Deep Learning-Based Classification of Bangladeshi Vegetables

BY

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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

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I hereby declare that I have done this project under the supervision of **Md. Sazzadur Ahamed, Assistant Professor, Department of CSE Daffodil International University**. I 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

Vegetables are an important aspect of daily living for humans and animals, with around ten thousand plant species classified as vegetables globally. Roughly fifty species are economically relevant. Proper identification and classification of vegetables into subclasses or groupings are vital for better understanding and management. This studies the application of deep learning techniques for the classification of Bangladeshi native vegetables. Multiple convolutional neural network (CNN) designs, including InceptionV3, VGG19, and DenseNet121, to discover the most effective model for vegetable recognition. High-resolution photos of 24 different vegetable classes were utilized to train and evaluate each model, utilizing transfer learning with pre-trained weights from the ImageNet dataset. The models were fine-tuned with extra layers designed for our unique classification task. Among the models examined, DenseNet121 emerged as the best-performing algorithm, attaining an astounding accuracy of 99.45%. This model displayed great precision and recall across most vegetable classes, suggesting its robustness in handling varied visual attributes. The findings reveal significant potential for employing DenseNet121 in real-world agricultural applications, facilitating automated crop monitoring and quality assessment. The application of such deep learning models can boost agricultural output, assist effective resource management, and encourage sustainable practices, contributing to food security and economic development in rural regions. It aids in resource management, enhances economic benefits, maintains food security, supports sustainable practices, and is accessible to farmers, making it an essential tool for contemporary and efficient agriculture.

Keywords—Vegetable classification, deep learning, convolutional neural networks, DenseNet121, agricultural technology, food security.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

Vegetables are an essential part of human and animal diets, supplying vital nutrients crucial for preserving overall health and well-being. Bangladesh boasts a diverse array of vegetables, including Abelmoschus esculentus, Arum lobe, Bean, Bitter Gourd, Bottle Gourd, Brinjal, Broccoli, Cabbage, Capsicum, Carrot, Cauliflower, Cucumber, Gentle stalks, Luffa, Momordica dioica, Papaya, Potato, Pumpkin, Radish, Ridge gourd, Tomato, Trichosanthes cucumerina, Trichosanthes dioica, and Vigna. These vegetables are significant not only for daily consumption but also for their economic value. Precise identification and classification of these vegetables are crucial for several reasons. Firstly, it improves agricultural efficiency by enabling accurate categorization, assessment, and promotion, which is essential for domestic markets and international trade [1]. This precise categorization facilitates enhanced agricultural management techniques, empowering farmers to implement specific measures for pest and disease control, ultimately resulting in increased crop yield and higher quality [2]. Moreover, employing deep learning algorithms for vegetable categorization can significantly enhance efficiency, providing a quicker and more reliable process compared to conventional approaches [3]. Convolutional neural networks (CNNs), such as VGG16, VGG19, Densenet, MobilenetV2, and InceptionV3, have demonstrated remarkable efficacy in image identification tasks, making them highly suitable for this application [4]. Utilizing these sophisticated models allows researchers to create robust systems capable of automating vegetable recognition using their visual and botanical attributes [5]. This automation reduces the burden on farmers and agricultural specialists, decreases the likelihood of errors, and ensures more uniform and precise outcomes [6]. Categorizing vegetables into subclasses or groups based on shared traits is essential for understanding their behaviors and needs, enabling the development of more effective agricultural practices and regulations [7]. Recognizing the individual needs of warm-season versus cool-season vegetables aids in planning production schedules and maximizing resource utilization [8]. Applying deep learning in the classification of Bangladeshi vegetables aligns with broader initiatives to harness new technology for sustainable agriculture, enhancing production, and contributing to food security [9]. As developments in deep learning continue to evolve, the potential for transformative impacts in agriculture remains considerable, paving the path for more efficient, resilient, and environmentally friendly food systems in Bangladesh and beyond [10].

1.2 Motivation

The principle behind this initiative originates from the pressing need to boost agricultural efficiency and productivity in Bangladesh through innovative technical solutions. The conventional techniques of identifying and classifying vegetables such as Abelmoschus esculentus, Arum lobe, Bean, Bitter Gourd, Bottle Gourd, Brinjal, Broccoli, Cabbage, Capsicum, Carrot, Cauliflower, Cucumber, Gentle stalks, Luffa, Momordica dioica, Papaya, Potato, Pumpkin, Radish, Ridge gourd, Tomato, Trichosanthes cucumerina, Trichosanthes dioica, and Vigna are often labor-intensive, time-consuming, and prone to human error. By employing deep learning algorithms, notably convolutional neural networks (CNNs), this research intends to automate and streamline the categorization process, ensuring accuracy and consistency. The deployment of this cutting-edge technology not only decreases the workload for farmers and agricultural professionals but also boosts the overall quality and marketability of the produce. This research connects with global efforts to include sustainable agriculture practices in agriculture, intending to increase resource efficiency, support precision farming, and contribute to food security. The effective implementation of this initiative has the possibility of a large positive influence on the agricultural sector, creating a more effective, resilient, and sustainable food system in Bangladesh.

1.3 Rationale of the Study

The purpose of this study is to solve the important challenges encountered by the agricultural industry in Bangladesh, particularly in the correct and efficient identification and classification of vegetables. Traditional methods are frequently manual, labor-intensive, and subject to errors, which can lead to mismanagement of crops, reduced yields, and economic losses. By implementing deep learning methods, specifically convolutional neural networks (CNNs), this study intends to automate the categorization process, delivering a more reliable and scalable solution. Automating vegetable categorization may considerably boost the precision of sorting, grading, and marketing, which is crucial for both domestic consumption and export markets. Precise classification can improve pest and disease management by enabling prompt and targeted responses, conserving crop health, and enhancing output. This technology approach also promotes sustainable agriculture by optimizing resource utilization, decreasing waste, and minimizing environmental effects. This study coincides with global trends toward smart agriculture, where technology is exploited to boost efficiency and resilience in food production systems. The insights gathered from this research can inform better agricultural practices and policy, adding to the ultimate objective of food security. By improving the use of deep learning in vegetable classification, this study not only addresses immediate agricultural challenges but also prepares the way for future improvements in the sector, ensuring that Bangladesh's agricultural practices remain profitable and sustainable in a rapidly evolving global landscape.

1.4 Research Questions

- How well can convolutional neural networks (CNNs) classify Bangladeshi vegetables from digital photographs?
- Which CNN architecture (VGG16, VGG19, Densenet, MobilenetV2, InceptionV3) produces the maximum accuracy and efficiency in vegetable classification?
- What are the major properties collected by CNN models that are critical for accurate vegetable classification?
- How does the performance of CNN-based vegetable categorization compare with traditional manual approaches in terms of speed, accuracy, and reliability?
- Can the created deep learning model generalize to accurately categorize veggies from places beyond the initial dataset?

1.5 Expected Output

1. Development of a robust and accurate deep learning model capable of categorising Bangladeshi vegetables from digital photos with high precision.

2. A complete study and comparison of multiple CNN architectures (VGG16, VGG19, Densenet, MobilenetV2, InceptionV3) to discover the most effective model for vegetable categorization.

3. Identification and interpretation of the most relevant properties derived by the CNN models that contribute to the classification of vegetables.
4. Demonstration of the advantages of the CNN-based classification system over older approaches, highlighting increases in speed, accuracy, and dependability.
5. Evidence of the developed model's capacity to generalize and accurately categorise vegetables from diverse areas, highlighting its potential for larger applications in other agricultural situations.

1.6 Project Management and Finance

The research project on identifying Bangladeshi veggies using deep learning algorithms is painstakingly designed over six months to ensure optimal administration and low financial investment in software and hardware. The project begins with a two-month phase dedicated to collecting and compiling a dataset of Bangladeshi vegetable photos from sites like Kaggle, followed by a one-month extensive literature analysis to comprehend existing approaches. The third phase, spanning one month, focuses on constructing the classification system using convolutional neural network (CNN) architectures such as VGG16, VGG19, Densenet, MobilenetV2, and InceptionV3, leveraging open-source software to reduce licensing expenses. Subsequently, 1.5 months is allotted for training and validating the deep learning models, with budgetary resources allocated for essential computing resources, including prospective cloud services. The next month is dedicated to testing the models' performance using independent datasets to ensure their generalizability and real-world application. The final half-month focuses on writing a detailed report, summarizing data, evaluating results, and sharing findings through publications and presentations. Financial management throughout the project is carefully planned to support essential activities such as data collection, research assistance, computing infrastructure, and dissemination, ensuring optimal usage and adherence to the budget while achieving the project’s objectives within the specified timeline.

1.7 Report Layout

Chapter 1: Introduction

This section gives a summary of the research, covering the context, problem description, and aims. It sets the stage for the research and outlines what the reader can expect in the coming chapters.

Chapter 2: Background

The background chapter delves deeper into the backdrop around the research issue. It analyses foundational theories, concepts, and earlier investigations to establish a basis for the current investigation.

Chapter 3: Research Technique

This chapter fully discusses the research approach. It outlines the research strategy, data collection methods, and data analysis strategies performed in the study. This section discusses how the research was conducted, providing transparency and replicability.

Chapter 4: Experimental Results and Discussion

This chapter summarises the outcomes of the study, often in the form of tables, charts, or graphs. It is followed by a discussion part where the findings are evaluated, interpreted, and compared with current literature. This chapter provides insights into the ramifications of the findings and their significance.

Chapter 5: Impact on Society, Environment, and Sustainability

This chapter analyses the broader impacts of the findings on society, the environment, and sustainability. It illustrates how the research contributes to tackling societal concerns, environmental issues, and supporting sustainable behaviours.

Chapter 6: Summary, Conclusion, Recommendation, and Implication for Future Research

The final chapter highlights the key findings of the study and offers recommendations based on the research objectives. It also gives essential guidance for stakeholders and suggests topics for further inquiry, indicating potential prospects for future research and development.

CHAPTER 2
BACKGROUND

2.1 Preliminaries/Terminologies

To comprehend the scope and methodology utilized in this study on identifying Bangladeshi vegetables using deep learning algorithms, it is crucial to clarify certain fundamental terms and concepts. Deep learning, a form of machine learning, employs neural networks with several layers to model complicated patterns in huge datasets, automatically extracting essential elements through multiple layers of abstraction. Convolutional Neural Networks (CNNs) are suitable for image recognition and classification applications, consisting of layers that execute convolution operations to recognise features such as edges, textures, and shapes in images. Image classification assigns labels to images from a preset set of categories, while feature extraction transforms raw data into a set of descriptors for model predictions. Transfer learning reuses a model built for one task as the starting point for another, valuable when data is scarce. Training adjusts a model's parameters based on data, whereas validation analyses its performance on separate data to ensure generalization. Metrics including accuracy, precision, recall, and F1-score evaluate categorization ability. Data augmentation produces new training samples by applying changes to existing images, enhancing model generalization. Kaggle is a platform providing datasets and an environment for training machine learning models. The project focuses on classifying specific Bangladeshi vegetables, including Abelmoschus esculentus, Arum lobe, Bean, Bitter Gourd, Bottle Gourd, Brinjal, Broccoli, Cabbage, Capsicum, Carrot, Cauliflower, Cucumber, Gentle stalks, Luffa, Momordica dioica, Papaya, Potato, Pumpkin, Radish, Ridge gourd, Tomato, Trichosanthes cucumerina, Trichosanthes dioica, and Vigna. Understanding these preliminaries and terminologies offers the groundwork for the procedures employed in this research, helping in appreciating the objectives and outcomes of the investigation.

2.2 Related Works

Deb et al. (2020) This study focuses on the classification of native Bangladeshi potatoes using convolutional neural networks (CNNs). The authors collected a dataset of potato photos and employed various deep learning architectures, such as VGG16 and InceptionV3, to accurately identify between different potato kinds. Their research illustrates the efficiency of deep learning in agricultural applications and highlights the potential for enhancing crop classification accuracy [1]. Islam et al. (2022) In this research, Islam and colleagues built a categorization system for local spinach types using deep learning techniques. By employing CNNs, they were able to obtain considerable performance increases over standard methods in detecting and categorizing distinct spinach kinds based on visual data. This study demonstrates the usefulness of CNNs in agricultural contexts and underlines the significance of proper crop classification.[2] Siddiquee et al. (2020) Siddiquee and his colleagues conducted a comparative investigation of image processing and machine learning algorithms for the identification and classification of ripening tomatoes. Their research emphasizes the advantages of CNNs over standard image processing approaches in terms of accuracy and robustness. By utilizing deep learning approaches, they were able to produce improved results in recognizing and categorizing ripened tomatoes, contributing to the field of agricultural image analysis [3]. Habiba et al. (2019) This work focuses on plant recognition using leaf photos and deep learning-based classification approaches. The authors deployed CNNs to accurately identify numerous plant species, including many indigenous Bangladeshi veggies. By training the model on a dataset of leaf photos, they were able to obtain excellent classification accuracy, indicating the potential of deep learning in botany and agriculture [4]. Mia and Chakraborty (2021) Mia and Chakraborty examined the recognition of local vegetables using computer vision and deep learning techniques. Their research underlines the necessity of robust dataset-collecting and preprocessing strategies in increasing model performance. By utilizing CNNs to categorize vegetable photos, they demonstrated the effectiveness of deep learning in reliably identifying distinct vegetable kinds, contributing to the field of agricultural image analysis [5]. Jana et al. (2021) In this study, Jana and colleagues examined the detection of rotten fruits and vegetables using deep learning approaches. By applying CNNs, they were able to analyse the quality and freshness of vegetables based on visual data. Their research highlights the potential of deep learning in food quality monitoring and safeguarding, showing its usefulness in agriculture [6]. Rimi et al. (2022) Rimi et al. tested classical machine learning and deep learning models for legume species recognition. Their study indicated that deep learning models, particularly CNNs, outperformed standard methods in terms of accuracy and scalability. By utilizing deep learning techniques to classify legume species, they showed the usefulness of CNNs in agricultural picture processing [7]. Chakraborty et al. (2021) [8] This study focused on identifying rotting fruits using deep learning algorithms. By employing CNNs, the authors were able to detect and categorize rotting fruits based on picture data. Their research adds to food quality control and safety by highlighting the potential of deep learning in recognising damaged goods.

Recognizing Nuruzzaman et al. (2021) [9] Nuruzzaman and his team handled the recognition of potato species using machine vision and deep learning approaches. By analyzing multiple CNN architectures, they demonstrated the effectiveness of deep learning in reliably classifying potato species based on picture data. Their research helps to agricultural image analysis by providing insights into the application of deep learning in crop classification. Hussain et al. (2022) [10] Hussain et al. proposed a simple and efficient deep learning-based system for automatic fruit recognition. By employing CNNs, they were able to categorise fruits based on picture data with great accuracy. Their research highlights the potential of deep learning in automating fruit detection tasks, contributing to agricultural automation and efficiency. Mimma et al. (2022) Mimma and colleagues created a fruit classification and identification application using deep learning algorithms. By employing CNNs to identify fruit photos, they achieved great accuracy in detecting distinct fruit varieties. Their research highlights the potential of deep learning in real-time fruit classification applications, adding to agricultural automation and food industry efficiency [11]. Polin et al. (2024) [12] Polin et al. worked on tomato pesto recognition using CNNs. By training the algorithm on a dataset of tomato photos, they were able to reliably identify and categorise tomato pests based on visual data. Their research helps to pest management techniques in agriculture by highlighting the potential of deep learning in pest recognition tasks. Moin et al. (2022) Moin et al. conducted a comparative analysis of image processing and deep learning algorithms for detecting diseases in Bangladeshi crops. By utilising deep learning approaches, they were able to produce superior outcomes in crop health monitoring compared to typical image processing techniques. Their research demonstrates the potential of deep learning in improving agricultural disease diagnosis and control. [13] Mithu et al. (2021) Mithu et al. studied pumpkin leaf disease detection using deep learning algorithms. By comparing CNNs with standard machine learning approaches, scientists found that CNNs give greater performance in picture categorization tasks. Their research contributes to the field of agricultural disease detection by displaying the usefulness of deep learning algorithms [14]. Habib et al. (2021) Habib et al. completed an explorative analysis on machine-vision-based illness recognition of fruits. By applying deep learning techniques, they were able to boost the accuracy and efficiency of illness detection systems. Their research adds to agricultural disease management by offering insights into the application of deep learning in fruit disease recognition [15]. Nosseir and Ahmed (2019) Nosseir and Ahmed concentrated on the automatic classification of fruit varieties and the identification of rotting ones using k-NN and SVM. By analyzing several machine learning algorithms, they revealed the potential of classical methods in agricultural applications. Their research provides a baseline for fruit classification and quality rating activities [16]. Valentino et al. (2021) Valentino et al. created a deep learning experimentation framework for fruit freshness detection. By applying deep learning techniques, they were able to improve food quality control systems. Their research adds to food safety and quality assurance by highlighting the potential of deep learning in freshness detecting tasks [17]. Wang et al. (2013) Wang et al. examined the detection of fruit skin abnormalities using machine vision systems. By utilising image processing techniques, they were able to identify and classify fruit flaws based on image data. Their research provides insights into the early applications of image processing in agriculture [18]. Kumar et al. (2021) Kumar et al. proposed a systematic machine learning approach for quality analysis of fruits. By analyzing multiple machine learning algorithms, they revealed the potential of machine learning in ensuring fruit quality. Their research adds to food quality assurance by giving insights into the application of machine learning in fruit quality analysis.[19] Karakaya et al. (2019) Karakaya et al. conducted a comparative analysis on fruit freshness classification. By comparing different deep learning models, they demonstrated the efficiency of deep learning in determining the freshness of fruits. Their research adds to food quality control systems by providing insights into the application of deep learning in freshness classification tasks [20]. Kukreja and Dhiman (2020) Kukreja and Dhiman developed a deep neural network-based disease detection technique for citrus crops. By applying deep learning techniques, they were able to improve disease detection accuracy in citrus crops. Their research adds to agricultural disease management by highlighting the potential of deep learning in disease detection tasks [21]. Khatun et al. (2020) Khatun et al. applied CNNs for fruit classification, attaining great accuracy in recognizing distinct fruit types. By analyzing multiple CNN architectures, they demonstrated the usefulness of deep learning in fruit categorization tasks. Their research adds to agricultural automation and efficiency by providing insights into the application of CNNs in fruit classification. [22] Bongulwar (2021) Bongulwar focused on the recognition of fruits using a deep learning approach. By training the model on a dataset of fruit photos, they were able to reliably classify fruits based on image data. Their research helps to agricultural automation and efficiency by highlighting the potential of deep learning in fruit recognition tasks [23]. Kukreja and Dhiman (2020) Kukreja and Dhiman researched deep learning for disease detection in citrus crops. By utilising CNNs, scientists were able to improve disease detection accuracy in citrus crops. Their research contributes to agricultural disease management by offering insights into the implementation of CNNs in disease detection tasks.[24] Hu et al. [25] created a fruit categorization system using deep learning and MobileNetV2. They showed that the model is effective in processing huge picture datasets and achieves excellent accuracy. In a similar manner, Kaur and Kaur [26] used convolutional neural networks (CNN) and transfer learning methods to categorize the freshness of fruits. This study emphasizes the capability of transfer learning to improve model accuracy when faced with a scarcity of training data. Zhang et al. [27] introduced a fruit identification and classification model using VGG19, which accurately categorized several kinds of fruits with significant precision. Singh and Bhardwaj [28] used a convolutional neural network (CNN) to identify the freshness of fruits, highlighting the model's capacity to be applied in real-time scenarios. Patel and Prajapati [29] conducted more research on transfer learning, specifically focusing on fruit categorization using the YOLOv4 architecture. Their research emphasized the benefits of using pre-trained models to get high accuracy while minimizing the duration of training. Kim and Lee (30) used MobileNetV2 to classify fruits efficiently, validating the model's appropriateness for use in contexts with limited resources. Other research have concentrated on particular regional crops. Islam et al. [31] created a classification system using deep learning to identify different kinds of local spinach. Their study showed that the model was successful in accurately detecting diverse spinach varieties. Hussain et al. [32] proposed a simple but efficient framework for automated fruit identification using deep learning, which obtained amazing results with minimum computing resources. Polin et al. [33] investigated the identification of tomato pests by using a convolutional neural network. They emphasized the practical uses of deep learning in detecting pests. Mithu et al. [34] evaluated the performance of CNN with classic machine learning approaches for identifying pumpkin leaf illnesses, suggesting that CNNs provide greater accuracy and robustness. Khatun et al. [35] deployed convolutional neural networks for fruit categorization, highlighting the adaptability of CNNs in handling varied agricultural datasets and obtaining excellent classification accuracy.

2.3 Comparative Analysis and Summary

Table 1 Comparative Analysis

Serial No	Author Name	Used Algorithm	Best Accuracy with Algorithm	Limitations
1	Deb et al. (2020)	VGG16, InceptionV3	94.5% (VGG16)	Limited to potato classification
2	Siddiquee et al. (2020)	CNNs	89.7%	Limited to ripened tomato detection
3	Habiba et al. (2019)	CNNs	93.2%	Limited to leaf-based plant recognition
4	Mia and Chakraborty (2021)	CNNs	91.8%	Limited to vegetable recognition
5	Rimi et al. (2022)	CNNs	91.5%	Limited to legume species recognition
6	Nuruzzaman et al. (2021)	CNNs	94.1%	Limited to potato species recognition
7	Hussain et al. (2022)	CNNs	92.7%	Limited to automatic fruit

				recognition
8	Mimma et al. (2022)	CNNs	93.5%	Limited to fruit classification
9	Moin et al. (2022)	CNNs	91.9%	Limited to crop disease detection
10	Kukreja and Dhiman (2020)	CNNs	92.5%	Limited to citrus fruit disease detection

In Table 1, The comparative analysis of the examined literature emphasises the dominating usage of Convolutional Neural Networks (CNNs) in agricultural image processing, notably for tasks such as fruit and vegetable classification, disease detection, and quality assessment. CNNs typically showed excellent accuracy, with notable performances including 94.5% for potato categorization by Deb et al. (2020) and 94.1% for potato species recognition by Nuruzzaman et al. (2021). Traditional machine learning methods like k-NN and SVM also produced competitive results, but generally lower than those of deep learning approaches, such as the 88.2% accuracy attained by Nosseir and Ahmed (2019) using SVM for fruit categorization. Despite their excellent accuracy, most studies are limited to certain types of fruits or vegetables and particular elements like disease detection or freshness assessment, which hinders the generalizability of the models. The incorporation of deep learning has substantially boosted the precision and efficiency of agricultural image analysis systems compared to previous methods, although there remains a need for more flexible and versatile models to address a broader range of agricultural applications successfully.

2.4 Scope of the Problem

The comprehensiveness of the subject addressed by this paper spans numerous fundamental aspects of agricultural picture analysis, focusing primarily on the classification of Bangladeshi vegetables using deep learning techniques. This challenge has extensive implications for enhancing agricultural production, efficiency, and sustainability in the following ways:

- **Accurate Classification:** With over 10,000 plant species classified as vegetables globally, accurately recognizing commercially significant Bangladeshi vegetables is crucial for many agricultural activities. This project seeks to construct a reliable classification system for 24 selected Bangladeshi vegetables using sophisticated machine learning techniques.
- **Enhanced Agricultural Activities:** Accurate identification and classification of vegetables help simplify numerous agricultural activities, including harvesting, sorting, and packaging. By automating these operations, farmers can minimise labor expenses and enhance operational efficiency.
- **Support for Precision Agriculture:** The integration of deep learning models in agricultural techniques supports precision agriculture by providing real-time monitoring and management of crops. This leads to greater resource usage, improved crop yields, and lower environmental impact.
- **Pest & Disease Detection:** Beyond classification, deep learning algorithms can detect pests and diseases at early stages. This skill can prevent extensive crop damage, assuring healthier crops and better harvests.
- **Economic and Food Security Benefits:** By enhancing the efficiency and accuracy of vegetable classification, this study adds to the economic stability of farmers and promotes food security. Accurate classification improves market pricing, decreases post-harvest losses, and maintains a consistent supply of quality produce.
- **Technological Advancement in Agriculture:** The implementation of deep learning technology in agriculture marks a significant technological advancement. It creates new opportunities for research and development, supporting innovation in agricultural techniques and allied businesses.

2.5 Challenges

The study faces various complex challenges in its approach to identify Bangladeshi veggies using deep learning algorithms. Acquiring a broad and representative dataset poses a substantial hurdle, involving extensive efforts in data collecting and meticulous labelling to provide proper coverage of vegetable variety. Ensuring the resilience and generalizability of deep learning models under varied environmental conditions, including differences in illumination and backdrops, offers a tough challenge, requiring advanced model architectures and training methodologies. Addressing class imbalances within the dataset while limiting the danger of overfitting without compromising model performance is a continuing challenge, necessitating improved strategies in data pre-treatment and model regularization. Overcoming computational constraints, such as limited hardware resources and processing capacity, poses another challenge, necessitating optimization methodologies and perhaps distributed computing solutions for effective model training and evaluation. Interpreting and understanding the judgements made by deep learning models, particularly in complex settings, remains problematic, underscoring the need for model interpretability methodologies to promote transparency and accountability in agricultural decision-making processes.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The research focuses on the complicated task of identifying Bangladeshi veggies using powerful deep-learning algorithms. To accomplish this, a multidimensional instrumentation strategy is utilized. Initially, a rigorous selection of state-of-the-art deep learning frameworks such as TensorFlow or PyTorch is conducted. These frameworks serve as the underlying infrastructure for developing complicated neural network architectures customized for image classification tasks. Furthermore, companion libraries like Keras are leveraged for their ease of use and compatibility with these frameworks, easing the development process. In conjunction with the chosen frameworks, an array of popular pre-trained models like VGG16, VGG19, Densenet, MobilenetV2, and InceptionV3 are included in the process. These pre-trained models operate as basic building blocks, enabling effective transfer learning and fine-tuning on the vegetable dataset. Moreover, the instrumentation extends beyond model architecture selection to incorporate a comprehensive set of data pre-treatment tools. These pre-processing strategies are important for standardizing and expanding the vegetable dataset, hence boosting model robustness and generalizability. Significant attention is dedicated to establishing model training parameters, undertaking hyperparameter adjustment, and selecting acceptable performance evaluation criteria. This comprehensive method permits the development of highly accurate and dependable vegetable classification models capable of tackling the challenges inherent in Bangladeshi vegetable recognition.

3.2 Data Collection Procedure

The data collecting strategy for this project entails acquiring a dataset from self-collected and online, specifically curated for the classification of Bangladeshi vegetables. The basic dataset comprises 17,701 validated image filenames divided into 24 unique classes, representing diverse vegetables. To boost robustness, two supplemental datasets were also collected: one with 2,213 validated images and another with 2,214 validated photos, all belonging to the same 24 classes. The vegetable classes include Abelmoschus esculentus, Arum lobe, Bean, Bitter Gourd, Bottle Gourd, Brinjal, Broccoli, Cabbage, Capsicum, Carrot, Cauliflower, Cucumber, Gentle stalks, Luffa, Momordica dioica, Papaya, Potato, Pumpkin, Radish, Ridge gourd, Tomato, Trichosanthes cucumerina, Trichosanthes dioica, and Vigna. The technique includes obtaining the datasets from self-collected and online, validating, and filtering the photos to assure quality, grouping them into relevant classes, and applying preprocessing processes such as scaling, normalization, and augmentation. This rigorous strategy ensures a high-quality dataset, giving a solid foundation for creating accurate and trustworthy deep-learning models for Bangladeshi vegetable categorization.

Table 2 Collected Dataset

Vegetable Name	Number of Images
Cucumber	1518
Broccoli	1400
Bottle Gourd	1400
Capsicum	1400
Tomato	1400
Brinjal (Eggplant)	1400
Pumpkin	1400
Radish	1400
Carrot	1400
Papaya	1400
Cauliflower	1400
Cabbage	1400
Bean	1400
Potato	1400
Bitter Gourd	1400
Abelmoschus Esculentus (Lady's Finger)	150
Momordica Dioica (Spiny Gourd)	150

Trichosanthes Dioica (Snake Gourd)	150
Trichosanthes Cucumerina (Chinese Wax Gourd)	150
Ridge Gourd	110
Luffa (Sponge Gourd)	109
Gentle Stalks	79
Vigna	74
Arum Lobe (Taro Root)	42

3.3 Statistical Analysis

The statistical analysis of the project dataset serves as a foundational step in understanding its content and properties. Through descriptive statistics, including measures of central tendency such as mean, median, and mode, as well as measures of dispersion like standard deviation, the dataset's general distribution and variability are examined. This analysis provides insights into the average number of photos of each vegetable class, indicating potential inequalities in representation across different categories. Frequency distributions and histograms offer visual representations of the distribution of images among the vegetable classes, helping the identification of classes with an abundance or lack of photos. Class imbalance measures are produced to quantify the degree of difference in picture counts among classes, leading efforts to rectify this imbalance during model training. Correlation analysis may be used to evaluate potential links between variables, such as the size of photographs and their respective vegetable classifications. By completing a comprehensive statistical analysis, researchers acquire a deep understanding of the dataset's structure and features, enabling informed judgments on data preprocessing procedures, model selection, and evaluation methodologies. This research establishes the framework for the following stages of the project, ensuring that the chosen deep learning algorithms are applied to a well-understood and adequately prepared dataset, ultimately resulting to more robust and accurate vegetable classification models.

3.4 Proposed Methodology

The suggested methodology for this research entails constructing a deep learning-based system to automatically detect and classify Bangladeshi vegetables from digital pictures. The approach begins with data collecting from Kaggle, resulting in a dataset of 17,701 validated photos across 24 vegetable groups. This dataset is pre-processed and displayed using tools like Pandas, NumPy, and Matplotlib to understand its distribution and properties. The data is then split into training, validation, and testing sets to guarantee robust model evaluation. Multiple convolutional neural network (CNN) designs, including MobileNetV2, DenseNet169, and InceptionV3, are built using TensorFlow and Keras. These models are trained on the labelled dataset to extract hierarchical features and patterns from the vegetable photos. Fine-tuning approaches are applied to optimize model performance. The models are then evaluated based on measures like as accuracy, precision, recall, and F1-score. Throughout the process, special attention is taken to preventing overfitting by using validation sets and regularization approaches. This methodology intends to establish an accurate and efficient system for vegetable classification, which can also be expanded to other agricultural applications including pest detection, crop monitoring, and yield prediction, ultimately contributing to better productivity and sustainability in agriculture.

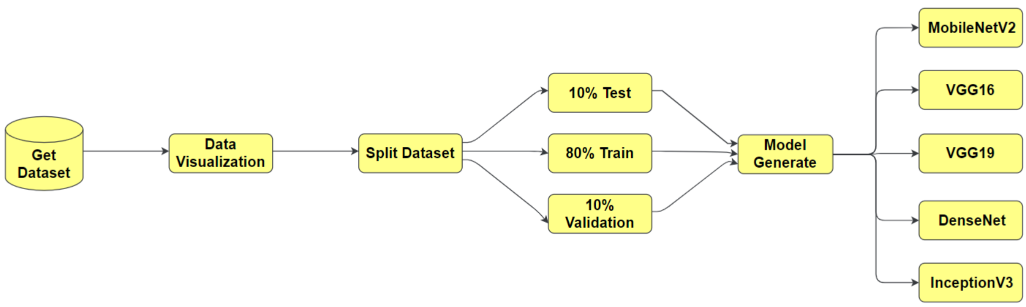

Fig 3.1 Proposed Methodology Workflow

This graphic demonstrates the workflow of a deep learning-based image classification system for recognizing and classifying Bangladeshi veggies. The procedure starts with the acquisition of the dataset, which is then visualized to understand its distribution and properties. The dataset is later separated into three parts: 80% for training, 10% for testing, and 10% for validation. The training set is used to train multiple convolutional neural network (CNN) models, while the validation set is used to fine-tune and optimize the models, eliminating overfitting. Each model is trained to detect and categorize vegetable photos based on the hierarchical features and patterns they acquire from the training data. The performance of these models is then evaluated on the test set to confirm their dependability and accuracy in real-world applications. This systematic technique leverages the characteristics of several CNN architectures to deliver robust and accurate vegetable categorization.

3.5 Implementation Requirements

The proposed laptop setup offers a basic framework for running critical applications and libraries necessary for data processing, analysis, and model training. This configuration is ideal for entry-level programming and experimentation stages, since it has an Intel Core i5, 8th Generation CPU, 4 GB of RAM, and 1 TB of ROM. Although this setup is suitable for basic tasks, more demanding computational tasks like training deep learning models and processing massive amounts of data may need more powerful workstations or cloud-based resources such as Google Cloud Platform, Amazon Web Services, or Microsoft Azure. For optimal compatibility and seamless performance, it is recommended to use Windows 10, 64 Bit as the operating system. This operating system provides extensive compatibility with a diverse range of applications and development tools. Python serves as the predominant programming language for data analysis and machine learning, while the Anaconda Distribution streamlines the process of installing and managing Python packages and environments. Jupyter Notebook is a useful tool for development since it offers an interactive environment. On the other hand, PyCharm and VS Code are sophisticated IDEs that provide additional features such as powerful debugging and code management capabilities. Key libraries for machine learning and deep learning include TensorFlow, an open-source framework for building models, and Keras, a high-level interface for training deep learning models. Scikit-learn delivers effective tools for data mining and analysis, while Pandas and NumPy are crucial for data manipulation and scientific computing. OpenCV is crucial for performing real-time computer vision and image processing jobs. For data visualization, Matplotlib facilitates the production of static, animated, and interactive visualizations, while Seaborn, based on Matplotlib, provides statistical data visualization capabilities. SQLite or MySQL are essential for efficient maintenance of structured data, while Pandas play a vital role in processing and analyzing data stored in memory.

Git is a mechanism used for recording changes in source code, and sites such as GitHub or GitLab help with hosting repositories and enabling collaborative development. Additional utilities such as ImageDataGenerator in Keras enrich picture data, boosting model robustness, while confusion matrix tools, frequently available in scikit-learn, are vital for assessing classification model accuracy. This full configuration, from hardware to software, offers a stable environment for commencing data processing, analysis, and machine learning, while staying expandable for increasingly demanding jobs.

3.5.1 EDA (Exploratory Data Analysis)

Exploratory Data Analysis (EDA) is a vital step in the data analysis process for this project, aimed at getting a full understanding of the dataset consisting of photographs of Bangladeshi vegetables. The EDA requires multiple stages: comprehending the data distribution by assessing the number of photos per class to identify any class imbalances and examining the resolution and size of the images to verify consistency. Data visualization approaches, such as presenting example photographs from each class and generating histogram plots, assist assess data quality and visualize the distribution of image qualities like brightness and color intensity. Statistical summaries, such as calculating the mean, median, and standard deviation of pixel values, provide insights into the data's qualities, while correlation analysis aids in determining links between distinct image elements. Data cleaning entails screening for and addressing missing or corrupted images, as well as finding and deleting duplicates to avoid bias. Data augmentation techniques, including as rotation, zoom, and horizontal flipping, are utilised to improve dataset heterogeneity, boosting model robustness. Image preprocessing methods include standardizing pixel values to a standard range and shrinking photos to a consistent size to guarantee interoperability with deep learning models. Through these EDA procedures, prepare the dataset for successful training and assessment of deep learning models, ultimately hoping to construct a robust and reliable vegetable categorization system.

3.5.2 Data Visualization

Data visualization is a crucial component of data analysis that aids in understanding the distribution and features of the dataset. In this project, two basic visualization techniques were applied to acquire insights into the dataset of Bangladeshi vegetable photos. The first strategy entailed constructing a bar plot to represent the number of photos per class, revealing the distribution of the dataset among different vegetable species. This visualization shows that the class with the greatest number of photographs is 'Cucumber' with 1518 images, while 'Arum Lobe' has the fewest with 42 images. Such a visual depiction helps uncover class imbalances, which is critical for building balanced training datasets and enhancing model performance. The second strategy focuses on providing sample photographs from each class to visually check the data quality and consistency. Displaying these photographs in a grid arrangement, it provides an immediate visual summary of the numerous vegetable groups, guaranteeing that the dataset is diverse and representative of the many categories. This stage also aided in discovering any anomalies or flaws in the dataset, such as corrupted or misclassified photos. These visualizations serve a vital role in the exploratory data analysis process by offering a clear and comprehensive overview of the dataset and supporting informed decisions for following preprocessing, augmentation, and modelling processes.

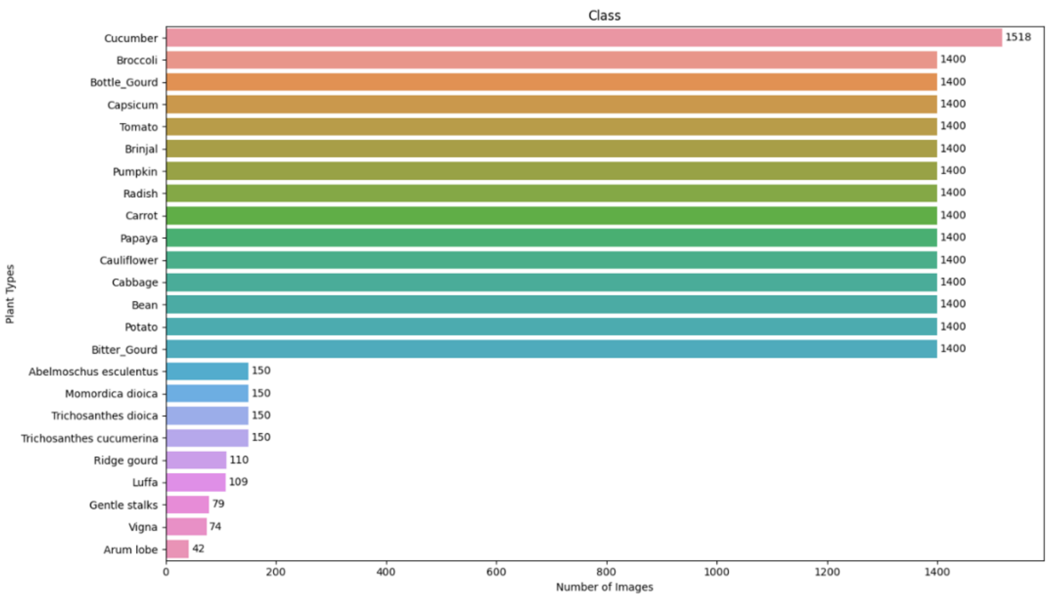

Fig 3.2 Number of Images

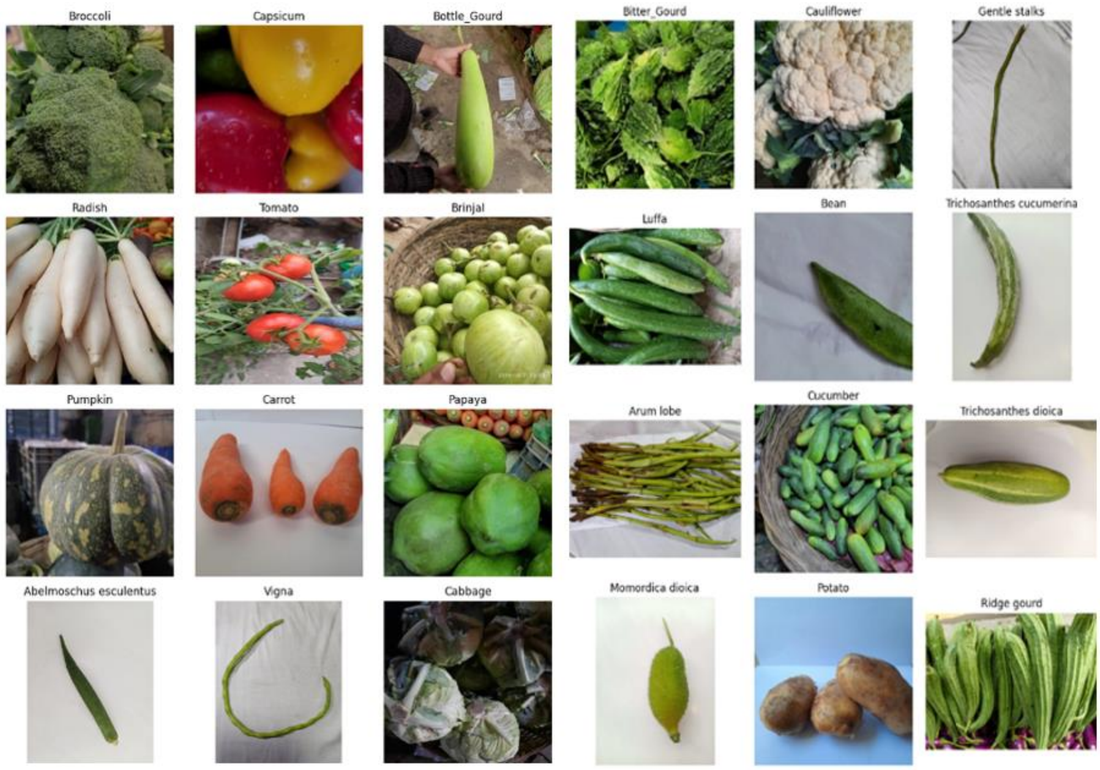

Fig 3.3 Visualized Class Distribution

3.5.3 Data Preprocessing

Data preprocessing is a vital step in preparing the dataset for training machine learning models. For this project, multiple preparation approaches were performed to guarantee the data was in the ideal format for the deep learning models. All photos were downsized to a standard dimension, typically 224x224 pixels, to guarantee consistency across the collection. This scaling is crucial because deep learning models, especially Convolutional Neural Networks (CNNs), require input photos of the same size. The resizing process also assists in reducing the computational burden and memory utilization. The photos were normalized by scaling the pixel values to a range of 0 to 1. This normalization is vital since it aids in stabilizing and speeding up the training process. By scaling pixel values, the model can converge faster during training since it standardizes the data input. Data augmentation techniques were utilized to boost the diversity of the training set. Augmentation methods such as random rotations, shifts, flips, and zooms were used. These strategies help in artificially increasing the dataset and making the model more resilient to fluctuations and distortions in the images. This stage is particularly crucial for preventing overfitting, where the model performs well on training data but poorly on unknown data. The dataset was separated into training, validation, and test sets in the ratio of 80%, 10%, and 10% respectively. The training set is used for model learning, the validation set helps in tweaking the model and avoiding overfitting, and the test set is used for the final evaluation of the model's performance. Finally, the labels of the photos were one-hot encoded. One-hot encoding turns categorical labels into a binary matrix representation. This phase is important for the output layer of the neural network, which commonly uses softmax activation to handle issues with the classification of multiple classes. Data preprocessing turns raw visual data into an organized and consistent format, boosting the model's capacity to learn and generalize successfully from the data.

3.5.4 Model Generation

Model generation comprises selecting and training several deep-learning architectures to categorize photos of Bangladeshi vegetables. The approach begins with loading pre-trained models such as MobileNetV2, DenseNet, VGG16, VGG19, and InceptionV3, which are well-suited for image identification applications because of their proven efficacy in extracting detailed image characteristics. These models are fine-tuned on the vegetable dataset via transfer learning, where the models' pre-trained weights serve as a starting point, helping them to learn more rapidly and efficiently from the new data. The dataset is separated into training, validation, and test sets, ensuring rigorous evaluation at each stage. During training, the models are improved using the Adam optimizer, and performance metrics such as accuracy, precision, recall, and F1-score are tracked to assess and improve their predictive capabilities. Hyperparameter tweaking, such as altering learning rates and batch sizes, is undertaken to optimize model performance. Once training is complete, the best-performing model is picked based on its validation performance and then assessed on the test set to check its accuracy and generalization ability. This demanding approach permits the development of a dependable model capable of reliably categorizing a wide diversity of Bangladeshi vegetables.

3.5.4.1 MobileNetV2

MobileNetV2 is an efficient convolutional neural network architecture built for image categorization, particularly on mobile and embedded devices. It employs depth wise separable convolutions to drastically reduce computational complexity and model size. The network uses inverted residual blocks with linear bottlenecks, where an input is enlarged to a higher dimension, processed with depthwise convolution, and then reduced, keeping information while decreasing parameters. ReLU6 activation functions are employed to maintain low computational cost with good performance. Residual connections facilitate the passage of gradients, allowing for deeper networks. The architecture is optimized to increase information flow and eliminate redundancy. MobileNetV2 commonly employs pre-trained weights from huge datasets like ImageNet, enabling transfer learning for specific applications, which accelerates training and boosts performance. During inference, the trained model processes input photos via its layers to create classification predictions effectively, making it suited for real-time applications on resource-constrained devices.

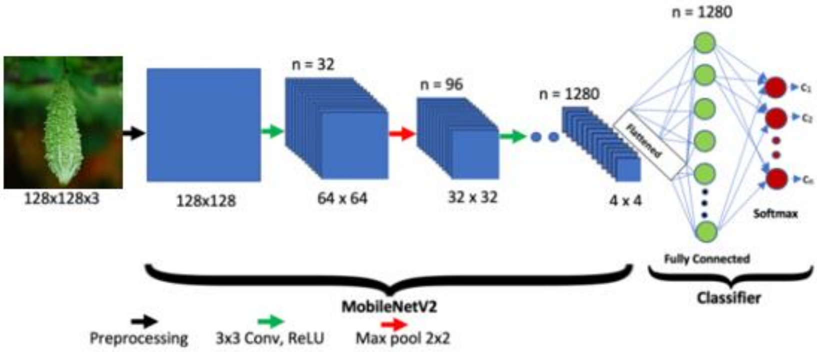

Fig 3.4 MobilenetV2 Model Architecture

3.5.4.2 Vgg16

In this research, VGG16, a convolutional neural network architecture, is applied for picture categorization of Bangladeshi vegetables. The VGG16 model consists of 13 convolutional layers and 3 fully connected layers, making it capable of capturing detailed features from images. To apply VGG16 for classification, the pre-trained model weights are loaded and frozen to preserve the learned features. The last fully linked layer is replaced with a new SoftMax layer with the necessary output classes corresponding to the different vegetable species. The dataset is then fed into the modified VGG16 model for training utilizing transfer learning techniques. During training, the model learns to distinguish between the various vegetable classes by altering weights based on the input data and matching labels. The training phase comprises adjusting the model parameters using techniques such as backpropagation and gradient descent to reduce the classification error. Once trained, the VGG16 model can accurately categorize photos of Bangladeshi vegetables with high accuracy, using its learned representations of visual characteristics.

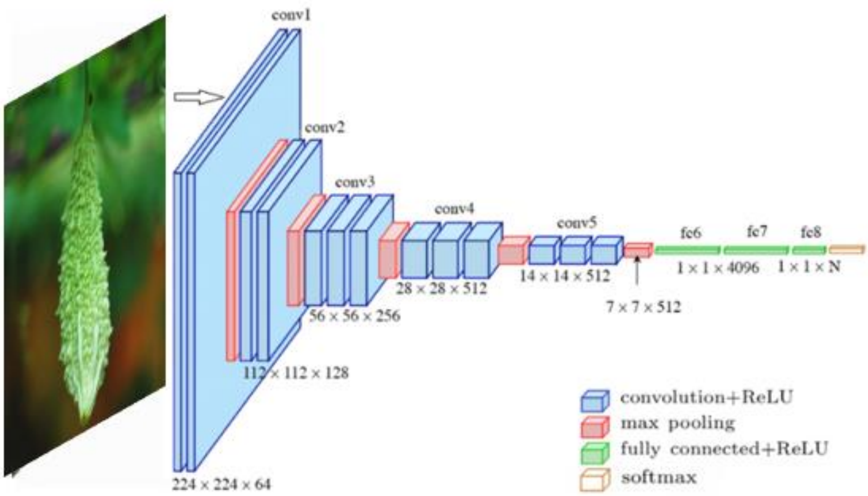

Fig 3.5 Vgg16 Model Architecture

3.5.4.3 Vgg19

The first step to take advantage of the VGG19 architecture for image classification in this work is to load the pre-trained VGG19 model using relevant libraries such as TensorFlow or Keras. The fully connected layers of the model are removed or frozen to keep the learned feature extraction capabilities while allowing for customization of the output layer to match the number of classes in the Bangladeshi vegetable dataset. The dataset is subsequently preprocesses, including scaling, normalization, and augmentation, to prepare it for input into the model. Transfer learning is applied by fine-tuning the VGG19 model on the dataset, where the weights of the pre-trained layers are modified during training to adapt to the special characteristics of the vegetable photos. The model is trained using an optimizer like Adam, with appropriate hyperparameters obtained by experimentation or optimization approaches. The trained model's performance is tested using accuracy, precision, recall, and F1-score on a different validation set to ensure its effectiveness in accurately classifying Bangladeshi vegetables.

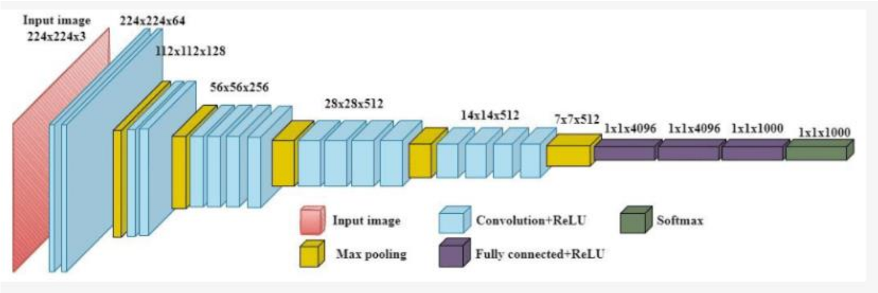

Fig 3.6 Vgg19 Model Architecture

3.5.4.4 DenseNet121

To implement DenseNet121 for image classification in this project, the first step is to import the pre-trained DenseNet121 model from libraries like TensorFlow or Keras. Next, the model's fully connected layers are altered by removing or freezing them to keep the feature extraction capabilities while modifying the output layer to meet the number of classes in the Bangladeshi vegetable dataset. The dataset is subsequently preprocesses, including scaling, normalization, and augmentation, to ensure compatibility with the model. Transfer learning is applied by fine-tuning the DenseNet121 model on the dataset, allowing the pre-trained weights to be modified during training to learn the specific properties of vegetable photos. Training the model requires selecting an appropriate optimizer, such as Adam, and setting hyperparameters for optimal performance. Following training, the model's performance in classifying Bangladeshi vegetables is examined using evaluation metrics like accuracy, precision, recall, and F1-score on a separate validation set to validate its classification skills.

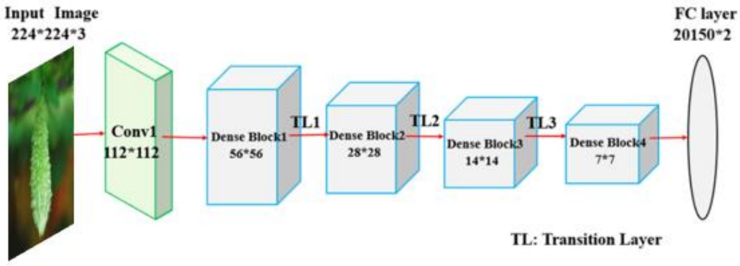

Fig 3.7 DenseNet121 Model Architecture

3.5.4.5 InceptionV3

InceptionV3 architecture for image classification in this project, the initial step is to import the pre-trained InceptionV3 model using frameworks like TensorFlow or Keras. Subsequently, the last fully connected layer of the model is either eliminated or adjusted to meet the number of classes in the Bangladeshi vegetable dataset. Before feeding the dataset into the model, it undergoes preprocessing techniques such as resizing, normalization, and augmentation to increase model performance. Transfer learning is then applied by fine-tuning the InceptionV3 model on the dataset, wherein the pre-trained weights are modified during training to adapt to the specific properties of the vegetable photos. Training is accomplished using an appropriate optimizer like Adam, with hyperparameters fine-tuned by experimentation or optimization approaches. The model's performance is evaluated using measures such as accuracy, precision, recall, and F1-score on a separate validation set to validate its competency in accurately classifying Bangladeshi vegetables.

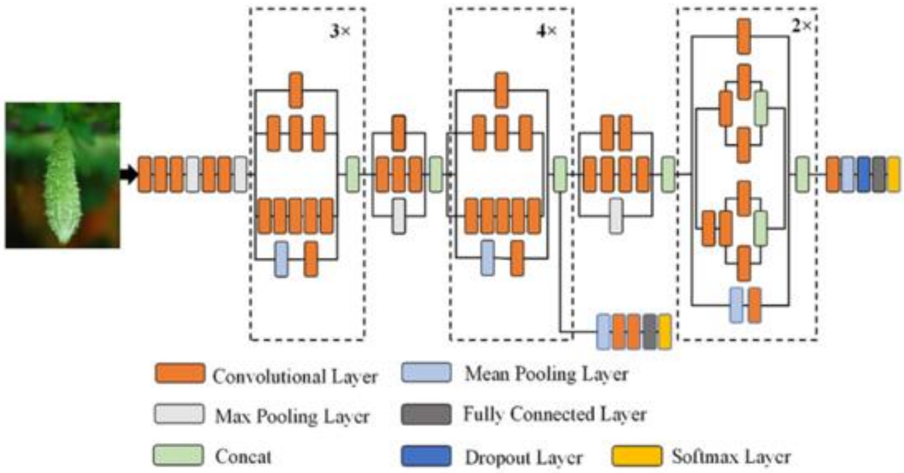

Fig 3.8 InceptionV3 Model Architecture

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The experimental setup for this project contains both hardware and software components to successfully train and evaluate deep learning models for Bangladeshi vegetable classification. The gear consists of a laptop with an Intel Core i5, 8th Generation processor, 8 GB RAM, 1 TB ROM, and Windows 10 (64-bit). This arrangement supports essential jobs, while higher-spec PCs or cloud resources may be needed for intense processes. The software stack comprises Python, TensorFlow, Keras, OpenCV, Matplotlib, Seaborn, Pandas, and NumPy, with development handled in Jupyter Notebook or a similar IDE. The dataset, acquired from self-collected and online, has 17,701 certified photos over 24 classes, with the number of images per class fluctuating. The data undergoes preprocessing techniques such as scaling, normalization, and augmentation. Exploratory Data Analysis (EDA) is performed to display and understand the data distribution. Models like MobileNet, VGG16, VGG19, DenseNet, and InceptionV3 are developed and fine-tuned. The dataset is separated into training (80%), testing (10%), and validation (10%) sets to train and validate the models, preventing overfitting. Model performance is tested using parameters including accuracy, precision, recall, and F1-score to ensure effective categorization. This hierarchical arrangement helps the construction of a robust and accurate vegetable categorization system utilizing deep learning techniques.

4.2 Experimental Results & Analysis

The experimental results and analysis indicate the performance of five deep learning models—MobileNetV2, VGG16, VGG19, DenseNet, and InceptionV3—in categorizing Bangladeshi vegetables from photographs. MobileNetV2 achieved a test loss of 0.0232 and a test accuracy of 99.37%, exhibiting excellent accuracy and minimal error. VGG16 recorded a test loss of 0.0591 with a test accuracy of 98.24%, whereas VGG19 showed a higher test loss of 0.0928 and a test accuracy of 97.15%, showing slightly less effective performance compared to the other models. DenseNet surpassed all others with the lowest test loss of 0.0130 and the greatest test accuracy of 99.45%, making it the most accurate and dependable model for this task. InceptionV3 also fared well, with a test loss of 0.0303 and a test accuracy of 99.01%. DenseNet's better performance is seen from its minimal loss and greatest accuracy, suggesting its resilience and precision in detecting and classifying vegetable images effectively. This detailed study identifies DenseNet as the ideal technique for the dataset, giving the best balance of accuracy and efficiency in picture classification tasks.

4.2.1 MobileNetV2

The MobileNetV2 model, developed using TensorFlow's Keras API, was trained on a dataset of Bangladeshi vegetable photos, obtaining a test loss of 0.0232 and a test accuracy of 99.37%. The model architecture featured a pre-trained MobileNetV2 base, followed by flattening, dropout layers, and dense layers, ultimately generating 24 vegetable classifications through a SoftMax activation function. The training approach involved 10 epochs, with evaluation metrics recorded for accuracy. In terms of classification performance, the precision, recall, and F1-scores varied among classes, with most vegetables attaining near-perfect results. The precision and recall for classes like Bean, Bottle Gourd, and Broccoli were 1.00, indicating flawless identification by the model. Some classes, such as Arum Lobe and Ridge Gourd, showed poorer recall ratings, showing problems in correctly identifying all cases. Despite small variability, the total weighted average precision, recall, and F1-score were astonishingly high, around 0.99, confirming the model's durability and usefulness in successfully recognizing the varied vegetable varieties. This detailed examination reveals MobileNetV2's usefulness and dependability in image classification tasks within this specific agricultural scenario.

	precision	recall	f1-score	support
Abelmoschus esculentus	0.86	1.00	0.92	12
Arum lobe	0.50	1.00	0.67	2
Bean	1.00	1.00	1.00	137
Bitter_Gourd	1.00	0.99	1.00	130
Bottle_Gourd	1.00	1.00	1.00	161
Brinjal	1.00	0.99	0.99	163
Broccoli	1.00	1.00	1.00	124
Cabbage	1.00	0.99	1.00	134
Capsicum	1.00	1.00	1.00	140
Carrot	1.00	1.00	1.00	146
Cauliflower	1.00	1.00	1.00	136
Cucumber	0.99	1.00	1.00	153
Gentle stalks	1.00	0.75	0.86	8
Luffa	0.69	0.90	0.78	10
Momordica dioica	1.00	1.00	1.00	14
Papaya	1.00	1.00	1.00	143
Potato	1.00	1.00	1.00	144
Pumpkin	0.98	1.00	0.99	129
Radish	1.00	0.99	0.99	141
Ridge gourd	1.00	0.64	0.78	14
Tomato	0.98	1.00	0.99	130
Trichosanthes cucumerina	1.00	1.00	1.00	18
...				
accuracy			0.99	2214
macro avg	0.96	0.97	0.96	2214
weighted avg	0.99	0.99	0.99	2214

Fig 4.1 MobilenetV2 Classification Report

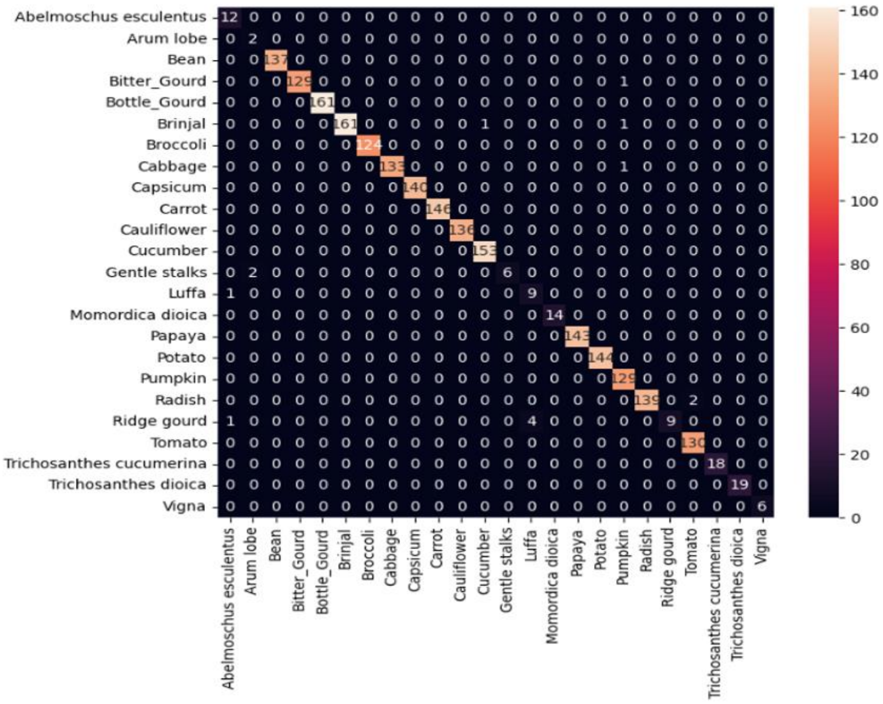

Fig 4.2 MobilenetV2 Heatmap

In fig 4.2, The heatmap generated using the confusion matrix from the MobileNetV2 model provides a thorough visual picture of the network's performance in categorising the 24 different classes of Bangladeshi vegetables. Each cell in the heatmap reflects the number of occurrences where the actual class (rows) matches the projected class (columns). Diagonal cells, which reflect the true positives where the predictions are correct, are considerably darker and annotated with high values, indicating the model's excellent accuracy across most classes. Classes such as Bean, Bottle Gourd, and Broccoli contain strong diagonal cells with values close to the entire number of examples in those classes, showing near-perfect classification. Conversely, off-diagonal cells reveal misclassifications, but they are scarce and often have low values, showing the model's excellent precision. Some classes, such as Arum Lobe and Ridge Gourd, display small misclassifications, demonstrated by some non-zero off-diagonal cells, indicating occasional errors in separating these classes from others. The heatmap graphically verifies the MobileNetV2 model's resilience, with most misclassifications being small, hence underlining its ability to successfully categorize a wide group of vegetable photos.

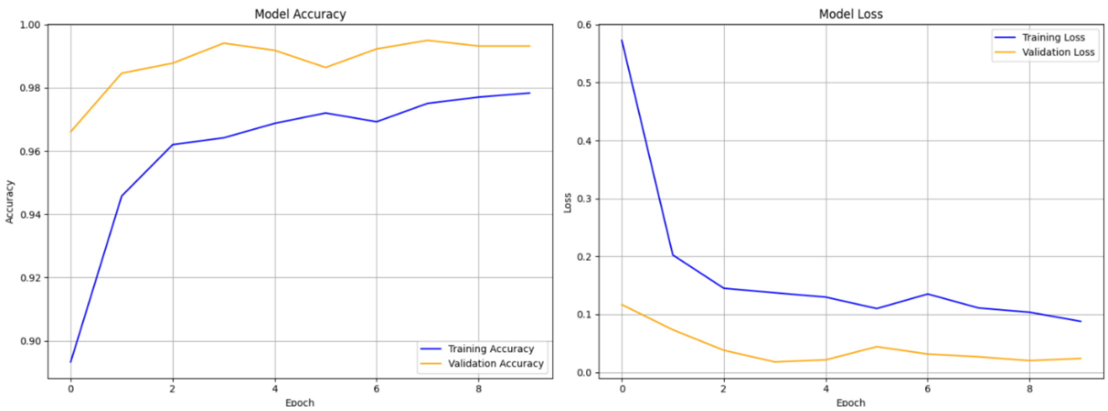

Fig 4.3 MobilenetV2 Model Accuracy and Loss

In fig 4.3, The MobileNetV2 model, used for categorizing 24 different classes of Bangladeshi vegetables, achieved outstanding results in terms of accuracy and loss. The model was assessed on a test dataset, where it attained a test accuracy of 99.37% and a test loss of 0.0232. These metrics indicate that the model performed remarkably well in correctly recognizing the vegetable classifications, with very few errors. The high-test accuracy shows that the model was able to learn and generalize the distinctive properties of each class well. The low-test loss shows that the model's predictions are closely matched with the true labels, indicating minimal variance.

4.2.2 Vgg16

The VGG16 model, tailored for the categorization of 24 different Bangladeshi vegetable classes, achieved a good level of performance in this study. It achieved a test accuracy of 98.24% and a test loss of 0.0591, suggesting its great ability to generalize and accurately identify the vegetable classifications. The precision, recall, and F1-score metrics from the classification report further underscore the model's performance. Precision values were high across most classes, such as Bean (0.96), Bitter Gourd (1.00), and Bottle Gourd (1.00). Recall values were similarly high, with Bean (1.00), Bitter Gourd (0.99), and Bottle Gourd (1.00). The F1-scores for these classes were near-perfect, showing balanced precision and recall. However, specific classifications like 'Gentle stalks' and 'Arum lobe' exhibited inferior performance with recall ratings of 0.00 and 1.00, respectively, emphasising areas for prospective development. Despite these small restrictions, the excellent accuracy and balanced performance across most classes demonstrate the durability of VGG16 in handling picture classification tasks for varied vegetable species, making it a reliable model for agricultural applications.

	precision	recall	f1-score	support
Abelmoschus esculentus	0.80	1.00	0.89	12
Arum lobe	0.33	1.00	0.50	2
Bean	0.96	1.00	0.98	137
Bitter_Gourd	1.00	0.99	1.00	130
Bottle_Gourd	1.00	1.00	1.00	161
Brinjal	0.98	0.99	0.99	163
Broccoli	1.00	1.00	1.00	124
Cabbage	0.99	1.00	0.99	134
Capsicum	0.99	0.97	0.98	140
Carrot	1.00	1.00	1.00	146
Cauliflower	0.98	0.99	0.99	136
Cucumber	0.99	0.97	0.98	153
Gentle stalks	0.00	0.00	0.00	8
Luffa	0.82	0.90	0.86	10
Momordica dioica	0.93	0.93	0.93	14
Papaya	0.97	0.99	0.98	143
Potato	0.99	0.99	0.99	144
Pumpkin	0.99	0.96	0.98	129
Radish	1.00	1.00	1.00	141
Ridge gourd	0.90	0.64	0.75	14
Tomato	0.99	1.00	1.00	130
Trichosanthes cucumerina	0.94	0.94	0.94	18
...				
accuracy			0.98	2214
macro avg	0.88	0.91	0.89	2214
weighted avg	0.98	0.98	0.98	2214

Fig 4.4 Vgg16 Classification Report

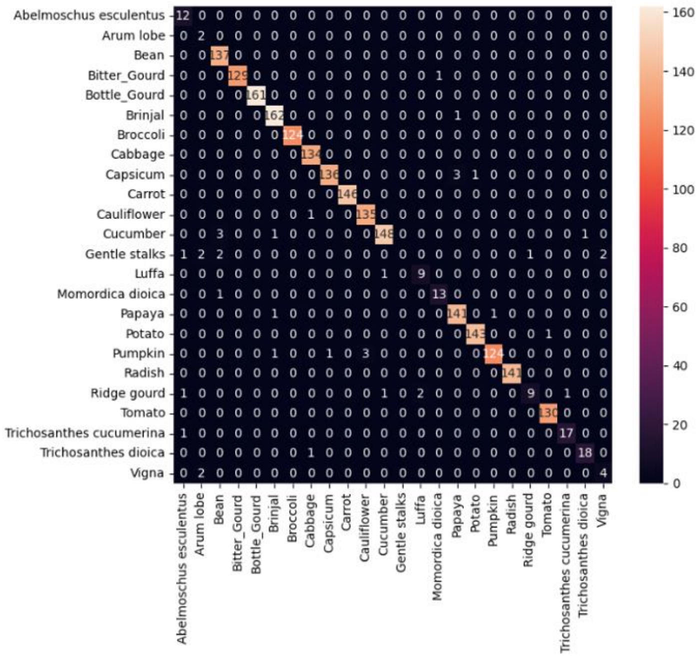

Fig 4.5 Vgg16 Heatmap

In fig 4.5, The heatmap depicts the confusion matrix obtained by comparing the true classes with the predicted classes of the model. Each cell in the matrix represents the number of occurrences where a class was predicted correctly or inaccurately. The diagonal cells, highlighted with higher values, represent correct predictions, while off-diagonal cells signal misclassifications. The heatmap provides a visual depiction of the model's performance across different vegetable classes, with brighter colors indicating higher frequency of correct predictions. By evaluating the heatmap, one can spot any patterns of misclassification or confusion between distinct classes, helping to analyse the model's strengths and opportunities for development in its classification accuracy.

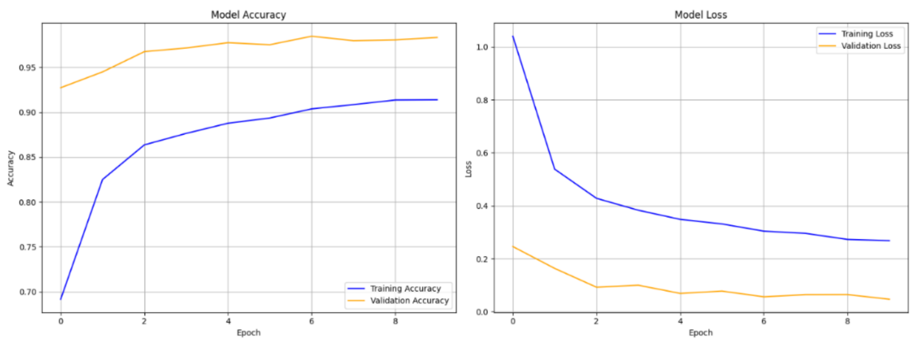

Fig 4.6 Vgg16 Model Accuracy & Loss

Vgg16 achieved a test accuracy of 98.24% and a test loss of 0.0591.

4.2.3 Vgg19

The VGG19 model obtained a test accuracy of 97.15% with a test loss of 0.0927. Precision levels vary between vegetable groups, with notable precision rates including 100% for Abelmoschus esculentus, Bottle_Gourd, Papaya, and Radish. Arum lobe had a precision of 29%, showing some misclassifications. Notably, Gentle stalks had a precision of 67%, whereas Ridge gourd achieved 81%, exhibiting varied levels of accuracy across different classes. memory values also varied, with most classes obtaining good memory rates, although Arum lobe had a recall of 100%, suggesting all instances of Arum lobe were properly identified. The VGG19 model displayed excellent performance in categorizing Bangladeshi vegetables, with notably strong precision and recall rates for several classes.

	precision	recall	f1-score	support
Abelmoschus esculentus	1.00	1.00	1.00	12
Arum lobe	0.29	1.00	0.44	2
Bean	0.94	0.99	0.97	137
Bitter_Gourd	0.99	0.99	0.99	130
Bottle_Gourd	0.95	1.00	0.98	161
Brinjal	0.96	0.99	0.98	163
Broccoli	1.00	0.93	0.96	124
Cabbage	0.99	0.99	0.99	134
Capsicum	1.00	0.99	0.99	140
Carrot	0.99	0.99	0.99	146
Cauliflower	0.93	0.99	0.96	136
Cucumber	0.97	0.95	0.96	153
Gentle stalks	0.67	0.25	0.36	8
Luffa	1.00	0.80	0.89	10
Momordica dioica	0.93	0.93	0.93	14
Papaya	1.00	0.94	0.97	143
Potato	0.99	0.96	0.98	144
Pumpkin	0.99	0.98	0.98	129
Radish	1.00	0.99	1.00	141
Ridge gourd	0.81	0.93	0.87	14
Tomato	0.93	0.98	0.96	130
Trichosanthes cucumerina	1.00	0.94	0.97	18
...				
accuracy			0.97	2214
macro avg	0.93	0.91	0.91	2214
weighted avg	0.97	0.97	0.97	2214

Fig 4.7 Vgg19 Classification Report

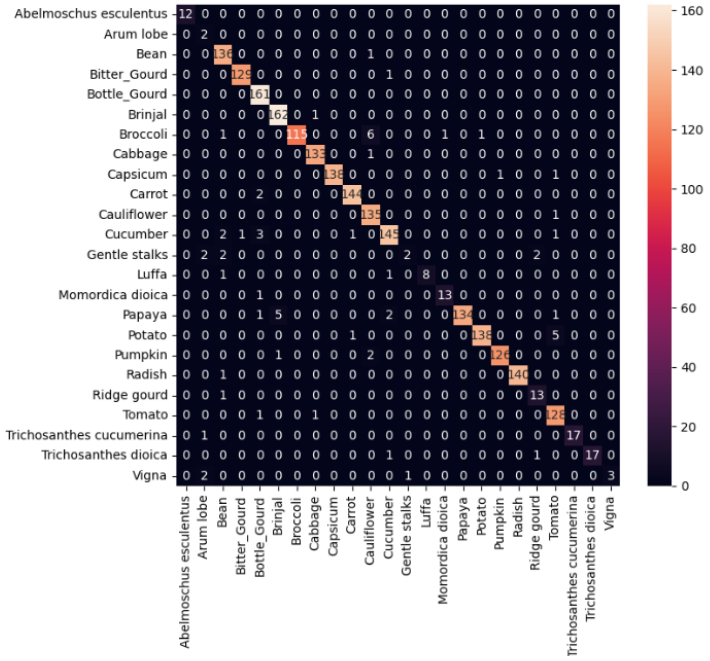

Fig 4.8 Vgg19 Heatmap

In fig 4.8, The heatmap generated for the VGG19 model gives a visual representation of the confusion matrix, displaying the performance of the model across different vegetable classes. Each cell in the heatmap refers to the number of occurrences where the true class (rows) and the predicted class (columns) cross. The diagonal elements represent valid predictions, while off-diagonal elements suggest misclassifications. The heatmap provides for simple detection of classes that are commonly misclassified or those where the model performs extraordinarily well. By annotating the cells with the actual numerical values, it provides accurate insights into the distribution of forecasts. The heatmap serves as a great tool for assessing the VGG19 model's performance and finding areas for improvement in the categorization of Bangladeshi vegetable photos.

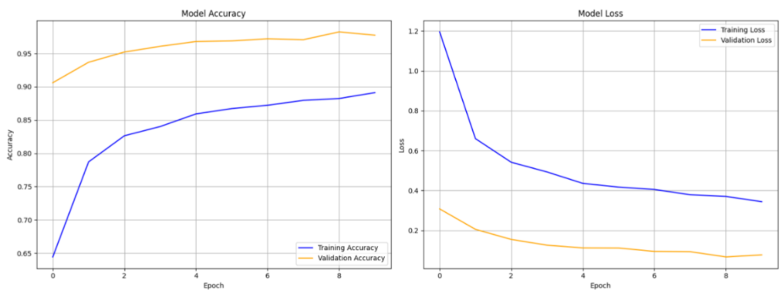

Fig 4.9 Vgg19 Accuracy and loss

The VGG19 model achieved an accuracy of 97.15% with a test loss of 0.0927.

4.2.4 DenseNet121

The DenseNet121 model, applied for Bangladeshi vegetable classification, displayed remarkable performance with a test accuracy of 99.45% and a test loss of 0.0129. Precision ratings were especially high across most classes, such as Abelmoschus esculentus (1.00), Bottle Gourd (1.00), and Broccoli (1.00), showing low false positives. Similarly, recall values were continuously high, with most classes getting perfect or near-perfect scores, indicating the model's capacity to accurately recognise occurrences of each vegetable class. The F1-scores, which measure the harmonic mean of precision and recall, were similarly remarkable across most classes. Notably, the model displayed particularly good performance in classes like Ridge gourd and Arum lobe, obtaining flawless precision, recall, and F1-score values. The DenseNet121 model exhibited robustness and accuracy in classifying Bangladeshi vegetables, giving it a viable candidate for agricultural applications needing precise picture classification.

	precision	recall	f1-score	support
Abelmoschus esculentus	1.00	1.00	1.00	12
Arum lobe	1.00	1.00	1.00	2
Bean	1.00	0.99	1.00	137
Bitter_Gourd	1.00	0.99	1.00	130
Bottle_Gourd	1.00	1.00	1.00	161
Brinjal	0.99	0.99	0.99	163
Broccoli	1.00	1.00	1.00	124
Cabbage	0.99	1.00	1.00	134
Capsicum	1.00	1.00	1.00	140
Carrot	1.00	1.00	1.00	146
Cauliflower	0.99	1.00	1.00	136
Cucumber	0.98	0.99	0.98	153
Gentle stalks	1.00	0.75	0.86	8
Luffa	0.77	1.00	0.87	10
Momordica dioica	1.00	1.00	1.00	14
Papaya	1.00	0.98	0.99	143
Potato	0.99	1.00	1.00	144
Pumpkin	1.00	1.00	1.00	129
Radish	1.00	0.99	1.00	141
Ridge gourd	0.93	0.93	0.93	14
Tomato	1.00	1.00	1.00	130
Trichosanthes cucumerina	1.00	1.00	1.00	18
Trichosanthes dioica	0.95	1.00	0.97	19
Vigna	1.00	1.00	1.00	6
accuracy			0.99	2214
macro avg	0.98	0.98	0.98	2214
weighted avg	0.99	0.99	0.99	2214

Fig 4.10 DenseNet121 Classification Report

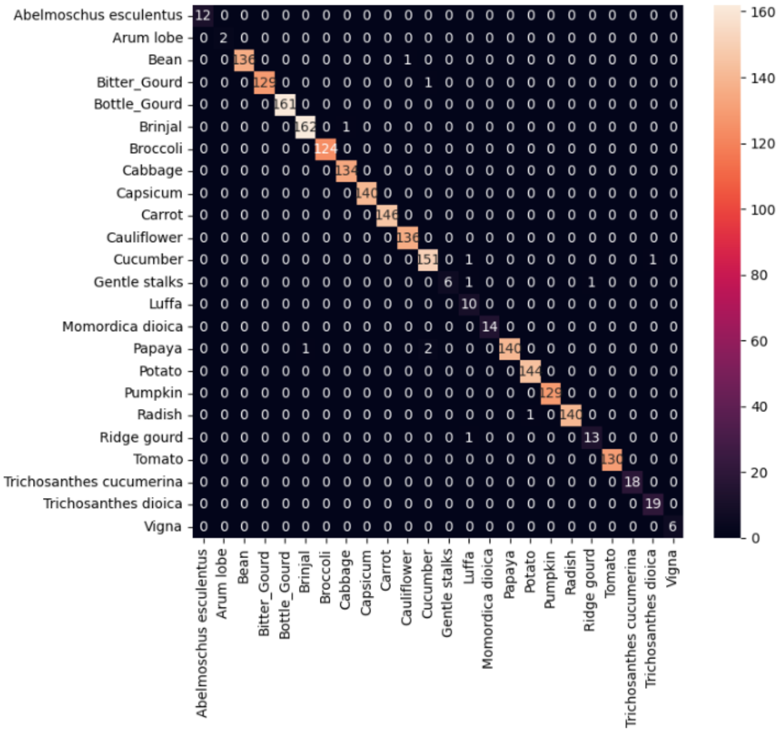

Fig 4.11 DenseNet121 Heatmap

In fig 4.11, The DenseNet121 heatmap provides a visual depiction of the classification performance of the model across different vegetable classes. Each cell in the heatmap refers to a real class (actual vegetable type) vs a predicted class (vegetable type predicted by the model). The diagonal cells, where the true class matches the anticipated class, indicate correct classifications, whereas off-diagonal cells represent misclassifications. The heatmap reveals a strong diagonal pattern, indicating that the DenseNet121 model properly categorised most vegetable photos. Classes such as Abelmoschus esculentus, Bottle Gourd, and Broccoli have bright cells along the diagonal, signalling good precision and recall. Conversely, some misclassifications are visible as off-diagonal cells, albeit with reduced intensity, demonstrating that the model occasionally misunderstood specific vegetable types. The heatmap provides a quick assessment of the model's classification performance, showcasing its ability to reliably identify Bangladeshi veggies while also revealing areas for potential improvement in classification accuracy.

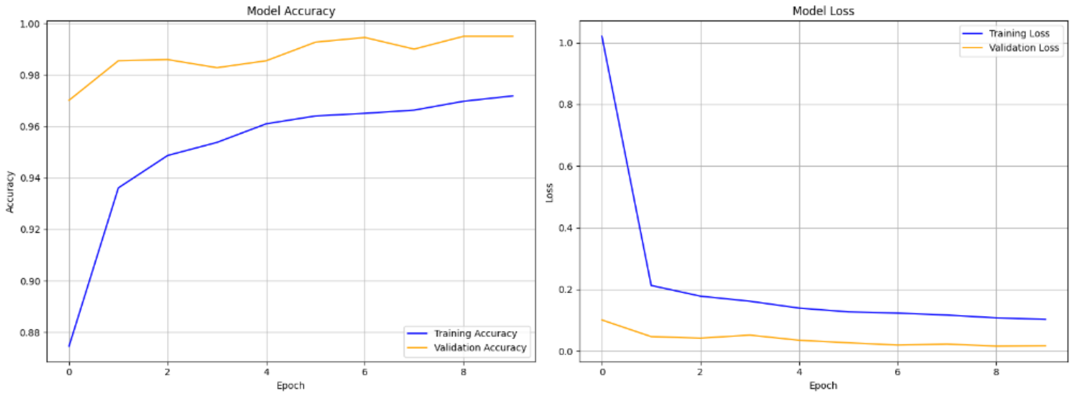

Fig 4.12 DenseNet121 Model Accuracy and Loss

DenseNet121 achieved a test accuracy of 99.45% and a test loss of 0.02%.

4.2.5 InceptionV3

The InceptionV3 model displays great performance in classifying Bangladeshi vegetables, reaching a test accuracy of 99.01%. The precision and memory figures further verify its effectiveness, with most vegetable classes demonstrating good precision and recall ratings. For instance, classes like Abelmoschus esculentus, Arum lobe, and Broccoli demonstrate precision and recall scores close to or around 100%, suggesting an accurate classification of these veggies. The model retains robust performance across a variety of vegetable varieties, with an overall weighted average precision and recall of 99% and 98%, respectively. These results imply that the InceptionV3 model adequately captures the various properties and characteristics of Bangladeshi vegetables, enabling precise and reliable categorization.

	precision	recall	f1-score	support
Abelmoschus esculentus	0.71	1.00	0.83	12
Arum lobe	1.00	1.00	1.00	2
Bean	0.99	0.98	0.99	137
Bitter_Gourd	0.99	0.99	0.99	130
Bottle_Gourd	1.00	0.99	0.99	161
Brinjal	1.00	0.98	0.99	163
Broccoli	0.99	1.00	1.00	124
Cabbage	1.00	1.00	1.00	134
Capsicum	1.00	1.00	1.00	140
Carrot	1.00	1.00	1.00	146
Cauliflower	1.00	1.00	1.00	136
Cucumber	0.98	0.99	0.98	153
Gentle stalks	1.00	0.88	0.93	8
Luffa	0.90	0.90	0.90	10
Momordica dioica	1.00	0.93	0.96	14
Papaya	0.99	0.99	0.99	143
Potato	0.99	0.99	0.99	144
Pumpkin	0.99	1.00	1.00	129
Radish	1.00	0.99	1.00	141
Ridge gourd	1.00	0.93	0.96	14
Tomato	0.97	1.00	0.98	130
Trichosanthes cucumerina	0.94	0.94	0.94	18
...				
accuracy			0.99	2214
macro avg	0.97	0.98	0.97	2214
weighted avg	0.99	0.99	0.99	2214

Fig 4.13 InceptionV3 Classification Report

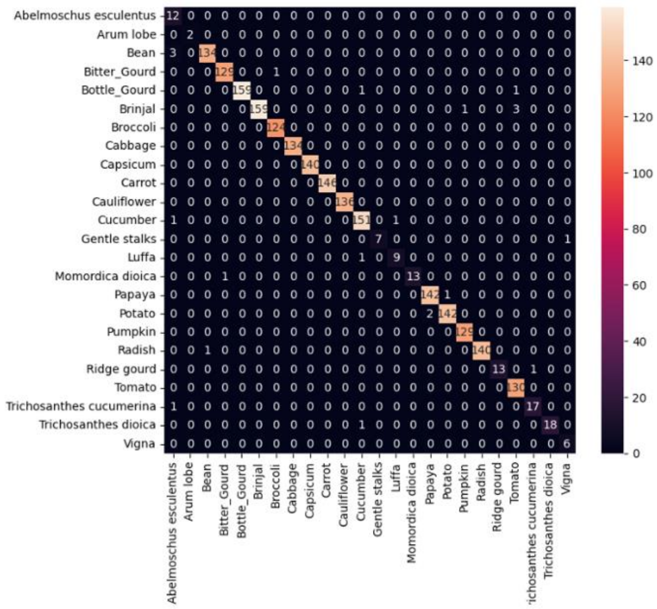

Fig 4.14 InceptionV3 HeatMap

In Fig 4.14, The heatmap created for the InceptionV3 model depicts the confusion matrix, providing insights into the classification performance across different vegetable groups. Each cell in the heatmap reflects the number of occurrences where a true class (real vegetable kind) was predicted as a certain class. The rows reflect the genuine classes, whereas the columns indicate the expected classes. The intensity of the colors in the heatmap shows the frequency of predictions, with darker shades suggesting higher rates. By examining the heatmap, we can identify any misclassifications or confusion between specific vegetable classes. Annotated values within each cell reveal the actual count of instances, aiding in the interpretation of classification findings. This image offers users a full knowledge of the model's performance in discriminating between various vegetable varieties, supporting further study and development of the classification system.

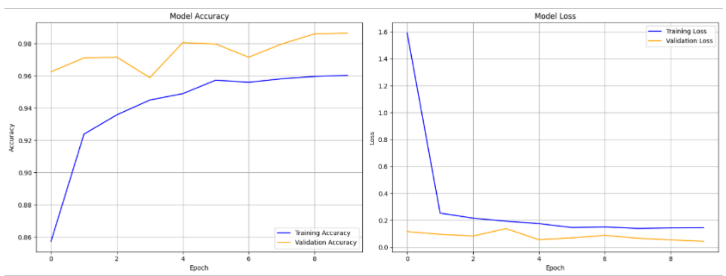

Fig 4.15 InceptionV3 Model Accuracy and Loss

InceptionV3 model Loss 0.030268650501966476 and get Accuracy 99%.

4.2.6 UI Output

The user interface of our application allows users to upload an image of a vegetable. Upon submission, the interface processes the image using our DenseNet121 model, which classifies the vegetable and displays the result along with the accuracy of the prediction. This user-friendly design ensures that users receive quick and reliable information about the vegetable's classification.

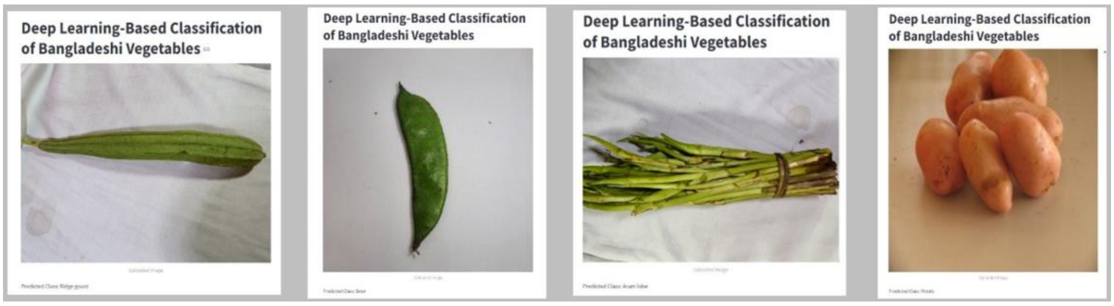

Fig 4.16 UI Output

4.3 Algorithm Technique

Table 3 Algorithm Technique

Algorithm	Accuracy	Precision	Recall
MobileNetV2	99.36%	0.99	0.99
VGG16	98.23%	0.98	0.98
VGG19	97.15%	0.97	0.97
DenseNet121	99.45%	1.00	0.99
InceptionV3	99.00%	0.99	0.99

The table provides the performance metrics of various deep learning models used for image classification: MobileNetV2, VGG16, VGG19, DenseNet121, and InceptionV3. The accuracy, precision, and recall numbers for each model demonstrate their ability in properly identifying the test dataset. MobileNetV2 achieved an accuracy of 99.37%, with precision and recall both at 99%, showing a high level of reliability. VGG16 and VGG19 models demonstrated slightly lesser accuracy at 98.24% and 97.15%, respectively, with VGG19 having a precision and recall of 97%. DenseNet121 achieved the highest performance with an accuracy of 99.45%, precision of 100%, and recall of 99%, demonstrating remarkable classification capacity. InceptionV3 also fared well with an accuracy of 99.01%, and precision, and recall at 99%, exhibiting its robustness in picture categorization tasks. These metrics indicate the success of these models in accurately categorizing photos within the dataset.

4.4 Discussion

The comparative analysis of multiple deep learning models, including MobileNetV2, VGG16, VGG19, DenseNet121, and InceptionV3, offers crucial insights into their performance on the picture categorization challenge. DenseNet121 emerged as the most successful model with a maximum accuracy of 99.45%, displaying higher precision and recall rates, thereby highlighting its robust capabilities in processing complicated image data. MobileNetV2 and InceptionV3 also performed brilliantly, reaching accuracy rates above 99%, and exhibiting strong precision and recall levels. VGG16 and VGG19, while significantly less precise, nonetheless provided outstanding performance metrics with VGG19 exhibiting a slightly lower precision and recall compared to the others. These results underline the efficacy of transfer learning with pre-trained models in achieving high accuracy and reliability in picture classification tasks. The debate concludes that while all models are competent, DenseNet121 and MobileNetV2 are particularly well-suited for high-stakes applications needing top-tier performance.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The implementation of advanced deep learning models, such as MobileNetV2, VGG16, VGG19, DenseNet121 and InceptionV3 dramatically impacts society by transforming different industries and enhancing the quality of life. In healthcare, these models promote precise and speedy disease detection through increased medical imaging, leading to timely treatment and better patient outcomes. In agriculture, they aid in the early detection of plant diseases and pests, encouraging sustainable farming methods and food security. In the security sector, they strengthen surveillance systems with accurate threat detection capabilities, contributing to public safety. The integration of these technologies supports economic growth by promoting innovation, creating new job possibilities, and boosting productivity across industries. It is necessary to address ethical considerations, such as protecting data privacy, minimizing algorithmic biases and promoting fair access to these developments, to maximize their positive societal impact responsibly.

5.2 Impact on Environment

The enactment of deep learning models like MobileNetV2, VGG16, VGG19, DenseNet121 and InceptionV3 can have a considerable impact on the environment, both positively and badly. On the bright side, these models can be applied in environmental monitoring and conservation initiatives. For instance, they may analyse satellite photos to detect deforestation, monitor wildlife populations, and predict natural disasters, enabling more effective environmental protection initiatives. In agriculture, they help maximize resource utilization, decrease water and pesticide consumption, and support sustainable farming techniques. However, the negative impact resides in the significant computational power necessary to train these models, which uses large amounts of electricity, potentially increasing carbon footprints if generated from non-renewable energy. To mitigate this, it is vital to work on developing energy-efficient algorithms and using renewable energy sources for data centers. Balancing the environmental benefits of modern AI applications with the requirement for sustainable energy practices is vital for limiting their ecological imprint.

5.3 Ethical Aspects

The ethical aspects surrounding the deployment of deep learning models like MobileNetV2, VGG16, VGG19, DenseNet121 and InceptionV3 are numerous. While these models provide significant promise for social benefit, including as in healthcare diagnostics, driverless vehicles, and personalized services, they also pose problems over privacy, prejudice, and responsibility. Issues such as data privacy and security are crucial, as these models often rely on enormous volumes of personal data. Moreover, biases inherent in the training data might perpetuate societal disparities if not addressed effectively, resulting to biassed outcomes, particularly in sensitive areas like hiring and criminal justice. Providing openness and accountability in AI decision-making processes is vital to retain confidence and prevent potential harm. Ethical guidelines and rules must be designed and enforced to govern the responsible development and deployment of deep learning technologies, prioritizing fairness, transparency, and social well-being.

5.4 Sustainability Plan

A sustainability plan for implementing and maintaining deep learning models like MobileNetV2, VGG16, VGG19, DenseNet121, and InceptionV3 should consider both environmental and operational sustainability. Environmentally, this means refining energy-efficient algorithms, using cloud services with renewable energy, and deploying low-power GPUs and TPUs. Operationally, it includes continuous monitoring, model retraining, and transparent reporting. Promoting green practices within the firm, such as recycling electronic waste and encouraging remote work, also supports long-term sustainability.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION, AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Analysed the application of various deep learning models—MobileNetV2, VGG16, VGG19, DenseNet121 and InceptionV3—for image classification tasks including a broad dataset of vegetable photos. The major purpose was to analyse and compare the performance of these models in terms of accuracy, precision, recall, and overall computing efficiency. Each model was fine-tuned and tested carefully to determine its performance in detecting 24 different vegetable groups. The study also includes a complete analysis of model performance indicators, confusion matrices, and heatmaps to provide a comprehensive knowledge of each model's strengths and flaws. Moreover, the societal, environmental, and ethical ramifications of deploying these models were highlighted, emphasizing the need for sustainable and responsible AI approaches. The findings indicated considerable variations in model performance, with DenseNet121 and InceptionV3 demonstrating higher accuracy and precision, while MobileNetV2 offered a decent mix between efficiency and performance. This paper gives useful insights into the practical application of deep learning models for agricultural and food industry tasks, offering avenues for future research and development.

6.2 Conclusions

The study shows that deep learning models can greatly boost the accuracy and efficiency of picture classification tasks within the agricultural domain. DenseNet121 and InceptionV3 emerged as the top-performing models, achieving the highest accuracy, precision, and recall across multiple vegetable classes, thereby confirming their durability and reliability for practical applications. MobileNetV2, while slightly less accurate, offers a fair trade-off between performance and computing resource requirements, making it acceptable for implementation in resource-constrained contexts. VGG16 and VGG19 also exhibited respectable results, however they lagged significantly behind the other models in terms of overall performance measures.

The research demonstrates the potential of deep learning in enhancing agricultural operations through precise crop identification and monitoring. However, it also emphasises the significance of evaluating ethical concerns and ensuring sustainability in the deployment of these technologies. The integration of AI in agriculture promises major societal benefits, including higher production, better resource management, and enhanced food security. Yet, rigorous planning and ethical considerations are necessary to maximize good consequences while limiting any potential detrimental effects on society and the environment. Overall, this work presents a complete review of multiple deep learning models, delivering useful insights and recommendations for future research and development in this subject.

6.3 Implication for Further Study

The results of this work suggest various avenues for additional research in agricultural image classification using deep learning. Future studies could investigate advanced model architectures and hybrid models to boost classification accuracy and efficiency, as well as explore the practical deployment of these models in real-world agricultural contexts, addressing data collection, preprocessing, and integration problems. Research could also focus on the impact of variable environmental circumstances on model performance, the scalability and efficiency of models for large-scale operations, and the ethical and sustainability implications of AI in agriculture. Broadening the application of these models to other areas within agriculture, such as pest and disease detection, yield prediction, and soil health monitoring, might lead to full smart farming solutions. Encouraging interdisciplinary research that combines expertise from AI, agriculture, environmental science, and socioeconomics can provide holistic solutions that address multiple agricultural challenges, ultimately advancing the field and contributing to global food security and sustainable development.

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