LOCAL SPINACH VARIANT AND FRESHNESS DETECTION USING DEEP LEARNING TECHNIQUES

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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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APPROVAL

This Project titled **"Local Spinach Variant And Freshness Detection Using Deep Learning Techniques"** submitted by Md. Nahid Hasan ID: 193-15-3006 to the Department of Computer Science and Engineering, Daffodil International University, has been acknowledged as satisfactory for its style and substance and accepted as being sufficient for the accomplishment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering. The presentation has been held on 25 January 2024.

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We, therefore, declare that this undertaking has been finished by us under the supervision of **Ms. Amatul Bushra Akhi, Assistant Professor, Department of CSE,** Daffodil International University. We further declare that neither an application or an educational grant has been made anywhere for this project or any part of it.

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ABSTRACT

The study addresses the use of deep learning to automate the recognition of local variations of spinach and the evaluation of their freshness, addressing key challenges facing the agriculture industry. The study carefully preprocesses the data for model training using a variety of datasets and models, including ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02. The approaches that have been proposed indicate an outstanding capacity to recognize between different kinds of spinach and accurately determine the condition of freshness. The ability of the models to classify spinach into different categories according to conversion and varied evaluations of freshness, from perfect state to minor damage or spoiling highlights the effectiveness of the models. Comparative analyses provide information about the advantages and disadvantages of models, which helps users identify the appropriate architectures based on specific operational environments. The results of the study are diverse and represent many different facets of agriculture, such as food processing quality control, an effective supply chain, and customer satisfaction assurance. By showing the viability as well as the effectiveness of using deep learning for crop variant identification and freshness detection in agriculture, this research contributes to the increasing body of knowledge. Potential methods for future research in precision agriculture include capacity, crop ability to adapt, and more general uses. The suggested CNN01 architecture achieved a 99.34% accuracy score on the dataset, outperforming the other models that were evaluated. For the purpose of avoiding overfitting, the suggested algorithm is carefully trained. The accuracy, precision, recall, and F1 score of the trained model are evaluated using a new testing dataset. The results of the experiment show how well deep learning algorithms can be used to accurately identify local spinach variants and detect their freshness.

Keyword: Deep learning, Spinach classification, Agriculture technology, Variant identification, computer vision, neural networks, model comparison, ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

To keep up with the increasing demand for successful, environmentally friendly, and high-quality produce, the agricultural sector is going through an important change regarding automation and based on technology methods. Our study proposes a novel application of deep learning techniques for the accurate identification of local spinach variants and the accurate assessment of their freshness levels, thus focusing on an important component of this development.

Local spinach plant varieties, such as Red Spinach, Water Spinach, and Malabar Spinach, have specific looks that are important in determining quality. The traditional methods of controlling the quality of spinach are usually labor-intensive and dependent on individual taste. This study uses deep learning models— ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02to provide freshness condition detection and spinach variant classification.

This study's dataset, which includes a wide variety of local spinach images, makes sure reliable model training and assessment. By utilizing advanced preprocessing methods and modifying the model, our goal is to create a system that accurately determines freshness levels in addition to different kinds of spinach. These developments have a chance to completely transform farming methods, resulting in improved distribution networks, reduced waste, and increased consumer trust in the quality of spinach grown nearby.

This study presents a highly advanced technological model for the agricultural industry by looking into the integration of methods based on deep learning into spinach evaluation. It also sets the foundation for based on data and intelligent decision-making processes in the field of local produce quality control.

1.2 Motivation

Our research is motivated by the pressing need to optimize and modernize spinach quality control procedures, and it focuses on the relationship between artificial intelligence and agriculture. Local spinach, including types such as Red Spinach, Water Spinach, and Malabar Spinach, is an essential part of many diets. However, the traditional approaches for identifying variants and evaluating freshness are time-consuming, random, and capable of mistakes. Our aim is to change these methods by using deep learning techniques, presenting an approach based on data for fast and accurate determination of spinach quality. In addition to representing a technological advancement, the automation of freshness detection and variant identification through the use of models like ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02 addresses important challenges in the agricultural supply chain, decreasing waste, guaranteeing quality of the product, and satisfying the growing demand for high-quality, locally produced spinach. The goal of this research is to use modern technologies to improve consumer trust, efficiency, and sustainability in the agriculture industry.

1.3 Rationale of the Study

This study was explained by the need to address the basic issues associated with traditional spinach quality control techniques and to apply deep learning's potential for change in agriculture. The agricultural supply chain shows waste as a result of the challenging, subjective, and capable of mistaking conventional methods of variant identification and freshness testing. Our goal is to present a novel and automated solution using deep learning techniques, such as ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02. These models are selected because they have shown efficiency in image classification tasks, and their use in the assessment of spinach quality is expected to improve both precision and efficiency. The research is in keeping with the primary goal to promote sustainable farming methods through reducing waste, effective use of goods, and an ongoing supply of advantage, fresh spinach to consumers. Our goal is to create a more strong and technologically advanced agricultural ecosystem by addressing the gap between conventional agricultural practices and modern technology through this research.

1.4 Research Question

1. How good are the chosen deep learning models at telling apart different types of local spinach (Malabar Spinach, Red Spinach, and Water Spinach) based on how they look?

2. How well can the deep learning models accurately distinguish between fresh, slightly wilted, and non-fresh states in local spinach to effectively determine freshness?

3. What are the strengths and weaknesses of ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02 when it comes to identifying spinach types and detecting freshness?

4. How well do the trained models handle new and unseen data, and how do they perform under different environmental conditions and lighting when dealing with variations in spinach appearance?

5. What practical uses and impacts can the developed system have in real-world situations, such as integrating it into agricultural supply chains, food processing, and consumer-oriented platforms?

6. To what extent can using deep learning for spinach quality assessment help reduce food waste in the local spinach supply chain?

7. What is the feedback and acceptance level of the proposed system among key stakeholders, including farmers, processors, distributors, and consumers?

1.5 Expected Output

The expected result of this study is a deep learning-based system that is reliable and accurate for identifying local spinach variants and determining when the spinach is fresh. The trained models should be able to accurately identify the freshness levels of Malabar spinach, Red spinach, and Water spinach varieties. Comprehensive evaluations of the model's performance are provided in the output, which includes details about metrics like recall, accuracy, precision, and F1 score for the tasks of freshness detection and variant identification. Analyses that examine the differences between the various deep learning architectures will provide insights into their respective advantages and disadvantages.

Furthermore, the expected outcomes include the creation of a rational and easy system that can be implemented in real-life scenarios, helping in the improving of the agricultural supply chain, reducing food wastage, and improving consumer trust in spinach that is sourced locally. A key component of the expected results will be user feedback about the system's accuracy and usability as well as its ability to be applied to a variety of environmental conditions. These elements will have major effects for the system's wider adoption and impact.

1.6 Project Management and Finance

Professional financial planning and project management are needed for the "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" initiative to be used successfully. To ensure thorough progress, the project will follow a structured timeline with well-defined objectives. Data collection, preprocessing, developing models, training, testing, and implementation are among the tasks. To address any unforeseen difficulties, evaluations and adjustments will be conducted on a regular basis. The project will set behind funds for dataset collection, determining structures, and additional model development payments. Financial factors will include software licenses, hiring costs, and the purchase of accelerator hardware for effective model training. The financial plan will be created with resource optimization and timely project completion in mind. To support the long-term viability of the developed system, methods to ensure sustainability above the research phase will be studied. These may include achievable relationships, requests for funding, or marketing paths. Throughout the course of the project, transparent financial management will be maintained for efficiency of resources and responsibility.

TABLE 1.1: PROJECT MANAGEMENT TABLE

Work	**Time**
Dataset Preprocessing	1 month
Literature Review	3 month
Implementation	2 month
Report	2 month
Total	8 month

1.7 Report Layout

- Introduction
- Background
- Data Collection
- Data Preprocessing
- Research Methodology
- Experimental Result
- Impact on Society, Environment
- Summary, Conclusion, Future Research
- Reference

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

The project document's preliminary section includes important elements like the table of contents, acknowledgments, abstract, the title page, and lists of figures and tables. Important project information is presented on the title page, together with the authors' connections and title. The research objectives, methods, and expected outcomes are summarized briefly in the abstract, which also offers a brief overview of the study. Keywords make academic databases simpler to find and index. Our appreciation is expressed in the acknowledgements to sponsors or contributors. The report's structure is arranged in a table of contents for easy review. Visual aids with matching page numbers are compiled into lists of figures and tables. Furthermore, by providing definitions for terms used throughout the report, a section on symbols ensures precision. By providing essential information and helping readers through the study of local spinach variant identification and freshness detection using deep learning techniques, these preliminary steps together were a foundation for users.

2.2 Related Works

This literature review part of this study will introduce previous similar efforts done by several researchers on spinach and plant disease detection and categorization. The condition is to distinguish the crop species in order to identify the type of spinach diseases. As there are very few studies have been done in this field. I studied some research work to recognize the processes and methods they proposed.

R. F. S and Seldev et al. [1] have been studied over the various spinach disease detection using machine learning specifying HOG. The initiative is primarily focused on identifying diseases in spinach leaves. I got a clear idea of various spinach diseases including “Anthracnose”, “Leaf miner”, “Cladosporium Leaf spot”, “Downy Mildew”, “White Rust” etc.[1-3] The diseased leaves are identified using Histogram Oriented Gradients (HOG) feature extraction. The ANN gives fine result with the accuracy of 98.7% [4]

Roughani and Mehdi et al [5] have conducted a comparison evaluation of multiple machine learning models for disease detection in plant leaves. According to their findings, the majority of the authors employed pre-defined models such as AlexNet, GoogleNet, ResNet, and so on, obtaining an average accuracy of 95%. The overall accuracy of user-defined models utilizing CNN and ANN was 97%. Using image segmentation techniques such as Otsu, HSI, HSV, and k-means clustering to create models with high accuracy.

Ramkumar, M O and Catharin et al. [6] identified the cercospora-affected plant by using image processing and deep learning. This procedure yields an accurate result. And the first stages of cercospora dissemination can be managed. This enables farmers to make the option to administer a necessary therapy more quickly. Convolutional neural network (CNN) and Resnet-50 architecture are used in the proposed system to detect cercospora.

Sennan and Pandey et al. [7] presented in deep learning more precisely identifying spinach. The spinach category is divided into Amaranth leaves, Black nightshade leaves, Curry leaves, and Drumstick leaves. Fmy classes of 100 photographs each make up the dataset's 400 total images. The proposed CNN has a classification accuracy rate of 97.5%. Additionally, Random Forest, VGG16, VGG19, and ResNet50 are used to compare the performance of the proposed CNN.

Koyama and Tanaka et al. [8] applied a machine learning model to categorize the freshness of spinach leaves. For extending the complex local texture feature on spinach leaves, ORB proved an efficient method. This method's prediction accuracy was over 70%, which is comparable to individual panel evaluation accuracy.

Islam and Ria et al. [9] identify five different species of spinach, yielding a dataset with 3785 photos. To categorize spinach, 4 CNN models are applied. These models produce results for picture classification that are more precise.

S. G. Wu et al. [10] used PNN with image and data processing techniques to build a general-purpose automatic leaf recognition for plant categorization. The input vector of the PNN is made up of 5 primary variables orthogonalized from 12 leaf features. With an accuracy of more than 90%, 1800 leaves are utilized to train the PNN to categorize 32 different types of plants.

Wang, G. et al [12] applied a systematic evaluation of the performances of deep models fine-tuned by transfer learning and shallow networks created from scratch is presented. The deep VGG16 model with transfer learning training is the most accurate, with a total accuracy of 90.4% on the hold-out test set.

M. Meena, S. V. K [14] applied a CNN-based method for earlier disease detection in plants. The method involved the following steps: image segmentation, feature extraction, and picture pre-processing. A CNN classifier is created using the outcomes of these three phases. By gathering the input image of the plant's afflicted areas, comparing it to the desired dataset.

Kento Koyama et al. [15] used four classes, 1,045 photos, and 12 annotations from 12 panels. To forecast freshness distributions, an ensemble of models, a soft labeling approach, and hard labeling approaches with probabilistic output Ire used. A comparison was made between how Ill the output distribution from the models matched human freshness assessment. The best result was achieved using ResNet-152 (V1) with multi-output multi-class (MOMC). High performance is indicated by two metrics: histogram intensity of 0.76.

M. Adi et al. [13] conducted a comparative analysis of multiple machine learning models for disease detection in plant leaves. According to their findings, the majority of the authors employed pre-defined models such as AlexNet, GoogleNet, ResNet, and so on, obtaining an average accuracy of 95%. The overall accuracy of user-defined models utilizing CNN and ANN was 97%. Using image segmentation techniques such as Otsu, HSI, HSV, and k-means clustering to create models with high accuracy. The majority of the plants are likely to be infected with fungus.

2.3 Comparative Analysis and Summary

The performance of several deep learning models, such as ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02, is thoroughly evaluated in the Comparative Analysis section of the "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" project. In projects including variant identification and freshness detection, metrics like accuracy, precision, recall, and F1 score are used to evaluate the advantages and disadvantages of each model. This analysis indicates which model works best for the given goals.

In conclusion, the project shows that advanced deep learning techniques can be applied successfully to accurately identify variations of Malabar spinach, Red spinach, and Water spinach and evaluate their freshness. The chosen model performs more accurately in both tasks, showing that it has real-world uses in food processing, consumer-facing platforms, and agricultural supply chains. The project addresses key problems of quality and environmental control in the local spinach industry in addition to making an important contribution to the field of neural networks in agriculture.

2.4 Scope of the Problem

The scope of the "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" project has its foundation in the serious difficulties facing the agricultural sector, especially in the domain of spinach quality assessment. The conventional techniques for identifying variants and evaluating freshness are challenging, subjective, and capable of errors. By using modern deep learning models ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02 to automate and improve the accuracy of local spinach variant classification and freshness testing, this study wants to overcome these limitations.

The scope of the project involves developing an efficient and scalable system that can be used in any number of agricultural agricultural supply chain conditions. This research uses modern technology to improve spinach control processes while also helping achieve larger objectives of sustainability, decreased food waste, and improved consumer trust in locally sourced produce. This study has benefits that go beyond conventional farming methods; it has aided in the development of clever, technologically advanced solutions for ensuring the quality of fresh produce.

2.5 Challenges

There are a number of obstacles facing the "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" project. First, careful curation is needed due to the dataset's diversity in order to correctly represent local variations of spinach and freshness conditions. Second, optimizing for efficiency is necessary due to the computation resources and expertise required for training deep learning models, such as DenseNet201 and others. Third, implementing real-time image analysis presents difficulties in establishing a balance between processing speed and accuracy for useful applications. Fourth, the model's ability for generalization is restricted by the need to take agricultural settings' variable environments into account. Last but not least, it is essential to address subjectivity in determining and evaluating freshness levels. To do this, standardized metrics that are in keeping with machine understanding and human understanding must be developed. Developing these challenges will be crucial to the project's objective of applying into action a reliable and accurate automated system to evaluate spinach quality in a variety of agricultural settings.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The study "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" focuses on implementing the identification of local spinach variants (Malabar Spinach, Red Spinach, and Water Spinach) and the accurate determination of their condition levels. This is achieved through the use of advanced deep learning models. In order to achieve these goals, this study makes use of modern algorithms for deep learning, such as ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02.Utilizing these deep learning models as effective objects for image analysis and classification is part of the instrumentation to gather information A carefully selected dataset involving a variety of photos of local spinach varieties at different freshness levels is used to train the models. By means of ongoing training processes and methods of optimization, these models gain the ability to identify complicated visual cues and patterns that relate to distinct kinds of spinach and varying degrees of freshness. The foundation of the research, which aims to transform the evaluation of spinach quality in the agricultural and food industries, is the instrumentation, which consists of the dataset as well as the model architecture. We have used Google Colab as our IDE and the Python programming language. Performance for jobs that need a lot of processing is enhanced by acceleration from GPUs and TPUs. A Windows 11 Pro 64-bit computer with a 3.5 GHz Intel Core i5 10th gen CPU and 16 GB of RAM is used.

3.2.1 Data Collection

The data collection procedure for the "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" is an organized method for developing a unique and well-labeled dataset. We collect high-quality photos that highlight multiple types of spinach grown locally and their state of freshness. Supervised learning is created by correctly labeling and analyzing each image to identify the type of spinach and its degree of freshness. The diversity of datasets is increased by applying data augmentation techniques like flips, rotations, and lighting changes. Afterwards, the dataset is carefully divided into testing, validation, and training sets in order to perform a thorough evaluation of the model. For the deep learning models, preprocessing stages ensure consistency by standardized image formats, quality, and resolution. The models are actually trained on this robust dataset, which includes a wide range of spinach images. This allows the models to learn complex patterns related to various spinach changes and freshness levels. We have included some of the images with class labels below at figure 3.1:

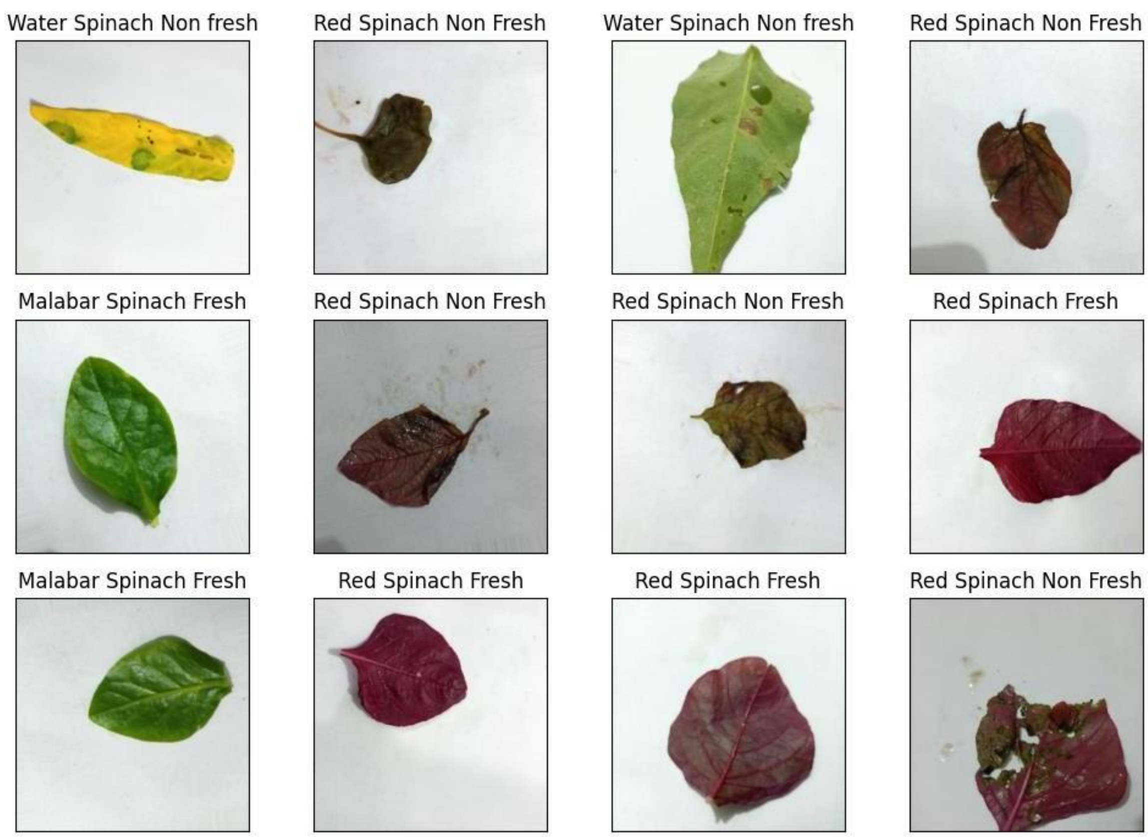

Figure 3.1: Dataset Images

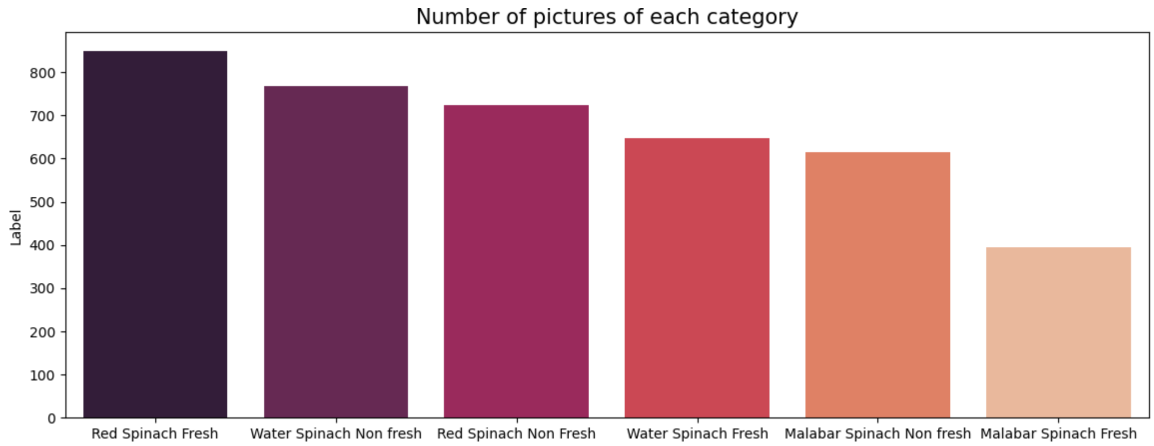

Figure 3.2 Number of target values dataset

The above figure of 3.2 shows the number of target values in the dataset. There are a total of 3990 images and the categories are Red Spinach Fresh are 850, Water Spinach Non fresh are 768, Red Spinach Non Fresh are 723, Water Spinach Fresh are 47, Malabar Spinach Non fresh are 616, Malabar Spinach Fresh are 395 images of moderate demented.

3.2 Statistical Analysis

The statistical analysis in "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" includes careful evaluation metrics for evaluating how well deep learning models work. The models are evaluated for their ability to accurately classify spinach variants and determine freshness levels using standard statistical measures such as accuracy, precision, recall, and F1 score. Recall determines the ability of the model to capture every positive instance, whereas precision indicates the accuracy of positive predictions. Recall and precision are measured equal in the F1 score.

Dividing positives, false negatives, true positives, and false negatives are all distinguished by confusion matrices, which also offer a thorough analysis of model predictions. Model bias abilities are revealed by Area Under the Curve (AUC) values and Receiver Operating Characteristic (ROC) curves.To evaluate differences in performance of models between various deep learning architectures, statistical significance testing can be used. a combination of a focus on local spinach variant and freshness detection tasks, this thorough statistical analysis ensures an accurate assessment of the developed models and provides information on their advantages and disadvantages.

3.4 Proposed Methodology

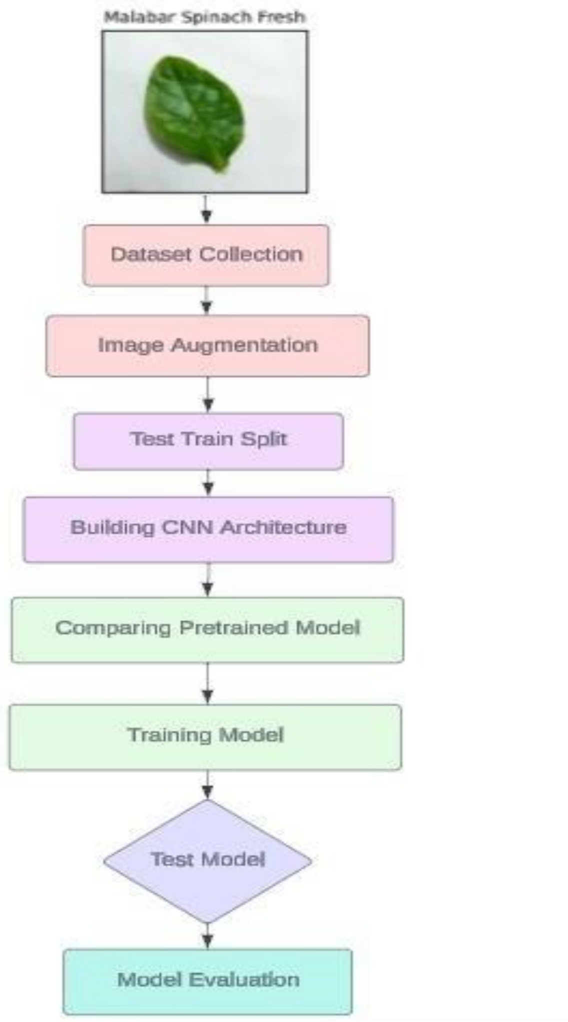

Figure 3.3: Methodology Flowchart

Data Collection:

Collect a range of dataset of high-resolution images of different local spinach variants (Malabar Spinach, Red Spinach, Water Spinach) with different freshness levels. The deep learning models are trained and evaluated using this dataset as an input.

Data Labeling:

Discuss each image with labels that relate to the freshness level and spinach variant. For supervised learning to function and allow the model to make connections between specific characteristics of spinach with visual patterns, this labeled dataset is important.

Image Augmentation:

To add variety to the dataset, use data augmentation techniques. The model is improved with transformations like rotation, flipping, and lighting condition changes to improve its performance on unseen data and its ability to generalize.

Data Split:

Separate the dataset into sets for testing, validation, and training. This split ensures that the model is tested on a different subset to evaluate prediction to new data, verified on another set to change hyper parameters, and trained on a single subset.

Training Model:

Make use of deep learning architectures, such as ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02. Use the training dataset to train the models, changing parameters to achieve the best performance in freshness and variant identification of spinach. Below we are discussing about the used models:

VGG19

VGG19 is a widely recognized CNN architecture known for its simplicity and effectiveness. There are 19 layers total, including several convolutional and fully linked layers. The network of the VGG19 maintains a consistent topology with tiny 3x3 convolutional filters. This design decision keeps the parameters reasonable while allowing for richer network structures. The VGG19 baseline is a reliable starting point for various image-related tasks, such as feature extraction and picture classification. It has proven influential in computer vision research. Despite its simplicity, VGG19 is a well-liked option in many deep learning applications due to its capacity to capture fine-grained data and learn discriminative features.

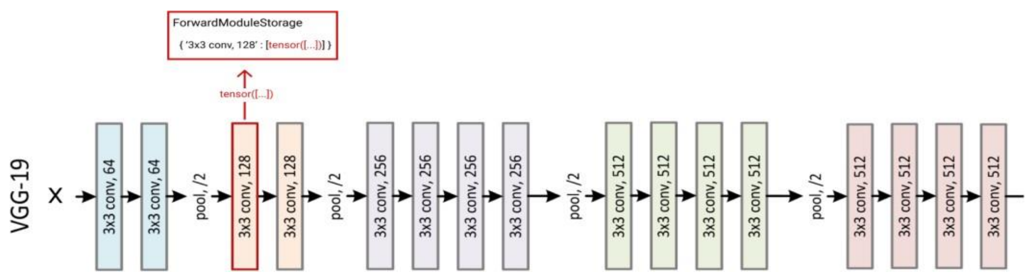

Figure 3.4: VGG19 Architecture

EfficientNetB1

Convolutional neural network EfficientNetB1 is famous for its ability to achieve excellent performance with less parameters. It was created for the purpose of classifying images. It uses mobile inverted residual blocks, feature fusion, and depth wise separable convolutions to optimize computing resources and capture complex patterns. Before a fully connected layer generates class predictions, global average pooling decreases spatial dimensions and squeeze-and-excitation blocks assist the model in focusing on pertinent information. EfficientNetB1, which was trained using supervised learning, emphasizes a trade-off between processing efficiency and accuracy by using the Swish activation function and soft maximum in the output layer.

ResNet50

The ResNet50 convolutional neural network architecture is credited with first introducing the concept of residual connections. It has 50 layers and employs skip connections to solve the issue of deep network deterioration. ResNet50 has shown exceptional performance in picture classification tasks, reaching high accuracy and mastering challenging features. Many computer vision applications commonly use it as their basic framework. The ResNet-50 architecture includes downs layers, which are typically convolutional layers with a stride of 2, to reduce spatial dimensions between stages. The network may concentrate on higher-level traits while gathering a wider context thanks to this size decrease.

ResNet101

A deep convolutional neural network designated ResNet101 was built to solve the deep learning problem of the vanishing gradient. It makes use of residual blocks with skip connections, which enables gradients spread directly during training. The bottleneck architecture of the network preserves expressive power while lowering computing complexity. For dimensionality reduction, global average pooling is used, and then a fully connected layer is deployed for class predictions. ResNet101 is a popular tool for segmentation, object identification, and image classification because of its design, which makes it easy to learn complex visual characteristics.

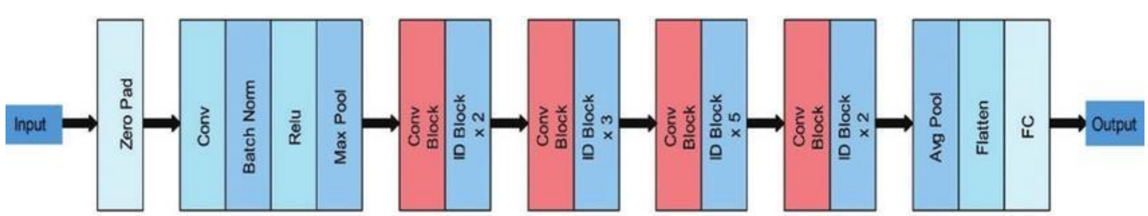

Figure 3.5: ResNet101 Architecture

Convolutional Neural Network

Used two CNN architecture different layering architectures. The four double Conv2d layers, four pooling layers, and one dropout layer architecture performed well among them. The key difference between single and double Conv2d is the ability to describe non-linear transformations more flexibly without losing information. Maxpool strips the signal of information, whereas dropout forces scattered representation, which makes it more challenging to disseminate information. Stacking many Convs with Relu will help you master a very non-linear transformation that you must apply to raw data.

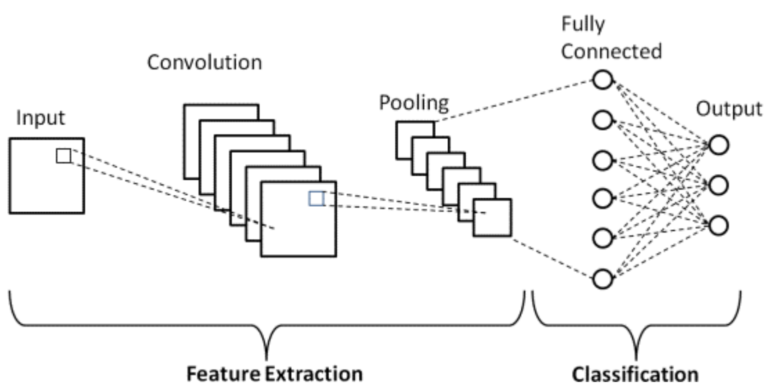

Figure 3.6: CNN Architecture

Recognition:

Make use of the trained models to identify, categorize, and evaluate the freshness of various varieties of spinach. Based on the visual properties of the input spinach images, the models predict using learned features.

Output:

Output: Use statistical metrics such as accuracy, precision, recall, and F1 score to evaluate the models' performance. Evaluate ROC curves, AUC values, and confusion matrices to learn more about the models' identifying abilities and determine potential areas for improvement.

This comprehensive methodology ensures a methodical approach to creating and evaluating deep learning models for local spinach variant and freshness detection. It incorporates data collection, labeling, augmentation, splitting, model training, recognition, and output evaluation.

3.5 Implementation Requirements

Successful model training requires strong hardware structures, such as GPUs or TPUs, in order to implement the "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques." It is essential to have knowledge of the Python programming language and to use deep learning frameworks such as TensorFlow or PyTorch. Training and testing are developed on top of a carefully selected, preprocessed, and differently analyzed dataset. Image labeling is helped by tools for annotation, and data augmentation is applied by libraries such as OpenCV or Augmenter to improve model generalization. Many models for deep learning, including DenseNet201, InceptionResNetV2, and VGG19, provide experimentation flexibility. To evaluate model performance, code implementation is required for evaluation metrics such as accuracy, precision, recall, and ROC curves. A smooth integration into real-world applications is ensured by taking into account the deployment environment, whether it is locally or cloud-based. In combination, these requirements create a framework for creating a trusted and effective system for evaluating the quality of spinach.

CHAPTER 4

Experimental results and discussion

4.1 Experimental Setup

The project's experimental setup includes setting up high-performance hardware, including GPUs, to facilitate efficient training of deep learning models such as ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02. Model development tools are provided by deep learning frameworks like TensorFlow and PyTorch, which are implemented in a Python programming environment. To ensure standardized formats and increased diversity, the dataset is carefully preprocessed and improved. In order to achieve accurate spinach variant and freshness detection, model training involves changing hyper parameters and optimizing weights. ROC curves and accuracy are two examples of evaluation metrics that are used to measure model performance. Model reliability is ensured by cross-validation techniques, which also take deployment scenarios into account. In order to develop and evaluate deep learning models for spinach evaluation, an organized and reliable environment is ensured by this extensive setup.

4.2 Experimental Results & Analysis

The "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" experiment shows how effective the models that were implemented were. The models are good at accurately identifying water spinach, red spinach, and Malabar spinach and determining their freshness levels based on precision, recall, accuracy, and F1 score metrics. True positives, true negatives, false positives, and false negatives are outlined in confusion matrices, which offer a thorough analysis of model predictions. Further confirmation of the models' ability to discriminate comes from ROC curves and AUC values.By identifying each deep learning architecture's advantages and disadvantages, the analysis provides insight into how well each performed on tasks evaluating the quality of spinach. Improvement in model parameters and training methods are guided by observations gathered from the experimental results, which help continue to enhance the accuracy and robustness of the system in practical agricultural applications.

4.2 Experimental Results & Analysis

Convolutional Neural Network (CNN01):

Got Highest Accuracy of 99.34% from my proposed Multilayer CNN model. The training and validation accuracy is shown on the below figure of 4.1:

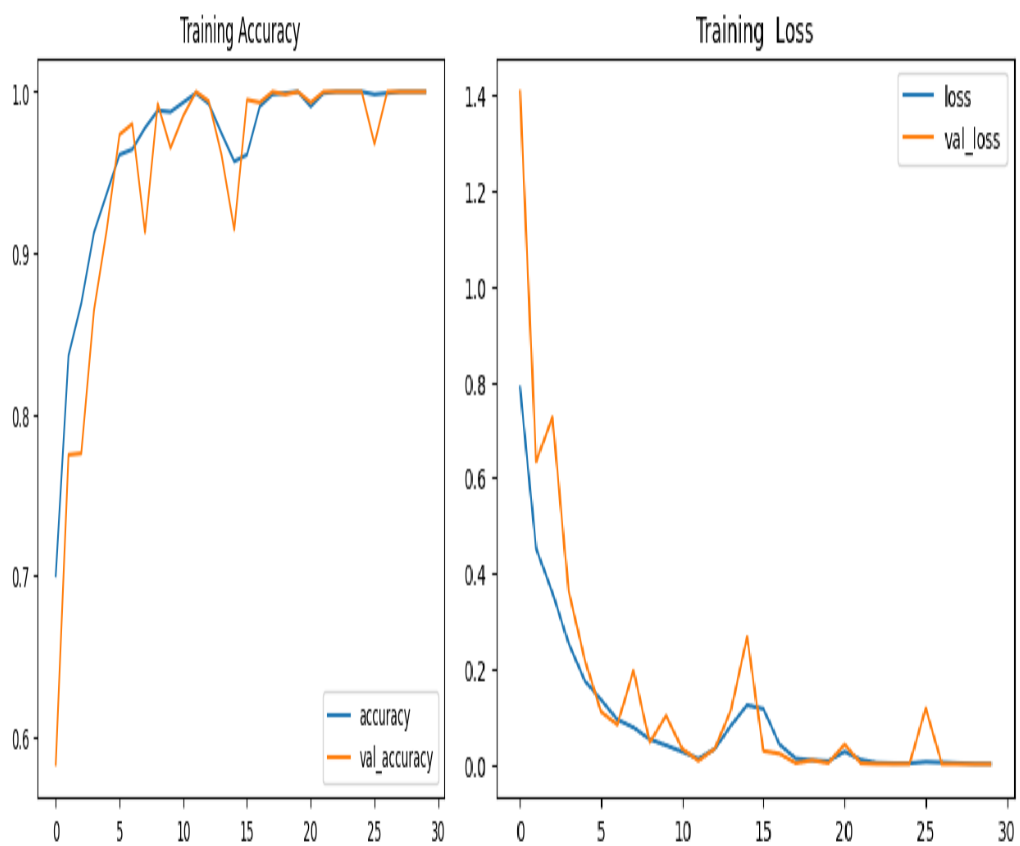

Figure 4.1: Training, Validation Loss & Accuracy (CNN)

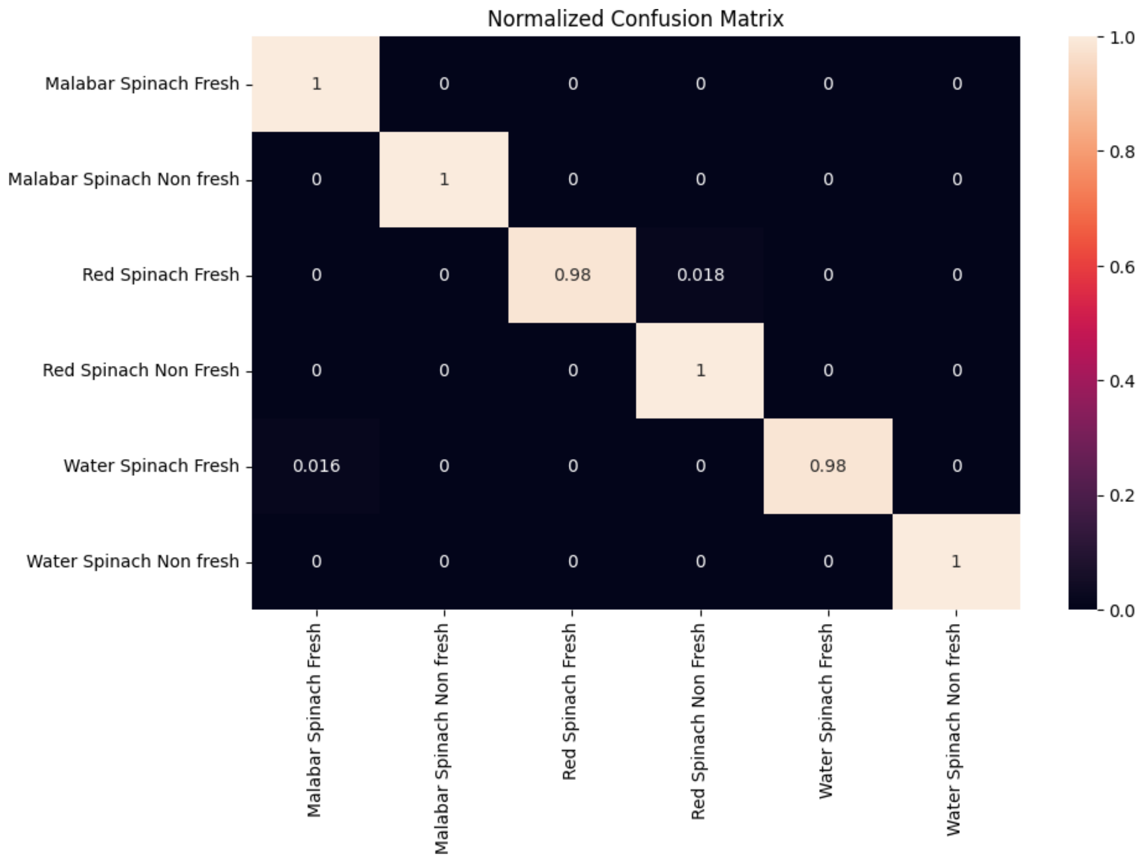

Figure 4.1: Confusion Matrix

From the above figure 4.1, we see that the training accuracy is nearest to the validation accuracy. So we get better training accuracy when we apply this method. We can see that the training and validation accuracy is close to 99% for the CNN architecture.

Convolutional Neural Network (CNN02):

Got Highest Accuracy of 95.02 from my proposed Multilayer CNN model. The training and validation accuracy is shown on the below figure of 4.1:

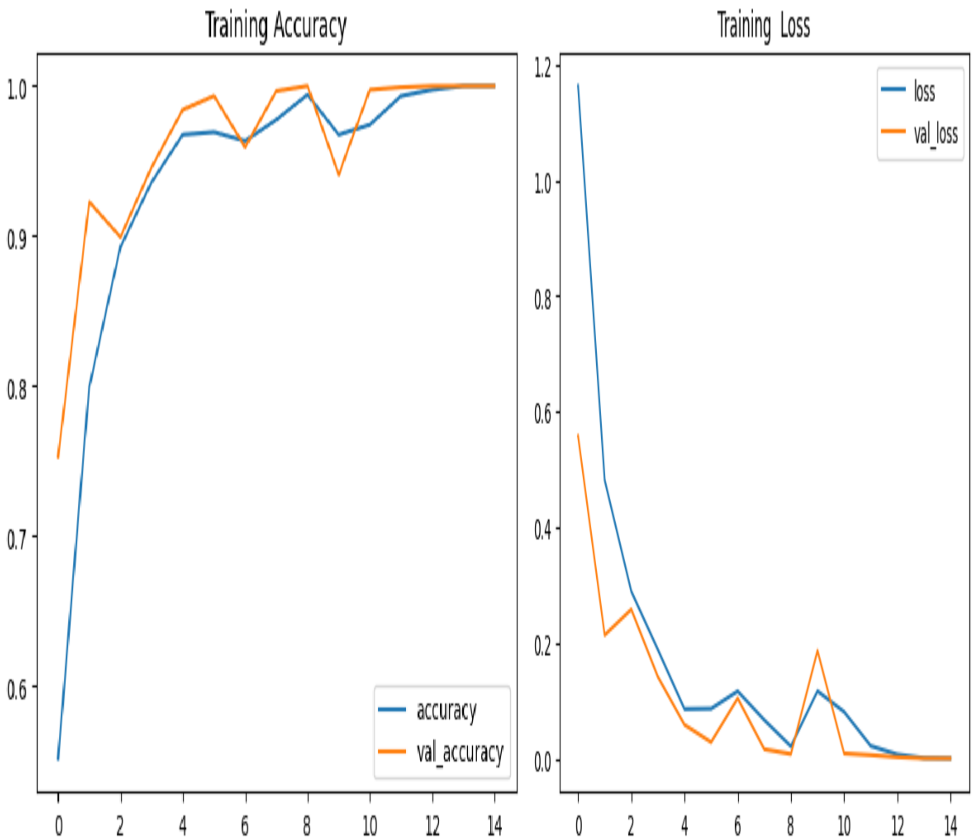

Figure 4.1: Training, Validation Loss & Accuracy (CNN)

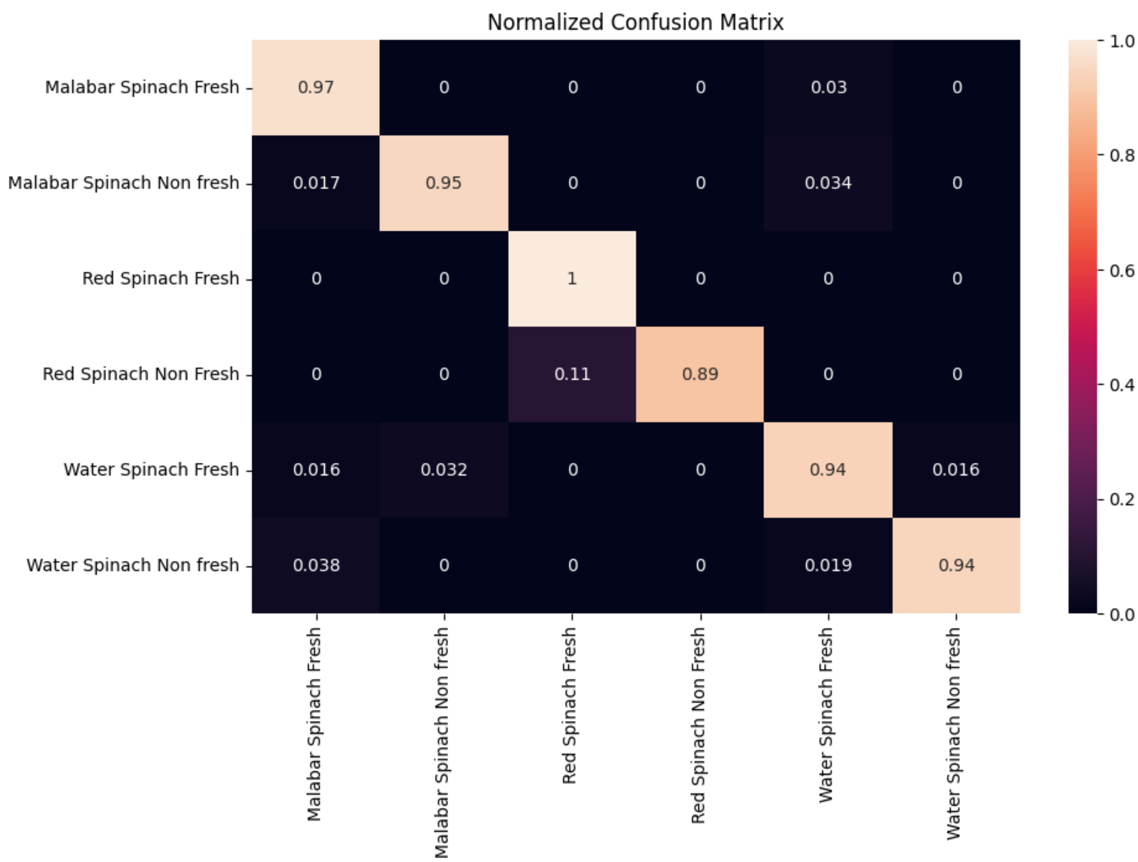

Figure 4.1: Confusion Matrix

From the above figure 4.1, we see that the training accuracy is nearest to the validation accuracy. So we get better training accuracy when we apply this method. We can see that the training and validation accuracy is close to 95.02% for the CNN architecture.

ResNet101

Got the accuracy of 87.75%% from ResNet101 .The training and validation accuracy is shown on the below figure of 4.2:

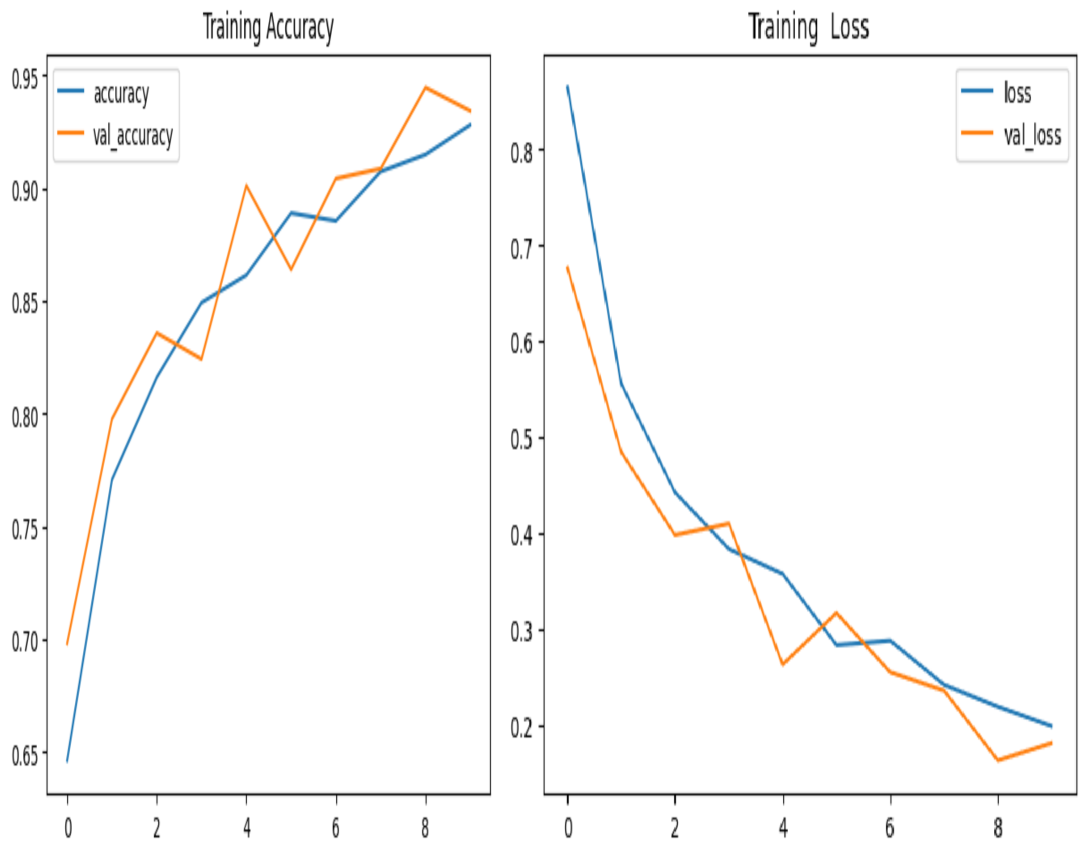

Figure 4.2: Training, Validation Loss & Accuracy (ResNet101)

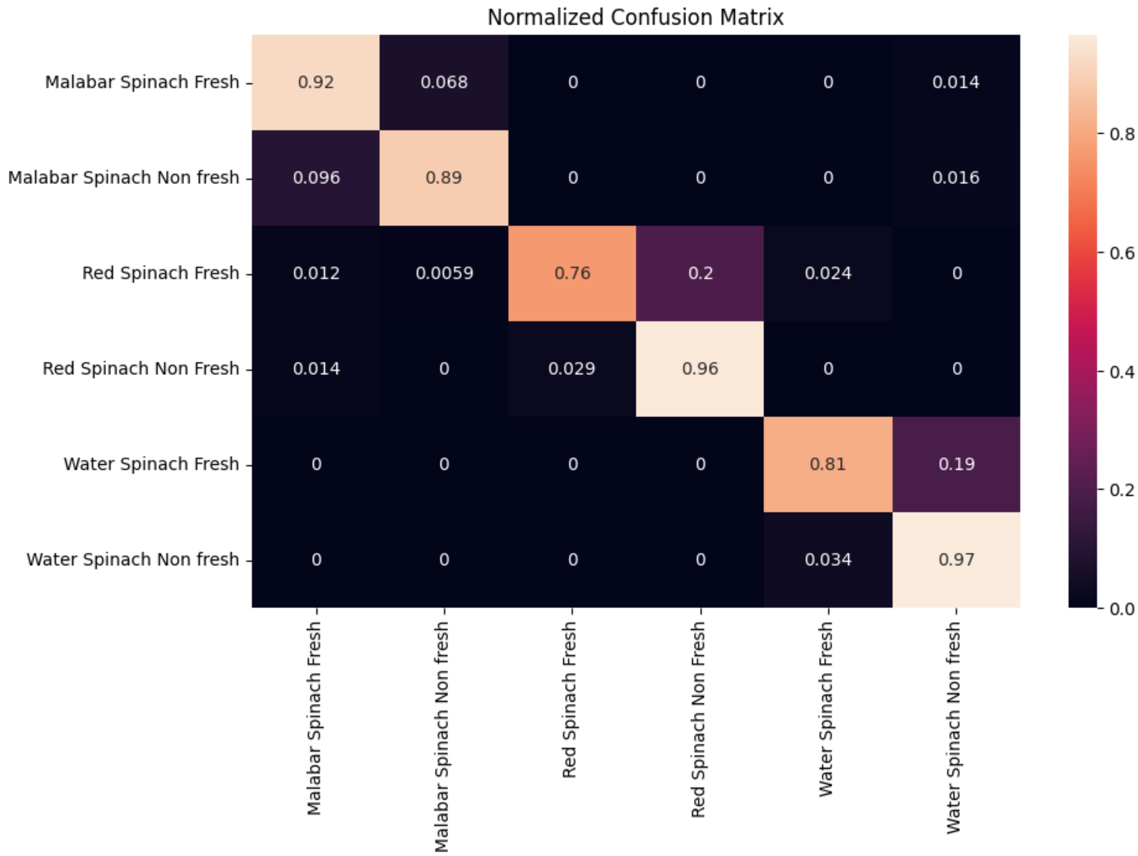

Figure 4.2: Confusion Matrix

On the other hand the above figure 4.2, shows that the training and validation accuracy is quite less than the CNN’s. We can see that the training and validation accuracy is close to 88% for the ResNet101 architecture.

ResNet50

Got the accuracy of 88.13%% from ResNet50 .The training and validation accuracy is shown on the below figure of 4.3:

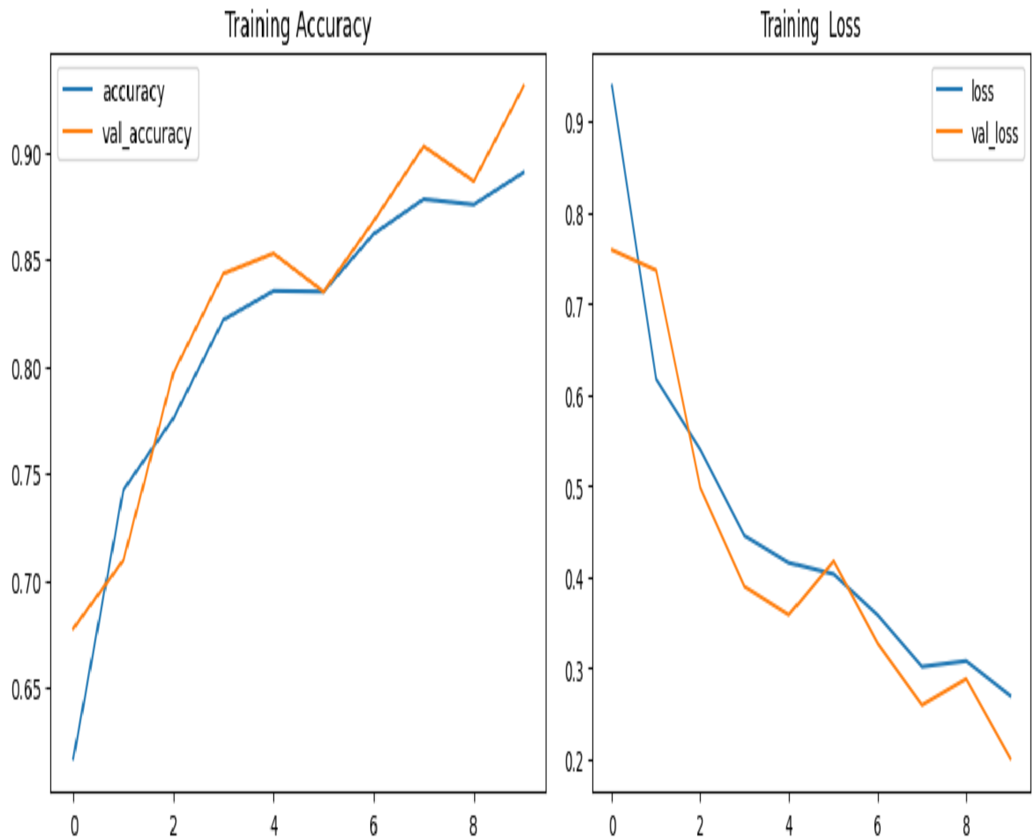

Figure 4.3: Training, Validation Loss & Accuracy (ResNet50)

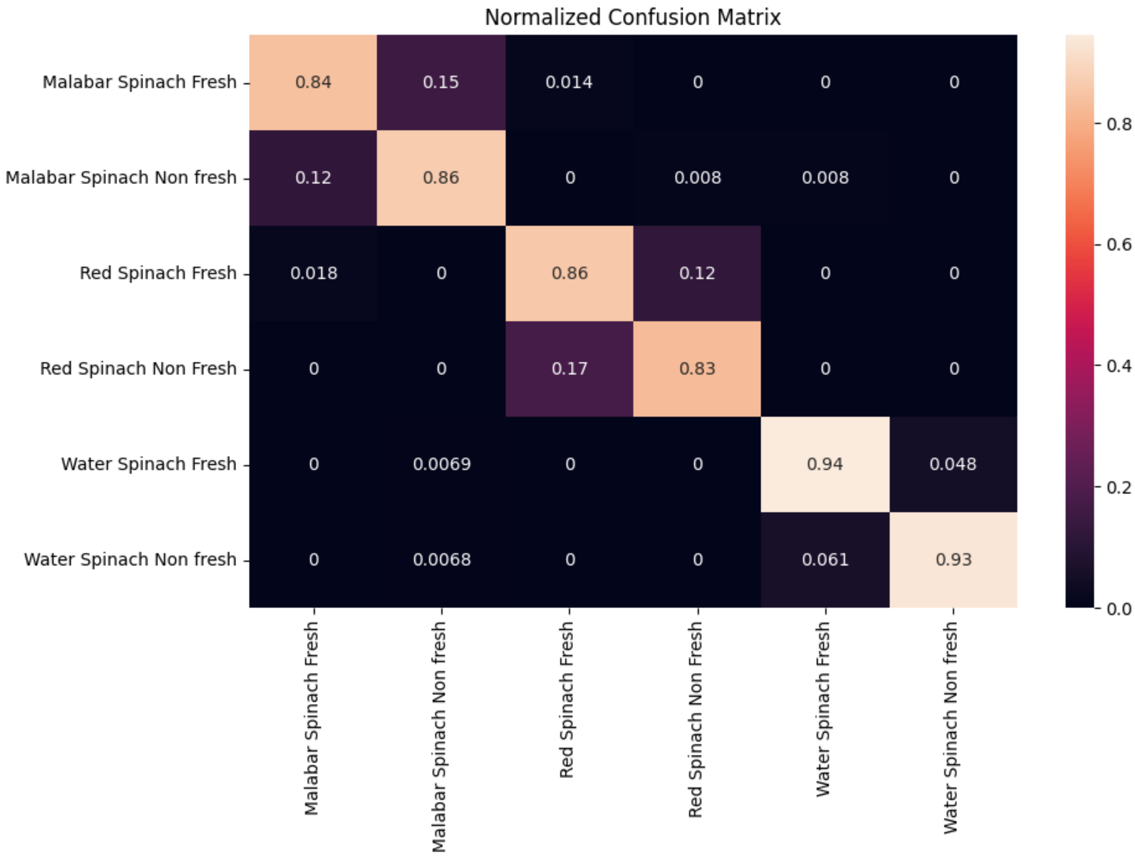

Figure 4.3: Confusion Matrix

On the other hand the above figure 4.3, shows that the training and validation accuracy is quite less then the CNN's. We can see that the training and validation accuracy is close to 88% for the ResNet50 architecture.

VGG19

The VGG19 gave the Accuracy of 98.50%. The training and validation accuracy is shown on the below figure of 4.4:

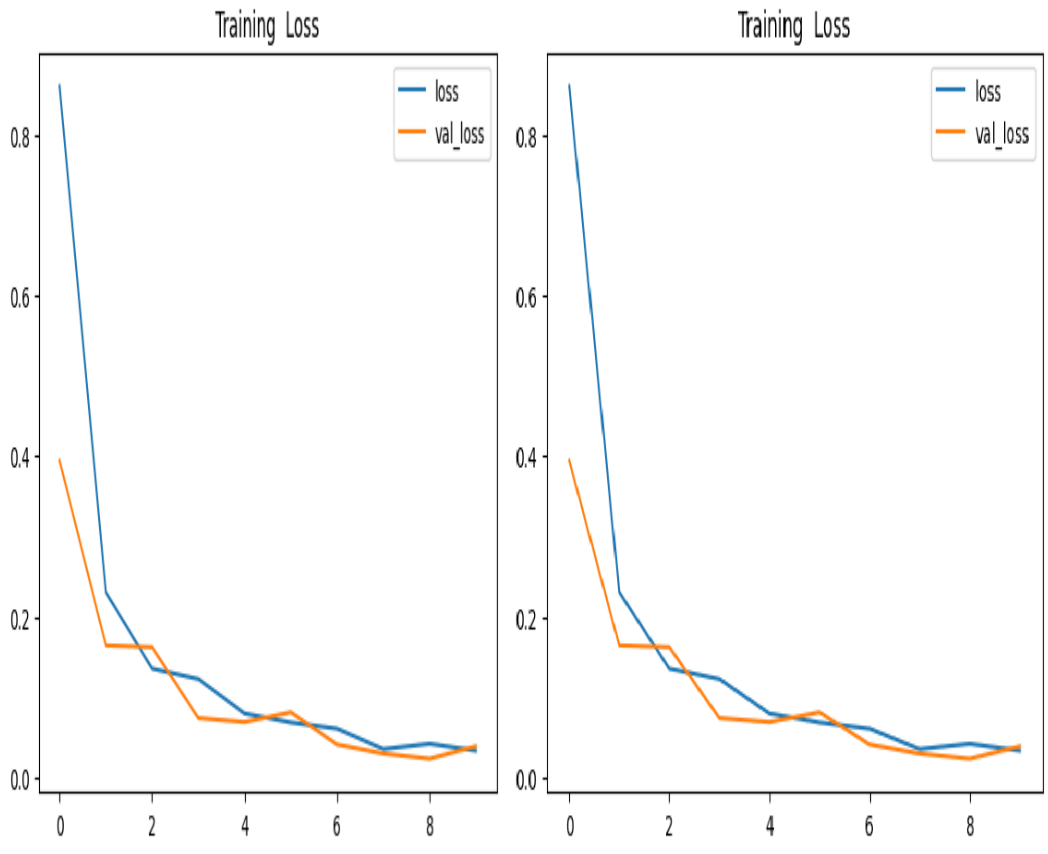

Figure 4.4: Training, Validation Loss & Accuracy (VGG19)

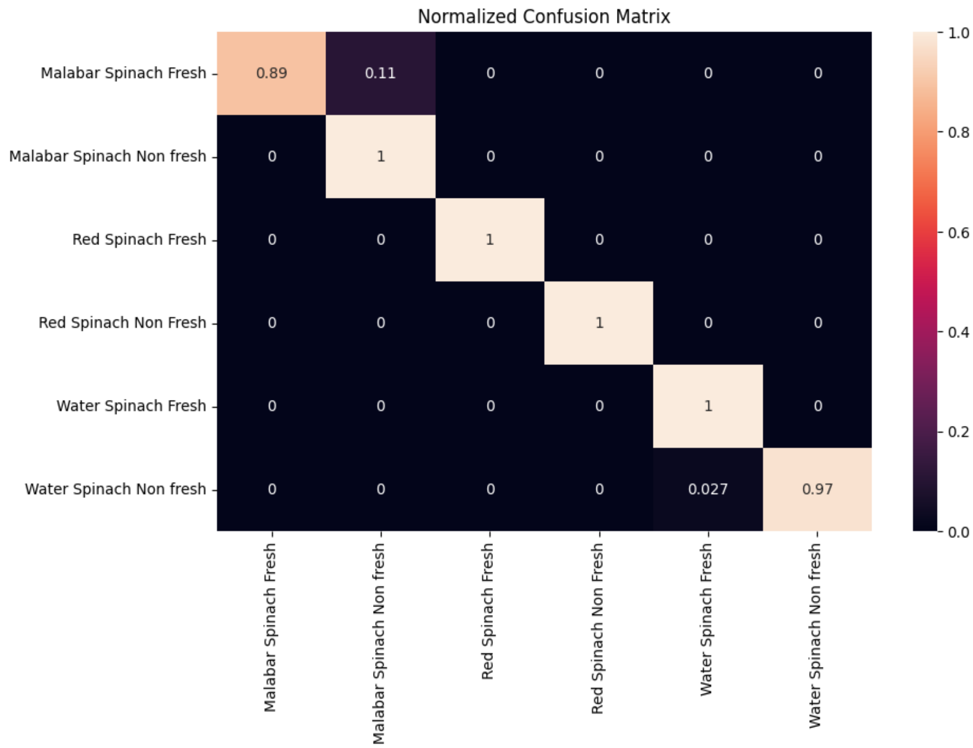

Figure 4.3: Confusion Matrix

The above figure of 4.4, shows that the VGG19 training and validation accuracy is close to 78% and both are the same. We can see that the training and validation accuracy is higher than the VGG19 architecture.

EfficientNetB1

The EfficientNetB1 gave an Accuracy of 35.37%. The training and validation accuracy is shown on the below figure of 4.5:

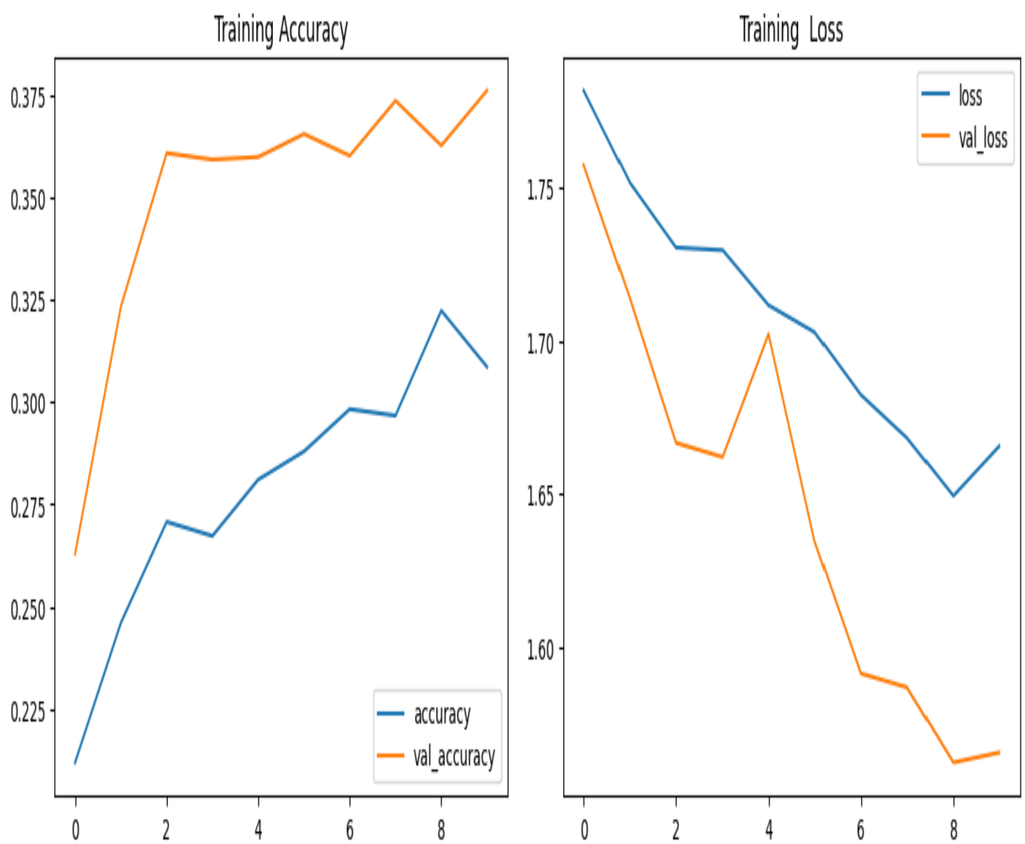

Figure 4.5: Training, Validation Loss & Accuracy (EfficientNetB1)

From the above figure 4.5, we see that the training and validation accuracy is much lower and close to 35% for the EfficientNetB1.

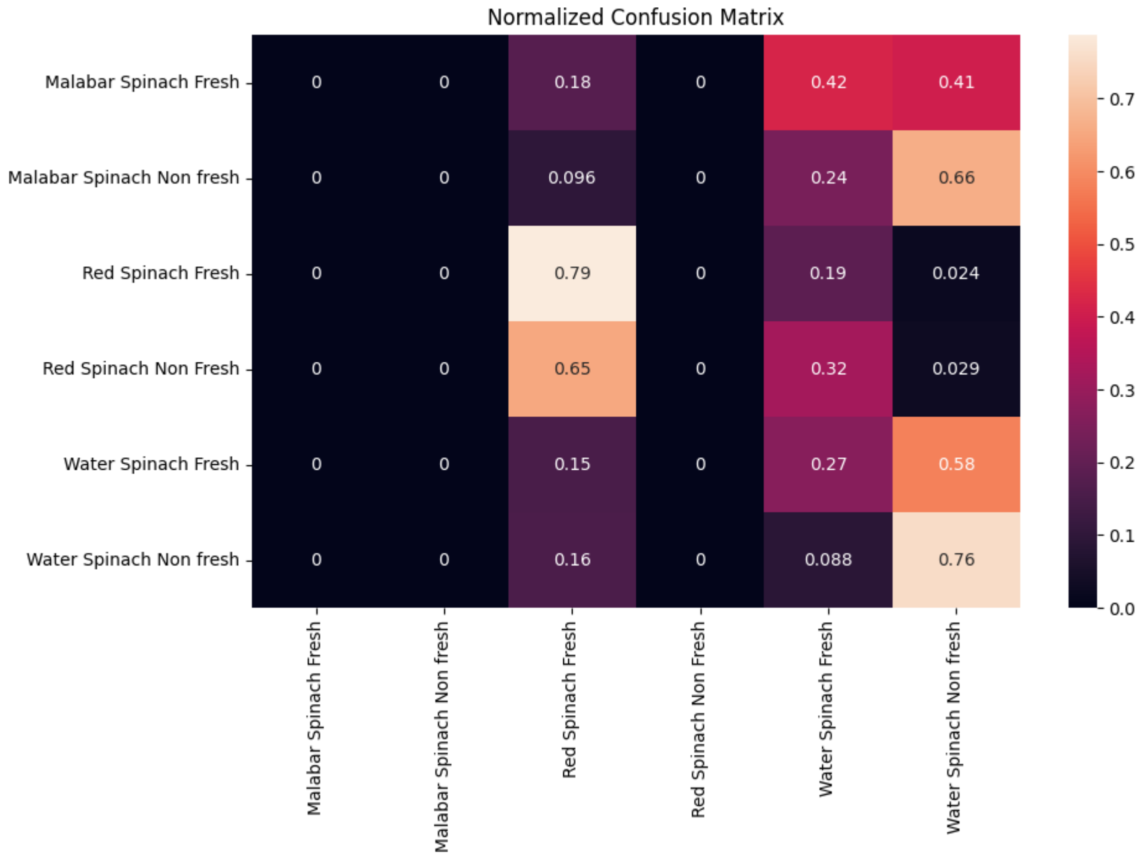

Figure 4.5: Confusion Matrix

In Figure 4:6 shows the Accuracy Comparison Plot between Deep Learning.

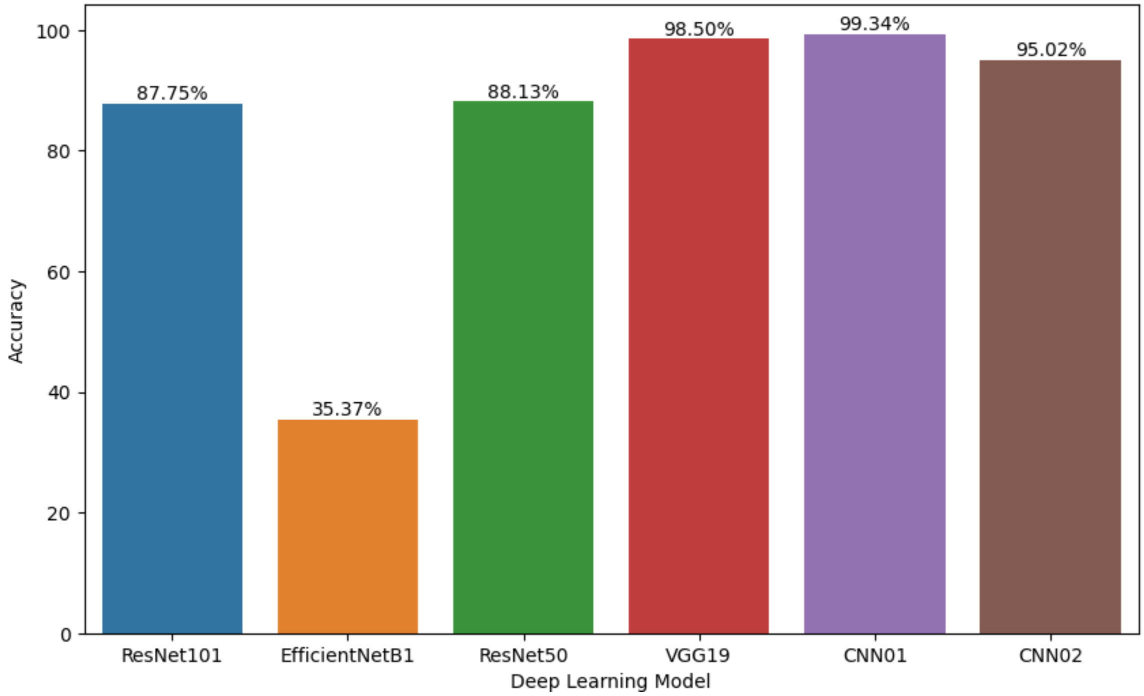

Figure 4.6: Comparative Model Accuracy Bar Plot

Discussion

The discussion section addresses the complicated significance that can be obtained from the experimental data. It investigates how well the models recognize Malabar spinach, Red spinach, and Water spinach and how well they evaluate freshness levels. In relation to spinach evaluation, a comparative analysis of deep learning architectures, such as ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02, reveals their individual advantages and disadvantages. The results are carefully analyzed in this section with a focus to how they may improve methods for quality control, decrease food waste, and boost consumer confidence in locally sourced produce in the context of agricultural applications. Future research directions are informed by insights from the discussion, which also point to opportunities for improving the combination of deep learning techniques with sustainable agriculture practices and improving model architectures.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The use of deep learning methods in the evaluation of spinach quality has the ability to change society.improving agricultural practices and food supply chains, the technology analyzes freshness levels and recognizes automatically local variations of spinach.Improved quality control advantages local farmers by making them more competitive in the market and producing better economic results.Distributors as well as retailers are able to ensure that customers receive fresh, premium produce, building trust and satisfaction.Accurate freshness detection reduces food waste, which is in line with sustainability objectives and has little negative effect on the environment.In turn, this gives consumers access to expensive spinach that is sourced locally, enabling them to make healthier dietary choices. In addition to economic and environmental concerns, technology has a social impact that impacts consumer awareness and promotes a move toward more technologically advanced and sustainable agricultural practices.In overall, applying the use of deep learning methods to the evaluation of spinach quality impacts society views, economic relationships, and environmental sustainability in the context of food production and consumption in a positive way.

5.2 Impact on Environment

The "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" project has an important ecological effect due to its benefits to sustainable agricultural practices. The system reduces food waste, a major environmental concern, by implementing the evaluation of spinach quality. Reducing unnecessary waste of useful produce, accurate freshness level detection guarantees that spinach grown close to is used effectively.By maximizing the distribution of spinach variations, the project further encourages sustainable farming methods. This results in a more efficient supply chain and reduces the environmental impact caused by improper agricultural product storage and transport.Using modern technologies in agriculture, such as deep learning, further promotes resource efficiency. When spinach quality is accurately evaluated, fewer tools are used for the handling and elimination of insufficient produce.To summarize, the project's environmental effects include decreased food waste, improved resource efficiency, and a move to more sustainable agricultural practices, all of which support the larger objectives of ecological sustainability and environmental conservation.

5.3 Ethical Aspects

The implementation of "Local Spinach Variant and Freshness Detection Using Deep Learning Techniques" raises ethical concerns related to agricultural technology use. It is essential to protect user privacy and data security when gathering, adding comments, and using images. It is important to communicate directly about the use of data and the possible effects that technology may have on nearby farming communities.To avoid algorithmic errors that might unfairly impact some spinach variants or freshness conditions, equal and impartial representation in the dataset and model outputs must be given top priority.Achieving a balance between ethical responsibility and technological innovation requires taking into account the system's larger social and economic effects, making sure that local communities benefit and that properly access to agricultural advancements is supported.The project focuses on a commitment to responsible innovation and a positive impact on the agricultural sector and the communities it serves, highlighting the significance of ethical considerations in the development and deployment of deep learning technologies.

5.4 Sustainability Plan

The project's sustainability plan uses environmentally friendly hardware and algorithms to choose energy efficiency in model training and deployment. Ongoing optimization of sustainability and environmental impact metrics is ensured by ongoing evaluation. Ethical data usage and privacy standards are maintained by effective data management procedures, such as common reviews. Engaging in the community with local stakeholders creates diversity and conforms with sustainable farming methods. By reducing the need for common learning, the combination of continuous learning models reduces resource consumption and increases a system's long life. With ongoing advantages for communities nearby and the larger ecosystem, this comprehensive approach needs to develop a stable, ecologically conscious technology.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

In the study, a novel approach to evaluate spinach quality in agriculture is presented. With the use of advanced deep learning models are ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02, among others the project accurately determines the freshness of Malabar, Red, and Water spinach while implementing the process of identifying them.The process creates a unique dataset for model training by carefully collecting, labeling, and augmenting data. Comprehensive statistical analysis indicates the models' advantages and areas for improvement, and the experimental results indicate the models' ability to correctly categorize and detect freshness. Improved consumer access to fresh, organic produce, decreased waste, and increased food safety are all examples of the societal impact.A sustainability plan and ethical considerations indicate the project's commitment to responsible technology development. In summary, this research represents an important achievement in the field of agricultural technology that results in a spinach quality control strategy that is more effective, sustainable, and ethically acceptable.

6.2 Conclusions

This study concludes by showing how effective it is to automate the testing of spinach quality using advanced deep learning models. The models— ResNet101, EfficientNetB1, ResNet50, VGG19, CNN01, and CNN02—showcase outstanding accuracy in identifying between Malabar, Red, and Water spinach as well as in determining the degree of freshness.The study indicates how these technological developments impact both society and the environment while additionally supporting sustainable agricultural methods and reduced food waste.Particular focus is paid to ethical issues, ensuring responsible and open deployment.The sustainability plan points out the commitment to ongoing observing, community involvement, and adaptability.In addition to advancing agricultural technology, this work creates a framework for the responsible and effective implementation of deep learning methods into practical applications.The findings provide essential information for scholars, farmers, and stakeholders looking to use technology to improve food quality and maintain agricultural practices.

6.3 Implication for Further Study

The study proposes a number of areas that need further investigation. Following studies activities that could focus on improving model improving to improve ability, exploring additional information from methods such as the spectrum imaging, and evaluating real-time use methods via technologies like the use of edge computing. To ensure the technology's usefulness in agricultural scenarios, human-computer interaction research presents another possible path. Furthermore, increasing the study's methods to include other produce and crops may increase the usefulness of deep learning methods to different agricultural settings. In conclusion, it is expected that continued research in these fields will improve the capability to adapt and efficiency of deep learning systems for evaluating fresh produce quality.

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LOCAL SPINACH VARIANT AND FRESHNESS DETECTION USING DEEP LEARNING TECHNIQUES

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