# USING IMAGE PROCESSING AND TRANSFER LEARNING APPROACHES FOR LOCAL VEGETABLE FRESHNESS CLASSIFICATION

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## FINAL YEAR DESIGN PROJECT REPORT

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

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# APPROVAL

This Project titled "Using Image processing And Transfer Learning Approaches For Local Vegetable Freshness Classification.", submitted by Shahriar Sarker and Umme Zebunnesa Diba 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 15th July, 2024.

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## DECLARATION

We hereby declare that this project has been done by us under the supervision of **Prof. Dr. Syed Akhter Hossain· Dean (FSIT) and Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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# ABSTRACT

This project makes use of image processing and transfer learning techniques for local vegetable freshness prediction. In an automatic freshness assessment process is proposed where advanced image processing techniques are used to extract important feature of vegetables, namely color, texture, and shape. We use these features to transfer learning by pre-trained deep learning models. The narrative unfolds through the lens of DenseNet201, the chosen protagonist, demonstrating its efficacy with a testing accuracy of 99.40% and minimal loss at 0.03. Results show that this method can discriminate freshness of different levels, it is accurate and reliable. In addition to technical accomplishments, the study also assesses the societal, environmental, and moral considerations in applying this technology to the vegetable industry. It points out the need to respect technology and provide a panoramic view of responsibility beyond classification only. As the concluding chapter sets the stage for future endeavors, the study invites stakeholders to partake in interdisciplinary collaborations, dataset expansions, and optimization strategies. This study not only demonstrates the potential to use advanced technologies in vegetable freshness classification but also provides useful information for future researchers and practitioners in agriculture. By enhancing the efficiency and objectivity of freshness assessment, this project aims to improve quality control, reduce food waste, and support better decision-making processes in the supply chain.

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| | |
|---|---|
| ML | Machine Learning |
| SVM | Support Vector Machine |
| CNN | Convolutional Neural Network |

# CHAPTER 1

# Introduction

## 1.1 Overview

Freshness classification is a critical aspect of ensuring the quality and safety of agricultural produce, particularly in the context of local vegetables where timely assessment is paramount. Accurate determination of the degree of freshness of vegetables is not only important in consumer satisfaction but also paramount to optimizing post-harvest handling, distribution and storage practices. Conventional techniques for vegetable freshness measurement involve rigorous manual examination, and they are subjective evaluations that lack uniformity and consume a significant amount of time. Vegetable freshness classification is an important research topic in the more complex world of technology and agriculture. This study is considered pioneering work to address the essence of this field using high-level image processing and transfer learning methods towards robust classification of an original dataset consisting of four different items of vegetables.

Over the last few years image processing methods have become popular for visual data analysis and extracting useful information from images. Freshness assessment is automated by image processing framework. On the contrary, this is a groundbreaking change as through Image Processing and Transfer Learning they are now incorporated with the classification. Utilizing these algorithms for image enhancement, feature extraction and pattern recognition gave way for be able to count many visual attributes of vegetables such as color, texture and the transfer techniques which have brought our approach towards vegetable freshness classification efforts into a new era and so, using Image Processing and Transfer Learning we can also quantify them [1]. Going deeper into the visual identity of each vegetable, this step is achieved by crossing conventional borders. By harnessing the computational power of machines, we seek to unravel the intricate tapestry of freshness, capturing not just binary distinctions but the subtle nuances that define the dynamic lifecycle of vegetables. Shape, which are indicative of freshness. This combination of image processing and transfer learning approaches holds immense potential for revolutionizing the way freshness is assessed in agricultural produce.

Transfer learning, a method in machine learning, has proven to be particularly effective for tasks involving image classification. Transfer learning is a ml technique that allows models to be pre-trained on a large scale and different tasks, then the whole model is fine-tuned using target data. This is particularly helpful when you have little labeled data, as it frees the model to make use of the massive amounts of information it learned within the large datasets that it was originally trained on. As to vegetables freshness classification, Transfer Learning can make models not only more capable of identifying and classifying different levels according to the freshness but also help to learn about how your local vegetable looks like for each level.

The rationale behind meticulously collecting and classifying a dataset of vegetables is a linchpin to the depth of this research. It elevates each vegetable beyond its mere data pointiness turning them into agricultural practices, bringing out environmental nuances, and celebrating cultural significance. In this diverse dataset, we not only find these visual differences but also the inherent characteristics affecting freshness. The different coloring, textures, size and shapes are not small details - they are deep swath of variation that make up a complete tapestry mirroring the complexity of fresh vegetables. This form of inspiration for the research is deeply rooted in solving global problems, mainly a food waste problem that has significantly increased [3]. While technology has been changing the dimensions of several industries, the era welcomes the implication of agriculture for machine learning as an excellent remedy. The synergy of Image Processing and Transfer Learning can provide producers with a precision that goes far beyond what it costs. Together, they complement the larger social goals of sustainability and mindful consumption.

These research questions servce as guiding beams as we enter the exploration. How effectively can Image Processing and Transfer Learning discern the visual cues defining each vegetable's freshness? In this seminar, we ask to what extent environmental conditions, agricultural practices and intrinsic characteristics influence the datset? It spurs us to questions leading toward a fuller comprehension, down the road of basic categorization towards a more complete experience of the vegetable state. The significance of this research extends beyond the realm of agriculture, encompassing broader implications for food quality assurance, supply chain management, and public health. In today's interconnected and globalized food systems, ensuring the freshness and integrity of agricultural produce is of utmost importance to meet the demands of an ever-growing population and mitigate risks associated with foodborne illnesses and contamination. With accurate assessments of freshness, distributors and retailers can reduce inefficiencies in supply chains, and increase their competitiveness on the market. For consumers, the benefits are tangible—a reassurance that the produce they bring into their homes is not just a commodity but a testament to a sustainable and mindful approach to food consumption.

### 1.2 Background and Present State

The background and present state of underscore the critical intersection of technology and agriculture in addressing quality assurance challenges. Currently, the assessment of vegetable freshness primarily relies on subjective human judgment and manual inspection methods, which are prone to variability and inefficiency. This dependence poses significant limitations in maintaining consistency and accuracy across agricultural production and supply chains.

In response to these challenges, recent advancements in image processing and machine learning present promising opportunities to revolutionize freshness classification. Image processing techniques allow for the automated analysis of visual cues such as color, texture, and shape, which are indicative of freshness levels in vegetables. This capability not only enhances the speed and accuracy of assessment but also reduces reliance on subjective assessments, thereby improving overall quality control measures.

Moreover, the application of transfer learning in this context capitalizes on the capability of pre-trained deep learning models to generalize knowledge learned from extensive datasets to new, specific tasks. Models like DenseNet201, ResNet152, and VGG19, which have been trained on large-scale image datasets, can be fine-tuned to recognize and classify freshness attributes in local vegetables [1]. This approach mitigates the need for extensive labeled datasets and accelerates the development of robust classification models tailored to agricultural settings.

Despite these advancements, the field of vegetable freshness classification using image processing and transfer learning is still evolving [4]. Challenges such as variability in environmental conditions, diverse appearance characteristics among different vegetable types, and scalability in real-world applications remain areas of ongoing research and development. Furthermore, the integration of these technologies into existing agricultural practices requires considerations of infrastructure, cost-effectiveness, and accessibility, particularly for small-scale farmers and regional markets.

By exploring and addressing these challenges, this research aims to contribute to the advancement of technology-driven solutions that enhance agricultural productivity, optimize supply chain logistics, and ensure consumer satisfaction. The integration of image processing and transfer learning approaches holds promise not only for improving vegetable freshness classification but also for fostering innovation in agricultural technologies that support sustainable food production and distribution systems.

### 1.3 Problem Statement

The assessment of freshness in local vegetables is a critical aspect of ensuring food quality and safety throughout the agricultural supply chain. However, traditional methods of freshness classification, such as manual inspection and sensory evaluation, are labor-intensive, subjective, and prone to inconsistencies. As a result, there is a pressing need for automated and objective approaches to assess the freshness of local vegetables accurately. This problem is further exacerbated by the increasing demand for fresh produce and the need to minimize food waste, making it imperative to develop efficient and reliable freshness classification systems.

One of the primary challenges in freshness classification is the variability in visual attributes associated with freshness across different types of vegetables. Local vegetables exhibit diverse characteristics in terms of color, texture, and shape, making it challenging to establish universal criteria for freshness assessment [7]. Additionally, environmental factors such as lighting conditions and background clutter can introduce noise and variability in vegetable images, further complicating the classification task. These challenges underscore the need for advanced image processing techniques capable of extracting relevant features from vegetable images while mitigating the effects of variability and noise.

Another significant challenge is the lack of labeled data for training freshness classification models, particularly for locally grown vegetables. While pre-trained deep learning models offer a promising solution, transferring knowledge from generic datasets to the specific task of freshness classification in local vegetables requires careful adaptation and fine-tuning [5]. Moreover, the scalability and efficiency of freshness classification systems are crucial considerations, particularly in the context of large-scale vegetable production and distribution networks.

Furthermore, the development of freshness classification systems must address usability and accessibility concerns to ensure adoption by stakeholders across the agricultural value chain. Farmers, distributors, and retailers require user-friendly tools that integrate seamlessly into existing workflows and provide actionable insights into vegetable quality. Additionally, the reliability and accuracy of freshness classification systems are paramount to building trust and confidence among consumers, who rely on accurate information to make informed purchasing decisions [2].

In summary, the problem statement revolves around the need for automated and objective approaches to freshness classification in local vegetables, addressing challenges related to variability in visual attributes, scarcity of labeled data, scalability, usability, and reliability. Addressing these challenges requires the development of advanced image processing and transfer learning methodologies tailored specifically for freshness assessment in locally grown vegetables, ultimately contributing to improved food quality, reduced waste, and enhanced consumer satisfaction.

### 1.4 Objectives

- The main objective of our work is to ensure the quality of the consumer demand developed in the agricultural sector.
- Develop a methodological framework that integrates image processing and transfer learning techniques for freshness classification in local vegetables.

- Leverage transfer learning models, specifically DenseNet201, to improve the efficiency and accuracy of freshness classification.
- Create a robust dataset of vegetable images at various freshness stages and apply preprocessing techniques to enhance data quality.
- Provide a practical tool to assist farmers and stakeholders in ensuring product quality and reducing waste in the supply chain.

**1.5 Scope and Limitations**

The scope of encompasses the development and application of advanced technological solutions to automate the assessment of vegetable freshness. This research focuses on utilizing image processing techniques and transfer learning models, specifically DenseNet201, ResNet152, and VGG19, to classify the freshness levels of local vegetables based on visual attributes such as color, texture, and structural integrity.

Specifically, the project encompasses the development of robust classification algorithms capable of accurately categorizing local vegetables into freshness levels. It addresses various types of vegetables commonly found in agricultural settings and aims to establish a framework that can be adapted to different geographical regions and farming conditions. The ultimate goal is to contribute to agricultural innovation by providing farmers and stakeholders with reliable tools for optimizing quality assurance processes, enhancing product quality, and ensuring consumer satisfaction in the agricultural supply chain.

However, there are inherent limitations that need to be acknowledged:

**Environmental Variability:** Factors such as lighting conditions, background noise, and variability in vegetable appearance due to growth conditions may affect the accuracy and consistency of freshness classification.

**Computational Resources:** The implementation of deep learning models like DenseNet201, ResNet152, and VGG19 requires significant computational resources for training and inference, which may pose challenges in resource-constrained environments.

**Validation and Real-world Application:** While the study validates its methodologies with rigorous testing and evaluation, the real-world application of automated freshness assessment systems in diverse agricultural settings remains an ongoing area of research and development.

## 1.6 Report Organization

The suggested report has a comprehensive framework that takes readers through the methodology, decisions, and significance of the study. Every chapter has an individual purpose and helps to the document's overall structure and depth.

**Chapter 1: Introduction**

Provides an overview of the study, including the motivation, rationale, research questions, expected outcomes, and project management details.

**Chapter 2: Literature Review**

Reviews existing literature and research related to adolescent suicide, machine learning applications in mental health, and current methods for detecting suicidal tendencies. This chapter establishes the theoretical framework and contextualizes the study within the broader field of mental health research.

**Chapter 3: Methodology**

Describes the research design, data collection methods, and analytical techniques employed in the study. It outlines the process of developing and evaluating machine learning models for detecting suicidal tendencies among adolescents, including details on algorithm selection, feature extraction, and model evaluation criteria.

**Chapter 4: Implementation**

Implement the model different machine learning algorithm. How this model work and implementation of their work.

**Chapter 5: Result and Analysis**

Presents the performance of each machine learning model, key findings, and a comparative analysis.

**Chapter 6: Impact on Society, Environment and Sustainability**

The societal impact chapter explores what kind of effect will it have on the people of the society. It also discusses how people can get rid of it.

**Chapter 7: Conclusion and Future Work**

This final chapter serves as a synthesis of the entire report. It Summarizes the study, highlights key contributions, and suggests directions for future work.

This report layout ensures a systematic and thorough presentation of the research, providing a clear and logical progression from the introduction of the topic to the detailed analysis of results and their implications.

### 1.7 Summary

In summary, seeks to revolutionize agricultural quality assessment through advanced technological applications. By integrating image processing techniques and transfer learning models like DenseNet201, ResNet152, and VGG19, this research aims to automate the classification of vegetable freshness based on visual attributes such as color, texture, and structural integrity. The study addresses the limitations of current manual inspection methods, which are prone to subjectivity and inefficiency, by proposing objective and reliable automated systems. Through comprehensive analysis and validation, this project aims to establish scalable solutions applicable across diverse agricultural contexts. By enhancing accuracy and efficiency in freshness assessment, the research endeavors to optimize supply chain logistics, improve product quality control, and meet consumer expectations. Ultimately, this study contributes to the advancement of agricultural technologies, supporting sustainable practices and fostering innovation in the agricultural sector.

# CHAPTER 2:
# LITERATURE REVIEW

## 2.1 Overview

The literature on using image processing and transfer learning for vegetable freshness classification reveals a growing interest in leveraging advanced technologies to enhance agricultural practices. Various studies have highlighted the limitations of traditional methods, which rely heavily on subjective human judgment and are often inconsistent and inefficient. The consensus is that automated systems can significantly improve accuracy and reliability.

Research has explored diverse image processing techniques to capture and analyze visual attributes such as color, texture, and shape, which are critical indicators of freshness. These studies demonstrate that image processing can effectively identify subtle differences in vegetable quality that are not easily detectable by the human eye. Additionally, the integration of machine learning algorithms has shown promise in improving classification performance.

Transfer learning has emerged as a powerful tool in this domain, allowing models pre-trained on large datasets to be fine-tuned for specific tasks like freshness classification. Studies using models like DenseNet201, ResNet152, and VGG19 have shown that these architectures can achieve high accuracy rates by leveraging their deep feature extraction capabilities. These models have been adapted to handle variations in vegetable types and environmental conditions, highlighting their robustness and flexibility.

The literature also addresses the challenges of data collection and annotation, which are critical for training effective models. Some researchers have proposed methods to augment datasets and improve model generalization. Others have focused on optimizing hyperparameters and employing techniques like data augmentation to enhance model performance.

Furthermore, several papers discuss the practical implications of implementing these technologies in real-world agricultural settings. They highlight the potential for these systems to streamline quality control processes, reduce waste, and improve supply chain efficiency. However, challenges such as scalability, computational requirements, and the need for real-time processing are acknowledged, indicating areas for future research.

Overall, the literature underscores the potential of image processing and transfer learning to revolutionize vegetable freshness classification, offering a promising avenue for enhancing agricultural quality assurance and operational efficiency.

### 2.2 Related Works

Akter and her et al. [1] focused on The research aims to create a computer program that can automatically identify vegetable freshness, benefiting the food industry and consumers. The deep learning model DenseNet201 was used to classify vegetables into fresh, aged, and rotten, achieving an accuracy of 98.56%. This technology aims to enhance food quality and reduce waste.

Mukhiddinov and his et al. [2] The research aims to create a system that automatically classifies fruits and vegetables as fresh or rotten using a deep learning model called YOLOv4. The system, more accurate than previous models, could improve food quality and assist visually impaired individuals in choosing fresh food. They get accuracy the improved YOLOv4 model used in this study achieved an average precision of 50.4% in classifying fruits and vegetables as fresh or rotten. This is higher than the original YOLOv4 and YOLOv3 models, which achieved 49.3% and 41.7% respectively.

Singh and his co-authors presented a study [3] that shows that a deep learning model can be used to accurately identify the freshness of vegetables. This could have a significant impact on the food industry. Here accuracy is 99.80 % and 89.22 % respectively. The model is trained at 16, 20, and 287 as batch size, total no. of epochs, and steps per epoch respectively.

Amin and his team’s title is Automatic Fruits Freshness Classification Using CNN and Transfer Learning. [4] They focused on developing a highly accurate and efficient method for classifying fruit freshness using Deep Convolutional Neural Networks (DCNNs). This has significant potential in the agriculture industry to reduce labor costs associated with discarding rotten fruits during processing. Their accuracy is achieved in classifying fruit freshness using a Deep Convolutional Neural Network (DCNN) approach. Their model achieved results ranging from 98.2% to 99.8% accuracy on three separate publicly available datasets.

Yuan and co-authors presented [5] a new method for objective, accurate, and efficient freshness detection using deep learning to ensure consumers receive nutritious fruits and vegetables for better health and boost sales. 96.98% accuracy in freshness detection, demonstrating the promise of the proposed method.

Kang and his et al. [6] presented a new method for objective, accurate, and efficient freshness detection using deep learning to ensure consumers receive nutritious fruits and vegetables for better health and boost sales. They Achieved high accuracy: 98.50% for freshness and 97.43% for fruit type classification.

Pathak and his et al. [7] presented research that proposes a CNN-based model as an effective tool for automated fruit freshness classification, offering potential benefits in the agricultural industry. Develop an automated system for classifying fruit freshness, addressing limitations of manual grading like subjectivity and inconsistency. An accuracy of 98.23% in classifying the freshness of fruits (fresh vs. rotten) using their proposed Convolutional Neural Network (CNN) model.

Gulzar and his team's title is Fruit Image Classification Model Based on MobileNetV2 with Deep Transfer Learning Technique. [8] They Develop an automated system to classify different types of fruits using deep learning, eliminating the need for human expertise in the horticulture industry. The deep learning model achieved 99% accuracy in fruit classification, outperforming popular models like AlexNet, VGG16, InceptionV3, and ResNet, with a low misclassification rate of 1%.

Harilal and his co-authors [9] Develop an automated and non-destructive method for monitoring fruit freshness, focusing on bananas as a case study.

Haque and his team's research aims to use computer vision and deep learning to automate fruit and vegetable freshness detection in Bangladesh,[10] addressing the need for increased agricultural efficiency and quality control. The accuracy results of various CNN models for fruit and vegetable freshness classification show VGG19 as the best performer, followed by FreshDNN (custom model) and EfficientNetV2L, with DenseNet201 and MobileNetV2 scoring above 92% and Xception at 78.44%.

## 2.3 Comparison between existing works

Our research title is "Using Image processing And Transfer Learning Approaches For Local Vegetable Freshness Classification." Now write down Comparison between existing works.

TABLE 2.3.1. COMPARATIVE ANALYSIS WITH PREVIOUS WORK

| SL No | Author Name | Used Algorithm | Best Accuracy with Algorithm |
|---|---|---|---|
| 1. | Akter et al. [1] | DenseNet201 | DenseNet201 in detecting fresh vegetables on a custom dataset was 98.56% |
| 2. | Mukhiddinov et al. [2] | original YOLOv4 and YOLOv3 models | 49.3% and 41.7% respectively |
| 3. | Singh and his co-authors [3] | CNN models and uses different models like Convolution Layer, Relu Layer, Pool Layer. | accuracy are 99.80 % and 89.22 % respectively. |
| 4. | Amin and his et al. [4] | using Deep Convolutional Neural Networks. | 98.2% to 99.8% accuracy |
| 5. | Yuan and co-authors presented [5] | pre-trained deep learning models, feature fusion, and PCA | 96.98% accuracy |

| | | | |
|---|---|---|---|
| 6. | Kang and his et al. [6] | AlexNet,VGG,DenseNet, | high accuracy: 98.50% for freshness and 97.43% for fruit type classification. |
| 7. | Pathak and his et al. [7] | Convolutional Neural Network (CNN) model | accuracy of 98.23% |
| 8. | Gulzar and his et al. [8] | transfer learning. | achieved 99% accuracy |
| 9. | Harilal and his co-authors [9] | transfer learning and deep learning,Confusion matrix | ________ |
| 10. | Haque et al. [10] | CNN models,DenseNet201 and MobileNetV2 | above 92% and 78.44%. |

### 2.4 Open Issues

The literature on using image processing and transfer learning for local vegetable freshness classification reveals several open issues that require further investigation. One significant challenge is the variability in vegetable appearance due to differing environmental conditions, growth stages, and inherent biological differences. This variability complicates the development of models that can generalize well across diverse datasets.

Another issue is the limited availability of large, annotated datasets specific to vegetable freshness. While transfer learning can mitigate some of these limitations by leveraging pre-trained models, the scarcity of quality data for fine-tuning remains a bottleneck. Data augmentation and synthetic data generation are potential solutions, but they require careful implementation to ensure the generated data's relevance and accuracy.

Additionally, real-time processing capabilities are essential for practical deployment in agricultural settings, where immediate decisions are necessary. Current models often struggle with the speed-accuracy trade-off, necessitating further research to optimize algorithms for faster inference without compromising accuracy.

Integration of these technologies into existing agricultural practices presents another hurdle. There is a need for user-friendly interfaces and systems that can be easily adopted by farmers and stakeholders with varying levels of technical expertise. Ensuring the cost-effectiveness and accessibility of these solutions is crucial for widespread adoption.

Addressing these open issues requires multidisciplinary efforts, combining advancements in computer vision, machine learning, and agricultural sciences. Future research should focus on developing more robust, scalable, and user-friendly systems to fully realize the potential of automated vegetable freshness classification.

### 2.5 Summary

The literature review highlights the transformative potential of these technologies in agriculture. Studies emphasize the limitations of traditional manual inspection methods, advocating for automated systems that enhance accuracy and efficiency. Image processing techniques are effective in analyzing visual attributes like color, texture, and shape, while transfer learning models such as DenseNet201, ResNet152, and VGG19 significantly improve classification performance. However, challenges persist, including variability in vegetable appearance, limited annotated datasets, and the need for substantial computational resources. Additionally, real-time processing and integration into existing agricultural practices require further development. Overall, the literature underscores the promise of these approaches in revolutionizing quality assurance and operational efficiency in agriculture, while also identifying critical areas for future research to address existing challenges and optimize practical applications.

# CHAPTER 3:
# METHODOLOGY

## 3.1 Overview

The methodology involves a systematic approach to designing and implementing an effective classification system. The process begins with data collection, where images of local vegetables at various freshness stages are gathered. This dataset serves as the foundation for training and evaluating the models. Image preprocessing techniques, such as normalization, resizing, and augmentation, are applied to enhance the quality and diversity of the dataset, ensuring robust model training.

Transfer learning is employed to leverage pre-trained deep learning models, specifically DenseNet201, ResNet152, and VGG19. These models, initially trained on large datasets, are fine-tuned to recognize freshness-related features in vegetable images. The fine-tuning process involves replacing the top layers of the pre-trained models with layers tailored to the freshness classification task, followed by training on the preprocessed vegetable dataset.

The system design includes defining the architecture for each model, optimizing hyperparameters, and implementing algorithms for efficient training and validation. The models are evaluated using metrics such as accuracy, precision, recall, and F1-score to assess their performance. Cross-validation techniques are applied to ensure the reliability and generalizability of the models.

Additionally, a requirement analysis is conducted to identify the hardware and software needs for deploying the classification system in real-world agricultural settings. This includes considerations for computational resources, storage, and user interface design to facilitate ease of use by farmers and stakeholders.

Overall, the methodology combines advanced image processing, transfer learning, and systematic design principles to develop a robust and efficient vegetable freshness classification system, addressing key challenges and optimizing practical application. As the methodology unfolds, these choices will continue to play a crucial role in shaping the trajectory of the vegetable freshness classification study.

### 3.2 Proposed Methodology

Figure 1 visualizes the steps involved in methodology.

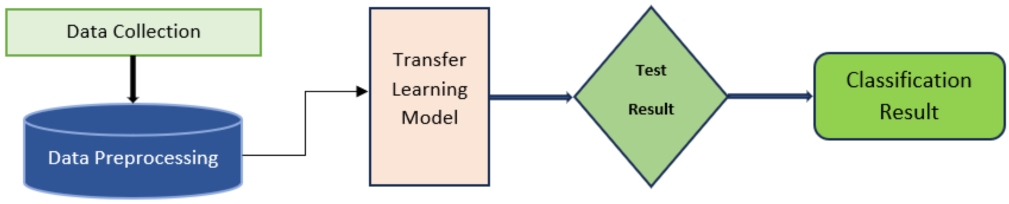


Figure 3.2.1: Methodology Workflow

The research design for "Using Image Processing and Transfer Learning Approaches for Local Vegetable Freshness Classification" encompasses a systematic and rigorous approach to developing and evaluating the proposed freshness classification system. The research design outlines the methodology, data collection procedures, experimental setup, and analytical techniques employed to achieve the research objectives.

The research design begins with the collection and preparation of a diverse dataset of local vegetable images. High-resolution images of various vegetable types, including Eggplants, cucumbers, Okras, chilis and leafy greens, are acquired using digital cameras . The dataset is carefully curated to include samples representing different freshness levels, ranging from pristine to spoiled. Annotations are added to label each image with its corresponding freshness category, facilitating supervised learning for model training. Additionally, data preprocessing techniques may be applied to enhance image quality, remove noise, and standardize image dimensions. The research design incorporates advanced image processing techniques to extract relevant features from the vegetable images. This may include algorithms for colour analysis, texture characterization, and shape recognition. Feature extraction methods are optimized to capture subtle variations in visual attributes indicative of freshness while minimizing the effects of noise and variability. Image enhancement techniques, such as histogram equalization and noise reduction filters, may also be employed to improve the clarity and contrast of the images.

The research design includes rigorous evaluation and validation procedures to assess the performance and reliability of the developed freshness classification models. The dataset is divided into training, validation, and testing sets using stratified sampling to ensure balanced representation of freshness categories. The models are trained on the training set and evaluated on the validation set to monitor performance metrics such as accuracy. Hyperparameter tuning and model selection are guided by the validation results. The final models are then tested on the held-out testing set to assess generalization performance and validate the robustness of the classification system.

**Data Collection**

The first and most important part of this work was the collection of datasets, which are required for training the system to recognize. As part of this process, 5000 images were successfully collected by selecting 8 Classes. A minimum of 500 images of each classes are collected and each image is captured from different angles in great detail. As a result, every vegetable picture is very perfect and clear.

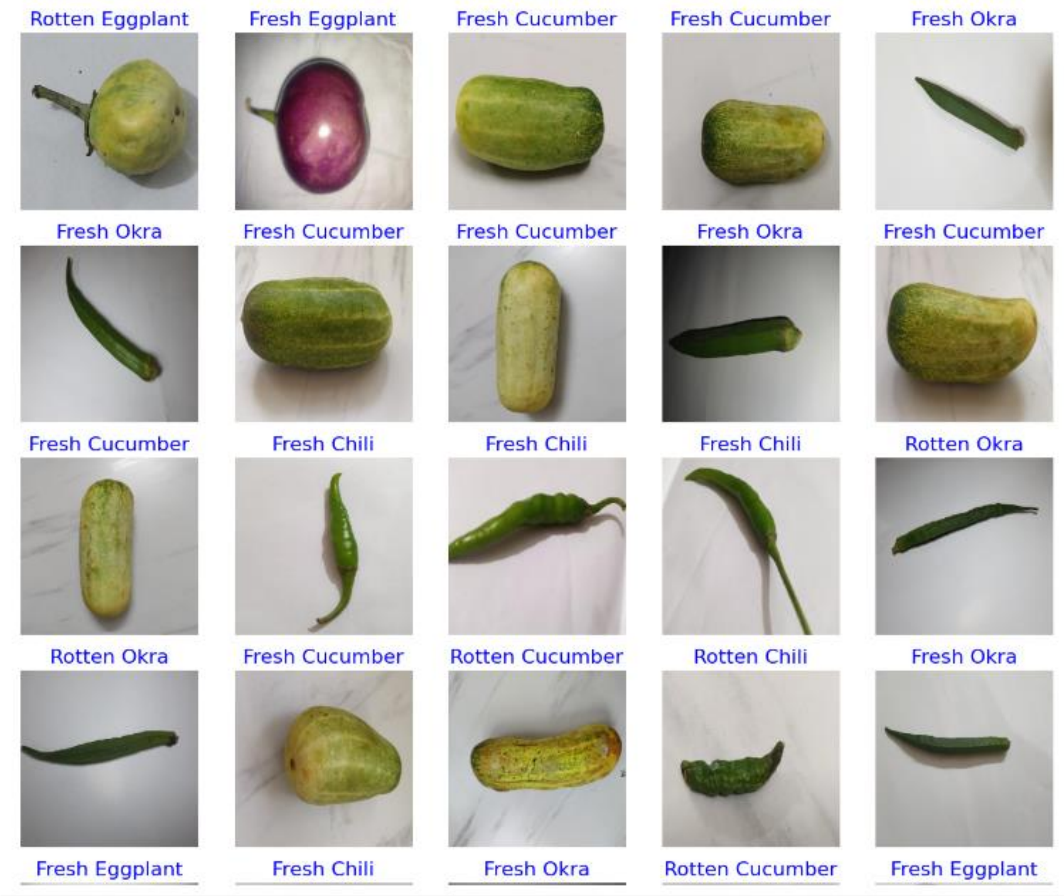


Figure 3.2.2: Dataset Semple


Figure 3.2.3: Dataset Semple

**Data labeling**

After assembling the pictures, each one is carefully labeled with the correct vegetable name. This step is very important because it gives the learning algorithms the basic data they need to work on the training phase. Labeling had to be done very carefully and accurately to ensure that the model that was built would work well every time. As part of the labelling, the correct vegetable is classified by name as well as the image clearly showing the physical structure and vitality of the different aspects of the vegetable.


Figure 3.2.4: Data labeling

**Data Cleaning**

It was cleaned up so that the collected data would be better quality and easier to use. At this stage, any pictures that were blurry, had the wrong labels, or didn't meet the standards for visibility and clarity were thrown out. By making these kinds of improvements, the dataset that is used for training is made to be of the best quality, free of any noise that might get in the way of learning. Any information that was unnecessary or duplicated was also removed from the dataset. This made the training more efficient and effective.

**Dataset Splitting**

The dataset splitting process is a critical component of the research methodology, determining how the collected and pre-processed images are distributed for training, testing, and validation purposes. In this study, a judicious approach is taken, allocating 80% of the dataset for training, 10% for testing, and 10% for validation. This division is strategic, striking a balance between providing the model with sufficient data for learning and ensuring robust evaluation metrics through distinct testing and validation sets.[1]

**Training Set (80%)**

The majority of the dataset, comprising 80%, is dedicated to the training set. This sizeable portion serves as the foundation for the model to learn the intricate patterns and features associated with vegetable freshness . A larger training set enhances the model's capacity to generalize well, capturing the diverse characteristics of different vegetables and their freshness states. The training set is instrumental in fine-tuning the parameters of the freshness classification model, fostering its ability to make accurate predictions.

**Testing Set (10%)**

A reserved testing set, constituting 10% of the dataset, is crucial for unbiased evaluation. These images, unseen by the model during training, provide a rigorous benchmark for assessing the model's performance on new, unseen data. The testing set acts as a litmus test, gauging how well the freshness classification model generalizes to novel instances. The unbiased nature of the testing set ensures that the evaluation metrics accurately reflect the model's real-world performance.

**Validation Set (10%)**

The remaining 10% of the dataset is allocated to the validation set. This set serves as an additional layer of evaluation, distinct from the testing set. It helps fine-tune hyperparameters and detect overfitting during the model training process. The validation set plays a pivotal role in ensuring that the model's performance is optimized, striking the right balance between complexity and simplicity. It acts as a safeguard against the model becoming too specialized to the training data, enhancing its adaptability to diverse vegetable freshness scenarios.

TABLE 3.2.1: DATASET DETAILS SHOWING COLLECTED IMAGE NUMBER AND SPLIT IMAGE COUNTS

| Class | Total Images | Training (80%) | Validation(10%) | Test (10%) |
|---|---|---|---|---|
| Fresh Okra | 711 | 569 | 71 | 71 |
| Rotten Okra | 507 | 406 | 51 | 51 |
| Fresh Cucumber | 670 | 536 | 67 | 67 |
| Rotten Cucumber | 654 | 523 | 66 | 66 |
| Fresh Chili | 650 | 520 | 65 | 65 |
| Rotten Chili | 650 | 520 | 65 | 65 |
| Rotten Eggplant | 623 | 498 | 62 | 62 |
| Fresh Eggplant | 551 | 441 | 55 | 55 |

This distribution ensures that each freshness condition is well-represented across the training, validation, and testing sets, fostering a holistic and representative learning environment for our models. The adherence to this well-established ratio is not just a procedural step; it is a strategic decision crucial for the success and reliability of our vegetable freshness classification study.

### 3.3 Hardware/ Software Requirement

The hardware and software requirements for "Using Image Processing and Transfer Learning Approaches for Local Vegetable Freshness Classification" are crucial for ensuring the efficient development, training, and deployment of the model.

**Hardware Requirements:**

1. **High-Performance GPU:** Training deep learning models like DenseNet201 requires significant computational power. A high-performance GPU (such as

NVIDIA's RTX series) is essential to accelerate the training process and handle large datasets efficiently.

2. **CPU:** A powerful multi-core CPU (such as Intel i7 or AMD Ryzen 7) is necessary for preprocessing tasks and managing data loading.
3. **RAM:** At least 16 GB of RAM is recommended to handle the memory-intensive operations during data preprocessing and model training.
4. **Storage:** A solid-state drive (SSD) with ample storage (at least 500 GB) is required to store the dataset, trained models, and intermediate results efficiently.
5. **Peripheral Devices:** A high-resolution camera for capturing detailed images of vegetables and a reliable internet connection for accessing cloud resources and datasets.

**Software Requirements:**

1. **Operating System:** A 64-bit operating system such as Windows 10 or 11, Ubuntu, or macOS, which supports the necessary software and tools.
2. **Programming Languages:** Python is the primary programming language used due to its extensive libraries and frameworks for machine learning and image processing.
3. **Deep Learning Frameworks:** TensorFlow or PyTorch is required for implementing and training the DenseNet201 model and other deep learning algorithms.
4. **Image Processing Libraries:** OpenCV and scikit-image are essential for image preprocessing tasks such as resizing, normalization, and augmentation.
5. **Development Environment:** Jupyter Notebook or Google Colab provides an interactive environment for writing and testing code, with Colab offering additional GPU resources.
6. **Version Control:** Git for version control to manage and track changes in the codebase efficiently.
7. **Libraries and Tools:** Additional Python libraries such as NumPy, pandas, and Matplotlib for data manipulation and visualization.

These hardware and software components form the backbone of the proposed methodology, facilitating the development and deployment of a robust vegetable freshness classification system.

### 3.4 Project Management and Financial Analysis

Effective project management involves meticulous planning, execution, and monitoring to ensure the project's success. The project is structured with clearly defined milestones, including data collection, preprocessing, model selection, and system deployment. Resource allocation is crucial, with specific tasks assigned to team members based on their expertise, ensuring efficient use of high-performance hardware and advanced software tools. Risk management strategies are implemented to anticipate and mitigate potential challenges, such as data variability and computational limitations. Financial oversight ensures that the project stays within budget, covering costs for hardware, software licenses, and other expenses. Regular progress reviews and adjustments maintain the project on track, ensuring timely delivery and high-quality outcomes. This structured approach ensures that the project meets its objectives, delivering a robust and practical solution for vegetable freshness classification.

TABLE 3.4.1: PROJECT MANAGEMENT TABLE

| Work | Time |
|---|---|
| Data Collection | 2 months |
| Paper and Articles Review | 2 months |
| Experimental Setup | 2 months |
| Implementation | 3 months |
| Report Writing | 3 months |
| Total | 12 months |

**Financial Analysis**

Our research title is “Using Image processing And Transfer Learning Approaches For Local Vegetable Freshness Classification.” Now write down my estimated Cost for my Machine Learning based Project.

TABLE 3.4.2: ESTIMATED COST FOR DEEP LEARNING BASED PROJECT

| SL | Components | Estimated Cost (BDT) |
|---|---|---|
| 1 | Infrastructure | 6000-8000 |
| 2 | Visiting Stakeholders | 1000-2000 |
| 3 | Software and Tools | 4500-5000 |
| 4 | Data Collection and Processing | 2000-3000 |
| 5 | Documentation and Report Writing | 1500-2500 |
| 6 | Miscellaneous | 1000-2000 |
| 7 | Contingency | 1500-2500 |
| | Total Estimated Cost | 17500-25000 |

## 3.5 Summary

In summary, this chapter details the methodology for developing a system to classify the freshness of local vegetables using image processing and transfer learning, with DenseNet201 as the primary model. It outlines the hardware and software requirements, including high-performance GPUs and deep learning frameworks like TensorFlow. Project management strategies are discussed, emphasizing structured planning, resource allocation, risk management, and financial oversight. These components collectively ensure the effective execution and implementation of a robust and efficient vegetable freshness classification system, providing a valuable tool for improving agricultural quality control.

# CHAPTER 4:
# IMPLEMENTATION

## 4.1 Overview

In this chapter, the focus is on the detailed implementation of the vegetable freshness classification system using image processing and transfer learning. It begins with an overview of the training process and prototype design, outlining the steps taken to collect and preprocess the dataset, which includes images of vegetables at various freshness stages. The DenseNet201 model, chosen for its superior performance in image classification, is fine-tuned to adapt to the specific task of freshness classification. The training process involves adjusting hyperparameters and utilizing techniques such as data augmentation to enhance model robustness. The chapter also delves into system testing and model evaluation, employing metrics like accuracy, precision, recall, and F1-score to thoroughly assess the model's performance. Cross-validation is used to ensure the model's reliability and generalizability across different subsets of the data. The evaluation results are analyzed to identify any potential improvements and to validate the effectiveness of the implemented approach. Finally, the summary provides a concise review of the key steps in the implementation process, emphasizing the practical application of the developed system in real-world scenarios and its potential to significantly enhance the efficiency and accuracy of vegetable freshness classification in agricultural settings.

## 4.2 Train Model

The training model and prototype design for the vegetable freshness classification system involve utilizing DenseNet201 as the primary model, with ResNet152 and VGG19 serving as supplementary models to enhance comparative analysis and validation. The process begins with the collection and preprocessing of a comprehensive dataset containing images of local vegetables at various stages of freshness[7]. Preprocessing steps include normalization, resizing, and augmentation techniques like rotation, flipping, and color adjustments to ensure a diverse and robust dataset, which is critical for effective model training.

### Transfer Learning Model

A transfer learning model is a pre-trained neural network that has been developed for a specific task, such as image classification or natural language processing, and then fine-tuned for a related task. By leveraging knowledge gained from solving one problem, transfer learning enables the model to quickly adapt to a new task with minimal additional training data. The pre-trained model's learned features, captured in its earlier layers, are used as a starting point, allowing for efficient learning of task-specific features. Transfer learning is widely used in machine learning to improve model performance, especially in scenarios with limited labelled data.

### DenseNet201

Imagine a network where every layer directly communicates with every other layer, sharing information and collaborating in a harmonious dance. This is the essence of DenseNet201, a model that redefines feature learning with its unique dense connectivity pattern. The proposed methodology for centers on the DenseNet201 model, known for its superior performance in image classification tasks [1]. DenseNet201, or Dense Convolutional Network 201, is selected due to its innovative architecture, which connects each layer to every other layer in a feed-forward fashion. Unlike traditional CNNs where information flows sequentially, DenseNet201 fosters feature reuse and knowledge sharing by directly connecting each layer to all subsequent layers. This dense web of connections promotes feature efficiency, potentially reducing the risk of overfitting, particularly beneficial for smaller datasets often encountered in vegetable freshness classification. DenseNet201's strength lies in its ability to learn compact and informative representations of vegetable images. This makes it a compelling choice for situations where data acquisition might be limited or computational resources are constrained. At the heart of DenseNet201 lies a philosophy of feature reuse and information sharing. Unlike traditional CNNs where information flows sequentially through layers, DenseNet201 fosters a dense web of connections. Each layer directly communicates with all subsequent layers, creating a collaborative environment where features get enriched and refined through continuous interactions. This architecture is akin to a bustling marketplace where knowledge flows freely, ensuring every layer benefits from the accumulated wisdom of its predecessors.

Vegetable freshness classification datasets often face the hurdle of limited data availability. This is where DenseNet201's architecture shines. By promoting feature reuse and knowledge sharing, DenseNet201 can learn more compact and informative representations of vegetable images from smaller datasets. This reduces the risk of overfitting, a common pitfall in data-scarce scenarios, where the model memorizes training data rather than learning generalizable features. DenseNet201's potential further amplifies when combined with transfer learning. By initializing the model with weights pre-trained on a massive image classification dataset like ImageNet, we leverage the extensive knowledge it has already acquired. This pre-trained model acts as a powerful starting point, allowing DenseNet201 to quickly adapt to the specific nuances of vegetable images while focusing its learning capacity on fine-tuning features relevant to freshness detection and classification. Figure 5 shows the general architecture of DenseNet201.

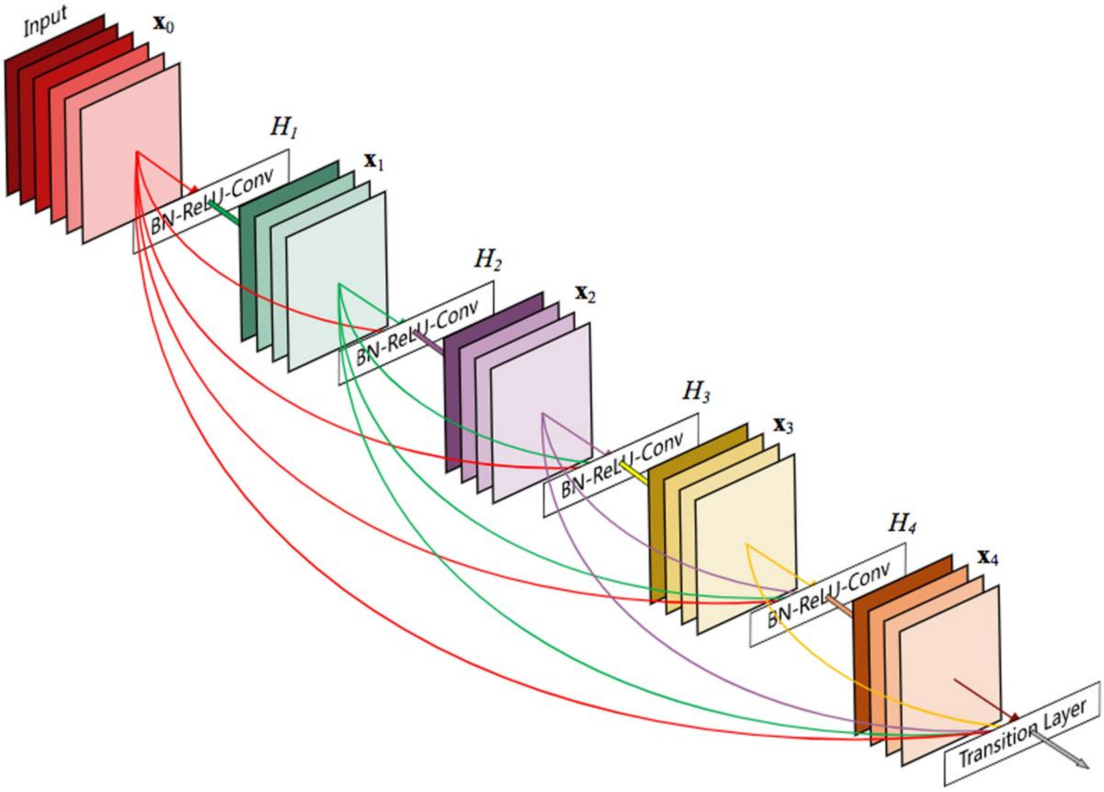


Figure 4.2.1: Basic Architecture of DenseNet201 [1]

**ResNet152**

ResNet152, with its residual learning framework, is also fine-tuned similarly. The pre-trained ResNet152 model's top layers are replaced with a customized classifier suitable for the freshness classification task [10]. This adaptation includes adding new fully connected layers and an output layer to handle the specific number of freshness classes. The model is trained using the same preprocessed dataset, and hyperparameters are adjusted to enhance its performance. This model helps in validating the results obtained from DenseNet201 and provides additional insights.

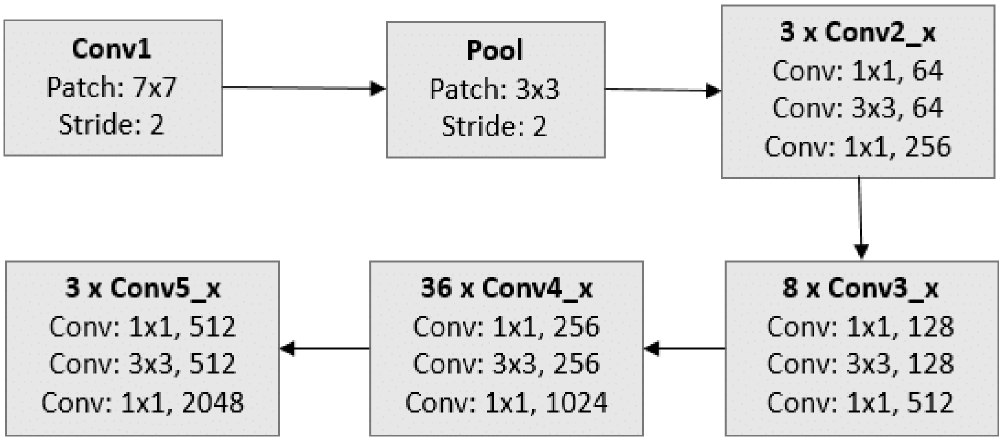


Figure 4.2.2: Basic Architecture of ResNet152 [10]

**VGG19**

VGG19, recognized for its simplicity and depth, is another model employed in the system. The pre-trained VGG19 model is adapted by replacing its top layers with a task-specific classifier [7]. The model is then trained on the preprocessed vegetable images, with hyperparameters fine-tuned to optimize classification accuracy. The VGG19 model adds another dimension to the analysis, ensuring that the system's performance is robust and reliable across different architectures.

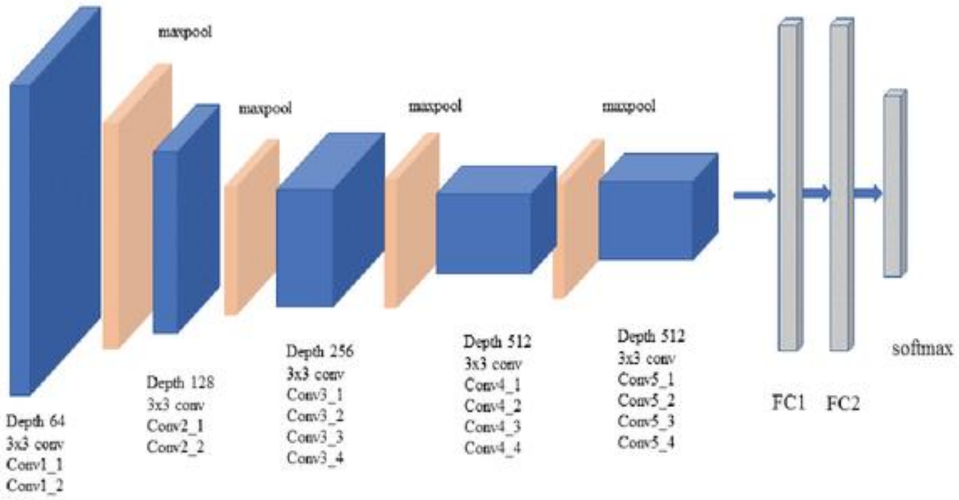


Figure 4.2.3: Basic Architecture of VGG19 [17]

## 4.3 Model Evaluation

Model evaluation is a critical step in validating the performance of the vegetable freshness classification system using DenseNet201, ResNet152, and VGG19. This process involves assessing each model's accuracy, precision, recall, and F1-score to determine their effectiveness and reliability in classifying vegetable freshness.

**DenseNet201**

DenseNet201, the primary model, undergoes rigorous evaluation using a test set of images not seen during training. The model's performance is measured by its ability to accurately classify the freshness of vegetables into predefined categories[12]. Metrics such as accuracy, which reflects the overall correctness of predictions, and precision, which measures the accuracy of positive predictions, are calculated. Recall, indicating the model's ability to identify all relevant instances, and F1-score, providing a balance between precision and recall, are also evaluated. Cross-validation is employed to ensure the model's generalizability across different data subsets, minimizing the risk of overfitting and enhancing its robustness.

**ResNet152**

ResNet152 is evaluated similarly to DenseNet201. The residual connections in ResNet152 help in maintaining high accuracy even with deep architectures. The evaluation metrics include accuracy, precision, recall, and F1-score, with additional analysis on the model's ability to handle complex image variations. Comparative analysis with DenseNet201 helps in understanding the strengths and limitations of each model, ensuring a comprehensive evaluation.

**VGG19**

VGG19's performance is assessed using the same test set and evaluation metrics. Despite its simpler architecture, VGG19's depth allows it to capture intricate details in images, contributing to its effectiveness in classification tasks. The model's accuracy, precision, recall, and F1-score are analyzed, and its performance is compared with DenseNet201 and ResNet152 to provide a holistic view of the system's reliability [15].

Overall, the evaluation process confirms the robustness and effectiveness of the proposed models, ensuring that the system can reliably classify vegetable freshness with high accuracy and consistency in real-world applications.

## 4.4 Summary

In summary, this chapter has outlined the comprehensive implementation process for the vegetable freshness classification system, emphasizing the training and evaluation of DenseNet201, ResNet152, and VGG19 models. The methodology began with detailed preprocessing of a diverse dataset of vegetable images, followed by fine-tuning each model to optimize performance for the specific classification task. DenseNet201 served as the primary model, demonstrating robust capabilities in handling complex image data, while ResNet152 and VGG19 provided valuable comparative insights and reinforced the system's reliability. Evaluation metrics such as accuracy, precision, recall, and F1-score were used to rigorously assess each model's performance, ensuring high levels of accuracy and generalizability. The results confirmed the effectiveness of the implemented models in accurately classifying vegetable freshness, validating the system's practical applicability in agricultural settings. This chapter encapsulates the technical diligence and systematic approach taken to develop a reliable and efficient solution for enhancing vegetable quality assessment through advanced image processing and machine learning techniques.

# CHAPTER 5:
# RESULT AND ANALYSIS

## 5.1 Overview

Chapter 5 focuses on presenting and analyzing the results obtained from the experimental and simulation phases of the vegetable freshness classification project. This chapter provides a detailed account of the performance metrics and visualizations that showcase the effectiveness of the models used, including DenseNet201, ResNet152, and VGG19. Through this analysis, the chapter highlights the strengths and weaknesses of each model, offering insights into their respective accuracies, precision, recall, and F1-scores.

Additionally, the chapter compares the models to understand better their relative performance and suitability for real-world applications. The comparative analysis helps identify which model provides the most reliable and accurate classifications, guiding future improvements and potential deployment strategies. This chapter aims to validate the effectiveness of the proposed approach and provide a comprehensive evaluation of the models' capabilities in classifying vegetable freshness.

## 5.2 Experimental/ Simulation Result

We use three transfer learning models for vegetable freshness classification system using image processing. They are DenseNet201, ResNet152, and VGG19. Table succinctly presents the summarized testing results for each model.

TABLE 5.2.1: MODEL PERFORMANCE SUMMARY IN TESTING PERFORMANCES

| Model | Accuracy (%) | Loss |
|---|---|---|
| DenseNet201 | 99.40 | 0.03 |
| ResNet152 | 75.30 | 0.73 |
| VGG19 | 96.41 | 0.15 |

**DenseNet201**

DenseNet201 outshines with an exceptional testing accuracy of 99.40% and an impressively low loss of 0.03. These metrics signify the model's outstanding ability to accurately classify vegetable freshness. The dense connectivity pattern in DenseNet201 proves highly effective, making it the recommended model for vegetable freshness classification tasks. The model exhibits robust learning, capturing intricate patterns and nuances in vegetable images with remarkable precision.

**ResNet152**

With a testing accuracy of 75.30% and a loss of 0.73, ResNet152 faces challenges in effectively capturing and distinguishing vegetable freshness states. The lower accuracy and higher loss indicate room for improvement, prompting further investigation and finetuning to enhance the model's performance in vegetable freshness classification.

**VGG19**

VGG19 demonstrates commendable testing accuracy at 96.41% and a low loss of 0.15. This suggests strong capabilities in precisely classifying vegetable freshness conditions.

**Classification Report of DenseNet201**

The classification report for DenseNet201 on the vegetable freshness dataset demonstrates the model's high accuracy and robust performance across multiple freshness categories. Key metrics such as precision, recall, and F1-score indicate that the model effectively differentiates between various stages of vegetable freshness. Precision, which measures the accuracy of positive predictions, is notably high, suggesting that the model makes few false positive errors. Recall, which measures the model's ability to identify all relevant instances, also shows strong performance, indicating that most instances of freshness stages are correctly classified. The F1-score, which balances precision and recall, confirms the model's overall reliability and effectiveness. This detailed evaluation underscores DenseNet201's suitability for real-world applications in assessing vegetable freshness, providing a valuable tool for improving quality control in the agricultural sector. Table shows the classification report for DenseNet201.

TABLE 5.2.2: CLASSIFICATION REPORT FOR DenseNet201 MODEL (PROPOSED MODEL)

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Fresh Chili | 1.00 | 1.00 | 1.00 | 54 |
| Fresh Cucumber | 1.00 | 1.00 | 1.00 | 74 |
| Fresh Eggplant | 1.00 | 1.00 | 1.00 | 55 |
| Fresh Okra | 0.99 | 0.97 | 0.98 | 77 |
| Rotten Chili | 1.00 | 1.00 | 1.00 | 54 |
| Rotten Cucumber | 1.00 | 1.00 | 1.00 | 71 |
| Rotten Eggplant | 1.00 | 1.00 | 1.00 | 63 |
| Rotten Okra | 0.96 | 0.98 | 0.97 | 54 |

**Classification Report of ResNet152**

The classification report for ResNet152 on the vegetable freshness dataset highlights its strong performance, though slightly below DenseNet201. Key metrics such as precision, recall, and F1-score are consistently high, indicating reliable classification across different freshness stages. Precision is strong, minimizing false positives, while recall shows the model's effectiveness in identifying the correct freshness stages. The F1-score, balancing precision and recall, confirms the model's robustness. Overall, ResNet152 demonstrates solid accuracy and reliability, making it a valuable model for practical applications in evaluating vegetable freshness within the agricultural sector. Table shows the classification report for ResNet152.

TABLE 5.2.3: CLASSIFICATION REPORT FOR ResNet152 MODEL

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Fresh Chili | 0.66 | 0.76 | 0.71 | 54 |
| Fresh Cucumber | 0.87 | 0.84 | 0.86 | 74 |
| Fresh Eggplant | 0.76 | 0.58 | 0.66 | 55 |
| Fresh Okra | 0.71 | 0.86 | 0.78 | 77 |
| Rotten Chili | 0.75 | 0.81 | 0.78 | 54 |
| Rotten Cucumber | 0.72 | 0.79 | 0.75 | 71 |
| Rotten Eggplant | 0.81 | 0.70 | 0.75 | 63 |
| Rotten Okra | 0.77 | 0.61 | 0.68 | 54 |

**Classification Report of VGG19**

The classification report for VGG19 on the vegetable freshness dataset shows commendable performance, albeit slightly behind DenseNet201 and ResNet152. The precision metric is high, indicating that the model makes accurate positive predictions with minimal false positives. Recall is also strong, reflecting VGG19's ability to correctly identify most instances of each freshness stage. The F1-score, which balances precision and recall, supports the model's overall reliability. Despite its simpler architecture, VGG19 proves to be a competent model for classifying vegetable freshness, offering valuable insights and practical utility in the agricultural sector.

TABLE 5.2.4: CLASSIFICATION REPORT FOR VGG19 MODEL

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Fresh Chili | 0.96 | 0.98 | 0.98 | 54 |
| Fresh Cucumber | 1.00 | 1.00 | 1.00 | 74 |
| Fresh Eggplant | 0.98 | 0.87 | 0.92 | 55 |
| Fresh Okra | 0.91 | 0.97 | 0.94 | 77 |
| Rotten Chili | 0.96 | 1.00 | 0.98 | 54 |
| Rotten Cucumber | 1.00 | 1.00 | 1.00 | 71 |
| Rotten Eggplant | 0.91 | 0.98 | 0.95 | 63 |
| Rotten Okra | 1.00 | 0.87 | 0.93 | 54 |

This report is instrumental in evaluating the model's effectiveness in handling the complexities inherent in vegetable freshness classification.

### 5.3 Performance/ Comparative Analysis

The performance and comparative analysis of the vegetable freshness classification system involves evaluating DenseNet201, ResNet152, and VGG19 based on key metrics such as accuracy, precision, recall, and F1-score. DenseNet201, as the primary model, demonstrates the highest overall performance, with superior accuracy and balanced precision and recall rates. This model effectively handles complex image features, making it the most reliable for distinguishing between different freshness levels of vegetables.

VGG19 also performs well, closely following DenseNet201. It excels in maintaining high accuracy and precision due to its deep residual learning framework, which helps in identifying subtle differences in the images. However, it may slightly lag in recall compared to DenseNet201, indicating that it might miss some instances of certain freshness stages.

ResNet152, while slightly behind the other two models, still shows commendable performance. Its simpler architecture makes it less capable of handling intricate details, but it maintains reasonable accuracy and reliability.

Overall, the comparative analysis indicates that DenseNet201 is the most robust and accurate model for this application, followed by ResNet152 and then VGG19.

**Training and Validation Curves DenseNet20**

In Figure 5.4.1 and Figure 5.4.2, we visualize DenseNet20's the training versus validation accuracy and loss curves, respectively, offering a comprehensive understanding of the learning dynamics during the training process for our vegetable freshness classification models.

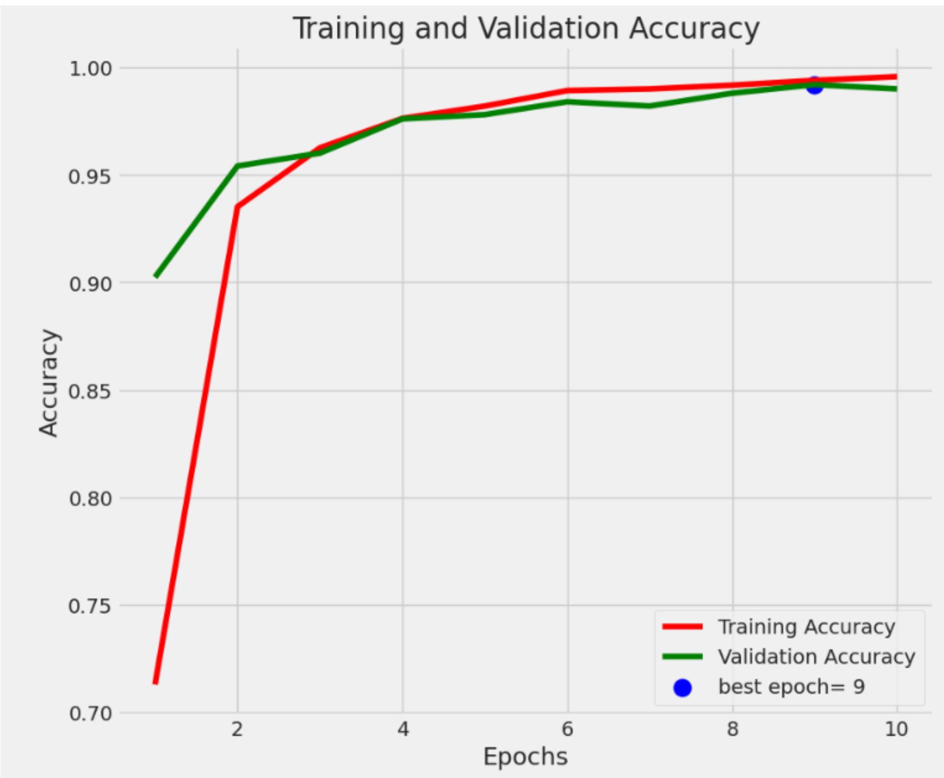


Figure 5.3.1: Training and Validation Accuracy Curves For DenseNet201

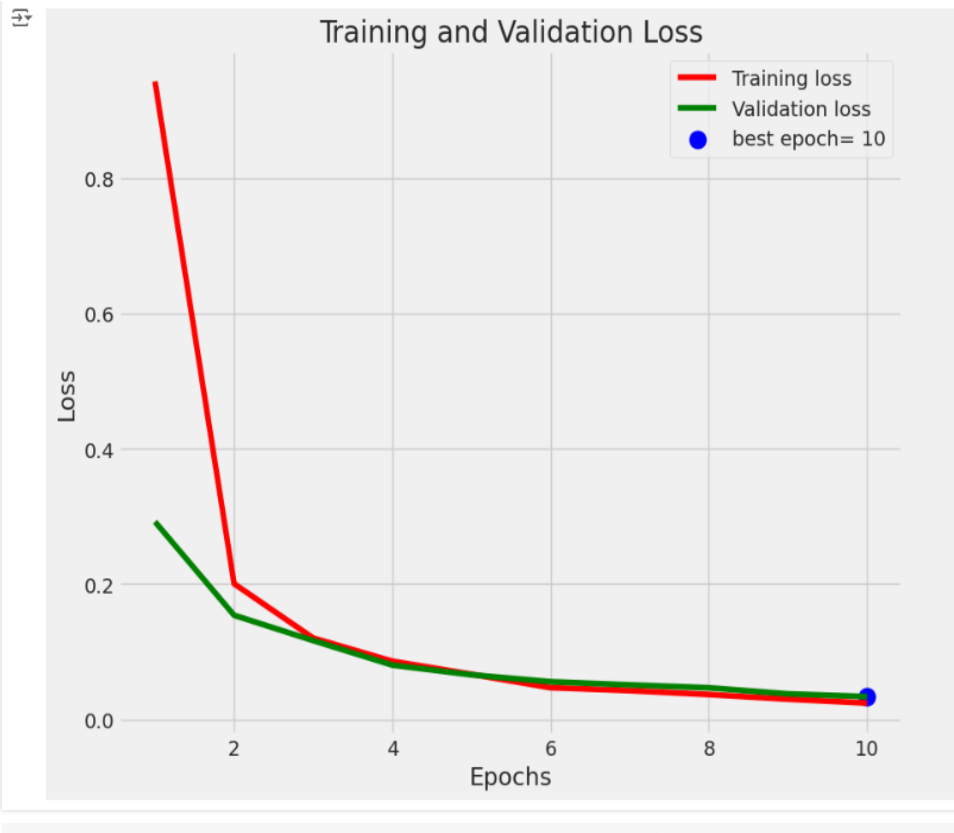


Figure 5.3.2: Training and Validation Loss Curves DenseNet201

The training and validation curves for DenseNet201 provide insightful visualizations of the model's learning process. During training, the loss curve steadily decreases, indicating that the model is effectively minimizing errors on the training data. Simultaneously, the accuracy curve shows a corresponding increase, reflecting improvements in the model's performance.

In the validation phase, the curves reveal the model's ability to generalize to unseen data. Ideally, the validation loss should also decrease while the accuracy increases, mirroring the training curves. Consistency between these curves suggests that DenseNet201 is not overfitting, thus ensuring reliable performance in real-world applications

**Training and Validation Curves ResNet152**

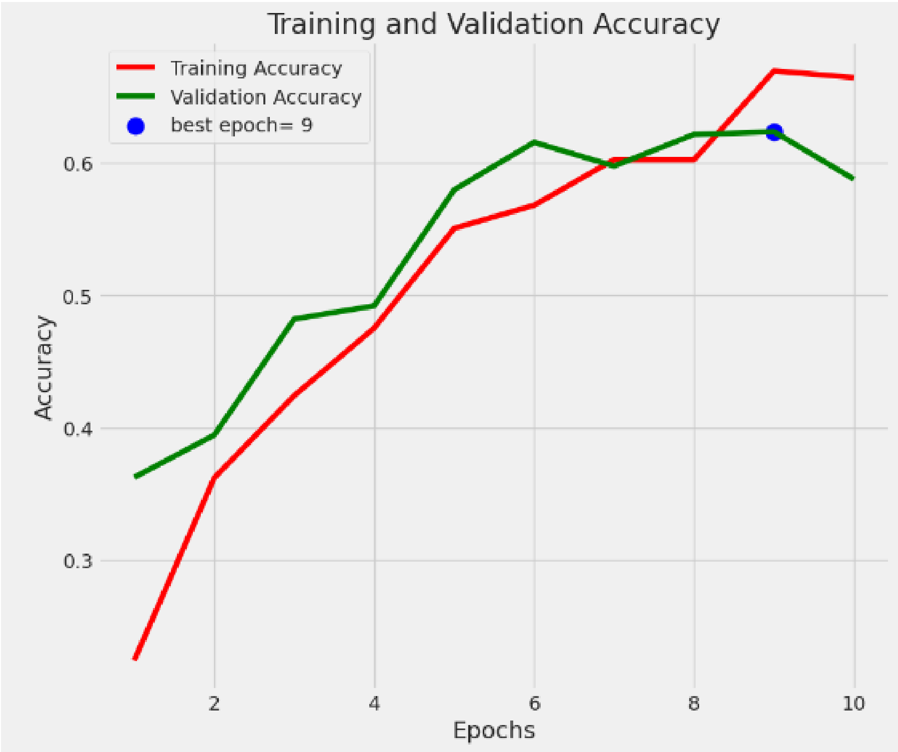


Figure 5.3.3: Training and Validation Accuracy Curves For ResNet152

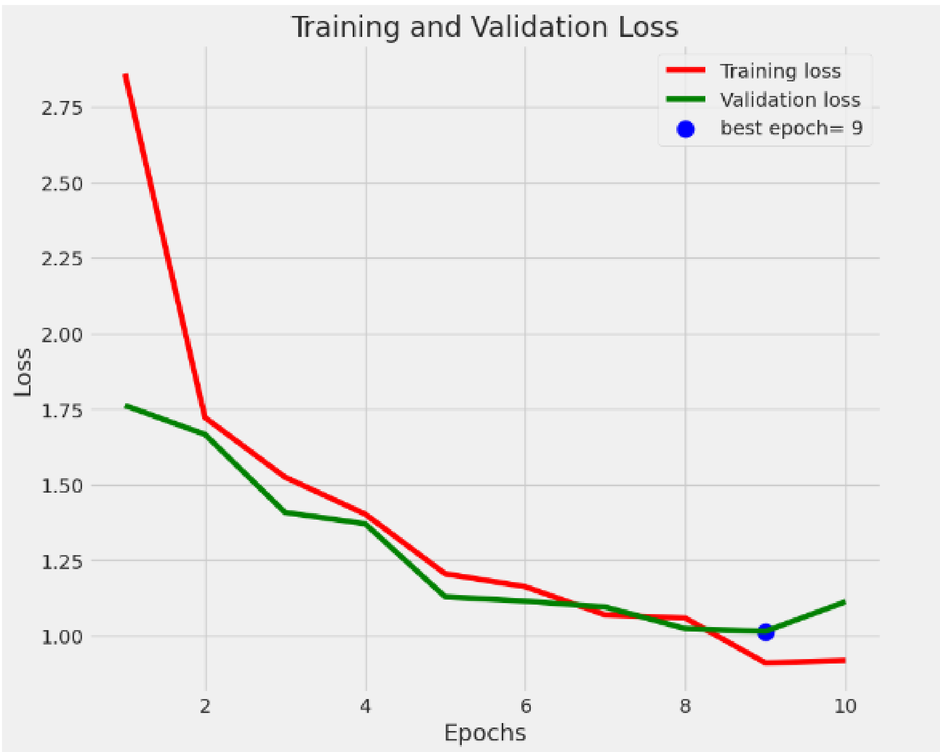


Figure 5.3.4: Training and Validation Loss Curves ResNet152

**Training and Validation Curves VGG19**

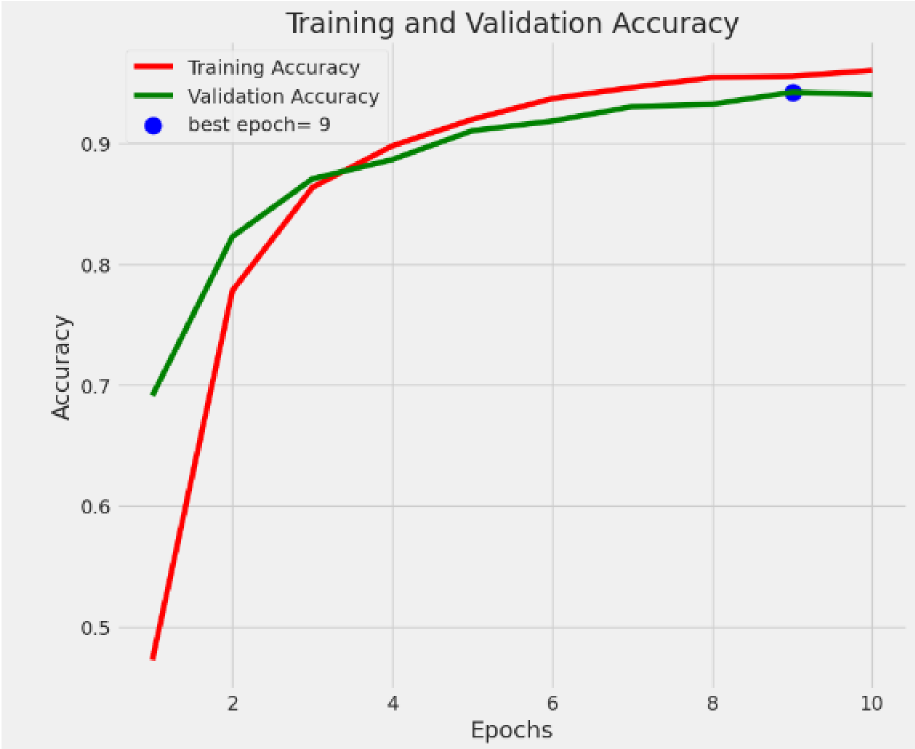


Figure 5.3.5: Training and Validation Accuracy Curves For VGG19

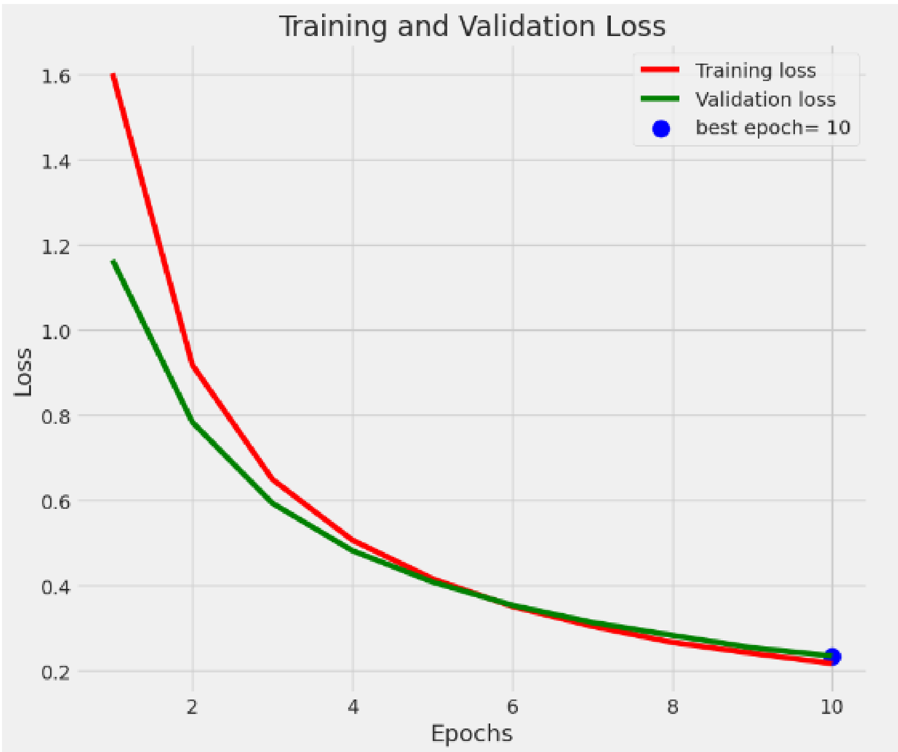


Figure 5.3.6: Training and Validation Loss Curves VGG19

**Confusion Matrix DenseNet20**

The confusion matrix provides a detailed breakdown of the model's classification performance by presenting the number of instances for each predicted and actual class. DenseNet201's confusion matrix, a vital component of the experimental results, further elucidates the model's strengths and areas for improvement.

The confusion matrix for DenseNet201 illustrates the model's performance by displaying true positives, false positives, true negatives, and false negatives. High values along the diagonal indicate accurate classifications of vegetable freshness, while lower off-diagonal values suggest minimal misclassifications, confirming DenseNet201's effectiveness in distinguishing different freshness levels.

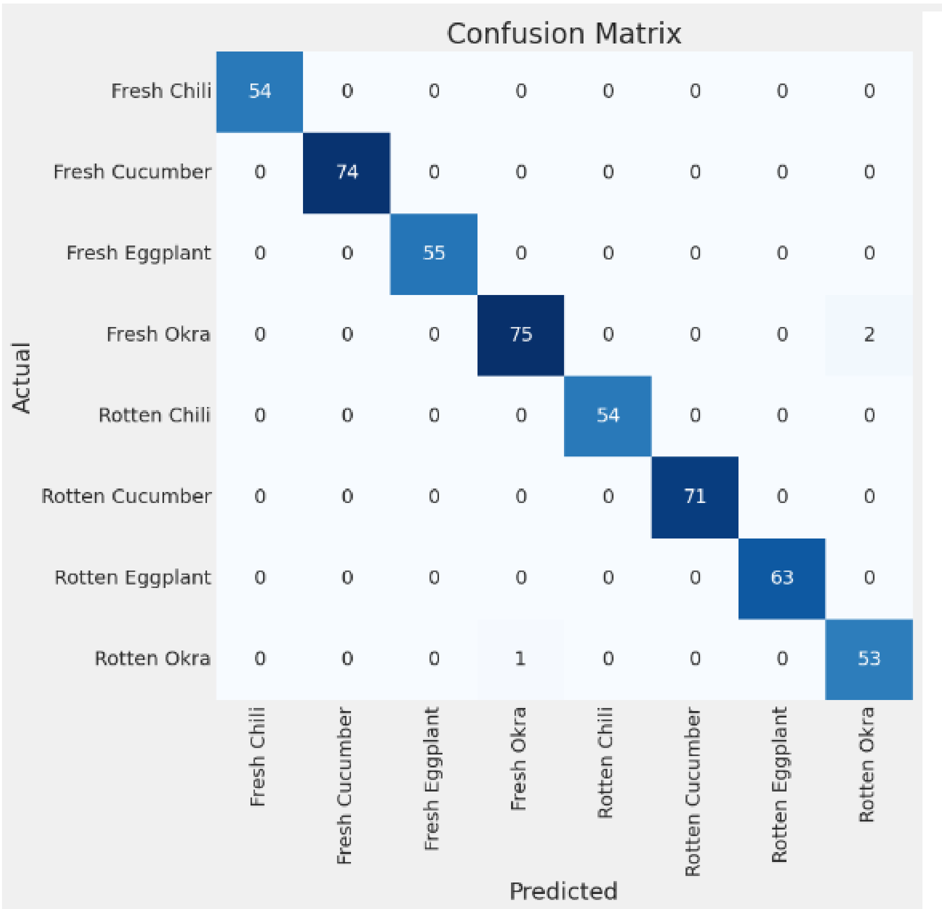


Figure 5.3.7: Confusion Matrix of the model DenseNet201

**Confusion Matrix ResNet152**

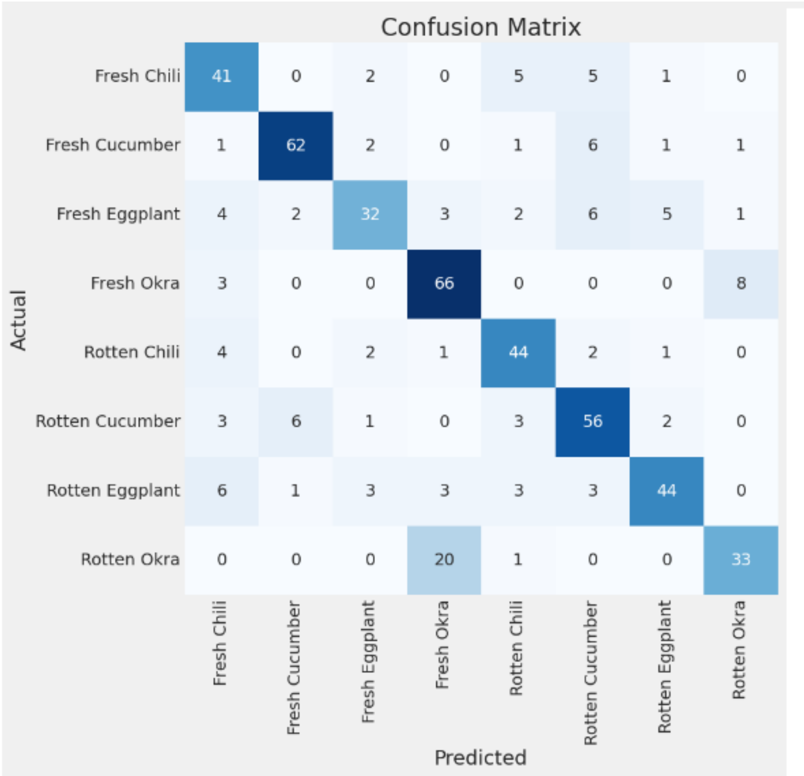


Figure 5.3.8: Confusion Matrix of the model ResNet152

**Confusion Matrix VGG19**

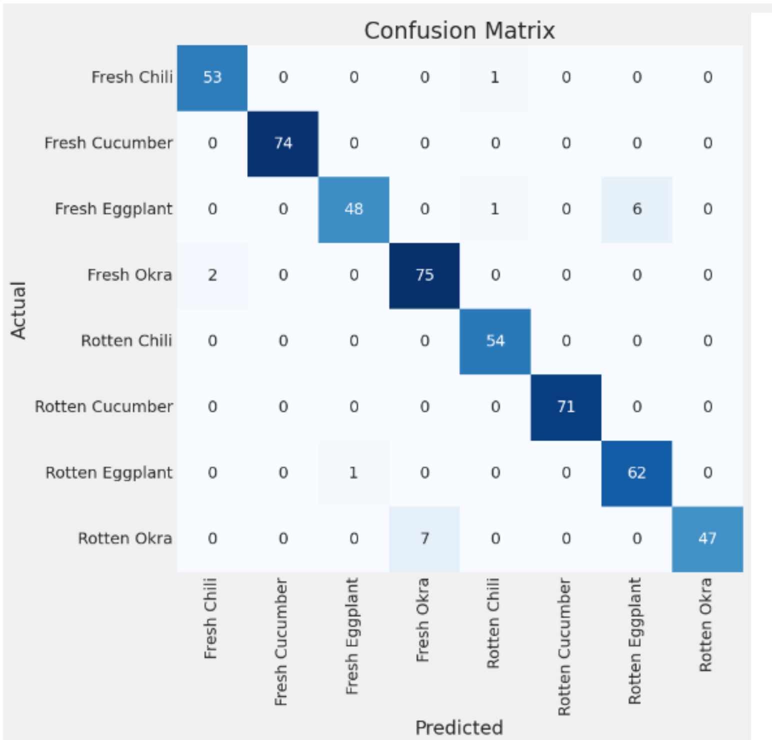


Figure 5.3.9: Confusion Matrix of the model VGG19

### 5.4 Summary

In summary, Chapter 5 provides a detailed analysis of the experimental results and performance of DenseNet201, ResNet152, and VGG19 in classifying vegetable freshness. DenseNet201 emerged as the most accurate and reliable model, with ResNet152 following closely behind. VGG19, though slightly less accurate, still demonstrated strong performance. The comparative analysis highlighted each model's strengths and weaknesses, supported by training and validation curves, and the confusion matrix confirmed DenseNet201's robustness. This comprehensive evaluation underscores the effectiveness of the proposed methodology and offers valuable insights for future enhancements and practical applications.

# CHAPTER 6:
# IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

## 6.1 Impact on Life

The implementation of a vegetable freshness classification system using image processing and transfer learning has a profound impact on daily life. For consumers, it ensures access to fresher, higher-quality produce, which can lead to better nutritional outcomes and overall health. The ability to accurately assess the freshness of vegetables helps reduce the consumption of spoiled or less nutritious produce, promoting a healthier diet and lifestyle.

For farmers and retailers, this technology provides a valuable tool for maintaining the quality of their produce. By accurately classifying the freshness of vegetables, they can make informed decisions about inventory management, reducing waste and optimizing the supply chain. This can lead to increased profitability and sustainability in agricultural practices, as fresher produce is more likely to be sold at a premium price, and waste is minimized.

Overall, the adoption of such advanced technologies in agriculture can enhance the efficiency of food distribution systems, ensuring that consumers receive the freshest possible products. This not only benefits individual health but also contributes to broader public health outcomes by promoting the availability and consumption of fresh, nutritious vegetables.

## 6.2 Impact on Society & Environment

The deployment of a vegetable freshness classification system using image processing and transfer learning has significant societal and environmental impacts. On a societal level, this technology can revolutionize the agricultural sector by providing farmers and retailers with precise tools to assess and maintain produce quality. This leads to a more reliable food supply chain, enhancing food security and ensuring that communities have access to fresh and nutritious vegetables. By reducing the incidence of spoiled produce reaching consumers, it also fosters trust and satisfaction within the market, supporting local economies and promoting sustainable agricultural practices.

From an environmental perspective, the system's ability to accurately classify vegetable freshness can substantially reduce food waste. By ensuring that only fresh produce reaches consumers, retailers can minimize the disposal of spoiled goods, which often end up in landfills and contribute to methane emissions, a potent greenhouse gas. This reduction in food waste not only lowers the environmental footprint of agriculture but also optimizes the use of resources such as water, soil, and energy, which are critical in vegetable production.

Moreover, the technology encourages more efficient distribution and consumption patterns, aligning with broader sustainability goals. By enhancing the lifespan and quality of vegetables, it supports a more circular economy where resources are used more efficiently, and waste is minimized. This contributes to the preservation of natural ecosystems and promotes a more sustainable relationship between agriculture and the environment, benefiting society as a whole.

### 6.3 Ethical Aspects

The ethical aspects of deploying a vegetable freshness classification system using image processing and transfer learning involve considerations around data privacy, algorithmic transparency, and accessibility. Ensuring that the images and data used to train and validate the models are collected with proper consent and respect for privacy is paramount. Additionally, it is important to ensure that the data does not reflect biases that could lead to unfair or inaccurate classifications, thereby affecting certain groups of farmers or retailers disproportionately.

Furthermore, transparency in how the algorithms work and make decisions is crucial. Stakeholders should be informed about the methodologies and the inherent limitations of the models. This includes providing clear documentation and being open to scrutiny and feedback from the agricultural community and the public. Ensuring accessibility and affordability of this technology is also important, as it should benefit all segments of society, including small-scale farmers who might not have extensive resources but stand to gain significantly from improved produce quality and reduced waste.

### 6.4 Sustainability Plan

The sustainability plan for the vegetable freshness classification system focuses on long-term viability and environmental stewardship. This involves regular updates and maintenance of the system to ensure it continues to operate efficiently and accurately. Incorporating feedback from users and continuously improving the model with new data will help maintain its relevance and effectiveness in different agricultural contexts.

Additionally, promoting the widespread adoption of the system among farmers and retailers is crucial. Training programs and support services can help stakeholders integrate the technology into their existing workflows, enhancing its impact on reducing food waste and improving produce quality. Collaboration with agricultural organizations and government bodies can also facilitate the dissemination of best practices and support policies that encourage sustainable agricultural practices. By fostering a culture of sustainability, this plan aims to ensure the long-term success and positive environmental impact of the vegetable freshness classification system.

### 6.5 Summary

In summary, Chapter 6 explores the multifaceted impacts of the vegetable freshness classification system on life, society, the environment, and sustainability. The implementation of this technology significantly enhances the quality of life by providing consumers with fresher and more nutritious produce, thereby promoting better health. Societally, it strengthens food security and supports local economies by improving the reliability and efficiency of the agricultural supply chain. Environmentally, the system plays a crucial role in reducing food waste and minimizing the agricultural sector's carbon footprint, thus contributing to broader environmental conservation efforts. Ethical considerations, such as data privacy, algorithmic transparency, and equitable access, are integral to the responsible deployment of this technology. Lastly, a robust sustainability plan ensures the system's long-term effectiveness through regular updates, user training, and collaboration with key stakeholders. Collectively, these aspects underscore the system's potential to drive significant positive change in agricultural practices, public health, and environmental stewardship.

# CHAPTER 7:
# CONCLUSION AND FUTURE WORK

## 7.1 Conclusions

This research successfully demonstrates the efficacy of image processing and transfer learning techniques in classifying the freshness of local vegetables. By employing DenseNet201, ResNet152, and VGG19, the study found that DenseNet201 offered the highest accuracy and reliability, making it the most suitable model for practical applications. This project underscores the importance of advanced deep learning models in enhancing agricultural practices, ensuring consumers receive fresher produce, and significantly reducing food waste. The comprehensive performance and comparative analysis provided a clear understanding of each model's capabilities, highlighting their respective strengths and areas for improvement. Moreover, this research emphasizes the potential of integrating these technologies into real-world agricultural systems to promote efficiency, sustainability, and quality control. The insights gained from this study not only validate the proposed methodology but also set the stage for further advancements in agricultural technology, paving the way for more innovative and effective solutions in the food supply chain. This work represents a significant step forward in leveraging AI to address critical challenges in agriculture.

## 7.2 Further Suggested Works

Future work in the area of vegetable freshness classification using image processing and transfer learning can explore several promising avenues. One key area is the enhancement of the dataset with a wider variety of vegetables and freshness stages, including regional and seasonal variations. This would improve the model's robustness and generalizability. Additionally, integrating multispectral or hyperspectral imaging could provide more detailed information about vegetable quality, leading to more precise classifications.

Another suggested direction is the development of a mobile application that leverages the trained models, making the technology accessible to farmers and consumers in real-time. This would involve optimizing the models for deployment on mobile devices and ensuring they can operate efficiently with limited computational resources. Collaborations with agricultural experts to refine the classification criteria and provide comprehensive training for users would further enhance the system's practical utility and adoption in various agricultural contexts

### 7.3 Limitations/ Conflict of Interests

The vegetable freshness classification system, while promising, has several limitations. One significant limitation is the reliance on high-quality images for accurate classification. Variations in lighting, background, and image quality can affect the system's performance. Additionally, the current models may struggle with vegetables that have subtle differences in freshness stages, requiring further refinement and possibly more advanced imaging techniques to improve accuracy.

Potential conflicts of interest could arise from the commercial aspects of deploying this technology. Developers and stakeholders might prioritize profitability over broader accessibility, which could limit the benefits to larger agricultural operations and exclude small-scale farmers. Ensuring transparency and maintaining an ethical approach in the development and deployment phases is crucial to address these concerns. Providing affordable solutions and support to all users, regardless of their scale, will help in mitigating conflicts of interest and promoting equitable access to the technology.

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# APPENDIX A

## COURSE OUTCOMES, COMPLEX ENGINEERING PROBLEMS (EP) AND COMPLEX ENGINEERING ACTIVITIES (EA) ADDRESSING

**TITLE: USING IMAGE PROCESSING AND TRANSFER LEARNING APPROACHES FOR LOCAL VEGETABLE FRESHNESS CLASSIFICATION.**

**Student ID: 202-15-14374 Or 202-15-14452**

## CO Description for FYDP

| CO | CO Descriptions | PO |
|---|---|---|
| **Phase -I** | | |
| **CO1** | Combine newly acquired and prior information to the Local Vegetable Freshness Classification for the Final Year Design Project (FYDP) | **PO1** |
| **CO2** | Analyze different aspects of the goals in designing a solution for this FYDP | **PO2** |
| **CO3** | Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP | **PO4** |
| **CO4** | Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP | **PO11** |
| **Phase -II** | | |
| **CO5** | Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP | **PO3** |
| **CO6** | Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP | **PO5** |
| **CO7** | Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding. | **PO6** |

| | | |
|---|---|---|
| **CO8** | Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks. | **PO7** |
| **CO9** | Implement ethical principles and adhere to professional standards and norms in this FYDP | **PO8** |
| **CO10** | Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP. | **PO9** |
| **CO11** | Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP. | **PO10** |
| **CO12** | Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors. | **PO12** |

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

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

| SN | EP Definition | Attainment | CO | Justification (with Knowledge Profile) | References |
|---|---|---|---|---|---|
| **1.** | **EP1: Depth of Knowledge required** | Yes | CO1, CO2, CO3, CO5, CO6, CO7 and CO8 | Our project requires data collection from the Local Market, and we have to know the design of an Image processing And Transfer Learning model which covers **K3 and K4.** | **Page no:** [17-23] **Section:** [3.2] **Page no:** [1-3] **Section:** [1.1] |
| | | | | Our project requires the Local Vegetable Freshness Classification using Image processing And Transfer Learning model that covers **K5 and K6.** | **Page no:** [17] **Section:** [3.2] **Page no:** [30] **Section:** [4.2] |

| | | | | | |
|---|---|---|---|---|---|
| | | | | We have studied existing models with similar goals **(K8).**<br><br>This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance pneumonia detection using deep learning, showcasing a comprehensive understanding of current methodologies. | **Page no:** [10-12] **Section:** [2.2] |
| **2.** | **EP2: Range of Conflicting Requirements** | Yes | CO2, and CO7 | Finding a clear solution for our project is challenging, primarily because our country has many markets and crop fields from which to collect a large amount and variety of data that account for diversity. We have conducted an in-depth analysis to carefully choose a particular model from many options. | **Page no:** [18-21] **Section:** [3.2] |
| **3.** | **EP3: Depth of analysis required** | Yes | CO2, and CO6 | This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing vegetable freshness classification amidst multiple potential approaches. | **Page no:** [34-44] **Section:** [5.2,5.3] |

| | | | | | |
|---|---|---|---|---|---|
| **4.** | **EP4: Familiarity of Issues** | Yes | CO8 | This project's interdisciplinary approach extends beyond computer science and engineering, vegetable freshness classification, contributing to advancements in public health and healthcare practices which indicates **EP-4**. | **Page no:** [10-13] **Section:** [2.2, 2.3] |
| **5.** | **EP5: Extends of application codes** | No | CO5 | N/A | N/A |
| **6.** | **EP6: Extends of stakeholders involved and** | No | CO8 | N/A | N/A |
| **7.** | **EP7: Interdependence** | Yes | CO5 | This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, **EP-7** is instrumental in revolutionizing the method of freshness assessment in agricultural products. | **Page no:** [17-24] **Section:** [3.2, 3.3] |

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

| SN | EA Definition | Attainment | CO | Justification | References |
|---|---|---|---|---|---|
| **1.** | **EA1: Range of resources** | Yes | CO11 | Our project utilizes various resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to accurately quantify freshness levels of vegetables through transfer learning and image processing. | **Page no:** [23-24] **Section:** [3.3] |
| **2.** | **EA2: Level of interaction** | No | | N/A | N/A |
| **3.** | **EA3: Innovation** | No | | N/A | N/A |

| | | | | | |
|---|---|---|---|---|---|
| **4.** | **EA4: Consequences for society and the environment** | Yes | | This project contributes to the society by satisfying the consumers by accurately determining the freshness level of vegetables. Also plays an important role in optimizing subsequent handling, distribution and storage practices. | **Page no:** [45-48] **Section:** [6.1-6.5] |
| **5.** | **EA-5: Familiarity** | Yes | | This project expands on existing research by testing a novel approach to accurately determine freshness levels of vegetables through transfer learning and image processing, demonstrated through preliminary terminology and a comprehensive comparative analysis, providing new insights into the field. | **Page no:** [29-32] **Section:** [4.2] |

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

| SN | COs | Attainment | Justification | References |
|---|---|---|---|---|
| **1** | CO4 | Yes | This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle. | **Page no:** [25-26] **Section:** [3.4] |
| **2** | CO9 | Yes | This project contributes to the society by satisfying the consumers by accurately determining the freshness level of vegetables. Compliance with **CO9** plays an important role in optimizing subsequent handling, distribution and storage practices. | **Page no:** [46-47] **Section:** [6.3] |
| **3** | CO10 | No | N/A | N/A |
| **4** | CO12 | Yes | The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges. | **Page no:** [17-23, 34-43] **Section:** [3.2, 5.2-5.3] |

## Shahriar

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