Optimizing Grape Leaf Disease Identification Through Transfer Learning and Hyperparameter Tuning

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***Abstract*—Grapes are a globally cultivated fruit with significant economic and nutritional value, but they are susceptible to diseases that can harm crop quality and yield. Identifying grape leaf diseases accurately and promptly is vital for effective disease management and sustainable viticulture. To address this challenge, we employ a transfer learning approach, utilizing well-established pre-trained models such as ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3, renowned for their exceptional performance across various tasks. Our primary objective is to identify the most suitable network architecture for the classification of grape leaf diseases. This is achieved through a rigorous evaluation process that considers key metrics such as accuracy, F1 score, precision, recall, and loss. By systematically assessing these models, we aim to select the one that demonstrates the best performance on our dataset. Following model selection, we proceed to the crucial phase of fine-tuning the model's hyperparameters. This fine-tuning process is essential to enhance the model's predictive capabilities and overall effectiveness in disease identification. To accomplish this, we conduct an extensive hyperparameter search using the Hyperband strategy. Hyperparameters play a pivotal role in shaping the behavior and performance of deep learning models, and by systematically exploring a wide range of hyperparameter combinations, our goal is to identify the most optimal configuration that maximizes the model's performance on the given dataset. Additionally, the study's results were compared with those of numerous relevant studies.**

***Keywords*—Grape disease recognition; disease identification; transfer learning; hyperparameter optimization; hyperband strategy; fine-tuning; deep learning**

I. INTRODUCTION

The presence of plant diseases can result in a notable reduction in agricultural yields, causing decreased crop productivity and financial setbacks for farmers [1], [2], [3], [4], [5], [6]. Prompt identification and timely management of these diseases are essential to minimize their adverse consequences and optimize crop yields. Swift detection and intervention strategies are key to preventing disease outbreaks and fostering sustainable crop production. Through swift detection and proactive measures against plant diseases, farmers can employ suitable control methods like precise fungicide applications or crop rotations to reduce yield losses and protect their harvests [7], [8]. Furthermore, timely disease detection can also assist in preventing the spread of diseases to nearby plants, preserving the overall well-being of agricultural ecosystems. Traditional approaches for diagnosing plant diseases have been acknowledged as problematic and ineffective in numerous agricultural contexts. These methods often depend on visual symptoms and physical inspections, posing challenges in accurately identifying diseases, particularly during their initial development stages. Relying solely on visual symptoms can be deceptive, as various diseases may manifest similar signs, resulting in misdiagnoses and improper treatments. Additionally, these traditional methods may not effectively detect pathogens that lack visible indications on plant surfaces, adding complexity to the diagnostic procedure. Acknowledging these constraints, there has been an increasing focus on embracing contemporary technology-driven solutions, including advanced image-based recognition systems and artificial intelligence-based methods, to enhance the precision and efficiency of plant disease diagnosis and management. Deep Learning (DL) and Machine Learning (ML) techniques have gained extensive utilization in image recognition applications across diverse fields. Including medicine [9], [10], [11], [12]. In self-driving cars [13], [14], [15], [16], [17], [18]. In agriculture [19], [20], [21], [22], [23]. Especially when it comes to automating the identification of plant diseases [24], [25], [26], [27], [28], [29], [30], etc.

This article makes a significant contribution to the agricultural and viticulture sectors by addressing the substantial challenges associated with grape disease management and precise identification. The study's primary contribution lies in the adoption of advanced technological solutions, including transfer learning and pre-trained models renowned for their exceptional performance such as ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3. By employing these cutting-edge techniques, the research aims to provide more accurate and efficient grape leaf disease classification, thereby bolstering disease management strategies. Additionally, the study highlights the critical role of fine-tuning model hyperparameters through extensive hyperparameter searches, which is pivotal in enhancing the predictive capabilities and overall effectiveness of the selected model. This comprehensive approach serves to optimize grape disease management and advance sustainable viticulture practices, making a valuable contribution to the field of agricultural research and disease management.

The structure of the paper is as follows: A comprehensive review of the literature is provided in Section II. The Grape Disease Recognition Methodology, comprising the Data Set, Data Preparation, and Model Evaluation Metrics, is described in Section III. Section IV describes the experimental system and final results. Section V provides a summary of the study's results, concluding notes, and a comparison of current approaches to our suggested model for a similar problem. Lastly, Section VI outlines potential avenues for future study.

II. Related Works

Recent advancements in deep learning methodologies, in particular, convolutional neural networks (CNNs) and models of transfer learning (TL), have demonstrated significant progress in automating agricultural disease identification techniques. Multiple studies have explored the utilization of deep learning techniques to identify leaf diseases in general, including grape leaves in particular. Researchers are actively exploring innovative approaches to enhance the accuracy of disease identification.

Ullah, Zahid, et al. in [31] introduces a hybrid deep learning (DL)-based approach, combining EfficientNetB3 and MobileNet into the EffiMob-Net model, to accurately detect tomato plant diseases from leaf images. The study addresses overfitting by employing techniques like regularization, dropout, and batch normalization. The proposed EffiMob-Net model achieved a 99.92% success rate in accurately identifying tomato leaf diseases when evaluated on a dataset of diseased and healthy tomato leaf images, highlighting its excellent feature extraction capabilities.

In [32], Jing, Jiaping, et al. visually differentiates between nine different infectious diseases in tomato leaves and healthy leaves. The study applied EfficientNetB5 to a dataset of tomato leaf diseases (TLD) without segmentation, achieving an impressive average test accuracy of 99.07%. To enhance model interpretability, the paper introduces the use of gradient-weighted class activation mapping (GradCAM) and local interpretable model-agnostic explanations. This interpretability is vital for improving predictive performance, fostering trust, and enabling the integration of the model into agricultural practices.

In [33], the authors have developed a lightweight model for identifying tomato leaf diseases, which they named Light-Mixer. This model combines a depth convolution with a Phish module and a light residual module. Experimental findings reveal that the LightMixer model achieved an impressive 99.3% accuracy when tested on public datasets, all while maintaining a minimal parameter count of 1.5 million.

In [34], the authors introduce a pipeline for automated tomato leaf disease identification, incorporating three compact convolutional neural networks (CNNs). They leverage transfer learning to extract deep features from The final fully connected layer within the Convolutional Neural Networks (CNNs), resulting in a more concise and high-level representation. These features are then combined from all three CNNs to harness the strengths of each structure, followed by the application of a hybrid feature selection method to generate a comprehensive feature set with reduced dimensions. Notably, the results demonstrate that the K-nearest neighbor and support vector machine classifiers achieved remarkable accuracy, reaching 99.92% and 99.90%, respectively, using a minimal feature set of 22 and 24 features.

The authors in [35] introduces a convolutional neural network-based model for the identification and classification of tomato leaf diseases. The model is trained using a publicly available dataset and supplemented with field photographs. To prevent overfitting, generative adversarial networks are employed to generate data with similar characteristics to the training set. The results demonstrate the model's exceptional performance, with an accuracy exceeding 99% on both the training and test datasets in the detection and classification of tomato leaf diseases.

In [36], an integrated deep learning solution is introduced for the detection and classification of banana diseases. The approach involves the examination of various parts of the banana plant, not just the leaves, utilizing convolutional neural networks (CNN) and a combined binary and multiclass Support Vector Machine (FSVM). This method yields outstanding results, with an impressive overall accuracy of 99%, alongside excellent precision-recall and F1-score performance metrics.

The research in [37], an efficient method for detecting rice plant diseases is developed, leveraging convolutional neural networks. The study concentrates discusses three major rice illnesses: leaf smut, brown spot (caused by fungus), and bacterial leaf blight (caused by bacteria). The proposed approach focuses on recognizing and identifying these diseases based on the size, shape, and color of lesions in rice leaf images. By employing Otsu's global thresholding method for binarizing images, background noise is effectively removed. The fully connected CNN model, trained with 4000 samples of each diseased and healthy rice leaf, demonstrates impressive performance, reaching 99.7% accuracy on the dataset.

The research in [38] introduces a CNN model for the classification of rice and potato plant leaf diseases. The study employs a dataset of 5932 rice leaf images and 1500 potato leaf images. The proposed CNN model effectively captures hidden patterns in raw images, achieving an impressive accuracy of 99.58% for rice leaf classification and 97.66% for potato leaves. The results reveal that the CNN model outperforms other machine learning image classifiers, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest.

The authors in [39] presents a novel approach for precise detection and classification of rice leaf diseases, utilizing a Deep Convolutional Neural Network (DCNN) with transfer learning. The method includes a modification of the VGG19-based transfer learning technique and successfully detects and diagnoses six distinct classes of rice leaf diseases. The maximum average accuracy achieved is 96.08% when using a non-normalized augmented dataset, with corresponding values of 0.9620 for precision, 0.9617 for recall, 0.9921 for specificity, and 0.9616 for the F1-score.

In [40], the authors employ convolutional neural network (CNN) methods to address the classification of five distinct potato disease classes, including Healthy, Black Scurf, Common Scab, Black Leg, and Pink Rot. Their study utilizes a dataset of 5000 potato pictures and compares their classification results with various alternative techniques, including Transfer Learning, R-CNN, VGG, Alexnet, and Googlenet. Notably, the deep learning method proposed in the paper outperforms existing approaches, achieving accuracy rates of 100% and 99% in some of the individual disease classes.

In [41], the impact of hyperparameters and training approaches on model performance is examined. The study evaluates the performance of four deep learning models, with three trained from scratch and one using a pre-trained ResNet50 model, in the context of detecting potato plant diseases, specifically early blight and late blight, using the plant village dataset. The experimental results demonstrate that models trained from scratch outperform the pre-trained ResNet50 model, achieving accuracies of 96.75% and 94.43% compared to 93.5%. This suggests that pre-trained models may not always be the best choice for all datasets.

The study in [42] introduces an efficient deep learning-based solution to detect crop diseases, effectively preventing disease spread and ensuring healthy plant growth. In the experiment, the model achieved an impressive overall accuracy of 99.55% in identifying three diseases in corn, potato, and tomato. Furthermore, individual testing of these plants revealed classification accuracies of 98.44% for corn, 99.43% for potato, and 95.20% for tomato, showcasing the effectiveness of the proposed model.

The author in [43] conducts a comprehensive exploration of deep transfer learning and deep convolutional neural networks (CNNs). The primary focus of the research is to put carried out a model that has been pre-trained, specifically ResNet50 for plant disease detection and classification, utilizing the ImageNet dataset. Corn (maize) and Potato images from the plant village dataset are used to assess the model's performance. The model processes input images of Corn (maize) or Potato leaves through preprocessing techniques like data augmentation and segmentation before using the Resnet50 model. The evaluation of the Resnet50 model yielded the following results: 98.0% accuracy, 77.0% precision, 99.0% recall, and 86.0% F1-score.

The study in [44] explores the use of well-known Convolutional Neural Network (CNN) models—EfficientNetB5, MobileNet, ResNet50, InceptionV3, and VGG16—for classifying plant diseases. Notably, EfficientNetB5 exhibited superior performance, achieving a remarkable 99.2% classification accuracy.

Numerous studies have been carried out concerning the application of deep learning for disease identification in grape leaves.

The study [45] introduces an approach for grape leaf disease detection by utilizing convolutional capsule networks, which represent a promising neural network paradigm in deep learning. These networks use capsules, groups of neurons, to effectively capture spatial feature information. The novelty of this work lies in the inclusion of convolutional layers before the primary caps layer, reducing the number of capsules and expediting the dynamic routing process. The suggested approach, tested on both augmented and non-augmented datasets, successfully identifies grape leaf diseases with an impressive accuracy of 99.12%.

In this research [46], authors introduces the EfficientNet B0 deep learning model for the classification of grapevine leaves. The proposed deep learning architecture is compared with established counterparts, and the grapevine leaf dataset serves as the training data with 3000 images. The EfficientNet B0 model is trained through transfer learning and fine-tuning approaches, ultimately achieving the highest accuracy of 99.67%. This outperforms classical CNN and state-of-the-art models like VGG19, MobileNet V2, Inception V3, and ResNet152.

The study [47] delves into the classification of grapevine leaves using deep learning techniques. Initially, 500 pictures of vine leaves from 5 different species were captured using a specialized self-illuminating system, and this dataset was subsequently expanded to 2500 images through data augmentation. The classification process involved three methods: fine-tuning a state-of-the-art CNN model, MobileNetv2; obtaining features from the pre-trained Logits layer of MobileNetv2 and employing several SVM kernels; and selecting and reducing 1000 features from MobileNetv2's Logits layer to 250 using the Chi-Squares method, followed by classification with different SVM kernels. The most successful method involved feature extraction and reduction, with the Cubic SVM kernel achieving an impressive classification accuracy of 97.60%.

In [48], the study centers on the early identification and classification of grape diseases, introducing a novel framework that combines deep learning with conventional architecture for superior performance. The process involves three key steps: (a) feature extraction using transfer learning with pre-trained deep models like AlexNet and ResNet101, (b) feature selection employing the novel Yager Entropy and Kurtosis (YEaK) technique to identify the best features, and (c) merging these strong features using a parallel approach, followed by classification through least squared support vector machine (LS-SVM). The approach is validated through simulations on infected grape leaves from the plant village dataset, achieving an impressive accuracy of 99%. The results indicate the exceptional performance of the proposed approach in comparison to various existing methods.

In [49], the authors aimed to enhance grape leaf disease identification accuracy within constraints of limited computing resources and a small training dataset, utilizing deep transfer learning and an improved MobileNetV3 model named GLD-DTL. By retraining the modified networks using a grape leaf diseases dataset with six diseases constructed with data augmentation and image annotation techniques, the authors achieved exceptional results, with an identification accuracy of 99.84% and a compact model size of just 30 MB.

Highlighting the significance of proactive disease control, agricultural specialists and researchers persistently strive to innovate advanced technologies and techniques aimed at early disease detection, thereby enhancing the resilience and productivity of crop production systems worldwide. Therefore, the purpose of this study is to focus on the adoption of advanced technological solutions, including powerful pre-trained models like ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3. The study leverages these state-of-the-art techniques to achieve more precise and efficient classification of grape leaf diseases, ultimately strengthening disease management strategies. Furthermore, the research underscores the critical importance of fine-tuning model hyperparameters through extensive hyperparameter searches, using a hyperparameter optimization algorithm called Hyperband, a pivotal step in enhancing the predictive capabilities and overall effectiveness of the chosen model.

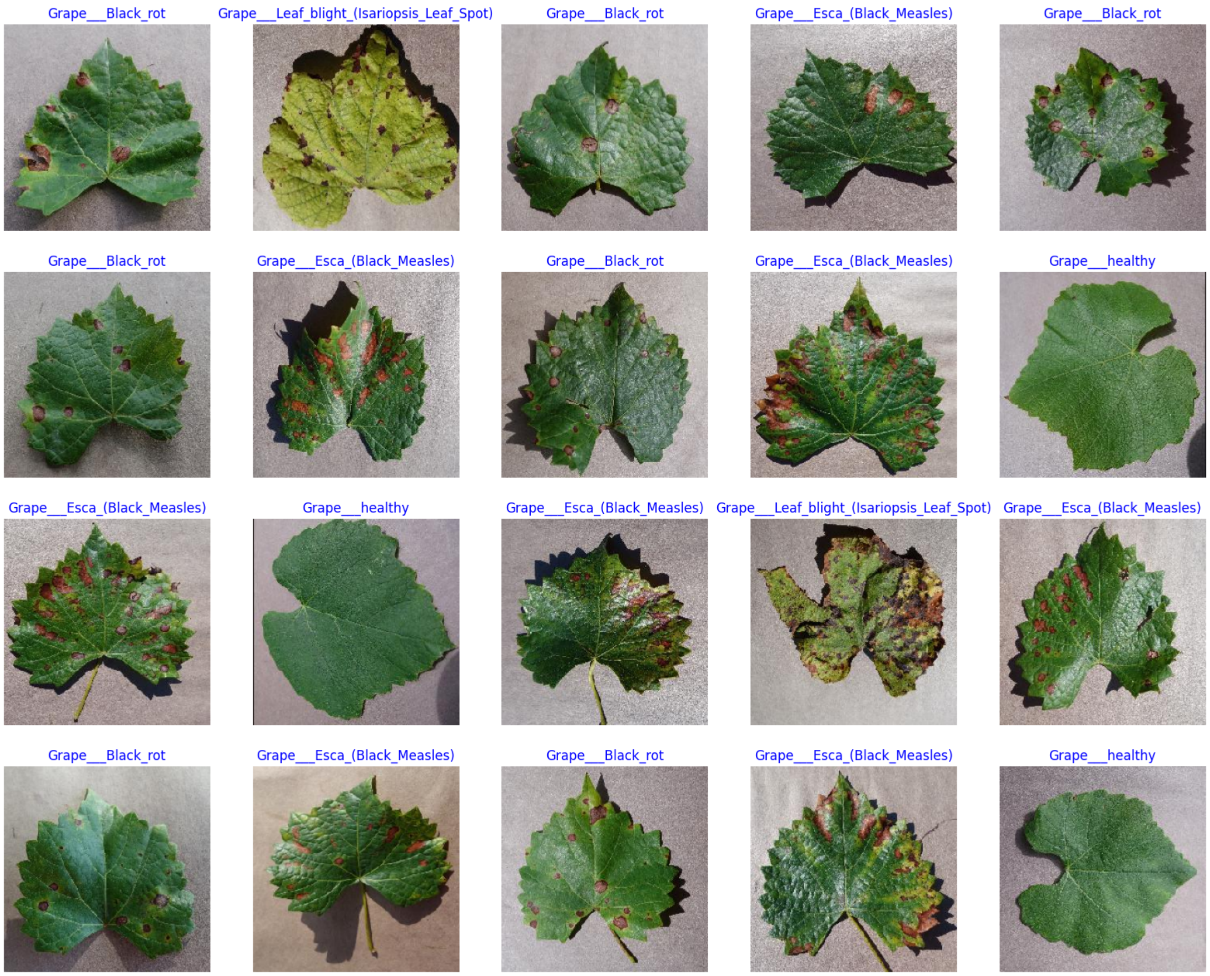

Fig. 1. Grape disease sample from the Grape Disease dataset.

III. Methodology

A. Data Collection and Preparation

In this study, we worked with a dataset comprising 9,027 images, sourced from Kaggle [50], known as the Grape Disease dataset. This dataset is divided into four classes: Grape-Esca-(Black-Measles) (Class 1), Grape-Black-rot (Class 2), Grape-Leaf-blight-(Isariopsis-Leaf-Spot) (Class 3), and Grape-healthy (Class 4). Sample images of grape diseases from this dataset are shown in Fig. 1, and the dataset distribution is visually represented in Fig. 2. Before proceeding with model training and evaluation, a preprocessing step is conducted on the images, which involves using an image preprocessing technique and sizing them to 224 x 224. The dataset is then divided into subsets, with 5,416 images allocated for the training set, 1,806 images for the validation set, and 1,805 images for the test set.

B. Overall Methodology

The research process can be divided into two primary phases.

1) Phase 1: Model selection and evaluation: The initial phase focuses on selecting the most suitable network architecture for classifying grape leaf diseases. This involves employing a transfer learning approach with established pre-trained models renowned for their performance. Rigorous evaluation criteria, including accuracy, F1 score, precision, recall, and loss, are used to assess these models. The objective here is to scientifically identify the model that performs best with the dataset (Fig. 3). Models used in this phase include: ResNet50V2 [51], ResNet152V2 [52], MobileNetV2 [53], Xception [54], and InceptionV3 [55].

2) Phase 2: Fine-tuning and hyper-parameter optimization: Following model selection, the next phase involves fine-tuning the chosen model's hyperparameters. This crucial step aims to improve the model's predictive abilities and overall effectiveness in identifying diseases. Extensive hyperparameter search utilizing the hyperband [56] strategy is conducted to refine and optimize the model's performance (Fig. 4).

The primary objective of hyperparameter optimization is to increase the efficiency and automate the hyperparameter tuning process. Unlike the model parameters (weights and

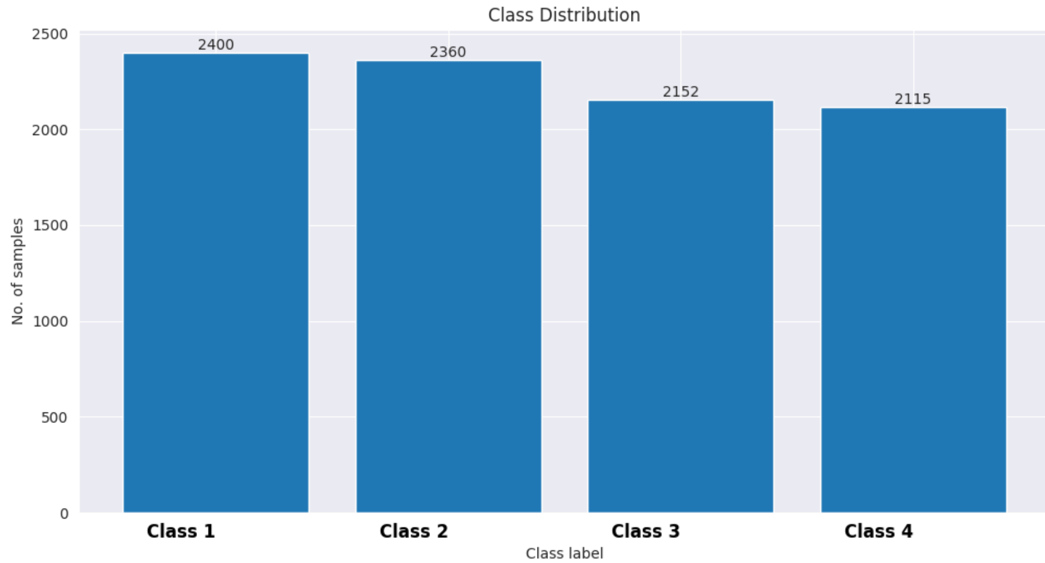

Fig. 2. A distribution of datasets.

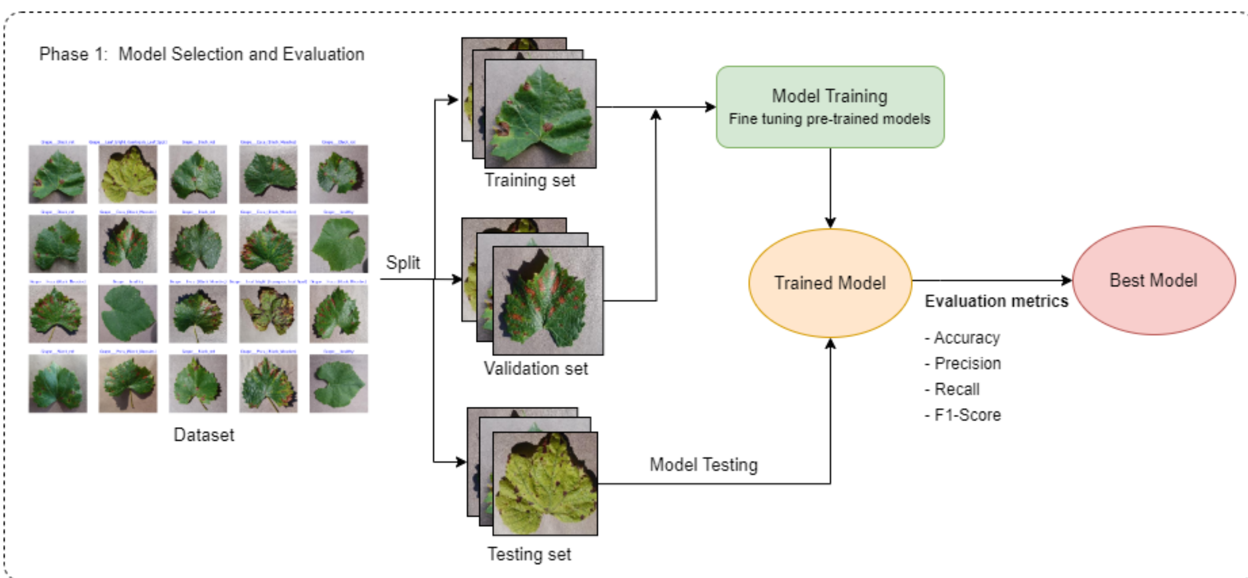

Fig. 3. The Process of model selection and evaluation.

biases), hyperparameters are set before the training begins and significantly influence the model's performance. The main goal is to find the most optimal set of hyperparameters that maximize the model's performance metrics. The ultimate goal of a hyperparameter optimization issues is to achieve Eq. (1).

$$x^* = \arg \underset{x \in X}{min} f(x) \tag{1}$$

Where $f(x)$ is the objective function; x^* represents the set of hyperparameter configurations that produce the best possible value for $f(x)$; The hyperparameter x can take on any value within the search space X.

C. Fine Tuning Pre-trained Models

In this research, the research team aim to employ a transfer learning methodology due to the scarcity of images depicting diseases on grape leaves. This approach offers substantial advantages in identifying crucial characteristics associated with grape leaf diseases. By utilizing trained models such as ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3, known for their high performance across diverse tasks, our goal is to determine the most suitable network architecture for our specific classification needs. These models will be adjusted before the training phase, keeping all of the original layer structure while adjusting the output using Batch Normalization layer. Additionally, they include a Global Aver-

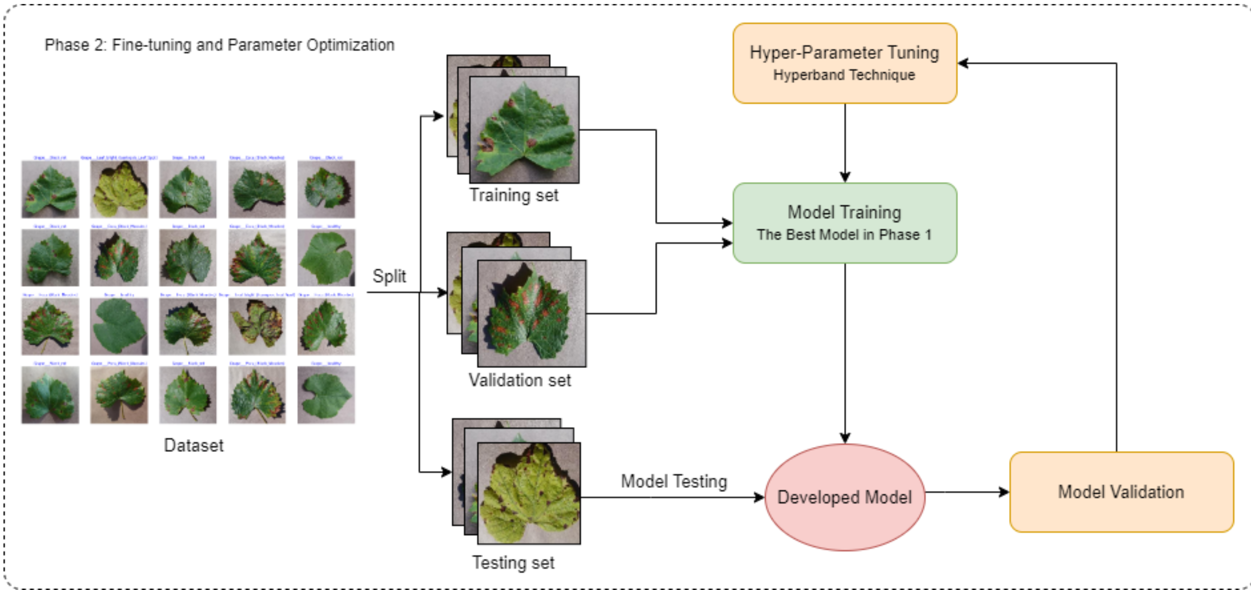

Fig. 4. The Process of fine-tuning and parameter optimization.

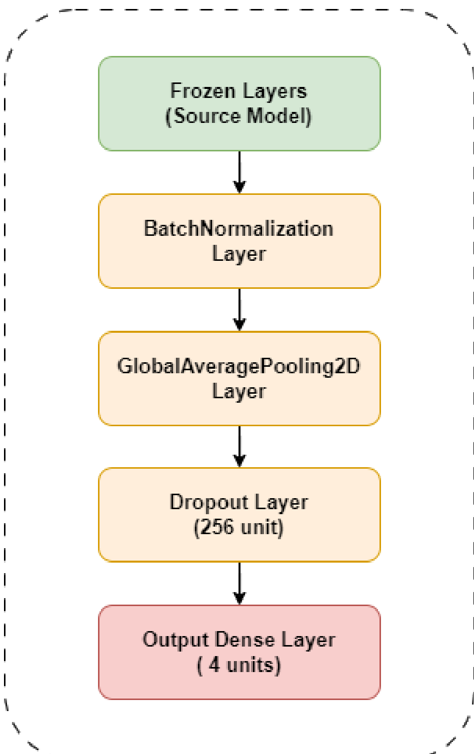

Fig. 5. Fine tuning pre-trained model.

age Pooling layer for spatial dimension reduction, a Dropout layer, a Dense layer featuring 256 units activated by ReLU, and finally, an output Dense layer with 'class count' units employing softmax activation for classification purposes. Fig. 5 shows an overview of the fundamental structure of fine tuning pre-trained model.

D. Performance Evaluation Measures

The evaluation of the proposed model involved a comprehensive analysis using various key metrics. Precision, which measures the accuracy of positive predictions among all predicted positives, showcased the model's capability to minimize misclassification of non-diseased instances in grape leaf disease classification. Recall, indicating the proportion of accurately predicted positives among all actual positives, highlighted the model's effectiveness in identifying all relevant disease instances. The F1-score, derived from the harmonic mean of precision and recall, offered a balanced evaluation of how well the model balances precision and recall. Accuracy, a crucial metric in classification tasks, assessed the model's ability to correctly predict instances overall within the dataset. Specifically in grape leaf disease recognition, accuracy indicated the model's general correctness in identifying and categorizing various disease types from input grape images.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F_1 - Score = \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

In which, FP stands for False Positive, TN for True Negative, TP for True Positive, and FN for False Negative.

IV. Results

A. Environmental Settings

The experiments were carried out using the Kaggle platform in order to obtain the experimental results. The Tesla P100-PCIE GPU, which was employed in the research, had 16GB of memory, and the system had 13GB of RAM. The model was trained using a batch size of 32 over a duration of 30 epochs.

B. Experiment

1) Experiment 1: Model selection and evaluation: Table I displays performance metrics for various models. Among them, MobileNetV2 stands out with the highest accuracy of 97.00%, coupled with strong precision, recall, and an F1 score, all at 97.00%. Additionally, MobileNetV2 boasts the lowest loss value of 0.175 among the listed models.

This demonstrates that MobileNetV2 not only achieves the highest accuracy but also maintains the lowest loss, signifying robust overall performance and superior generalization compared to other models in this context. Therefore, MobileNetV2 remains in use for phase 2 to fine-tune hyperparameters and strengthen the model's robustness. Details on the Training/Validation Loss and Accuracy of the models in this study during training are presented in Fig. 6, Fig. 7, Fig. 8, Fig. 9, and Fig. 10.

TABLE I. The Fine-tuning Model's Testing Set Result

Models	Accuracy	Precision	Recall	F1 score	Loss
ResNet50V2	95.45%	96.00%	95.75%	95.75%	0.227
ResNet152V2	93.29%	93.50%	93.75%	93.50%	0.290
MobileNetV2	**97.00%**	**97.00%**	**97.00%**	**97.00%**	**0.175**
Xception	91.30%	91.75%	91.75%	91.50%	0.389
InceptionV3	89.19%	89.75%	89.75%	89.50%	0.415

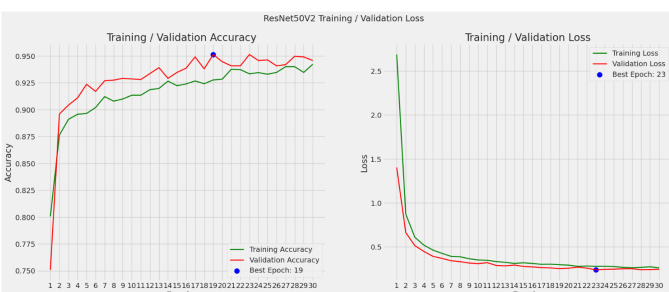

Fig. 6. ResNet50V2 training / validation accuracy and loss.

2) Experiment 2: Fine-tuning and hyper-parameter optimization: The search space for hyperparameters such as: Dropout rate, The number of units, Optimizer and Learning rate is given in Table II.

TABLE II. The Hyperparameter Search Space

The hyperparameters	Space for research
Dropout rate	Search space=[0.2, 0.3, 0.4, 0.5]
The number of units	Search space =[128, 256, 512, 1024]
Optimizer	Search space=['Adam', 'RMSprop', 'SGD', 'Adamax']
Learning rate	Search space=[1e-1, 1e-2, 1e-4, 1e-6]

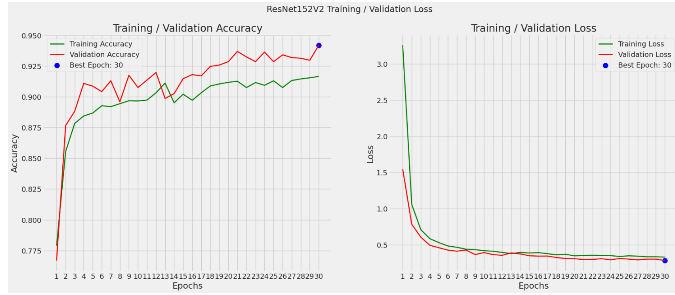

Fig. 7. ResNet152V2 training / validation accuracy and loss.

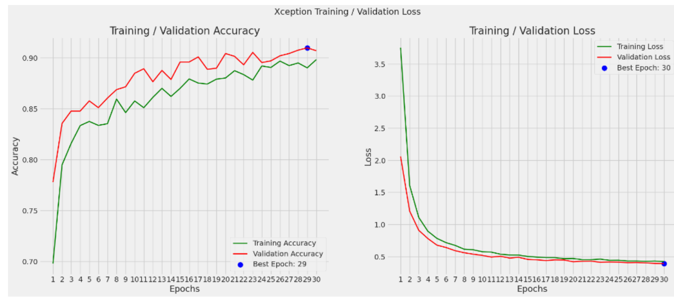

Fig. 8. Xception training / validation accuracy and loss.

After a thorough investigation of hyperparameters using Hyperband approaches and 45 trials, we achieved an outstanding 99.94% validation accuracy on the test set. The Test Loss that has been recorded is 0.144. Through careful tuning, the model was greatly improved, indicating an important improvement of 2.94%. The optimized hyperparameters, determined using Hyperband Optimization for fine-tuning the pre-trained MobileNetV2-based model, are presented in Table III.

TABLE III. Hyperparameter Values Found using Hyperband Optimization

Hyper parameter	Value
Dropout rate	0.4
Number of units	512
Optimizer	Adamax
Learning rate	0.0001

The best architectural model, obtained after determining the hyperparameter values, is shown in Fig. 11.

The presentation of Fig. 12 showcases a detailed comparison chart illustrating the performances of the best models concerning accuracy and loss scores.

And the confusion matrix of the best architectural model is shown in Fig. 13.

Table IV presents a comparative examination of the proposed model (the fine-tuned MobileNetV2-based model) with the state-of-the-art approaches on related issues. The table includes The plant's name, the number of disease labels, the number of pictures in the dataset, the detection method, and the accuracy rate.

According to research results, model proposed achieved a

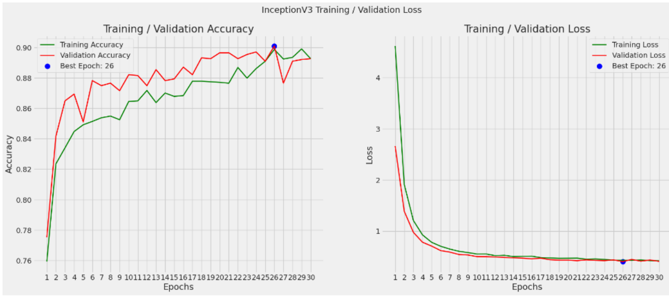

Fig. 9. InceptionV3 training / validation accuracy and loss.

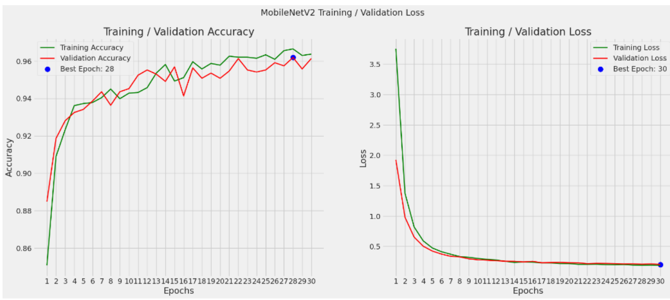

Fig. 10. MobileNetV2 training / validation accuracy and loss.

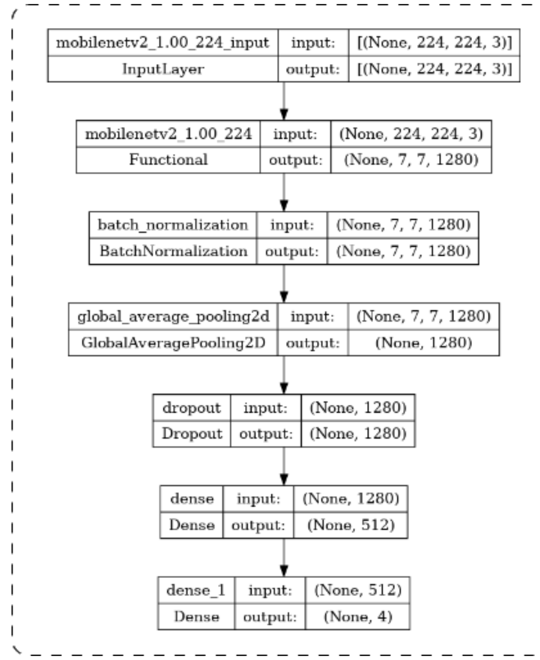

Fig. 11. The best architectural model, obtained after determining the hyperparameter values.

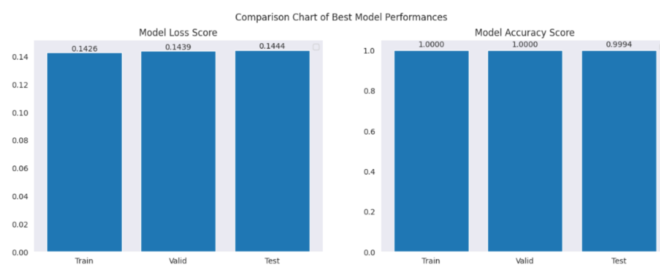

Fig. 12. Comparison chart of best model performances.

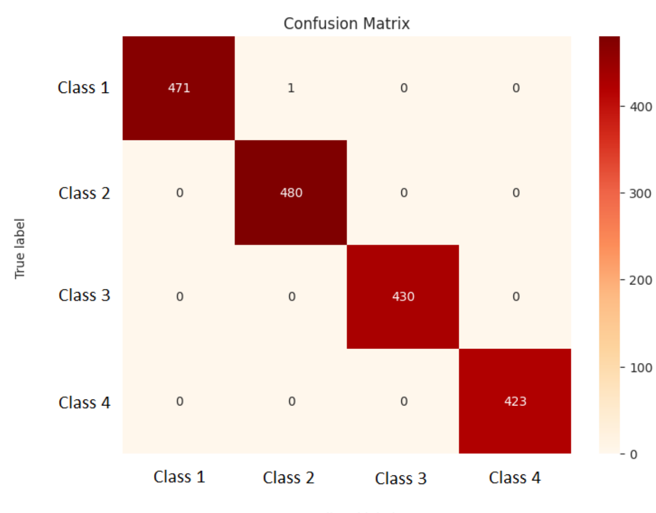

Fig. 13. The confusion matrix of the best architectural model.

99.94% accuracy rate, outperforming all other techniques listed in the table for similar problems.

V. Conclusion

Growing grapes is an important worldwide enterprise that is essential for both nutritional value and economic survival. However, the quantity and quality of the crop are seriously threatened to a number of diseases. It is critical to identify these illnesses as soon as possible in order to maintain grape health and guarantee maximum yields.

To address this critical problem, we utilized a transfer learning approach that made use of a collection of reliable pre-trained models, including ResNet50V2, ResNet152V2, MobileNetV2, Xception, and InceptionV3. These deep learning models are known for their outstanding performance on a variety of tasks.

We carried an in-depth evaluation of these models, taking into consider a range of important metrics including as accuracy, F1 score, precision, recall, and loss. This comprehensive evaluation aims to determine which model performed the best given our particular dataset.

TABLE IV. Compare Current Approaches to our Suggested Model for a Similar Problem

Study	Dataset	No. Classes	No. Images	Method of Use	Accuracy
[57]	Soybean Diseases	4	12,673	CNN model	99.32%
[58]	PlantVillage's Apple Crop	4	2,086	VGG16	90.40%
[59]	Apple Leaf Disease	6	2,462	DenseNet-121	93.71%
[60]	PlantVillage' Tomato Leaves	7	13,262	AlexNet	97.49%
[61]	Apple Leaf Disease	9	1,100	MobileNetV2	96.23%
[62]	Tomato Leaves Diseases	9	14,828	GoogleNet	99.18%
[63]	The Tomato Plant	10	19,553	Inception-V3	99.75%
[46]	The grapevine leaves	5	3000	EfficientNet B0	99.67%
[64]	Grape Leaf Diseases	4	3,885	GoogleNet	94.05%
[65]	Grape Leaf Diseases	4	9,027	EfficientNet B7	98.70%
[47]	Grapevine Leaves	5	2,500	MobileNetv2	97.60%
This study	**Grape Leaf Diseases**	**4**	**9,027**	**Fine-tuned MobileNetV2-based model Hyperparameter optimization uses the Hyperband approach**	**99.94%**

We then moved on to the crucial step of fine-tuning the hyperparameters of the model that was performing at its best. This fundamental improvement process increases the model's overall efficacy in accurately recognizing grape leaf illnesses.

Our approach to fine-tuning involved an extensive exploration of hyperparameters using the hyperband strategy. This configuration was aimed at maximizing the model's performance specifically within the context of our dataset.

By using these careful procedures—model evaluation, selection, and refinement combined with carefully hyperparameter optimization, the model's accuracy on the test set was 99.94% and its loss was 0.1444.

VI. Future Works

Further investigations could explore into examining the influence of alternate hyperparameters based on optimization techniques—like weight decay, activation functions and batch sizes—aimed at enhancing the efficacy of transfer learning models in detecting grape leaf diseases.

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