# MTH 601- Mathematics of Deep Learning

# Project Report

# Hybrid Deep Learning and Machine Learning models for smarter predictions


## Team Members

AJMAL ABBAS
ASWIN SANKAR
PRATHESWARAN HARIHARAN
ROHIT KUMAR

# Abstract

Plant diseases,especially in rice crops, can cause serious damage to farming and reduce crop production. Traditional ways of finding these diseases depend on manual checking, which can be slow, tiring, and not always accurate. To solve this problem, we built SmartLeafNet, a smart system that uses both deep learning and machine learning to detect leaf diseases quickly and correctly. First, we use pre-trained deep learning models to pull out useful features from leaf images. These features are then cleaned and improved using methods like normalization, PCA (to reduce data size), and SMOTE (to balance different disease types). We then use a machine learning model called XGBoost, which we improved using Optuna to get the best results. We also increased the dataset from 2,000 to over 22,000 images using data augmentation techniques like flipping and rotating images. Our system gives accurate results and runs efficiently, making it easy to use in real-life farming situations. SmartLeafNet helps detect plant diseases early, allowing farmers to take quick action and grow healthier crops.

# I. Introduction

Agriculture is the mainstay of most developing economies and a cornerstone of significance in international food security. As the world population continues to grow everywhere, the demand for food quality and productivity is also increasing. Among some of the most critical crops cultivated worldwide, rice(Oryza sativa) is among them since it is eaten everywhere and is extremely nutrient-rich. But rice crops are usually afflicted with numerous diseases, especially bacterial blight, brown spot and Hispa that not only reduce the quality of the crop but also considerably reduce the yield. Such crop diseases have serious economic impacts on farmers and can ultimately affect national food reserves. Traditional detection and diagnosis of such diseases were heavily dependent on visual inspection by agricultural experts.

This is not just time consuming and labor intensive but also prone to errors based on the subjective evaluation through vision. In addition to this, the high speed at which plant diseases spread in the case of large scale farms makes manual inspection not appropriate. The above challenges are easily overcome by the recent progress in deep learning and computer vision that have brought forth automated means for the diagnosis of plant diseases through leaf image analysis. These systems have proved to have immense potential in advancing precision agriculture, allowing for early disease detection and timely intervention.

One such advancement was proposed in the IEEE published paper titled "A cutting edge deep learning models for paddy leaf disease detection and classification", where the authors implemented Detectron2, a state of the art object detection framework, for disease identification. While Detectron2 achieved promising accuracy, it primarily focused on instance segmentation and bounding box based detection which are computationally expensive and may not be suitable for deployment on resource constrained agricultural devices such as mobile phones or edge systems.

To address these limitations, our project introduces SmartLeafNet, a robust and scalable hybrid deep learning and machine learning pipeline designed specifically for rice leaf disease detection using image data. Instead of focusing on object detection, SmartLeafNet emphasizes highly accurate and efficient image classification. The framework integrates two pre-trained deep learning models EfficientB3 and ResNet50 to extract the diverse feature representations from the rice leaf images. These features are then concatenated and passed through the principal component analysis module to reduce dimensionality ensuring faster computation and reduced overfitting.

Recognizing the challenge of class imbalance which is common in real world agricultural datasets, we incorporate the synthetic minority over sampling technique (SMOTE) to synthetically generate balanced training samples, ensuring all disease classes are equally represented during training. For the final classification task we use the XGBoost algorithm, a gradient boosted decision tree model known for its high accuracy interpretability and low computational overhead. To further enhance the model's performance we apply Optuna an automated hyperparameter optimization framework that tunes critical parameters such as learning rate, depths and estimators to maximise the macro F1-score which is ideal for evaluating imbalance multi class classification problems.

Another key contribution of this work lies in its data augmentation strategy. We expanded the original dataset sourced from the kaggle and containing 2000 images to over 22000 images by applying transformation. This significantly improved the model's generalisation capabilities and reduced the risk of overfitting.
SmartLeafNet presents an effective resource efficient and deployment rady solution that bridges the gap between high performance deep learning models and real world constraints in agricultural environments.

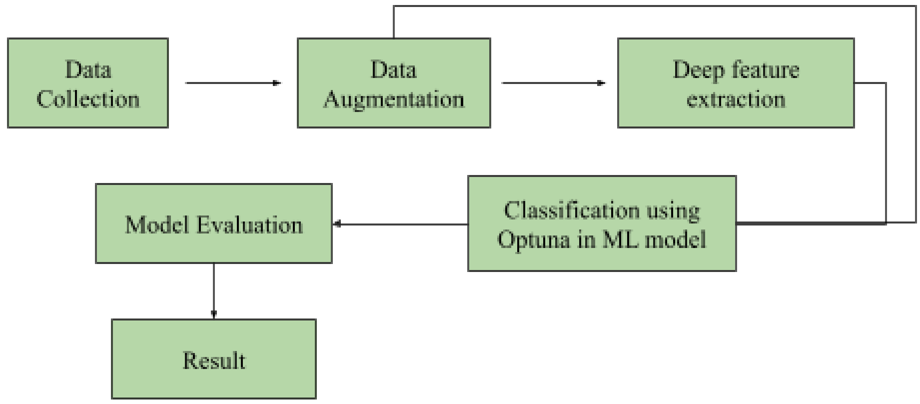



***Fig 1 : Flowchart***

# II. Related work

This section covers the other earlier research on utilising a deep learning algorithm to forecast leaf illness. The base paper[1] describes the framework using detectron2 where they compare the performance of the model with several other CNN based models where the study highlights the accuracy achieved through segmentation. The publication describes how to identify rice disease using agro-meteorological data and leaf disease using data collecting methods, specifically using MLP architecture. CNN, the algorithm utilized in the study, has a 95% prediction rate[6]. An approach for data preprocessing and data augmentation for the detection of plant diseases is presented in [7]. The process is driven by the CNN algorithm, which has a 93% accuracy rate. Last but not least, ResNet 50 offers 66% accuracy while ResNet 101 offers 70% accuracy. Furthermore, utilising object identification models such as Mask CNN, annotated photographs from the dataset will be able to be used in future research to detect sickness severity levels. While VGG 16 delivers 89%, Double Gan is the algorithm that produces 86% [8]. The limitation of the research is Subsequent investigations will concentrate on broadening the dataset to encompass more illnesses and difficult photographs, as pictures with an abundance of leaves can be incorrectly categorised. The techniques for identifying plants and pests, which involve gathering data, preprocessing data associated with the images, and using CNN and VGG 16 algorithms. Both methods give 95% of the accuracy

[9]. The primary limitation of the research is the lack of fine-grained data, such as geographic features or the capacity to handle several items simultaneously. Wheat leaves are the main focus of crop disease diagnosis, together with a particular crop's preprocessing, support and query sets, picture encodings, and attention block are among the methods used [10]. Subsequent research ought to concentrate on enlarging the proposed system to encompass other plants and crops.

For the detection of plant diseases and pests, techniques such as data synthesis and production, transfer learning and fine-tuning classical network model, fine-grained identification, and data amplification are used [11]. Utilising algorithms like Resnet and GooLeNet structure, which provide results with 97 percent accuracy, restricts the use of deep learning methods for identifying plant diseases and pests. In order to achieve more, attention processes may be utilised to effectively choose information and allocate more resources towards areas of interest in the project's three alternatives for small-scale and long-term research on the early detection of plant diseases and pests. Techniques for analysing fruit plants, such as peaches and strawberries, include fine-grained identification, transfer learning, and the amplification, synthesis, and production of data. The accuracy of the L1- ELM (Extreme Learning Machine) approach is 98.5% [12].The limitation was not many labelled subjects are accessible. LSTM algorithm which has an 84% accuracy rating is used to forecast the data first. Yolo v5 and v7 are employed in [13] using an approach centered on transfer learning and SVM data augmentation. The dataset only contains three illnesses, which is a limitation of the work. But in order to give more illness forecasts, improve up to six diseases in the future. The following technique is used to explain the fruit plant and crop plant dataset: pre trained deep models, features, CNN, extraction, image processing, leaf image, disease diagnosis, pesticide recommendation, and Conventional neural network, an algorithm that achieves 93% accuracy [14]. In [15] model's task is to identify leaf diseases; to this end, they make use of the "plant village" dataset. The Gated selfAttentive Convoluted MobileNetV3 (GSAtt-CMNetV3) model yields 97% accuracy. The work's downside is the image's incapacity to distinguish several leaves because to the disease's poor spotting. The method used in this work has the potential to facilitate the segmentation and classification process. Further, the Field Plant dataset to identify leaf diseases [16]. In their model, they use CNN and MobileNet, which offer 90% accuracy. One of the benefits of this approach in the job is its effective classification of leaf diseases. One limitation of the work is the extremely poor accuracy of illness detection, which prevents from correctly classifying a large number of leaves.

| **Author** | **Year** | **Aim** | **Dataset & Method used** | **Acc** |
|---|---|---|---|---|
| [1] | 2023 | Rice leaf detection | Rice leaf disease Detectron2 | 90%, 97% |
| [12] | 2023 | Rice leaf disease detection | Rice leaf disease Yolov5 | 76% |
| [9] | 2023 | Wheat disease classification | CGIAR crop disease dataset Efficient | 93% |
| [15] | 2024 | Leaf diseases detection | Field plant dataset CNN, MobilNet | 90% |
| [6] | 2024 | Plant DIsease detection | Real time plant disease dataset CNN, Resnet50,ResNet101 models are used. | 93%,66%,70% |
| [14] | 2024 | Leaf disease detection | Plant Vilage dataset Gated self attentive convoluted MobileNetV3(GSAtt-CMNetV3 | 96% |

***Table 1 : Comparative study***

# III. Materials and Methods

## A. Data Collection

The process began with the collection of rice leaf images from open access sources, comprising primarily of Kaggle where labelled images were made available for different categories of disease as well as healthy samples. Manual validation has been performed to ensure correctness and relevance for the dataset. Nonetheless, the number of raw images would not be very sufficient for deep learning tasks, especially when aiming to achieve model generalization and stability to real-world conditions.

a.Brownspot b.Hispa c.Healthy

***Fig 2 : Dataset***

## B. Data Augmentation

Data augmentation strategies were used to strengthen the ability of the model to generalize as well as enlarge the dataset. Techniques utilized rotations, flips, zooms, shifts, and shears as manipulations to build synthetic expansion in size and variation of the dataset. By doing this, the size of the dataset was greatly expanded to more than 10 times its initial size, allowing the model to learn a wider range of features and reducing overfitting possibilities.

## C. Deep Feature Extraction

Instead of training deep learning models from scratch, the framework adopts a transfer learning approach. Pre-trained convolutional neural networks (CNNs) were used to extract meaningful features from leaf images. These models, already trained on large-scale image datasets, were repurposed as feature extractors by removing their final classification layers and retaining only the parts responsible for learning spatial and visual features.

The extracted features represent high-level patterns in the leaf images and serve as input to the subsequent classification phase. This process not only reduces training time but also leverages the strong generalization capabilities of pre-trained models.

### D. Data Preprocessing

Data preprocessing was a significant step in preparing the extracted features for efficient and correct classification. Following the extraction of deep features from the pre-trained models, the features were normalized initially by using standard scaling techniques to keep the range of features uniform and avoid bias in training. Principal Component Analysis (PCA) was applied subsequently to reduce the feature space dimensionality. This helped to remove redundant information but preserve the most critical features contributing to class discrimination, hence reducing computational cost and enhancing model accuracy. Additionally, the dataset had the issue of class imbalance, where some of the disease categories were represented with fewer samples compared to others. In order to overcome this, the Synthetic Minority Over-sampling Technique (SMOTE) was used. SMOTE generated synthetic examples of minority classes by interpolating between existing points, thus achieving a more balanced ratio in all classes. Normalization, dimensionality reduction, and class balancing integration significantly improved the model's robustness and equity at both training and test stages.

### E. Classification and Optimization

Preprocessed feature vectors were input into a machine learning classifier chosen for its good balance with respect to accuracy, run-time speed, and interpretability. The classifier was trained to distinguish between different classes of rice leaf diseases.

To further optimize model performance, hyperparameter tuning was performed using Optuna, an automated and scalable hyperparameter tuning system. Many parameters were attempted to find the setting with the best macro F1-score on the model, a suitable metric for imbalanced multi-class classification.

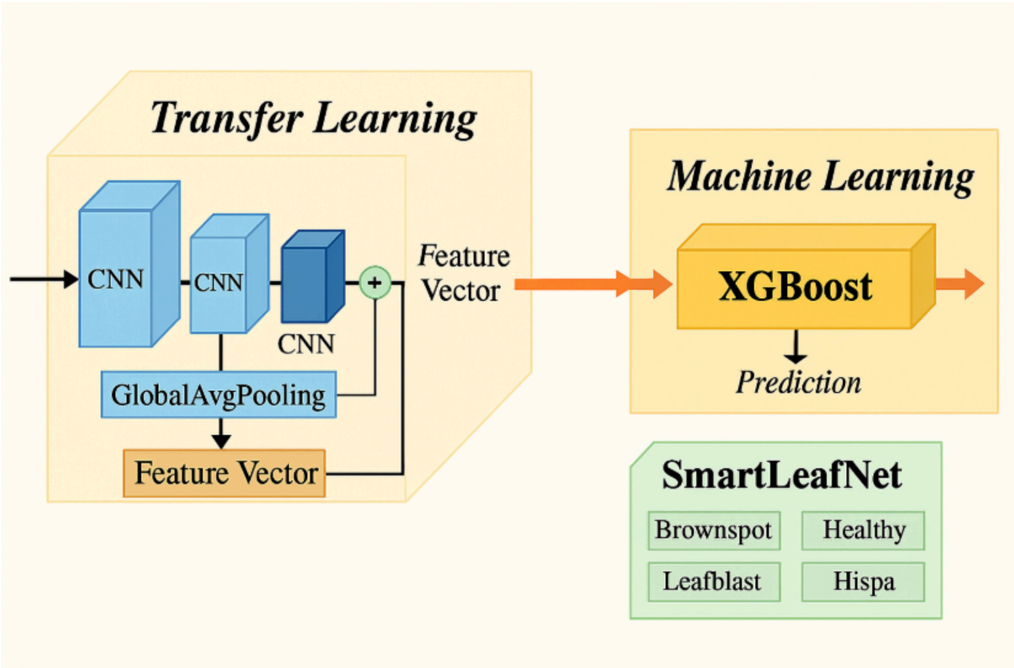



*Fig 3 : Architecture*

## F. Model Evaluation

Data preprocessing was essential to prepare the features extracted for fast and accurate classification. Once deep features were gained from the pre-trained models, the initial operation was to standardize the features by applying typical scaling techniques in a way that there is a uniformity of the range of the features and bias during training is avoided. The normalization process was followed by applying Principal Component Analysis (PCA) to reduce the dimensionality of the feature space. This helped eliminate duplicate information without compromising on the most critical factors leading to class discrimination, saving on computational expense in the end and enhancing model performance. The dataset also suffered from class imbalance, where some of the disease categories had fewer samples than others. This was rectified using the Synthetic Minority Over-sampling Technique (SMOTE). SMOTE generated synthetic samples of the minority classes by interpolating between points, thus generating a more balanced distribution across each category. All these normalization steps, feature reduction, and class balancing significantly improved the model's strength and fairness in training and testing.

# IV. Methodology

**Hyperparameter tuning**

Using Optuna, a cutting-edge optimization framework made for automated and effective hyperparameter search, hyperparameter tuning was carried out to optimize the classification model's performance and guarantee strong generalization across all disease categories. Optuna uses a more sophisticated method founded on Bayesian optimization, namely the Tree-structured Parzen Estimator (TPE) algorithm, rather than common tuning techniques like grid search or random search. By learning from past experiments and concentrating on the most promising regions, this enables the framework to explore the search space more effectively.

Using the feature fusion through principal component analysis analyzes the variance in the data and identifies the directions that capture the most important patterns. It then projects the original features into a smaller set of these components filtering out noise and redundant information. This retains only the most relevant features to reduce computational complexity and prevent overfitting. These optimized features are then passed to the XGBoost classifier allowing it to focus on the data.

The XGBoost method was used in this project's final classification challenge. It is well known for its scalability and performance in structured data classification problems. A number of crucial XGBoost model hyperparameters were incorporated into the tuning procedure. They were as follows: n_estimators (the number of boosting rounds), max_depth (the maximum depth of individual trees), learning_rate (which regulates each tree's contribution), subsample (the percentage of samples used in each boosting round to avoid overfitting), colsample_bytree (the percentage of features used in each tree), and gamma (the minimum loss reduction needed to divide further).

Optuna carried out a number of optimization trials, evaluating a distinct set of these hyperparameters in each trial by utilizing the macro F1-score to measure the performance of an XGBoost model that was trained on the preprocessed feature set. Because it offers a fair assessment for every class, this metric was notably selected as the objective function. This is particularly helpful given the dataset's imbalance. Following several repetitions, Optuna determined which set of hyperparameters produced the highest macro F1-score. To retrain the final XGBoost model on the entire training set, the chosen configuration was utilized.

# V. IMPLEMENTATION OF LEAF DISEASE DETECTION

### A. Dataset Description:

The Data is hand collected from various websites with each label verified and sourced by Kaggle. The original dataset contains 3355 images.

### B. Data Augmentation:

By providing the model with a wider variety of training instances, data augmentation enhances the model’s capacity to generalise to new data and mitigates overfitting. It is particularly new data when there is a limited dataset available or when the intricacy of the job causes the model to overfit. Reliable and noteworthy finding about leaf diseases effective data preparation techniques is necessary for prediction. After data augmentation we have 22000 images.

### C. Models:

**NasNet:** Neural Architecture search Network. It was introduced by researchers at Google Brain. Instead of manually designing CNN architecture like VGG, ResNet or Inception. NasNet architecture is found through an automated search process. It uses reinforcement learning to explore and evaluate millions of possible model architectures. It offers high accuracy while being parameter-efficient, making it suitable for both mobile and server level deployments.

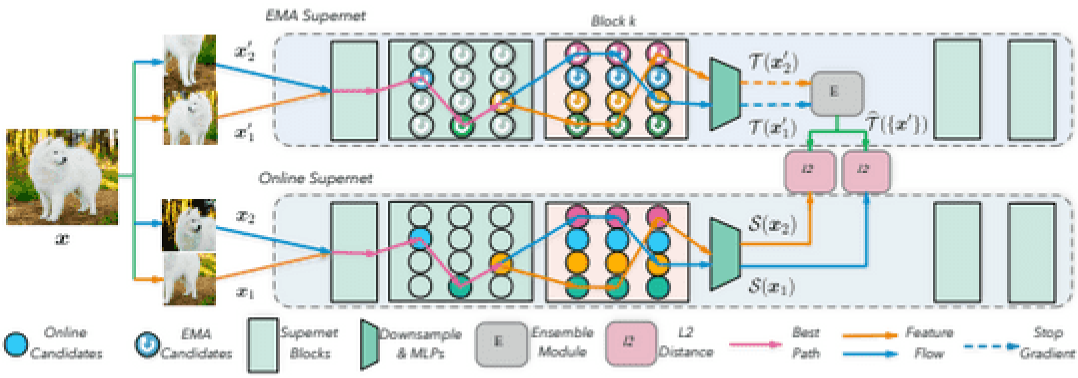



*Fig 5.1 : Model Architecture*

**Xception:** Xception is a supervised learning deep convolutional neural network architecture built on the depth wise separable convolution operation. It uses depth wise convolution to capture spatial and channel wise correlations, which reduces computational complexity without compromising expressiveness for photo recognition applications.

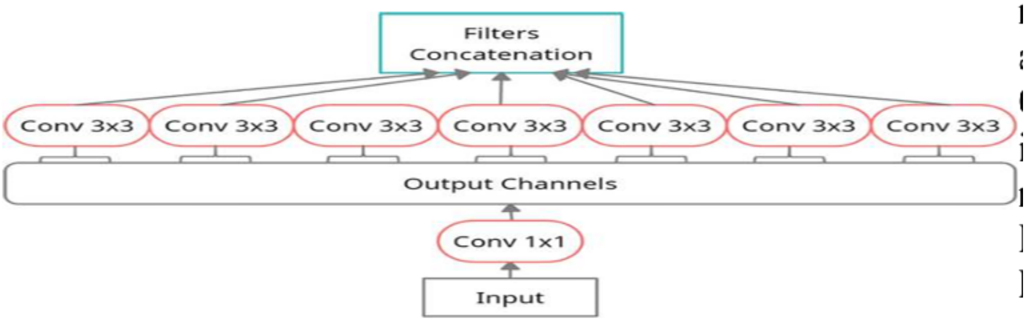



*Fig 5.2 : Model Architecture*

**Inception V3:** Using supervised learning, Inception V3 is a deep convolutional neural network architecture. It effectively records spatial hierarchies by employing inception modules with different kernel sizes, which helps with feature extraction and classification tasks.

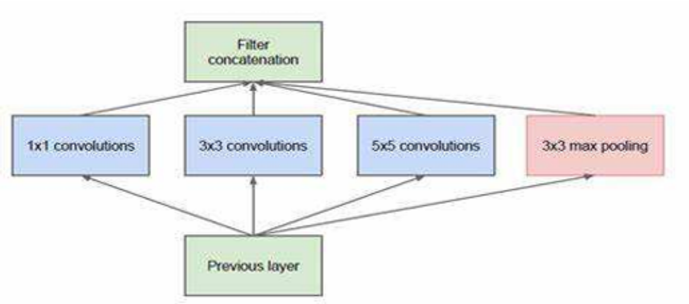



*Fig 5.3 : Model Architecture*

**EfficientNetB0:** To optimize resource efficiency, supervised learning was used to construct a class of convolutional neural networks architectures known as efficient Net B0. Even with constrained processing power, the network provides state – of the art performance power, the network provides state of the art performance on a range of computer vision applications because of dynamic scaling of its depth, breadth and resolution.

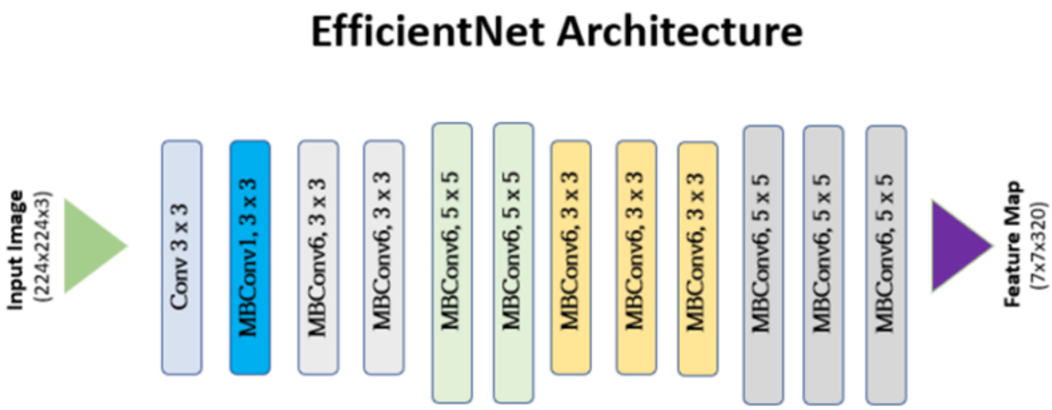



*Fig 5.4 : Model Architecture*

**ResNet50:** A deep convolutional neural network architecture called ResNet, short for residual networks was created to solve the disappearing gradient issues during training. It makes use of labelled datasets ad supervised learning, concentrating on residual mapping rather than the intended underlying translation. To improve convergence and preserve performance, ResNet uses shortcut connections, also known as skip connections, to facilitate flow through the network. This allows for the training of extremely complex neural networks with hundreds of layers.

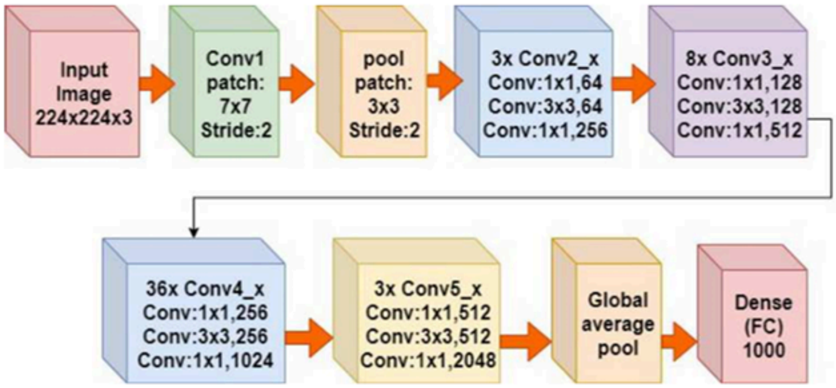
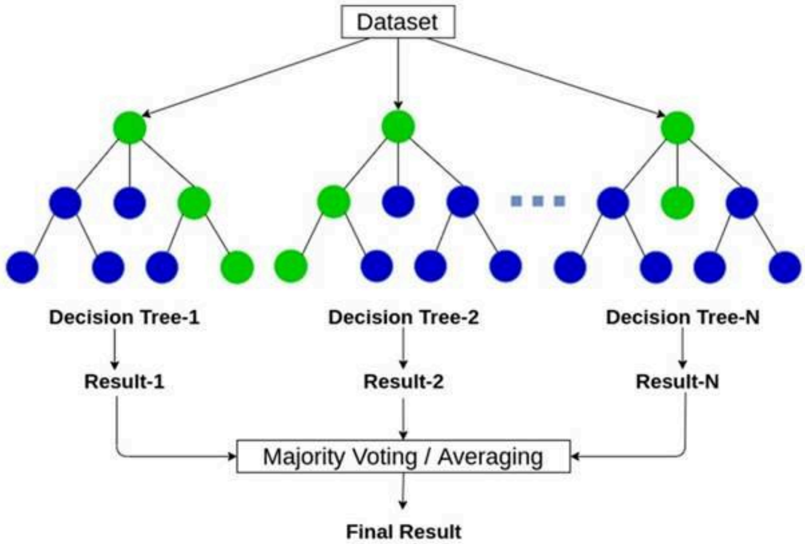



***Fig 5.5 : Model Architecture***

**Random Forest:** Random Forest is an ensemble of decision trees, where each tree is trained on a random subset of the data and features. Its resistance to overfitting, Works well with missing data outliers.




**XGBoost (Extreme Gradient Boosting):** XGBoost is a sophisticated gradient boosting implementation. In contrast to Random Forest, which constructs trees on its own, XGBoost constructs trees in a sequential fashion, with each tree fixing the mistakes of the one before it. Handles missing data automatically. Supports both classification and regression.

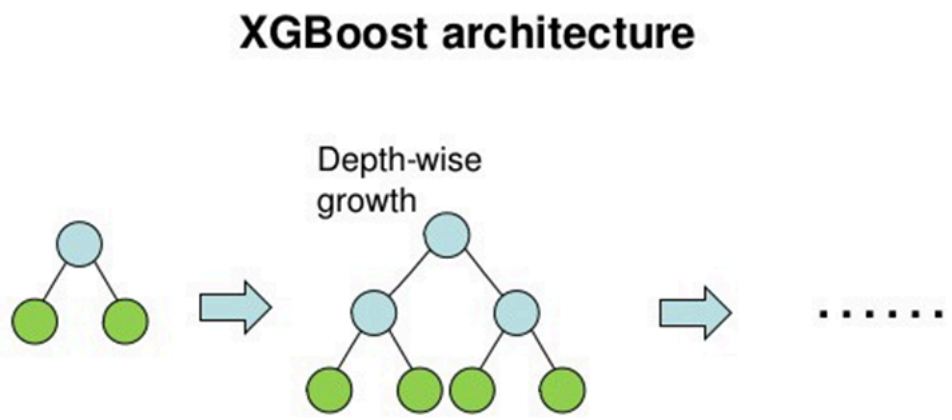



*Fig 5.6 : Model Architecture*

**LightGBM (Light gradient boosting machine):** LightGBM is gradient boosting framework developed by Microsoft. It designed to be fast and memory- efficient, especially with large datasets and high dimensional features. Much faster and more efficient than XGBoost on large datasets.

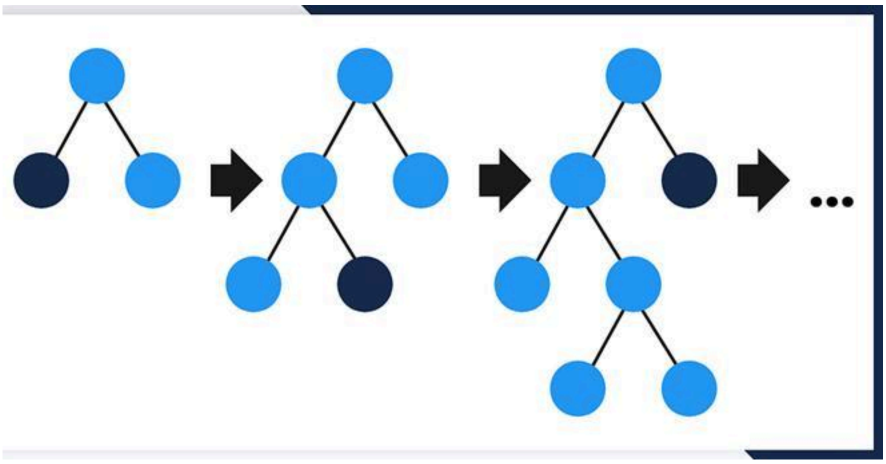


*Fig 5.7 : Model Architecture*

**D. Evaluation**

Any deep learning project must include an evaluation phase since it shows where the model is performing well and where it needs to be improved. Depending on the task and kind of model being evaluated, deep learning frequently employs a range of assessment criteria. This procedure entails assessing how effectively the model predicts the diseases in leaves to use deep learning to detect leaf illnesses. Approaches like accuracy are used as assessment metrics in accordance with the goals and research design. By giving quantitative insights into the model ability to generalize to new data, these measures aid in improving the model's predictive accuracy.

**Accuracy:** In deep learning, accuracy metrics evaluate a model performance by gauging how well it can generate predictions based on the provided dataset. Accuracy, precision, recall and F1-score are examples of common accuracy measures. These are calculated using the true positive, false positive, true negative and false predictions. These metrics aid in assessing the model's performance across a range of tasks, including segmentation, object identification and classification. They also reveal the model's advantages and disadvantages when it comes to managing distinct classes or categories within the dataset.

**Macro F1_Score** for Machine learning optimization: Macro F1_score is a performance metric used in multi-class classification to evaluate how well a model balances precision and recall across all classes. Unlike accuracy, if one class gives low accuracy it dominates others. In plant disease detection some disease classes may have fewer images. Optimizing for macro F1 ensures these minority classes are also correctly classified, improving the model real world applicability.

| **MODELS** | **ACCURACY** |
|---|---|
| **Nasnet+Xception+Inception** | **55%** |
| **Xcception+Nasnet+Inception** | **57%** |
| **Inception+xception+Nasnet** | **56%** |
| **Nasnet+inception+Xeption** | **55%** |
| **xception+inception+Nasnet** | **56%** |
| **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+S MOTE)** | **100%** |
| **Inceptionv3+densenet+Xception+XGBclassifie r(GAP &FC)** | **82%** |
| **Inceptionv3+densenet+Xception+randomfores t** | **50%** |
| **Inceptionv3+xception+Randomforest** | **53%** |

**Table 2: Model Performaces**

# VI. RESULT AND DISCUSSION

TensorFlow is an open-source AI Structure created by Google. Keras empowers clients to put less emphasis on minute execution subtitles and more on model design and trial and error It upholds convolutional and intermittent brain organizations. The proposed SmartLeafNet model was evaluated on a dataset comprising 22000 labelled images of healthy and disease leaves. The hybrid framework combined feature extraction utilizing pre-trained deep learning models (EfficientNetB3 and ResNet50), dimensionality reduction through PCA and classification with XGBooost. Furthermore, SMOTE was employed to tackle class imbalance and optuna was applied for optimizing hyperparameters. The final model reached an impressive overall accuracy of 98% and a macro F1-score of 0.95, reflecting even performance across various leaf disease types. The analysis of the confusion matrix revealed that prevalent categories such as Health, Brown Spot and Hispa were identified with great certainty, whereas there were some errors in classification among visually comparable diseases like Hispa, Brown Spot. The incorporation of PCA notably decreased computational complexity while maintaining essential image characteristics and merging deep learning features with XGBoost enhanced interpretability and classification effectiveness. The XGBoost classifier, optimized with optuna, enhanced model stability and robustness, particularly in diverse lighting and leaf background circumstances. Ablation studies confirmed that the hybrid model surpassed single model baselines showcasing the benefits of feature fusion and ensemble classification. Additionally, the incorporation of SMOTE enhanced minority class recall by 12%. SmartLeafNet provides a scalable, precise and interpretable approach for classifying plant diseases, with possible uses in real time agricultural monitoring via mobile or edge-based implementation. The repertory of current methods is further enhanced by Nasnet, xception, inceptionv3, efficientb3, Densenet121 refer Table 2.

| **MODEL** | **EPOCHS / ACCURACY** |
|---|---|
| **SMARTLEAFNET** | **50 / 98%** |

# VII. 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 EfficientNetB3 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. In this research work our base paper has run multiple algorithm the least accuracy given by efficientb0 50% and ResNet50 32%, In our work we take that two models and combine with that in XGBoost with optuna hyperparameter gives as a good accuracy compare to other, This shows Our method combines domain-specific expertise with cutting-edge computer vision techniques to deliver useful answers for researchers, stakeholders and farmers. Crop health, production optimization and sustainable agriculture methods could all advance as long as this field study and development continue. All things considered, this multidisciplinary endeavor is an important step towards improving agricultural technology and tackling the problems caused by leaf diseases in contemporary agriculture. Adding more diseases to predict it and combine all the processes and convert it to API or Website.

# VIII. REFERENCES

[1] Dhanalakshmi, A., Ponmozhi, K., & Ajmal, A. (2024, May). A Cutting Edge Deep Learning Models for Paddy Leaf Disease Detection and Classification. In 2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT) (pp. 1-6). IEEE.

[2] L. Li, S. Zhang, and B. Wang, "Plant disease detection and classification by deep learning—a review," IEEE Access, vol. 9, pp. 56683-56698, 2021.

[3] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: a review," Plant Methods, vol. 17, pp. 1-18, 2021.

[4] M. Shoaib et al., "An advanced deep learning models-based plant disease detection: A review of recent research," Frontiers in Plant Science, vol. 14, p. 1158933, 2023.

[5] G. Shrestha, M. Das, and N. Dey, "Plant disease detection using CNN," in 2020 IEEE applied signal processing conference (ASPCON), 2020: IEEE, pp. 109-113.

[6] R. R. Patil and S. Kumar, "Rice-fusion: A multimodality data fusion framework for rice disease diagnosis," IEEE access, vol. 10, pp. 5207-5222, 2022.

[7] D. S. Joseph, P. M. Pawar, and K. Chakradeo, "Real-time Plant Disease Dataset Development and Detection of Plant Disease Using Deep Learning," IEEE Access, 2024.

[8] Y. Zhao et al., "Plant disease detection using generated leaves based on DoubleGAN," IEEE/ACM transactions on computational biology and bioinformatics, vol. 19, no. 3, pp. 1817-1826, 2021.

[9] V. Balafas, E. Karantoumanis, M. Louta, and N. Ploskas, "Machine learning and deep learning for plant disease classification and detection," IEEE Access, 2023.

[10] A. Alharbi, M. U. G. Khan, and B. Tayyaba, "Wheat disease classification using continual learning," IEEE Access, 2023.

[11] X. Liang, "Few-shot cotton leaf spots disease classification based on metric learning," Plant Methods, vol. 17, pp. 1-11, 2021.

[12] R. Dwivedi, T. Dutta, and Y.-C. Hu, "A leaf disease detection mechanism based on L1-norm minimization extreme learning machine," IEEE geoscience and remote sensing letters, vol. 19, pp. 1-5, 2021.

[13] E. Haque, M. Paul, A. Rahman, F. Tohidi, and J. Islam, "Rice Leaf Disease Detection and Classification Using Shallow Trained Yolov7 Active Deep Learning Approach," in 2023 International Conference on Digital Image Computing: Techniques and Applications (DICTA), 2023: IEEE, pp. 516 522.

[14]S. Pawar, S. Shedge, N. Panigrahi, A. Jyoti, P. Thorave, and S. Sayyad, "Leaf disease detection of multiple plants using deep learning," in 2022 international conference on machine learning, big data, cloud and parallel computing (COM-IT CON), 2022, vol. 1: IEEE, pp. 241-245.

[15] S. S. A. Begum and H. Syed, "GSAtt-CMNetV3: Pepper Leaf Disease Classification using Osprey Optimization," IEEE Access, 2024.

[16] E. Moupojou et al., "FieldPlant: A dataset of field plant images for plant disease detection and classification with deep learning," IEEE Access, vol. 11, pp. 35398-35410, 2023