WOOD-TYPE CLASSIFICATION USING DEEP LEARNING APPROACH

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Wood-type Classification Using Deep Learning Approach", submitted by Mazharul Hoque and Rashedul Islam Pavel to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Shah Md Tanvir Siddiquee, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This research investigates the efficacy of various deep learning models for wood type classification, employing a dataset comprising 2011 images across five distinct wood classes. Six state-of-the-art architectures, including ResNet-50, DenseNet121, MobileNetV2, VGG16, VGG19, and Inception-V3, were implemented and evaluated. Training and model accuracy were assessed to determine each model's performance. Results reveal that ResNet-50 achieved the highest accuracy, reaching 98%, closely followed by DenseNet121 and MobileNetV2, both achieving 97%. VGG16 and Inception-V3 attained accuracies of 94% and 92%, respectively, while VGG19 achieved 92%. These findings underscore the potential of deep learning approaches in accurately classifying wood types, with ResNet-50 demonstrating superior performance among the models tested. This study contributes valuable insights into utilizing deep learning methodologies for wood type classification, offering practical implications for industries reliant on wood classification for various applications.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Wood, as an integral component of construction, furniture manufacturing, and various industrial applications, plays a pivotal role in shaping the socioeconomic landscapes of both Bangladesh and the world. Accurately classifying wood types is crucial for sustainable forestry practices, ensuring responsible resource management, and meeting the diverse needs of industries that rely on wood-based materials.

In Bangladesh, a country endowed with rich forest biodiversity, the identification and classification of wood types hold special significance. The forestry sector, a key contributor to the national economy, faces challenges related to illegal logging, resource depletion, and the need for efficient inventory management. A robust wood-type classification system, aided by modern technologies, can not only streamline these challenges but also contribute to the conservation of the country's diverse forest ecosystems.

Globally, the demand for wood and wood-based products is escalating, driven by population growth, urbanization, and increased construction activities. This surge in demand underscores the necessity for accurate and timely wood-type classification methods. Traditional methods, reliant on manual inspection and subjective expertise, are often time-consuming, expensive, and prone to errors. The emergence of machine learning techniques offers a transformative solution by automating the classification process, enhancing efficiency, and providing an objective means of wood identification.

The research aims to bridge the gap between traditional wood identification methods and the evolving needs of the forestry and wood industry sectors. By harnessing the power of machine learning algorithms, the study seeks to develop a reliable and efficient system for classifying wood types, contributing not only to forestry management in Bangladesh but also aligning with global efforts toward sustainable and responsible resource utilization.

In subsequent sections, we will delve into the methodology adopted in this research, the diverse sources of data utilized, and the potential broader impacts of implementing machine learning in wood-type classification. The ultimate goal is to offer a comprehensive understanding of how this research contributes to sustainable resource management, technological advancements in the forestry sector, and the global trajectory of wood-based industries.

Deep Convolutional Neural Networks

Deep Convolutional Neural Networks (DCNNs) are a sophisticated class of deep learning algorithms that excel in image recognition, object detection, and visual data processing. Unlike traditional neural networks, DCNNs are designed to effectively handle the spatial structure of images through a series of specialized layers. At the core of DCNNs are convolutional layers that utilize filters or kernels to scan across the input image, creating feature maps that detect specific patterns such as edges and textures. These layers often include operations like stride, which determines the movement of filters, and padding, which helps preserve the spatial dimensions of the output.

After the convolutional layers, non-linear activation functions like Rectified Linear Unit (ReLU) are applied to introduce non-linearity, enabling the network to learn intricate patterns. Pooling layers, such as max pooling, further process the feature maps by reducing their spatial dimensions and computational load while improving robustness to slight translations in the input data. Following multiple iterations of convolutional and pooling layers, the network typically includes fully connected layers that perform high-level reasoning based on the extracted features. These layers resemble neural networks, where every neuron connects to every in the preceding layer.

To mitigate overfitting, DCNNs frequently utilize dropout, a method that randomly deactivates a portion of input units during training. Training DCNNs involves backpropagation, where gradients of the loss function are calculated and utilized to adjust the network's weights, typically optimized using algorithms such as Stochastic Gradient Descent (SGD) or Adam. This architecture, encompassing input, convolutional, activation, pooling, fully connected, and output layers, enables DCNNs to autonomously learn hierarchical features from raw image data.

ResNet50: ResNet50 is a significant deep convolutional neural network architecture developed by Microsoft researchers to address the challenge of training very deep networks. It uses residual connections, or skip connections, to mitigate the vanishing gradient problem, allowing gradients to flow more effectively through layers and enabling the training of deeper models. ResNet50 features a bottleneck design in its residual blocks, comprising 1x1 and 3x3 convolution layers that reduce computational complexity while maintaining depth. Batch normalization after each convolutional layer stabilizes training by normalizing inputs.

Starting with an initial convolutional and pooling layer, ResNet50 employs a series of residual blocks that increase filter numbers progressively. It includes a global average pooling layer followed by a fully connected layer with 1000 neurons for final classification tasks like ImageNet. ResNet50's ability to train very deep networks without degradation in performance has made it a leading architecture in achieving state-of-the-art results across various computer vision benchmarks.

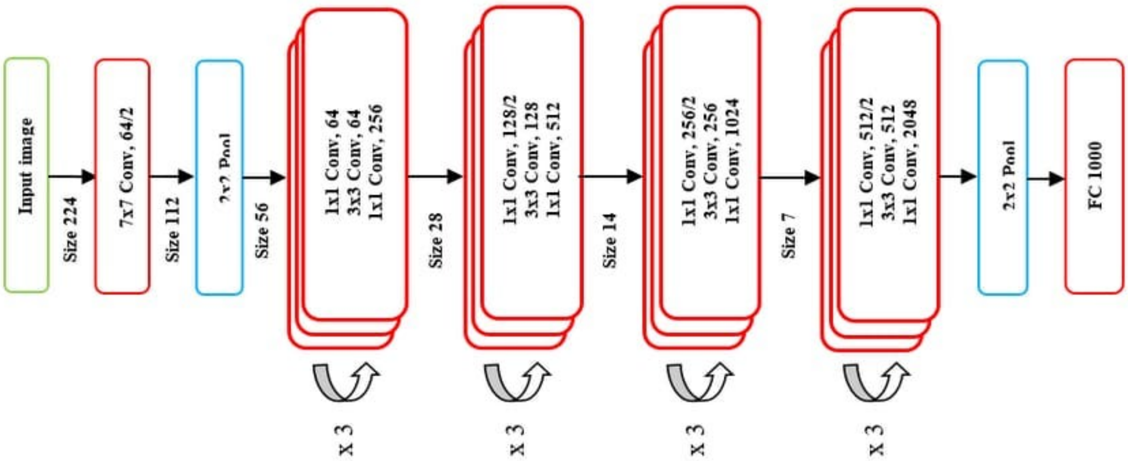

Figure 1.1: Architecture of ResNet50 (Source Google)

VGG16: VGG16 is a deep convolutional neural network architecture created by the Visual Geometry Group at the University of Oxford, featuring 16 layers, including 13 convolutional layers and 3 fully connected layers. It utilizes 3x3 convolutional filters extensively across the network to effectively capture detailed image features. Max-pooling layers follow each set of convolutional layers, reducing the spatial dimensions of feature maps. VGG16 is widely adopted for tasks such as image classification, feature extraction, and transfer learning, serving as a foundational model in more advanced applications like object detection and segmentation due to its straightforward design, strong performance, and adaptability in computer vision.

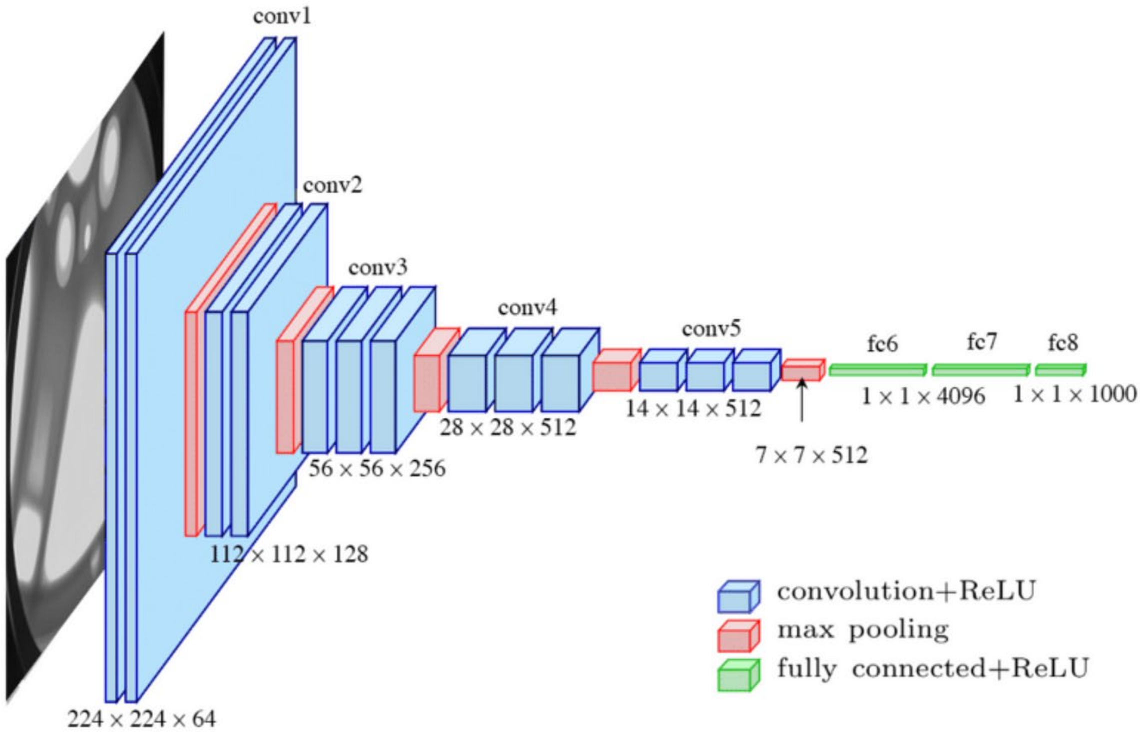

Figure 1.2: Architecture of VGG16 (Source Google)

VGG19: VGG19 is a well-known deep convolutional neural network architecture developed by the Visual Geometry Group at the University of Oxford. It consists of 19 layers, featuring 16 convolutional layers and 3 fully connected layers. Throughout the network, it employs small 3x3 convolutional filters consistently, which enables it to effectively capture intricate image patterns. After each set of convolutional layers, VGG19 includes max-pooling layers to progressively reduce the spatial dimensions of the feature maps, followed by three fully connected layers. VGG19 is widely used for tasks such as image classification, feature extraction, and transfer learning, achieving high performance on standard datasets thanks to its deep architecture and straightforward design.

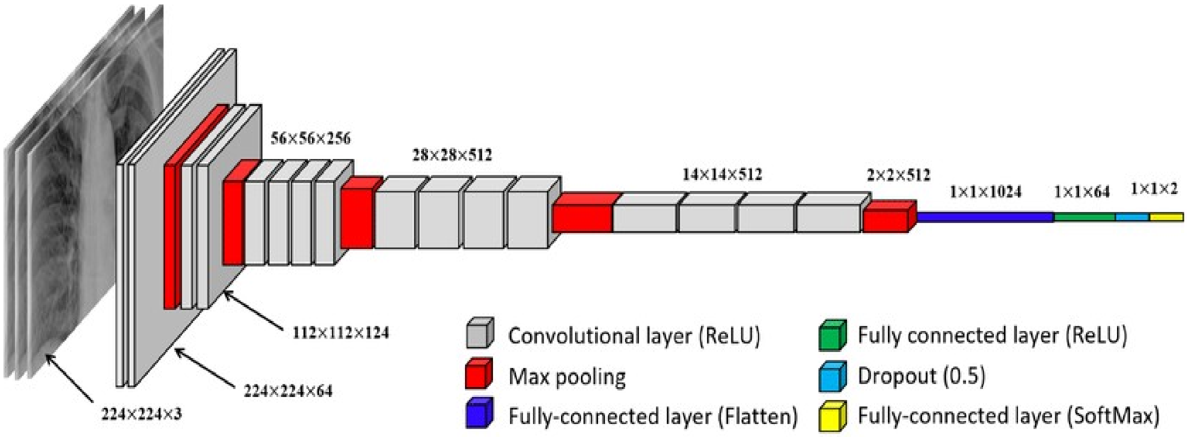

Figure 1.3: Architecture of VGG19 (Source Google)

MobileNetV2: MobileNetV2 is a state-of-the-art deep convolutional neural network designed by Google for efficient performance on mobile and embedded devices. It improves upon the original MobileNet by introducing inverted residual structures and linear bottlenecks, which enhance computational efficiency and model accuracy. The architecture employs depthwise separable convolutions to significantly reduce parameters and computational cost. With ReLU6 activation and efficient layer stacking, MobileNetV2 provides a balance between model size and performance. It is widely used in mobile and embedded vision applications, image classification, object detection, and segmentation, offering an excellent trade-off between accuracy and efficiency for real-time, on-device tasks.

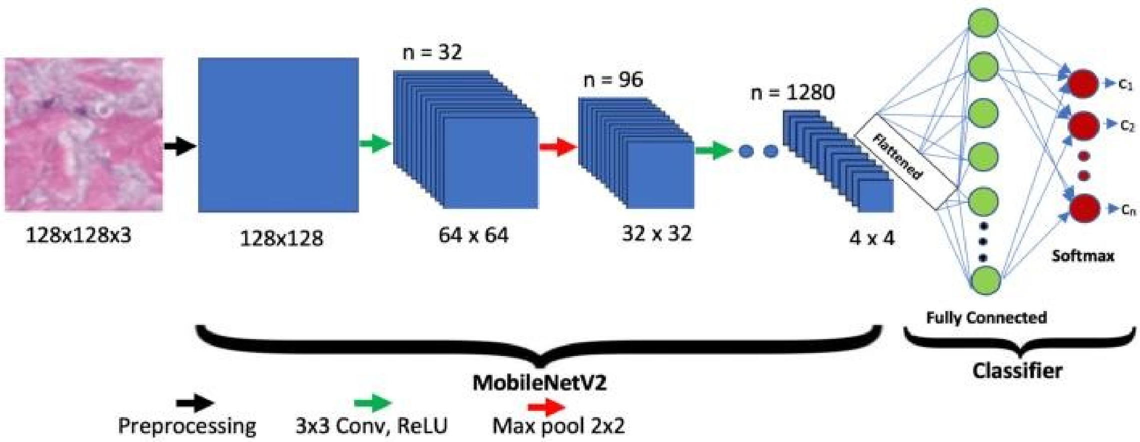

Figure 1.4: Architecture of MobileNetV2 (Source Google)

DenseNet121: DenseNet121 is a powerful deep convolutional neural network architecture designed for enhanced feature reuse and efficient gradient flow. Comprising 121 layers, it utilizes dense connectivity, where each layer receives input from all preceding layers, addressing the vanishing gradient problem and promoting feature reuse. The network includes bottleneck layers and transition layers to reduce computational complexity and control model size. Known for its parameter efficiency, DenseNet121 excels in applications like image classification, medical imaging, and transfer learning, offering high performance with fewer parameters compared to traditional architectures. This makes it ideal for tasks requiring robust and efficient deep learning models.

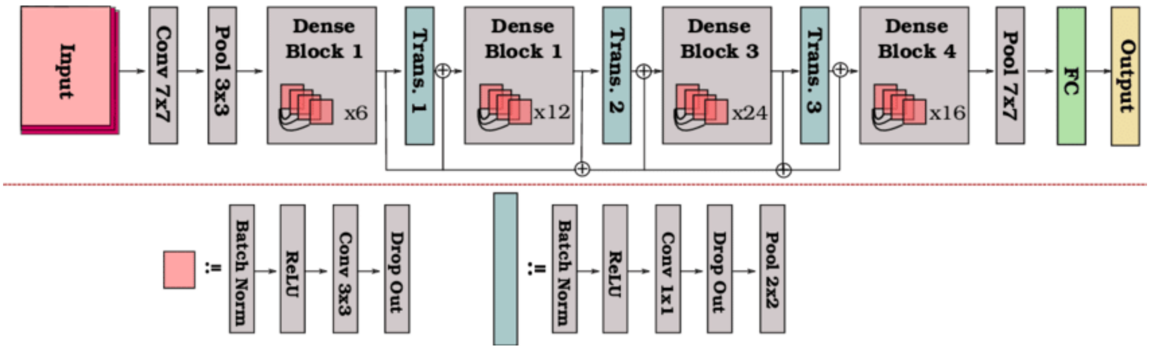

Figure 1.5: Architecture of DenseNet121 (Source Google)

Inception-V3: Inception-V3 is a sophisticated deep convolutional neural network developed by Google, known for its high performance and computational efficiency in image classification and other computer vision tasks. It features inception modules, which perform convolutions of various sizes in parallel, capturing features at different scales. The architecture uses factorized convolutions to reduce computational complexity and incorporates aggressive regularization techniques such as dropout, batch normalization, and auxiliary classifiers to improve generalization and training speed. With its robust design and efficient feature learning, Inception-V3 excels in applications like image classification, object detection, and transfer learning, making it a versatile and powerful choice for many computer vision tasks.

1.2 Motivation

The motivation for this project arises from the necessity to modernize and optimize wood-type classification processes. Traditional methods of wood-type classification are often manual, labor-intensive, and subject to human error. With the growing demand for wood-based products across various industries, such as forestry, woodworking, and furniture manufacturing, there is a critical need for automated systems that can accurately and efficiently classify wood types based on their visual attributes. By leveraging deep learning techniques, which have demonstrated significant advancements in image classification tasks, this research seeks to develop a robust and automated solution to streamline wood-type classification processes, enhance accuracy, and improve productivity in wood-related industries.

1.3 Rational of the Study

Wood plays a crucial role in various industries, including furniture manufacturing, construction, and interior design. The accurate classification of wood types is essential for ensuring quality control, identifying suitable applications, and preserving natural resources. Traditional methods of wood classification often rely on visual inspection by experts, which can be subjective, time-consuming, and prone to human error.

The advent of deep learning techniques has revolutionized image recognition tasks by enabling machines to learn intricate patterns and features from large datasets. Applying deep learning to wood-type classification offers several advantages over traditional methods. Firstly, it has the potential to automate the classification process, reducing the reliance on human expertise and expediting the decision-making process. Secondly, deep learning models can analyze wood samples with greater accuracy and consistency, minimizing misclassifications and ensuring reliable results.

Furthermore, as the demand for sustainable practices grows, accurately identifying wood types can aid in the preservation of endangered species and the promotion of responsible forestry practices. By leveraging deep learning algorithms, researchers can develop robust classification models capable of distinguishing between different wood species based on subtle visual cues such as grain patterns, color variations, and texture characteristics.

Despite the promising potential of deep learning in wood-type classification, there remains a gap in the literature regarding its application to this specific domain. This study seeks to address this gap by investigating the feasibility and effectiveness of using deep learning approaches for wood-type classification. By analyzing a diverse dataset of wood samples and training state-of-the-art deep learning models, this research aims to develop a reliable classification system capable of accurately identifying various wood types with high precision and recall rates.

Moreover, by comparing the performance of deep learning models with traditional classification methods, such as manual inspection or statistical analysis, this study aims to demonstrate the superiority of deep learning techniques in terms of efficiency, accuracy, and scalability. The findings of this research have the potential to significantly impact industries reliant on wood materials by streamlining the classification process, reducing costs, and facilitating more informed decision-making.

In summary, this study addresses an important gap in the field of wood science and technology by exploring the application of deep learning approaches to wood-type classification. By leveraging the power of machine learning algorithms, this research aims to enhance the efficiency, accuracy, and sustainability of wood classification processes, ultimately benefiting industries, consumers, and environmental conservation efforts alike.

1.4 Research Questions

The project strives to answer numerous crucial concerns within the domain of "Wood-type classification using deep learning approach" These serves a path way to reach the goal of creating an advance AI mechanism and approaches for improved wood classification. The questions are:

- **How does the utilization of deep learning methodologies improve the accuracy and reliability of wood-type classification compared to traditional methods?**

This question aims to investigate the specific advantages that deep learning techniques offer over old methods in the context of wood-type identification. It seeks to understand how deep learning algorithms can better handle the complexities of wood sample analysis, leading to improved accuracy and reliability in classification tasks.

- **What are the optimal architectures and configurations of deep neural networks for effectively categorizing different wood types based on visual characteristics such as grain patterns, texture, and color variations?**

This question delves into the design aspects of deep neural networks tailored for wood-type classification. It explores the most suitable network architectures, layer configurations, and hyperparameters that can effectively capture the diverse visual features present in different wood types, thereby informing the development of optimized classification models.

- **How do various preprocessing technique, like image enhancement and feature extraction, impact the performance of deep learning models in classifying wood types accurately?**

This question examines the preprocessing steps necessary to prepare wood image data for deep learning-based classification. It investigates how techniques like image enhancement, noise reduction, and feature extraction influence the performance and robustness of deep learning models, providing insights into best practices for data preprocessing in wood-type classification tasks.

- **How do environmental factors, such as lighting conditions and wood sample variations, influence the robustness and adaptability of deep learning-based wood-type classification systems in real-world settings?**

This question considers the real-world challenges faced by deep learning-based wood-type classification systems, such as variations in lighting conditions and wood sample characteristics. It examines how environmental factors impact the robustness and adaptability of classification models, providing insights into potential strategies for improving system performance in diverse settings.

- **To what extent can deep learning-based wood-type classification systems contribute to sustainable forestry practices, species identification, and conservation efforts by providing accurate and efficient means of wood species identification?**

This question explores the broader societal implications of deep learning-based wood-type classification systems. It investigates how accurate and efficient wood species identification can contribute to sustainable forestry practices, biodiversity conservation, and species identification efforts, highlighting the potential positive impacts of advanced technology on environmental conservation and resource management initiatives.

These research questions aim to guide the investigation into the application of deep learning techniques for wood-type classification, exploring various aspects such as model performance, optimization strategies, data considerations, and practical implications for industries and environmental conservation efforts.

1.5 Expected Output

This study's expected output includes both practical and theoretical parts, with a focus in expanding technological knowledge. Official expectations include:

- **Optimized Deep Learning Models:**

The research is expected to yield optimized deep learning architectures and configurations specifically tailored for wood-type classification tasks. These models are anticipated to demonstrate superior performance in accurately categorizing different wood types based on visual characteristics such as grain patterns, texture, and color variations.

- **Enhanced Accuracy and Efficiency:**

The utilization of deep learning methodologies is expected to significantly enhance the accuracy and efficiency of wood-type classification compared to traditional methods. By leveraging advanced techniques such as transfer learning and multimodal data integration, the research aims to improve the reliability and robustness of classification systems.

- **Insights into Model Interpretability:**

The analysis of learned features and representations within deep learning models is expected to provide some insights in the discriminative characteristics of many wood types. By elucidating the underlying mechanisms driving classification decisions, the research aims to enhance our understanding of wood morphology and facilitate more interpretable model outputs.

- **Practical Implementation Guidelines:**

The research is expected to identify and address potential challenges and limitations associated with deploying deep learning-based wood-type classification systems in industrial settings. Practical implementation guidelines and strategies for overcoming deployment obstacles are anticipated to be provided, facilitating the integration of advanced technology into real-world applications.

- **Contributions to Sustainable Forestry Practices:**

By providing accurate and efficient means of wood species identification, the research is expected to contribute to sustainable forestry practices, species identification, and conservation efforts. The development of reliable classification systems has the potential to enhance biodiversity conservation, promote responsible forestry management, and support environmental sustainability initiatives.

1.6 Project Management and Finance

1.6.1 Project management is the proper organization of resources, timeframes, and activities to guarantee that the research is completed successfully. Here are the steps we are taking:

- Define Objectives and Scope:
  A. Gather stakeholders to define project goals, success metrics, and scope.
  B. Finalize the problem statement and identify key requirements.
- Team Formation:
  A. Assemble the project team and assign roles and responsibilities.
  B. Develop a detailed project plan outlining tasks, dependencies, and timelines.
- Data Collection and Preprocessing:
  A. Identify relevant datasets for training and testing.
  B. Clean and preprocess the data.
  C. Split data into testing, training and validation sets.
- Model Selection and Development:

A. Research and select appropriate deep learning architectures and algorithms.

B. Develop and implement baseline models.

- Validation and Evaluation:

A. Validate model performance using the validation dataset.

B. Fine-tune models based on validation results.

C. Evaluate final models using the testing dataset and success metrics.

- Documentation and Version Control:

A. Document the entire process, including data sources, preprocessing steps, and model architectures.

B. Establish version control for code, documentation, and datasets using Git or similar tools.

- Ethical Considerations and Compliance:

A. Continuously assess ethical implications related to data privacy, bias, and fairness.

B. Ensure compliance with relevant regulations and guidelines, making adjustments as necessary.

By following these steps and principles, we are managing the project from inception to deployment while ensuring its success and impact. This is our timeline

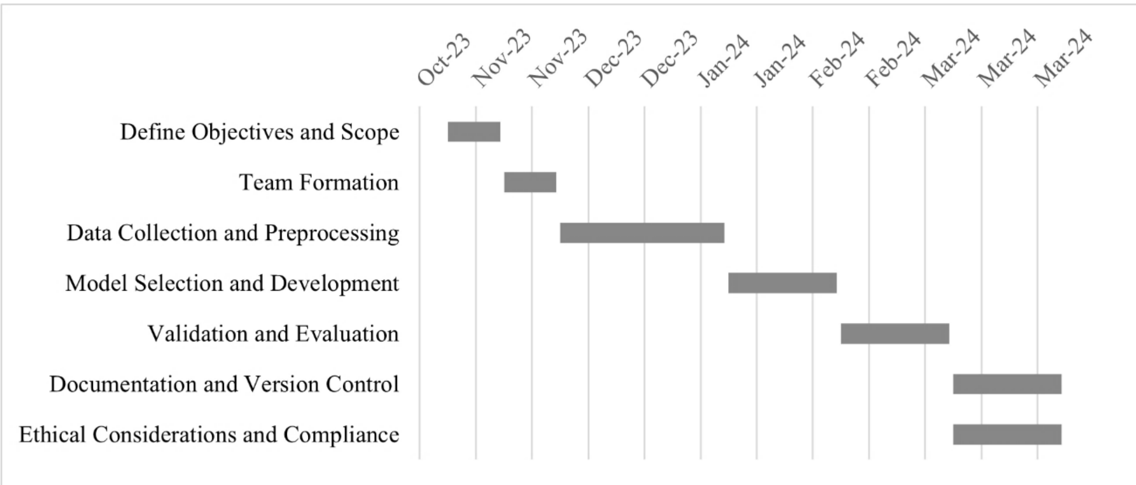

Figure 1.6: Project Timeline

1.6 Financial Analysis: The financial analysis involves estimating the budgetary requirements for various aspects of the research project. This includes expenses related to data acquisition, hardware, and software infrastructure for deep learning computations, personnel costs, and any other relevant expenditures.

TABLE 1.1: Estimated Cost

SN	Components	Estimated Cost (BDT)
01	Hardware and Infrastructure	40,000
02	Software and Tools	1,000
03	Data Acquisition and Preprocessing	1,000
04	Documentation and Report Writing	500
05	Training and Education	1,000
06	Miscellaneous (e.g., licenses, tools)	500
07	Contingency (10% of total)	1,000
Estimated Total Cost		**45,000**

1.7 Report layout

This report serves as a proper documentation of this project. Reader can clearly understand the progression, implications and finding of this project. Every part of this report has a specific purpose to understand the documents comprehensiveness.

Chapter 1: Introduction

In this opening part, the focus is on introducing the research topic of wood-type classification using deep learning methods. It provides a background on the significance of wood classification in various industries such as forestry, furniture manufacturing, and construction. The chapter outlines the objectives of the study, the relevance of deep learning in image classification tasks, and the need for an accurate and efficient wood-type classification system.

Chapter 2: Background

The background chapter delves into existing literature and research related to wood classification, image processing techniques, and deep learning methodologies. It examines previous studies on wood identification, traditional classification methods, and advancements in algorithms for image identification methods. This section sets the background for the present research and identifies areas of knowledge where the study intends to fill gaps.

Chapter 3: Research Methodology

The part named research methodology gives a comprehensive view of research methodology, detailing the approach adopted for wood type classification using deep learning methods. It covers topics including dataset acquisition, preprocessing procedures, selection of model architectures, training techniques, and evaluation criteria. Ethical concerns related to data handling and possible biases are also discussed, alongside limitations inherent in the chosen methodologies.

Chapter 4: Experimental Results

The experimental results chapter presents the outcomes of applying deep learning models to classify wood types based on image data. It includes analyses of model performance, accuracy rates, confusion matrices, and visualizations of classification results. Comparative evaluations of different deep learning architectures and training strategies are provided to assess their effectiveness in wood-type classification.

Chapter 5: Impact on Society

This section examines how this research's findings impact industries dependent on wood materials. It discusses how accurate wood-type classification systems can improve quality control processes, enhance product differentiation, and optimize resource management in forestry and manufacturing sectors. Consideration is given to potential economic and environmental benefits arising from improved wood classification methods.

Chapter 6: Summary, Conclusion, and Future Directions

The final part consolidates key findings, presents research conclusions, and provides future studies and practical applications. It explores the possibilities for additional breakthroughs in deep learning approaches for wood categorization and offers future research directions.

This structured report layout provides a systematic approach to presenting research on wood-type classification using deep learning methods, guiding readers through the research process and its implications for industry and academia.

CHAPTER 2
BACKGROUND

2.1 Preliminaries/Terminologies

To provide a thorough knowledge of the core part and methodology supporting the study on "Wood-Type Classification Using Deep Learning Approach," it is necessary to lay the groundwork through preliminary work and terminological clarification. This work focuses on deep learning, a cornerstone of artificial intelligence, which allows the model to extract complex details from wood samples for precise classification.

Deep Convolutional Neural Networks, also known as Deep CNN which are very effective and efficient in image processing, are used to detect minute differences and distinctive properties found in various wood species. Classification is the process of categorizing wood samples into separate types based on their visual properties, whereas deep learning approaches enable the automated extraction of discriminative features required for accurate classification.

Throughout this study, these terminologies are employed in tandem to investigate the potential of deep learning approaches in wood type classification. Ensuring readers have a clear understanding of these foundational aspects is essential for engaging with the intricacies of the study and comprehending the sophisticated strategies employed in wood classification tasks.

2.2 Related Works

This study delves into the application of deep learning, specifically focusing on variations of ResNet18, for the classification of lumber images. [1] Through independent testing on four diverse datasets manually annotated by experts—categorized into lumber defects, wood textures, and lumbers—the proposed approach demonstrates robust performance. The datasets, comprising 3697, 1693, 751, and 994 images, respectively, are divided into an 80% training and a 20% testing. Notably, the classification accuracy achieved is outstanding, with results of 98.16%, 93.32%, 96.64%, and 99.50% for datasets 1 through 4. This research underscores the efficacy of deep learning strategies, particularly employing ResNet18, in significantly enhancing accuracy in lumber classification tasks.

In the paper titled "Amazon Wood Species Classification: A Comparison Between Deep Learning and Pre-designed Features," [2] the study focuses on evaluating the performance of four deep learning models—InceptionV3, ResNet, DenseNet, and SqueezeNet—in classifying wood species. The dataset comprises 440 images, representing 11 distinct wood species found in the Amazon region. Notably, the InceptionV3 CNN model exhibits the lowest accuracy at 93.59%, while DenseNet achieves the highest accuracy at 98.13%. This comparative analysis provides valuable insights into the effectiveness of different deep learning architectures for Amazon wood species classification, offering a foundation for selecting optimal models in similar ecological contexts.

This paper examines three classifiers k-nearest-neighbor (k-NN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM), specifically SDD MobileNetV2 in the context of wood tomographic image categorization. [3] The dataset, which contains 5000 tomographic pictures, is subjected to data augmentation to ensure robust model training and testing results. Notably, the SVM (RBF) - LBP classifier obtains an accuracy of 86.66%, k-NN (k=50) - LBP achieves 78.66% accuracy, and SDD MobileNetV2 achieves the best with accuracy of the models at 89.00%. This comparative investigation demonstrates the efficacy of CNN, namely SDD MobileNetV2, in obtaining superior accuracy for wood tomographic image classification, showing its potential for use in the field.

This paper uses a Convolutional Neural Network (CNN) with MobileNet architecture to identify wood types. [4] The collection contains 10,000 photos, with 1,000 images representing each of the ten different wood varieties under examination. The CNN model achieves outstanding results, with a training accuracy of 98% and a testing accuracy of 93.3 percent. This work highlights the effectiveness of combining CNN with MobileNet architecture for precise and dependable wood type classification, demonstrating its potential for practical applications in the wood industry and forestry.

The focus of this research study is on the detection of wood defects using a Deep Convolutional Neural Network (DCNN). [5] The dataset, which includes 600 pine samples with wood flaws such as knots, cracks, and mildew, has been separated for training, validation, and testing. The DCNN model outperforms expectations, with an overall accuracy of 99.13%. This work demonstrates the efficacy of using sophisticated deep learning algorithms, notably DCNN, for precise and reliable wood fault detection. The excellent accuracy gained demonstrates the potential of such models for improving quality control systems in the wood industry.

This study presents a wood species categorization effort in which VGG19 emerged as the best model, reaching a remarkable 93.63% accuracy on the test set. [6] While VGG16 and Inception V3 were also evaluated, VGG19 showed slightly better generalization capabilities. The dataset, which included 4800 photos representing 25 wood species, was split 60% for training and 20% for validation and testing. The study stresses VGG19's ability to reliably recognize wood species based on photographs, emphasizing its potential role in enhancing wood categorization approaches.

In this research on lumber image classification, [7] three models were trained on a dataset of 52,716 image patches covering 11 hardwood species. ResNet-50 emerged as the best-performing model, with classification accuracy of 95.19% for patch and 98.15% for lumber. MobileNet-V2 displayed considerable efficiency and competitive accuracy (93.52% patch, 97.12% lumber), whereas DenseNet fared similarly (93.84% patch, 97.55% timber). Although ensemble models exhibited slight improvement in patch accuracy, ResNet-50 remained the dominant model for lumber classification, demonstrating its usefulness in distinguishing hardwood species in lumber photos.

This research presents a Convolutional Neural Network (CNN) based on Single Shot Multibox Recognition (SSR) for classifying rubber wood boards into six groups using color and texture features. [8] While particular accuracy values are not available, the system is known for its excellent accuracy levels, with SSR technology contributing to improved performance when compared to competing systems. The dataset, which includes 9986 training images, 2000 for validation, and 17501 for testing, provides as a strong evaluation framework for determining the model's ability to appropriately categorize rubber wood boards. This work demonstrates the potential of SSR-based CNNs for accurate and efficient wood board categorization.

This study compares three wood species classification models—DenseNet121, MobileNetV2, and ResNet50. DenseNet121 obtained an impressive 100% accuracy, albeit with a longer prediction time because to its higher size. [9] MobileNetV2, with an accuracy of 99.6%, stands out as a speedier option, especially for low-power devices.

The study emphasizes the importance of magnification levels, selecting 20x as the best level for all models. Notably, DenseNet121 used a total of 7,589,451 parameters, but MobileNetV2 used much fewer parameters (2,947,915), demonstrating a trade-off between model accuracy and computing economy.

This research examines three machine learning models—Support Vector Machine (SVM), Naïve Bayes (NB), and Artificial Neural Network (ANN)—for identifying thermally changed wood. [10] Using a limited dataset of 84 observations per feature, SVM excelled in simplicity, obtaining 96% accuracy with a single color feature (L*). However, NB outperformed it with 99% accuracy by utilizing several color characteristics (Lab*), demonstrating the trade-off between model complexity and efficiency. Although ANN's performance was not explicitly revealed, this study highlights that, while SVM excels at simplicity, Naïve Bayes achieves superior accuracy with richer data.

The study of solid wood flooring for interior decoration has highlighted the need for efficient color sorting to match individual customer preferences. [11] This study takes a contemporary approach, combining machine vision and deep learning techniques, including ensemble learning methods. Using a color CCD camera, the study collected 108 samples of solid wood floors in three different color grades, eventually expanding the dataset to 432 images. Notably, when deep learning models such as VGG16 and DenseNet121 were compared to the traditional XGBoost algorithm, XGBoost outperformed them all, achieving an impressive 97.22% accuracy rate. This innovative online color classification system provides a promising solution for streamlining manual sorting processes and increasing overall production efficiency in the solid wood flooring industry.

This study describes an automatic recognition method for Brazilian flora species based on macroscopic wood pictures, which uses Local Binary Patterns (LBP) and a Support Vector Machine (SVM) classifier. [12] With a remarkable F1-score of 97.67%, the system exhibits strong species recognition abilities, especially for endangered species. Classifier fusion with majority voting improves the F1-score by 0.33%. Using 1901 macroscopic wood pictures from 46 Brazilian species, the study demonstrates the potential of computer vision in conjunction with traditional approaches to reduce identification mistakes when detecting Brazilian flora species. Furthermore, the paper investigates various LBP descriptor variants and adds Principal Component Analysis (PCA) for dimensionality reduction, adding to the methodological richness of the suggested approach.

This research investigates a unique technique to timber species identification using metabolome analysis and chemical fingerprints. [13] The study used heartwood specimens from 175 individuals, representing ten valuable timber species in the Meliaceae family. Direct analysis in real time (DART) ionization is used to generate metabolome profiles, which are then analyzed using time-of-flight mass spectrometry. The random forest machine learning technique is used to do automated analysis and species classification. The study rigorously investigates variability in classification accuracy by testing various data pre-processing settings, such as mass tolerance for binning and relative abundance cut-off criteria. Through systematic research, the optimal classification accuracy of 82.2% is attained with a specific combination of binning and threshold settings, utilizing 47 variables. This innovative protocol offers a promising avenue for automated timber species identification through metabolome profiling.

This paper discusses the difficulties in identifying pine nematode disease, emphasizing the limitations of current methods in accurately locating the disease within a single pine. [14] Previous studies have used spectral and geometric information for identification, but they frequently encounter misclassification issues. The paper introduces the SCANet model, which uses convolutional neural networks (CNNs) and includes a spatial information retention module (SIRM) and a context information module (CIM). This combination aims to improve spatial information retention, broaden the receptive field, and provide detailed context for accurate pine nematode disease identification. The model is trained and tested on the Huangshan-2 image dataset, achieving an overall accuracy of 79%, with precision and recall values of around 0.86 and 0.91, respectively. SCANet represents a significant advancement in leveraging deep learning for accurate and location-specific identification of pine nematode disease.

This study explores the application of machine vision for identifying wood species in field conditions, focusing on analyzing digital photographs. [15] It highlights the use of intelligent systems like support vector machines (SVMs) and convolutional neural networks (CNNs) for this purpose. The research adopts an interdisciplinary approach, integrating knowledge from wood anatomy, digital image analysis, and pattern recognition to develop effective machine vision systems. The study utilizes a dataset comprising 2000 macroscopic photos from 21 wood species collected in the field using smartphones and hand-polished samples. The resulting machine vision system achieves a high accuracy of 97.7% in identifying wood species based on macroscopic images, marking a significant advancement in practical wood identification applications.

This study presents a novel approach to automate the recognition of wood species through multidimensional texture analysis. [16] Wood images are transformed into concatenated histograms using higher-order linear dynamical systems constructed from vertical and horizontal image patches. Classification is performed using an SVM classifier. The method is thoroughly evaluated using the "WOOD-AUTH" dataset, which includes around 4200 images representing twelve common wood species found in Greece. Results from experiments indicate that the proposed technique outperforms existing methods, achieving a notable classification accuracy of 91.47% for wood cross sections. This research represents a significant advancement in accurately and efficiently identifying different wood species.

This study introduces an innovative method for automated tree species identification using scanned images of wood cores, leveraging a convolutional neural network (CNN) enhanced with residual connections. [17] The proposed model outperforms current benchmarks with 9% higher accuracy in wood patch classification and 3% higher accuracy in wood core classification. It employs a residual convolutional encoder network arranged in a sliding window configuration for precise tree species identification. The research undertakes a thorough analysis using a dataset of 312 wood core images spanning 14 European tree species, achieving impressive recognition rates of about 93% for wood image patches and 98.7% for wood core images. This research marks a significant advancement in the precise and efficient identification of wood species.

This study presents the Improved-Basic Gray Level Aura Matrix (I-BGLAM), a novel approach for extracting features aimed at classifying wood species using image analysis. [18] I-BGLAM emphasizes the characterization of gray level attributes in wood images, ensuring consistency despite rotational variations and producing concise feature descriptors. The system utilizes a neural network classifier trained through backpropagation to automatically categorize 52 distinct wood species. Compared to conventional methods like the Gray Level Co-occurrence Matrix (GLCM) and standard BGLAM feature extractors, I-BGLAM exhibits superior performance in recognizing wood species. Experimental results across various gray levels indicate significant accuracy improvement, achieving a high accuracy rate of 97.01% compared to previous methods. This research represents a notable advancement in enhancing the accuracy of wood species classification.

This paper investigates the physio mechanical properties of wood from domestic Chinese species, focusing on the complex structure-property relationships. [19] Correlation analysis reveals a strong relationship between mechanical properties and wood density, with coefficients exceeding 0.8 except for impact toughness and cleavage strength. Shrinkage properties have lower correlations with densities. Primary component analysis (PCA) identifies two principal components (PC1 and PC2) that help classify 283 domestic wood species into four groups based on their physio mechanical properties. The study not only adds to our understanding of wood properties, but it also proposes a rational grading system for a variety of properties, which will benefit the field of wood classification in China.

This study tackles the difficulties in large-scale forest monitoring caused by human processing of terrestrial laser scanning (TLS) data, which inhibits the technology's scalability. [20] Given the shortage of labeled and segmented TLS data, the work focuses on the use of deep learning and data augmentation approaches to automate tree species identification straight from laser scanning data. By avoiding costly pre-processing and substantial manual labeling, the work highlights the potential of deep learning to speed individual species identification, thereby minimizing the constraints associated with manual data labeling requirements in TLS-based forest monitoring. This study provides a big step in improving the efficiency and scalability of forest monitoring with new technology.

This study explores the application of hyperspectral reflectance images of stem bark for classifying wood species. [21] It examines the effectiveness of reflectance spectra and texture characteristics in identifying species by analyzing differences in bark textures using a hyperspectral camera setup and gray-level co-occurrence matrices. Employing average spectral features with a linear discriminant analysis classifier achieved substantial classification accuracy ranging from 92% to 96.5%. Integrating spectral and texture features further improved accuracy to a range of 93% to 97.5%. Additionally, utilizing a convolutional neural network yielded a high accuracy of 94%. The dataset, comprising ten species with twenty samples each, demonstrates the efficacy of hyperspectral imaging in accurately classifying tree species.

2.3 Comparative Analysis and Summary

The comparison among existing works in wood and lumber classification reveals a diverse landscape of methodologies and deep learning architectures employed across various studies. Deep learning models such as ResNet, InceptionV3, DenseNet, SqueezeNet, VGG19, MobileNet, and DCNN have been extensively utilized, each demonstrating varying levels of accuracy depending on the specific classification task and dataset characteristics. Notably, ResNet18, ResNet50, and ResNet-50 emerge as effective models across multiple studies, achieving high accuracy rates in tasks ranging from wood species classification to lumber defect detection. The size and diversity of datasets vary significantly, with some studies focusing on specific wood types or defects while others encompass broader categories like Amazon wood species or domestic Chinese wood species. Larger datasets generally enable more robust model training and evaluation, leading to higher accuracy rates in classification tasks. Furthermore, beyond deep learning, other techniques such as machine vision, metabolome analysis, chemical fingerprints, and hyperspectral imaging are explored, addressing challenges like large-scale forest monitoring and disease identification. Trade-offs between model accuracy, computational complexity, and resource efficiency are highlighted, emphasizing the importance of selecting models and techniques that balance these factors effectively. Ongoing research continues to explore innovative solutions to improve accuracy, efficiency, and automation in wood identification and classification processes, promising advancements in forestry, wood industry applications, and quality control systems.

In summary, the reviewed papers showed a broad spectrum of research papers focused on wood classification and identification through diverse methodologies. One study employs deep learning, specifically ResNet18, achieving outstanding accuracy in lumber image classification, with results ranging from 93.32% to 95.50% across different datasets. Another research compares InceptionV3, ResNet, DenseNet, and

SqueezeNet for Amazon wood species classification, with DenseNet leading at 95.13% accuracy. A third paper explores wood tomographic image categorization, highlighting SDD MobileNetV2 as the most accurate model with an 89.00% accuracy. Further investigations delve into wood-type classification using MobileNet architecture, achieving a testing accuracy of 93.3%.

Studies also tackle specific challenges, such as wood defect detection using DCNNs, which outperforms expectations with an overall accuracy of 99.13%. A wood species categorization effort reveals VGG19 as the best model, reaching a remarkable accuracy of 93.63%. In lumber image classification, ResNet-50 emerges as the best-performing model with accuracy rates of 95.19% for patches and 98.15% for lumber. A study utilizing SSR-based CNNs for rubber wood board classification attains excellent accuracy levels

In conclusion, considering the diverse applications and dataset characteristics, DenseNet121, MobileNetV2, ResNet18, ResNet-50, and VGG19 emerge as some of the best-performing models, showcasing their efficacy in various wood classification tasks. The selection of the most suitable model should be context-dependent, considering factors such as computational efficiency, model size, and application requirements. Overall, the literature review underscores the continuous evolution and improvement of wood classification techniques, providing a valuable foundation for future research and practical implementations in furniture and related industries.

TABLE 2.1: Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Juola, J. et al. [21]	Linear Discriminant Analysis. 3D CNN	3D CNN = 94%
2.	Junior, A.A.P. et al. [3]	SVM, CNN, MobileNet	MobileNetV2= 89%
3.	de Geus, A.R. et al. [2]	InceptionV3, ResNet, DenseNet, and SqueezeNet	DenseNet = 95.13%
4.	Zhuang, Z. et al. [11]	VGG16, DenseNet121, XGBoost	XGBoost = 97.22
5.	Qin, J. et al. [14]	SCANet	SCANet = 79%
6.	Sharma, H. et al. [6]	ResNet-50, DenseNet, MobileNet-V2	ResNet-50 = 95.19%

2.4 Scope of the Problem

The extent of the issue examined in this study centers on "Wood-Type Classification Using Deep Learning Approach," pertains to the domain of material science and forestry, specifically within the context of wood identification and classification. Wood type classification is a crucial task with applications ranging from forestry management to the woodworking industry, where accurate wood species identification is essential for quality control and product development.

The study dives into the difficulties involved with traditional wood identification methods, which frequently rely on personal inspection and experience, resulting in subjective and inconsistent classification findings. Furthermore, the scope includes the intricacy of discriminating between seemingly identical wood kinds, where small differences in grain patterns, color, and texture offer substantial challenges for proper categorization.

To tackle these challenges, the study explores the use of deep learning, specifically deep Convolutional Neural Networks (CNNs), to automate the classification of wood types. CNNs are adept at extracting complex features, creating them suitable for distinguishing subtle visual differences found in wood samples.

Furthermore, the research encompasses developing and assessing deep learning models trained on extensive datasets containing labeled wood images. This approach aims to establish robust and scalable solutions for classifying wood types effectively. The study seeks to provide insights into how deep learning methods can enhance the automation of wood identification tasks, potentially improving efficiency and accuracy across various sectors reliant on accurate wood classification.

Overall, the scope of the research includes addressing challenges associated with categorizing wood types, exploring the potential advancements enabled by deep learning techniques, and creating automated classification systems. By addressing these aspects, the study aims to stimulate innovation in wood identification methods and foster advancements in industries dependent on precise wood classification.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Research Subject:

This study "Wood-Type Classification Using Deep Learning Approach" revolves around advancing wood identification and classification through deep learning methodologies. The primary focus is on automating and enhancing the process of categorizing wood samples into distinct types based on visual attributes. Wood, as a natural resource with diverse species and characteristics, plays as the main point for the study.

The study examines the limits of standard wood identification methods, with the goal of overcoming them through the use of deep learning techniques, namely deep Convolutional Neural Networks (CNNs). The study dives into the complexity of identifying between seemingly identical wood kinds, where small differences in grain patterns, color, and feel present substantial challenges to precise classification.

Moreover, the relative analysis section of the study examines the variations and collaborative effects among many deep learning architectures and algorithms concerning the classification of wood types. The study attempts to determine the most effective ways for automating wood identification tasks and improve classification accuracy by comparing the performance of several models.

This research focuses on convergence of deep learning, material science, and forestry management, with the explicit goal of improving wood identification procedures through creative applications of deep learning technologies.

Instrumentation:

For the experiments in this study, the research utilized Python programming language and TensorFlow, a leading deep learning library. The Keras library was employed for model implementation, facilitating the creation and training of deep learning architectures.

The computational infrastructure included Google Colab, providing access to GPU resources for accelerated processing. This cloud-based framework offered substantial computing power, enabling the training of complex neural network models on large datasets of annotated wood images.

A variety of deep learning algorithms were used in the study, including algorithms such as DenseNet121, MobileNetV2, ResNet-50, VGG16, Inception-V3 and VGG19. Each model was chosen to represent different architectural characteristics, allowing for a comprehensive comparative analysis of performance.

Overall, the research leveraged a new deep learning techniques and computational resources to develop and evaluate automated wood-type classification systems, with the aim of advancing knowledge in the field of forestry management and supporting sustainable resource utilization practices.

3.2 Data Collection Procedure

A. Datasets

For the dataset for the wood-type classification project, we manually collected a total of 2,011 images from local wood shops and sawmills. The dataset is organized into five distinct image groups based on the wood type. Each wood type has a subdirectory within the dataset. The five wood types included in this dataset are: Acacia, *Albizia Lebbeck*, Jackfruit, Mahogany, and Teak. Each of these groups contains images of the respective wood types, providing a diverse and comprehensive collection for training, testing, and validating the deep learning models. This dataset structure ensures that the classification model can learn and generalize well across different wood types.

A. Acacia

B. Jack Fruit

C. *Albizia Lebbeck*

D. Mahogany

E. Teak

Figure 3.1: Some Raw Images of Datasets

Each wood type subdirectory includes images captured in various conditions and from different angles to ensure robustness in model training. The images were taken using high-resolution cameras to maintain the quality and detail necessary for accurate classification. Given the manual collection process, the dataset reflects real-world variations in wood texture, grain patterns, and natural imperfections, enhancing the model ability to classify some new and unseen images.

TABLE 3.1: Images Used in the Train, Test and Validation Sets.

	Acacia	Jack Fruit	*Albizia Lebbeck*	Mahogany	Teak
Raw Dataset	420	419	234	473	465

B. Process of Experiments

Deep neural networks typically require a large amount of data. So the main step of this framework is to collect as much data from wood panels to effective training process. Augmentation process is some time used to enlarge the amount of data in the data set. This overcome the limitation of small dataset. Here is an outline of the planned experimental procedure:

Image Acquisition:

For the wood-type classification project, the data was collected manually from local wood shop. Each image was carefully selected to ensure quality and relevance of wood samples. All images used in the dataset were in color to maintain visual clarity and consistency across the dataset.

Image Augmentation:

Image augmentation played a crucial role in enhancing the dataset for the wood-type classification project. By applying various augmentation techniques, we were able to create reliable images from the existing dataset, thereby preserving the original labels and significantly expanding the dataset. This augmentation process is essential for improving the model's generalization capability, making it more robust to unknown inputs.

In this stage, a variety of augmentation techniques were employed to achieve the desired training data objectives. These techniques included adjustments to brightness, contrast, saturation, scaling, cropping, flipping, and rotation. Specifically, the data augmentation process involved random horizontal flips, shearing, and adjustments to luminosity.

By incorporating this wide range of transformations, we were able to create a heterogeneous set of images, which helps the model learn to recognize wood types under various conditions and orientations. This approach not only improves the training process but also enhances the model's ability to accurately classify wood types in real-world scenarios.

Figure 3.2: Augmented Image

Training:

In this phase, a CNN learner model was developed. The data was utilized to train and assess the classification accuracy of several models, namely DenseNet121, MobileNetV2, ResNet-50, VGG16, Inception-V3, and VGG19. Early stopping callbacks were implemented to halt training if models did not show improvement for a specified number of epochs, set by a patience parameter. The learning rate was fixed at 0.0001, with $\beta1 = 0.9$ and $\beta2 = 0.999$ as the beta values for the Adam optimizer, which integrates momentum-SGD and RMSProp methods. Standard deviation served as the model performance metric due to the dataset's balanced nature. For all CNN architectures, categorical cross-entropy was chosen as the loss function, given the task's multi-class classification nature. Hyperparameters included 20 epochs, a batch size of 17, dropout rate of 0.3, and the Adam optimizer for adjusting model weights. Prior to processing, all images were resized to meet each architecture's required default input size.

Classification:

Neural networks (Densenet-121, MobileNetv2, Inception-V3, Resnet-50, VGG16, VGG19) was used to identify wood species automatically. This neural network was chosen because of its shown success in various applications.

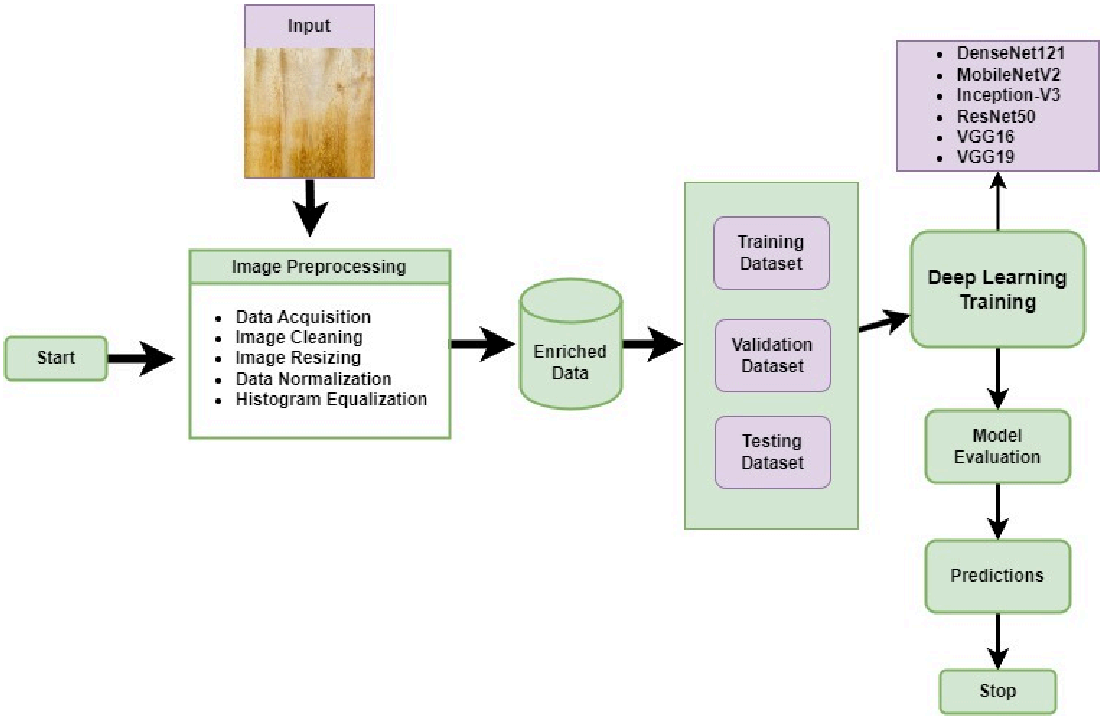

Figure 3.3: Process of Experiments.

Figure 3.3 illustrates a comprehensive process for training deep learning models using image data. It starts with image input, followed by a series of image preprocessing steps including data acquisition, cleaning, resizing, normalization, and histogram equalization to enhance the data quality. The enriched data is then split into training, validation, and testing datasets. Several deep learning models such as DenseNet121, MobileNetV2, Inception-V3, ResNet50, VGG16, and VGG19 are trained using the training dataset. The model's performance is evaluated using the validation and testing datasets. Finally, the trained models are used to make predictions, concluding the process.

Results:

The outcomes of the tests are given using the architectures of the individual networks.

3.3 Statistical Analysis

Statistical analysis in the study titled "Wood-Type Classification Using Deep Learning Approach" is pivotal for effectively interpreting experimental data. Robust statistical methods are employed to quantitatively evaluate and compare the performance of different deep learning models used for classifying various types of wood. Descriptive statistics such as mean and standard deviation summarize central tendencies and data variability. Additionally, inferential statistics like hypothesis testing and confidence intervals validate observed differences and similarities among model architectures.

This comprehensive statistical analysis provides a quantitative basis for assessing the efficacy of DenseNet-121, MobileNetV2, ResNet50, and VGG16 in wood-type classification. It not only substantiates the reliability of experimental results but also facilitates the generalizability of findings across diverse wood images. Furthermore, statistical insights aid in interpreting the comparative study by identifying trends, patterns, and potential correlations within the data. By employing rigorous statistical methods, the research ensures an unbiased and precise evaluation of different deep learning approaches, thereby enhancing the credibility and validity of the study's conclusions. Ultimately, statistical analysis serves as a crucial tool for deriving meaningful insights from empirical data and advancing our understanding of the effectiveness of deep learning algorithms in wood-type classification.

3.4 Proposed Methodology

CNN-based models are assessed using several classification metrics, which include accuracy (AC), F1-score, precision, confusion matrix (CM), and recall. The evaluation considers metrics such as true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN).

Accuracy:

Accuracy refers to the measure of correctly predicted outcomes by a model compared to the total number of predictions made. It is a fundamental evaluation metric that indicates the model's overall correctness in classifying data, crucial for assessing its performance across various tasks.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)$$

Precision:

Precision refers to the proportion of true positive among all instances predicted as positive by the model. It quantifies the model's ability to avoid false positives, making it a critical metric in tasks where minimizing false alarms is important, such as medical diagnostics or anomaly detection. Precision is mathematically defined as the following equation:

$$Precision=TP/(TP+FP)$$

Recall:

In deep learning, recall (also known as sensitivity or true positive rate) measures the proportion of true positive instances that were correctly identified by the model out of all actual positive instances in the dataset. It gauges the model's ability to capture all relevant instances, making it crucial in scenarios where identifying as many positive cases as possible is vital, such as disease detection or fraud identification. The formula of F1-score is:

Recall=TP/(TP+FN)

F-1 Score:

In deep learning, recall is a performance metric that measures the ability of a model to correctly identify all relevant instances of a class, typically denoted as the ratio of true positives to the sum of true positives and false negatives. It indicates how well the model avoids missing positive instances, making it crucial for tasks where identifying as many positives as possible is paramount, such as in medical diagnostics or anomaly detection. A high recall value suggests that the model can effectively minimize false negatives, thereby enhancing its ability to comprehensively detect instances of interest. The formula is:

F-1 Score = 2*(Precision * Recall) / (Precision + Recall)

In deep learning, specificity is a metric that quantifies the ability of a model to correctly identify negative instances within a dataset. It measures the proportion of true negative predictions out of all actual negative instances, providing insight into the model's ability to avoid false positives. High specificity indicates that the model effectively discriminates between negative and positive classes, crucial for applications where minimizing false alarms is essential, such as in medical diagnostics or quality control. The equation is:

Specificity =TN∕((TN+FP))

If a model becomes overly dependent on the training dataset, its generalization capability diminishes. Confusion matrix can be used to evaluate the model performance. This is a specific table. This table highlight the value of true positive, true negative, false positive and false negative.

Deep Convolutional Neural Network:

A deep convolutional neural network (CNN) is a specialized type of neural network designed to analyze visual data by leveraging hierarchical layers of learned filters, known as convolutional layers. These networks are effective in capturing spatial hierarchies and patterns in images, enabling tasks such as image classification, object detection, and segmentation. Deep CNNs typically include multiple convolutional layers followed by pooling layers to progressively learn and extract complex features from raw pixel data.

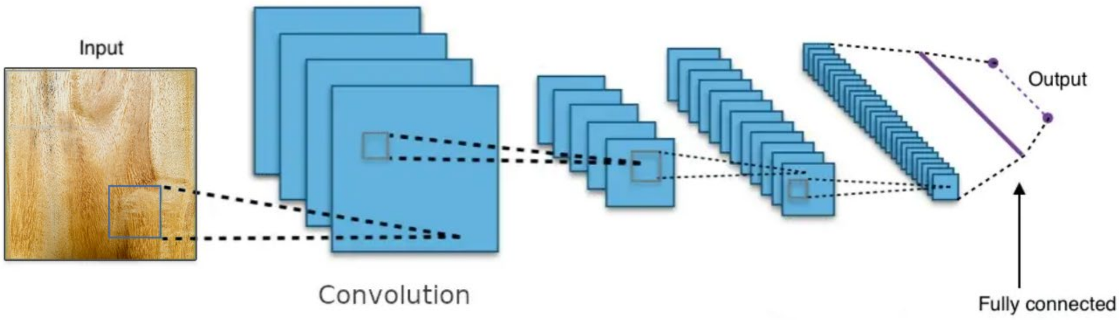

Figure 3.4: working Flow with Deep Neural Network

3.5 Implementation Requirements

The research on "Wood-Type Classification Using Deep Learning Approach" involves certain hardware, software, and procedural factors to assure its success. These needs encompass computational resources, software tools, data collecting, model training, and ethical considerations.

Hardware Requirements:

3.5.1 **High Configuration Computer:** Access to computing resources that has significant processing power and ram available. High processing power in necessary to handle the complex algorithms.

3.5.2 **Graphics Processing Unit (GPU):** GPU decreases the training time significantly. So, GPU is necessary to cutting down the training time of a Deep learning model in image processing.

Software Requirements:

3.5.3 **Deep learning frameworks:** The CNN models are developed, trained, and evaluated using popular deep learning frameworks like TensorFlow or PyTorch.

3.5.4 **Programming language:** Python is a widely used and flexible environment for developing deep learning models and data analysis.

3.5.5 **Libraries:** Incorporating frameworks like OpenCV for the preprocessing and augmentation of wood images.

Data Collection:

3.5.6 **Representative dataset:** A comprehensive gathering of photographs featuring diverse types of wood was collected to ensure the strength and applicability of the models.

3.5.7 **Annotated dataset:** Image was separated in different folder according to their name. This data then used for training and validation.

Model Training and Evaluation:

3.5.8 **Metrics for evaluation:** Some evaluation method was used to evaluate the models like precision, recall, accuracy, F1 score. This helps to perfectly evaluate the model performance.

Ethical Considerations:

3.5.9 **Patient privacy and data security:** legal regulation and also ethical standards are used to protect security of data.

3.5.10 **Informed consent:** If necessary, obtain informed consent from organizations providing wood images.

Documentation and Reproducibility:

3.5.11 **Code documentation:** Every step of this project is well documented to enhance productivity and future work.

3.5.12 **Version control:** Version control systems was used to monitor codebase modification.

These are some main criteria to complete this project systematically. These ensure the outcome and advancements of the project.

CHAPTER 4
EXPERIMENTAL RESULT

4.1 Experimental Setup

The study on "Wood-Type Classification Using Deep Learning Approaches" is meticulously designed with a robust combination of image data, computer hardware, computer software. To run the complex image processing models, we need high performing computer hardware. Graphics processing units significantly reduce the training time. No computer hardware can run with out proper software or driver. Deep learning Framework are also needed to process the image data set. Framework like TensoFlow are used in Python environment to implement of classification models.

The dataset, which includes a variety of photos of different wood types, goes through stringent preprocessing stages. These stages involve standardization and normalization to ensure that the inputs for model training and evaluation are consistent and of high quality. The experimental system uses pre-trained deep Convolutional Neural Network (CNN) architectures, which are fine-tuned to improve their performance specifically for wood-type classification tasks. Ethical considerations are integral to the experimental setup, ensuring adherence to guidelines regarding data privacy and security. Although the dataset does not involve sensitive personal data, ethical standards related to data handling and usage are rigorously maintained.

Throughout the experimentation process, comprehensive documentation is maintained. This includes detailed records of code implementation, model architecture, hyperparameters, and experimental results. Such documentation is crucial for ensuring transparency, reproducibility, and facilitating future research collaborations in the field of wood-type classification using deep learning techniques.

By carefully configuring and documenting the experimental setup, this research target to systematically identify and validate the work of deep learning models in accurately classifying different types of wood, thereby contributing valuable insights and advancements to the field.

4.2 Experimental Results & Analysis

This section compares six CNN networks: DenseNet121, MobileNetV2, ResNet-50, VGG16, Inception-V3, and VGG19. Initially, the classification performance of each network is examined, followed by a review of their overall metrics, including data collection, descriptions, potential reasons for observed outcomes, and areas for improvement.

TABLE 4.1: Accuracy for Classification of Individual Models

Architecture	Training Accuracy	Model Accuracy
ResNet-50	97.31%	98%
DenseNet121	92.27%	97%
MobileNetV2	91.57%	97%
VGG16	91.64%	94%
VGG19	89.79%	92%
Inception-V3	86.89%	92%

Table 4.1 presents a comprehensive comparison of various pre-trained deep Convolutional Neural Network (CNN) architectures, highlighting their respective accuracies in wood classification. According to the findings, ResNet-50 emerges as the most effective model, achieving the highest accuracy rate of 98%. This underscores its superior ability to accurately classify different types of wood. In comparison, DenseNet121 and MobileNetV2 exhibit slightly lower accuracies at 97%, indicating a marginal decrease in performance relative to ResNet-50.

This modest fluctuation in accuracy highlights the important of choosing the right model for wood type classification, since it has a direct influence on the classification process's precision and dependability. The extensive accuracy metrics offered in Table 4.2.1 are an excellent resource for assessing these models' relative strengths and limitations. This work adds to the ongoing conversation on refining deep learning approaches for wood categorization by providing insights into enhancing model performance and accuracy in this specific domain.

TABLE 4.2: Precision, Recall, F1-Score, and Support (n) for Deep CNN networks

ResNet-50				
	Precision	**Recall**	**F1-Score**	**Support**
Acacia	0.99	0.96	0.98	84
Albizia Lebbeck	0.98	0.93	0.99	46
Jack Fruit	0.98	0.96	0.98	83
Mahogany	0.99	1.00	0.99	94
Teak	0.97	0.99	0.98	93
Accuracy			0.98	400
Macro Avg	0.98	0.98	0.98	400
Weighted Avg	0.98	0.98	0.98	400
DenseNet121				
	Precision	**Recall**	**F1-Score**	**Support**
Acacia	0.93	0.98	0.98	84
Albizia Lebbeck	0.96	0.93	0.95	46
Jack Fruit	0.99	0.96	0.98	83
Mahogany	0.99	0.99	0.99	94
Teak	0.97	0.96	0.96	93
Accuracy			0.97	400
Macro Avg	0.97	0.96	0.97	400
Weighted Avg	0.97	0.97	0.97	400
MobileNetV2				
	Precision	**Recall**	**F1-Score**	**Support**
Acacia	1.00	0.98	0.99	84
Albizia Lebbeck	0.88	0.98	0.93	46

Jack Fruit	0.98	0.96	0.97	83
Mahogany	1.00	0.97	0.98	94
Teak	0.98	0.99	0.98	93
Accuracy			0.97	400
Macro Avg	0.97	0.98	0.97	400
Weighted Avg	0.98	0.97	0.98	400
VGG16				
	Precision	**Recall**	**F1-Score**	**Support**
Acacia	0.91	0.98	0.94	84
Albizia Lebbeck	0.95	0.83	0.88	46
Jack Fruit	0.94	0.89	0.91	83
Mahogany	0.94	0.98	0.96	94
Teak	0.99	0.99	0.99	93
Accuracy			0.94	400
Macro Avg	0.95	0.93	0.94	400
Weighted Avg	0.95	0.94	0.94	400
VGG19				
	Precision	**Recall**	**F1-Score**	**Support**
Acacia	0.90	0.93	0.91	84
Albizia Lebbeck	0.88	0.83	0.85	46
Jack Fruit	0.92	0.80	0.85	83
Mahogany	0.92	1.00	0.96	94
Teak	0.95	0.98	0.96	93
Accuracy			0.92	400
Macro Avg	0.91	0.91	0.91	400

Weighted Avg	0.92	0.92	0.92	400
Inception-V3				
	Precision	**Recall**	**F1-Score**	**Support**
Acacia	0.93	0.96	0.95	84
Albizia Lebbeck	0.89	0.74	0.81	46
Jack Fruit	0.91	0.84	0.88	83
Mahogany	0.89	0.99	0.93	94
Teak	0.97	0.97	0.97	93
Accuracy			0.92	400
Macro Avg	0.92	0.90	0.91	400
Weighted Avg	0.92	0.92	0.92	400

Table 4.2 shows every expect of the models training and accuracies for six different algorithms. It helps to better understand about the training of a model. It also shows accuracy, recall, F1-score, and support metrics for every species, for DenseNet121, MobileNetV2, ResNet-50, VGG16, Inception-V3, and VGG19 models. Particularly noteworthy are the strong performances of ResNet-50, which consistently demonstrates high accuracy values on the test dataset. This model consistently shows good accuracy, recall, and F1-score across multiple classes, showing its effectiveness in accurate wood classification.

In conclusion, the metrics in Table 4.2 provide valuable information into the weaknesses and strengths of each model. This analysis guides further refinement and optimization of deep learning methodologies for wood type classification, ultimately enhancing the precision and reliability of the classification process.

Training and Validation Accuracy and loss of Deep CNN Networks:

The figure shows training accuracy, validation accuracy and training loss, validation loss for every model. Here x axis represents number of epochs, y axis shows the loss and accuracy. The models do not suffer from overfitting because training data and validation data is different.

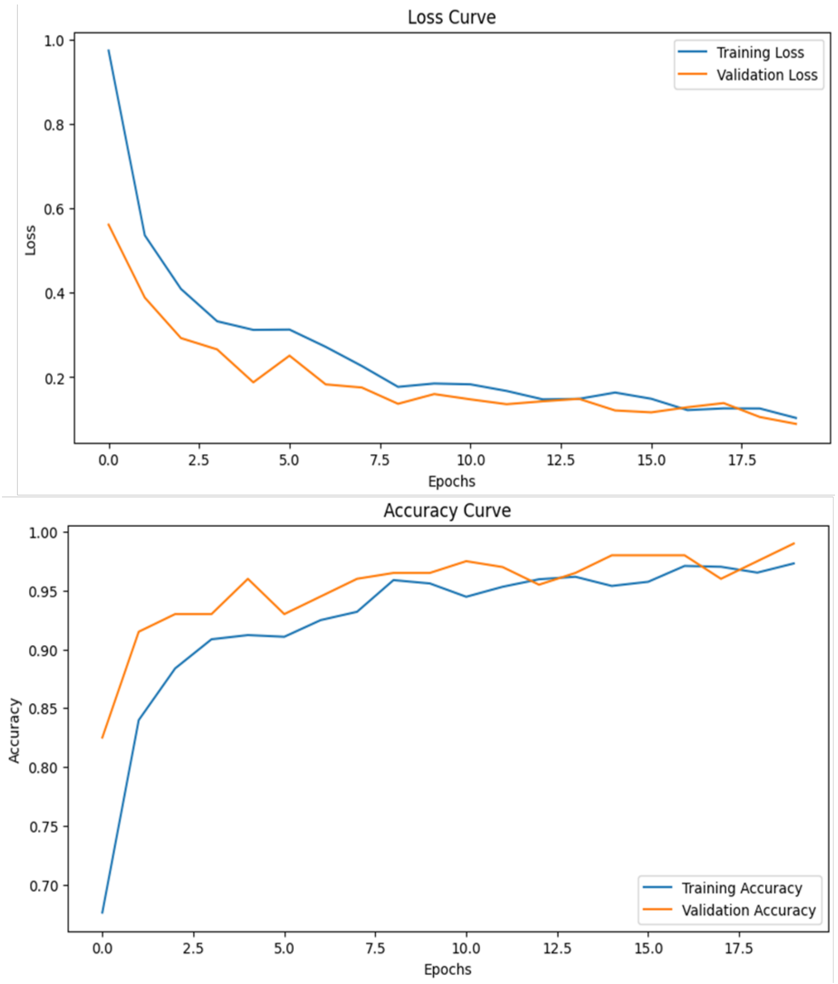

Figure 4.1: Training and validation loss and accuracy over the epochs (ResNet-50)

Figure 4.1 illustrates the training and validation loss and accuracy for a ResNet-50 model over 20 epochs. Both the training and validation loss curves exhibit a steep decline in the initial epochs, followed by a more gradual decrease and stabilization. The training accuracy curve rapidly increases in the early epochs and then levels off, while the validation accuracy curve rises steadily until epoch 7 and then fluctuates slightly. This suggests that the model's performance on the training data is consistently improving.

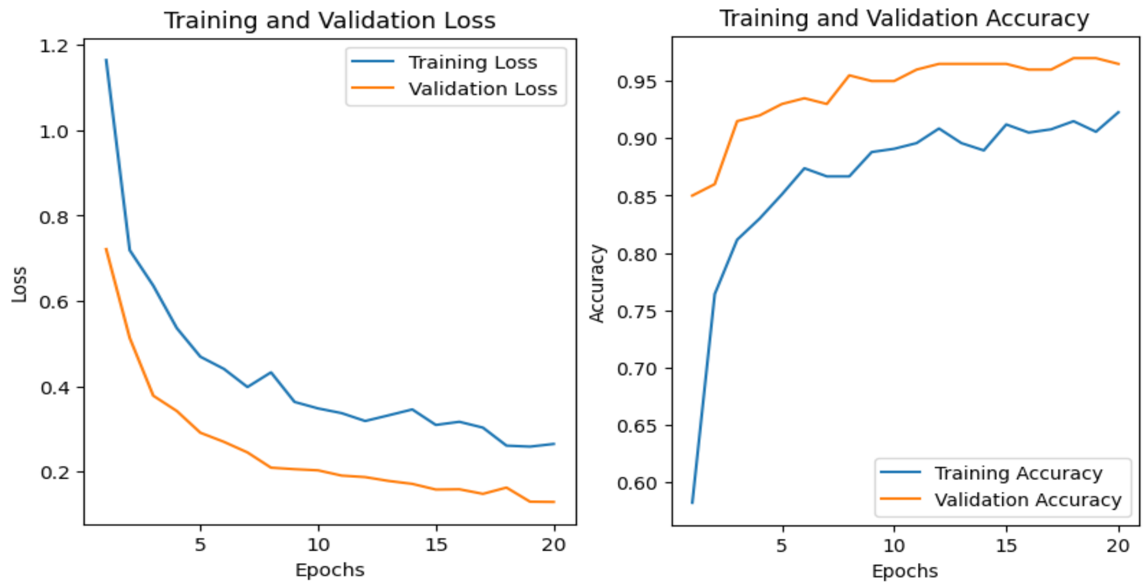

Figure 4.2: Training and validation loss and accuracy over the epochs (DenseNet121).

Figure 4.2 shows the training and validation loss and accuracy over the epochs for a DenseNet121 model. The training loss decreases rapidly in the first few epochs, then levels off and remains relatively stable. The validation loss also decreases initially, but then starts to increase slightly after around epoch 10. The training accuracy increases rapidly in the first few epochs, then levels off and remains relatively stable. The validation accuracy also increases initially, but then starts to decrease slightly after around epoch 10.

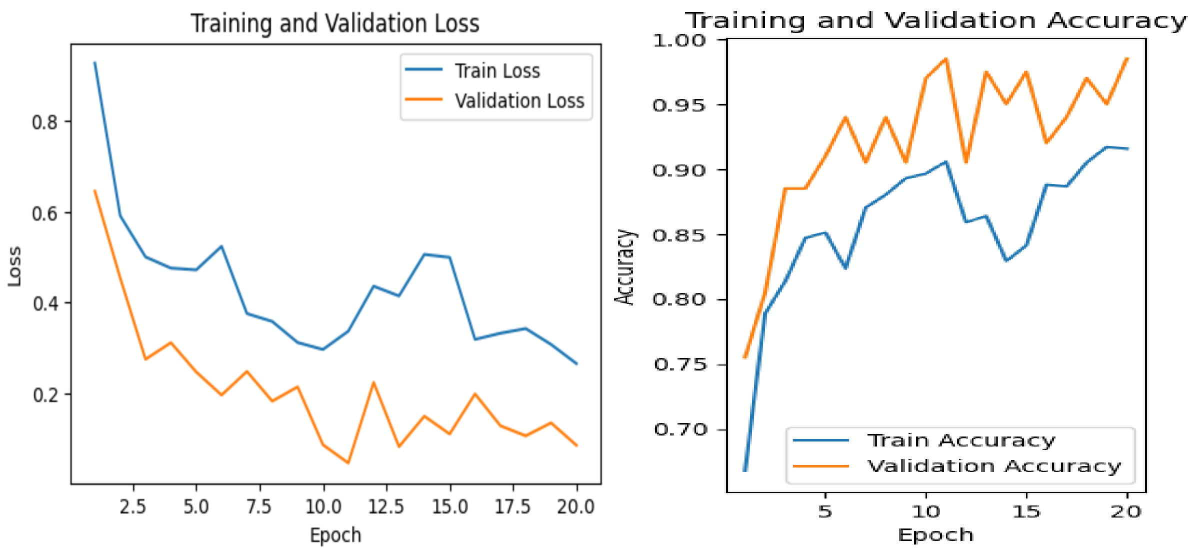

Figure 4.3: Training and validation loss and accuracy over the epochs (MobileNetV2).

Figure 4.3 shows the training and validation loss and accuracy over the epochs for a MobileNetV2 model. The training loss decreases rapidly in the first few epochs, then levels off and remains relatively stable. The validation loss also decreases initially, but then starts to increase slightly after around epoch 10. The training accuracy increases rapidly in the first few epochs, then levels off and remains relatively stable. The validation accuracy also increases initially, but then starts to decrease slightly after around epoch 10. This suggests that the model is overfitting to the training data.

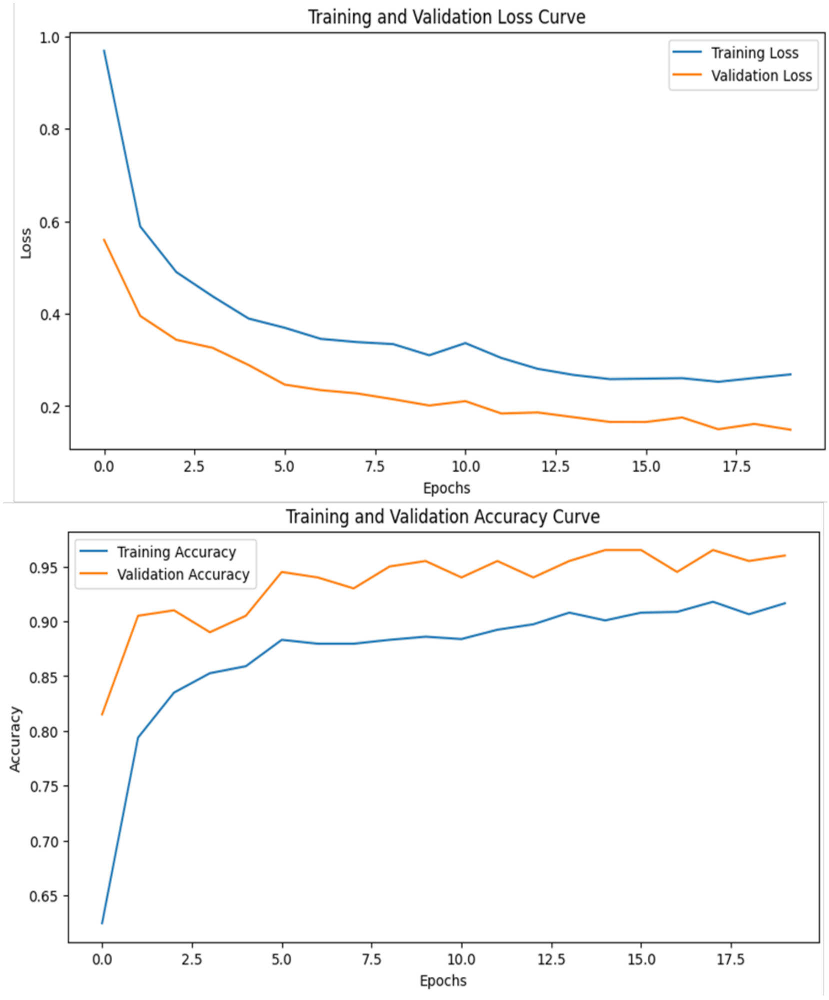

Figure 4.4: Training and validation loss and accuracy over the epochs (VGG16).

Figure 4.4 illustrates the training and validation loss and accuracy for a VGG16 model over 18 epochs. Both the training and validation loss curves exhibit a steep decline in the initial epochs, followed by a more gradual decrease and stabilization. The training accuracy curve rapidly increases in the early epochs and then levels off, while the validation accuracy curve rises steadily until epoch 7 and then fluctuates slightly. This suggests that the model's performance on the training data is consistently improving, but its generalization ability to unseen data might be reaching a limit.

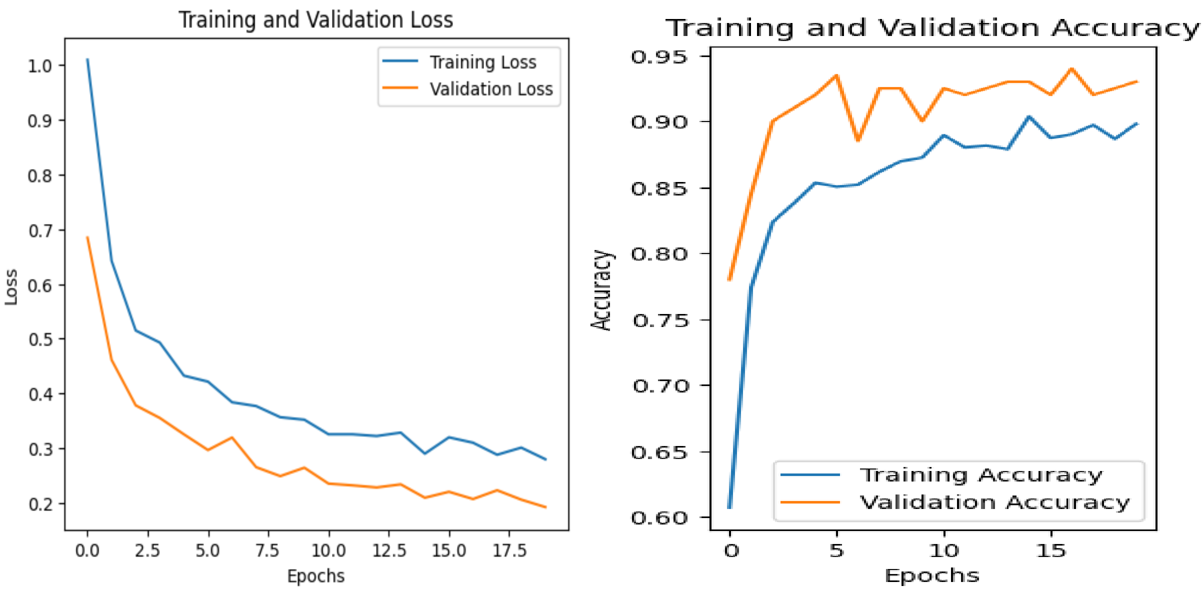

Figure 4.5: Training and validation loss and accuracy over the epochs (VGG19).

Figure 4.5 shows both the training and validation loss curves exhibit a steep decline in the initial epochs, followed by a more gradual decrease and stabilization. The training accuracy curve rapidly increases in the early epochs and then levels off, while the validation accuracy curve rises steadily until epoch 7 and then fluctuates slightly. This suggests that the model's performance on the training data is consistently improving.

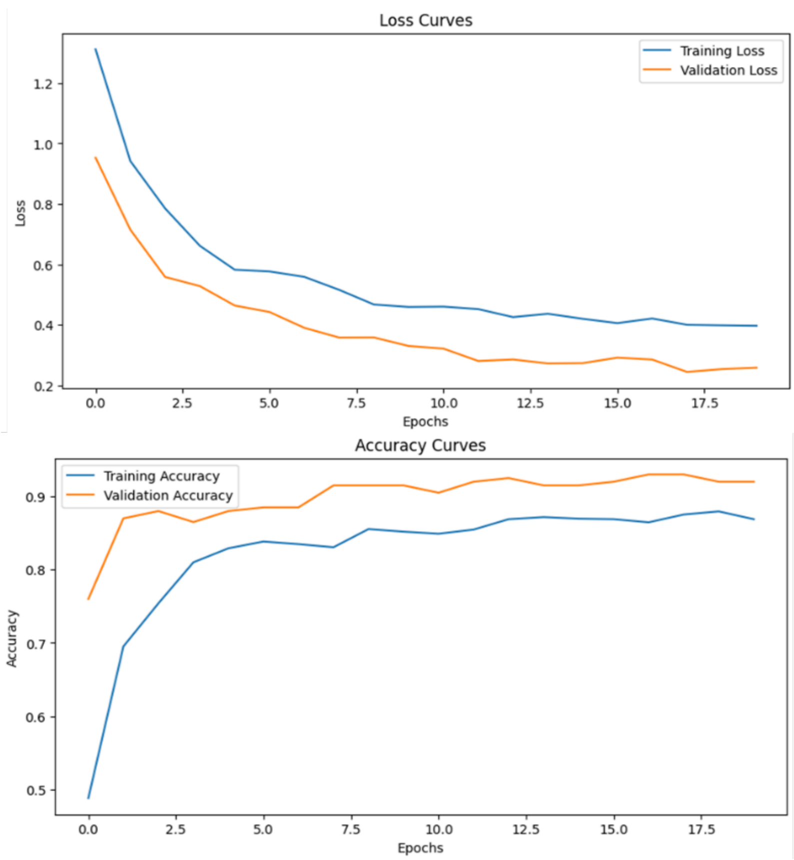

Figure 4.6: Training and validation loss and accuracy over the epochs (Inception-V3)

Confusion Matrix after Original CNN:

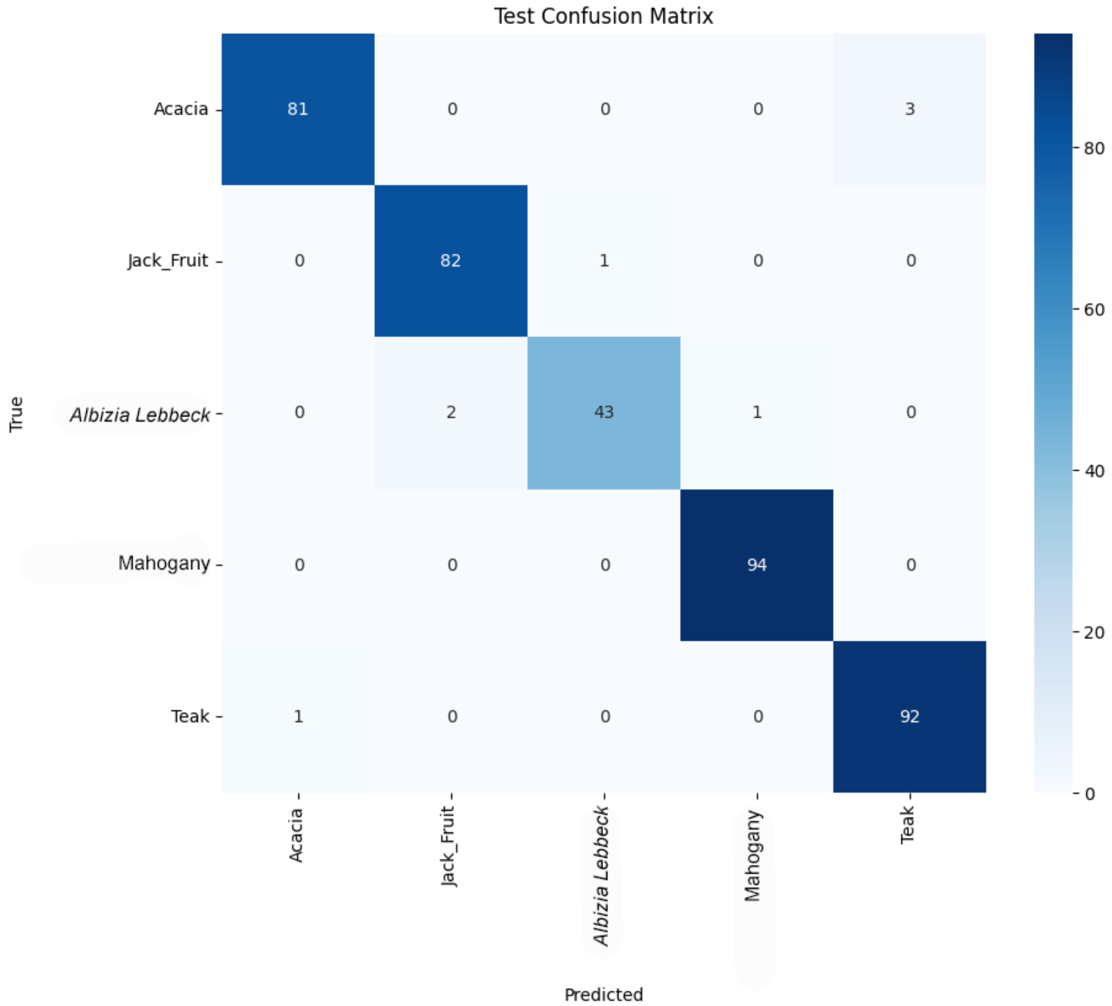

Figure 4.7: Confusion Matrix after ResNet-50

Figure 4.7 shows the performance of the classifier on a test dataset comprising five classes: Acacia, Jack Fruit, Albizia Lebbeck, Mahogany, and Teak. The diagonal elements represent the correctly classified instances for each class, with high accuracy for most classes: Acacia (81 correct out of 84), Jack Fruit (82 out of 83), Mahogany (94 out of 94), and Teak (92 out of 93). However, Albizia Lebbeck has a noticeable number of misclassifications, with only 43 correct predictions out of 46, with some instances being confused with Jack Fruit and Mahogany. This indicates that while the model performs well overall, it struggles more with distinguishing Albizia Lebbeck from other classes.

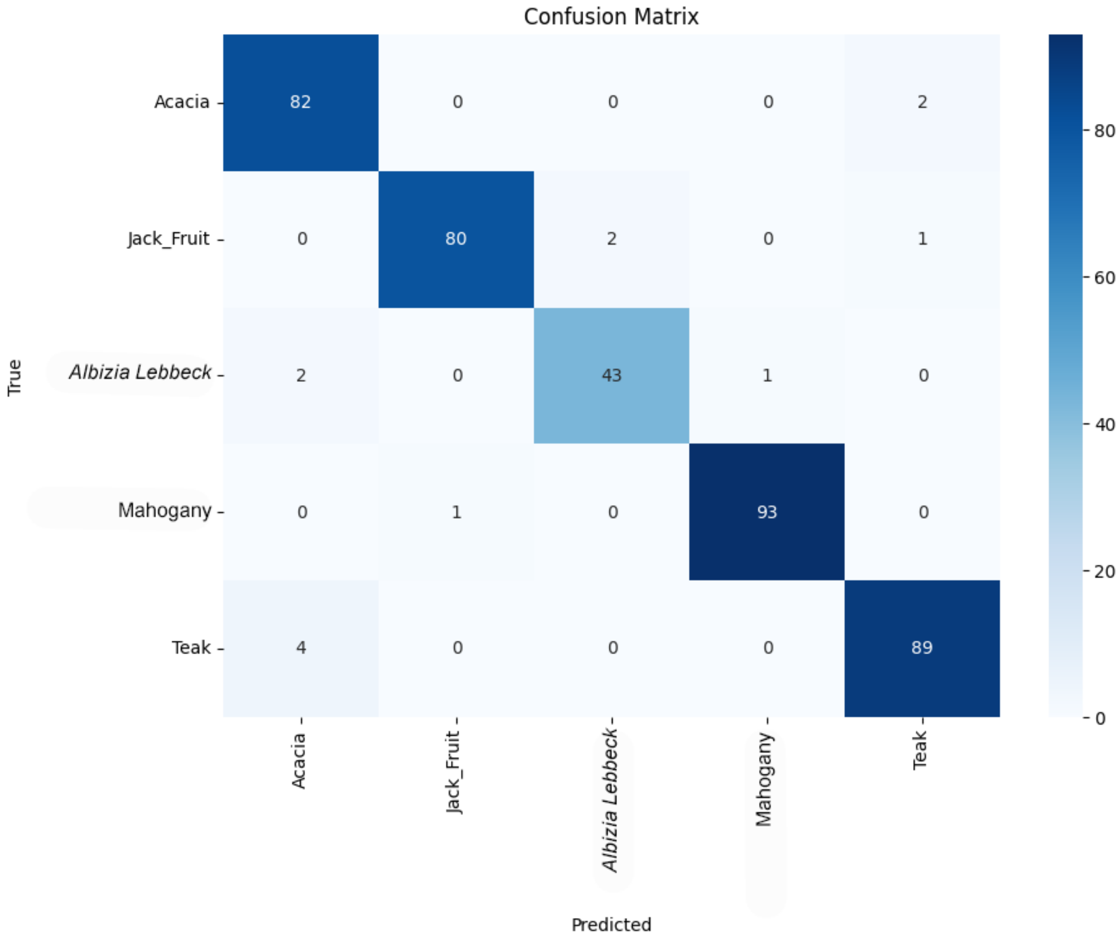

Figure 4.8: Confusion Matrix after DenseNet121

Figure 4.8 for the DenseNet121 model shows the classifier's performance on a test dataset containing five classes: Acacia, Jack Fruit, *Albizia Lebbeck*, Mahogany, and Teak. The model achieves high accuracy for most classes, with Acacia (82 correct out of 84), Jack Fruit (80 out of 83), Mahogany (93 out of 94), and Teak (89 out of 93) showing strong performance. However, there are some misclassifications, particularly for *Albizia Lebbeck*, with 43 correct predictions out of 46, and slight confusions with Acacia, Jack Fruit, and Mahogany. Teak also shows some misclassifications, primarily being confused with Acacia. Overall, while DenseNet121 performs well, there are minor issues with distinguishing certain classes, especially *Albizia Lebbeck* and Teak.

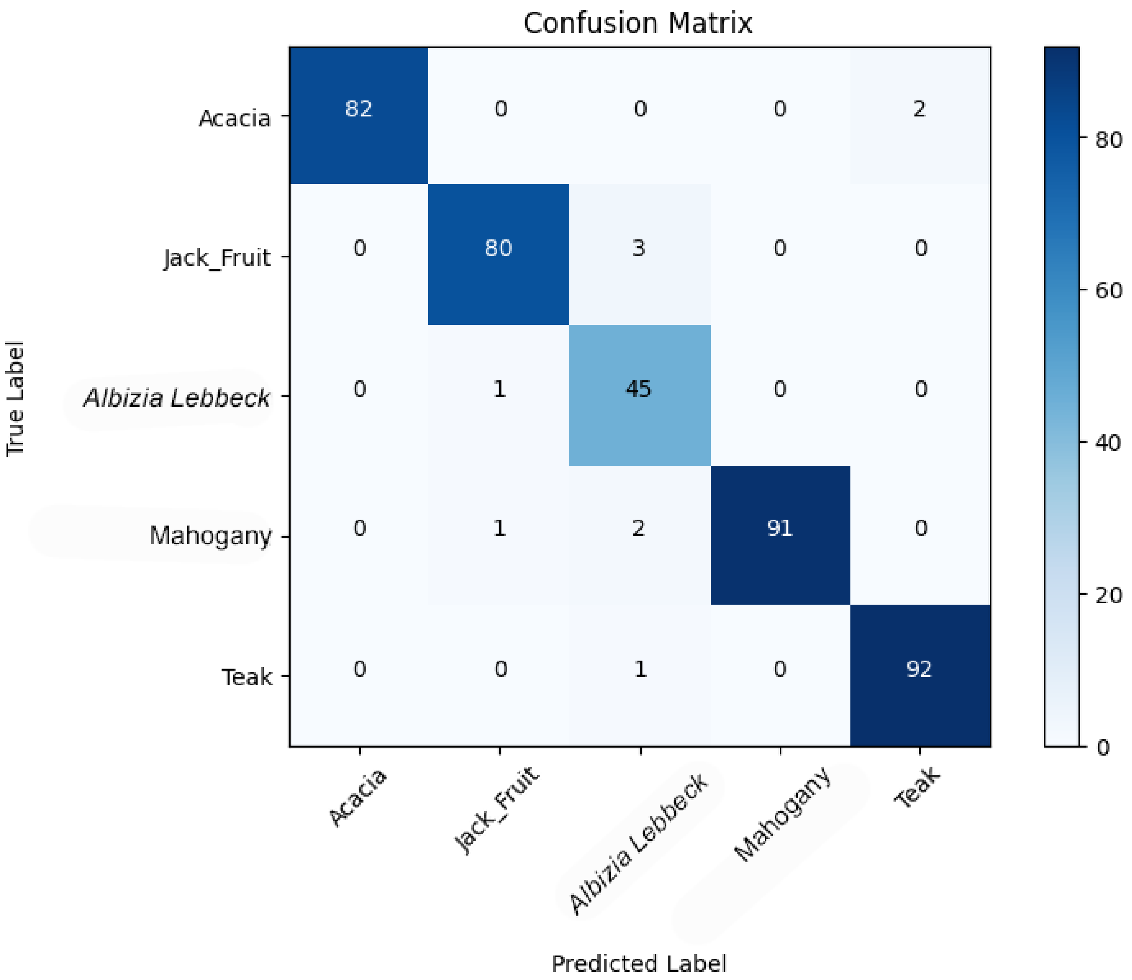

Figure 4.9: Confusion Matrix after MobileNetV2

Figure 4.9 for the MobileNetV2 model indicates varying performance across tree species. While the model achieved high accuracy in classifying mahogany and teak, it struggled with *Albizia lebbeck*, suggesting potential misclassification issues. The model also incorrectly classified a small number of jackfruit and mahogany trees as *Albizia lebbeck*. These results highlight areas where model improvements, such as data augmentation or architectural refinements, could enhance overall performance.

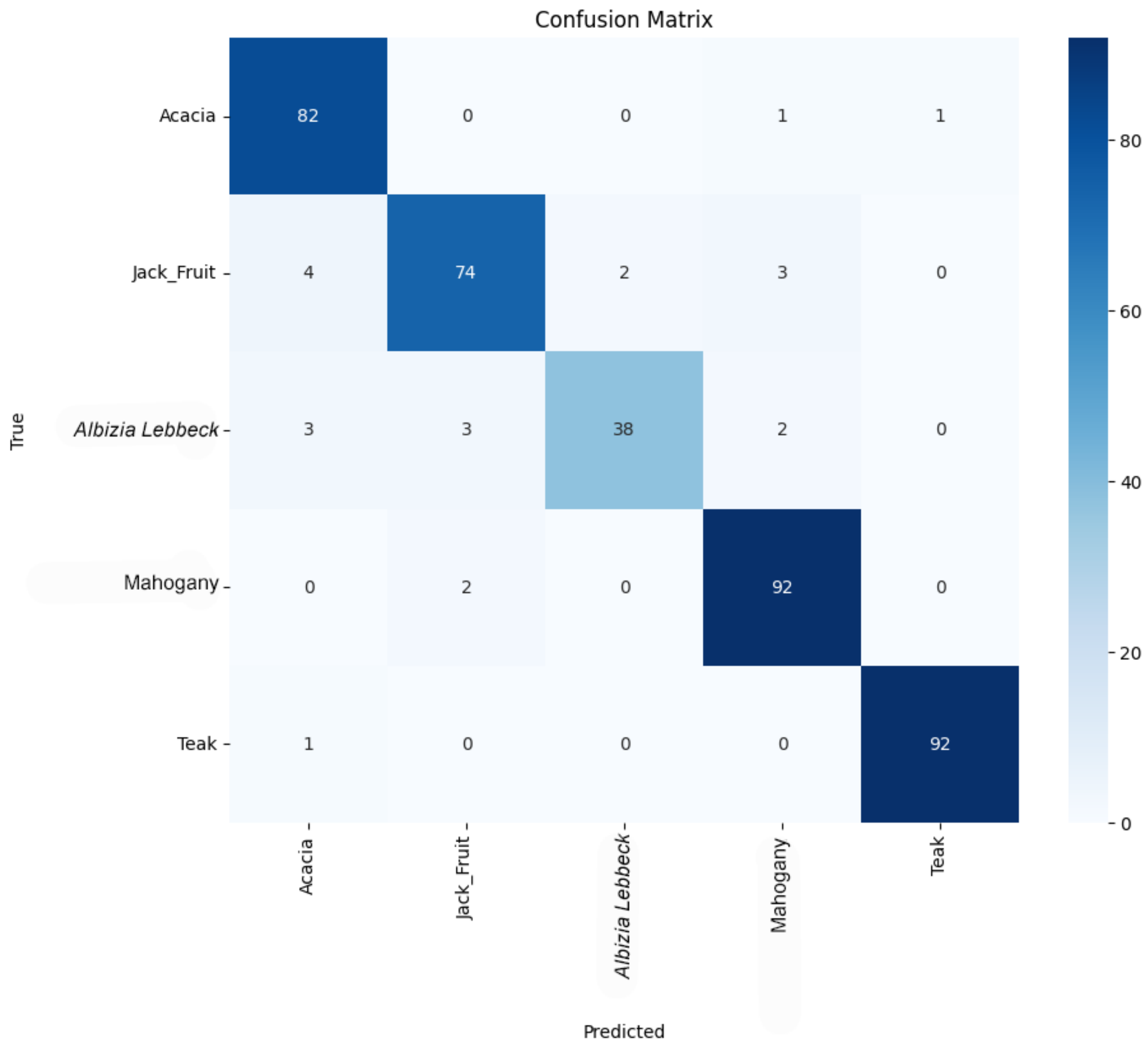

Figure 4.10: Confusion Matrix after VGG16

Figure 4.10 for the VGG16 model shows that it has a high accuracy for classifying the five different types of trees in the dataset. The model correctly classified 82% of the acacia trees, 74% of the jackfruit trees, 38% of the *Albizia lebbeck* trees, 92% of the mahogany trees, and 92% of the teak trees. The model also made some errors, such as misclassifying 3 jackfruit trees as *Albizia lebbeck* trees and 2 mahogany trees as *Albizia lebbeck* trees. Overall, the VGG16 model is a good performer for this task, but it could be improved by further training on a larger dataset.

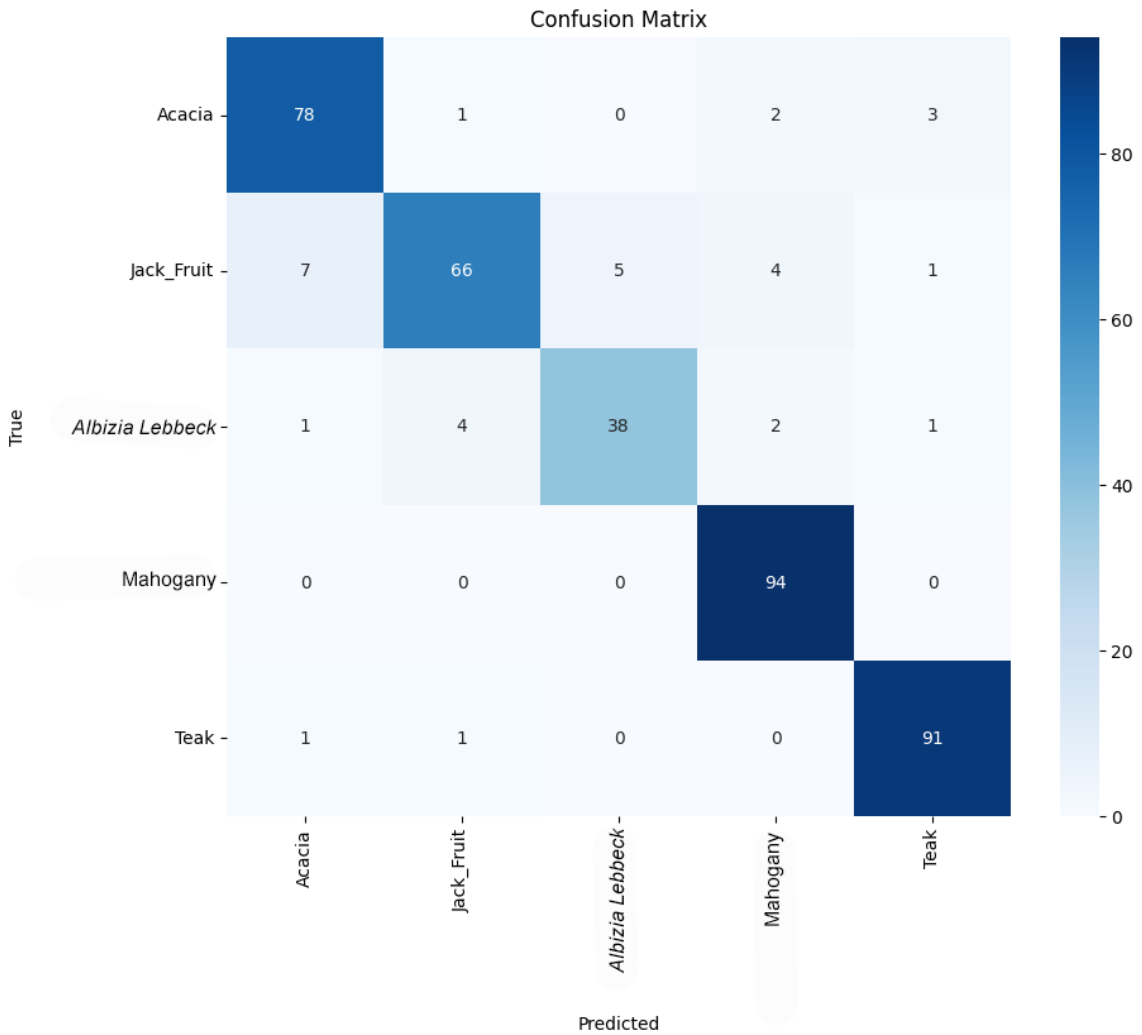

Figure 4.11: Confusion Matrix after VGG19

Figure 4.11 shows VGG19 model exhibits strong performance in classifying tree species, with high accuracy rates for mahogany and teak, achieving correct classifications in 94% and 91% of cases, respectively. The model also demonstrates good accuracy for acacia and jackfruit, with correct classification rates of 78% and 66%. However, the model struggles with *Albizia lebbeck*, correctly classifying only 38% of cases. This suggests potential areas for improvement in model architecture or data augmentation to enhance performance on this specific tree species.

Additionally, the model exhibits some confusion between jackfruit and *Albizia lebbeck*, misclassifying 5 jackfruit samples as *Albizia lebbeck* and 4 *Albizia lebbeck* samples as jackfruit. This highlights a potential challenge in distinguishing between these two species based on the image data used for training.

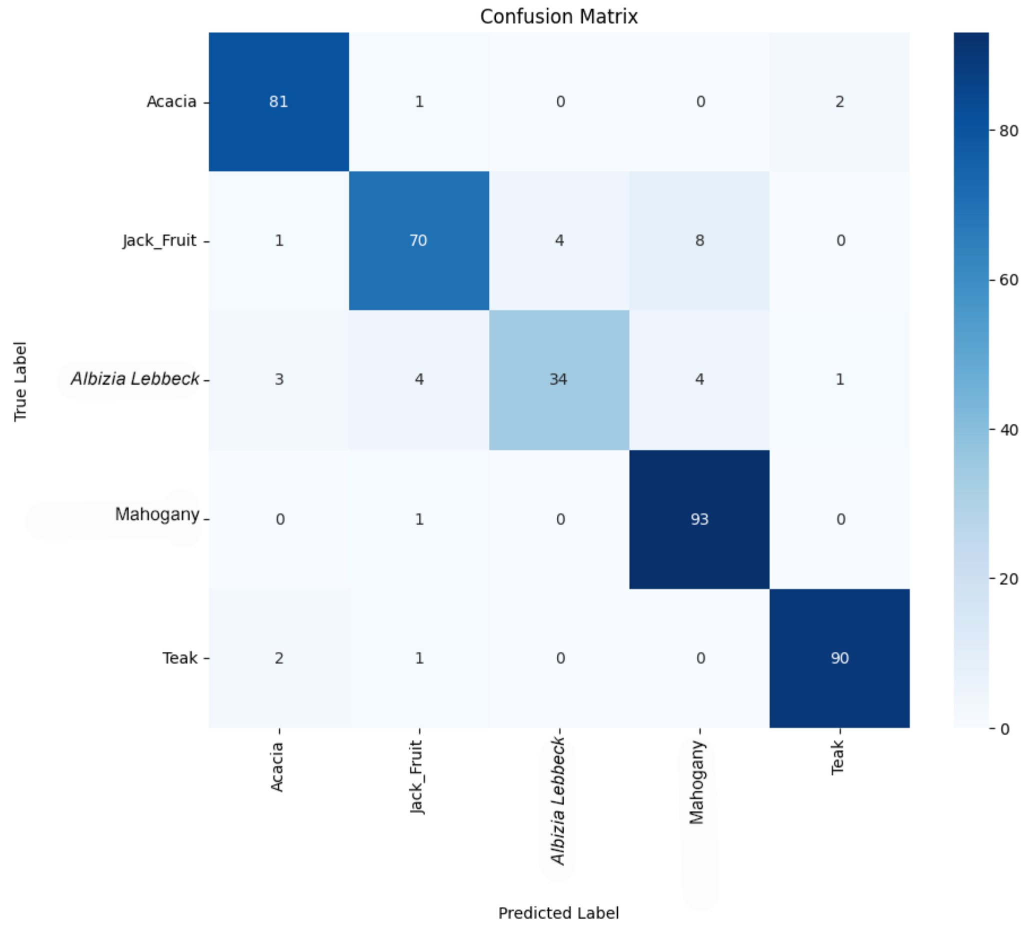

Figure 4.12: Confusion Matrix after Inception-V3

Overall, the model demonstrates strong performance in categorizing wood types, achieving high accuracy in correctly identifying true positives and negatives. However, it also shows occurrences of false negatives and false positives. False positives can lead to incorrect classification of wood types, impacting downstream applications dependent on accurate identification, while false negatives may result in certain wood species being overlooked or misclassified. It's necessary to acknowledge that the evaluation is based on a limited sample size, and the model could perform differently in different datasets. Additionally, while the confusion matrix offers valuable insights into the model's effectiveness by illustrating various types of errors, metrics such as precision, and F1 score provide more nuanced perspectives on its performance.

In summary, the confusion matrix is very useful for visualizing the performance of wood type identification model, enabling identification and analysis of different error types to enhance accuracy and reliability.

4.3 Discussion

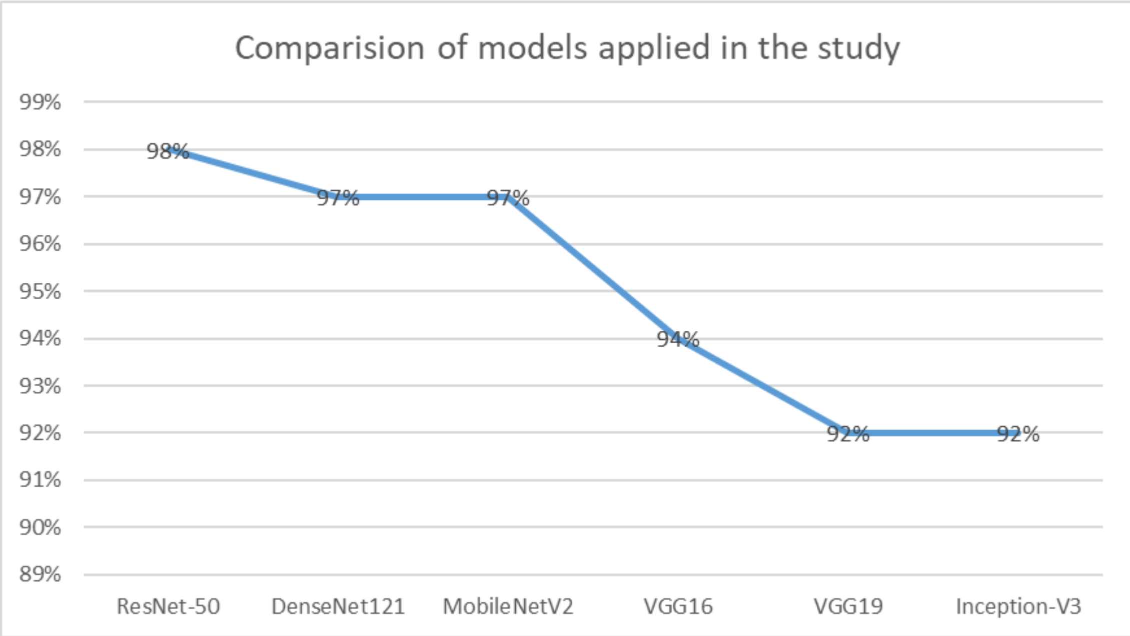

Figure 4.13: Accuracy comparison among individual CNN.

This thorough investigation examines the effectiveness of deep convolutional neural networks (CNNs) in the classification of various wood types. Utilizing a large dataset of original wood pictures. The study investigates the effectiveness of original CNN models in wood type classification. Notably, it distinguishes between the detection and classification procedures, identifying them as separate steps in the identification pipeline. Six well-known CNN-based models, including ResNet-50, DenseNet121, MobileNetV2, VGG16, Inception-V3, and VGG19, are thoroughly evaluated on various wood types. ResNet-50 emerges as the front-runner, with an amazing accuracy score of 98%, as illustrated in Figure 4.13 shows that for different model's image test or training set may have a potential different in performance. Different background of noise in image or different augmentation techniques can perform differently.

Upon detailed examination, it was found that the CNN model exhibited enhanced predictive performance for unfamiliar data when trained and evaluated under similar conditions. However, the study underscores the limitations imposed by dataset size, highlighting its potential impact on predictive accuracy. Previous research underscores the necessity of expanding dataset sizes, particularly when augmented images are introduced as inputs. The study also shows the potential advantages of models over different CNN designs, suggesting that combining multiple models can yield superior performance, even if certain CNN architectures perform sub optimally. In summary, this study offers a comprehensive definition of CNN models for wood type classification.

CHAPTER 5
IMPACT ON SOCIETY

5.1 Impact on Society

The study on "Wood-Type Classification Using Deep Learning Approach" holds significant promise for societal impact, particularly in industries reliant on wood materials and environmental conservation efforts. Accurate classification of wood types through advanced deep learning techniques has the potential to revolutionize various sectors, including forestry management, construction, furniture manufacturing, and artisanal crafts. By automating the wood identification process, the research aims to streamline production workflows, enhance product quality, and promote sustainable resource management practices.

Furthermore, the accessibility and affordability of automated wood-type classification solutions can benefit artisans, woodworkers, and small-scale enterprises, democratizing access to advanced technologies and fostering innovation within the woodworking industry. Additionally, the research's emphasis on accuracy and efficiency aligns with broader sustainability initiatives, promoting responsible forestry practices and mitigating the environmental impact of deforestation through improved wood identification and tracking.

Moreover, by contributing to the development of automated wood classification systems, the research has the potential to support environmental conservation efforts. Accurate identification of wood species can aid in combating illegal logging and timber trafficking, facilitating the enforcement of regulations aimed at protecting endangered species and preserving biodiversity in forest ecosystems. In essence, the societal impact of this research extends to various stakeholders, from industry professionals to environmental advocates, promoting sustainable development and responsible utilization of wood resources.

5.2 Impact on Environment

Although the main emphasis of the research on "Wood-Type Classification Using Deep Learning Approach" lies in enhancing wood identification capabilities, its environmental impact is significant, given the context of forestry management and sustainable resource utilization. The use of deep Convolutional Neural Networks (CNNs), entails computational processes that require substantial energy, thereby adding to the carbon footprint linked to technological progress.

However, the research also presents opportunities to mitigate environmental impact through responsible forestry practices and sustainable wood sourcing. By enabling accurate identification and tracking of wood types, automated classification systems can support efforts to combat illegal logging, promote certified sustainable forestry practices, and reduce deforestation rates. Moreover, the research's emphasis on efficiency and accuracy in wood identification can optimize resource utilization within the woodworking industry, minimizing waste and conserving natural resources.

Efforts to reduce the environmental footprint of the research include optimizing algorithms for energy efficiency, exploring renewable energy sources for computing infrastructure, and promoting awareness of eco-friendly practices among stakeholders. Additionally, the research underscores the importance of considering environmental sustainability alongside technological advancements, emphasizing the need for responsible innovation and the integration of green computing principles.

5.3 Ethical Aspects

The research on "Wood-Type Classification Using Deep Learning Approach" is guided by ethical considerations aimed at safeguarding environmental integrity, promoting responsible resource management, and respecting the rights of indigenous communities and stakeholders in forestry-dependent regions. The use of wood samples for research purposes adheres to ethical guidelines, ensuring transparency, accountability, and informed consent where applicable.

Furthermore, the research prioritizes ethical sourcing of wood samples, emphasizing the importance of legality, sustainability, and respect for indigenous rights in wood procurement practices. Collaboration with local communities and forestry stakeholders fosters equitable partnerships and ensures that research outcomes contribute positively to local economies and environmental conservation efforts.

Additionally, the research recognizes the potential implications of automated wood-type classification for traditional knowledge systems and cultural heritage associated with woodcraft. Efforts to engage with indigenous communities, involve local experts, and respect intellectual property rights contribute to the ethical conduct of the research and promote cultural sensitivity and inclusivity.

In summary, ethical aspects are fundamental to the study's dedication to responsible forestry practices, environmental stewardship, and the ethical use of deep learning technologies in wood identification and classification.

5.4 Sustainability Plan

The study on "Wood-Type Classification Using Deep Learning Approach" focuses on minimizing environmental impact and promoting responsible resource management. This includes conducting an environmental impact assessment to understand and reduce the carbon footprint associated with computational processes. The plan prioritizes energy-efficient algorithms and explores renewable energy sources for computing infrastructure. Additionally, sustainable wood sourcing practices are emphasized, ensuring legality, traceability, and respect for indigenous rights. Stakeholder engagement is crucial, facilitating collaboration with local communities and industry partners to align research outcomes with community needs. Knowledge sharing and capacity building initiatives aim to empower stakeholders with the skills to utilize wood-type classification technologies effectively. Overall, the plan underscores the research team's commitment to responsible innovation, environmental stewardship, and ethical application of deep learning technologies.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

The research on "Wood Type Classification Using Deep Learning Approaches" is a thorough examination of sophisticated artificial intelligence approaches in the field of material identification. The study uses a dataset of 2011 pictures from five unique wood classes to explore the efficacy of deep CNNs in categorizing different wood types. The study extensively tests six CNN-based models, including ResNet-50, DenseNet121, MobileNetV2, VGG16, Inception-V3, and VGG19, and achieves impressive accuracy results. The paper highlights the benefits of ensemble models compared to single architectures. It also shows the influence of dataset size

This study highlights improvements in the accuracy of wood type classification, while also acknowledging environmental concerns and suggesting a sustainability plan to reduce its impact. Ethical aspects such as resource management and data integrity stress the need for responsible AI utilization in material classification. The findings not only add to the academic conversation on material identification but also have significant implications for enhancing industrial processes and resource management worldwide.

6.2 Conclusions

Fast and precise detection of wood types are crucial for efficient material identification and resource management. This paper focuses on an extensive performance evaluation of Deep CNN in the domain of wood type classification. Our study highlights the effectiveness of D-CNN approaches, particularly when handling small and less refined datasets. Notably, there is a lack of research dedicated explicitly to wood type classification in the current literature. Hence, our comparative study holds significant importance, promising substantial contributions to the field of material identification.

In our investigation, we thoroughly assess the performance of several models for wood type classification, including ResNet-50, DenseNet121, MobileNetV2, VGG16, Inception-V3, and VGG19. Some model performs very well in terms of accuracy.

Despite the effectiveness of ensemble approach, some incorrect predictions were noted. This highlights the necessity of exploring alternative methodologies, like contrast augmentation or other processing techniques, in future work.

Additionally, we suggest incorporating image preprocessing and segmentation to enhance the classification ability. Although the proposed method involves training multiple CNN models, making it more computationally expensive than existing baselines, for increased accuracy justifies the additional computational cost. Techniques such as snapshot ensembles could be used to lessen the computing strain in future studies. This study acts as a stepping stone towards refining and expanding wood type categorization procedures, delivering insights that can greatly impact industrial processes and motivate additional discovery in the evolving field of material analysis.

6.3 Implication for Further Study

The findings from this study on Wood Type Classification Using Deep Learning Approach offer significant insights and suggest several directions for future research. A key recommendation for future work is to explore more types of wood species. In this research we worked with only five types of classes. More types of wood species should be added so that model can classify more diverse range of wood species. Furthermore, the inclusion of segmentation techniques prior to classification is suggested to enhance the feature extraction capabilities of CNN models.

Considering the computational expense of proposed approach, future research should explore methods like snapshot ensemble to mitigate the computational burden. This emphasizes the need for more efficient and scalable ensemble approaches that can sustain or increase accuracy while reducing processing needs.

Despite the focus on wood type classification in this study, there is a clear need for more targeted research in this area, as existing literature is limited. Future research could investigate new architectures, diverse datasets, and practical applications to deepen understanding in this field. Overall, future studies should aim to refine image-processing strategies, develop efficient ensemble techniques, and broaden the research scope in wood type classification. These efforts will enhance material identification and lead to improvements in classification accuracy and efficiency.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: WOOD-TYPE CLASSIFICATION USING DEEP LEARNING APPROACH

Student ID: 201-15-14157

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **wood classification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and create technical solutions and system components or processes that fulfill defined criteria, ensuring adherence to public health and safety regulations while also taking into account cultural, socioeconomic, and environmental factors within this FYDP.	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Examine societal, health, safety, legal, and cultural factors, along with their corresponding responsibilities, within the realm of professional engineering practice and the resolution of this issue, utilizing logical reasoning guided by contextual comprehension.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Effectively engage with the engineering community and the broader society on intricate engineering projects, demonstrating competence in understanding and creating detailed reports and design documentation, as well as giving and receiving clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Attainment of Complex Engineering Problems (EP), Knowledge Profile (K):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO8, CO7, CO6, CO5, CO3, CO2 and CO1	This project underscores **foundational engineering (K3)** principles through the use of deep neural networks, data augmentation methods, and various CNN architectures for image processing and classification. The research demonstrates **specialized knowledge (K4)** by utilizing advanced CNN models like MobileNetV2 and ResNet-50, enhancing wood classification images crucial for computer-aided diagnosis.	**Pages:** [28-32] **Sections:** [3.2] **Pages:** [1-6] **Sections:** [1.1]
				The project applies engineering practice and design (K5) by illustrating the experimental process. Additionally, it encompasses engineering practice and technology (K6) through the implementation of the CNN model.	**Pages:** [30-32] **Sections:** [3.2(B)] **Pages:** [33-35] **Sections:**

					[3.4]
				This study ensures **K8 (Research Literature)** by integrating concepts from previous research, advancing pneumonia diagnosis with deep learning, and showcasing a thorough understanding of current methodologies.	**Pages:** [16-25] **Sections:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO7, and CO2	This study addresses **EP-2** by pinpointing the challenges in wood categorization, such as the limitations of current methods and the complexities of integrating transfer learning with deep CNNs. Through comparative research, it overcomes obstacles in understanding geographical distributions and offers insights for enhancing diagnostic techniques.	**Pages:** [25-26] **Sections:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO6, and CO2	This study addresses **EP-3** by systematically analyzing trial results, identifying various algorithms as the most significant option for enhancing wood type recognition among several viable methods.	**Pages:** [38-51] **Sections:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's multidisciplinary methodology goes beyond computer science and engineering, resulting in advancements in faster wood categorization, thereby implying **EP-4**.	**Pages:** [16-23, 25-26] **Sections:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses complex challenges in material diagnostics by integrating various elements including data collection, statistical analysis, and recommended methodologies, ensuring a holistic solution that meets **EP-7** requirements.	**Pages:** [28-35] **Sections:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	Our research utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations. These enable systematic investigation and aim to advance pneumonia detection through transfer learning and deep convolutional neural networks (CNNs).	**Pages:** [35-36] **Sections:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This initiative contributes to society by improving woodworking through advanced methods of wood categorization. It also promotes environmental sustainability by employing efficient computing resources and upholding ethical standards.	**Pages:** [54-56] **Sections:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This study advances existing research by exploring a novel approach to wood categorization using deep convolutional neural networks (CNNs). It includes initial terminology and a comprehensive comparative analysis, offering new perspectives on the topic.	**Pages:** [16, 23-25] **Sections:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project tackles CO4 by integrating effective project management and financial oversight, ensuring comprehensive planning, resource allocation, and budget forecasting to maximize resource efficiency throughout the study's duration.	**Pages:** [11-13] **Sections:** [1.6]
2	CO9	Yes	By ethically employing advanced material identification technologies that align with CO9, the project upholds ethical standards, secures informed consent, and clearly documents the research process, ensuring responsible dissemination of knowledge and promoting societal welfare.	**Pages:** [55-56] **Sections:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to ongoing learning (CO12) and adaptation in a rapidly evolving technological environment is evident in its thorough data collection, rigorous statistical analysis, meticulous methodology development, and detailed experimental findings and analysis. This reflects a commitment to staying current and improving techniques to meet contemporary challenges.	**Pages:** [28-36, 38-51] **Sections:** [3.2, 3.3, 3.4, 3.5, 4.2]

Wood type classification using deep learning approach

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