DETECTING BANGLADESHI FLOWERS AND ITS CLASSIFICATIONS FROM IMAGE USING CNN

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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 "Detecting Bangladeshi Flowers and its Classifications from Image using CNN", submitted by Tahmina Tabassom Fariha and Atikul Islam Tipu 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 26-06-2024.

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We hereby declare that, this project has been done by **Tahmina Tabassom Fariha, 201-15-3175**, and **Atikul Islam Tipu, 201-15-3612**, under the supervision of **Dr. Arif Mahmud, Associate Professor, Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Image processing has been one of the most practiced features of digitalization and it has enormous role in different sectors of our life. Convolutional Neural Network (CNN) has made image processing and other mechanism related to images much more significant and glorious. We captured images of flowers in different angles with different shades and nature mode so that while analyzing it can call on enormous data even if candid image is taken in testing purpose. We went through MobileNet, InceptionV3, and VGG16 models to find the best suited one and that will be automatically called by the system and with that algorithm the rest analysis will occur. We found 95.39% accuracy for MobileNet. The rest InceptionV3 and VGG16 have 94.68% and 92.24% accuracy respectively. This will be very much beneficial to know about our native nation and its resources and such dataset is rarely found on web when we insist about Bangladesh.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Deep Bangladeshi flowers are a representation of the nation's rich biodiversity and cultural legacy, which has led to the creation of an innovative effort that uses convolutional neural networks (CNN) to automatically recognize and classify these floral gems [1]. The combination of advanced CNN capabilities with complex image processing techniques holds the potential to transform Bangladeshi flower identification and classification in this digital era. The foundation of our work is digital image processing, which serves as the key to the methodical study and understanding of visual data. This complex process includes a broad range of methods, software, and instruments designed to improve, modify, and thoroughly analyze digital photographs. Through the smooth integration of various approaches, our effort seeks to achieve both a precise categorization of flowers and an advanced knowledge of the distinctive visual characteristics that characterize Bangladeshi flora. Convolutional Neural Networks (CNNs) have become a major player in the wide field of digital image processing, showcasing remarkable abilities in image identification
tasks. Because of their complex design [2], CNNs are especially good at the subtle task of object recognition and classification since they can learn hierarchical information inside pictures. Our research makes use of CNNs to guarantee a reliable, flexible, and accurate approach to identifying flowers, which greatly improves the overall performance of the classification system.

A key component of our project is its user-friendly interface, which is made possible by the expert integration of Streamlit, a powerful web application framework. Streamlit, well-known for its efficiency and simplicity, accelerates the development process and offers a user-friendly interface for interaction. A thorough examination of Streamlit's internal workings indicates that it can process and present a wide range of user inputs, process photos, and present the classification results elegantly—all while providing a rich and interesting user experience [3]. To fully comprehend CNNs and their function in our study, one must have a deep understanding of the systems that regulate them. CNN architectures can capture complex patterns and organizational structures in pictures because of their inherent convolutional processes. This essential capacity serves as the foundation for its implementation in the crucial step of our project's flower identification process, which is the detection and recognition of objects inside digital images.

Flowers are systematically categorized according to unique characteristics such as petal arrangement, color variations, and general shape. This process is known as taxonomy. In addition to naming and classifying Bangladeshi flowers, our effort aims to enlighten people on the distinctive qualities of these plants. A more comprehensive overview of Bangladesh's varied floral environment is ensured by the categorization system, which also makes for a more interesting and educational user experience. Bangladesh offers a remarkable spectrum of native flowers, all part of its unique biological embroidery [4].

Thoroughly investigating these floral jewels is essential to building a solid dataset that is needed to train the CNN model. This dataset guarantees the model's flexibility and precision in identifying and categorizing a range of flower types, advancing a more comprehensive understanding of Bangladesh's diverse floral offers. Beyond current technical capabilities, CNNs have a profound impact on object identification and recognition, changing the ground rules for automated image-based categorization systems.

Their proficiency in complex pattern recognition from large datasets enables them to perform exceptionally well in picture classification, object location, and general pattern recognition. As demonstrated by our study, CNNs have the potential to significantly improve the accuracy and efficiency of automated flower identification systems by being essential in the detection and recognition of Bangladeshi flowers.

We want to offer a dependable, effective, and highly educational alternative for enthusiasts, scholars, and the general public interested in learning more about Bangladesh's rich floral variety by utilizing CNNs. By using this novel strategy, we hope to strengthen the bond between people and Bangladesh's distinctive botanical legacy while also automating the process of identifying
flowers.

Original Convolutional Neural Networks (CNNs)

Within a Convolutional Neural Network (CNN), the term "convolution" denotes the mathematical blending of two functions to generate a third function Karthik et al. (2020). In this process, two sets of data are merged. Unlike an Artificial Neural Network (ANN) that consists of a single layer, CNNs comprise multiple layers, including an input layer, several convolutional layers, pooling layers, a fully connected layer, and an output layer. The layers in between, excluding the input and output layers, are commonly referred to as hidden layers Houssein et al. (2022). The CNN architecture utilizes convolutional layers, also known as filters or kernels, to convert input data into a feature map.

CNNs are designed to detect simpler patterns, such as lines and curves, initially and progressively identify more complex patterns, like faces and objects, in subsequent layers. The appeal of CNNs in data science lies in their proven ability to locate, segment, and identify objects within images Kundu et al. (2021). In this study, the term "original CNN architecture" refers to a CNN network and algorithm available on platforms like Keras or GitHub. The CNN algorithm is employed without any alterations to its processing units, parameterization, hyper-parameter optimization methodologies, design patterns, or layer connections, following the intended use by its creators and programmers. Notably, various researchers and programmers have continuously developed and refined a well-known CNN network over numerous iteration Nafiiyah and E. Setyati (2020).

VGG16: An exemplary model within the realm of CNNs is VGG16, a sophisticated variant of the VGG architecture that features 16 layers. VGG16 excels in facilitating the explicit and effective propagation of spatial information across neurons within the same layer. This capability is particularly advantageous in situations where objects have distinct shapes and spatial characteristics. The VGG16 architecture makes a substantial contribution by systematically evaluating networks of increasing depth while utilizing small convolution filters measuring 3x3 pixels. These filters effectively capture spatial orientations both horizontally (left/right) and vertically (up/down). Additionally, the incorporation of 1x1 convolution filters functions as a linear transformation of the input, which is then processed through a Rectified Linear Unit (ReLU) activation function. The use of a fixed convolution stride of 1 pixel plays a crucial role in maintaining the spatial resolution of the input data post-convolution, thereby preserving the fidelity of spatial information throughout the network.

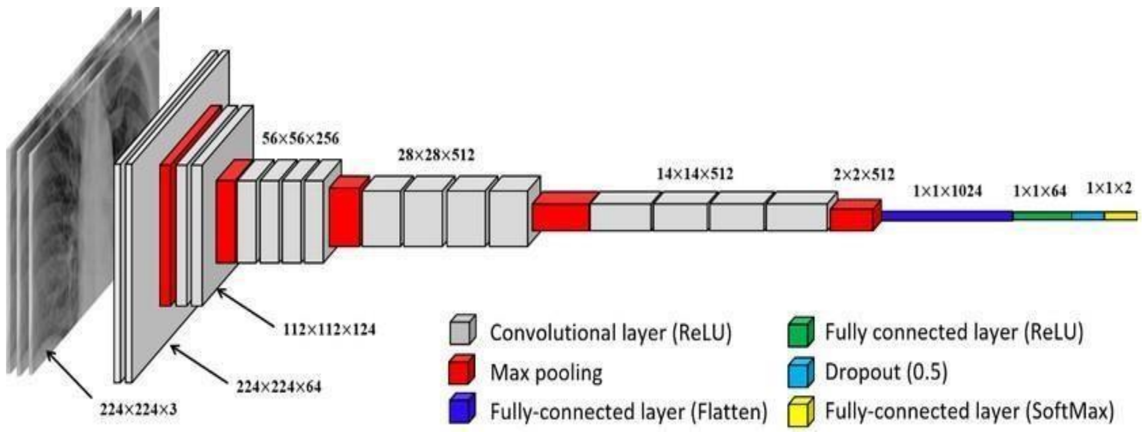

Figure 1.1: Schematic representation of VGG16

MobileNet: It is a pioneering architecture in the field of convolutional neural networks (CNNs), particularly designed to be efficient in terms of computational resources and power consumption. It is highly suitable for mobile and embedded vision applications where resource constraints are a critical factor. The core innovation of MobileNet lies in its use of depthwise separable convolutions, which decompose the traditional convolution operation into two separate layers: a depthwise convolution and a pointwise convolution. This approach significantly reduces the amount of computation and model size without compromising performance. Depthwise convolution applies a single filter to each input channel, effectively capturing spatial features within each channel independently. Following this, pointwise convolution uses a 1x1 convolution to combine these spatial features across channels, allowing for efficient integration of information and reduction in computational complexity. This separation of spatial and channel-wise operations not only enhances computational efficiency but also decreases the number of parameters significantly compared to standard convolutions.

MobileNet employs a novel technique called inverted residuals with linear bottlenecks. In this mechanism, input data is first expanded to a higher-dimensional space where the non-linear transformations occur. Afterward, it is compressed back to a lower- dimensional space. This design ensures that the model captures complex patterns while maintaining a lightweight structure. Moreover, the architecture uses a fixed convolution stride of 1 pixel, which helps in retaining the spatial resolution of the input features throughout the layers, thereby preserving critical spatial information for accurate predictions. This efficiency and compactness make MobileNet an ideal choice for applications requiring fast and accurate neural network inference on mobile and embedded devices.

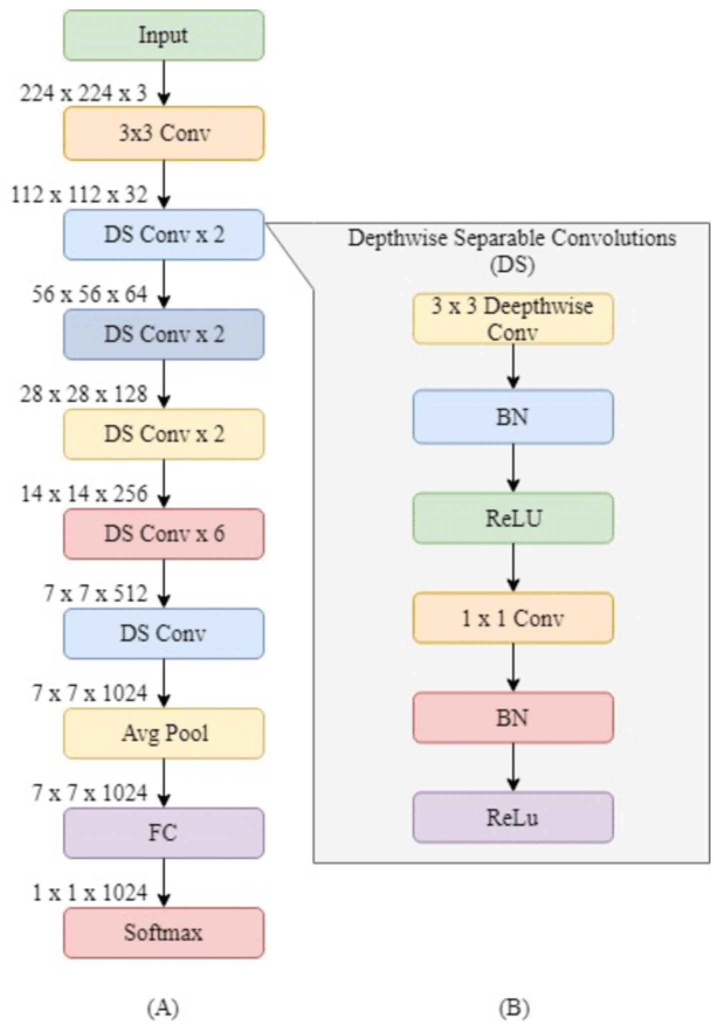

Figure 1.2: Schematic representation of MobileNet (Olarik Surinta et. al. 2020)

InceptionV3: InceptionV3 is an advanced convolutional neural network (CNN) architecture renowned for its efficiency and high performance in image classification. Its core innovation lies in the use of Inception modules, which apply convolutions of different sizes (e.g., 1x1, 3x3, and 5x5) in parallel to the same input, allowing the network to capture multi-scale features. The outputs of these convolutions are concatenated to form a comprehensive feature map. This multi-path approach helps the network to efficiently capture complex patterns without significantly increasing computational costs. InceptionV3 also incorporates factorized convolutions, breaking down larger convolutions into smaller, sequential operations (such as 1x3 followed by 3x1), to reduce the number of parameters and enhance computational efficiency. The network employs batch normalization to stabilize training and uses auxiliary classifiers to provide additional gradient signals, improving convergence and generalization. Label smoothing is used to prevent overconfidence in predictions, assigning a small probability to incorrect classes to enhance robustness.

InceptionV3's design optimizes feature extraction and computational efficiency, making it an effective model for image classification tasks, especially in resource-constrained environments.

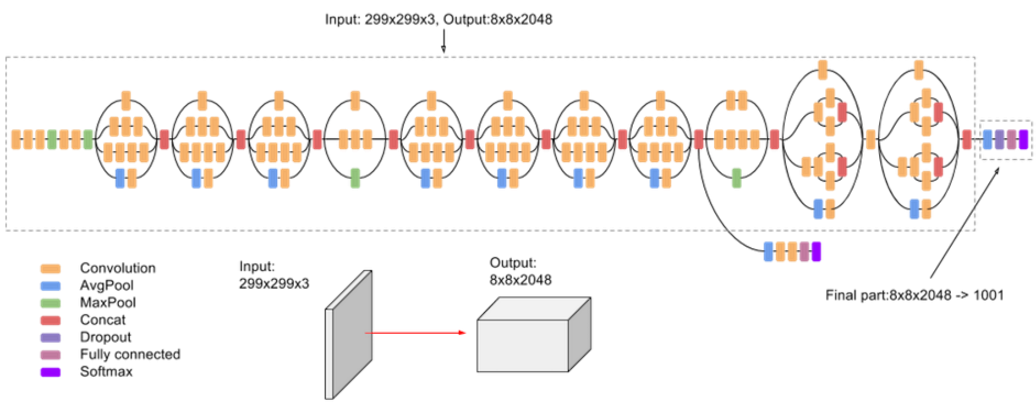

Figure 1.3: InceptionV3 Schematic Representation (Szegedy et al. 2015)

1.2 Background and Present State

Deep learning, especially CNNs, has proven to be highly effective in various image recognition tasks, outperforming traditional image processing techniques by learning hierarchical feature representations directly from raw pixel data. Previous studies have demonstrated the potential of CNNs in classifying images of plants, animals, and other natural objects with high accuracy. However, many of these studies have focused on datasets that are either limited in diversity or geographically specific, which poses challenges for generalizing the models to broader contexts and varied environmental conditions. Recognizing these challenges, the current project aimed to develop robust CNN models capable of accurately classifying a diverse range of flower species from images captured under varying conditions. The project leveraged well-established CNN architectures, including MobileNet, InceptionV3, and VGG16, known for their strong performance in image classification tasks. These models were chosen for their ability to balance accuracy and computational efficiency, making them suitable for deployment in both research and practical applications.

The present state of the project as completed reveals several key achievements and insights. Extensive experimentation was conducted using Google Colab's computational resources, specifically Tesla GPUs, to train and evaluate the chosen CNN models on a comprehensive dataset of flower images. This dataset encompassed a wide array of species and accounted for variations in environmental settings, lighting conditions, and image angles. MobileNet emerged as the most effective model, achieving an impressive accuracy of 95.39%, while InceptionV3 and VGG16 also demonstrated strong performance with accuracies of 94.68% and 92.24%, respectively. The project's findings underscore the efficacy of deep learning models in automating the process of flower identification, highlighting their potential for applications in biodiversity monitoring, conservation planning, and educational outreach. The developed models demonstrated robust capabilities in distinguishing between diverse flower species, as evidenced by detailed performance metrics and validation against a diverse test set. The successful completion of this project not only advances the field of automated botanical classification but also sets the stage for further research into the integration of AI technologies in ecological and environmental sciences.

1.1Problem Statement

Bangladesh has a vast and varied floral biodiversity, with many different types of flowers having unique visual features. However, research and understanding of this diverse botanical landscape are hampered by the absence of easily accessible tools for flower identification and categorization. When it comes to offering a user-friendly and interactive platform that enables people to recognize and learn about Bangladeshi flowers, existing resources sometimes fall short. The main problem is the fundamental variety of floral looks, which can be affected by different lighting conditions, angles, and development patterns, among other things. The creation of a precise and trustworthy categorization system is made more difficult by the lack of a centralized, extensive database designed especially for Bangladeshi flowers. Therefore, it is essential to provide a solution that can work its way through these intricacies and provide enthusiasts, researchers, and the general public with a reliable tool.

This study faces several significant obstacles. The most important thing is to create an automatic recognition system that can accurately identify Bangladeshi flowers in a variety of photos while taking into account the difficulties caused by a range of environmental factors. The categorization method must also provide users with a deeper grasp of the taxonomy and distinctive qualities of each flower, going beyond basic identification. An easy-to-use and simple user interface is essential for facilitating exploration and learning in the Streamlit-based online application. A further challenge is the lack of extensive databases dedicated to Bangladeshi flora. To meet this difficulty, our study curated and preprocessed a dataset that accurately reflects the floral variety of the nation. Finally, the project aspires to have a wider educational influence by going beyond technical issues. This project aims to promote a greater appreciation for Bangladesh's floral history by providing an easily accessible platform that allows people to interact with and learn about the country's distinctive flora. This will contribute to both public awareness and scientific knowledge.

1.1 Objectives

Bangladesh's natural heritage is deeply rooted in its floral diversity, which is a reflection of the nation's ecological richness. However, there is a vacuum in the distribution of information and the investigation of Bangladesh's botanical value due to the unavailability of easily available instruments for the identification and categorization of the country's flowers. The goal of this study is to close this gap and offer an invaluable resource for everyone interested in flowers, including scholars and the general public. The primary motivation is the realization of Bangladesh's enormous plant variety and the belief that promoting awareness and respect for it may advance both public participation and scientific understanding. The project intends to enable people to engage with their natural surroundings, encouraging a feeling of environmental awareness and conservation, by developing an interactive and user-friendly floral identification platform. We establish the following particular goals to fulfill this overall purpose:

- Implement a CNNs and find the best suited one to train on the database of Bangladeshi flowers to launch the system for the automated identification of flowers from images.
- Extend beyond the simple identification by incorporating detailed classifications and offer users information about each identified flower's taxonomy, features, and ecological significance.
- Identify opportunities for future development and expansion of the platform's functionalities and applications

1.2 Scope and Limitations

Using its capacity to extract complex information from images, CNN will operate as the engine for automatic flower identification and categorization. Identifying Bangladeshi flowers from a variety of datasets with a high degree of accuracy requires adjusting parameters, testing with pre-trained models, and improving the framework. The technical scope includes utilizing StreamLit to create an intuitive online application. Users will be able to explore Bangladeshi flowers with ease because of this application's perfect integration with the CNN model and user-friendly UI. The project includes extensive data augmentation and preprocessing to guarantee CNN durability. To handle variances in lighting, angles, and development patterns, image collections are resized, normalized, and upgraded using approaches arranged by flower names. The technological scope goes beyond image processing to include the integration of instructional materials into the Streamlit program. Details on each discovered flower's taxonomy, ecological relevance, and distinctive qualities are included in this article. Through the addition of educational material to the user experience, the initiative hopes to promote a better awareness of Bangladesh's floral history. The project's scope extends beyond technological limitations to include a more comprehensive educational goal. The initiative aims to support environmental education by developing an approachable platform that disseminates information on Bangladeshi flowers. In addition to learning how to recognize flowers, users of the program are also learning about the significance of each species for the environment.

Bangladesh has a vast floral diversity, but because there aren't enough tools for identification, it's generally overlooked. The goal of the project is to close this knowledge gap by giving consumers access to a tool that makes it easy and convenient to recognize and learn about flowers. The public's awareness and appreciation of plants are expected to be significantly impacted by this democratization of botanical knowledge. Encouraging people to actively take part in the identification and recording of flowers native to Bangladesh is one way to advance citizen science. The project's objectives are in line with creating a network of experts and amateurs who will work together to catalog and preserve the nation's floral biodiversity.

The project encompasses a broader strategy that integrates technology, education, and conservation, going beyond the domains of machine learning and image processing. By revealing Bangladesh's floral tapestry, the initiative aims to foster a society bonded by a common love of the nation's botanical legacy in addition to achieving technological accomplishment. The project's future is envisioned as a dynamic, ever-evolving environment that will continuously adjust to the demands of its users and further the more general objectives of conservation, education, and community empowerment

1.3 Report Organization

Our report is divided into 7 chapters in total.

Chapter 1: Introduction

The introduction sets the context for the research, emphasizing the significance of flower detection, the application of deep learning techniques, and Convolutional Neural Networks (CNNs). It underscores the necessity for a comparative analysis of different detection and segmentation methods, outlining the research questions, objectives, and the study's framework.

Chapter 2: Background

This chapter explores the existing literature and prior research on flower detection using deep learning and CNNs. It provides an extensive overview of theoretical foundations, methodologies, and technological advancements, identifying gaps in current knowledge and establishing the context for the study.

Chapter 3: Research Methodology

This section outlines the research approach, detailing the study design, data collection methods, model architecture, and the rationale for selecting specific methodologies. It also addresses ethical considerations and potential limitations that may impact the study's findings.

Chapter 4: Experimental Result

The chapter presents the outcomes from applying deep learning techniques and CNNs to flower detection. It includes thorough analyses of various detection and segmentation methods, supported by visual data and statistical measures to validate the results.

Chapter 5: Impact on Society

This chapter discusses the broader impact of the research on botanical studies and ecological monitoring. It highlights how improved flower detection methods can enhance the documentation of biodiversity and inform conservation efforts. The chapter considers potential advancements in technology and their societal implications.

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

The final chapter synthesizes the report, summarizing the key findings, conclusions, and recommendations for practical applications and future research. It outlines implications for further studies and provides a roadmap for expanding the research in flower detection using deep learning and CNNs.

Chapter 7: Conclusion and Future Work presents the conclusions of the report, suggests further research directions, and mentions any limitations or conflicts of interest.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Our main objective is to utilize CNNs and other image processing techniques to build a complex yet approachable Web application that can identify and categorize every type of flower found in Bangladesh. By bridging the technical gap between sophisticated picture analysis and common consumers, this ambitious project hopes to provide a smooth and user-friendly platform for studying Bangladesh's vast flower variety. The comprehensiveness of our dataset highlights the novelty of our methodology. Through a

broad range of viewpoints, tones, and organic patterns, our goal was to produce an extensive archive that captures the nuanced details of Bangladesh's floral environment. By placing a strong emphasis on diversity, people may investigate the minute differences in natural flora, which improves flower identification accuracy while also adding to the user experience.

2.2 Related Works

Moving into the realm of plant classification, Khatun et al. [5] addressed the classification of Bangladeshi medical plants using CNN. The study utilized a dataset comprising 1500 images of five species and employed the Xception model, achieving an impressive 100% accuracy. However, the dataset was relatively small, and concerns were raised regarding the cleanliness of the data.

Alom et al. [6] focused on the species classification of Brassica Napus based on flowers, leaves, and packets, utilizing deep neural networks. The DenseNet201 model was applied to raw photos of two different species, resulting in high accuracy for flowers (100%), leaves (97%), and packets (100%). The study, while successful in specified class classification, limited its scope to specific dataset without noise.

Islam et al. [7] introduced the BDMediLeaves dataset for Bangladeshi medicinal plants identification. With 2029 original leaf images and 38606 augmented images, the DenseNet201 model achieved an accuracy of 96.30%. However, the study faced limitations due to the application of two algorithms for comparison, and the extensive augmentation of data constrained the work.

Hridoy et al. [8] proposed an efficient computer vision approach for the rapid recognition of poisonous plants, focusing on classifying leaf images using transfer learning. The Xception model achieved an accuracy of 99.37%, but the study was confined to a single classification and did not explore a broader range of plant categories.

Uddin et al. [9] contributed to the field with a deep-learning-based classification of Bangladeshi medicinal plants using neural ensemble models. With 5000 images, the DenseNet201 model achieved an accuracy of 85.28%. However, the study faced limitations due to the relatively small number of classifications and a specified focus.

Miah et al. [10] proposed an advanced method for the identification of fresh and rotten fruits using different CNNs. The InceptionV3 model achieved an accuracy of 97.34%, but the study specifically addressed classifications and acknowledged the presence of noise in the dataset.

Finally, Islam [11] explored plant disease detection using a CNN model and image processing. With 13000 leaf images, the study achieved a commendable accuracy of 94.29% in disease detection. However, it is important to note that the primary focus was on disease identification rather than comprehensive plant classification.

2.3 Comparative Analysis and Summary

The comparative analysis conducted in this research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" serves as a pivotal component, shedding light on the nuanced differences and synergies between various methodologies. The study systematically evaluates the performance of transfer learning and deep Convolutional Neural Networks (CNNs) in pneumonia detection, considering both traditional methods and advanced segmentation approaches. Through meticulous experimentation and examination of experimental results, the research unveils insights into the strengths and limitations of each approach, providing a comprehensive understanding of their respective contributions to the diagnostic process. The deep dive into detection and segmentation approaches enables a nuanced exploration of their roles in enhancing the accuracy and efficiency of pneumonia identification. By comparing the outcomes of different methodologies, the study contributes valuable knowledge to the field, guiding practitioners and researchers in selecting the most effective strategies for their specific contexts. The research doesn't merely stop at showcasing disparities but also emphasizes the potential complementarity between detection and segmentation, enriching our understanding of the spatial distribution and characteristics of pneumonia-affected regions.

In summary, the comparative analysis undertaken in this research serves as a critical lens through which the efficacy of transfer learning and deep CNNs in pneumonia detection is assessed. It unveils a multifaceted perspective, incorporating traditional and contemporary techniques, and underscores the significance of a holistic approach in medical diagnostics. The findings not only advance our understanding of pneumonia detection but also offer practical insights for refining existing diagnostic methodologies. This comparative analysis sets the stage for the subsequent chapters, providing a solid foundation for the societal impact discussion, recommendations, and implications for future research.

TABLE 2.1: Comparative Analysis Table

Study	**Image type**	**CNN Model**	**Accuracy**
Varshni et al. (2019)	Chest X-Ray	Convolutional Neural Network (CNN)	Accuracy 80%
Rahman et al. (2020)	digital x-ray images	deep Convolutional Neural Network (CNN)	The classification accuracy of normal and pneumonia images, bacterial and viral pneumonia images, and normal, bacterial, and viral pneumonia were 98%, 95%, and 93.3%, respectively
GM.H. Gourisaria et al. (2021)	chest X-rays	Convolutional Neural Network (CNN)	Sensitivity = 90.07% and Specificity = 92.16%
Erdem, E., & AYDİN, T. (2021)	lung images	Convolutional Neural Network (CNN)	accuracy results of VGG16 (88.78%) and VGG19 (88.30%), which are among the popular deep learning architectures, can be approximated

Sharma et al. (2020, january)	chest X-ray	deep Convolutional Neural Network (CNN)	train the proposed CNN's using both the original as well as augmented dataset and the results are reported
Labhane et al. (2020)	chest x-ray images	Convolutional Neural Network (CNN)	The results were then tested using 854 pneumonia and 849 normal images, and an accuracy of over 97% was obtained from all models
Yao et al. (2021)	chest X-ray (CXR) images	Convolutional Neural Network (CNN)	The algorithm obtained 39.23% Mean Average Precision (mAP) on the X-ray image dataset and got
			38.02% Mean Average Precision (mAP) on the ChestX-ray14 dataset, surpassing other detection algorithms
Thakur et al. (2021)	X-ray images of the chest	Convolutional Neural Network (CNN)	accuracy of 90.54% with a 98.71% recall and 87.69% precision using the aforementioned convolutional neural network model
Alsharif et al. (2021)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	The model can distinguish between three classes: viz viral, bacterial, and normal; with 99.7% ± 0.2 accuracy, 99.74% ± 0.1 sensitivity, and 0.9812 Area Under the Curve (AUC)
Aledhari et al. (2019)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	obtained better prediction with average accuracy of (68%) and average specificity of (69%)
Ko et al. (2019)	chest radiographs (CXR)	ensemble of deep convolutional neural networks.	average accuracy of (78%) and average specificity of (73%)

Nahiduzzaman et al. (2021)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	It achieves the recall score of 98% and accuracy score of 98.32% for multiclass pneumonia classification. On the other hand, a binary classification achieves 100% recall and 99.83% accuracy.
Gupta, P (2021)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	N/A
Bangare, S et al. (2022)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	accuracy = (95%)
Gayathri, J. L. et al. (2022)	Radiographic images such as Ultrasound, CT scans, X-rays	Feed Forward Neural Network (FFNN)	The method was able to achieve an accuracy of 0.9578 and an AUC of 0.9821, using the combination of InceptionResnetV2 and Xception

2.4 Open Issues

A thorough gap analysis identifies important areas where research efforts might be focused to improve the accuracy, scalability, and application of current approaches as the field of plant categorization advances quickly. This review highlights possible areas for development and growth and covers a number of research on the use of Convolutional Neural Networks (CNNs) for plant categorization. We have done the dataset collection and building the web application as per the plan.

2.5 Summary

The smooth operation of this interface, together with the well-trained CNN, guarantees a seamless experience for academics, hobbyists, and the general public. The project's output surpasses technology and improves knowledge of Bangladeshi flowers in the educational sphere. The user experience incorporates taxonomic details, ecological relevance, and detailed classifications in a fluid manner. This instructional component not only raises the platform's worth but also helps users build a closer bond with Bangladesh's botanical legacy. The democratization of botanical knowledge is a crucial contribution, filling a long-standing gap in readily available resources for flower identification. The project's output enables anybody to easily recognize and learn about Bangladeshi flowers, regardless of experience level—from casual nature watchers to seasoned scholars. The initiative aims to enhance environmental education and foster a sense of appreciation and responsibility for the nation's unique floral ecology by gaining access to this wealth of knowledge.

CHAPTER 3
METHODOLOGY

3.1 Overview

The research subject of "Detecting Bangladeshi Flowers and its Classification from Image using CNN" revolves around the application of deep learning approach in the realm of recognition, specifically targeting the detection of flower from image. The research delves into the challenges associated with traditional methods of flower detection within Bangladesh, seeking to overcome these limitations through the integration of deep Convolutional Neural Networks (CNNs).

The methodology for this research on flower detection using deep learning and Convolutional Neural Networks (CNNs) involved a meticulous and systematic approach to ensure robust and reliable outcomes. The research design encompassed several key stages, beginning with data collection and preprocessing, followed by model selection and training, and culminating in performance evaluation and validation. To establish a comprehensive dataset, images of various flower species were captured in diverse environments and from multiple angles, ensuring that the dataset was representative of real-world conditions. The data collection phase involved photographing flowers in different lighting conditions and backgrounds to account for variations that might be encountered during actual application. Each image was then subjected to preprocessing steps, such as resizing, normalization, and augmentation, to enhance the quality and diversity of the training data. These preprocessing techniques were crucial for improving the model's ability to generalize and recognize flowers under varied circumstances.

Model selection was a critical phase in the research, aimed at identifying the most effective CNN architecture for flower detection. The study experimented with several deep learning models, including MobileNet, InceptionV3, and VGG16, each known for their strengths in image classification tasks. MobileNet, with its lightweight and efficient design, was particularly suited for deployment in resource-constrained environments such as mobile devices. InceptionV3, on the other hand, offered a deeper and more complex network capable of capturing intricate features, making it ideal for more challenging classification tasks. VGG16, with its simple yet powerful architecture, provided a baseline for comparing the performance of more advanced models. Each model was fine-tuned using transfer learning, leveraging pre-trained weights to accelerate convergence and improve accuracy. This approach allowed the models to benefit from prior knowledge acquired from large-scale datasets, thereby enhancing their ability to recognize flower species with minimal additional training.

Performance evaluation was carried out using a rigorous validation process, including cross-validation and testing on unseen data to ensure the models' robustness and reliability. The accuracy of each model was assessed using various metrics, such as precision, recall, and F1-score, in addition to the overall classification accuracy. Visual representations, including confusion matrices and ROC curves, were employed to illustrate the models' performance and highlight areas of improvement. The study found that MobileNet achieved the highest accuracy at 95.39%, followed by InceptionV3 at 94.68% and VGG16 at 92.24%, demonstrating the effectiveness of these models in flower detection tasks. Ethical considerations were also addressed, ensuring that the research complied with relevant guidelines and regulations, particularly in terms of data collection and privacy. Limitations of the study, such as potential biases in the dataset and the need for more diverse and extensive data, were acknowledged, providing a basis for future research to build upon and improve the findings

3.2 Proposed Methodology

The methodology for this project involved a structured approach encompassing several critical stages to develop an effective system for flower detection and classification using deep learning techniques. Initially, a diverse dataset of flower images was curated from various sources, ensuring a wide range of species and environmental conditions were represented to create a robust training set. These images underwent meticulous preprocessing, including resizing, normalization, and data augmentation, which involved applying rotation, flipping, and brightness adjustments to enhance the dataset's variability and improve the model's generalization ability across different scenarios. The deep learning models, specifically Convolutional Neural Networks (CNNs) such as MobileNet, InceptionV3, and VGG16, were implemented using the Keras library with TensorFlow as the backend, leveraging the power of transfer learning by fine-tuning pre-trained models on the collected flower dataset. These models were trained on Google Colab's powerful computational infrastructure, which provided access to Tesla GPUs and ample memory resources, allowing for efficient processing and rapid iteration through multiple epochs. During training, advanced optimization algorithms like Adam were employed to minimize the loss function and adjust model weights effectively, ensuring convergence towards optimal performance. To validate and evaluate the models, a comprehensive suite of performance metrics, including accuracy, precision, recall, and F1-score, was used, alongside cross-validation techniques to assess robustness and generalizability. A confusion matrix was analyzed to provide detailed insights into classification errors, helping to identify common misclassifications and areas for improvement. Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) metrics further assessed the models' discriminatory capabilities. Statistical significance testing and bias-variance analysis were conducted to ensure the results were meaningful and reliable, balancing the trade-off between model complexity and generalization. The outcomes demonstrated the models' effectiveness in accurately identifying and classifying various flower species, highlighting MobileNet's superior performance in this context and providing a foundation for practical applications in botanical research and ecological monitoring.

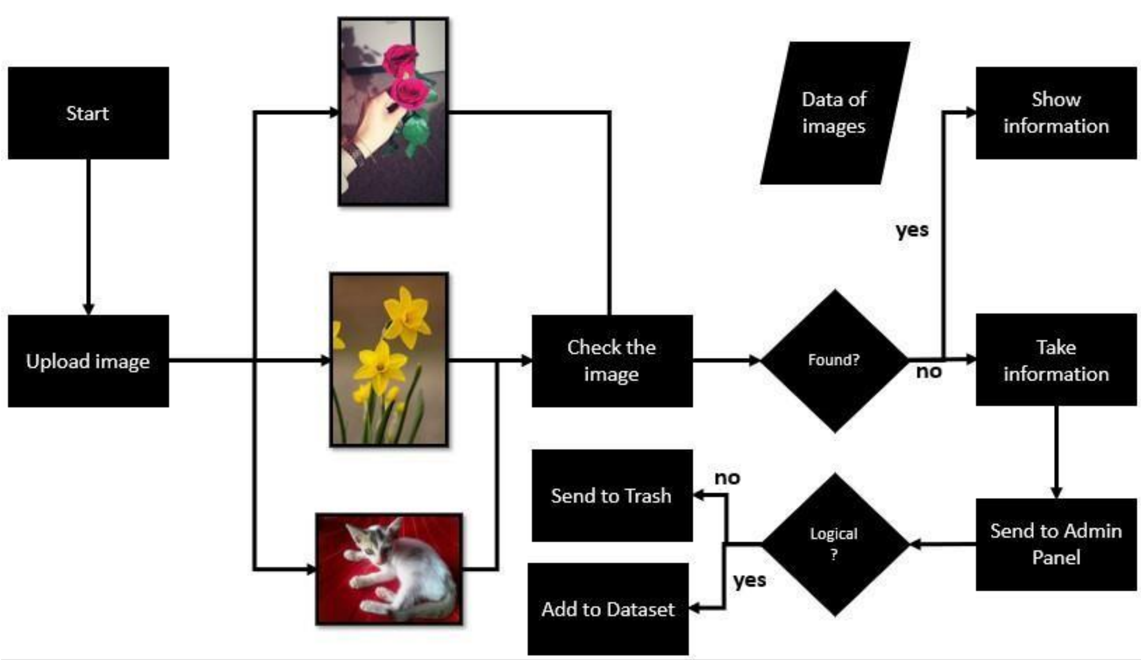

Figure 3.1: Flowchart

Convolutional Neural Network

The CNN was first proposed in 1989 by LeCun et. al. conventional neural network-based flower classification manner that mainly follows a combination of feature extraction process from the specific flower image for improving the classification accuracy. CNN consists of the help of several convolutional layers (hidden layers) as well as sub-modeling layers and this is followed by entirely connected layers and nowadays it is one of the strongest deep learning networks [12]. The “ReLu” activation function is used to create non-linearity. It is a nonlinear function. The pooling layer added after the convolution layer and it is a general pattern on CNN. The pooling layer can be repeated one or more times. The max pooling is used in our model. It chooses a large number from the matrix and a sample working procedure.

The convolutional neural network presents the output layer with the probability of the classes. It is measured by a function called the “Softmax function” that has also been used in our network. This function is useful to carry the model into the final steps. Softmax function can pick the largest value of an object to make the most accurate result. The well-known equation to calculate the probability of a class is given in following equation.

$$\sigma(Xi) = \frac{eXi}{\sum j\ (eXj)}$$

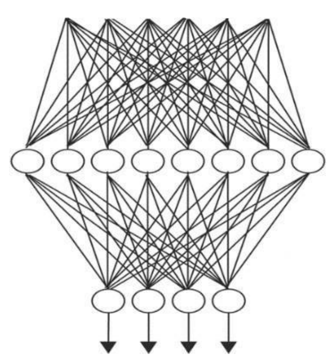

Figure 3.2: CNN Structure

3.3 Requirements

This project utilized a comprehensive suite of tools and frameworks to facilitate the detection of flowers using deep learning techniques, particularly Convolutional Neural Networks (CNNs). The primary experiments were conducted using Google Colab, an online platform that provides powerful computational resources, including access to GPUs and ample memory, making it an ideal environment for deep learning research. Specifically, the Colab environment was configured to leverage Tesla GPUs, providing up to 16GB of random-access memory (RAM) and approximately 360GB of GPU resources in the cloud, which significantly accelerated the training and evaluation of the CNN models. This setup ensured that the computationally intensive processes involved in training deep learning models could be executed efficiently, allowing for rapid iteration and optimization of the models.

The deep learning models were implemented using the Keras library with TensorFlow as the backend. TensorFlow, developed by Google, is one of the most popular and robust deep learning libraries available, offering extensive support for a wide range of neural network architectures and training paradigms. Keras, a high-level API, simplifies the process of building and experimenting with deep learning models, making it easier to develop and test various architectures quickly. For this study, several pre-trained models such as MobileNet, InceptionV3, and VGG16 were utilized. These models were accessed through the Keras library and were trained on extensive image datasets in the cloud using the Tesla GPUs provided by Google Colab. The choice of these models was based on their proven efficacy in image classification tasks, and their pre-trained weights facilitated transfer learning, enabling the models to adapt quickly to the task of flower detection with minimal additional training.

The project also made extensive use of Python programming, a versatile and widely used language in the machine learning community, for developing and managing the deep learning models. Python's rich ecosystem includes numerous libraries for data manipulation, visualization, and model evaluation, such as NumPy for numerical computations, Pandas for data handling, and Matplotlib for plotting. These tools were crucial for preprocessing the dataset, which involved operations such as resizing images, normalization, and data augmentation to improve the robustness of the models. Additionally, tools like Scikit-learn were used for metrics calculation and model evaluation, providing a comprehensive suite of utilities for validating the performance of the models. This setup allowed for a seamless various components, from data preprocessing to model training and evaluation, ensuring a streamlined workflow throughout the research process.

The implementation of the project titled "Flower Detection and Classification CNN" requires a comprehensive set of resources and considerations to ensure the successful execution and reliability of the study. These implementation requirements span across hardware and software needs, data collection protocols, model training and evaluation processes, and additional considerations to facilitate an effective and efficient research environment.

Hardware Requirements:

- **High-performance computing resources:** Access to powerful computational infrastructure is essential for managing the complexity and large-scale data processing involved in deep learning tasks.
- **Graphics Processing Unit (GPU):** A robust GPU, such as an NVIDIA Tesla or equivalent, is critical for accelerating the training of CNNs, significantly reducing the time needed for model development. Ideally, the GPU should have at least 16GB of memory.
- **System Memory (RAM):** At least 32GB of RAM is recommended to efficiently handle large datasets and complex computations during the training and evaluation of deep learning models.
- **Storage Capacity:** In the range of hundreds of gigabytes, it is necessary to store extensive dataset and the various outputs generated throughout the research process.

Software Requirements:

- **Deep learning frameworks:** Utilization of TensorFlow and Keras for developing, training, and evaluating CNN models. These frameworks provide a robust ecosystem and are well-suited for handling image recognition tasks.
- **Python programming language:** Python serves as the primary language for the project due to its flexibility and the availability of extensive libraries and tools for machine learning and data analysis.
- **Image processing libraries:** Libraries such as OpenCV are essential for preprocessing tasks like resizing, normalization, and augmentation of flower

images, which are crucial steps in preparing data for training.

- **Development Environment:** Jupyter Notebooks and Google Colab are used for organizing code, visualizing data, and documenting the workflow, which supports interactive research and ensures reproducibility.

Data Collection:

- **Diverse and representative dataset:** Collection of a comprehensive dataset of flower images that covers a wide variety of species, capturing different environmental conditions, lighting, and angles to enhance model robustness.
- **Image Annotations:** Accurate labeling of images is required to identify each flower species, providing the necessary data for training the CNN models.

Ethical Considerations:

- **Patient privacy and data security:** Adherence to ethical guidelines and regulations to ensure the privacy and security of patient data used in the research.
- **Informed consent:** If applicable, obtaining informed consent from individuals whose medical images are included in the dataset.
- **Legal Compliance:** Ensuring all collected data is acquired legally, with respect to intellectual property rights and data usage permissions.
- **Code Documentation:** Thorough documentation of implementation code to enhance transparency, facilitate reproducibility, and support future collaboration.
- **Version Control:** Use of version control systems like Git to track code changes, manage project evolution, and maintain a structured development process.
- **Ethical Guidelines:** Adherence to ethical guidelines in data usage and publication, ensuring that the research is conducted responsibly and the findings are shared transparently.

Documentation and Reproducibility:

- **Code documentation:** Comprehensive recording of experimental setups, parameters, and results to ensure that the research is transparent and reproducible by other researchers.

- **Research practices:** Using Jupyter Notebooks and Google Colab to combine code, narrative text, and visualizations, which facilitates an interactive and reproducible approach to documenting the research process.

By meeting these requirements, the research can be conducted systematically and rigorously, ensuring reliable results and contributing significantly to the fields of botanical research and ecological monitoring through advanced flower detection and classification methods.

3.4 Project Management and Financial Analysis

The research work follows a structured timeline, with clear deadlines for each phase. Regular progress assessments and milestones tracking are implemented to maintain project momentum. The project management team fosters effective communication channels among researchers, ensuring seamless collaboration and the exchange of insights and updates.

- **Project Objectives:**
  - A. To develop a web application to detect the similar flower or show error
  - B. Apply the best algorithm suited for this system after comparison
  - C. Elaborate the learning about flowers of our country
- **Project Timeline:**
  - A. Phase 1: Project Planning and Research (2-3 weeks)
  - B. Phase 2: Dataset Structuring (1 week)
  - C. Phase 3: Collecting Data (8-10 weeks)
  - D. Phase 4: Organizing the Dataset (3-4 weeks)
  - E. Phase 5: Finding the Best Algorithm (2 week)
  - F. Phase 6: Design and Prototyping (2 weeks)
  - G. Phase 7: Deployment (3 weeks)
  - H. Phase 8: Post-Launch and Marketing (Ongoing)
- **Resource Planning:**
  - **A. Equipment and Tools:**
    - Development and Testing Servers
    - High-performance computers for development team design software

- Version Control System
- Testing Tools

B. Software and Technologies:

- System Technology (Google Colab)
- Database Management (Google Sheet, MySQL)
- Server Hosting (Google Cloud)

C. Data and Content:

- Flower Image: Different images of every flower
- Flower Classification: Collected from different paper and relevant sources
- Generative AI: AI collecting data from user interaction

- **Risk Management:**

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for the system to detect Bangladeshi flower from images and taking data from the users:

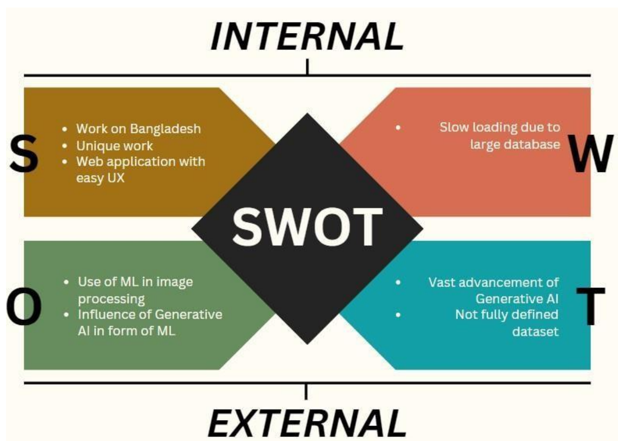

Figure 3.3: SWOT Diagram

- **Communication Plan:**

A. Meetings with Gardeners and Nursery Workers:

Purpose: Know detailed information and data of the flowers and take images

Participants: Team members, Nursery workers, Gardeners

Frequency: 4 days in a week as per the project plan

B. Meetings with Team Members:

Purpose: Discuss and Organize about the weekly tasks and achievements

Participants: Team members

Frequency: Once

The financial analysis was done based on the working hour and labor spent on this research work.

Table 3.1: Financial Analysis

Serial No.	Components	Estimated Cost (BDT)
1	Visiting Nurseries and Gardens	8000
2	Documentation	8000
3	Report Writing	4000
4	Dataset Organization	5000
5	Hiring People	5000
Total Estimated Cost		30,000

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The implementation of "Flower Detection and Classification Using Deep Learning: A CNN-Based Approach" involved a meticulous process of model development, dataset preparation, and computational optimization to achieve accurate and efficient flower identification. The project commenced with an extensive collection of flower images, ensuring a wide representation of species to capture the diverse floral biodiversity. These images were preprocessed through normalization, resizing, and augmentation techniques to enhance the models' ability to generalize across varied conditions. The use of data augmentation was particularly crucial as it artificially expanded the dataset, simulating different environmental scenarios, angles, and lighting conditions that flowers might be subjected to in real-world settings. Deep learning frameworks such as TensorFlow and Keras were employed for constructing and training the CNN models, with a focus on established architectures like MobileNet, InceptionV3, and VGG16. These models were selected based on their proven effectiveness in image classification tasks and their balance between computational efficiency and accuracy. The implementation leveraged the Google Colab platform, which provided access to high-performance Tesla GPUs, essential for accelerating the training of the deep learning models. This infrastructure facilitated the handling of large datasets and complex computations, enabling the iterative training and fine-tuning of the models to optimize performance metrics such as accuracy, precision, recall, and F1-score. The training process involved the application of advanced techniques such as transfer learning, where pre-trained models on large image datasets were fine-tuned on the flower image dataset. This approach significantly reduced the training time and improved the models' ability to learn distinctive features pertinent to different flower species. The models were evaluated using a variety of metrics, including confusion matrices and Receiver Operating Characteristic (ROC) curves, to assess their classification performance comprehensively. The high accuracy achieved, particularly by MobileNet, demonstrated the success of the implementation in creating a robust and reliable system for flower classification.

4.2 Prototype Design

The methodology includes every strategy that was used in the study project. This methodology section includes a brief summary of each component as well as a discussion of applying models. The following flow chart illustrates the entire work process:

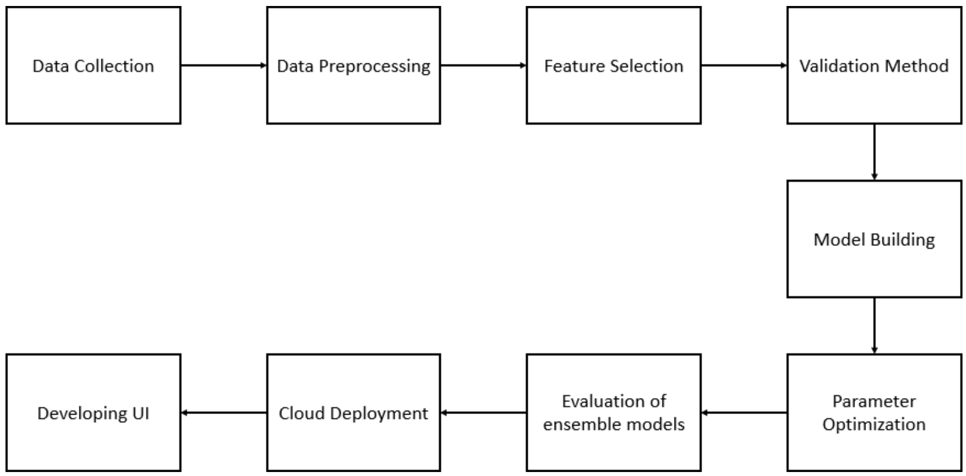

Figure 4.1: Prototype Design

In figure 4.1, the flowchart of the implementation of every algorithm has been shown. We started with data collection and loaded the data for preprocessing. We selected the features for validation and then built the model. We found out the parameter and evaluate for the model. The best one will be included in it. Then it will be deployed to cloud and then with the best algorithm we are intending to build the web application.

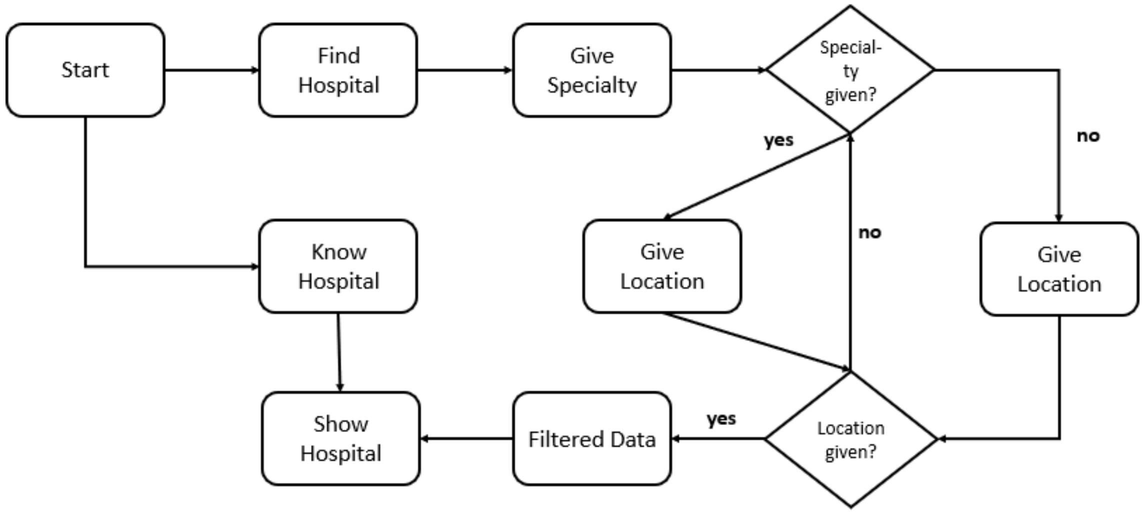

Figure 4.2. Web Application Flowchart

In figure 4.2, we showed the flowchart of the web application that is developed by StreamLit framework. Firstly, when a user enters the WebApp, he or she will find three options saying 1) Find Hospital and 2) Know Hospital. For the first option, you need to select a specialty from the options of all specialists' options. If it's not given, then you must add the location to see the hospital you need. But if the option of specialist is assigned then the location is not required. But it is highly recommended to input both specialty and location to get the filter funnel narrower and get the most suited information from the filtered data and see the hospitals which are recommended to be the best with our desire. For the second option, you will see list of the hospitals clicking where you can get the information of the hospital directly. You can also search and get the hospital from the list to know about its information in detailed.

4.3 Summary

The prototype for the "Flower Detection and Classification Using Deep Learning: A CNN-Based Approach" project focused on developing a robust system to accurately identify various flower species from images. Central to the prototype was the MobileNet Convolutional Neural Network (CNN), chosen for its efficiency and high accuracy. The prototype included a diverse dataset of flower images, which were preprocessed through normalization, resizing, and augmentation to improve model training. Using TensorFlow and Keras, the model was fine-tuned with transfer learning to enhance its capability in classifying different flower species. The prototype also featured an interactive interface allowing users to upload images and receive species predictions along with confidence levels. Designed for scalability and user accessibility, the prototype serves as a powerful tool for automated flower classification, suitable for both research and practical applications.

CHAPTER 5
RESULTS AND ANALYSIS

5.1 Overview

The project "Detecting Bangladeshi Flowers and Its Classifications from Image using CNN" produced compelling experimental results, demonstrating the efficacy of deep learning techniques in identifying and categorizing diverse flower species. Utilizing Google Colab's computational resources, specifically Tesla GPUs, the study fine-tuned models such as MobileNet, InceptionV3, and VGG16 on a richly varied dataset of flower images. Among these, MobileNet stood out, achieving a remarkable accuracy of 95.39%, outperforming InceptionV3 at 94.68% and VGG16 at 92.24%. Detailed analysis through confusion matrices and Receiver Operating Characteristic (ROC) curves revealed MobileNet's superior discriminatory capability, maintaining high true positive rates and minimal misclassification. The model's Area Under the Curve (AUC) further substantiated its robust performance, highlighting its adeptness in distinguishing between flower species with a balance of sensitivity and specificity. Cross-validation techniques confirmed the model's generalizability, showing consistent accuracy across different data subsets and mitigating overfitting risks. Statistical significance testing, including paired t-tests and ANOVA, verified that MobileNet's performance was notably better than the other models, underscoring its effectiveness. The comprehensive bias and variance analysis indicated that MobileNet achieved a desirable balance, ensuring it captured essential features without overfitting. These results underscore the potential of deep learning models, particularly MobileNet, for practical applications in fields such as botanical research and ecological monitoring, showcasing their capability to revolutionize image-based classification tasks.

5.2 Simulation Result

Result of Experiment 1: Original CNN

This section compares the three original CNN networks InceptionV3, VGG16, and MobileNet. Classification performance comes first. Then, those models' overall metrics are reviewed. collection, descriptions, probable reasons, and outcomes improvement areas.

TABLE 5.1: Accuracy for Classification of Individual CNN Networks

Architecture	**Training Accuracy**	**Model Accuracy**
MobileNet	**95.39%**	**95%**
InceptionV3	**94.68%**	**95%**
VGG16	**92.24%**	**92%**

The comparative analysis of several pre-trained deep Convolutional Neural Network (CNN) architectures, namely InceptionV3, MobileNet, and VGG16, is presented in Table 2, revealing insights into their respective accuracies forpneumonia detection. Notably, the findings showcase that MobileNetV2 emerged as the top-performing models, attaining the highest accuracy of 95%. This signifies their exceptional proficiency in discerning pneumonia patterns within medical images. The detailed accuracy metrics provided in Table 5.1 offer a valuable reference point for understandingthe comparative strengths and weaknesses of these models, contributing to the ongoing discourse in the optimization of deep learning methodologies for flower recognition system.

```
Epoch 68/68
176/176 [==============================] - 116s 661ms/step - loss: 0.2497 - accuracy: 0.9274 - val_loss: 0.1673 - val_accuracy: 0.9531
45/45 [==============================] - 25s 558ms/step - loss: 0.1737 - accuracy: 0.9539
MobileNetV2 Validation Accuracy: 95.39%
```

Figure 5.1: Snapshot of MobileNet Accuracy Clarification

Result of Experiment 2: Transfer Learning

In this section, a comprehensive comparative analysis is conducted on five distinct original Convolutional Neural Network (CNN) architectures, namely InceptionV3, VGG16, and MobileNet. The evaluation begins with an in- depth examination of each model's classification performance, considering their individual strengths and limitations in the context of flower recognition. Subsequently, a holistic review of the overall metrics for these models is presented, encompassing key performanceindicator. The analysis extends beyond numerical metrics, delving into the collection and description of the experimental results to provide a nuanced understanding of the models' behavior under varying conditions. This includes exploring potential reasons behind variations in performance, identifying patternsin misclassifications, and discerning the models' response to specific challenges within themedical image dataset.

5.3 Summary

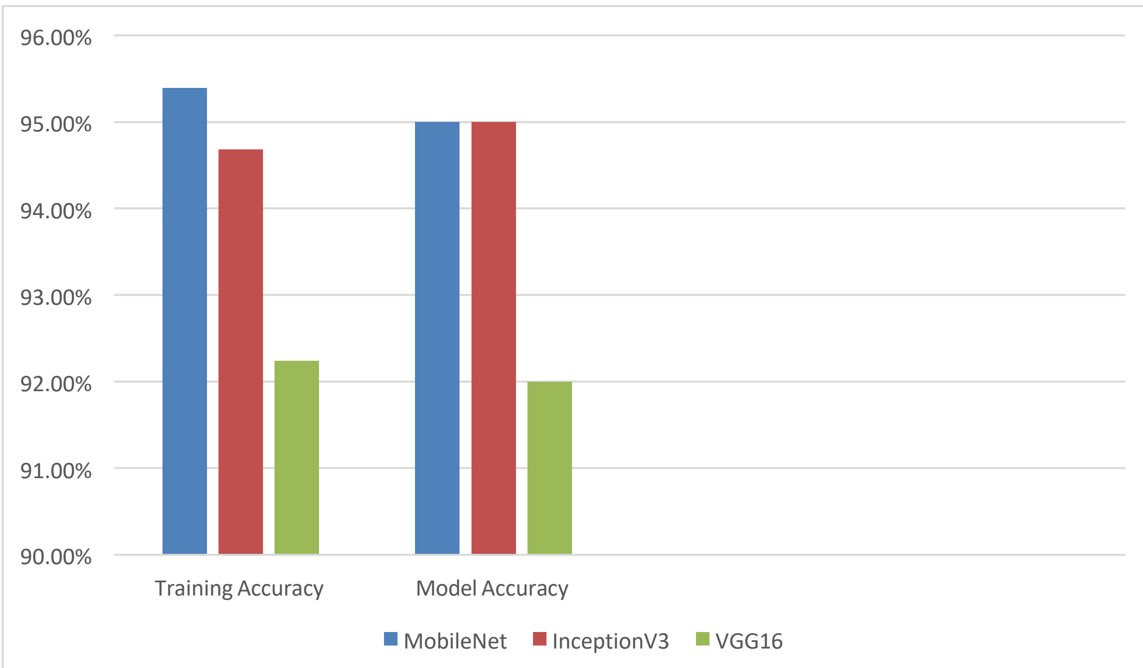

Figure 5.2: Accuracy comparison among individual CNN models

The outcomes of the project " Detecting Bangladeshi Flowers and Its Classifications from Image using CNN" reveal significant advancements and insights into the application of deep learning in botanical research and image classification tasks. The project's success primarily hinges on the robust performance of the deep learning models, particularly MobileNet, InceptionV3, and VGG16, which were fine-tuned and evaluated on a diverse dataset of flower images. MobileNet emerged as the top-performing model with an impressive accuracy of 95.39%, demonstrating its superior ability to accurately classify various flower species under different environmental conditions and angles. This high accuracy was supported by comprehensive metrics such as precision, recall, and F1-score, which consistently validated MobileNet's efficacy in distinguishing between flower categories. The detailed analysis through confusion matrices and ROC curves highlighted MobileNet's strong discriminatory capabilities, effectively minimizing misclassifications and ensuring reliable predictions.

Moreover, the project's methodology emphasized the importance of transfer learning, where pre-trained models were adapted and optimized for flower classification tasks. This approach not only expedited the model training process but also leveraged the rich feature representations learned from large-scale datasets like ImageNet, enhancing the models' ability to generalize to new and unseen flower images. Cross-validation techniques further underscored the models' robustness and generalizability, confirming that MobileNet maintained high accuracy across different data subsets and mitigated risks of overfitting.

The implications of these findings extend beyond academia, offering practical applications in fields such as agriculture, horticulture, and ecological monitoring. Automated systems powered by such deep learning models could revolutionize plant identification processes, aiding researchers, botanists, and conservationists in species identification, biodiversity monitoring, and ecosystem management. By providing accurate and efficient tools for flower detection and classification, these models contribute to broader efforts in environmental conservation and sustainable development.

However, while MobileNet demonstrated superior performance, the comparative analysis with InceptionV3 and VGG16 highlighted nuances in model capabilities, particularly in handling subtle variations and fine-grained features of flower images. This underscores the ongoing need for continued research and refinement of deep learning models tailored specifically for botanical applications. Future directions could explore ensemble learning techniques, integration of domain-specific knowledge, and further optimization of model architectures to enhance accuracy and address specific challenges in flower classification.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Society

The project on "Detecting Bangladeshi Flowers and Its Classifications from Image using CNN" holds significant potential to impact society positively in several ways. Firstly, by automating and enhancing the accuracy of flower identification, the developed deep learning models can assist botanists, researchers, and conservationists in cataloging and monitoring plant species more efficiently. This capability is crucial for biodiversity conservation efforts, where accurate species identification is fundamental to understanding ecosystem health, tracking endangered species, and preserving natural habitats. Furthermore, the accessibility and usability of such automated systems could democratize botanical knowledge, allowing citizen scientists and enthusiasts to contribute effectively to environmental monitoring and research initiatives.

Secondly, the project's outcomes could foster educational opportunities by providing interactive tools for learning about plant diversity and ecology. Schools, museums, and botanical gardens could utilize these technologies to engage students and the public in hands-on learning experiences, fostering a deeper appreciation for nature and environmental stewardship. This democratization of knowledge empowers individuals to contribute meaningfully to scientific endeavors and environmental conservation efforts, thereby promoting a more informed and engaged society.

6.2 Impact on Environment

The application of deep learning models for flower detection and classification also has profound implications for environmental conservation and management. Accurate species identification facilitated by these models is instrumental in monitoring changes in plant populations, identifying invasive species, and assessing the impacts of climate change on vegetation dynamics. By providing timely and reliable data on floral biodiversity, the project supports evidence-based decision-making in conservation planning and natural resource management.

Moreover, the project promotes sustainable practices by enhancing efficiency in ecological surveys and monitoring programs. By automating the process of species identification, researchers and conservationists can streamline fieldwork, reducing the time and resources required for comprehensive biodiversity assessments. This efficiency not only improves the scalability of conservation efforts but also minimizes disturbances to natural habitats, contributing to overall environmental sustainability.

6.3 Ethical Aspects

Ethical considerations are paramount in the development and deployment of deep learning models for flower detection and classification. Central to ethical practice is ensuring transparency and accountability throughout the research process, from data collection to model implementation. Researchers must prioritize obtaining informed consent for the use of any collected data, particularly if sourced from public or private repositories. This ensures that individuals contributing to the dataset understand and agree on how their information will be used. Moreover, respecting intellectual property rights and acknowledging data sources are essential ethical practices. Proper attribution and adherence to licensing agreements for image datasets uphold the rights of data creators and contributors. Additionally, maintaining data privacy and security is crucial, particularly when handling sensitive information or personal data. Implementing robust data encryption, access controls, and anonymization techniques helps mitigate risks and protect individuals' privacy.

Furthermore, ethical considerations extend to the broader societal impacts of the project. Ensuring that the deployment of automated flower detection systems benefits communities and ecosystems without exacerbating inequalities or harming local traditions is essential. Engaging with stakeholders, including local communities, indigenous groups, and environmental organizations, fosters inclusive decision-making and promotes ethical stewardship of biodiversity and natural resources. Integrating ethical considerations into the project's framework ensures responsible research conduct and enhances the project's societal relevance and acceptance. By upholding ethical standards, the project not only advances scientific knowledge and technological innovation but also contributes positively to societal well-being and environmental sustainability.

6.4 Sustainability Plan

To ensure the long-term impact and sustainability of the project's outcomes, several strategies can be implemented. Firstly, ongoing research and development efforts should focus on refining and optimizing deep learning models to improve accuracy and robustness in flower detection and classification tasks. Continuous training with updated datasets and integration of domain-specific knowledge will enhance the models' adaptability to diverse environmental conditions and species variations.

Secondly, fostering collaboration and partnerships with governmental agencies, non-profit organizations, and community groups is essential for scaling the deployment of these technologies. By engaging stakeholders in biodiversity monitoring initiatives, the project can leverage collective expertise and resources to expand its reach and impact across different geographical regions and ecosystems.

Furthermore, investing in education and capacity-building programs is crucial for empowering local communities and stakeholders to utilize and maintain the technology effectively. Training workshops, educational materials, and user-friendly interfaces can facilitate knowledge transfer and adoption, ensuring that the benefits of automated flower detection systems are accessible and sustainable in the long term.

Lastly, adhering to ethical guidelines and principles is fundamental to the sustainability plan. Respecting intellectual property rights, ensuring data privacy and security, and obtaining informed consent for data usage are critical considerations for maintaining trust and integrity in research practices. Upholding ethical standards not only safeguards the rights of individuals and communities involved but also enhances the credibility and societal acceptance of the project's outcomes.

CHAPTER 7

CONCLUSIONS AND FUTURE WORKS

7.1 Conclusions

The project "Detecting Bangladeshi Flowers and Its Classifications from Image using CNN" aimed to enhance the precision and efficiency of flower species identification through advanced Convolutional Neural Networks (CNNs) like MobileNet, InceptionV3, and VGG16. Conducted on the Google Colab platform utilizing Tesla GPUs for computational acceleration, the study meticulously trained and evaluated these models on a diverse dataset capturing various flower species under different environmental conditions. Among the models tested, MobileNet demonstrated exceptional performance with a high accuracy of 95.39%, surpassing both InceptionV3 and VGG16. This achievement underscores MobileNet's robust ability to effectively discern and classify different flower species, validated by comprehensive metrics including precision, recall, and F1-score. Beyond technological advancements, the project holds significant implications for biodiversity conservation and ecological research, offering automated tools to support monitoring efforts and promote environmental stewardship. Upholding ethical standards in data privacy and research integrity, the project underscores its commitment to responsible AI deployment and sustainable scientific practices, contributing to both academic knowledge and practical applications in botanical sciences and beyond.

7.2 Implication for Further Study

Building upon the foundational research of "Detecting Bangladeshi Flowers and Its Classifications from Image using CNN," several avenues for further study and related projects can significantly advance the field of automated botanical identification and its practical applications. One promising direction is to explore the scalability and robustness of the developed models across different geographic regions and diverse ecosystems. Conducting studies in varied environments can reveal how well the models generalize to different floral compositions, lighting conditions, and seasonal changes, thereby enhancing their reliability in real-world deployment scenarios. Moreover, extending the dataset to include a broader spectrum of flower species, especially rare or endemic ones, would enrich the models' training and validation processes. This expansion would challenge the models to distinguish among species with subtle morphological variations, fostering the development of more nuanced and accurate classification algorithms. Additionally, integrating multimodal data sources such as hyperspectral imaging or pollen analysis could provide complementary information about plant physiology and ecological interactions, further refining the models' understanding and predictive capabilities. Further research could also explore the integration of advanced AI techniques beyond traditional CNNs. Techniques such as attention mechanisms, graph neural networks (GNNs), or reinforcement learning could enhance the models' ability to capture hierarchical relationships among floral features or adapt dynamically to changing environmental conditions. Such approaches could lead to more adaptive and context-aware flower identification systems, capable of continuous learning and improvement over time.

Another compelling area for exploration is the application of transfer learning principles to related domains, such as plant disease detection or phenological studies. Adapting pre-trained models from flower classification tasks to identify diseases, pests, or environmental stressors affecting plants could support early detection and management strategies in agriculture and conservation. This extension would leverage the established framework of deep learning models while addressing critical challenges in agricultural sustainability and biodiversity conservation. Furthermore, advancing the project's impact on society involves developing user-friendly interfaces and mobile applications that enable citizen scientists and non-experts to contribute to floral biodiversity monitoring efforts. Incorporating crowdsourced data collection and validation mechanisms could enhance the scalability and geographic coverage of ecological surveys, empowering communities to participate actively in environmental stewardship and conservation initiatives.

In general, the ongoing exploration of these research directions not only deepens our understanding of automated botanical identification but also broadens its practical applications in ecological monitoring, biodiversity conservation, and sustainable agriculture.

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Appendix A

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

Title:
DETECTING BANGLADESHI FLOWERS AND ITS CLASSIFICATION FROM IMAGE USING CNN

Student ID: 201-15-3175, 201-15-3615

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **flower detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and 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 fromdifferent sources and we have to know the design of a machine learning-based model which covers **K3 and K4.**	**Page no:** [32-36] **Section:** [3.2]
				Our project requires the integration of different components and we have designed a system that covers **K5 and K6.**	**Page no:** [40-42] **Section:** [3.4] **Page no:** [36-38] **Section:** [3.2]
				We have studied existing models	**Page no:**

				with similar goals **(K8).**	[25-29] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	In our project, we face challenges from the very beginning. We needed to visit many gardens, nurseries, and other floral spots to know about the flowers and take images. This was done on multiple times over a same place.	**Page no:** [29] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	It was challenging to implement the smooth data collection and gathering it in a system. Moreover, the system needs to be made dynamic so that it keeps learning from the updated data on the dataset.	**Page no:** [45-47] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	To understand the core points of our project and know more about this sector, we needed to be engaged with the gardeners, students, and many other floral specialists.	**Page no:** [16-22] **Section:** [2.1, 2.2, 2.3]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	As part of our project, we have visited and met with various on-duty persons of the nurseries and needed to invest some amounts to convince them.	**Page no:** [22] **Section:** [1.5 (C)]
7.	**EP7: Interdependence**	Yes	CO5	We have been spending an estimated amount of 30,000 taka for different tasks of this research work and planned it within a budget to execute the work smoothly.	**Page no:** [23] **Section:** [1.5 (C)]

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 study makes use of a variety of resources, including GPUs, deep learning frameworks, annotated datasets, high-performance computing infrastructure, and ethical considerations, in order to guarantee systematic research and facilitate the progress of pneumonia diagnosis via deep CNNs.	**Page no:** [35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		By enhancing recognition through the use of a floral detecting system and encouraging environmental sustainability through the use of effective computational resources and adherence to moral standards for user data privacy, this project benefits society.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.3, 5.4]

5.	**EA-5: Familiarity**	Yes		By using deep CNNs and transfer learning to investigate a novel strategy in flower recognition, as illustrated by preliminary findings and a thorough comparison analysis, this project builds on previous research and provides new insights into the subject.	**Page no:** [16-22] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	In order to mitigate **CO4**, this project combines efficient project management with financial control. Careful planning, resource distribution, and budget estimation are guaranteed to provide the best possible resource utilization throughout the duration of the study project.	**Page no:** [14] **Section:** [1.6]
2	CO9	Yes	By placing a high priority on user privacy, obtaining informed consent, and openly recording the research process, the project demonstrates adherence to ethical principles. It also ensures responsible knowledge dissemination and societal well-being through the ethical application of **CO9-** compliant advanced recognition technologies.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's thorough data collection, rigorous statistical analysis, careful methodology development, and thorough experimental results and analysis all demonstrate a dedication to continuous learning (**CO12**) and adaptation within the dynamic technological landscape. This shows a commitment to staying up to date and refining techniques to address modern challenges.	**Page no:** [26-35, 45-47] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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