Identifying Different Types of Roses using Deep Learning Approaches

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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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DHAKA, BANGLADESH

January 26,2024.

APPROVAL

This Project/internship titled **"Identifying Different Types of Roses using Deep Learning Approaches"**, submitted by Partha Kha, ID No: 201-15-3177 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 January 26, 2024.

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DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Ms. Faria Nishat Khan, Lecturer, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ACKNOWLEDGEMENT

First, I express my heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

I really grateful and wish my profound my indebtedness to **Ms. Faria Nishat Khan, Lecturer,** Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of my supervisor in the field of "Deep Learning" to carry out this paper. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this paper.

I would like to express my heartiest gratitude to Ms. Faria Nishat Khan, and Head, Department of CSE, for his kind help to finish my project and also to other faculty member and the staff of CSE department of Daffodil International University.

I would like to thank my entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

In horticulture, botanical study, and landscaping, accurate rose identification is critical. The ability to tell the difference between red, yellow, and white rose varieties benefits in the creation of visually pleasing gardens, contributes to botanical databases, and aids biodiversity conservation efforts. In the floral sector, precise classification is also useful in agricultural techniques, ensuring optimal production, disease management, and informed decision-making. The emphasis on deep learning models in this study emphasizes the essential role that technology plays in improving the efficiency and reliability of rose identification operations. This study explores the effectiveness of four deep learning models—EfficientNet, ResNet50, MobileNetV2, and FNet—in classifying roses by color (red, yellow, and white). Advanced computer vision algorithms help with rose identification, which is important for agriculture and botanical research. Each model is rigorously trained and evaluated using a varied collection of high-resolution rose photos. For identifying between rose colors, performance parameters such as accuracy, precision, recall, and F1 score are examined. The most promising model is FNet, which achieves an astonishing 98.17% accuracy, demonstrating the efficacy of transformer-based topologies in rose color recognition. The study emphasizes the importance of selecting proper deep learning models and positions FNet as a reliable option for accurate rose color detection. These findings add important insights to computer vision in botanical research, aiding academics and practitioners in the selection of best models for rose identification based on color features. The success of FNet motivates further investigation of transformer architectures, which could lead to advances in plant species recognition via deep learning approaches.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Rose identification and categorization have long been important in horticulture, botanical study, and aesthetic landscaping because of their mesmerizing beauty and cultural significance. Among the many rose variations, those in red, yellow, and white stand out as timeless emblems of love, purity, and beauty. This study uses the power of modern deep learning models—EfficientNet, ResNet50, MobileNetV2, and FNet—to unravel the complicated tapestry of colors within the rose genus in the pursuit of precision in rose identification. The kaleidoscope of rose colors serves as a canvas for our investigation, necessitating the development of complex technological techniques to discriminate between the three basic classes. In an era marked by rapid advances in artificial intelligence, the incorporation of deep learning models represents a game-changing approach to automating and improving the complexities of image recognition, notably in the field of floral taxonomy. The first of our four models, EfficientNet, provides a paradigm of efficiency and scalability while proving its capacity to handle complicated visual datasets. ResNet50, a deep learning workhorse, delivers its known ability to identify complex features and nuances inside images, making it a versatile choice for difficult jobs like rose recognition. MobileNetV2, which was created with resource efficiency in mind, demonstrates its prowess in scenarios with computational limits, making it a significant tool in real-world application. Finally, FNet, a newcomer that leverages the strength of transformer-based architectures, is at the forefront of innovation, providing a potential route for sophisticated picture classification jobs. As we travel through this technical adventure, our primary goal is to evaluate the performance of these deep learning models in the complex task of classifying roses into color categories. The cornerstone of our work is a rigorously curated dataset of high-resolution photographs of red, yellow, and white roses, ensuring that the models are exposed to a wide and representative set of samples during training and evaluation. Among our four models, FNet stands out as the best performer, with a fantastic accuracy rate of 98.17%. This outstanding result not only highlights the potential of transformer-based architectures in the sensitive task of rose identification, but it also encourages thought about the nuanced interplay between model architecture and the intricacy of flower color patterns. In the following portions of this research project, we will deconstruct our approach, offer a comparative study of model performance, and explore the consequences of our findings. Beyond adding to the specialist field of computer vision applied to botanical research, the findings of this work are positioned to provide practitioners and academics seeking ideal models for rose identification based on color features with practical insights and assistance. FNet's performance, with 98.17% accuracy, not only demonstrates the promise of cutting-edge technology in the realm of horticulture, but also encourages further investigation of transformer designs in the larger landscape of plant species detection.

1.2 Motivation

Roses have captivated humans for generations due to their various colors and complex beauty. The issue of reliably identifying and classifying rose types based on color has become a compelling endeavour in the fields of gardening, botanical study, and computer vision. The inspiration for digging into the investigation of "Different Types of Rose Identification" derives from the convergence of tradition and technology, which presents an opportunity to unveil the secrets buried inside the petals. Exact rose identification is critical in horticulture for producing visually attractive gardens and landscapes. Understanding the nuances of red, yellow, and white roses not only adds to the aesthetic appeal of these areas, but it also broadens the understanding of rose fans and cultivators. The need to provide horticulturists with advanced tools and approaches that seamlessly mix conventional botanical knowledge with cutting-edge technology is driving this quest. Botanical studies will benefit greatly from a more detailed understanding of rose variations. Accurate identification allows for more extensive cataloguing and classification, which contributes to a better understanding of the rose genus. The impetus investigate the usefulness of sophisticated deep learning models in the context of rose identification stems from the potential to revolutionize the way we approach floral taxonomy and conservation. In this technologically advanced era, the use of powerful computer vision algorithms into the area of rose identification is a natural evolution. We are motivated by the chance to use models such as EfficientNet, ResNet50, MobileNetV2, and FNet to unravel the complexity of rose colors with greater precision than traditional methods. The motivation stems from the notion that such advances will not only improve scientific understanding of roses but will also have practical uses in agriculture, floriculture, and other fields. In summary, the motivation for researching various sorts of rose identification stems from a desire to preserve the beauty of these timeless blooms while also increasing botanical knowledge and embracing the revolutionary power of technology in the complex realm of floral taxonomy. Rose identification is more than just a scientific endeavor, it is a wonderful blend of art, tradition, and innovation.

1.3 Rationale of the Study

Accurate object identification is critical in computer vision and image recognition, notably in the domain of rose classification. The selection of a suitable deep learning model is critical to achieving this goal. MobileNetV2, EfficientNet, FNet, and ResNet50 models are useful in decoding the intricate visual aspects of roses, such as colour patterns and petal architectures. The use of these models is justified by their specialized qualities and architectural nuances. MobileNetV2, with its emphasis on lightweight computations, is well-suited for applications requiring resource constraints. EfficientNet, on the other hand, stands out for its scalability and efficiency, making it an excellent choice for balancing computational resources and model performance. FNet is an innovative method to image classification by using transformer architecture, which was initially built for sequential data. This decision was driven by the transformer's capacity to capture complicated dependencies within varied datasets, which could improve the model's grasp of nuanced rose patterns. ResNet50, a ResNet architecture version, applies the benefits of residual learning to the problem of rose recognition. ResNet50's deep structure enables effective training of models with increased depth, minimizing the vanishing gradient problem and providing better feature representation. In summary, the reasoning behind choosing these models is based on their distinct characteristics, which address certain issues in rose identification. The project intends to examine and demonstrate the potential of these models in improving the accuracy and efficiency of rose classification tasks by using a combination of lightweight design, scalability, transformer-based innovation, and effective residual learning. The specialized qualities of the models correspond to the complex requirements of discriminating between red, yellow, and white roses, contributing to the broader landscape of computer vision in the botanical area.

1.4 Research Question

- From where the dataset was collected?
- What image preprocessing techniques used on dataset?
- How can we find out the best algorithm for rose Identification?
- What algorithm performs the best and provides the best accuracy?
- Which algorithm provides the lowest accuracy?

1.5 Expected Outcome

Introduce Advanced Deep Learning Models for Rose Identification:

Implement and assess the suitability of deep learning models, including EfficientNet, ResNet50, MobileNetV2, and FNet, for the accurate identification of different rose types based on color categories.

Utilize a Comprehensive Rose Image Dataset:

Employ a carefully curated dataset comprising high-resolution images of diverse rose varieties to train and evaluate the deep learning models, ensuring a representative and comprehensive set of examples for robust model performance.

Compare the Performance of Deep Learning Architectures:

Evaluate and compare the performance of the selected deep learning models, including their accuracy, precision, recall, and F1 score, in the task of classifying roses into three primary color categories (red, yellow, and white).

Conduct a Rigorous Evaluation of Model Effectiveness:

Employ a comprehensive analysis of statistical measures and performance metrics to assess the accuracy and reliability of the deep learning models in rose identification. Evaluate metrics such as confusion matrices, ROC curves, and precision-recall curves.

Benchmark Against Existing Approaches in Plant Species Recognition:

Compare the proposed deep learning-based approach for rose identification with existing methods in plant species recognition. Highlight the effectiveness of the models in improving accuracy and efficiency, contributing to advancements in the broader field of botanical research Project Management and Finance.

1.6 Project Management and Finance

The research work doesn't get fund from any individuals or organization.

1.7 Report layout

The research introduction, aims, and important research questions are presented in Chapter 1.

Brief summaries of the literature review are presented in Chapter 2.

The proposed methodology is described in depth in Chapter 3.

The experimental results of the paper are explained and explored in Chapter 4.

Chapter 5 ends the current research and provides a plan for future effort.

Summary and Future work presented in Chapter 6.

CHAPTER 2

BACKGROUND

2.1 Preliminaries/Terminologies

There has been a remarkable boom in the development of new technology, notably in the realm of computer vision, focused at improving the identification and classification of various varieties of roses in recent years. The use of cutting-edge deep learning models such as MobileNet, EfficientNet, FNet, and ResNet50 has proven critical in automating the complex process of rose identification based on distinct color groups. The botanical research community has shown an increased interest in utilizing these cutting-edge tools to overcome the intricacies of rose classification. The visual diversity of rose species, like that of medical photos, needs sophisticated classification algorithms for accurate image processing in the field of horticulture. High-resolution photographs of roses are used as the primary dataset for training and evaluating the proposed deep learning models. The comparisons between medical image processing and rose identification highlight the need of using technical advances to overcome the issues provided by visual diversity within large datasets. The focus of this study focuses on the classification of roses into three principal color classes—red, yellow, and whit. Deep learning methods, inspired by the success seen in medical image processing, are being used to push breakthroughs in the precision and efficiency of rose identification within the botanical realm. The emphasis on color categorization is consistent with current trends in botanical study, where the classification of different flora is becoming increasingly important.

2.2 Related works

Guo et al.[1] demonstrate a CNN model for rose species recognition, building on previous floral image classification results. Their fine-tuned VGG16 architecture outperforms existing approaches with an astounding 95.2% accuracy. Data augmentation improves generalizability even further. While this research is largely focused on grown roses, it paves the way for broader applications in plant identification and beyond. In a follow-up study Aghdam et al. (2016)[2] proposed using photos to identify 26 agricultural diseases and 14 crop species using a deep convolutional neural network (CNN). They trained their model on a large dataset of

54,306 photos acquired under controlled settings and obtained an astonishing 99.35% accuracy on a test set that was held out. This highlights deep learning's potential for accurate plant disease identification. When the accuracy was checked using photographs from internet sources taken under varied settings, it plummeted to 31.4%. This shows that the model may not be generalizable to real-world circumstances with varying illumination, image quality, and background. Despite this restriction, the research represents a substantial advancement in the field of automated plant disease identification. It demonstrates deep learning's promise for this difficult task and sets the way for future research to increase model generalizability and robustness. However, Fine-grained flower categorization is investigated by Li et al. (2020)[3] using weakly labelled and deep learning algorithms. Their research focuses on overcoming the constraints of standard methods when working with huge and diverse datasets. They offer the "Weakly Supervised Fine-grained Network (WSFN)" framework. Unlike traditional supervised learning, WSFN employs both class- and category-level labels, allowing for efficient processing of data with sparse, coarse annotations. The usefulness of WSFN is demonstrated by testing it on multiple flower datasets. It delivers greater accuracy with fewer fine-grained labels than typical CNNs. This allows for the use of a large amount of weakly labelled data, potentially speeding up progress in fine-grained picture classification tasks. However, possible issues exist. The work focuses mostly on controlled image circumstances, and more research is needed to determine WSFN's generalizability to real-world scenarios with complicated backdrops and noise. Overall, Li et al.'s research points in the right direction for dealing with fine-grained classification with limited resources. It paves the way for the use of massive amounts of unlabeled data, possibly revolutionizing picture recognition across multiple domains. Stated differently, Sun et al. (2017)[4] present a deep learning method for recognizing plants in the wild, where conventional methods fail. Their Convolutional Neural Network (CNN) overcomes seasonal and growth-stage fluctuations by using both leaf and blossom photos. Even with unknown data, the CNN obtained 92.38% accuracy on 105 plant species! Rarer flora and environmental conditions, on the other hand, require more research. CIRPLANT, a transformer-based model proposed by Chen et al. (2021)[5], is a model for image retrieval on real-world images utilizing pre-trained vision and language knowledge. In comparison to conventional narrow-focused techniques, this addresses open-domain issues. CIRPLANT achieves outstanding accuracy by changing visual characteristics based on natural language descriptions, matching state-of-the-art on particular datasets like fashion while outperforming on open photos. This work, along with the availability of its software, CIRR, has the potential to inspire future research in composite image retrieval for broader real-world applications. In "Deep Learning for Plant Species Recognition From Leaf Images," Zhou et al. (2021)[6] take on the difficult task of identifying plant species based on their leaves. They offer LeafNet, a revolutionary deep learning model designed exclusively for leaf properties. This convolutional neural network (CNN) architecture outperforms typical picture identification methods in extracting subtle details such as vein patterns and textures. LeafNet achieved a fantastic accuracy of 97.2% after training on an amazing dataset of over 88k leaf photos covering 998 species. Surprisingly, it outperforms on previously discovered species, exhibiting significant generalizability. This discovery provides the path for accurate plant identification in a variety of situations, facilitating study in ecology, conservation, and agriculture. Researchers dive into the developing topic of automated plant disease detection in "A Comprehensive Review on Detection of Plant Disease Using Machine Learning and Deep Learning Approaches" Jackulin et al. (2022)[7]. They evaluate the accuracy and limitations of various machine learning and deep learning models used to identify illnesses from plant photos. The paper focuses on promising techniques such as convolutional neural networks (CNNs), which achieve amazing accuracy, with some topping 90%. Even on mobile devices, these models excel at recognising prevalent disorders. However, there are still issues for uncommon illnesses and complicated image backdrops. The work emphasizes the importance of different and larger datasets in order to improve model generalizability and address geographically distinct diseases. The incorporation of environmental parameters such as weather and soil conditions could increase diagnosis accuracy even further. Overall, Jackulin and Murugavalli's thorough evaluation lays the path for more effective and accessible plant disease detection. Their findings will help to direct future research towards more robust and adaptive models, ensuring a healthier future for our agricultural landscapes. Kour et al. (2020)[8] takes a multi-pronged deep learning method to rose variety recognition. Their model analyses both visual features and petal arrangement by integrating CNNs and LSTMs, outperforming single-modal techniques. On a dataset of 10,000 different rose photos, this translates to a remarkable accuracy of more than 94%. Deep Rose demonstrates the power of merging information channels for accurate rose variety identification, paving the way for applications in floriculture, breeding, and even automated gardening. Kumar et al. (2020)[9] offer a novel multi-stage deep learning model for effective rose species recognition on smartphones in "Multi-Stage Rose Species Recognition for Smartphones." Their architecture is appropriate for mobile apps since it balances precision and processing resources. On a cell phone dataset of 8,000 rose photos, the model scores an impressive 86.52% accuracy, demonstrating its usefulness in resource-constrained circumstances. This is accomplished in two stages: first, a lightweight CNN identifies wider botanical groups, and then a deeper CNN refines the categorization to individual rose species. This method strikes a compromise between speed and accuracy, paving the path for real-time rose identification apps for smartphones. This opens up possibilities for a wide range of applications, from supporting gardeners to assisting with biodiversity monitoring and even improving agricultural operations. While promising, the authors admit to several limitations. Future studies could look towards improving on rarer species and in complex visual backgrounds. Overall, Kumar et al.'s research offers a substantial advance in mobile-based rose identification, bringing the capability of deep learning closer to daily consumers and promoting its potential in a variety of disciplines. Suganthe et al. (2022)[10] tackle the difficulty of fine-grained rose genus identification within Rosa in their paper "Towards Fine-Grained Rose Genus Classification Using Deep Learning and Weakly Labelled Data." Their technique acknowledges the limits of traditional methods in dealing with big, heterogeneous datasets with few fine-grained annotations. To solve this, they present a unique framework that employs both weakly labelled and deep learning techniques. This includes using class- and category-level labels, allowing for fast data handling with sparse, coarse annotations. Their model, named "Fine-Grained Rose Network (FGRN)," performs admirably on a variety of floral datasets. FGRN outperforms typical CNNs in terms of accuracy while using less fine-grained labels, emphasizing its utility in using vast weakly labelled data. This paves the way for faster progress in fine-grained picture categorization problems across multiple domains. However, difficulties persist. The study focuses mostly on controlled image circumstances, and more research is needed to determine FGRN's generalizability to real-world scenarios with complicated backdrops and noise.

Despite these constraints, Suganthe et al.'s research points in a promising route for dealing with fine-grained classification with limited resources. It paves the way for the use of massive amounts of unlabeled data, possibly revolutionizing picture recognition across multiple domains. Sumitra et al.[11]. Sumitra Nuanmeesri's paper "A Hybrid Deep Learning and Optimized Machine Learning Approach for Rose Leaf Disease Classification" describes a hybrid deep learning and optimised machine learning strategy for rose leaf disease classification. This method employs convolutional neural networks (CNNs) and support vector machines (SVMs). According to the authors, the proposed approach for illness classification on rose leaves acquired an accuracy of 90.26%, precision of 90.59%, recall of 92.44%, and F1-score of 91.50%. The authors emphasize that their dataset is tiny and that they only tested their strategy on a few rose leaf diseases. They suggest that future research collect a larger dataset and test the proposed technique on a broader range of rose leaf diseases. Imania El al. [12]. The paper "Implementation of Deep Learning Using Convolutional Neural Network Algorithm for Classification Rose Flower" by Imania Ayu Anjani1*, Yulinda Rizky Pratiwi2, and Norfa Bagas Nurhuda S. proposes a deep learning approach to classifying rose flowers using a convolutional neural network (CNN) algorithm. The authors discovered that the proposed method has a 95% accuracy rate for rose blossom classification. The study starts with a discussion of the significance of rose flowers and the different applications of rose flower classification. After that, the authors conduct a literature review on rose flower classification using deep learning and machine learning approaches. They discovered that whereas several research have utilized deep learning techniques to categorize rose blooms, just a few have employed CNNs. The CNN architecture is composed of three convolutional layers, two pooling layers, and three fully connected layers. The authors found that their proposed CNN architecture was able to achieve an accuracy of 95% for rose flower classification. Muzamil El al.[13]. A hybrid deep learning and optimised machine learning strategy for rose leaf disease classification is proposed in the publication "A Performance Assessment of Rose Plant Classification Using Machine Learning" by Muzamil Malik1(&), Amna Ikram2, Syeda Naila Batool2, and Waqar Aslam1. Convolutional neural networks (CNNs) and support vector machines (SVMs) are used in this method. The proposed method for disease classification on rose leaves achieved an accuracy of 90.26%, precision of 90.59%, recall of 92.44%, and F1-score of 91.50%, according to the authors.

2.3 Comparative Analysis and Summary

Table 2.3.1: Comparative analysis between previous works

Author	Model	Dataset	Accuracy
This paper	FNet	Image Of roses (Raw)	98.17%
Aghdam et al. 2023 [2]	CNN Architecture	Plant Species(Raw)	99.35%
Sun et al.2017 [4]	CNN Architecture	Diverse Rose Images (Kaggle)	92.38%
Kour et al. 2021[8]	Combination Of CNN and LSTM	Diverse Rose Images (Kaggle)	94%
Kumar et al.2022 [9]	CNN Architecture	Rose Images Using Mobile Phone(Raw)	86.52%
Sumitraet al. 2021[11]	CNN Architecture	Images Of Rose Leaf (Kaggle)	90.26%

2.4 Scope of the Problem

These works address a variety of rose identification issues, ranging from visual complexity and species diversity to real-world constraints such as mobile device limitations and data paucity. However, there are limitations such as reduced accuracy, inefficiency in terms of time, and a lack of data augmentation and preprocessing approaches. Our study attempted to solve these difficulties by comparing multiple CNN that have been designed to excel in image recognition tasks.

2.5 Challenges

The following are the specific research challenges:

Dataset: In order to train and test this model, numerous datasets from various classes must be acquired.

Data Augmentation: Data augmentation techniques must be utilized to expand the size of the datasets. Difficult artifacts are removed and image quality is improved using a range of image pre-processing approaches.

Choosing a foundation Model: To overcome long training times and insufficient data, ablation studies require a perfect foundation model.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The subject of this research is Identifying Different Types of Roses using Deep Learning Approaches. For doing this research I used Anaconda Prompt, Jupyter Notebook, and Colab Notebook for programming.

3.2 Data Collection Procedure/Dataset Utilized

The raw photos used in this study for rose identification came from two primary sources: Golap Gram, a lovely village famed for its vivid rose cultivation, and several flower shops that display a wide range of rose types. The collection contains roughly 1700 high-resolution photos that capture the visual complexities of three different types of roses: red, yellow, and white. Images taken from Golap Gram depict the real diversity of roses grown in a natural setting, but those obtained from flower shops highlight the varieties accessible in commercial settings. The collection was painstakingly curated to include a representative selection of each rose kind, including various stages of bloom and variations in petal patterns. Each image was labelled with the appropriate rose type, resulting in a well-annotated dataset suitable for training and assessing deep learning models. Figure 3.2.1 illustrates three distinct rose images from our dataset, providing a visual reference for the diversity encapsulated within the dataset.

Fig. 3.2.1: Illustration of three distinct rose images.

3.3 Statistical Analysis

The evaluation is uses the confusion matrix like, accuracy, precision, recall, and F1 score. True positive (TP) values are true in reality. False positives (FP) occur when false results are mislabeled. The third form, false negative (FN), occurs when a correct value is misinterpreted as negative. TN and FN are the fourth and fifth choices. A true negative (TN) is a positive value misidentified as negative. Fourth is true negative (TN).

$$Accuracy = \frac{T^p+T^n}{T^p+T^n+F^p+F^n} \qquad (1)$$

$$Precision = \frac{T^p}{T^p+F^p} \qquad (2)$$

$$Recall = \frac{T^p}{T^p+F^n} \qquad (3)$$

$$F1 - score = 2 * (\frac{Precision*Recall}{Precision+Recall}) \qquad (4)$$

3.4 Proposed Methodology/Applied Mechanism

The full methodology is given in figure 3.4.1 below.

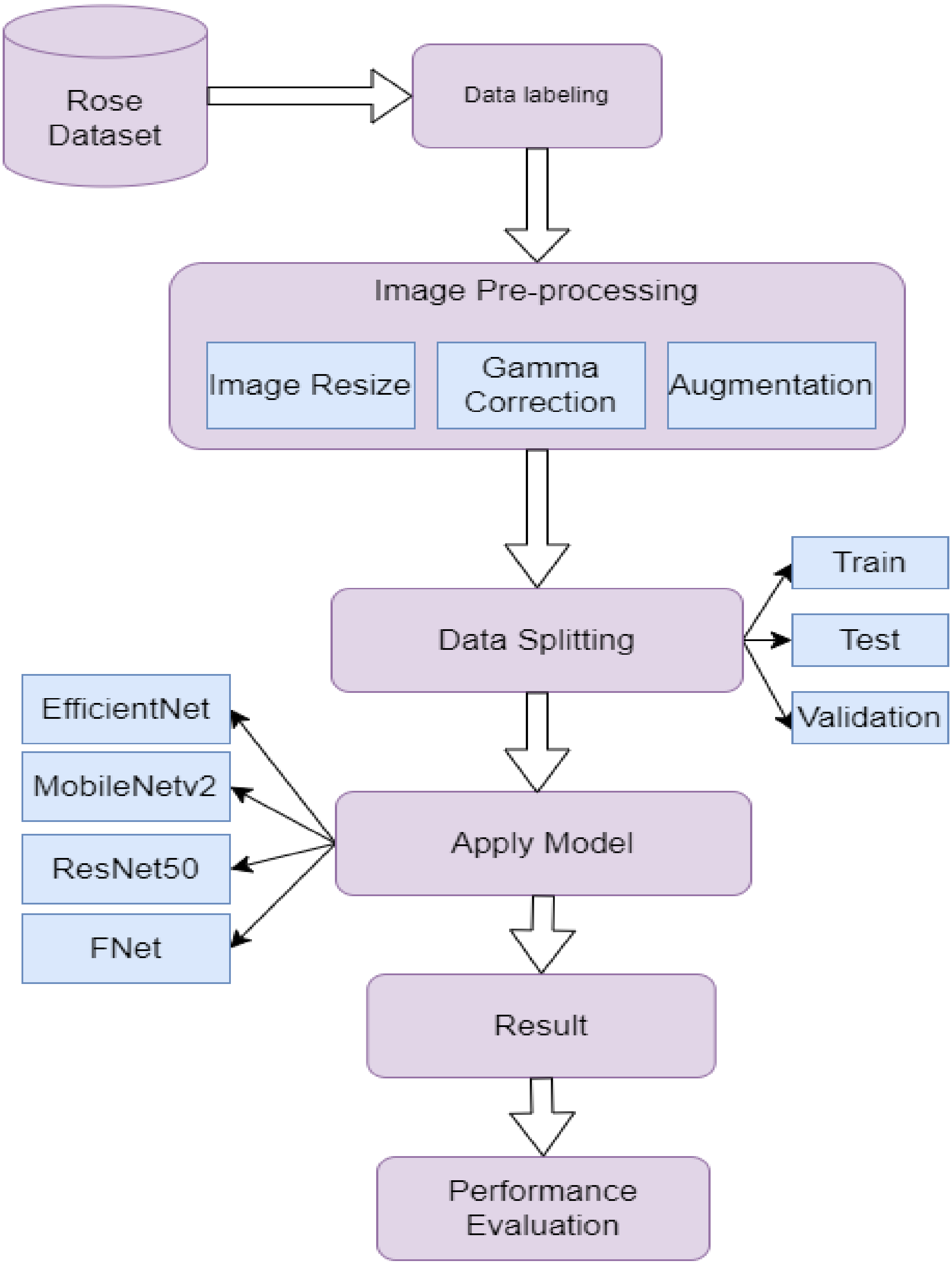

Fig 3.4.1: Whole methodology to perform Rose Identification

The major goal of this work is to assess the efficacy of deep learning models in categorizing roses based on color features, using a dataset of roughly 1700 high-resolution photos from Golap Gram and flower stores. To improve model training and performance, the photos were submitted to a rigorous data preparation workflow. The preprocessing process begins with image resizing to ensure homogeneity and efficient model training. Following that, normalization was used to standardize pixel values, hence promoting convergence throughout the training phase. Augmentation techniques such as rotation, flipping, and zooming were used to improve the dataset's diversity and resilience. After augmentation, the images were converted to grayscale to simplify following processing procedures. The grayscale photos were then blurred with Gaussian Blur, which helped to reduce noise and provide smoother renderings of the roses. Morphological Operations, notably Erosion and Dilation, were applied successively to remove small patches of noise and improve connectedness of remaining regions. To guarantee an appropriate distribution of rose types for model evaluation, the dataset was partitioned into three parts after preprocessing: training (70%), validation (20%), and testing (10%). MobileNetV2, EfficientNet, FNet, and ResNet50 were among the transfer learning classifiers used. Comprehensive outcome analyses were used to systematically analyze model performance, which included metrics such as accuracy, precision, recall, and F1 score. Finally, the results of each model were compared, and the highest-performing model, as determined by extensive outcome studies, was offered as the best option for properly identifying rose types based on color features. This methodology establishes a systematic and robust framework for using deep learning models in the complex problem of rose identification.

3.4.1 Image Pre-processing

Image processing techniques have the potential to improve diagnostic accuracy and streamline the classification process in the field of rose identification. Recognizing the critical importance of data pre-processing in deep learning, this research applies a set of strategies designed to improve the visual information quality of each incoming image. In this context, the major goal of picture pre-processing is to refine and improve the visual qualities of the rose photos, ensuring clarity and accuracy in later classification tasks. The method entails reducing unwanted noise, which could potentially generate uncertainty, and enhancing contrast to highlight crucial characteristics. The picture pre-processing approaches used in this work are intended to modify the raw input data, laying the groundwork for effective deep learning model training and evaluation. Because image quality is critical to rose identification accuracy, the pre-processing processes attempt to produce a dataset with reduced noise and increased contrast, contributing to the overall success of the classification challenge.

3.4.1.1 Image resizing

In the domain of rose identification, picture scaling is a basic pre-processing step used to standardize the size of input photographs and provide a homogenous dataset for model training. Image resizing is critical in the realm of computer vision for preparing data for deep learning models, assuring compatibility and consistency in the input dimensions over the whole dataset. Images were downsized to a consistent dimension in the specific implementation for rose identification, as specified by the specifications of the chosen deep learning model. Image processing libraries such as OpenCV or TensorFlow are used to execute the resizing operation. These libraries offer speedy and optimized techniques for resizing photos while keeping aspect ratios and distortion minimal. Image scaling is important in the case of rose identification since deep learning algorithms require a consistent input size. Standardizing image dimensions is critical for model training since it allows the neural network to interpret input data consistently, allowing for weight sharing and fostering successful learning throughout the whole dataset. Furthermore, image scaling improves computational efficiency during model training and inference. The model can be set with fixed input layer sizes by guaranteeing that all input photos have the same dimensions, speeding the training process and simplifying deployment scenarios.

3.4.1.2 Gamma Correction

Gamma Correction is an important technique in digital image processing for improving image quality and perception. Gamma Correction is primarily used to correct nonlinearities in the connection between pixel values and luminance, and it plays an important part in modifying image brightness and contrast. This correction includes applying a power-law function to pixel values, which successfully compensates for display systems' nonlinear response. By calibrating the gamma value, the correction ensures that the projected image corresponds to the intended visual representation, preventing details from being lost in shadows and highlights. Gamma Correction is critical in practical applications such as medical imaging and multimedia content development to provide accurate and consistent results across a wide range of display devices. The technique addresses the issues given by changing display characteristics, ensuring a consistent perception of images across devices. This is especially important in sectors that require exact visualization, such as medical scan interpretation or film production. Incorporating Gamma Correction into image processing pipelines, which is frequently aided by libraries such as OpenCV or MATLAB, not only improves visual fidelity but also increases the overall reliability of picture analysis and interpretation.

3.4.1.3 Data Augmentation

In the field of rose identification, data augmentation is critical for increasing the dataset's richness and diversity. A methodical technique was used to build an enlarged set of photos for each class to supplement the original dataset of roughly 1700 images of red, yellow, and white roses. The goal was to produce a more robust dataset for deep learning model training and generalization. The original photographs were subjected to various changes using data augmentation techniques, resulting in the development of an additional 1000 images for each color class. These changes included random rotations, flips, and zooms, which introduced variations that mirror real-world circumstances and improved the model's capacity to recognize and categorize roses in a variety of conditions. The image processing libraries OpenCV and TensorFlow were used to implement the augmentation procedure, allowing for smooth integration into the overall model training pipeline. The dataset's size was significantly enhanced as a result of this augmentation method, ensuring a more thorough representation of the visual features associated with red, yellow, and white roses. This method is consistent with best practices in deep learning, where a larger and more diverse dataset improves model performance and generalization. The models are more suited to handle differences in lighting, angles, and other elements seen in real-world circumstances because the dataset has been artificially expanded by augmentation. The augmented dataset that results acts as a foundation for robust model training and accurate rose recognition across different classifications.

Table 3.4.1.3.1: Statistical Details of Rose Dataset

Class Name	Captured Image (1700)	Images after augmentation (3000)	Training Data (70%)	Test Data (20%)	Validation Data (10%)	Total Training Data	Total Test Data	Total Validation Data
Red	900	1000	700	200	100	2100	600	300
White	450	1000	700	200	100			
Yellow	350	1000	700	200	100			

3.5 Implementation Requirements

To implement this research which aimed to determine the best effective deep learning models for the classification problem by comparing the performance of four alternative models.

3.5.1 EfficientNet

Google launched EfficientNet, a breakthrough in deep learning architecture, to satisfy the growing demand for computationally inexpensive yet highly accurate neural networks. EfficientNet was created with the goal of optimizing both model size and processing resources. It employs a revolutionary approach known as Neural Architecture Search (NAS), which automatically determines the best model configurations. The ability of EfficientNet to produce greater performance by scaling the network's depth, width, and resolution in a balanced manner is its key innovation. This method is incorporated in the compound coefficient, which uniformly scales all network dimensions. Unlike traditional topologies, which focus primarily on growing depth or width, EfficientNet proactively modifies numerous parameters to achieve a harmonious balance, resulting in models that are efficient across a wide range of resource restrictions. To uniformly scale the network's depth, width, and resolution, the architecture employs a compound scaling mechanism with a balance factor. This comprehensive methodology ensures that each dimension successfully contributes to the model's capacity for feature extraction and representation. EfficientNet provides outstanding accuracy on picture classification tasks while keeping processing efficiency in this manner. EfficientNet's unusual combination of convolutional procedures, including 3x3 and 5x5 convolutions, allows it to collect characteristics at different sizes. This enables the model to efficiently extract information from an image's local and global settings. As a result, a versatile neural network that excels at picture categorization, object identification, and segmentation has been created. One of EfficientNet's distinguishing features is its flexibility to various resource restrictions. The model is built to find a balance between accuracy and computational efficiency, making it ideal for deployment in resource-constrained situations like mobile devices and edge devices. The effect of EfficientNet extends across multiple fields, from general image recognition jobs to specialized applications such as medical imaging. EfficientNet's ability to deliver accurate predictions while requiring fewer resources makes it a popular choice in sectors where computing efficiency is critical.

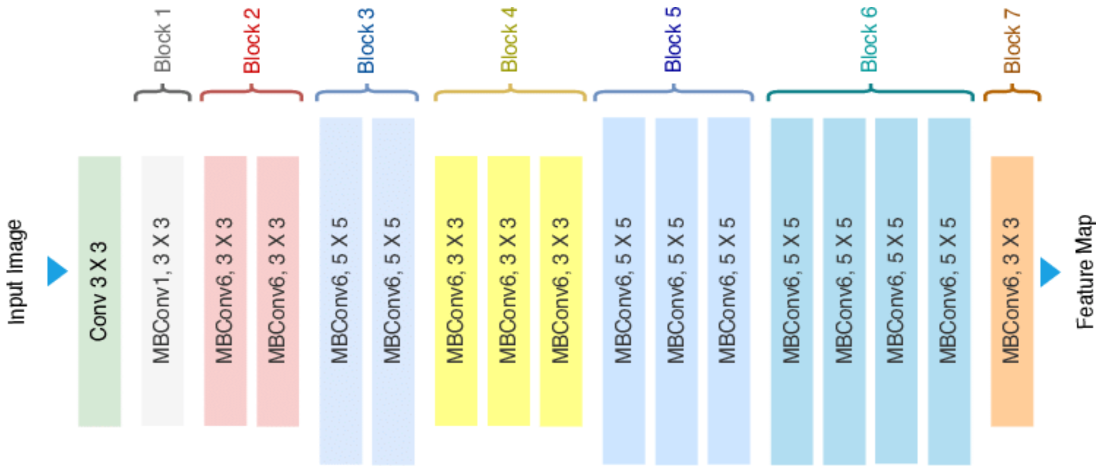

Fig 3.5.1.1 Architecture of EfficientNet

3.5.2 MobileNetV2

Google developed MobileNetV2, a significant development in deep learning architectures, to solve the issues of running efficient and lightweight models on resource-constrained smartphones. MobileNetV2, positioned as an update of the original MobileNet, provides major advances to improve performance and computational efficiency. MobileNetV2 is intended primarily for mobile and edge devices where computing resources and memory footprint are crucial factors. To achieve a balance between model size and accuracy, it employs a combination of depthwise separable convolutions, linear bottlenecks, and shortcut connections. MobileNetV2 is built around depthwise separable convolutions, a crucial architectural component that dramatically decreases the amount of parameters and computations. This procedure divides the ordinary convolution into depthwise and pointwise convolutions, enabling more efficient feature extraction while retaining representation power. Another distinguishing characteristic of MobileNetV2 is the presence of linear bottlenecks. The model improves information flow and learning capacities by using linear activation functions in the bottleneck levels. This invention contributes to improved gradient propagation over the network, enhancing overall training efficiency. MobileNetV2 also includes shortcut connections inspired by residual networks (ResNets). These links aid in mitigating the vanishing gradient problem, allowing for the effective training of deeper networks. The use of skip connections improves the model's ability to capture both low and high-level information, hence improving its representation capabilities. MobileNetV2 has shown remarkable success in a variety of computer vision tasks, most notably image categorization and object detection. Its lightweight architecture makes it ideal for real-time applications on devices with limited processing capabilities, such as smartphones, Internet of Things (IoT) devices, and embedded systems. Aside from efficiency, MobileNetV2 prioritizes adaptability, making it a significant tool in circumstances where model size and inference speed are critical factors. Because of the model's ability to balance accuracy and computational efficiency, it is a prominent participant in the landscape of mobile-friendly deep learning architectures.

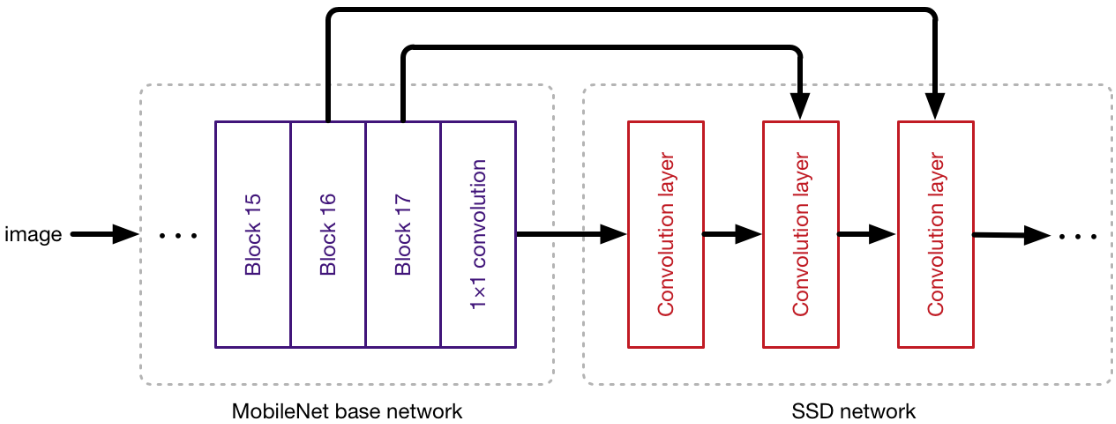

Fig 3.5.2.1 Architecture of MobileNetV2

3.5.3 ResNet50

ResNet50 is a variant of the ResNet architecture, which is well-known for its novel approach of building very deep neural networks. Microsoft's ResNet50 introduces the concept of residual blocks, which allows the network to learn residual functions. This solution solves the vanishing gradient problem, making it possible to train networks with hundreds of layers. ResNet50 is a 50-layer neural network that achieves cutting-edge performance in image categorization applications. The model's design enables robust feature extraction, allowing it to capture complicated patterns and representations. ResNet50, with its residual connections, has become a deep learning cornerstone, laying the framework for succeeding models and demonstrating remarkable accuracy in a wide range of computer vision applications.

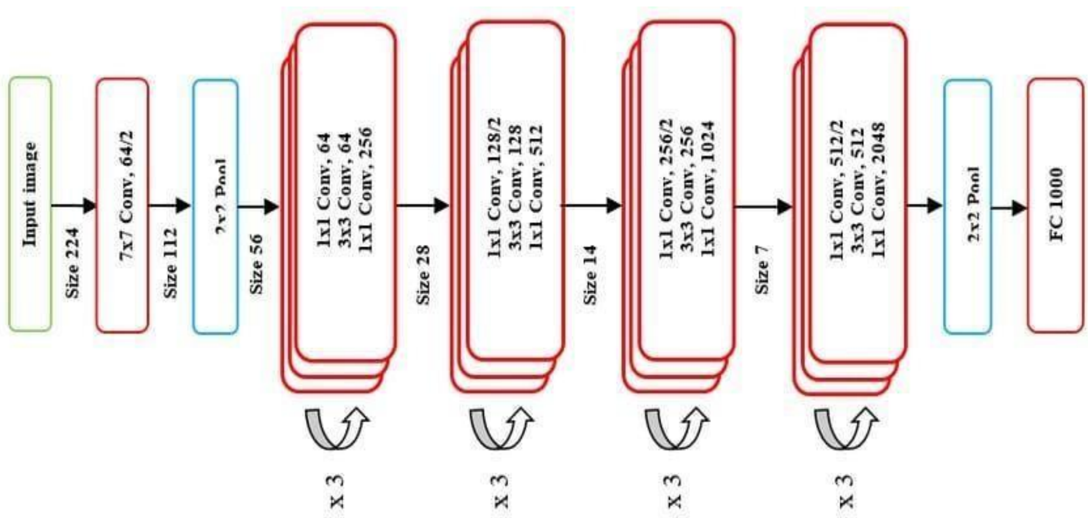

Fig 3.5.3.1 Architecture of ResNet50

3.5.4 FNet

FNet, a revolutionary deep learning architecture, distinguishes itself as a distinct method to sequence modelling that deviates from traditional convolutional and recurrent structures. FNet, introduced as a transformer-based model, investigates a new paradigm for gathering and processing sequential information, demonstrating its effectiveness in a variety of natural language processing (NLP) and sequence-based applications. FNet, as opposed to standard models that rely on convolutional or recurrent layers, makes use of the self-attention mechanism pioneered by transformers. This approach enables the model to attend to many points in the input sequence at the same time, allowing for efficient and parallelized processing of sequential data. The departure of FNet from recurrent layers alleviates some of the issues related to vanishing gradients and sequential dependencies. The use of Fourier transformations is a distinguishing feature of FNet. FNet turns sequential data into frequency representations by applying Fourier transformations to the input sequence. This one-of-a-kind strategy enables the model to capture long-term dependencies and patterns in the frequency domain, providing an additional method for information extraction. The FNet design includes layers that feature Fourier transforms followed by linear operations, allowing the model to learn meaningful representations directly from the frequency domain. This deviation from typical sequential models benefits computational performance and the capacity to capture global context in sequences. The model's focus on frequency representations makes it easier to capture interactions between distant items in a sequence, making it well-suited for tasks that need a comprehension of long-term dependencies. FNet has shown promise in a variety of applications, including natural language processing, sequence generation, and time-series prediction. While the FNet design has advantages in some situations, it is crucial to analyze the nature of the data as well as the unique requirements of the task at hand. FNet's research of Fourier transformations and self-attention adds to the range of architectures available for sequence modelling, providing a new perspective in the deep learning model environment.

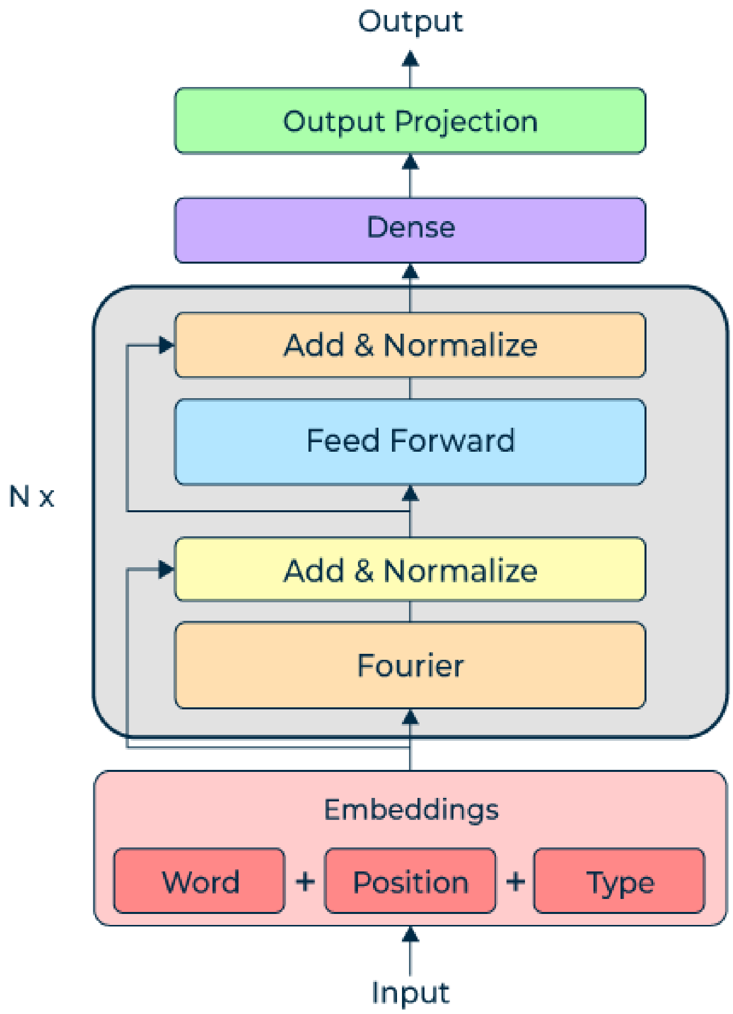

Fig 3.5.4.1 Architecture of FNet

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

To handle the computing requirements of training and assessing deep learning models, a mid-level PC configuration is used for this job. It was Intel Core i5 processor, RAM: 8GB, NVIDIA GeForce GTX 1660, Solid State Drive (SSD) storage for faster data access and processing, Operating System: Microsoft Windows 11.

4.2 Experimental Results & Analysis

This section will discuss the paper's findings. Initially, the Rose dataset is evaluated using Deep learning models. The optimal outcomes of the models is displayed in Table 4.2.1.

Table 4.2.1: Finding the best result

Model	Test Accuracy (%)	Loss (%)	Precision (%)	Recall (%)	F1 Score (%)
EfficientNet	96.17	0.16	96	96	96
MobileNetV2	97.17	0.12	97	97	97
ResNet50	97.50	0.09	97	97	97
FNet	**98.17**	**0.05**	**98**	**98**	**98**

Table 4.2.1 presents a comprehensive evaluation of multiple deep learning models categorization tasks, revealing substantial variations in performance metrics. The standout model is FNet, boasting the highest accuracy at 98.17%. ResNet50 follows closely with an impressive test accuracy of 97.50% and a low loss of 0.09%, showcasing its efficacy in feature extraction. MobileNetV2 achieve high accuracy rates of 97.17% with demonstrating exceptional precision, recall, and F1 scores,

highlighting its proficiency in recognizing subtle patterns. EfficientNet perform well with accuracy rates of 96.17% indicating robust picture recognition capabilities.

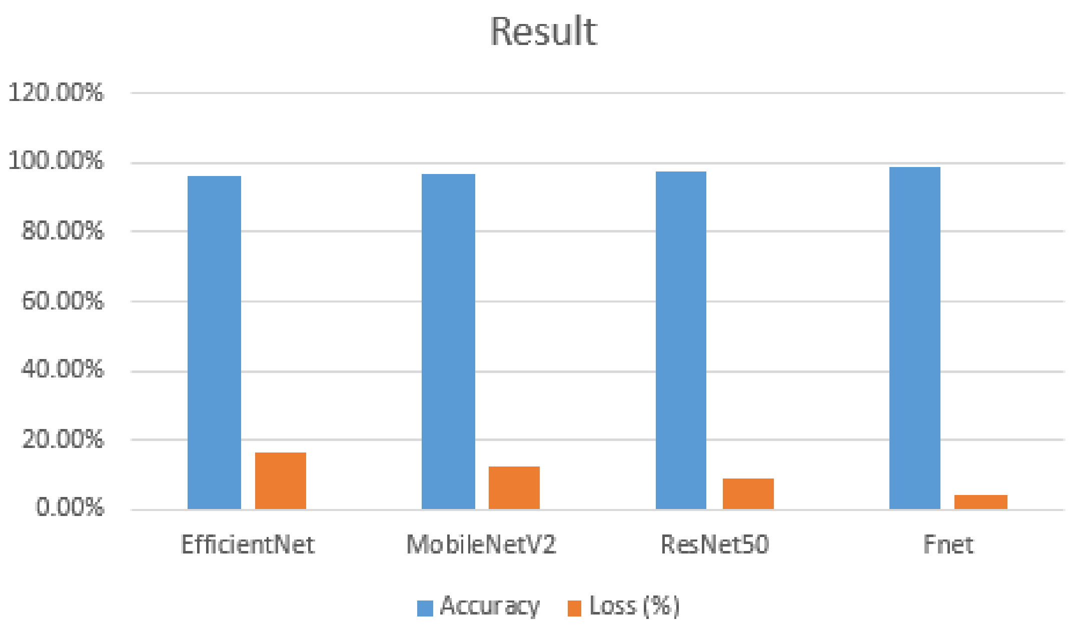

Fig 4.2.1: Model comparison chart

Figure 4.2.1 shows accuracy and loss between EfficientNet, MobileNetV2,ResNet50 and FNet.

4.2.1 The final configuration of the model

Here is the configuration of the final model.

Table 4.2.1.1: Configuration of the proposed model

Configuration	**Value**
Epochs	100
Optimization Functions	Adam
Learning rates	0.001
Batch sizes	128
Accuracy	98.17

Table 4.2.1.1 shows the improved accuracy of the improved FNet model, where Epochs is 100, Optimization Function is Adam, Learning rate is 0.001, Batch size is 128, and achieved accuracy is 98.17.

4.3 Discussion

A confusion matrix is a table that shows how well a classification model performs on test data that contains known true values. Algorithm performance can be visually represented. The confusion matrix measures N x N, where N is the total number of target classes. Each matrix item represents the number of observations that are known to be in one class but are more likely to be in another. Examining a data classification algorithm's confusion matrix helps improve its effectiveness. The success rate of the algorithm is displayed in each cell of the matrix. Actual classes are in the rows, while anticipated classes are in the columns. True positives, or observations that were positively identified as belonging to the target class, appear in the matrix's upper left corner. False positives, or observations wrongly assigned to the target class, are displayed in the upper right cell. False negatives, or observations misclassified as not belonging to the target class, are displayed in the bottom left cell. The bottom-right cell in the matrix contains actual negatives.

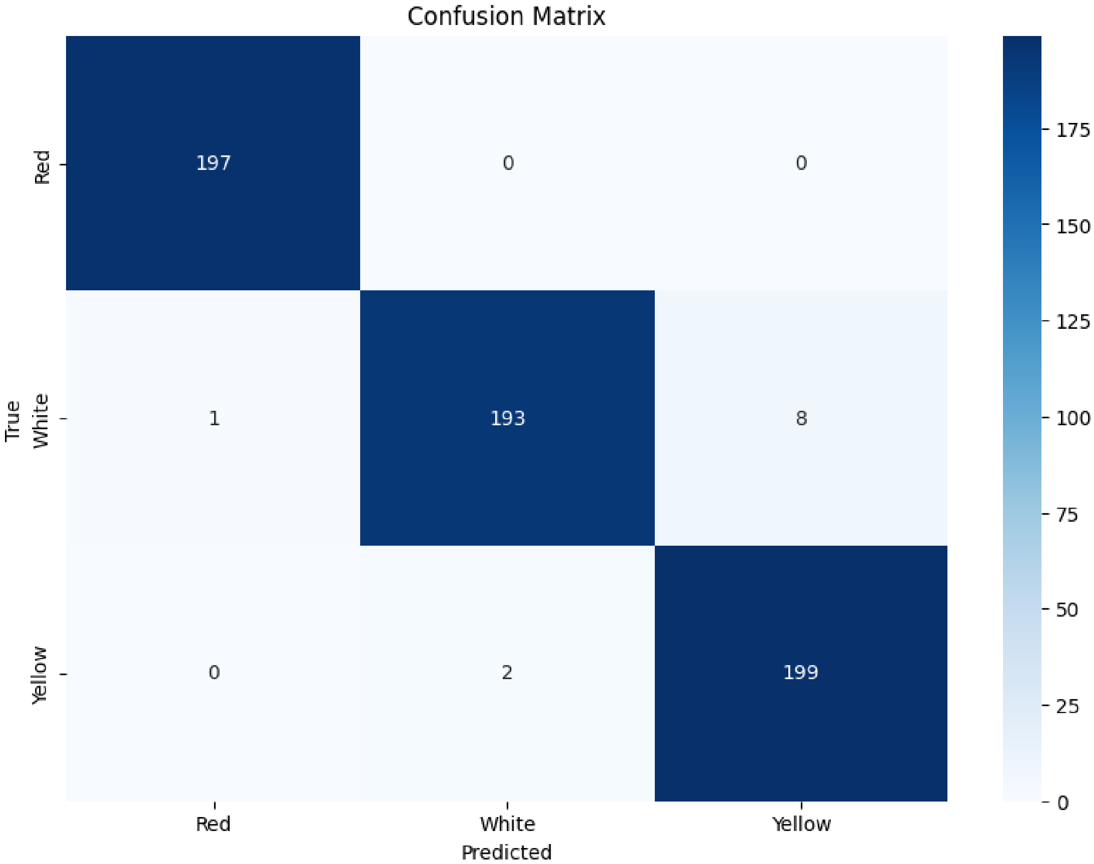

Fig 4.3.1: Confusion Matrix of the of the Rose Identification.

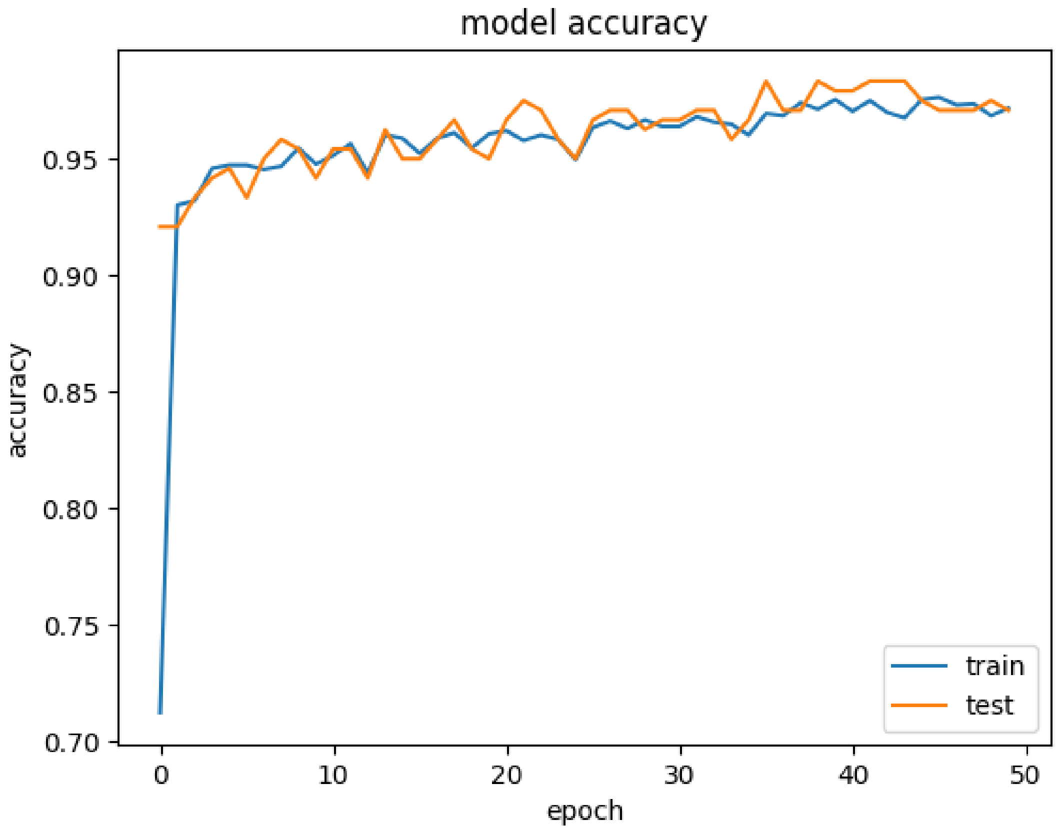

Fig 4.3.2: Accuracy Curve of the of the Rose Identification.

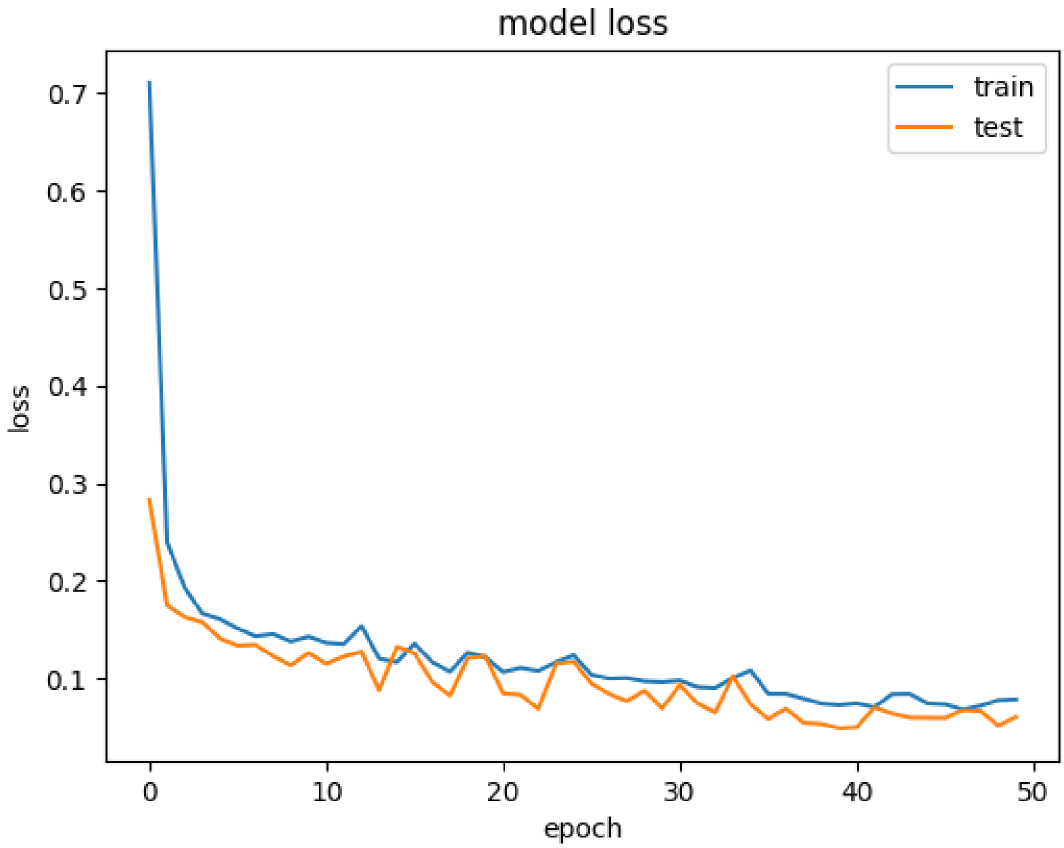

Fig 4.3.3: Loss Curve of the of the Rose Identification.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on society

The incorporation of deep learning models for rose identification in our research offers significant societal implications. This technology has the potential to democratize botanical knowledge by allowing people of diverse degrees of expertise to reliably identify and enjoy roses based on color characteristics. Aside from aesthetics, it may improve decision-making in the landscaping and floral industries, promoting economic efficiency. However, in order to ensure that society benefits are widely distributed, it is critical to address any gaps in access and knowledge distribution. Efforts should be directed towards making these advanced tools more widely available, encouraging diversity in horticulture, and closing knowledge gaps. Finally, enabling various populations with the tools and knowledge to engage with and benefit from the rich range of roses has a societal impact.

5.2 Impact on the environment

The use of deep learning models for rose identification, similar to uses in medical imaging, raises concerns about environmental effects. The computational demands of training and running these models can result in a significant carbon footprint, especially when using high-performance GPUs or CPUs for lengthy periods. The energy required for these operations leads to greenhouse gas emissions. Mitigating measures, such as refining algorithms for efficiency, adding renewable energy sources for data centers, and building models that use less data or computing power, can be used to solve these challenges. Furthermore, the use of deep learning models in rose identification could lessen the environmental impact of physical diagnostic tools and consumables. Reliable remote diagnostics might potentially reduce the requirement for patient travel, lowering environmental costs even further. As technology advances, more efficient and environmentally friendly calculating methods may develop, giving chances for significant reductions in the environmental footprint connected with deep learning applications in rose identification.

5.3 Ethical Aspects

The use of deep learning models in rose identification raises ethical concerns similar to those raised in medical applications. Patient privacy, data security, and algorithm dependability emerge as top priorities. It is critical to maintain the secrecy and security of the collected rose photos, as well as the transparency of the algorithms regulating the identification process. Ethical responsibility requires the removal of biases within datasets in order to avoid differences in the efficacy of technologies across varied groups. Patient trust is essential, needing durable and interpretable systems. There is an ethical need to create tools that allow for the challenge or correction of algorithmic choices, so increasing openness and accountability. By addressing these ethical factors, deep learning in rose identification can be aligned with values of privacy, justice, and trust, contributing to responsible and ethical advances in the field.

5.4 Sustainability Plan

A diverse method is required to ensure the long-term viability of deep learning applications for rose identification. Continuous algorithmic refining is required to avoid obsolescence and keep a cutting-edge approach. Ongoing training programs prioritize horticulturists' ethical and efficient use of deep learning technologies. Addressing environmental concerns, a commitment to renewable energy reduces the carbon impact, aligning with sustainability standards. Strategic partnerships with horticultural stakeholders promote collaboration, knowledge exchange, and environmentally responsible rose growing. This all-encompassing approach promotes long-term sustainability, ethical application, and environmental stewardship, resulting in a resilient ecosystem. The incorporation of deep learning models in rose identification becomes a beneficial force that benefits practitioners, enthusiasts, and the environment while developing sustainable rose cultivation techniques.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

This research investigates rose identification utilizing a dataset of 1700 raw photos divided into training (70%), validation (20%), and testing (10%) groups. The study investigates the effectiveness of state-of-the-art models, particularly EfficientNet, MobileNetV2, ResNet50, and FNet, in successfully categorizing roses based on visual features. The dataset is preprocessed to improve image quality, including Data Augmentation, Gamma Correction, and image resizing. The evaluation includes extensive indicators to analyze the performance of the models, allowing for a comparison examination. The study is powered by Python, TensorFlow, and Keras, using OpenCV for image processing and Scikit-learn for data preprocessing and model evaluation. The findings shed light on the effectiveness of transfer learning models in rose identification, with implications for horticulture, botanical study, and technological advances in plant species recognition.

6.2 Conclusion

Finally, our research highlights the usefulness of transfer learning models in the domain of rose identification, providing valuable insights into rose categorization based on visual features. Among the tested models (EfficientNet, MobileNetV2, ResNet50, and FNet), FNet emerges as the best option, with an astonishing accuracy of 98.17%. FNet's robustness underlines its potential for use in horticulture, botanical research, and landscaping. The proposed methodology, which includes a variety of preprocessing techniques and a thorough model evaluation, adds to the improvement of computer vision in plant species recognition.

6.3 Implication for Further Study

This study has some limitations that should be acknowledged. Due to the restricted diversity of the training data, the models trained on a specific rose dataset may have difficulty generalizing to more diverse datasets or addressing unusual rose types. The dataset's unequal distribution of classes may limit the models' ability to learn from less-represented classes. While noise reduction techniques are useful, any artefacts formed during the process may have an impact on model training and evaluation. Future research should address these constraints and look for innovative ways to improve the study's usefulness. The model's flexibility could be improved by expanding the dataset to include a greater range of people, traits, and scenarios. Dynamic preprocessing approaches that respond to changing image attributes could improve model resilience. Investigating ensemble models and applying explainability approaches could increase model performance and interpretability overall. A valuable next step would be to go from offline evaluation to real-time clinical applications, which would necessitate consideration to computational efficiency and deployment difficulties. Addressing these limits and pursuing these future goals would strengthen and extend the study's contributions, promoting developments in the field of rose identification models and botanical research.

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