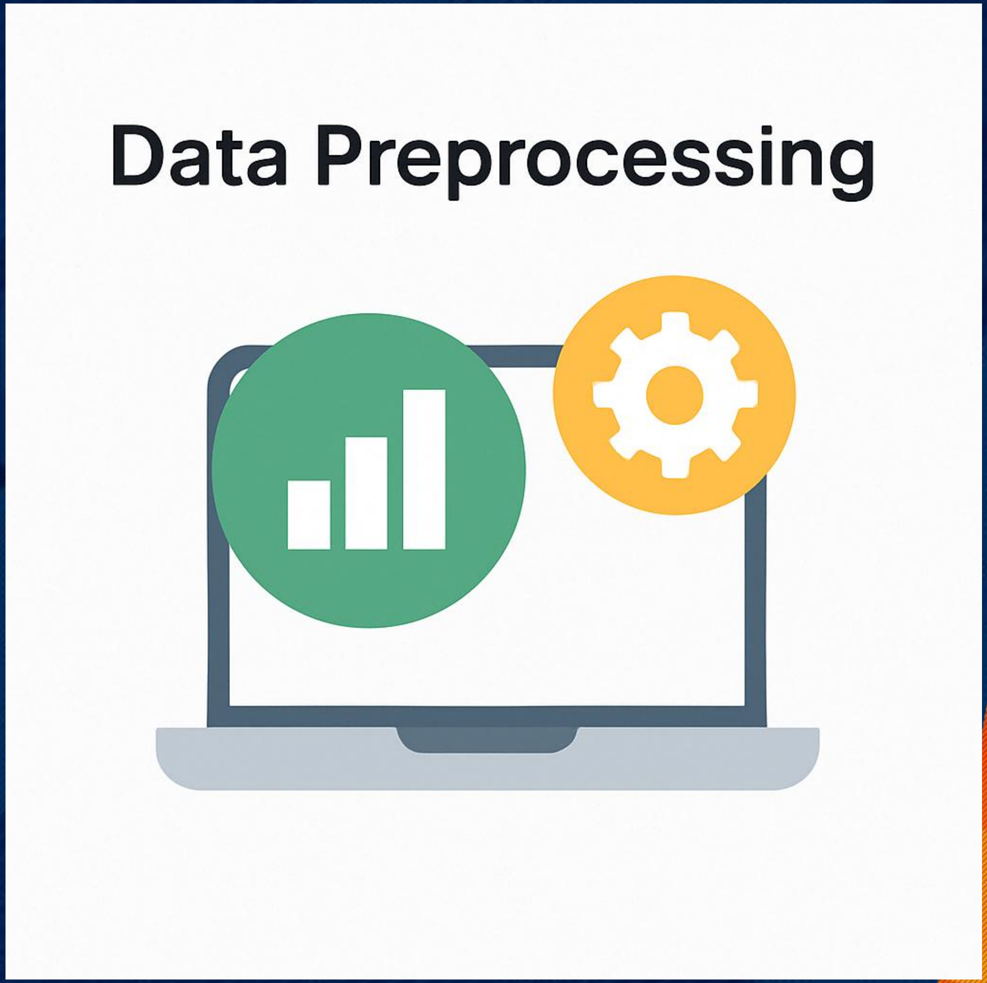
DEEP FEATURE EXTRACTION USING TRANSFER LEARNING

Two pre-trained CNN architectures—EfficientNetB0 and ResNet50—were used as frozen base models to extract deep features. Each model was augmented with: A GlobalAveragePooling2D layer 256-unit ReLU dense layer with L2 regularization dropout layer (rate 0.5)A SoftMax output layer for multi-class classification



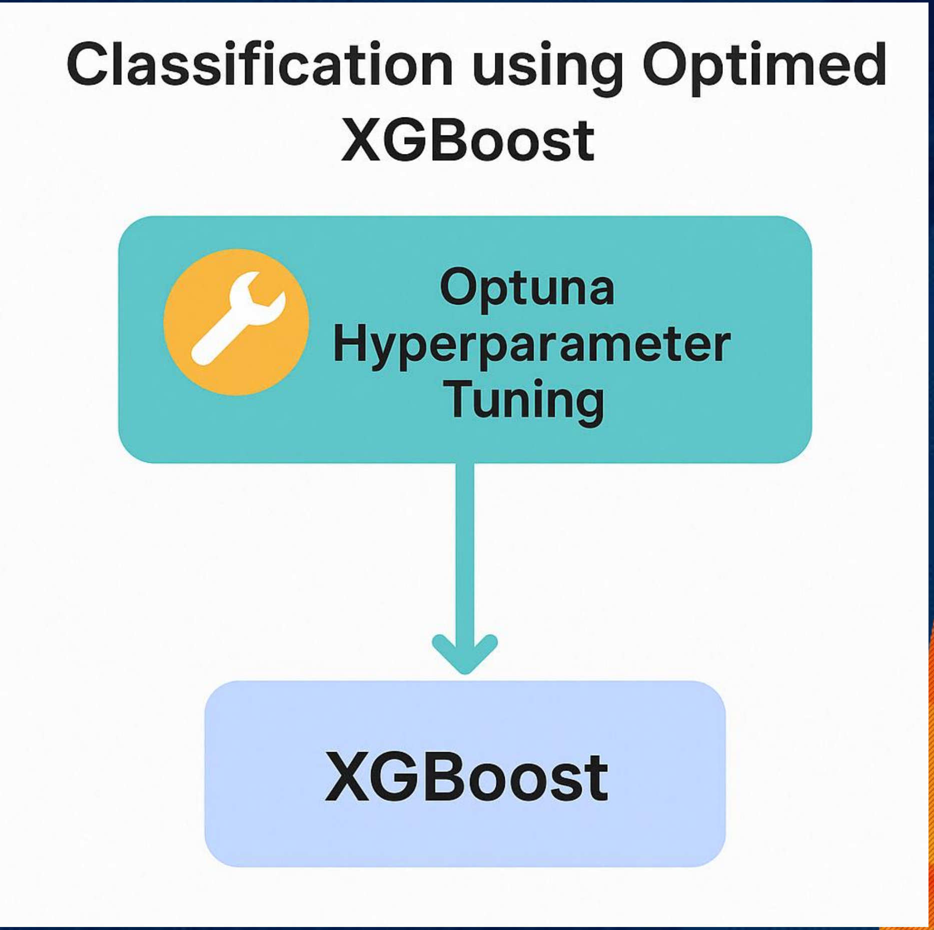
DATA PREPROCESSING

The feature vectors obtained from both models were concatenated to form a comprehensive feature representation. These were then: Normalized using StandardScalerReduced in dimensionality using PCA to retain 100 principal components Balanced using SMOTE to handle class imbalance by synthetically oversampling minority classes.



CLASSIFICATION USING OPTIMIZED XGBOOST WITH OPTUNA HYPERPARAMTER

The resampled feature set was split into training and validation subsets. A multi-class XGBClassifier was tuned using Optuna to maximize the macro F1-score.The hyperparameter search space included tuning of n_estimators, max_depth, learning_rate, subsample, colsample_bytree, and gamma. The best-performing model was then retrained on the entire resampled dataset.



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EVALUATION METRICS

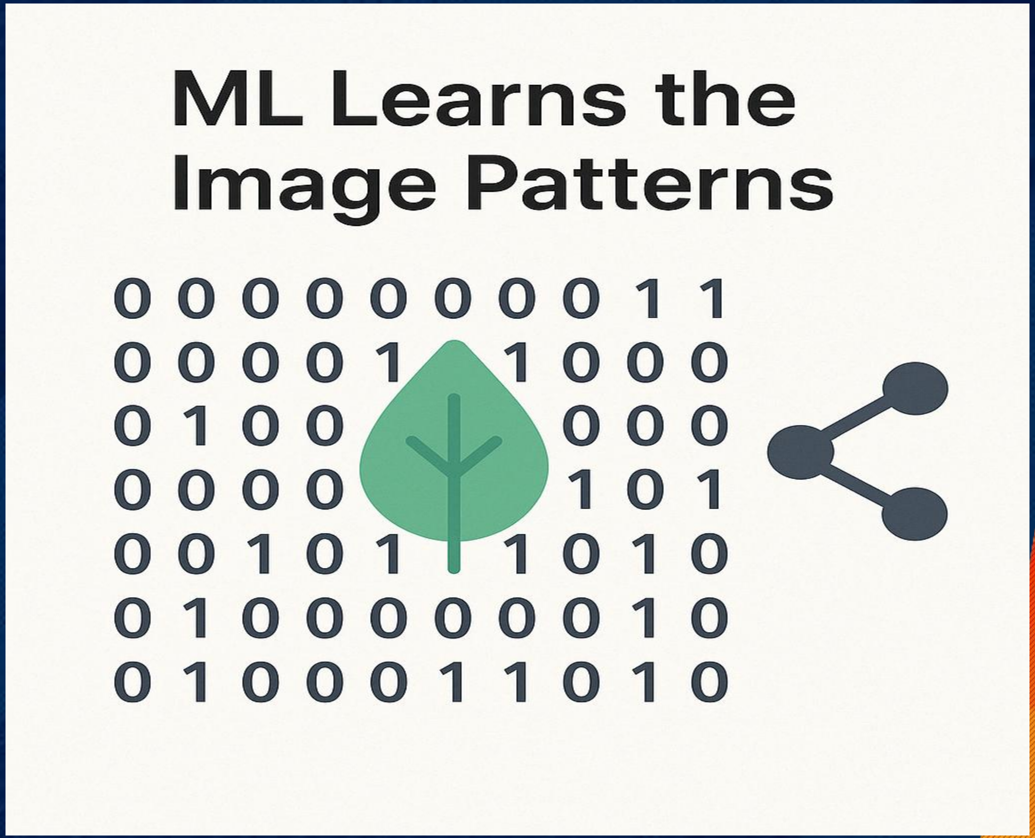
Model performance was evaluated using:

- **Classification reports** including precision, recall, an
F1-score
- **Macro F1-score** as the optimization metric
- **Accuracy scores** on both training and validatio
datasets.

SMARTLEAFNET(SLN) WORKING

SLN is the hybrid model which contains EfficientNetB0 and ResNet50 + XGB+ PCA + SMOTE.

- Image Input:
  → An image of a diseased leaf is passed through EfficientNetB3 and ResNet50.
- Feature Vector Output:
  → Each model generates a dense feature representation.
- Feature Fusion + PCA:
  → The feature vectors are concatenated and reduced using PCA.
- SMOTE Resampling:
  → The reduced feature set is resampled using SMOTE to balance class distributions.
- Optuna Optimization + XGBoost Classifier:
  → XGBoost is trained on the resampled data using Optuna-tuned hyperparameters.
- Output:
  → The final prediction is returned along with class probabilities (e.g., "Hispa", "Healthy").



MODEL COMPARISON

MODELS	ACCURACY
Nasnet+Xception+Inception	55%
Xcception+Nasnet+Inception	57%
Inception+xception+Nasnet	56%
Nasnet+inception+Xeption	55%
xception+inception+Nasnet	56%
SMARTLEAFNET (Efficient b0 , resnet 50 , XGB(PCA+Optuna+smote))	98%
Efficentnet + LightBGM +optuna +smote	94%
Efficentnet + LightBGM +optuna +smote+ PCA	37%
Efficentnet + Resnet +LightBGM +(Stratified sampling, focal loss+optuna+smote+PCA)	88%
Efficientnet+Densenet+Xception	59%
Inception+resnet+xception	58%
Inceptionv3+DenseNet+Xception+XGB(PCA+optuna+smote)	100%
Inceptionv3+DenseNet+XGB(PCA+Optuna+SMOTE)	100%
Inceptionv3+densenet+Xception+XGBclassifier(GAP &FC)	82%
Inceptionv3+densenet+Xception+randomforest	50%
Inceptionv3+xception+Randomforest	53%

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PREDICTION

```
    x = np.expand_dims(x, axis=0)
    return x

x = preprocess_image(r"E:\2nd trimester project works\leaf detection\train\Hispa\IMG_20190419_095421.jpg")
```

```
predictions = model.predict(x)
predictions[0]
```

```
1/1 [==============================] - 2s 2s/step
```

```
[8]: array([0.00577065, 0.29449183, 0.69853956, 0.00119789], dtype=float32)
```

```
labels = train_generator.class_indices
labels = {v: k for k, v in labels.items()}
labels
```

```
[9]: {0: 'BrownSpot', 1: 'Healthy', 2: 'Hispa', 3: 'LeafBlast'}
```

```
predicted_label = labels[np.argmax(predictions)]
print(predicted_label)
```

```
Hispa
```

```
    img = load_img(image_path, target_size=target_size)
    x = img_to_array(img)
    x = x.astype('float32') / 225.
    x = np.expand_dims(x, axis=0)
    return x

x = preprocess_image(r"E:\2nd trimester project works\leaf detection\train\Hispa\IMG_20190419_095421.jpg")
```

```
predictions = model.predict(x)
predictions[0]
```

```
1/1 [==============================] - 0s 439ms/step
```

```
[6]: array([0.20233434, 0.49827772, 0.28319395, 0.016194  ], dtype=float32)
```

```
labels = train_generator.class_indices
labels = {v: k for k, v in labels.items()}
labels
```

```
[7]: {0: 'BrownSpot', 1: 'Healthy', 2: 'Hispa', 3: 'LeafBlast'}
```

```
predicted_label = labels[np.argmax(predictions)]
print(predicted_label)
```

```
Healthy
```

CONCLUSION

SmartLeafNet presents a robust and scalable solution for real-world agricultural disease detection by synergizing deep learning and machine learning techniques. By leveraging the feature extraction power of pre-trained CNNs like EfficientNetB0 and ResNet50 and coupling it with the efficiency of an Optuna-tuned XGBoost classifier, the system achieves high accuracy with reduced computational overhead. The incorporation of data augmentation, PCA, and SMOTE further strengthens the pipeline by enhancing generalization and addressing class imbalance. This hybrid approach not only overcomes the limitations of standalone models but also makes SmartLeafNet well-suited for deployment in resource-constrained agricultural environments. Ultimately, the proposed framework offers a practical and efficient tool to aid in early crop disease diagnosis, thereby contributing to sustainable agriculture and global food security.

Q/A SESSION ?

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