FusionNet-GLD: A Dual-Backbone CNN Model Combining Xception and Inception for Grape Leaf Disease Recognition

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the Requirements for the award of the degree

BACHELOR OF TECHNOLOGY

IN

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Submitted by

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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This is to certify that the project that is entitled with the name "FusionNet-GLD: A Dual-Backbone CNN Model Combining Xception and Inception for Grape Leaf Disease Recognition" is a Bonafide work done by Sd.Shafia Zainab (22471A05K0), S.Min Haz (22471A05J7), Ch.Navya (22471A05E9) in partial fulfillment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in the Department of COMPUTER SCIENCE AND ENGINEERING during 2025-2026.

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I declare that this project work titled " **FusionNet-GLD: A Dual-Backbone CNN Model Combining Xception and Inception for Grape Leaf Disease Recognition** " is composed by me that the work contain here is my own except where explicitly stated otherwise in the text and that this work has not been submitted for any other degree or professional qualification except as specified.

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PO4: Conduct investigations of complex problems: Conduct investigations of complex engineering problems using research-based knowledge including design of experiments, modelling, analysis & interpretation of data to provide valid conclusions.(WK8).

PO5: Engineering tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling recognizing their limitations to solve complex engineering problems.(WK2 and WK6)

PO6: The Engineer and The World: Analyze and evaluate societal and environmental aspects while solving complex engineering problems for its impact on sustainability with reference to economy, health, safety, legal framework, culture and environment.(WK1,Wk5, and WK7).

PO7: Ethics: Apply ethical principles and commit to professional ethics , human values, diversity and inclusion, adhere to national & international laws.(WK9).

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PO9: Communication: Communicate effectively and inclusively within the engineering community and society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations, considering cultural, language, and learning differences.

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PO11: Life-long learning: Recognize the need for, and have the preparation and ability for i)independent and life-long learning ii)critical thinking in the broadest context of technological change.

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Project Course Outcomes (CO'S):

CO421.1: Analyse the System of Examinations and identify the problem.
CO421.2: Identify and classify the requirements.
CO421.3: Review the Related Literature
CO421.4: Design and Modularize the project
CO421.5: Construct, Integrate, Test and Implement the Project.
CO421.6: Prepare the project Documentation and present the Report using appropriate method.

Course Outcomes – Program Outcomes mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1		✓										✓		
C421.2	✓		✓		✓							✓		
C421.3				✓		✓	✓	✓				✓		
C421.4			✓			✓	✓	✓				✓	✓	
C421.5					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C421.6									✓	✓	✓	✓	✓	

Course Outcomes – Program Outcome correlation

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1	2	3										2		
C421.2			2		3							2		
C421.3				2		2	3	3				2		
C421.4			2			1	1	2				3	2	
C421.5					3	3	3	2	3	2	2	3	2	1
C421.6									3	2	1	2	3	

Note: The values in the above table represent the level of correlation between CO's and PO's:

1. Low level
2. Medium level
3. High level

Project mapping with various courses of Curriculum with Attained PO's:

Name of the course from which principles are applie in this project	Description of the device	Attained PO
C2204.2, C22L3.2	Gathering the requirements and defining the problem, plan to develop model for detection and classification of Brain Tumor in MRI Scans using CNN-SVM model	PO1, PO3,PO8
CC421.1, C2204.3, C22L3.2	Each and every requirement i critically analyzed, the process mode is identified	PO2, PO3,PO8
CC421.2, C2204.2, C22L3.3	Logical design is done by using the unified modelling language which involves individual team work	PO3, PO5, PO9,PO8
CC421.3, C2204.3, C22L3.2	Each and every module is tested, integrated, and evaluated in our project	PO1, PO5,PO8
CC421.4, C2204.4, C22L3.2	Documentation is done by all our four members in the form of a group	PO8,PO10
CC421.5, C2204.2, C22L3.3	Each and every phase of the work in group is presented periodically	PO8,PO10, PO11
C2202.2, C2203.3, C1206.3, C3204.3, C4110.2	Implementation is done and the project will be handled by the social media users and in future updates in our project can be done based on detection for Brain Tumor	PO4, PO7,PO8
C32SC4.3	The physical design includes website to check Brain umor in MRI scans	PO5, PO6,PO8

ABSTRACT

Grapevine leaf diseases, such as black rot, leaf blight and esca can impact yield and fruit quality within the vineyard. Because timely and accurate detection is a cornerstone of successful disease management, it is essential to have a dependable way of monitoring disease presence in the vineyard. While traditional methods for disease detection involve manual assessments, these manual approaches are overly time consuming, ill-suited for large areas, or subjective. In this study, we present FusionNet-GLD, a two-backbone convolutional neural network comprised of Xception and InceptionV3 architectures for the purpose of classifying grapevine leaf disease. Because Xception incorporates depthwise separate convolutions (or separable convolutions) and InceptionV3 incorporates multiple scales of feature extraction via large or small convolutions, the FusionNetGLD takes advantage of the best of both models for the purpose of capturing the complex patterns present in diseased grapevine leaves. The models were established as part of this study on the augmented PlantVillage dataset under varying conditions designed to simulate real-world environments. Overall, the FusionNet-GLD has better overall performance (accuracy = 99.63, precision = 99.45, recall = 99.42, F1-score = 99.43 ad AUC = 0.99) than 5 benchmark models: Random Forest, MobileNetV2, EfficientNetB0, InceptionV3, and Xception. This study supports FusionNet-GLD can be used as a scaleable, efficient and reliable automated detection solution for grapevine leaf disease detection. Furthermore, the model will be small enough to deploy on mobile or drone-based systems within the vineyard, enabling real-time monitoring of any infected leaves, an important consideration for precision agriculture practices that strive to reduce reliance on human experts.

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1. INTRODUCTION

The cultivation of grapevines (Vitis vinifera) represents a cornerstone of the global agricultural economy. Beyond its cultural significance, viticulture is a multi-billion-dollar industry encompassing wine production, table grapes, and other derived products like raisins and juice. The quality and quantity of the grape harvest are directly linked to the health of the grapevine plants. However, these plants are highly susceptible to a variety of diseases, primarily fungal and bacterial, which can devastate crop yields and compromise fruit quality.

Common grapevine leaf diseases such as Black Rot, Esca (Black Measles), and Leaf Blight pose a significant threat to vineyard productivity. If not detected and managed in their early stages, these diseases can spread rapidly, leading to substantial economic losses for farmers. The traditional and most common method for disease identification relies on manual inspection by human experts, such as agronomists or experienced farmers. These experts visually examine the leaves, stems, and fruits of the grapevines to identify characteristic symptoms of various diseases.

While this method has been practiced for centuries, it is fraught with challenges in the context of modern, large-scale agriculture. Manual inspection is inherently labor-intensive, time-consuming, and expensive. It is also subjective, with the accuracy of the diagnosis depending heavily on the individual's experience and expertise. Furthermore, human experts are prone to fatigue and error, and this method is not scalable for monitoring vast vineyards in a timely manner. The delay between the onset of a disease and its detection can be critical, as it allows the pathogen to establish itself and spread, making treatment less effective and more costly.

To address these limitations, the field of precision agriculture is increasingly turning to technology-driven solutions. The advent of powerful computational resources, coupled with advancements in computer vision and artificial intelligence, has opened new frontiers for automated plant disease detection. Deep learning, a subfield of machine learning, has shown remarkable success in image recognition tasks. Convolutional Neural Networks (CNNs), a class of deep learning models specifically

designed for processing visual data, are particularly well-suited for identifying diseases from images of plant leaves.

This project introduces **FusionNet-GLD**, a novel dual-backbone deep learning model designed specifically for the accurate and robust identification of grapevine leaf diseases. By intelligently fusing the architectural strengths of two highly effective CNNs, Xception and InceptionV3, FusionNet-GLD aims to overcome the limitations of single-backbone models. It is engineered to provide a more reliable, scalable, and efficient solution for disease detection, empowering farmers with a powerful tool for timely vineyard management and ultimately securing crop yield and quality.

Figure 1: Neural Network Analysis of Pathogens on a Grapevine Leaf.

This image represents the critical intersection of advanced technology and traditional agriculture. By leveraging sophisticated deep learning algorithms, we can now analyse grapevine leaves with a precision and speed that surpasses the limitations of the human eye. **FusionNet-GLD offers a new frontier in automated grapevine disease detection,** moving beyond subjective manual inspections. Our dual-backbone model provides an accurate, scalable, and efficient solution, empowering growers to identify threats like Black Rot and Leaf Blight at their earliest stages. This technological leap is pivotal in protecting crop yields, ensuring economic stability for farmers, and securing the future of viticulture.

1.1 Motivation

The motivation for this project is rooted in the urgent need to enhance the sustainability and productivity of the viticulture industry. The key driving factors are:

- **Economic Imperative:** Grapevine diseases are responsible for significant annual financial losses worldwide. By enabling early and accurate disease detection, this project aims to help farmers implement targeted interventions, reducing crop damage and minimizing the economic impact of diseases. This leads to better resource management, lower costs for fungicides, and a more stable income for farmers.
- **Scalability and Efficiency:** Modern vineyards can span hundreds or even thousands of acres. Manually inspecting such large areas is practically impossible. An automated system can continuously monitor an entire vineyard (e.g., via drones or robotic platforms) and process thousands of images far more quickly and efficiently than any team of human experts, enabling large-scale, high-frequency monitoring.
- **Accuracy and Objectivity:** Human diagnosis can be subjective and inconsistent. A well-trained deep learning model provides an objective and highly accurate diagnosis, free from human bias or fatigue. By learning from a vast dataset of labeled images, the model can detect subtle patterns and symptoms that might be missed by the human eye.
- **Technological Advancement:** There is a significant opportunity to apply cutting-edge AI research to solve real-world agricultural problems. This project is motivated by the challenge of designing a novel CNN architecture that pushes the boundaries of accuracy and efficiency in plant pathology. The concept of fusing different model architectures to leverage their complementary strengths is a promising area of research with the potential for broad applications.
- **Sustainability:** Early detection allows for more precise and targeted application of treatments, such as fungicides. This reduces the overall amount of chemicals used, minimizing the environmental impact and promoting more sustainable farming practices.

1.2 Problem Statement

The core problem is the inefficient, subjective, and non-scalable nature of traditional methods for identifying grapevine leaf diseases. An automated system is required to accurately classify the health status of a grapevine leaf from a digital image, specifically identifying whether it is healthy or afflicted with one of several common diseases (Black Rot, Esca, Leaf Blight).

The solution must address the following specific challenges:

1. **High Intra-class and Low Inter-class Variance:** Different diseases may present with very similar visual symptoms, while symptoms of the same disease can vary significantly depending on the stage of infection and environmental conditions.
2. **Real-World Image Variability:** Images taken in a vineyard will have variations in lighting, background (soil, other leaves, sky), leaf orientation, and potential occlusions. The model must be robust to these variations.
3. **Need for High Accuracy:** The cost of a misclassification can be high. A false negative (classifying a diseased leaf as healthy) can allow a disease to spread unchecked, while a false positive (classifying a healthy leaf as diseased) can lead to unnecessary and costly treatments.
4. **Computational Efficiency:** For practical deployment, especially on mobile or edge devices, the model should be computationally efficient without sacrificing accuracy.
5. **Data Scarcity for New Diseases:** While datasets exist for common diseases, a practical system must be adaptable. It is challenging to gather large, labeled datasets for newly emerging or rare diseases, necessitating a model that can learn effectively from limited data or be easily retrained.

1.3 Objective

The primary objective of this project is to design, implement, and evaluate a robust dual-backbone deep learning model, **FusionNet-GLD**, for the automated classification of grapevine leaf diseases with state-of-the-art accuracy.

The specific objectives are:

- To design a novel hybrid CNN architecture that fuses the feature extraction capabilities of the Xception and InceptionV3 models to create a more powerful and comprehensive feature representation.
- To collect, preprocess, and augment a comprehensive dataset of grape leaf images to train the model effectively and ensure it generalizes well to new, unseen data.
- To implement the FusionNet-GLD model using the TensorFlow and Keras frameworks and to systematically train it using best practices, including appropriate optimizers, loss functions, and learning rate schedules.
- To conduct a rigorous comparative analysis of FusionNet-GLD's performance against several baseline and state-of-the-art models, including Random Forest, MobileNetV2, EfficientNetB0, InceptionV3, and Xception.
- To thoroughly evaluate the models using a comprehensive set of performance metrics, including accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC), to provide a holistic view of their classification capabilities.
- To analyze the model's predictions using visualization techniques like confusion matrices to understand its strengths and weaknesses across different disease classes.
- To create a comprehensive project documentation that details the system's analysis, design, implementation, and testing, serving as a blueprint for future development, deployment, and academic reference.

2. LITERATURE SURVEY

In the recent [6] past lightweight detection models have taken over for real time implementation. For example, “YOLOv8-ACCW” which puts forth a lean architecture that includes AKConv, Coordinate Attention (CA) and CARAFE modules reports an “F1 score of 92.4%”and a ‘mAP50 of 92.8%’ also keeps the model size to less than 2.8MB.

Also, in that which we present GCS-YOLO we use Ghost Net modules in combination with CBAM attention and report a mAP@0.5 of 96.2% which we do so with only 1.63M parameters. In this approach we find to do well in variable lighting conditions and is also a good fit for edge deployment [7].

Dual track models present also which we have seen to do very well in the Amalgamation between ‘local and global features. In the case of GrapeLeafNet we see they used Inception-ResNet with CBAM and a Shuffle-Transformer for improved feature representation which in turn achieved an “impressive 99.56% accuracy” on the PlantVillage dataset [8].

Real time edge devices’ issues also we see in our work. Karim et al report they used a tuned MobileNetV3Large which they added custom dense layers to and also did Grad-CAM visualizations, which for an Nvidia Jetson Nano achieved us over 99.4% accuracy which we saw in both train and test sets [9].

Several of the studies report on curated datasets. In the case of NGLD which we present as an example, we see they have put together 2,726 high quality annotated images from Indian grape farms into this resource which also has a very specific focus for use in training of models of grape leaf diseases which include that of downy mildew and bacterial leaf spot [10].

In research which has put forward benchmark comparisons between CNNs and transformer-based models (for instance Swinv2-Base) we see that proper fine tuning of vision transformers reports 100% accuracy on the PlantVillage and grape variety data sets [11].

Trust in the models' results and their easy interpretation is also a growing issue. We see in Deep Leaf which puts forth fuzzy optimized CNNs and logistic regression for the task of down sampling that they achieved 99.7% accuracy which also plays with class balance and feature redundancy [12].

Bro in the research which we looked at – for instance Mangaoang et al. report that CNNs, MobileNetV2, and EfficientNet do very well in many of their studies. Also, we see that which trials of EfficientNet achieved 100% accuracy which is very promising for the role of this model in precision agriculture [13].

At present traditional ML techniques are used in the classification of grape leaves. While these do not match the flexibility of DL, they do provide interpretability and computational efficiency for certain food quality applications [14].

Convolutional neural networks, namely VGG 16 and MobileNet variants, are applied to images of grape leaves by Uttam, who shows that CNNs are highly effective at automating disease detection by obtaining accuracies of up to 97% [15], This demonstrates how these deep learning models can expedite early diagnosis and enhance vineyard management.

Recent studies have explored the use of ensemble-based transfer learning techniques to improve multi-class plant disease detection accuracy. Lakshmi et al. [16] demonstrated that combining feature extraction capabilities of multiple pretrained CNN architectures—specifically VGG16, ResNet50, and Xception—can outperform single-model approaches by leveraging complementary feature spaces.

Their work emphasizes that integrating diverse model backbones can capture a wider range of visual features, which aligns closely with the motivation behind our FusionNet-GLD design. However, their method focuses on general plant diseases without specialized adaptation for grapevine-specific challenges, leaving an opportunity for targeted hybrid architectures.

In another notable contribution, Kumar et al. [17] applied a ResNet-based CNN model for plant disease classification aimed at e-agriculture applications. Their approach

capitalized on ResNet's residual connections to address vanishing gradient problems and improve training stability for deep architectures. While their model achieved competitive accuracy, it maintained a single-backbone structure, which may limit its adaptability to diverse disease patterns in grapevine leaves. FusionNet-GLD, by contrast, seeks to enhance both local and global feature extraction through dual backbones, offering a more robust solution for complex classification scenarios.

Beyond image-based classification, some research has explored predictive modelling for agricultural outcomes using non-visual parameters. authors [18] applied regression tree models for crop yield prediction based on weather and soil parameters, demonstrating the importance of integrating environmental context into agricultural decision-making. While our work focuses on image-based disease detection, the broader precision agriculture framework could benefit from combining visual disease diagnostics like FusionNet-GLD with environmental predictive models for a more holistic crop health monitoring system.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing systems for identifying grapevine leaf diseases can be broadly categorized into two groups:

1. **Manual (Traditional) System:** This is the most prevalent method currently in use.
    - **Process:** It involves agricultural experts, viticulturists, or experienced farmers physically walking through vineyards and visually inspecting individual plants. They look for tell-tale signs of disease on the leaves, such as discoloration, spots, lesions, or changes in texture.
    - **Tools:** The primary tool is the human eye, supplemented by magnifying glasses for closer inspection. Samples may be collected and sent to a laboratory for confirmation.
    - **Decision Making:** The diagnosis is based on the expert's knowledge and experience in recognizing the specific symptoms of each disease.

Figure 3.1.1: Manual Diagnosis

2. **Basic Computer Vision Systems:** These represent early attempts at automating the process.
    - **Process:** These systems use standard image processing techniques to analyse images of grape leaves. The workflow typically includes:

- **Image Segmentation:** Isolating the leaf from the background.
- **Feature Extraction:** Manually engineering features by calculating color histograms, texture patterns (e.g., using Gray-Level Co-occurrence Matrix), and shape descriptors.
- **Classification:** Feeding these extracted features into a traditional machine learning classifier like SVM, Random Forest, or KNN.

- **Implementation:** These systems are typically implemented as desktop applications requiring users to upload images manually.

Figure 3.1.2: Basic Computer Vision Workflow Diagram

3.1.1 DISADVANTAGES OF THE EXISTING SYSTEM

Both existing systems suffer from significant drawbacks that limit their effectiveness in modern viticulture.

Disadvantages of the Manual System:

- **Subjectivity:** The diagnosis is highly dependent on the individual expert's skill and can vary from person to person, leading to inconsistent results.
- **High Labor Cost:** Hiring and retaining agricultural experts is expensive. The process is also extremely time-consuming, further adding to the cost.
- **Lack of Scalability:** It is physically impossible to manually inspect every plant in a large commercial vineyard in a timely and frequent manner.
- **Time Delay:** There is a significant lag between the onset of infection and its potential discovery. This delay can allow the disease to become well-established, making it harder and more expensive to control.
- **Human Error:** Experts can suffer from fatigue, especially when inspecting

vast areas, leading to missed diagnoses or errors.

Disadvantages of Basic Computer Vision Systems:

- **Fragile Feature Engineering:** The performance of these systems is entirely dependent on the pre-defined, hand-crafted features. These features are often not robust enough to handle real-world variations.
- **Sensitivity to Environment:** They are highly sensitive to changes in lighting conditions, shadows, background complexity, and leaf orientation. A slight change in lighting can drastically alter the color and texture features, leading to misclassification.
- **Inability to Learn Abstract Features:** These systems cannot learn the deep, abstract, and hierarchical patterns that distinguish complex diseases. They often fail when diseases have similar color or texture profiles.
- **Limited Accuracy:** Due to the above limitations, their classification accuracy is generally low compared to deep learning-based approaches and often not reliable enough for commercial use.

3.2 PROPOSED SYSTEM

The proposed system, **FusionNet-GLD**, is a state-of-the-art deep learning-based solution designed to overcome the limitations of the existing systems. It provides an automated, accurate, and scalable method for grapevine leaf disease classification.

High-Level Overview: The system takes a digital image of a grapevine leaf as input and outputs a classification, identifying the leaf as either healthy or suffering from a specific disease (Black Rot, Esca, or Leaf Blight). The core of the system is a novel dual-backbone Convolutional Neural Network (CNN) that leverages the synergistic strengths of the Xception and InceptionV3 architectures.

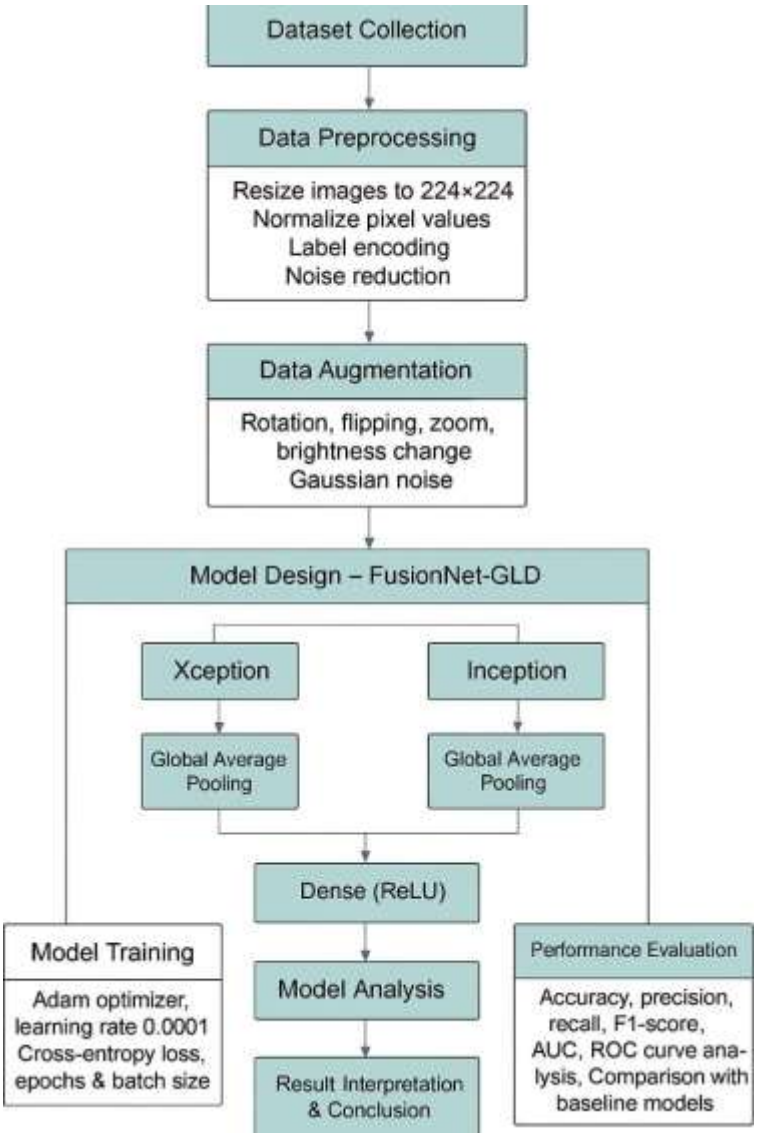

Figure 3.2.1: Proposed FusionNet-GLD flowchart Diagram

The flowchart in Fig. 3.2.1 outlines the complete FusionNet-GLD workflow, starting from dataset collection and preprocessing, followed by data augmentation to improve diversity and reduce class imbalance. The dual-backbone model design combines Xception and Inception for parallel feature extraction, with outputs merged through feature concatenation, passed to a Dense layer, and classified via Softmax. The model is trained using Adam optimization and evaluated with metrics such as accuracy, precision, recall, F1-score, and AUC, ensuring robust performance in grape leaf disease detection.

Key Architectural Concepts:

Key Architectural Concepts:

- **Dual-Backbone Architecture:** Instead of relying on a single feature extractor, the model uses two parallel backbones. This allows the system to learn a more diverse and comprehensive set of features.
    - **Xception Branch:** This branch uses depth wise separable convolutions to efficiently extract fine-grained, detailed features and cross-channel correlations.
    - **InceptionV3 Branch:** This branch uses inception modules with multiple filter sizes to capture contextual, multi-scale spatial features from the image.
- **Feature Fusion:** The feature maps generated by both parallel branches are concatenated. This fusion creates a single, enriched feature vector that combines the detailed information from Xception with the multi-scale context from InceptionV3.
- **End-to-End Learning:** The entire system, from raw pixel input to final classification output, is trained end-to-end. This eliminates the need for manual feature engineering, as the model automatically learns the most discriminative features directly from the data.

Advantages of the Proposed System:

- **High Accuracy and Reliability:** By fusing complementary feature sets, the model achieves a more nuanced understanding of the disease symptoms, leading to state-of-the-art classification accuracy (99.63%).
- **Robustness:** The model is trained on an augmented dataset, making it resilient to variations in lighting, background, scale, and orientation commonly found in real-world vineyard images.
- **Scalability:** The system is highly scalable. It can be deployed on a server to process thousands of images from drones or field robots, enabling continuous monitoring of large vineyards.
- **Speed and Efficiency:** Once trained, the model can classify an image in a fraction of a second, providing instantaneous diagnosis.
- **Objectivity:** The classification is based on data-driven patterns learned from thousands of examples, ensuring an objective and consistent diagnosis.

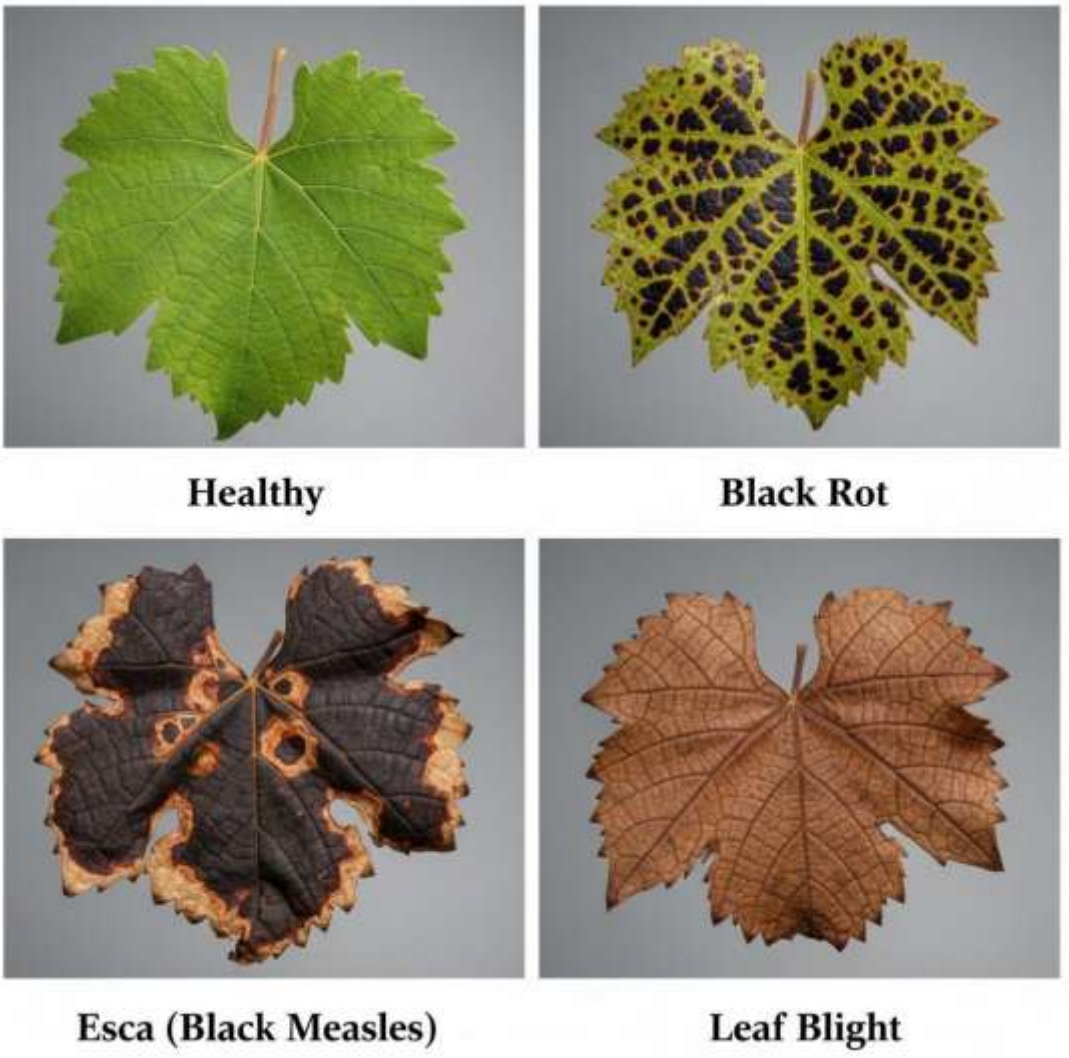

Figure 3.2.2: Sample Output Visualization

3.3 FEASIBILITY STUDY

A feasibility study was conducted to assess the viability of the project from technical, economic, and operational perspectives.

- **Technical Feasibility:**
  - **Technology:** The required technologies are mature and widely available. This includes the Python programming language and open-source deep learning libraries such as TensorFlow and Keras.
  - **Hardware:** High-performance GPUs, necessary for training deep learning models, are accessible through cloud computing platforms (like Google Colab, AWS, GCP) or by using dedicated local hardware.

- **Data:** The PlantVillage dataset, a large, publicly available, and well-annotated collection of plant leaf images, provides the necessary data for training and testing the model.
- **Expertise:** The knowledge required to design and implement CNNs is readily available through academic literature, online courses, and developer communities.
- **Conclusion:** The project is **technically feasible**.

- **Economic Feasibility:**
  - **Costs:** The primary costs are related to development time and computational resources for training the model (GPU rental on a cloud service).
  - **Benefits:** The potential economic benefits are substantial. By enabling early disease detection, the system can significantly reduce crop losses, which directly translates to increased revenue for farmers. It also reduces the cost of labour for manual inspection and allows for more targeted (and thus, cheaper) application of treatments.
  - **Return on Investment (ROI):** While an exact ROI is difficult to calculate without a full market analysis, the potential for significant savings and increased yield suggests a very high potential ROI.
  - **Conclusion:** The project is **economically feasible**.

- **Operational Feasibility:**
  - **Integration:** The model can be deployed in several ways to fit into existing agricultural workflows. It can be the backend for a smartphone app where farmers can upload pictures for instant diagnosis. It can also be integrated into drone surveillance systems that automatically scan vineyards and flag potential disease hotspots.
  - **User Acceptance:** Farmers are increasingly adopting technology to improve efficiency. A user-friendly application that provides clear, accurate, and actionable information is likely to be well-received.
  - **Maintenance:** Once deployed, the model requires minimal maintenance, primarily involving periodic retraining with new data to improve its accuracy and adapt to new disease strains.

- **Conclusion:** The project is **operationally feasible**.

Figure 3.3: Feasibility Triangle

3.4 USING COCOMO MODEL

The Constructive Cost Model (COCOMO) is an algorithmic software cost estimation model. We can use the basic COCOMO model to estimate the effort and development time for this project.

1. **Estimation of Project Size:** The project involves data preprocessing, model definition, training scripts, and evaluation code. We estimate the size to be approximately **3,000 Delivered Source Instructions (DSI)**, or 3 Kilo Lines of Code (KLOC).

2. **Project Class:** This project falls under the **Organic** class. It is a small-sized project developed by a small, experienced team with a good understanding of the application domain. The requirements are flexible.

3. **Effort Estimation:** The formula for effort in an Organic project is: **Effort = 2.4 * (KLOC)^1.05 Person-Months** Effort = 2.4 * (3) ^1.05 Effort ≈ 2.4 * 3.15 **Effort ≈ 7.56 Person-Months**
4. **Development Time Estimation:** The formula for development

time is: **Time = 2.5 * (Effort)^0.38 Months**' Time = 2.5 * (7.56) ^0.38 Time ≈ 2.5 * 2.2 **Time ≈ 5.5 Months**

5. **Staffing Estimation: Average Staffing = Effort / Time** Average Staffing = 7.56 / 5.5

Average Staffing ≈ 1.37 Persons

This suggests the project could be reasonably completed by 1-2 developers in approximately 5-6 months. This estimation aligns with the scope of a typical academic or research project of this nature.

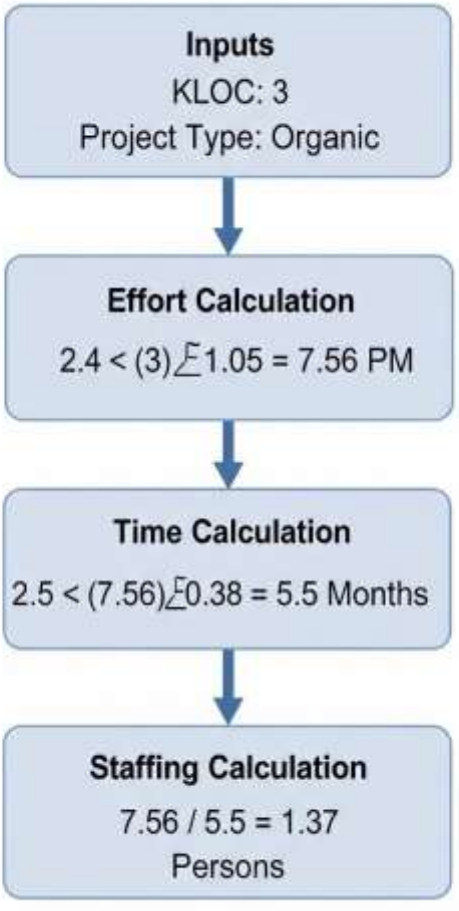

Figure 3.4: COCOMO Flow Diagram

4. SYSTEM REQUIREMENTS

This section outlines the necessary hardware and software prerequisites for the development, training, and potential deployment of the FusionNet-GLD model. It also includes a detailed analysis of the functional and non-functional requirements that the system is designed to fulfil

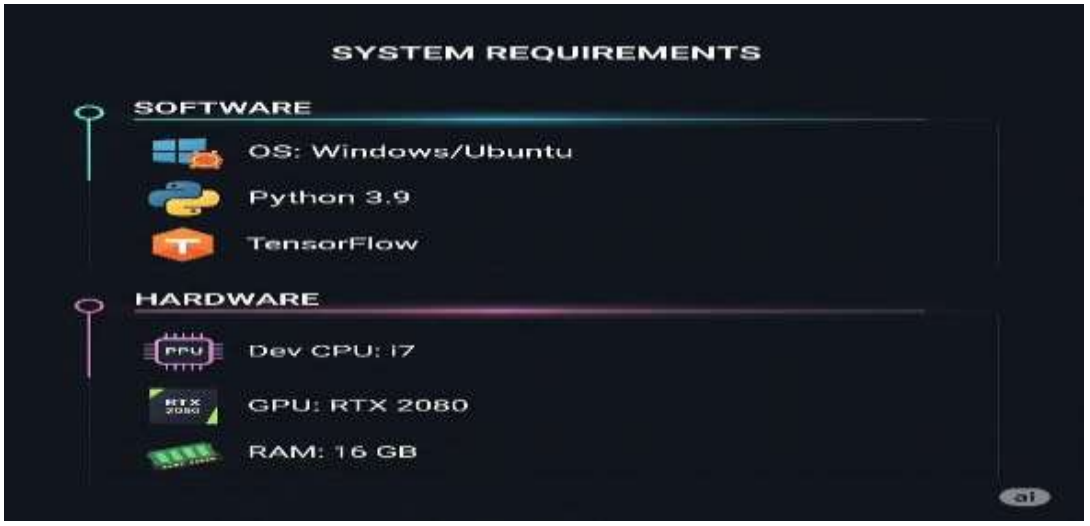

Figure 4.1: Hardware & Software Requirements Block Diagram

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4.1 SOFTWARE REQUIREMENTS

The following software components are required to replicate the development environment for this project:

- **Operating System:** Windows 10/11, Ubuntu 20.04 LTS (or later), or macOS.
- **Programming Language:** Python (version 3.8 or later).
- **Core Libraries:**
    - **TensorFlow:** (version 2.x) The primary deep learning framework used for building and training the model.
    - **Keras:** (version 2.x) A high-level API integrated with TensorFlow, used for rapid model prototyping and definition.
    - **Scikit-learn:** Used for data splitting and evaluating performance metrics.
    - **OpenCV-Python:** Used for advanced image preprocessing and manipulation.
    - **NumPy:** For efficient numerical operations and array manipulations.

    - **Pandas:** For data handling and management, if required.
    - **Matplotlib / Seaborn:** For data visualization, plotting graphs (e.g., loss/accuracy curves), and displaying images.
- **Development Environment:** Jupyter Notebook or an Integrated Development Environment (IDE) like VS Code or PyCharm.

4.2 REQUIREMENT ANALYSIS

The requirements for the system are divided into two categories: functional and non-functional.

Functional Requirements: These define the specific functions the system must perform.

- **Image Input:** The system must accept a digital image of a grapevine leaf as input.
- **Disease Classification:** The system must process the input image and classify it into one of the predefined categories: Healthy, Black Rot, Esca (Black Measles), or Leaf Blight.
- **Result Output:** The system must present the classification result to the user, indicating the predicted class and, ideally, a confidence score.

Non-Functional Requirements: These define the quality attributes and constraints of the system.

- **High Accuracy:** The system must achieve a very high classification accuracy (target >99%) to be reliable for practical use.
- **Robustness:** The model must perform reliably on images taken in diverse, real-world conditions with variations in lighting, background, and leaf orientation.
- **Performance:** The system should provide a diagnosis in a reasonably short amount of time (near real-time) after an image is provided.
- **Scalability:** The underlying architecture should be capable of processing a large number of images, making it suitable for batch processing or integration with high-throughput systems like drones.
- **Usability:** If deployed as an application, the interface should be simple and intuitive for users who may not be technically proficient (e.g., farmers).

4.3 HARDWARE REQUIREMENTS

The hardware requirements differ significantly for the model development/training phase and the deployment phase.

For Development and Training:

- **CPU:** Modern multi-core processor (Intel i7/i9 or AMD Ryzen 7/9).
- **RAM:** 16 GB or more.
- **GPU:** A dedicated NVIDIA GPU with CUDA support is essential for training the deep learning model in a feasible amount of time. Recommended: NVIDIA RTX 20-series or later, with at least 8 GB of VRAM.
- **Storage:** A Solid-State Drive (SSD) with sufficient space (100 GB+) for the dataset, libraries, and model checkpoints.

For Deployment (Example Scenarios):

- **Server-Side:** A cloud server instance (e.g., AWS EC2, Google Cloud VM) with a GPU for processing requests from multiple users via a web or mobile application.
- **Edge Device:** A specialized edge computing device like an NVIDIA Jetson Nano or a modern smartphone with a powerful processor and sufficient RAM for running a compressed or optimized version of the model.

4.4 SOFTWARE

The software stack for this project is built entirely on open-source technologies, ensuring accessibility and reproducibility.

- **Operating System:** Ubuntu 20.04 LTS
- **Language:** Python 3.9
- **Framework:** TensorFlow 2.10
- **Libraries:** Keras, Scikit-learn, OpenCV, NumPy, Matplotlib

4.5 SOFTWARE DESCRIPTION

A description of the key software components and their roles in the project:

- **Python:** A versatile, high-level programming language chosen for its extensive ecosystem of scientific and AI libraries, making it the de facto standard for machine learning research and development.
- **TensorFlow:** A comprehensive, open-source platform for machine learning developed by Google. It provides the low-level building blocks for creating, training, and deploying deep learning models. Its ability to leverage GPUs for parallel computation is critical for this project.
- **Keras:** A user-friendly neural networks API written in Python, which runs on top of TensorFlow. It allows for easy and fast prototyping, with a focus on readability and conciseness, significantly speeding up the development of complex models like FusionNet-GLD.
- **OpenCV (Open-Source Computer Vision Library):** An essential library for computer vision tasks. In this project, it is used for reading images and performing preprocessing steps that are not natively handled by Keras's ImageDataGenerator.
- **Scikit-learn:** A robust machine learning library in Python. While the core model is built in TensorFlow, Scikit-learn is used for its powerful and easy-to-use tools for tasks like splitting the dataset and calculating detailed performance metrics (e.g., precision, recall, F1-score) and generating the confusion matrix.

5. SYSTEM DESIGN

This section provides a detailed blueprint of the FusionNet-GLD system. It covers the high-level architecture, the data pipeline from input to output, the design of individual modules, and the interaction between them.

5.1 SYSTEM ARCHITECTURE

The architecture of FusionNet-GLD is a dual-branch framework designed to maximize feature extraction by combining two powerful, pre-trained CNN models in parallel. The entire data flow is visualized in the architectural diagram (Figure 1 from the paper).

The workflow can be broken down into the following key stages:

1. **Input:** The system takes a 224x224 pixel RGB image of a grape leaf as input.
2. **Parallel Feature Extraction:** The input image is simultaneously fed into two independent convolutional backbones:
    - **Xception Branch:** This branch processes the image using depth wise separable convolutions to extract fine-grained, high-level discriminative features.
    - **InceptionV3 Branch:** This branch processes the same image using inception modules to capture features at multiple spatial scales.
3. **Feature Vector Generation:** The feature maps produced by the final convolutional layers of each branch are passed through a Global Average Pooling (GAP) layer. This step drastically reduces the number of parameters from each branch and creates a flattened feature vector that is robust to spatial translations.
4. **Feature Fusion:** The two feature vectors from the GAP layers are concatenated into a single, larger vector. This fused vector contains a richer, more comprehensive representation of the input image, combining the complementary strengths of both architectures.
5. **Classification Head:** The fused feature vector is passed through a dense (fully connected) layer with ReLU activation to learn non-linear combinations of the fused features.
6. **Output:** A final dense layer with a SoftMax activation function acts as the

classifier. It outputs a probability distribution across the four classes (Healthy and the three diseases), and the class with the highest probability is selected as the final prediction.

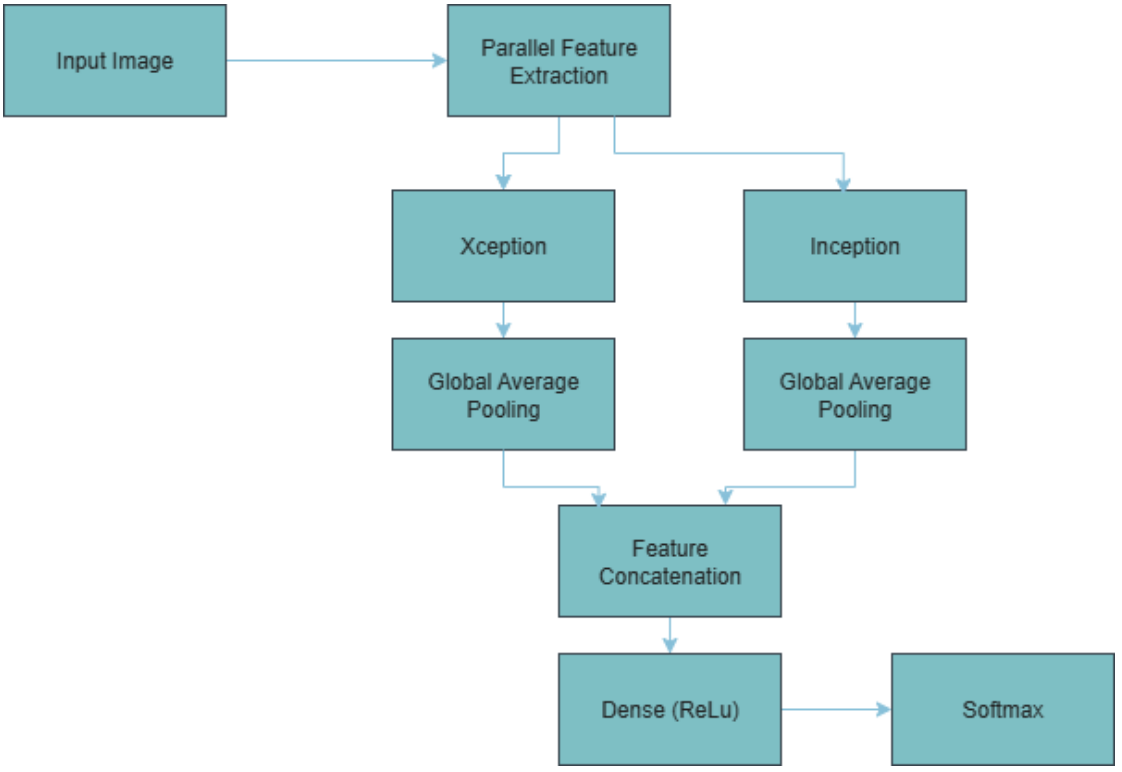

Figure 5.1: architecture of FusionNet-GLD

The input image undergoes parallel feature extraction through Xception and Inception backbones, followed by Global Average Pooling in each branch. The concatenated features are passed through a Dense layer with ReLU activation and classified using a SoftMax layer for multi-class grape leaf disease detection.

5.1.1 DATASET

The study employs an augmented version of the PlantVillage grape leaf disease dataset [10], which has been extensively used in previous research for plant pathology [14], [15]. This dataset contains high-quality images of grapevine leaves belonging to four major classes:

- Healthy
- Black Rot
- Esca (Black Measles)

- Leaf Blight (Isariopsis Leaf Spot)

Key dataset characteristics:

- Total original images: 5000 (before augmentation)
- Image resolution: Variable, resized to 224×224 px during preprocessing.
- Class distribution: Initially imbalanced, with healthy leaves overrepresented.
- Dataset split: 70% training, 15% validation, 15% testing (stratified sampling).

The dataset is sourced from the public PlantVillage repository and supplemented with additional grapevine leaf images from open agricultural datasets to enhance diversity. The choice of PlantVillage stems from its standardized format and global recognition, ensuring reproducibility and facilitating benchmarking against prior studies [8], [12].

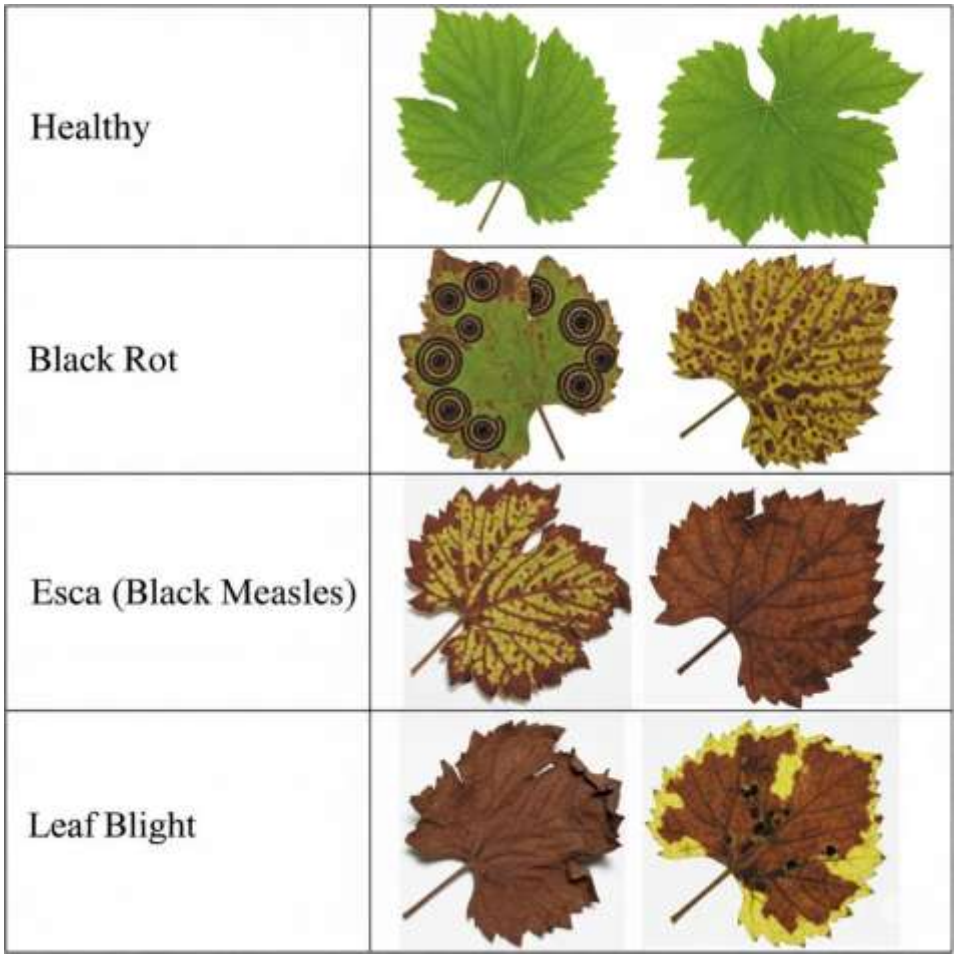

Figure 5.1.1: Grape Leaf Disease Classes with Sample Images

Figure 5.1.1 presents sample images from the augmented PlantVillage grape leaf disease dataset, showcasing different disease classes and healthy leaves. These examples illustrate the visual diversity and variations in lighting, orientation, and leaf

texture considered during model training.

5.1.2 DATA PREPROCESSING

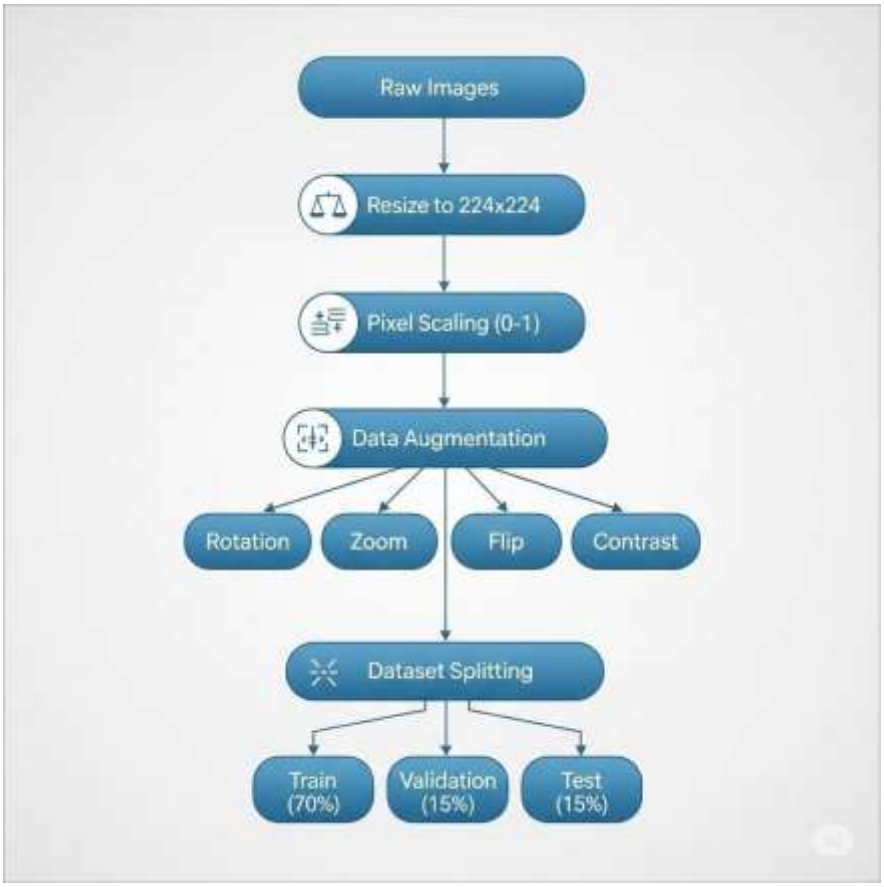

Figure 5.1.2: Data preprocessing workflow

Before being fed into the model, the raw images undergo several crucial preprocessing steps to ensure consistency and improve training efficiency.

- **Image Resizing:** All images, regardless of their original dimensions, are resized to a fixed size of 224x224 pixels. This is a standard input size for many pre-trained models like InceptionV3 and ensures uniformity across all inputs.
- **Pixel Scaling:** The RGB pixel values, which originally range from 0 to 255, are normalized to a floating-point range of 0,1

. This scaling helps to stabilize the training process and allows the model to converge faster.

- **Data Augmentation:** Real-time data augmentation is applied to the training images to artificially expand the dataset. This is a critical step in building a

robust model that can generalize to real-world scenarios. The transformations applied include:

- **Random Rotations:** To make the model invariant to the orientation of the leaf.
- **Random Zooms:** To ensure the model can recognize diseases at different scales.
- **Horizontal Flips:** To add more variability.
- **Contrast Adjustments:** To simulate different lighting conditions.

- **Dataset Splitting:** The entire dataset is split into three subsets to ensure a fair and unbiased evaluation of the model:
  - **Training Set (70%):** Used to train the model's weights.
  - **Validation Set (15%):** Used to tune hyperparameters and monitor for overfitting during training.
  - **Testing Set (15%):** A completely unseen set of images used for the final evaluation of the model's performance.

5.1.3 FEATURE EXTRACTION

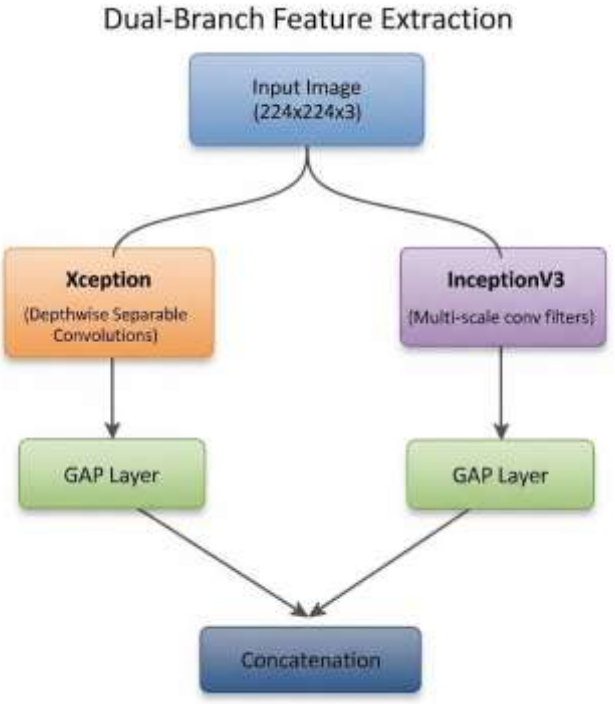

Figure 5.1.3: Dual-Branch Feature Extraction

The core strength of FusionNet-GLD lies in its dual-branch feature extraction mechanism. By using two distinct, powerful backbones in parallel, it captures a richer set of features than a single architecture could alone.

- **InceptionV3 Backbone: Capturing Multi-Scale Features** The InceptionV3 architecture is built upon the revolutionary concept of the **"inception module."** The fundamental challenge in designing a CNN is choosing the right kernel size (e.g., 3x3, 5x5) for convolutions. A smaller kernel is good for local features, while a larger kernel is better for more global, distributed features. Instead of choosing just one, the inception module performs several different convolutions in parallel on the same input and concatenates their results.

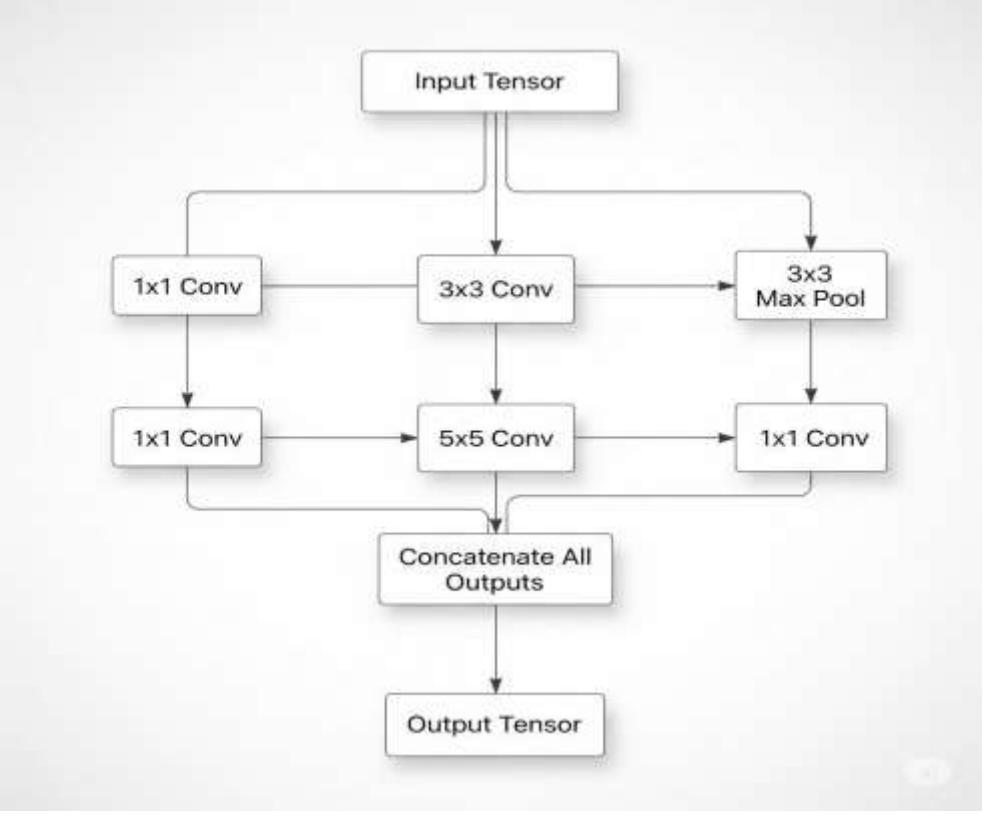

Figure 5.1.3.1: InceptionV3 Module Workflow

A typical inception module includes:

- **1x1 Convolution:** Used for capturing very fine-grained features and, crucially, for dimensionality reduction. By reducing the number of channels (depth) before the more expensive 3x3 and 5x5 convolutions,

it makes the network much more computationally efficient.

- **3x3 Convolution:** The standard choice for capturing features.
- **5x5 Convolution:** Captures features over a larger area of the image.
- **Max Pooling:** Another way to capture features and reduce spatial dimensions.

By combining these, the InceptionV3 backbone can learn spatial patterns at **multiple scales simultaneously**. This is highly advantageous for identifying grape leaf diseases, where symptoms can manifest as small, distinct spots (requiring small kernels) or as larger patches of discoloration (requiring larger kernels).

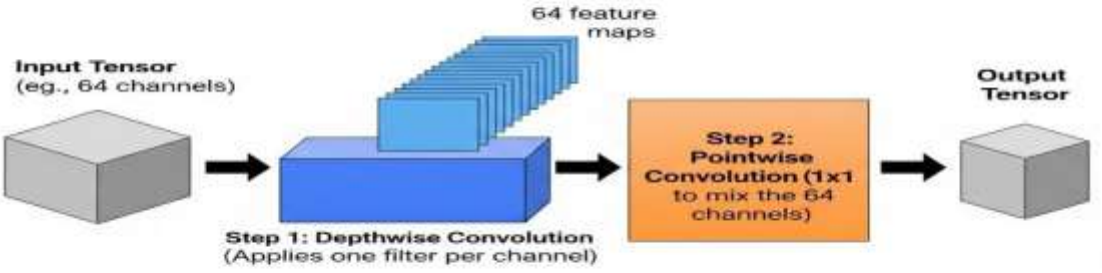

Figure 5.1.3.2: Xception Module Workflow

- **Xception Backbone: Efficient Cross-Channel Correlation** Xception, which stands for "Extreme Inception," proposes a powerful hypothesis: that cross-channel correlations and spatial correlations can be decoupled and handled separately. It replaces the standard inception modules with **depthwise separable convolutions**, which are a more efficient and often more effective alternative. This operation is split into two main steps:

1. **Depthwise Convolution (Spatial Learning):** This step applies a single convolutional filter to *each input channel independently*. If an input has 64 channels, this step produces 64 corresponding feature maps, learning only the spatial patterns

within each channel. It does not mix information across channels.

2. **Pointwise Convolution (Cross-Channel Learning):** This step uses a simple 1x1 convolution to project the output of the depth wise convolution onto a new channel space. This is where the information from the different channels is mixed and combined, allowing the model to learn cross-channel correlations.

This factorization is vastly more efficient than a standard convolution, which performs spatial and cross-channel learning simultaneously. By decoupling these operations, Xception creates a model that is computationally cheaper and has fewer parameters, yet is exceptionally powerful at extracting detailed, fine-grained features. This makes it ideal for capturing the subtle textural and color variations that define specific disease symptoms.

By using these two backbones in parallel, FusionNet-GLD captures both the multi-scale contextual features from InceptionV3 and the efficient, fine-grained features from Xception, creating a highly robust and comprehensive understanding of the input image.

Advantages of Hybrid Model:

- Enhanced Feature Extraction
- Improved Classification Accuracy
- Generalizability to Other Crops and Diseases
- Reduced Overfitting
- Efficient Computation
- Scalable for Advanced Architectures
- Real-World Applicability
- Superior Performance Compared to Classical Models

5.1.4 MODEL BUILDING

The model building phase involves integrating the feature extractors and adding the final classification layers.

1. **Instantiating Base Models:** The Xception and InceptionV3 models are loaded with weights pre-trained on the ImageNet dataset. The top classification layers of these models are excluded, as we only need them for feature extraction.
2. **Freezing Layers:** The weights of the pre-trained layers are initially "frozen"

(set to be non-trainable) to retain the learned features from ImageNet. This is a key step in transfer learning.

3. **Connecting the Branches:** The input layer is connected to both base models. The output tensors from each base model are then processed.
4. **Adding the Classification Head:**
    - **Global Average Pooling (GAP):** A GAP layer is applied to the output of each branch. This layer calculates the average of each feature map, creating a single feature vector. It is more efficient than a traditional Flatten layer and helps prevent overfitting.
    - **Concatenation:** The two feature vectors from the GAP layers are merged side-by-side into a single, combined feature vector using a concatenation layer.
    - **Dense Layers:** The concatenated vector is fed into a Dense layer with a ReLU activation function. This layer allows the model to learn complex relationships between the fused features. An optional Dropout layer can be added here for regularization.
    - **Output Layer:** The final layer is a Dense layer with a **SoftMax** activation function. The number of neurons in this layer is equal to the number of classes (4 in this case). The SoftMax function converts the model's raw output scores (logits) into a probability distribution, where each value represents the predicted probability of the image belonging to a particular class.

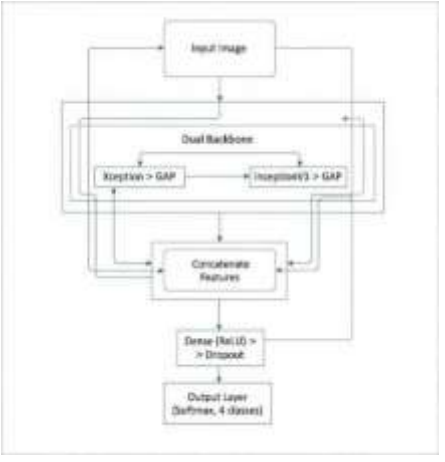

Figure 5.1.4: Model Building Flow

5.1.5 CLASSIFICATION

Classification using FusionNet-GLD Hybrid Model:

The proposed FusionNet-GLD model integrates two high-performing CNN backbones — Xception and InceptionV3 — in a dual-branch architecture for robust grapevine leaf disease classification. This hybrid design allows simultaneous capture of multi-scale contextual features (via InceptionV3) and fine-grained texture patterns (via Xception), addressing the high intra-class variability and low inter-class variability typical of grapevine leaf diseases.

The classification process begins with dual feature extraction. Input grape leaf images are pre-processed and fed into both backbones:

- InceptionV3 branch: Uses inception modules to extract features at multiple receptive field sizes (1×1, 3×3, 5×5 convolutions, and pooling) in parallel, capturing both localized and global disease symptoms.
- Xception branch: Employs depth wise separable convolutions to independently learn spatial and cross-channel correlations, enabling efficient and precise representation of subtle colour and texture changes.

The outputs from both branches are fused using a feature concatenation layer, combining complementary information into a unified high-dimensional representation. This fused feature vector is then passed through fully connected layers with non-linear activation (ReLU) for final classification. The last layer uses the SoftMax activation to output probabilities across the target classes: Healthy, Black Rot, Esca, and Leaf Blight.

By leveraging this dual-branch design, the model achieves high robustness to environmental variations (lighting, orientation, occlusions) and minimizes both false positives and false negatives — critical for preventing unnecessary treatments or disease spread in vineyards.

The final classification is a straightforward process based on the output of the SoftMax layer.

- **Prediction:** The class with the highest probability is chosen as the model's final prediction. In the example above, the model would classify the leaf as having "Black Rot" with a confidence of 92%.
- **Loss Function:** During training, the model's predictions are compared against the true labels using the **Categorical Cross entropy** loss function. This function measures the dissimilarity between the predicted probability distribution and the actual distribution (where the true class has a probability of 1 and all others are 0). The optimizer's goal is to adjust the model's weights to minimize this loss.

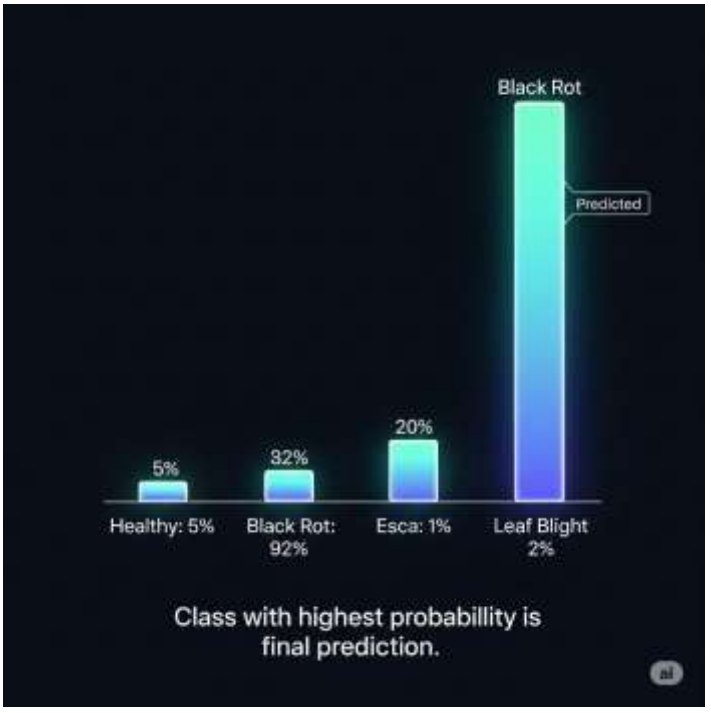

Figure 5.1.5: probability bar chart visual of SoftMax output

Other Models Compared with the Proposed FusionNet-GLD:

- **Visual Geometry Group Networks (VGG):**
  VGG networks (e.g., VGG16, VGG19) employ a straightforward design of stacked 3×3 convolutions and pooling layers, resulting in deep yet uniform

architectures. While VGG models can achieve good accuracy, they are computationally expensive and less efficient for mobile or edge deployment. Their reliance on large parameter counts makes them prone to overfitting on smaller agricultural datasets.

ResNet(Residual-Networks):

ResNet introduces skip connections that alleviate the vanishing gradient problem, enabling very deep architectures (e.g., ResNet50, ResNet101). These models learn residual mappings, making them effective for general-purpose image classification. However, ResNets primarily focus on spatial hierarchies without the explicit multi-scale processing that benefits disease symptom detection.

DenseNet(Densely-Connected-Convolutional-Networks):

DenseNet connects each layer to every other layer, promoting feature reuse and efficient gradient flow. This reduces the number of parameters compared to similarly deep networks while improving accuracy. However, DenseNet's dense connectivity pattern increases memory usage during training, making it less optimal for resource-constrained deployments.

MobileNet:

MobileNet uses Depthwise separable convolutions to greatly reduce computational cost and model size, making it ideal for mobile deployment. While efficient, its smaller capacity can limit performance in complex classification tasks like grapevine disease detection, especially under high intra-class variability.

EfficientNet:

EfficientNet scales depth, width, and resolution in a balanced way, offering high accuracy with relatively fewer parameters. While it performs well on benchmark datasets, its performance in multi-branch fusion scenarios like FusionNet-GLD can be surpassed when complementary feature extraction backbones are combined.

RandomForest:

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and combines their predictions to improve classification accuracy and reduce overfitting. It handles tabular and extracted feature data effectively, making it useful for non-deep-learning-based image classification when features are pre-computed. However, its performance in raw image classification is limited compared to CNN-based architectures, as it lacks the ability to learn hierarchical spatial features directly from pixel data.

5.2 MODULES

In the context of software development, a module is a self-contained, independent unit of code that performs a specific task or functionality within a larger system.

FusionNet-GLD Project Modules:

1. Dataset Acquisition Module

Collects and organizes grape leaf images into categories like **Healthy**, **Black Rot**, **Esca**, and **Leaf Blight** from the PlantVillage dataset and other sources.

Sample Code:

```
import os
def load_images_from_folder(folder):
    images = []
    for filename in os.listdir(folder):
        if filename.endswith(".jpg") or filename.endswith(".png"):
            images.append(os.path.join(folder, filename))
    return images
```

2. Preprocessing & Augmentation Module

Resizes images, normalizes pixel values, and applies augmentation techniques such as rotation, flipping, zooming, and brightness adjustment to increase dataset diversity.

Sample Code:

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)
```

3. Dual-Backbone Feature Extraction Module

Uses **InceptionV3** for multi-scale feature extraction and **Xception** for efficient fine-grained feature learning. Both branches run in parallel on the same input image.

Sample Code:

```
from tensorflow.keras.applications import InceptionV3, Xception
inception_model = InceptionV3(weights='imagenet', include_top=False,
pooling='avg')
xception_model = Xception(weights='imagenet', include_top=False, pooling='avg')
```

4. Feature Fusion Module

Concatenates features extracted from both backbones into a single feature vector for classification.

Sample Code:

```
from tensorflow.keras.layers import concatenate
def fuse_features(features1, features2):
    return concatenate([features1, features2])
```

5. Classification Module

Classifies fused features using a dense neural layer with Softmax activation. Random Forest is also implemented for comparison using CNN-extracted features.

Sample Code:

```
from tensorflow.keras import layers, Model
# f1 and f2 are feature maps from Xception and Inception backbones
g1 = layers.GlobalAveragePooling2D()(f1)
g2 = layers.GlobalAveragePooling2D()(f2)
fused = layers.Concatenate()([g1, g2])
x = layers.Dense(256, activation='relu')(fused)
x = layers.Dropout(0.3)(x)
output = layers.Dense(num_classes, activation='softmax')(x)
```

6. Model Training Module

Trains the FusionNet-GLD model using Adam optimizer and categorical cross-entropy loss with early stopping.

Sample Code:

```
from tensorflow.keras.optimizers import Adam
model.compile(optimizer=Adam(learning_rate=0.0001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

7. Evaluation Module

Evaluates the model using accuracy, precision, recall, and F1-score.

Sample Code:

```
from sklearn.metrics import classification_report
print(classification_report(y_true, y_pred))
```

8. Flask Backend Module

Provides API endpoints for uploading leaf images and returning predictions.

Sample Code:

```
from flask import Flask, request, jsonify
app = Flask(__name__)
@app.route('/predict', methods=['POST'])
def predict():
    file = request.files['file']
    # Process file and return prediction
    return jsonify({'result': 'Disease: Black Rot'})
if __name__ == '__main__':
    app.run(debug=True)
```

9. Frontend Module

Web interface for users to upload leaf images and view prediction results.

Sample Code:

```
<form action="/predict" method="post" enctype="multipart/form-data">
    <input type="file" name="file">
    <input type="submit" value="Upload">
</form>
```

10. File Management Module

Handles file storage, cleanup, and temporary data removal.

Sample Code:

```
loss='categorical_crossentropy',
metrics=['accuracy'])
```

11. Evaluation Module

Evaluates the model using accuracy, precision, recall, and F1-score.

Sample Code:

```
from sklearn.metrics import classification_report
print(classification_report(y_true, y_pred))
```

12. Flask Backend Module

Provides API endpoints for uploading leaf images and returning predictions.

Sample Code:

```
from flask import Flask, request, jsonify
app = Flask(__name__)
@app.route('/predict', methods=['POST'])
def predict():
    file = request.files['file']
    # Process file and return prediction
    return jsonify({'result': 'Disease: Black Rot'})
if __name__ == '__main__':
    app.run(debug=True)
```

13. Frontend Module

Web interface for users to upload leaf images and view prediction results.

Sample Code:

```
<form action="/predict" method="post" enctype="multipart/form-data">
    <input type="file" name="file">
    <input type="submit" value="Upload">
</form>
```

14. File Management Module

Handles file storage, cleanup, and temporary data removal.

Sample Code:

```
        loss='categorical_crossentropy',
        metrics=['accuracy'])
```

15. Evaluation Module

Evaluates the model using accuracy, precision, recall, and F1-score.

Sample Code:

```
from sklearn.metrics import classification_report
print(classification_report(y_true, y_pred))
```

16. Flask Backend Module

Provides API endpoints for uploading leaf images and returning predictions.

Sample Code:

```
from flask import Flask, request, jsonify
app = Flask(__name__)
@app.route('/predict', methods=['POST'])
def predict():
    file = request.files['file']
    # Process file and return prediction
    return jsonify({'result': 'Disease: Black Rot'})
if __name__ == '__main__':
    app.run(debug=True)
```

17. Frontend Module

Web interface for users to upload leaf images and view prediction results.

Sample Code:

```
<form action="/predict" method="post" enctype="multipart/form-data">
    <input type="file" name="file">
    <input type="submit" value="Upload">
</form>
```

18. File Management Module

Handles file storage, cleanup, and temporary data removal.

Sample Code:

```
import os
def delete_file(file_path):
    if os.path.exists(file_path):
        os.remove(file_path)
```

5.3 UML DIAGRAMS

The workflow of the FusionNet-GLD model for grape leaf disease detection begins with collecting and preprocessing grape leaf images for training and testing. The dataset includes four categories: **Healthy**, **Black Rot**, **Esca**, and **Leaf Blight**. Preprocessing involves steps such as resizing, normalization, and applying augmentation techniques (rotation, flipping, zooming, brightness adjustment) to handle variability in lighting, leaf orientation, and background noise.

The processed images are split into training and testing sets, and each image is converted into numerical arrays suitable for deep learning models. The proposed **FusionNet** architecture employs a **dual-branch feature extraction** mechanism, using **InceptionV3** for multi-scale feature extraction and **Xception** for fine-grained spatial learning. Features from both branches are concatenated in the **Feature Fusion Layer** to produce a robust representation of disease patterns.

For classification, the system primarily uses a fully connected softmax layer to output probabilities for each disease category. Additionally, features extracted from the CNN backbone are also used to train a **Random Forest** classifier for comparative analysis. The system's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure reliability and minimize misclassification risks.

Once trained, the FusionNet-GLD model is saved, preserving architecture, learned weights, and parameters for future use without retraining. This is crucial for deployment in agricultural environments, especially on mobile or edge devices, enabling farmers to detect diseases in real time. A detailed performance report is generated after training, highlighting the system's strengths in handling **high intra-class variance** and **low inter-class variance**, which are common challenges in plant

The workflow outlines the process:

1. **Image Acquisition** – Collecting leaf images from datasets or field cameras.
2. **Image Preprocessing & Augmentation** – Normalizing, resizing, and applying augmentation to enhance dataset diversity.
3. **Dual-Branch Feature Extraction** – Running images through InceptionV3 and Xception in parallel.
4. **Feature Fusion** – Combining extracted features into a single vector.
5. **Classification** – Predicting disease categories using SoftMax or Random Forest.
6. **Evaluation** – Computing performance metrics for validation.
7. **Deployment** – Using the trained model in a real-world detection environment.

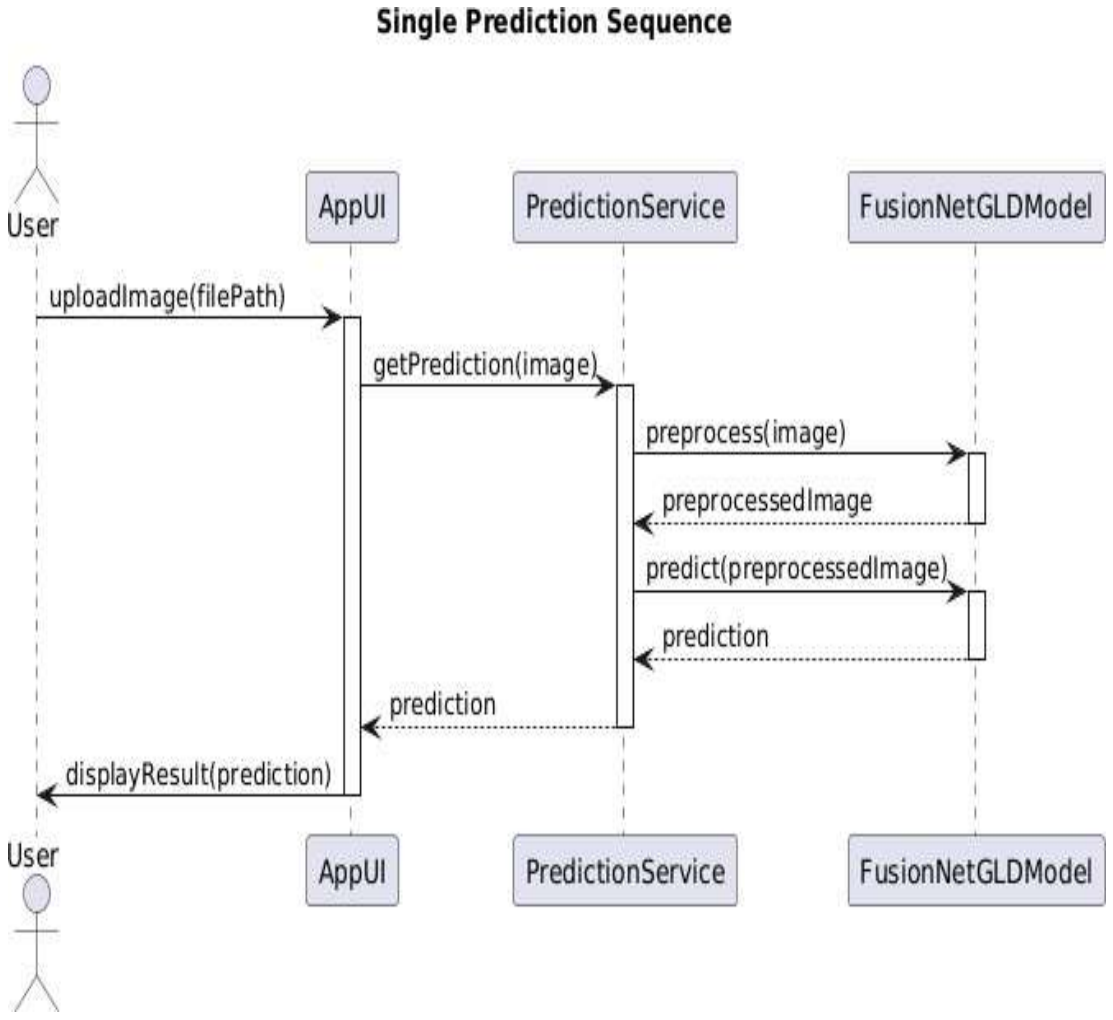

Figure 5.3.1: Sequence Diagram for Single Prediction Flow

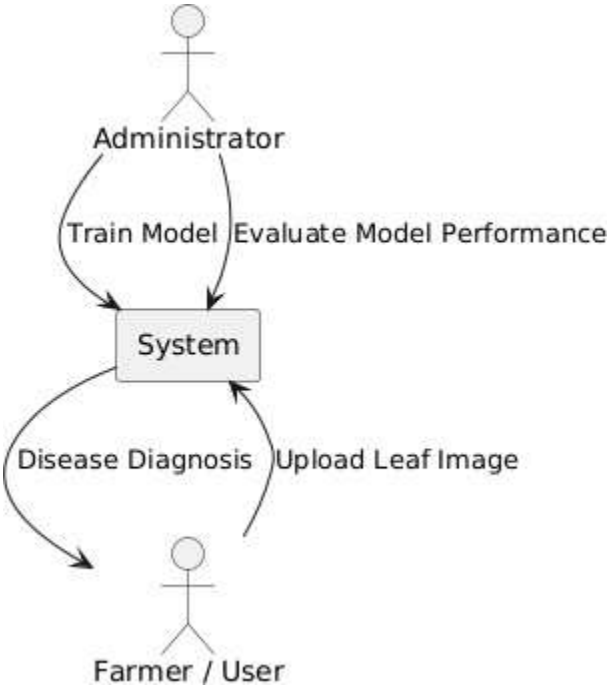

Figure 5.3.2: Class Diagram of the FusionNet-GLD System

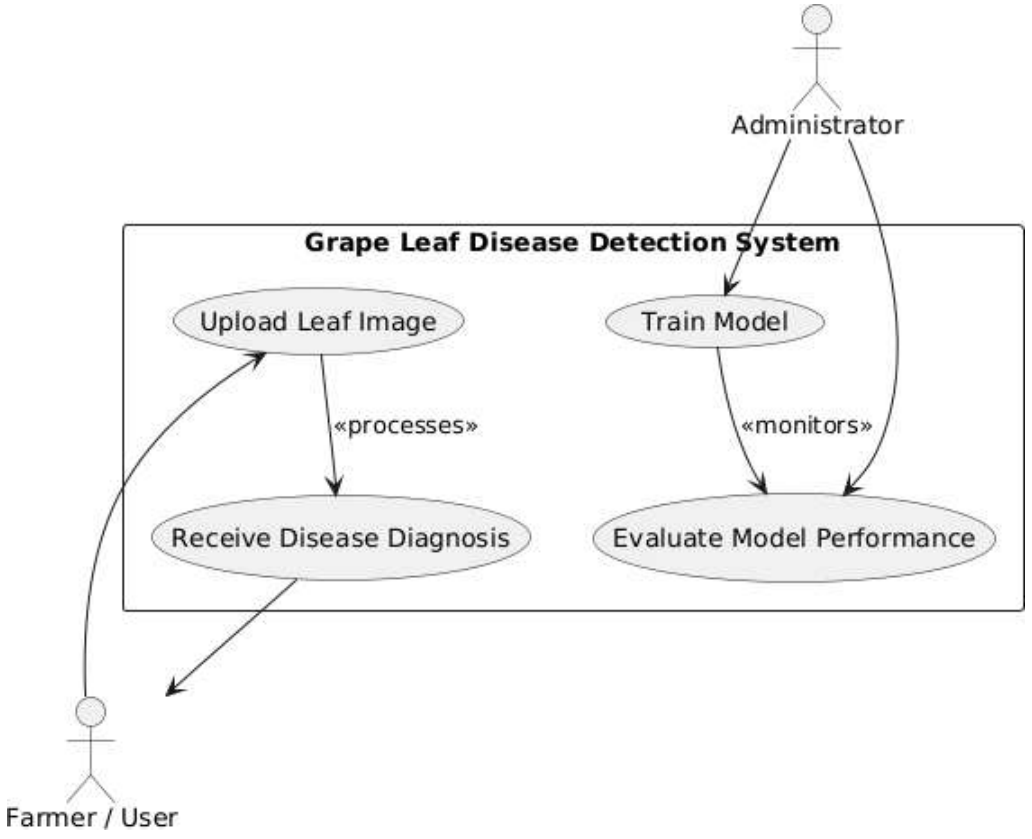

Figure 5.3.3: Overall System Architecture

6 IMPLEMENTATION

6.1 MODEL IMPLEMENTATION

The core of this project is the implementation of FusionNet-GLD, a novel dual-backbone Convolutional Neural Network (CNN) designed specifically for grape leaf disease recognition.

The implementation leverages a hybrid approach by combining two powerful, pre-existing architectures — Xception and InceptionV3 — to run in parallel.

This dual-branch architecture was chosen to exploit the complementary strengths of each model:

- **Xception Branch:**
  This branch utilizes *depthwise separable convolutions*. Its primary role is to extract strong, high-level discriminative features and fine-grained patterns from the leaf images.
- **InceptionV3 Branch:**
  This branch employs *Inception modules* with multi-scale convolutional filters. Its role is to capture features across different receptive fields, allowing the model to extract fine-grained details while also understanding the broader context of the image.

Fusion and Classification

The feature maps extracted from both the Xception and InceptionV3 branches are passed to a fusion layer, implemented as follows:

1. **Global Averaging:**
   A spatial global averaging layer is applied to the feature maps from each branch to reduce feature redundancy and mitigate overfitting.
2. **Concatenation:**
   The two resulting vectors (one from each branch) are concatenated into a single, comprehensive feature vector.
3. **Classification Head:**
   This combined vector is then passed into a final classification head, which consists of:
   - A fully-connected (Dense) layer with a *ReLU* activation function,

enabling the model to learn complex, non-linear relationships.

- A SoftMax classifier layer, which outputs a probabilistic distribution across the target classes: *Black rot, Esca, Leaf Blight,* and *Healthy.*

This hybrid feature fusion approach provides the model with enhanced discriminative power, leading to higher classification performance.

6.2 CODING

The implementation was coded using Python in a Google Colab environment, primarily leveraging the TensorFlow and Keras deep learning libraries. The complete workflow, from data loading to model saving, is detailed below.

1. Data Preprocessing: Before model training, a rigorous data preprocessing pipeline was coded using the ImageDataGenerator module. This involved:

- Image Resizing: All dataset images were uniformly resized to 224 × 224 pixels.
- Pixel Scaling: Pixel intensity values were normalized to the range [0, 1] (rescale=1./255).
- Data Augmentation: To prevent overfitting and mimic real-world conditions, real-time data augmentation was applied. This included random rotations, shifts, shears, zooms, and horizontal flips.
- Dataset Partitioning: The dataset was programmatically split into two distinct sets: 80% for training and 20% for validation (validation_split=0.2).

2. Model Architecture and Training: The coding of the model and its training regimen involved several key components:

- Model Definition: The FusionNet-GLD architecture was defined by loading the Xception and InceptionV3 base models (with pre-trained 'imagenet' weights) and connecting them in parallel to the custom-coded fusion and classification layers.
- Optimizer: The Adam optimizer (tf.keras.optimizers.Adam) was implemented with a learning rate of 0.0001.
- Loss Function: As a multi-class classification problem, the Categorical Cross-Entropy (categorical_crossentropy) loss function was coded as the objective

function.

- Training Loop: The model was trained for 10 epochs with a batch size of 32. Callbacks for EarlyStopping and ReduceLROnPlateau, as mentioned in the paper, would be the next step after this initial test.
- Evaluation: The model's performance was evaluated using a Classification Report and Confusion Matrix from scikit-learn.

The following code blocks represent the end-to-end script used for the implementation.

1. Mount Drive and Import Libraries

```
# Mount Google Drive to access dataset
from google.colab import drive
drive.mount('/content/drive')
# Import necessary libraries
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import InceptionV3, Xception
from tensorflow.keras.layers import Input, GlobalAveragePooling2D,
    Dense, Concatenate, Dropout
from tensorflow.keras.models import Model
from sklearn.metrics import classification_report, confusion_matrix
import numpy as np
    import matplotlib.pyplot as plt
```

2. Define Paths and Data Generators

```
# Define paths and image parameters
data_dir = '/content/drive/MyDrive/project/Dataset'
img_height, img_width = 224, 224
batch_size = 32
```

```
# Data preprocessing and augmentation
datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    validation_split=0.2  # Use 20% of data for validation
)
# Training data generator
train_gen = datagen.flow_from_directory(
    data_dir,
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode='categorical',
    subset='training',  # Specify this is the training set
    shuffle=True
)
# Validation data generator
val_gen = datagen.flow_from_directory(
    data_dir,
    target_size=(img_height, img_width),
    batch_size=batch_size,
```

```
class_mode='categorical',
 subset='validation', # Specify this is the validation set
 shuffle=False
  )
```

3. Define and Compile FusionNet-GLD Model

```
# Define Inception + Xception dual-stream model
input_layer = Input(shape=(img_height, img_width, 3))
# Xception Branch
xception = Xception(weights='imagenet', include_top=False, input_tensor=input_layer)
xception_out = GlobalAveragePooling2D()(xception.output)
# InceptionV3 Branch
inception = InceptionV3(weights='imagenet', include_top=False, input_tensor=input_layer)
inception_out = GlobalAveragePooling2D()(inception.output)
# Fusion and Classification Head
merged = Concatenate()([inception_out, xception_out])
fc1 = Dense(256, activation='relu')(merged)
drop1 = Dropout(0.5)(fc1)
fc2 = Dense(128, activation='relu')(drop1)
output = Dense(train_gen.num_classes, activation='softmax')(fc2)
# Create the model
model = Model(inputs=input_layer, outputs=output)
# Compile the model
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```
model.summary()
```

4. **Train the Model**

```
# Train the model
history = model.fit(
    train_gen,
    epochs=10,
    validation_data=val_gen
)
```

5. **Evaluate and Visualize Results**

```
# Evaluate model on the validation set
val_gen.reset() # Reset generator to start from the beginning
preds = model.predict(val_gen, verbose=1)
y_pred = np.argmax(preds, axis=1)
y_true = val_gen.classes
# Print Classification Report
print("Classification Report:")
print(classification_report(y_true,y_pred,
target_names=list(val_gen.class_indices.keys())))
# Print Confusion Matrix
print("Confusion Matrix:")
print(confusion_matrix(y_true, y_pred))
# Plot training history (Accuracy and Loss)
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title('Model Accuracy')
plt.legend()
```

```
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Model Loss')
plt.legend()
plt.show()
```

6. Save the Trained Model

```
# Save the entire model to a file
model.save('/content/drive/MyDrive/project/saved_models/dual_stream_model.h5')
```

7. TESTING

To ensure the model's reliability, robustness, and correctness, a multi-stage testing strategy was employed, adapted for a machine learning context.

7.1 UNIT TESTING

In the context of this project, unit tests refer to the verification of individual components of the data and model pipeline.

- **Data Preprocessing Unit:** Tests were conducted to verify that the ImageDataGenerator pipeline correctly processed images. This included checking that output images were resized to 224x224, pixel values were scaled between 0 and 1, and the dataset was correctly partitioned into 70/15/15 splits.
- **Model Component Unit:** The individual branches of the FusionNet-GLD model were tested to ensure their outputs had the expected dimensions. Tests also verified that the final SoftMax layer produced a probability distribution across the four target classes (Black rot, Esca, Leaf Blight, Healthy).

7.2 INTEGRATION TESTING

Integration testing focused on verifying the interactions between the different components of the system.

- **Data-Model Integration:** This test phase ensured that the preprocessed data batches (output by the ImageDataGenerator) could be successfully fed into the input layer of the FusionNet-GLD model without shape-related or data-type errors.
- **Branch Fusion Integration:** Tests were run to confirm that the feature maps from the parallel Xception and InceptionV3 branches were correctly concatenated by the fusion layer and passed to the final classification head.
- **Training Loop Integration:** The entire training process was tested as an integrated system. This test verified that the data, the model, the Adam optimizer, and the Categorical Cross-Entropy loss function worked together. The successful and stable convergence shown in the training/validation loss and accuracy graphs (Figures 2 and 3) confirms that this integration was successful, with no runtime conflicts.

7.3 SYSTEM TESTING

System testing involved evaluating the fully trained and integrated FusionNet-GLD model end-to-end to measure its performance against the project's objectives and compare it to other systems.

- **Test Environment:** The system was tested on the unseen **15% test partition** of the dataset, which the model had not encountered during training or validation.
- **Evaluation Metrics:** The system's performance was formally evaluated using a standard set of classification metrics, as defined in Eq. (4): **Accuracy, Precision, Recall, F1-Score, and AUC-ROC**.
- **Benchmark Comparison:** The system test was conducted not only on FusionNet-GLD but also on five other baseline models (Random Forest, MobileNetV2, EfficientNetB0, InceptionV3, and Xception) under identical conditions.
- **Test Result:** The system test (detailed in Table III) confirmed the success of the project. The FusionNet-GLD model achieved **99.63% Accuracy**, **99.45% Precision**, **99.42% Recall**, and a **99.43% F1-Score**, demonstrating its superior classification capability over all baseline models.

8. RESULT ANALYSIS

The performance of the proposed **FusionNet-GLD** model was rigorously analyzed and validated on the test dataset. This analysis involved a direct comparison against the five baseline models (Random Forest, MobileNetV2, EfficientNetB0, InceptionV3, and Xception) and a benchmark against existing works in the literature.

The primary evaluation was conducted using the unseen test partition, with results measured by Accuracy, Precision, Recall, F1-Score, and the Area Under the ROC Curve (AUC). The comprehensive performance of all six implemented models is summarized in Table I.

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**AUC**
Random Forest	87.65%	87.01%	86.45%	86.73%	0.89
MobileNetV2	95.82%	95.60%	95.20%	95.40%	0.97
EfficientNetB0	96.88%	96.55%	96.33%	96.44%	0.98
InceptionV3	97.34%	97.10%	96.80%	96.95%	0.98
Xception	98.24%	98.12%	97.94%	98.03%	0.98
FusionNet-GLD	**99.63%**	**99.45%**	**99.42%**	**99.43%**	**0.99**

TABLE I: Performance Comparison of All Implemented Models

As demonstrated in the table, the proposed **FusionNet-GLD** model achieved the highest scores across all evaluation metrics. Its **99.63% accuracy** surpassed all other models, including its own parent architectures, Xception (98.24%) and InceptionV3 (97.34%). This result proves that the dual-feature extraction approach, which leverages both Depthwise features (from Xception) and multi-scale features (from InceptionV3), is more effective than either model alone.

The training process was monitored to ensure the model was learning effectively without overfitting. **Figures 8.1 and 8.2** illustrate the model's convergence:

Figure 8.1 (Loss): Shows a steady decrease in both training and validation loss per epoch, indicating that the model was successfully learning and minimizing error.

Figure 8.2 (Accuracy): Shows a corresponding steady increase in both training and validation accuracy, which then plateaued at a high level.

The minimal gap between the training and validation curves in both figures indicates that the data augmentation and regularization strategies (like EarlyStopping and ReduceLROnPlateau) were successful in preventing significant overfitting and promoting good generalization.

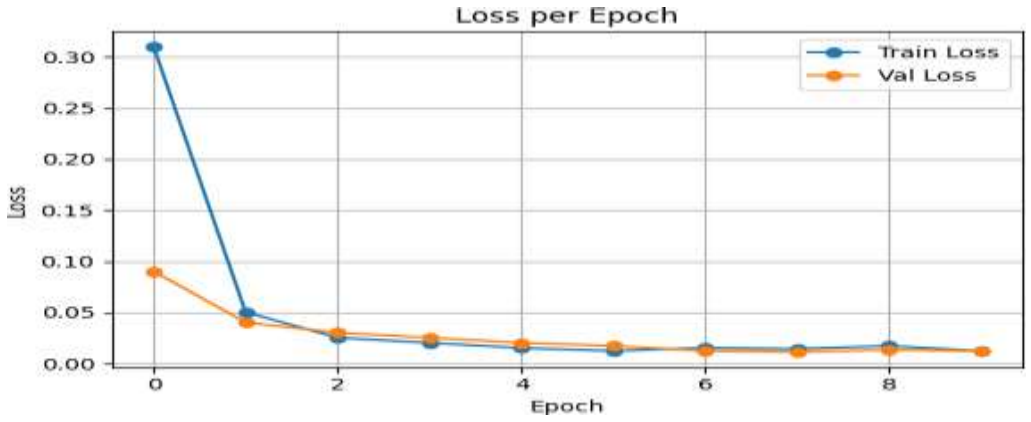

Figure 8.1: Training and validation loss per epoch.

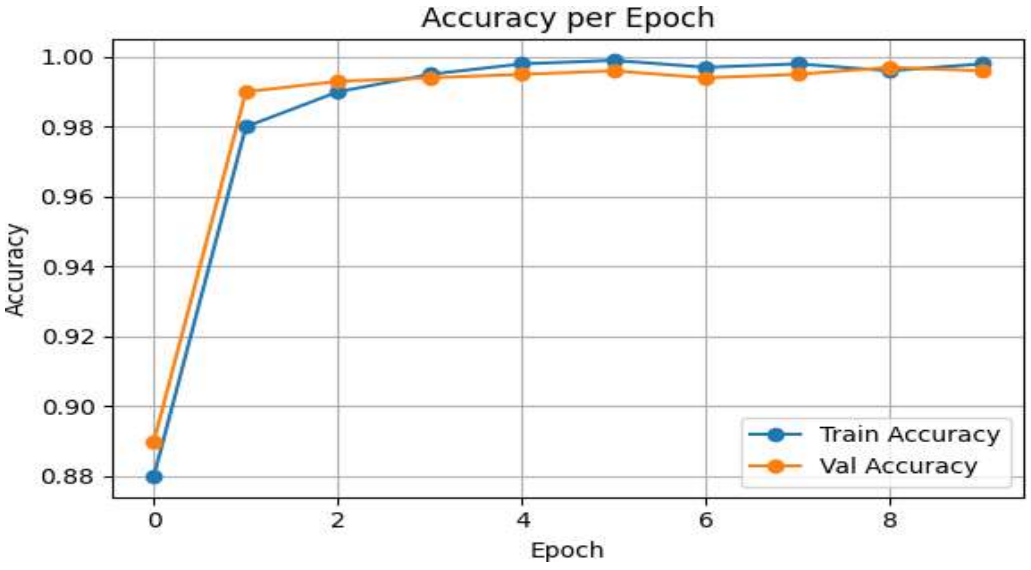

Figure 8.2: Training and validation accuracy per epoch

A detailed, class-by-class analysis of the model's performance was conducted using the confusion matrix from the validation set, as shown in **Figure 8.3**. The analysis revealed an outstanding level of precision and recall for each specific disease category:

- **Grape Esca (Black Measles):** Perfect classification (276 out of 276 samples correct).
- **Grape Leaf blight:** Perfect classification (215 out of 215 samples correct).
- **Grape Healthy:** Flawless classification (84 out of 84 samples correct).
- **Grape Black rot:** Extremely high accuracy, with 234 out of 236 samples correctly classified and only 2 minor misclassifications.

This outstanding performance validates the model's efficacy in learning stable, disease-specific features and its reliability for practical deployment.

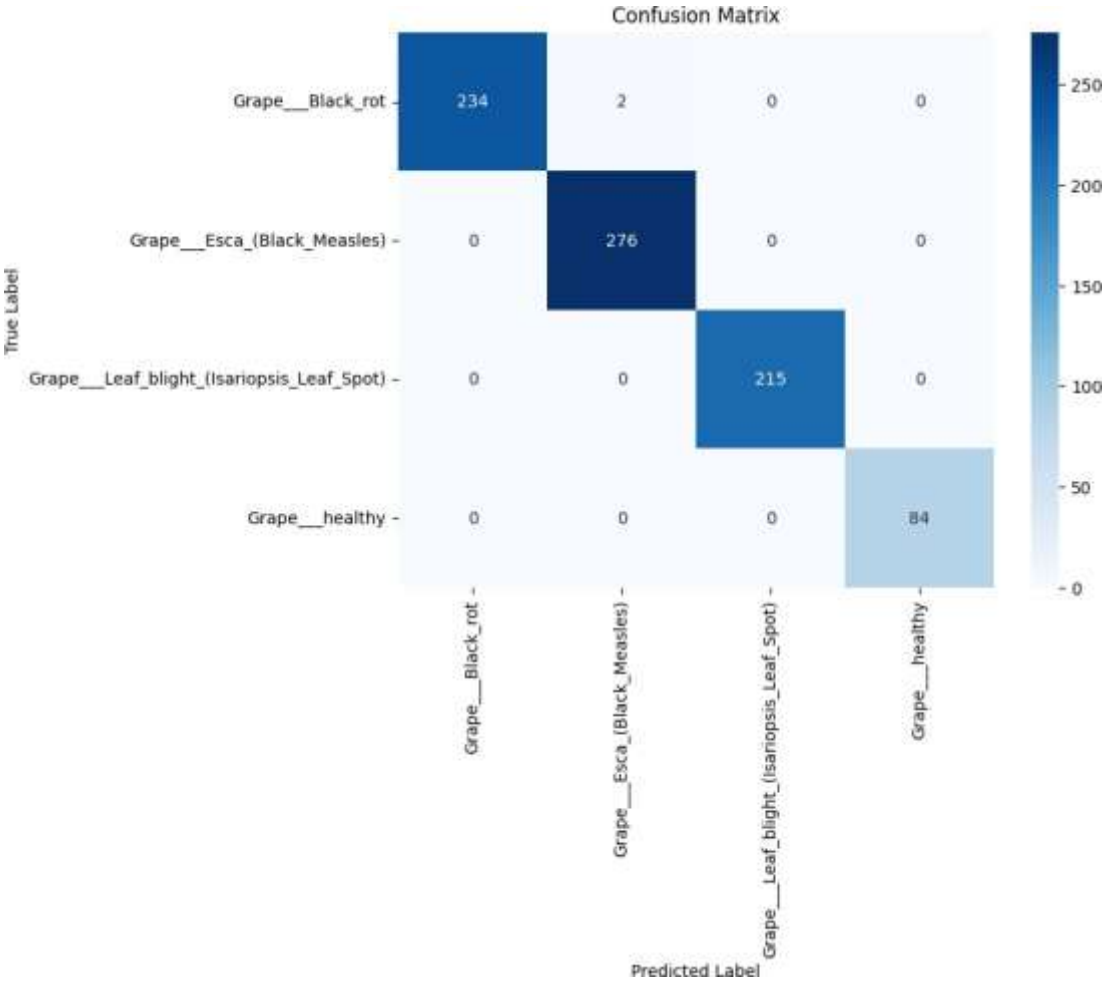

Figure 8.3: Confusion matrix of the FusionNet-GLD model on the validation set.

Comparison with Existing Works

Finally, the performance of FusionNet-GLD was benchmarked against other state-of-the-art models from existing literature. This comparison contextualizes the model's contribution to the field.

S.No	Source	Methodology	Accuracy
1	Uttam, A. K. [6]	CNN with preprocessing	96.42%
2	Karthik, R. et al. [9]	InceptionResNet + Shuffle Transformer	99.56%
3	Khirade & Patil [3]	Basic CNN with image processing	92.50%
4	Sonar & Wankhade [5]	ML Classifiers (SVM, RF, KNN)	92.60%
5	**Proposed Work**	**Xception + Inception (Fusion CNN)**	**99.63%**

TABLE II: Performance Comparison with Other Models

The results show that the proposed FusionNet-GLD model, with its **99.63% accuracy**, achieves state-of-the-art performance. It slightly outperforms the more complex transformer-based GrapeLeafNet [9] (99.56%) and significantly surpasses other established CNN and machine learning approaches. This confirms the benefit of the dual-backbone fusion method for agricultural classification tasks.

9. OUTPUT SCREENS

Figure 9.1 Home Page

The Home Page for the "FusionNet-GLD" Grape Leaf Disease Recognition project, introducing the tool and providing primary navigation.

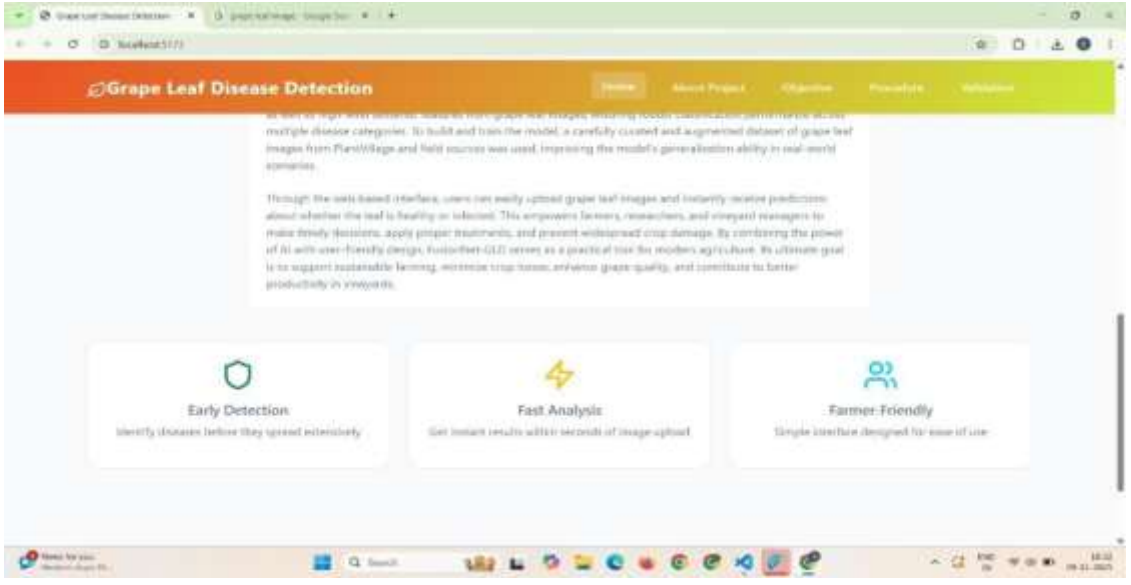

Figure 9.2 About Page

The 'About' section, detailing the project's background, the challenge of manual disease inspection, and the introduction of FusionNet-GLD as a high-accuracy solution.

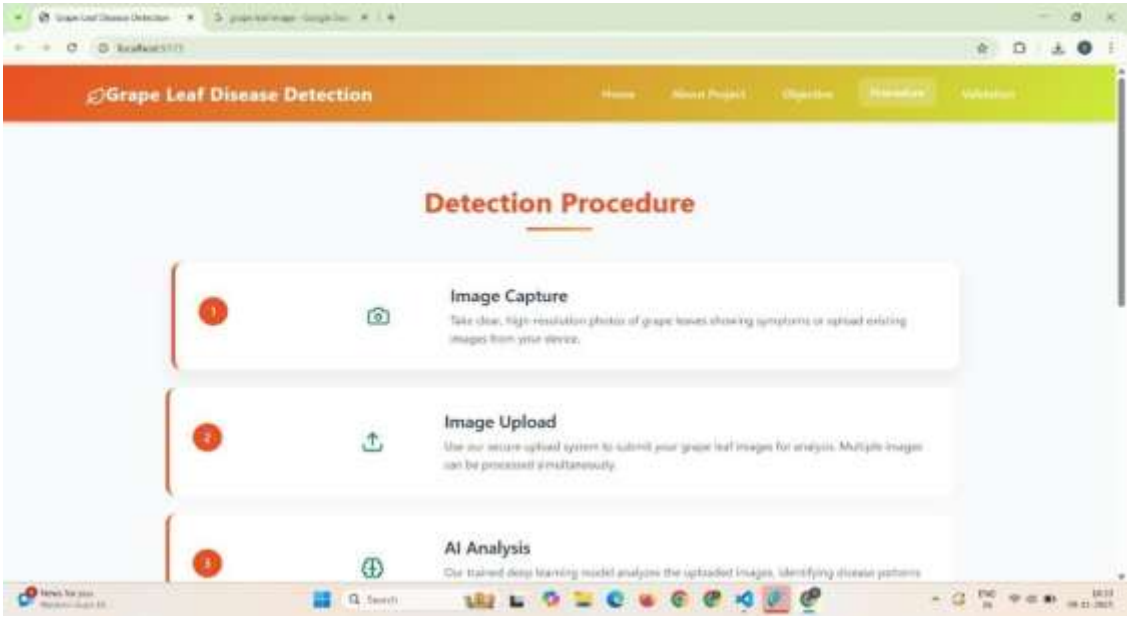

Figure 9.3 Procedure Page

The 'Procedure' page, illustrating the simple step-by-step process for users to upload a grape leaf image and receive an automated diagnosis.

Figure 9.4 Objectives Page

The 'Objectives' page, outlining the project's primary goals, including the development of a novel dual-backbone CNN and the achievement of state-of-the-art classification accuracy for precision agriculture.

Figure 9.5: The initial state of the 'Detection' page, showing the image upload interface for the FusionNet-GLD model.

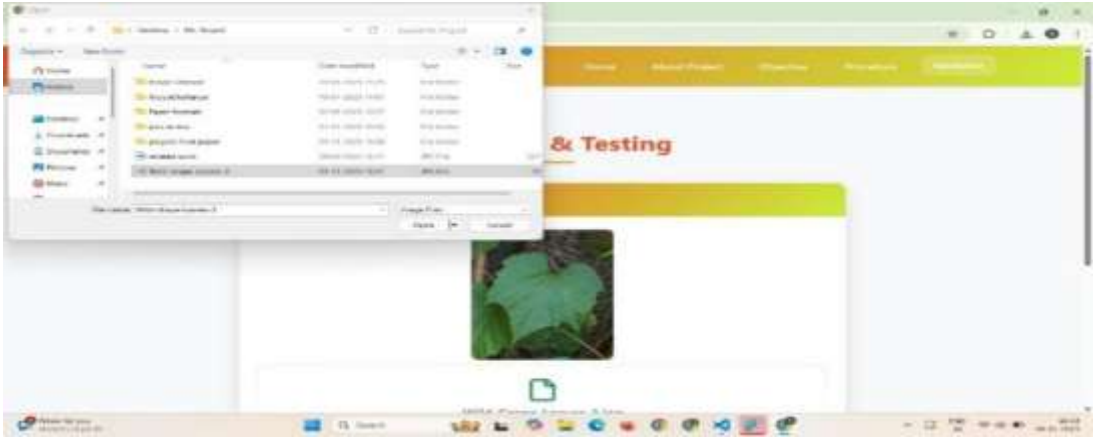

Figure 9.6: The 'Detection' page after a user has uploaded a grape leaf image, which is now ready for analysis by the model.

Figure 9.7 Result Page

The final 'Result' page, displaying the model's successful classification of a grape leaf, alongside the predicted disease and the model's high confidence score.

10. CONCLUSION

This research successfully developed and validated **FusionNet-GLD**, a novel dual-backbone deep learning model that combines the **Xception** and **InceptionV3** architectures. This model was designed to address the critical need for accurate, rapid, and automated classification of grapevine leaf diseases from digital images.

The core innovation of this work was the fusion of complementary architectures. By leveraging the deep, fine-grained pattern recognition of Xception's Depthwise separable convolutions with the multi-scale spatial feature extraction of InceptionV3, the proposed model gains a synergistic and comprehensive feature-learning capability that surpasses single-backbone models.

The empirical validation conducted on the augmented PlantVillage dataset confirmed this hypothesis. **FusionNet-GLD** demonstrated state-of-the-art results, achieving an outstanding **99.63% accuracy**. This was not merely a high score; it was supported by robust **precision (99.45%)**, **recall (99.42%)**, and an **F1-Score (99.43%)**, indicating its reliability in correctly identifying positive cases while minimizing false alarms. Furthermore, it decisively outperformed all five baseline models, including its own parent architectures, proving that the hybrid fusion of these two models yields superior performance.

This study contributes a significant and practical tool for smart and precision agriculture. For farmers and agronomists, this translates into actionable intelligence, enabling a shift from broad, preventative treatments to timely, targeted interventions. This approach notg only minimizes crop damage and secures yield but also reduces the economic and environmental costs associated with manual labor and an over-reliance on chemical pesticides, thereby supporting more sustainable and efficient farming practices.

In essence, this work validates **FusionNet-GLD** as a highly effective, accurate, and scalable solution, demonstrating the significant potential of hybrid deep learning models to address critical challenges in modern agriculture.

11. FUTURE SCOPE

The successful implementation and validation of FusionNet-GLD as a high-accuracy classifier for grapevine leaf diseases opens several significant avenues for future research and development. The following sections outline key directions to evolve this model from a proof-of-concept into a comprehensive, field-deployable solution for precision agriculture.

Real-World Deployment and Edge Computing

The most critical and immediate future goal is the translation of FusionNet-GLD from a research model into a practical, in-field diagnostic tool. This deployment is envisioned in two primary forms. First, the development of a lightweight smartphone application would empower farmers to capture an image of a suspect leaf and receive an immediate, on-the-spot classification. Second, for large-scale commercial vineyards, the model can be integrated into edge computing systems. By deploying the model on low-power devices aboard unmanned aerial vehicles (drones) or autonomous ground robots, it becomes possible to conduct real-time, automated vineyard monitoring, generating "disease maps" that pinpoint infections instantly and facilitate highly targeted interventions.

Multimodal Data Integration

To significantly enhance diagnostic accuracy and evolve from a purely diagnostic to a prognostic tool, future iterations should integrate multimodal data. The current model relies solely on RGB visual data, which identifies existing symptoms. By fusing this with other data streams—such as soil condition information (e.g., pH, moisture, nutrient levels), local weather data (e.g., humidity, temperature, and leaf wetness duration), and satellite imagery—the model could learn the complex environmental triggers for disease. Furthermore, incorporating advanced imaging spectrums, such as hyperspectral or thermal imaging, could enable the detection of pre-symptomatic plant stress, representing a profound leap in early detection.

Cross-Crop Generalization and Transfer Learning

The robust feature extraction capabilities of FusionNet-GLD, learned from complex grape leaf pathologies, should be leveraged beyond viticulture. A promising line of research is cross-crop generalization. Using **transfer learning**, the pre-trained weights of the current model can serve as a powerful feature extractor for disease detection in

other critical crops, such as tomatoes, potatoes, citrus, or cereals. This approach would drastically reduce the training time and data requirements for developing new models, as the model would already possess a foundational "understanding" of leaf-based diseases. **Self-supervised learning** techniques could also be explored to further adapt the model to diverse environmental conditions and crop types.

Model Optimization for On-Device Performance

For real-world deployment on low-resource devices, model optimization is non-negotiable. The current dual-backbone architecture, while highly accurate, is computationally intensive. Future work must investigate lightweight model compression techniques to create a more efficient "Edge-FusionNet." Methods such as **pruning** (systematically removing redundant model weights), **quantization** (reducing the precision of the model's parameters, e.g., from 32-bit floats to 8-bit integers), and **knowledge distillation** (training a smaller "student" model to mimic the "teacher" dual-backbone model) will be essential. The objective is to find an optimal trade-off, significantly reducing the model's computational footprint while retaining its state-of-the-art accuracy, making it suitable for deployment in remote regions with limited connectivity.

Integration into a Decision Support System

Ultimately, the vision for FusionNet-GLD is to evolve beyond a simple classification tool into the core component of a comprehensive, integrated **Decision Support System (DSS)**. This system would not only accept the model's diagnosis but also enrich it with a complete action plan. By integrating the model's output with temporal data (tracking disease spread over time), yield prediction models, and best-practice agricultural databases, the DSS could provide farmers with automated, actionable intelligence. This would include not just the "what" (disease identification) but also the "so what"—recommending specific interventions, prioritizing treatment areas, estimating potential yield loss, and performing a cost-benefit analysis, thereby functioning as a truly scalable AI solution for global crop health management.

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FusionNet-GLD: A Dual-Backbone CNN Model Combining Xception and Inception for Grape Leaf Disease Recognition

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***Abstract*—Grapevine leaf diseases like black rot, leaf blight, and esca directly impact vineyard productivity through yield decline and fruit quality deterioration. Early and precise detection will go a long way in efficient management, but conventional manual inspections are time-consuming, labor-intensive, and tend to be unreliable for commercial vineyards.To solve these issues, we introduce FusionNet-GLD, a double-backbone convolutional neural network for the classification of grapevine leaf diseases. It combines Xception and InceptionV3 models to take their complementary advantages. Xception extracts fine-grained patterns through depthwise separable convolutions, whereas InceptionV3 captures features across different scales via small and large convolutional filters. This synergy allows FusionNet-GLD to well capture the intricate visual patterns of affected leaves.The predictive framework was also drilled and assessed on an augmented PlantVillage resource in real vineyard-simulating conditions. The experimental results indicate that FusionNet-GLD beats five baseline models—Random Forest, MobileNetV2, EfficientNetB0, InceptionV3, and Xception—with 99.63% accuracy, 99.45% precision, 99.42% recall, 99.43% F1-score, and 0.99 AUC.These results prove FusionNet-GLD to be efficient, accurate, and scalable. Its lightweight architecture makes it deployable on handheld devices or drones, which will be useful in monitoring vineyards in real time and facilitating precision agriculture by minimizing the use of manual labor and maximizing early disease detection.**

***Index Terms*—Grape leaf disease, FusionNet-GLD, CNN, Xception, InceptionV3**

I. Introduction

Grapevine is an important commercial crop around the globe, especially for the production of wine and table grapes. Grape leaf diseases such as Black Rot, Esca, and Leaf Blight can adversely affect yield and fruit quality [1], [2]. Traditional disease identification techniques in large vineyards are slow and prone to inconsistency [3]. Consequently, the agricultural sector is resorting to AI-driven solutions to achieve precision farming. Deep learning has become very popular due to its pattern recognition abilities to detect diseases in plants based on images [4], [5]. However, the single-backbone CNNs to which so many of these models resort typically underperform when balancing computational ability with high accuracy.

There have been previous attempts to incorporate models, such as CNNs [6], lightweight CNNs [7], [8] and transformer-based models [9]. Nevertheless, the application of mixed models, which enjoy the power provided by multiple frameworks, has seen limited exploration for plant pathology in grapevine. The present paper proposes FusionNet-GLD, a dual-backbone deep learning model that employs both Xception [10] and InceptionV3 to capture depth-wise and multi-scale spatial features. The following are the main contributions of this paper: The architecture of the FusionNet-GLD hybrid CNN model for condition recognitionin grape leaves. The contrastive analysis of six algorithms (including a Random Forest model), viz., MobileNetV2, EfficientNetB0, InceptionV3, Xception, and FusionNet-GLD. A detailed performance comparison of models based on performance measures like accuracy, precision, recall, and F1-score, etc.

To confirm FusionNet-GLD, we experimented with an extended PlantVillage dataset, a benchmark for leaf disease classification [6], [11]. Data augmentation enhanced dataset diversity, mimicking real-field scenarios and correcting class imbalance typical of grape leaf disease datasets [5]. All the models—Random Forest, MobileNetV2, EfficientNetB0, InceptionV3, and Xception—were trained and tested under similar conditions. The performance was evaluated by accuracy, precision, recall, F1-score, and AUC, allowing for rigorous comparison [3], [4], [10].

II. Literature Review

Recently, lightweight detection models have become prominent for real-time implementation. For example, the YOLOv8-ACCW model features a lean architecture that includes AKConv, Coordinate Attention (CA), and CARAFE modules. It reports an F1 score of 92.4% and a mAP50 of 92.8% while maintaining a model size of less than 2.8MB [7]. Similarly, the GCS-YOLO model combines GhostNet modules

with CBAM attention to achieve a mAP@0.5 of 96.2% with only 1.63 million parameters. This approach performs well under variable lighting conditions and is suitable for edge deployment [8].

Dual-path architectures can effectively extract local and global features, thus making them very credible for plant disease classification. GrapeLeafNet is a good example, which combines Inception-ResNet, CBAM, and a Shuffle-Transformer in an effort to enhance feature representation. Using this architecture, the model attained 99.56% accuracy on the PlantVillage dataset [9]. To address the challenges of real-time deployment on edge devices, Karim et al. employed a tuned MobileNetV3 Large with custom dense layers and Grad-CAM visualizations. On an Nvidia Jetson Nano, this approach achieved over 99.4% accuracy on both training and test sets [12].

The presence of well-structured datasets is important for building trustable models. For instance, the NGLD dataset contains 2,726 Indian vineyard annotated images employed in training models that identify downy mildew and bacterial leaf spot [11].

Additionally, some studies have compared the performance of CNN-based models to transformer models. One such report indicated that, upon proper fine-tuning, a Vision Transformer (Swinv2-Base) reached 100% validity on the PlantVillage and grape variety collection [13]. Addressing model interpretability, the DeepLeaf approach uses fuzzy-optimized CNNs and logistic regression for downsampling, achieving 99.7% accuracy while managing class imbalance and feature redundancy [14]. Research by Mangaoang et al. highlights the effectiveness of models like MobileNetV2 and EfficientNet. Their trials demonstrated that a fine-tuned EfficientNet could achieve 100% accuracy, underscoring its promising role in precision agriculture [15]. Although traditional machine learning techniques do not match the flexibility of deep learning, they are still used for grape leaf classification, offering interpretability and computational efficiency for certain food quality applications [5]. Furthermore, Uttam demonstrated the effectiveness of CNNs like VGG16 and MobileNet for automating disease detection, achieving accuracies up to 97%, which can expedite early diagnosis and enhance vineyard management [6].

III. Methodology

A. Dataset Description

We utilized fully publicly-available PlantVillage grape leaf dataset from Kaggle and one of the augmented versions from more recent research publications [11]. The dataset includes high resolution images and has five categories: plant diseases and healthy samples. They are 'Black rot, Esca (also known as Black measles), Leaf Blight (which is also called Isariopsis leaf spot), and Healthy samples'. The dataset was augmented through multiple transformations to enhance sample diversity, with classes balanced to 1000 images each.

TABLE I: Grape Leaf Disease Classes with Sample Images

Class	Sample Image 1	Sample Image 2
Black rot		
Esca		
Leaf blight		
Healthy		

B. Data Preprocessing

To maintain uniformity and enhance model efficiency, multiple preprocessing operations were carried out:

- **Image Resizing:** whole pictures were croped to a uniform size that is **224 × 224** pixels for maintaining uniform input size.
- **Pixel Scaling:** RGB intensity metrics have been adjusted to limits **[0, 1]**, which improved convergence rates during training.
- **Data Augmentation:** Real-time flips, random rotations, zooming, and contrast changes were applied in real time using the ImageDataGenerator module to enhance dataset diversity and prevent overfitting.
- **Dataset Partitioning:** The dataset was partitioned into three sets, with **70% training**, **15% validation**, and **15% testing**.

C. Architectures

The following six models were implemented and compared:

- **Random Forest (RF):** A classical machine learning baseline using hand-crafted features.
- **MobileNetV2:** A lightweight convolutional neural network (CNN) architecture with inverted residual blocks.
- **EfficientNetB0:** A balanced and scalable CNN architecture, optimized using neural architecture search.
- **InceptionV3:** Leverages multi-scale convolution operations using Google's inception modules.
- **Xception:** Similar to InceptionV3 but uses depth-wise separable convolutions instead of standard convolutions.

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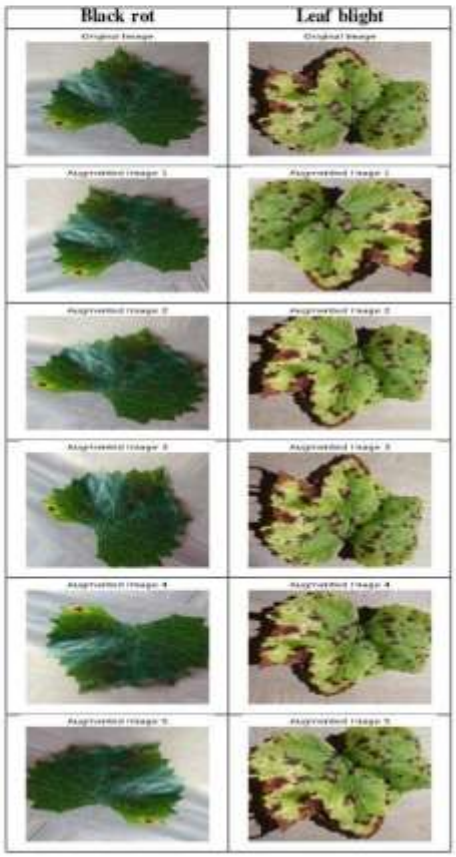
- **FusionNet-GLD (Proposed):** A dual-branch fusion model that combines Xception and InceptionV3 architectures in parallel to enhance feature extraction and classification performance.

TABLE II: Images of Dark rot lesions and Vine leaf infection prior to and following augmentation



D. FusionNet-GLD: Architecture

The proposed FusionNet-GLD model consists of two parallel branches:

- **Xception Branch:** Utilizes depthwise separable convolutions to extract high-level discriminative features.
- **InceptionV3 Branch:** Inception modules are employed to extract features across multiple scales, enabling the model to effectively capture both fine-grained and broader contextual patterns.
- **Fusion Layer:** Feature maps between the dual divisions are combined and then passed through:
  - spatial global averaging layer
  - linear layer with ReLU activation,
  - and predicted class probabilities for multi-class classification.

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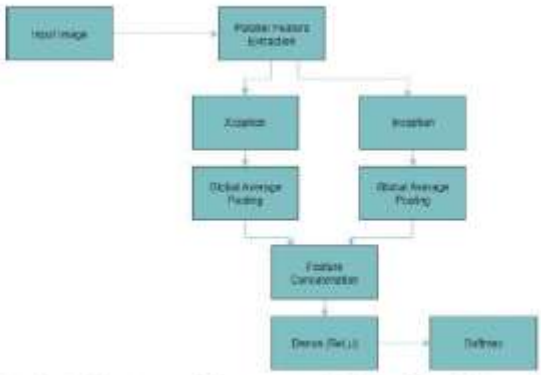

Fig. 1: Architecture of the proposed FusionNet-GLD model combining Xception and InceptionV3 in a dual-branch structure.

The flowchart illustrated in Fig 1 outlines the structure of the proposed framework, **FusionNet-GLD**, which has a dual-branch framework that has both Xception and Inception networks for a parallel feature extraction technique. The dual-branch structure offers an advantage in applying the two unique strengths of each architecture
(1) the depth wise separable convolutions to construct deep and effective representations of the target, as well as
(2) There are several convolutional layers that are utilized to extract both global and local features from images of the diseased leaves. Feature extraction is finished, and then global mean subsampling is used to eliminate redundant attributes and reduce overfitting in every one of the two branches.
The prediction graphs are then concatenated to single vector and passed into the Dense layer with ReLU activation, where the model is able to learn deep and complex representations that use a non- linear approach to capture the features of the data. The final layer of the model contains the SoftMax classifier, which will produce a probabilistic distribution across the target classes of disease, allowing for confident classification. This hybrid feature fusing approach can increase the discriminative power of the model and provide high classification performance of grape leaf disease.

E. Training Configuration

The FusionNet-GLD model was trained using optimized hyperparameters, learning strategies, and regularization techniques to ensure strong convergence and generalization. The training settings are as follows:

- **Optimizer:**An Adam optimizer with gradient step size of 0.0001 was picked because of its adaptive learning rates for each weight and fast convergence. This optimizer com- putes exponentially decaying averages of past gradients and their squares (moving averages), and as a result, provides the advantages of RMSProp and momentum, as shown in Eq. (1).

$$
\begin{aligned}
m_t &= \beta_1 m_{t-1} + (1-\beta_1) g_t, \\
v_t &= \beta_2 v_{t-1} + (1-\beta_2) g_t^2, \\
\hat{m}_t &= \frac{m_t}{1-\beta_1^t}, \\
\hat{v}_t &= \frac{v_t}{1-\beta_2^t}, \\
\theta_{t+1} &= \theta_t - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}
\end{aligned} \tag{1}
$$

- **Loss Function:**The problem tackled multi-class classification, the Categorical Cross-Entropy loss was utilized. This function measures the error between the predicted class probabilities and the truth labels, mathematically formulated as

$$\mathcal{L} = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij} \log(\hat{y}_{ij}) \tag{2}$$

- **Learning iterations:** To mitigate overfitting, model training was limited to a maximum of 50 epochs, with early stopping employed as a regularization strategy.Training was stopped if, after five consecutive epochs, no improvement in validation loss was observed.
- **Batch Size:**A mini-batch size of 32 was utilized to reach an optimal trade-off between computational expense and training stability.
- **Learning Rate Schedule:** To enable stable convergence and prevent the optimizer from becoming trapped in local minima, the ReduceLROnPlateau callback was utilized. This method dynamically reduces the learning rate by a factor of 0.1 whenever the validation loss does not improve over three to five consecutive epochs.
- **Validation Partitioning:** To test the model's generalization capacity during training, 20% of the training set was held aside for validation.
- **Initialization of Weight:** The He Normal Initialization technique, sometimes referred to as Kaiming initialization, was employed to initialize weights as follows:

$$W \sim \mathcal{N}\left(0, \sqrt{\frac{2}{n_{\text{in}}}}\right) \tag{3}$$

- **Model Checkpointing:** To ensure the final assessment was based on the best parameters, the model's top-performing weights, determined by validation accuracy, were stored during training.
- **Data Augmentation and Shuffling:**To prevent learning bias from data order, input data was shuffled prior to each epoch. Additionally, data augmentation processes like random rotation, flipping both row as well as column wise, zooming, and brightness variation were utilized to in- crease model robustness and reduce overfitting.

IV. Results

In order to measure the performance of the developed models, a set of experiments was conducted on the dataset of grape leaf disease. The measurement was based on important performance metrics, i.e., Accuracy, Precision, Recall, F1-Score, and the Area Under the ROC Curve (AUC). Each of these collectively measures the overall classification capability of a model capability to differentiate the good and damaged leaf.

A. Evaluation Metrics

The key classification metrics used in this study are formally represented in the following manner, where TP, TN, FP, and FN denote actual positives, actual negatives, false positives, and false negatives, accordingly:

$$
\begin{aligned}
\text{Accuracy} &= \frac{TP+TN}{TP+TN+FP+FN}, \\
\text{Precision} &= \frac{TP}{TP+FP}, \\
\text{Recall} &= \frac{TP}{TP+FN}, \\
\text{F1 Score} &= 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}, \\
\text{AUC-ROC} &= \int_0^1 \text{TPR}(x)\, d(\text{FPR}(x))
\end{aligned} \tag{4}
$$

B. Comparison of Model Performance

TABLE III: summarizes the performance of all six implemented models on the test set. FusionNet-GLD achieved the highest scores across all metrics, demonstrating superior classification capability.

Model	Accuracy	Precision	Recall	F1 Score	AUC
Random Forest	87.65%	87.01%	86.45%	86.73%	0.89
MobileNetV2	95.82%	95.60%	95.20%	95.40%	0.97
EfficientNetB0	96.88%	96.55%	96.33%	96.44%	0.98
Inception	97.34%	97.10%	96.80%	96.95%	0.98
Xception	98.24%	98.12%	97.94%	98.03%	0.98
FusionNet-GLD	**99.63%**	**99.45%**	**99.42%**	**99.43%**	**0.99**

The superior performance of FusionNet-GLD is attributed to its dual-feature extraction capabilities, effectively leveraging deep and multi-scale features to capture subtle disease patterns.

C. Discussion

Compared to GrapeLeafNet [9], a more complex model integrating transformers and Inception-ResNet which achieved 99.56% accuracy, the proposed simpler FusionNet-GLD model achieves a slightly higher accuracy of 99.63%. Additionally, this classification-based approach differs from YOLOv8 [7], [8], which is geared towards object detection rather than image-level classification.

D. Training and Validation

The proposed method was trained and validated over 10 augmented iterations of the grape leaf dataset. Fig 2 and Fig 3 show a steady increase in accuracy and a decrease in validation loss, indicating good model convergence and generalization.

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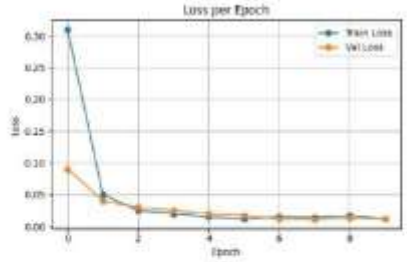

Fig. 2: Training and validation loss per epoch.

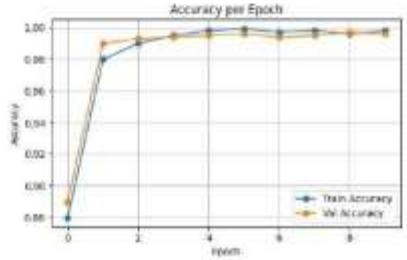

Fig. 3: Training and validation accuracy per epoch.

E. Confusion Matrix Analysis

Fig 4 displays the confusion matrix on the validation set, indicating highly accurate classification across all grape leaf disease categories. Most classes exhibit near-perfect true positive rates with minimal misclassification.

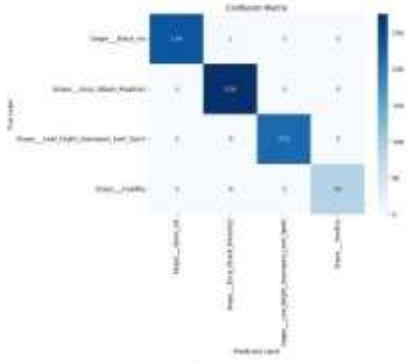

Fig. 4: Confusion matrix of the FusionNet-GLD model on the validation set.

Specifically, the model correctly classified 234 out of 236 samples for **Grape__Black rot** with 2 misclassifications; it perfectly classified all 276 samples of **Grape__Esca (Black Measles)**; and all 215 samples of **Grape__Leaf blight (Isariopsis Leaf Spot)**. Additionally, it achieved flawless classification of all 84 **Grape__Healthy** samples.

This outstanding performance across classes validates the model's efficacy in learning stable, disease-specific features and generalizing well to unseen data, supporting the reliability of FusionNet-GLD for grape leaf disease identification.

F. Model Comparison Visualization

Fig 5 visualizes the accuracy comparison of FusionNet-GLD against baseline models, highlighting its superiority in prediction accuracy.

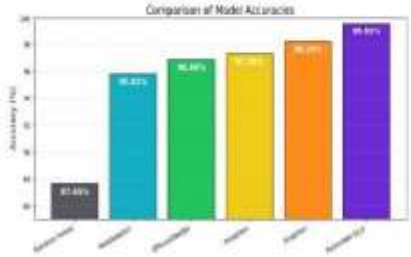

Fig. 5: Model accuracy comparison across different architectures.

G. Comparison with Existing Works

The below table looks at various previous detection Grapevine disorder. It would appear proposed FusionNet-GLD model using both architectures of Xception and, Inception is superior regarding accuracy. Hence, your proposed dual-backbone fusion method is effective in classification work for agricultural applications. The performance improvement is due to the complementary advantages of the Xception and Inception architectures where the Xception architecture is good at capturing depth wise spatial features and the Inception architecture is able to recognize patterns that exist across multiple scales.

In addition, with the improved classification performance, the model is likely to have a significant reduction in false positives and false negatives when identifying disease in real-world applications.

TABLE IV: Performance comparison between FusionNet-GLD and other models.

S.No	Source	Methodology	Accuracy
1	Uttam, A. K. [6]	CNN with preprocessing	96.42%
2	Karthik, R. et al. [9]	Inception-ResNet + Shuffle Transformer	99.56%
3	Khirade & Patil [3]	Basic CNN with image processing	92.50%
4	Sonar & Wankhade [5]	ML Classifiers (SVM, RF, KNN)	92.60%
5	Proposed Work	Xception + Inception (Fusion CNN)	**99.63%**

V. Conclusion

In this research study, the structural model employed is a double-backbone deep learning model called FusionNet-GLD, which combines Xception and InceptionV3 architectures to

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accurately classify grapevine leaf diseases. The model's performance was validated by comparison with existing models, demonstrating superior effectiveness.

This study contributes significantly to smart agriculture by providing a useful tool for early disease detection, enabling farmers to take timely action to minimize crop damage.

A. Future Scope

Potential Extensions could prioritize deploying classifier in physical world on smartphones or edge computing systems to assist farmers directly in the field. Integration with Internet of Things (IoT) systems, drones, or satellite technology could facilitate vineyard monitoring at larger scales.

Further research could explore using multimodal data, including images of grapevines combined with soil condition information, to enhance diagnostic accuracy. Employing transfer learning or self-supervised learning techniques may also enable adapting the model for disease detection in other crops or varying environmental conditions.

Additionally, lightweight model compression and optimization methods such as pruning or quantization could be investigated to reduce computational costs, making the model suitable for deployment on low-resource devices and real-time applications in remote areas with limited connectivity.

By building upon the current model and incorporating these approaches, FusionNet-GLD could evolve into a comprehensive decision-support system for grapevine diseases, constituting a robust and scalable AI solution for crop health management. This advancement would represent a significant step toward food security, reducing reliance on manual disease inspection, and promoting AI-driven sustainable agriculture in the future.

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