DEEP LEARNING FOR RECOGNITION OF NUTS BREED

By

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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 **"Deep Learning for Recognition of Nuts Breed"**, submitted by **Md. Shahadat Hossain**, ID No: **211-15-14607** and **Md. Jakir Hasan Rony, ID No: 211-15-14584** 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 12 January, 2025.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of Mr. Md. Sazzadur Ahamed, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The nut is one of the most widely grown and economically important crops in the world. Nut breeds must be correctly recognized for a variety of applications in breeding, agriculture, and trade. In recent years, deep learning algorithms have emerged as powerful tools for image recognition tasks, inspiring researchers to investigate their potential for nut breed recognition. This release presents extensive research on the application of deep learning for nut recognition. Nut recognition has been successfully applied to deep learning models, including VGG16, ResNet50, MobileNet, Inception V3, and Xception. These models were trained on images of different nuts and learned to differentiate between different nut breeds based on their various visual characteristics, including size, shape, color, texture, and skin pattern. The MobileNet model is the most accurate deep learning model. The accuracy of the MobileNet model was 95.83%. We don't only judge accuracy. We evaluated a few parameters, including F1-score, precision, and recall. Extensive testing and evaluation are used to assess the deep learning models' performance and accuracy.

Keywords: Nut breed, Deep learning, Pre-trained model, Performance metrics, Accuracy.

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Chapter 1

Introduction

This chapter presents a summary of the research, detailing its aim, importance, and objectives. This establishes the study's setting and presents the issue of nut breed identification tackled by deep learning.

1.1 Introduction

Nuts are an important agricultural product that is prized for both its economic worth and nutritional value. They are an important part of diets all around the world since they are a great source of proteins, healthy fats, vitamins, and minerals. Accurate nut breed recognition is now essential for supply chain management, quality control, and agricultural research due to the growing need for a wide variety of nut kinds.

Nut production has increased dramatically worldwide due to rising demand in the culinary industry and health-conscious consumers. The world's nut trade is worth billions of dollars, with the biggest producers being the United States, China, India, and Turkey. Nuts that support millions of livelihoods, including cashews, walnuts, pistachios, and almonds, are important in export markets. Nuts have been cultivated for thousands of years; evidence of their usage can be discovered in ancient civilizations, where they were prized for their cultural and therapeutic importance in addition to their nutritional benefits.

Manual examination, which is time-consuming, labor-intensive, and prone to errors, is a major component of traditional nut breed recognition techniques. These limitations have increased demand for automated systems that can accurately and effectively recognize breeds. Deep learning in particular, a recent development in artificial intelligence, provides a revolutionary solution to this problem. Deep learning systems can handle massive picture collections, extract intricate visual properties, and accurately recognize images by utilizing effective neural network designs.

Nowadays, machine learning (ML) applications have a big influence on a lot of things in modern life, such as agricultural services. It enables a variety of operations, including determining the appropriate price for the farmer's output and analyzing the negative impacts of specific medications. It contributes to the reduction of agricultural production costs. Machine learning has become quite easy to implement because of modern technologies. One of them is the creation of mobile phones. We are working on a thesis on deep learning for image-based recognition. Reliable techniques for recognizing various crops and recognizing a range of agricultural diseases are deep learning algorithms. As a result, we can utilize effective deep learning algorithms to recognize various nut breeds.

This paper presents and analyzes five different implementations of advanced deep CNN models. These five models include the Xception, ResNet50, Vgg16, MobileNet, and Inception V3. After closely examining the data, we determined that the MobileNet model had the best accuracy. For nut breeds, ResNet50 has the lowest level of identification accuracy, despite Inception V3 being quite close to a MobileNet model.

The important contributions of our research are summarized as follows:

1. To start the process of addressing the problems with automated nut breed recognition by utilizing deep learning models.
2. To collect reliable image data in order to organize different breeds using different CNN/classification techniques.
3. To work on more models in order to get exact accuracy.

We were able to examine nut breeds using our technical expertise. We are now capable of designing and creating solutions. We made use of modern tools like TensorFlow, Keras, NumPy, and many more. We reviewed and examined a variety of information sources from the engineering and general public. We succeeded in establishing a significant impact on environmental integrity. In terms of teamwork, we both gathered data and authored the report, and one of us programmed the entire project. We used Google Meet to communicate.

1.2 Motivation

The goal of automating and improving the method of recognition is the motivation behind the use of deep learning for nut breed recognition. Nut breed recognition using traditional methods usually requires human examination, which can be time-consuming and susceptible to mistakes. We are developing deep learning techniques for nut image recognition so that nut breeds may be easily recognized. Farmers, researchers, and agricultural enterprises can utilize it to save time and effort while making well-informed decisions on breeding, disease control, and cultivation.

The manual investigation and expert judgment used in traditional nut breed recognition methods are labor-intensive, time-consuming, and prone to human error. It is becoming more difficult to correctly recognize and categorize the growing number of nut breeds. The goal is to create automated models that can accurately assess and categorize nut images according to their breeds by utilizing the capabilities of deep learning, particularly VGG16, ResNet50, MobileNet, Inception V3, and Xception models. Deep learning may decrease human participation, speed up the process of recognition, and produce consistent and dependable results for a range of agricultural applications by overcoming the drawbacks of conventional techniques.

1.3 Objectives

Our main objective is to create a dependable and accurate deep learning model that will make the process of recognizing nut breeds easier. This involves creating an extensive library of images that depict different breeds of nuts, which will be used as a foundation for evaluation and training. Our goal is to investigate and choose the best deep learning architectures and methodologies for image recognition, making use of transfer learning strategies to make use of pre-trained models and improve recognition accuracy. We concentrate on using regularization techniques and hyperparameter optimization to increase model accuracy and endurance in order to ensure the best outcomes. Furthermore, we use appropriate evaluation parameters to thoroughly evaluate the performance of the created models, ensuring their dependability and efficiency in practical uses. The purpose of this study is to evaluate how well deep learning models and current methods recognize various nut breeds. It involves investigating how several elements, including light conditions, picture quality, and developmental stages, affect the accuracy of recognition. The study also looks into strategies for handling variations in skin texture, color, and shape. Additionally, it explores if the model can be used for real-time breed recognition of nuts on useful platforms such web-based or mobile applications. The objective is to offer suggestions and insights to improve the accuracy and durability of nut recognition techniques based on deep learning. This approach has the potential to improve breeding programs, crop management, and quality control in the agricultural sector by providing accurate and automated recognition of nut breeds.

This study is primarily concerned with the following issues:

1. Which model has more accuracy to recognize nut breeds?
2. Which model is the least accurate at recognizing nut breeds?
3. How well do these models recognize nut breeds?

1.4 Methodology

Research techniques include collecting a variety of nut breed image datasets, preprocessing and augmenting the data, selecting an appropriate deep learning model architecture, determining on pre-trained models through transfer learning, training, evaluating model performance with datasets, adjusting hyperparameters and applicable metrics, implementing the model in a system or application, and continuously developing the model. The quality and diversity of the information, careful model selection, and model changes are necessary for accurate recognition of nut breeds.

1.5 Project Outcome

Deep learning has the potential to greatly improve agricultural procedures and offers a wealth of research opportunities to recognize nut breeds. By developing accurate and effective deep learning models, researchers can automate and consistently recognize nut breeds. It might fundamentally change quality control, crop management, and breeding procedures in the agricultural sector. Expanding research into real-time recognition, scalability, flexibility, and disease and pest detection may potentially increase the impact of this work. The results may be useful for several crops, promoting information sharing across disciplines and supporting a variety of agricultural uses. Farmers and field workers may also benefit from practical and approachable solutions through investigating the integration of multimodal data, putting models into effect on mobile and edge computing platforms, and encouraging data sharing and collaboration. All things considered, this area has a lot of unexplored research potential that might result in more sustainable and effective nut cultivation.

1.6 Organization of the Report

There are six sections to our report. The introduction, motivation, objective, expected results, problem description, study topics, research techniques, and research potential were all covered in chapter one. We covered terminology, previous research gaps, and summaries in chapter two. The overview, study methodology, dataset, data preprocessing, gamma correction, split, deep learning, and summary were all covered in chapter three. Evaluation Technique, Performance Analysis, Visualization, Model Analysis, and Result Discussion were covered in chapter four. We covered the sustainability strategy, the impact on the environment, and the impact on society, project management and financial analysis, complex engineering problem in chapter five. Chapter six concluded with a discussion of Conclusion, Limitations, and Future Work.

Chapter 2

Background

This chapter examines the fundamental information and pertinent literature necessary for comprehending the research. It examines current research, technologies, and approaches pertinent to nut breed identification and deep learning.

2.1 Introduction

Our research's primary objective is to recognize different nut breeds. Since there are several nut breeds worldwide, it's important to recognize their differences. Particularly those who reside in developing countries. Bangladesh is a farming country. The agriculture industry in Bangladesh is essential to the country's GDP, employment, and income. Bangladeshi agriculture benefits from nuts in a number of ways. Nuts are an essential food crop that contributes to food security by providing the population with a consistent source of carbohydrates. Nut farming is a significant source of revenue for farmers due to its short growing season and quick return on investment. The prosperity of farmers and Bangladesh depends on the recognition of nut breeds.

2.2 Literature Review

The study uses image-based morphological data and near-infrared (NIR) spectroscopy to classify seven pine nut species. CNN models (VGG16, VGG19, Xception, InceptionV3, ResNet50) and conventional machine learning models (DT, RF, MLP, SVM, NB) were assessed. With NIR data, the MLP model's accuracy was 99%, whereas InceptionV3's was 96.4% for pictures. Important NIR wavelengths for categorization were found, such as 951-457 nm. CNNs were used to train preprocessed pictures (224 x 224) with ReLU activation and SGD optimization. F1 score, accuracy, and precision were performance metrics. The findings support quality control and anti-adulteration initiatives by demonstrating the efficiency of machine learning for quick, non-destructive pine nut categorization. [1]

This study used a convolutional neural network (CNN) and hyperspectral imaging (HSI) to develop a non-destructive approach for estimating the quality of Canarium indicum nuts. The model achieved 93.48% overall accuracy, with class-wise accuracy of 95.59%, 90.00%, and 95.83%, respectively, by classifying nut quality based on peroxide values (PV) into good, medium, and bad categories. A 1×1-pixel kernel enhanced performance by lowering parameters, according to ablation testing. The results demonstrate the potential of HSI and deep learning for precise, real-time evaluation of nut quality. [2]

A deep CNN-based approach was presented in this work to predict the ripening phases (Khalal, Rutab, Tamar) and identify Shahani dates as either healthy or faulty. The model, which was based on the VGG-16 architecture, had thick layers, max-pooling, dropout, and batch normalizing. It was trained on an unstructured dataset of images taken using a smartphone. The model outperformed conventional feature-engineered techniques with a classification accuracy of 96.98%. The CNN model addresses important demands in the food sector by streamlining the categorization process and offering an effective way to detect maturation stages and differentiate faulty dates. [3]

Using machine learning and image attributes, this study created a computer vision-based system for cashew nut grading that can distinguish between whole and split nuts. After processing images taken at 17 cm in HSV color space, 275 characteristics (texture, color, and form) were extracted, 30 of which were chosen through optimization. The accuracy of an SVM classifier using a radial basis kernel was 98.53%. Additionally, an 8-layer CNN was created, demonstrating its potential for accurate and quick nut categorization.[4]

The deep learning models for potato breed detection examined in this work are VGG16, ResNet50, MobileNet, Inception-v3, and a customized CNN. In order to categorize breeds according to size, shape, color, texture, and skin patterns, the models were trained using pictures. In-depth analyses showed that the tailored CNN performed the best, with an accuracy of 94.84%. The potential of deep learning in precise and effective potato breed recognition was demonstrated by the evaluation of other measures, such as F1-score, recall, and accuracy, to guarantee strong performance. [5]

In this work, hazelnut kernels were divided into four groups using deep learning: "whole kernel," "damaged kernel," "shell," and "undersized." The InceptionV3 model obtained 97.85% accuracy after being trained on 2094 photos per class. The accuracy of the EfficientNetB2 and EfficientNetB3 models was 99.28% when they used transfer learning with ImageNet weights. It was discovered that EfficientNetB3 was four times more effective than EfficientNetB2, providing a way to lessen financial loss brought on by inaccurate hazelnut categorization. [6]

In this research, eight Hyacinth bean breeds in Bangladesh are identified using a CNN-based Local Hyacinth Bean Breed Recognition (CNN-LHBR) approach. The nutritional benefits of these beans, including their high protein and vitamin B complex content, are highlighted in the study. The customized CNN model had the greatest accuracy of 97.50% out of the three CNN models that were evaluated. CNN's efficacy in breed recognition was demonstrated by evaluating the models' performance using a confusion matrix and training, validation, and testing accuracy.[7]

The deep learning-based object recognition technique used in this work uses a double-camera setup and a cartesian manipulator to distinguish between open-shelled and closed-shelled pistachios. The system determines the locations of the pistachios, computes their actual coordinates and sorts them without causing any harm to the kernels. The detection accuracy provided a quick and safe way to sort pistachios, with 98% for open-shelled pistachios and 85% for closed-shell pistachios. [8]

This work uses CNN models, Inception V3 and Xception, to use transfer learning for nut type classification on a dataset of 1,320 photos representing 11 different nut species. The data was divided between 60% training and 40% validation after preprocessing. With an accuracy of 86.36% on validation data compared to 74.05% for Inception V3, the Xception model surpassed the latter, indicating Xception's superior nut type prediction capabilities. [9]

In this work, industrial datasets are used to categorize pistachios as open or closed using deep learning algorithms. These datasets were used to train Inception V3 and AlexNet, which achieved test accuracies of 96.54% and 96.13%, respectively. The desktop dataset fared badly (61.75% accuracy), but AlexNet trained on the industrial dataset obtained 99.84% accuracy when tested with industrial data, according to a comparison of the two datasets. This demonstrates how well industrial datasets work for accurate categorization in practical applications. [10]

Based on acoustic emission signals, this work creates a one-dimensional CNN model for pistachio nut sorting. The model beat conventional techniques like random forest and multilayer perceptron, achieving 98.75% accuracy. With its exceptional performance in pistachio classification for online, non-invasive sorting systems, the CNN—which was trained on raw time-domain data—offers a dependable, astute solution for industrial applications. [11]

An enhanced VGG16 model is created in this work to recognize and categorize 12 peanut types with 96.7% accuracy. This is 8.9% better than the original VGG16 and outperforms other models such as AlexNet, ResNet, and GoogLeNet. The robustness of the model was demonstrated by further validation of its efficacy on maize grain types. The suggested approach has a lot of promise for classifying and identifying crop varieties in agricultural settings. [12]

This study created a dataset of 1751 photos of walnut leaves from 18 different types and used CNN models to classify them. The VGG16 model had the highest accuracy following preprocessing and data augmentation, with 85.52% accuracy on the original dataset and 90.55% accuracy on the supplemented dataset. The findings show that deep learning techniques can successfully classify walnut types, demonstrating their potential for accurate and efficient categorization. [13]

This study examines a deep convolutional neural network (CNN) based computer vision grading system for cashew nuts. The approach overcomes difficulties in cashew grading and sorting by utilizing CNN's capacity to automatically extract characteristics for categorization. The focus of the study is on CNN parameter optimization for efficient nut grading. [14]

This work reduces labor, time, and expense in the sorting process by classifying hazelnut types using deep learning algorithms, notably InceptionV3 and ResNet50. The dataset, which has 100% classification accuracy, contains pictures of Giresun, Ordu, and Van hazelnuts. InceptionV3 and ResNet50 were used to create a data fusion model with feature reduction. Both professionals and non-experts benefited from the model's use in a mobile app for on-field categorization, which also increased economic value by facilitating patentable improvements in the sector. [15]

A computer vision approach for counting open-mouth and closed-mouth pistachios in films is proposed in this work. A RetinaNet object detector was trained using a fresh dataset consisting of six films including 3927 tagged pistachios. The model ensures precise tracking of pistachios between frames by addressing issues like occlusion and distortion. The system counts pistachios with 94.75% accuracy using a bespoke counter algorithm and tracker, increasing production efficiency and sorting by shell type.[16]

In this study, an effective image-processing methodology for detecting fresh fragrant coconuts is presented. The hue of the coconut's bottom shell, which is correlated with its age, is used by the IAC (Identification of Aromatic Coconuts) technique to determine aromacy. The region of interest is examined in HSV color space after the image is segmented using K-Means. The quantity of white pixels is measured using polynomial regression, which forecasts the scent of the coconut. This technique offers a precise and non-intrusive substitute for tasting. [17]

This study suggests utilizing drilled hole identification to sort faulty drilled lotus seeds online. In terms of accuracy and performance, a YOLOv3-based model fared better than faster R-CNN and SSD models. Real-time sorting is guaranteed by a sorting control algorithm that achieves 95.8% accuracy. The technique gives insights for sorting various agricultural items based on local feature identification and a workable solution for online lotus seed sorting. [18]

In this work, a deep learning framework for identifying bolt-nut losses in steel bridges is developed. In classification and detection tasks, the CNN model outperformed LSTM (93%) and YOLOv4 (76.5%) with an accuracy of 95.60% using CNN, LSTM, and YOLOv4 algorithms. According to the results, CNN's excellent accuracy and speed make it the most efficient tool for monitoring the structural health of bridges. [19]

The goal of this research is to apply deep learning to distinguish between healthy and unhealthy areca nuts. Techniques like Wavelet and GLCM are used to extract the nuts' textural characteristics. In contrast to conventional visual approaches, a CNN model trained on more than 180 photos was able to detect diseases. Classification is another use for support vector machines. [20]

This study uses low-latency deep neural network image identification to create a super-high purity seed sorting system that can reliably eliminate harmful weeds from mixed seed products at high throughput. The system detects and tracks images at 500 frames per second with little loss of targeted seeds. By guaranteeing high purity and efficiency in seed sorting, it performs better than conventional optical sorting systems. [21]

Here is a comparative analysis of literature review and this research is in Table 2.2.1 below, which we utilized to guide our next steps.

Table 2.2.1 Summary of literature review

Author	Year	Problem Dealt with	Size of image Data Set	No. of Classes	Methodology	Key Findings
This Paper	Null	Deep Learning for Breed Recognition of Nuts	4800	6	VGG16, ResNet50, MobileNet, Inception V3, Xception	Best Algorithm Model: MobileNet, MobileNet Algorithm Accuracy: 95.83%
Huang et al. [1]	2022	Applications of machine learning in pine nuts classifcation.	303	*NM*[1]	VGG16, VGG19, Xception, InceptionV3 and ResNet50.	Best Algorithm Model: InceptionV3

						, InceptionV3 Algorithm Accuracy: Close to 96.04%.
Rahman et al. [5]	2024	Deep learning modeling for potato breed recognition.	6000	10	VGG16, ResNet50, MobileNet, Inception V3, Customize CNN Model	Best Algorithm Model: Customize CNN Model, Customize CNN Model Accuracy: 94.84%
Ünal et al. [6]	2023	Classification of hazelnut kernels with deep learning.	2096	4	EfficientNet B0, EfficientNet B1, EfficientNet B2, EfficientNet B3 and InceptionV3.	Best Algorithm Model: EfficientNet B2 and EfficientNet B3, EfficientNet B2 and EfficientNet B3: 99.28%
Khan et al. [7]	2024	Machine Vision Based Local	1200	6	ResNet50, Inception-v3,	Best Algorithm

		Hyacinth Bean Breed Recognition Using Convolutional Neural Network.			Customized CNN model	Model: Customize CNN Model, Customize CNN Model Accuracy: 97.50%
Fawwaz et al. [9]	2023	Implementation of Transfer Learning in CNN for Classification of Nut Type.	1320	11	Transfer Learning, Convolutional Neural Network, Nut Classification, Inception V3, Xception	Best Algorithm Model: Xception, Xception Accuracy: 86.38%
Hosseinpour-Zarnaq et al. [11]	2022	Acoustic signal-based deep learning approach for smart sorting of pistachio nuts.	1620	*NM*[1]	CNN, RF, MLP	Best Algorithm Model: CNN, CNN Accuracy: 94.9% 98.75% Mean squared error 0.01
Karadeniz et al. [13]	2023	Identification of Walnut Variety from The Leaves Using Deep Learning Algorithms.	1751	18	CNN, Machine learning, Deep learning.	Best Algorithm Model: CNN, CNN Accuracy:

						85.22 on the original dataset and 0.9055 on the additional data set.

NM[1] – not mentioned

This study shows how well deep learning (DL) techniques work for agricultural quality control and categorization. Using image data, InceptionV3 achieved 96.4% for pine nut species, recognizing crucial NIR wavelengths for non-destructive categorization. Customized CNN models demonstrated their accuracy in visual feature analysis by performing better in recognizing potato breeds and hyacinth bean breeds in Bangladesh. Additionally, CNNs improved agricultural management by detecting diseases in rice leaves early. Transfer learning using Xception outperformed InceptionV3 in nut classification, predicting 11 nut species with 86.36% accuracy. These results highlight how DL techniques may be used in agriculture to manage diseases and classify data quickly and reliably, improving production, quality assurance, and food security.

2.3 Gap Analysis

Table 2.3.1 Gap Analysis

Research Gap	**Description**
Limited generalization across nut types	Most studies focus on specific nut varieties rather than creating generalized recognition models.
Lack of multimodal data integration	Few works combine image-based features with other modalities like spectral or acoustic data.
Dataset diversity and scalability	Limited datasets used, often specific to one nut type or region, reducing model applicability.

Comprehensive evaluation metrics	Studies lack robust metrics beyond accuracy, such as robustness to noise or cross-validation.
Real-time and industrial applicability	Limited exploration of real-time applications and scalability in industrial contexts.
Inclusion of advanced augmentation techniques	Few studies leverage advanced augmentation for improved performance on small datasets.

Despite advancements in nut breed recognition, the current body of research lacks comprehensive studies in this domain. This highlights a significant gap between the current state of research and the potential for progress in these areas. The identified research gaps underscore the necessity for scalable, comprehensive, and multimodal approaches to nut breed recognition. Future research should focus on addressing these shortcomings to improve the effectiveness, applicability, and resilience of recognition systems.

2.4 Summary

This work uses CNN-based models to classify different kinds of nuts to fill a gap in the current state of the art in research conducted on the topic. Particularly in developing nations, nuts are an important agricultural product with the potential to help reduce the hunger crisis. Although previous studies proved that the deep learning (DL) methods are effective in agriculture applications, such as disease detection and crops classification, there are much more limited investigations on the nut breeds recognition. In this study, CNN-based models are examined to efficiently and accurately classify six types of nuts. These findings could have several applications including enhancing agricultural productivity, accuracy and boosting developing countries like Bangladesh economically.

Chapter 3

Research Methodology

This chapter delineates the research strategy, data gathering methodologies, and experimental technique employed in the study. It emphasizes the methodologies and instruments utilized to attain precise identification of nut varieties.

3.1 Methodology

This section delineates the methodical strategy employed for the research, encompassing procedures for data preparation, model selection, training, and assessment. It offers a systematic account of the methodologies employed for precise nut breed identification.

3.1.1 Overview

Usually, researchers use two different kinds of approaches:

1. Qualitative Method
2. Quantitative Approach

The qualitative investigation focuses on attitudes and how they are understood, whereas the survey technique emphasizes statistics and statistical data. Hypotheses can be tested more easily with quantitative methods, and parameters were compared. We may explore concepts and interactions in more detail thanks to qualitative methods. Our study is therefore quantitative in nature.

3.1.2 Proposed Methodology

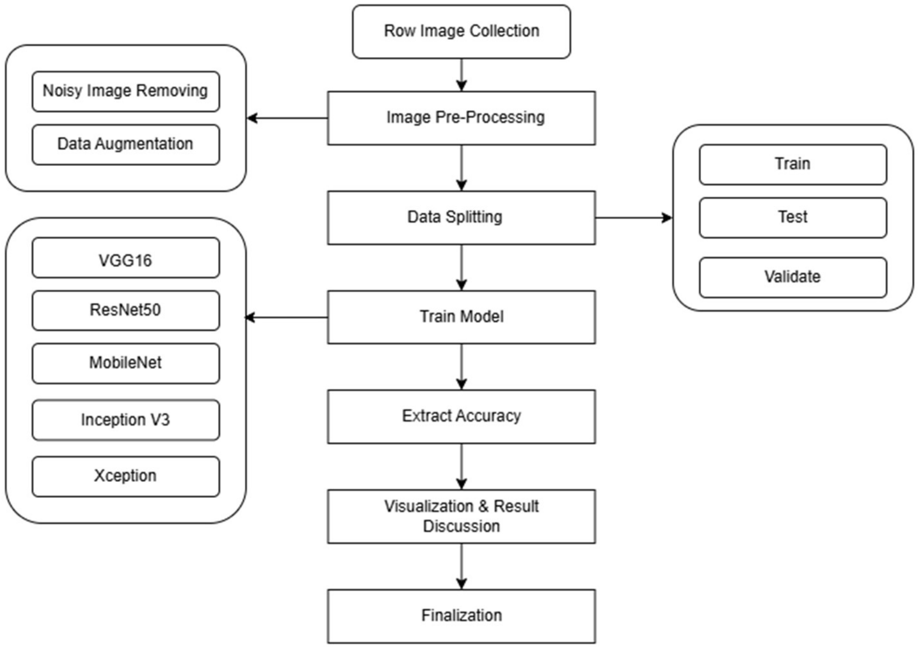


Figure 3.1.2.1 Methodology Process

The 3.1.2.1 figure represents the proposed method of nut breed classification using deep learning methods. It begins with the act of collecting raw pictures, followed by image preprocessing which includes removing noisy images and data expansion. Next, the data is split into three parts, namely training, testing, and validation. Different deep learning models such as VGG16, ResNet50, MobileNet, Inception V3 and Xception are used to get the accuracy. The findings are presented and discussed before the conclusions are drawn. Using this systematic approach ensures accurate identification of varieties among the nuts.

3.1.3 UI Design

The user interface for our thesis project is built using Python Flask and React, allowing users to upload images and classify nut breeds with our designed model. The interface displays the predicted class and corresponding image in a clean, interactive design.

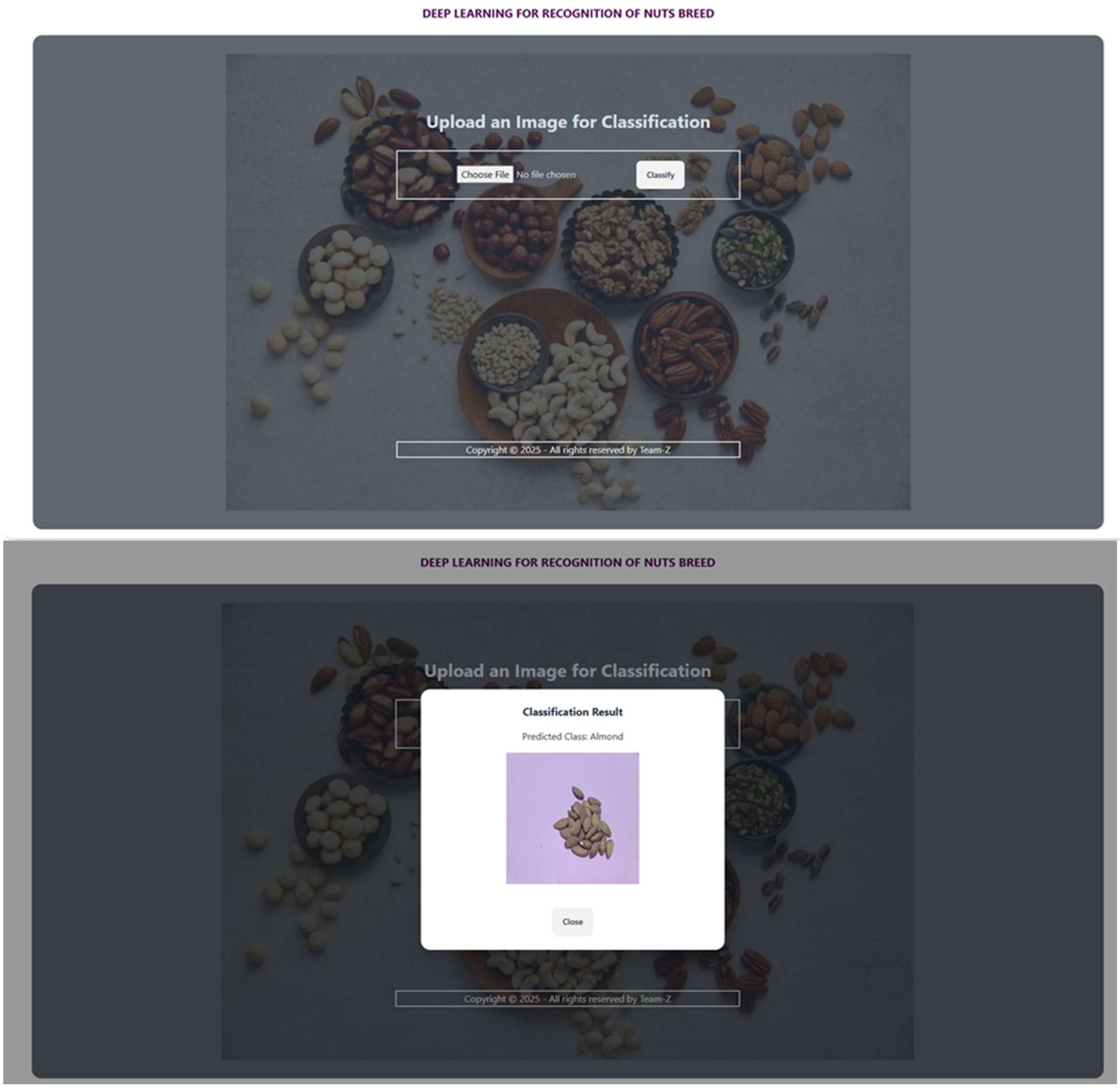


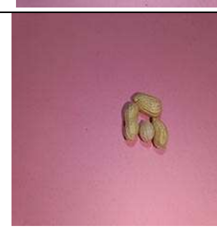
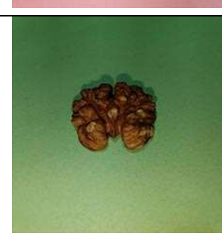
Figure 3.1.3.1 User Interface

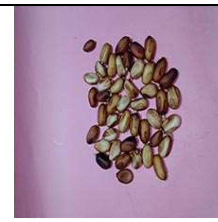
3.2 Detailed Methodology and Design

3.2.1 Dataset

The standard deep learning method requires a significant quantity of input data to train. However, the latest advancements in transfer learning techniques demonstrate that a robust CNN model that can perform well throughout the forecasts may be trained and built with a minimal dataset. We collected real datasets from nearby shops. This dataset provides correct and genuine information. We collected pictures of six different nut breeds. Nut breeds are Almond, Cashew, Peanuts, Pistachio, Walnuts, and Wild Almond. We stored 6 folders including six different nut breeds in the database after collecting the data. The total number of images in the database is 4800.

Table 3.2.1.1 Sample Collected Dataset

Breeds	**Specimen Images**		
Almond			
Cashew			
Peanuts			
Pistachio			
Walnuts			

Wild Almond			

3.2.2 Data Pre-Processing

Image preprocessing is the first and most crucial step before training the model. Preprocessing is an essential step in getting picture data ready for use in a vision-based model. Preprocessing is essential for the efficacy of work and theory. CNN is a widely used computer vision architecture that requires all pictures to be arrays of the same size in order to have completely connected layers. It is quite difficult to comprehend the first or original data set using any model since it is nearly always sufficient. Therefore, preprocessing aims to improve picture information by eliminating unnecessary subtractions or by improving some image attributes that are essential for producing noticeably better and more efficient results. In this study, we used row data.

3.2.3 Noisy Image Removing and Data Augmentation

Noisy image removal is an important step in image processing with the objective of removing distracting noise and artifacts from damaged images. There are several techniques used to restore image quality while preserving important information, such as filtering and deep learning-based algorithms. Noisy images have been eliminated from our dataset since deep learning-based techniques will be used.

Image augmentation is an efficient approach to developing a CNN that improves the training set's evaluation without using more images. The basic concept is to produce different replica pictures based on the kind of augmentation. The range of augmentation and the quantity of data that will be supplied to the models for training, testing, and validation after augmentation are displayed in Tables 3.2.3.1 and 3.2.3.2

Table 3.2.3.1 Introduction of parameters and After augmentation data quantity

Variety name	Captured image	Types of Augmentation and Criteria	After augmentation or new dataset
Almond	200	Rotation range = 40 Width shift range = 0.2 Height shift range = 0.2 Shear range = 0.2 Zoom range = 0.2 Horizontal flip = True Fill mode = 'nearest'	800
Cashew	200		800
Peanuts	200		800
Pistachio	200		800
Walnuts	200		800
Wild Almond	200		800

Table 3.2.3.2 addition of parameters and a large amount of information for analysis and validity.

Augmentations Name	Parameters
rescale	1.0/256

3.2.4 Split

Data splitting, also known as the train-test split, is the process of dividing data into smaller groups for independent model assessment and training. The resulting subsets, train_ds, val_ds, and test_ds, represented the training, validation, and test sets, respectively. These selections were then used for further investigation, model training, and evaluation. The distribution of the data across the different sets was illustrated by printing the number of samples in each subset. The preprocessing and data preparation steps ensure that the dataset is properly divided and ready for the subsequent phases of the project, including model training and evaluation. The complete dataset was divided into 80% training, 10% validation, and 10% training at random.

3.2.5 Training dataset

The collection of data that was utilized to adjust the model. A training data set is a group of samples that are used throughout the learning process to meet the requirements of such a classifier. The goal is to create a classification classifier that performs effectively when applied to novel, unidentified data. The accuracy of the fitted model in categorizing new data is assessed using "new" examples from the held-out data sources (validation and test datasets). Combinations of variables from the training data set are utilized to categorize data using supervised learning techniques. We have trained 4800 pictures for this study.

3.2.6 Validation dataset

Data collection for evaluating how well a model fits a training dataset while adjusting model hyperparameters. The evaluation becomes more and more biased as the model setup collects the skill from the validation data. The validation set is used to evaluate a particular model, but this is done often. The validation set is also known as the dev set or the development set. This makes sense as the dataset is helpful for the "development" stage of the model. There are 480 images in the validation dataset. Every time a classification parameter needs to be changed, overfitting must be avoided by having a validation data set available in addition to the test and training datasets. The test data set is used to determine performance metrics like accuracy, sensitivity, specificity, F_1-score, and others. The training data set is used to train different candidate classifiers, and the validation data set is used to compare their performances and select one to use.

3.2.7 Test dataset

A data set is used to evaluate how well the training data is fitted by the finished model. It is only used when the train and validate sets have been used to thoroughly train the model. Although it is common practice, using the validation set as the test set is not advised. There are 480 photos in the test dataset. It covers all the variations that its model could face in practice and contains information that was carefully gathered. A test set is a group of examples used just to evaluate a fully defined classifier's performance. The test set's instances are categorized using these final model predictions. These predictions are compared with the actual classifications of the events to assess the accuracy of the model. The final model selected during the validation step is usually evaluated using the test dataset after both the validation and test datasets have been used. The test dataset can only be utilized as an initial model evaluation once the original data set has been separated into training and test datasets.

3.2.8 Deep Learning

Deep learning is a subset of CNN that enables computers to learn from experience and perceive the world as a hierarchy of abstractions. It is not required for a human computer operator to explicitly explain all of the data that the computer requires since the computer learns through experience. The computer can understand large concepts by building them from simpler ones thanks to the concept hierarchy; a graph that depicts these hierarchies would have several layers. Deep learning is part of data science, which also covers statistics and pattern recognition.

3.2.9 VGG16

Convolutional neural networks, a subset of artificial neural networks, are also known as ConvNets. A convolutional neural network consists of several hidden layers, an input layer, and an output layer. Convolutional Neural Network (CNN) variation VGG16 is one of the best models for computer vision to date. The creators of this model examined the networks and increased the intricacy by employing an architecture with minuscule (3x3) convolutional filters, which showed a significant improvement over the most advanced configurations. This method has been updated to include dense 256. 80% of the entire dataset is used to train this algorithm, 10% is used for testing, and 10% is used for validation. This division is made at random. There were 480 data points in the test and 3840 data points in the train after a random split. In this case, the image sized 224 x 224 pixels. The training method lasted 40 epochs with 32 batch sizes, and it used data augmentation techniques like random flipping and rotation to improve resilience. It states that nut breeds can be accurately recognized using the model. When it comes to categorizing 1000 images into 1000 distinct categories, the object recognition and clustering method VGG16 has an excellent accuracy rate. It is a popular method for recognizing images that is easy to use with transfer learning.

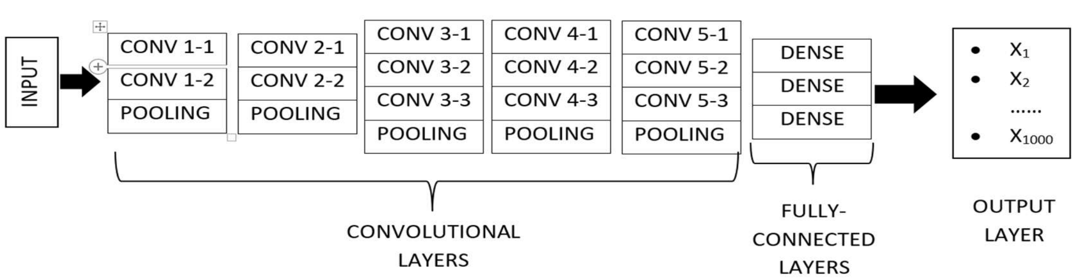


Figure 3.2.9.1 VGG16 Architecture

3.2.10 ResNet50

There are 48 convolution layers, 1 MaxPool layer, and 1 standard pool layer in the ResNet model version known as ResNet50. The number of floating-point operations is 3.8 x 109. We have looked closely at the ResNet50 design, which is a widely used ResNet model. Although they contain different amounts of layers, additional ResNet variations employ the same fundamental concept. Resnet50 is the name of the form that can function with 50 neural network layers.

A convolution with 64 different kernels, each having a phase of 2, and a kernel input of 7 x 7 yields one layer. Following that, we see maximum pooling at a step length of 2. The following convolution has three layers: a 1x1,64 kernel, a 3x3,64 kernel, and a 1x1,256 kernel. These three levels were repeated three times, for a total of nine layers in this phase. The kernel of 1 x 1,512 is next shown, followed by the kernels of 1 x 1,128 and 3 x 3,128. We repeated this method up to four times, or 12 layers. Then comes a kernel with a value of 1 x 1,256, followed by two additional kernels with values of 3 x 3,256 and 1 x 1,1024; this process is repeated six times, resulting in a total of 18 layers. Finally, a 1 x 1,512 kernel was introduced, followed by two additional kernels: 3 x 3,512 and 1 x 1,2048. This technique was repeated three times, yielding a total of nine layers. Then we average the pool, conclude with a totally connected layer of 1000 nodes, and add a softmax activation function to create one layer.

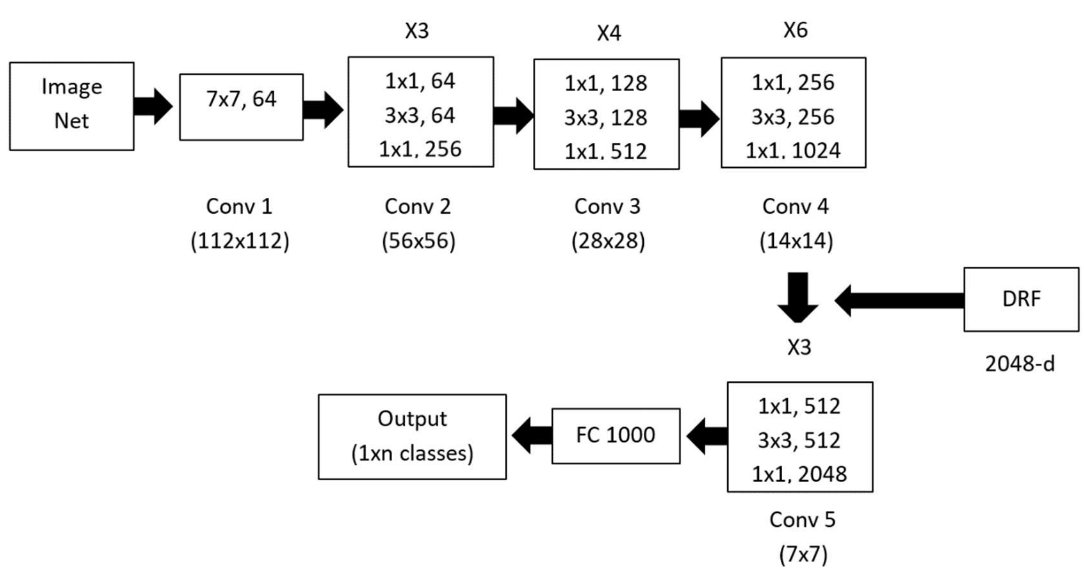


Figure 3.2.10.1 ResNet50 Architecture

3.2.11 MobileNet

The MobileNet model consists of two layers of depth-wise separable convolutions. There are two categories of convolutions: pointwise and depthwise. Each input channel in MobileNet's depth-wise convolution is filtered by a single filter. The pointwise convolution then uses a 1 x 1 convolution to mix the outputs of the depthwise convolution. We can readily investigate network structure to identify a pleasant network by describing the network in such basic ways. The remaining layers are fully linked, with the exception of the final fully connected layer, which feeds into a classification function akin to a softmax function and lacks any nonlinear features. A batch norm and ReLU nonlinearity follow every layer in MobileNet. After each convolutional layer, a factorized layer with depthwise convolution, 1 x 1 pointwise convolution, batch norm, and ReLU nonlinearity is contrasted with a layer with batch norm, ReLU nonlinearity, and conventional convolutions. Strided convolution is used to handle down sampling in the first layer and buried layer convolutions. A last average pooling reduces the spatial resolution to 1 before to the fully connected layer. MobileNet contains 28 layers when depthwise and pointwise convolutions are treated separately. The depthwise separable convolution technique is used by MobileNet to significantly reduce the convolution kernel's redundancy when compared to standard 3D convolution. It improves the model's identification accuracy in addition to reducing its size and optimizing latency. This method has been updated to include dense 256. 80% of the entire dataset is used to train this algorithm, 10% is used for testing, and 10% is used for validation. There were 580 data in the test and 3800 data in the train after a random split. The image's dimensions were 224 × 224 pixels. In order to improve resilience, the training method included data augmentation techniques such as random flipping and rotation throughout 40 epochs with 32 batch sizes.

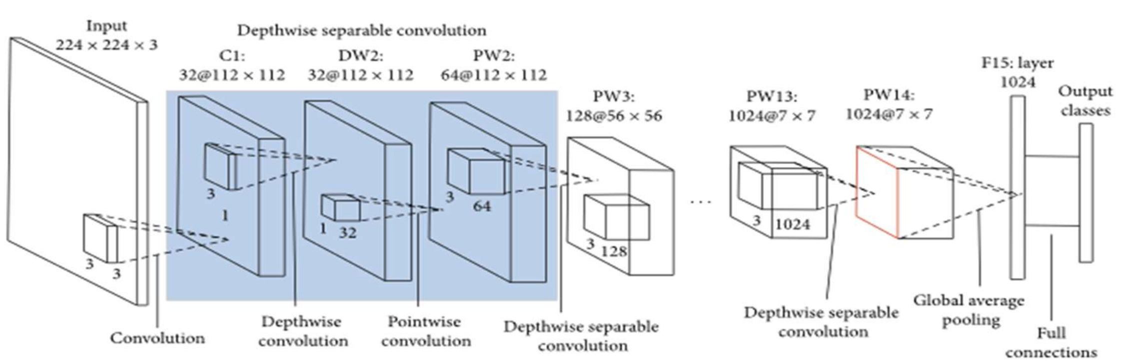


Figure 3.2.11.1 MobileNet Architecture

3.2.12 InceptionV3

Inception V3 is the third version of Google's Deep Learning Convolutional Implementations. Inception V3 produced 1,000 classes from the original ImageNet dataset, which was trained using over 1 million pictures; however, the Tensorflow edition has 1,001 classes since it includes a "background" type that was absent from the original ImageNet. The performance of the system is decreased by factorized convolutions since they employ fewer components in a network. It also keeps an eye on the network's efficacy. If smaller convolutions are employed instead of bigger ones, training will definitely be finished faster.

In an asymmetric convolution, a 3x3 convolution might be converted to a 1x3 convolution, which would then be followed by a 3x1 convolution. If a 3x3 convolution were replaced with a 2x2 convolution, the number of variables would be somewhat more than the recommended asymmetric convolution. An auxiliary classifier is a small CNN that is added between layers during training and whose loss contributes to the parent network's loss. GoogleNet employs auxiliary classifiers for a bigger network, in contrast to Inception v3, which utilizes them as a regularization term. The grid's size is usually decreased by pooling operations. Consequently, a better approach is recommended to deal with the intricacy of the algorithm's restrictions.

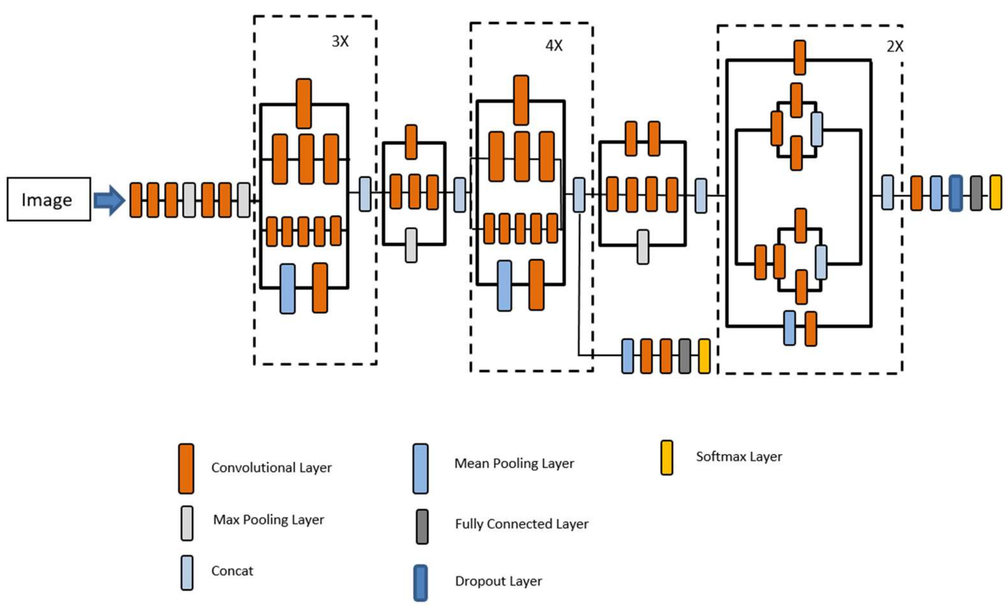


Figure 3.2.12.1 Inception V3 Architecture

3.2.13 Xception

Google created the Xception CNN architecture in 2016. It is an altered Inception architecture that substitutes depthwise separable convolutions for conventional convolutions. Xception is quicker and uses less memory than InceptionV3 because depthwise separable convolutions are more effective than conventional convolutions. The inception modules that make up the Xception architecture are in charge of feature extraction from pictures. Each inception module is made up of several activation functions, pooling layers, and depthwise separable convolutional layers. A deep neural network is created by stacking the inception modules. Xception is much quicker and uses less memory than InceptionV3, and it has been demonstrated to provide state-of-the-art results on the ImageNet ILSVRC dataset. Numerous computer vision issues may be resolved with the help of this potent CNN architecture.

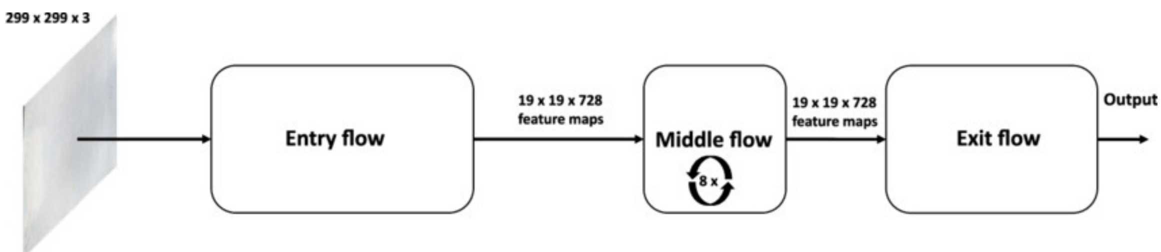


Figure 3.2.13.1 Xception Architecture

3.3 Project Plan

The project plan delineates the organized timetable, resources, and milestones necessary for the effective implementation of this research on nut breed recognition with deep learning. It offers a framework to guarantee the methodical advancement of the research while conforming to established objectives and timelines.

Table 3.3.1 Project Plan

Phase	Activities	Duration	Outcome
Phase 1: Problem Identification and Literature Review	Identify the research problem, review existing	2 weeks	Comprehensive understanding of the research

	literature, and define scope and objectives.		problem and clear project goals.
Phase 2: Data Collection and Preprocessing	Collect nut images, clean data (remove noise), and apply data augmentation techniques.	3 weeks	A well-prepared and diverse dataset ready for experimentation.
Phase 3: Model Development	Select and implement deep learning models (e.g., VGG16, ResNet50, MobileNet).	4 weeks	Optimized and trained models for nut breed recognition.
Phase 4: Model Evaluation and Analysis	Evaluate models using test/validation datasets, extract metrics, and analyze performance.	2 weeks	Detailed performance analysis and identification of the best model.
Phase 5: Result Visualization and Documentation	Visualize results, interpret findings, and document the research.	2 weeks	Completed visualization and structured thesis documentation.
Phase 6: Finalization and Submission	Review work, address feedback, and submit the final thesis.	1 week	Finalized and submitted project that meets academic standards.

This 3.3.1 table offers a succinct summary of the project plan, explicitly detailing the actions, length, and anticipated consequences of each phase.

3.4 Task Allocation

The thesis had been done jointly by two people and the responsibilities were assigned in accordance with their expertise. One member focused on literature review, data collection, pre-processing, and the deep learning models. A second member handled the management of model evaluation, outcome analysis, visualizations, and documentation. The two worked together on the report, ensuring it conformed to all standards of academia and timeliness.

3.5 Summary

This chapter describes the systematic process used in identifying the nut types including data preparation, modelling, training and validation. It uses a quantitative methodology with statistical and computational tools. The proposed approach begins with acquiring images and their preparation, including noise removal and data augmentation. The data set contains 4800 images of each of the 6 varieties of Nut, which are held in 80% train, 10% validate and 10% test | Almond, Cashew, Peanuts, Pistachio, Walnuts and Wild Almond. Preprocessing involves to resize images and use augmentation approaches to improve robustness.

This work uses several deep learning models, such as VGG16, ResNet50, MobileNet, Inception V3, and Xception. All models are utilizing transfer learning with additional data for accuracy and performance. These designs were chosen for their shown effectiveness in picture classification difficulties. The model is trained on 224x224-pixel images with 40 epochs and a batch size of 32 as hyperparameters. We perform comparative evaluations of these models to determine which method is better suited for nut breed classification.

A thorough project plan ensures on-time completion, with targets for data collection, preprocessing, model installation, training, and evaluation. Such a systematic method helps promote accurate and reliable classification results.

Chapter 4

Implementation and Results

This chapter delineates the execution of the suggested model, the outcomes of the trials, and the assessment of the model's efficacy. It encompasses analysis and insights obtained from the results.

4.1 Environment Setup

Our research, which mostly employs deep learning techniques, seeks to identify nut breeds from smartphone photographs. Our Python-based study employed Google's Tensor Flow and the Keras deep learning framework for image processing. The models for the experiment were created using the Google Collaboratory's GPU and Jupyter notebook. The scikit-learn, Pandas, and NumPy libraries were utilized to create a deep learning-powered model. We utilized Google Collaboratory to create and simulate our models. The photos are separated into three categories: training, test, and validation data, totaling around 4800. The study's proposed model worked successfully.

4.2 Performance Analysis

Metrics must be measured using a confusion matrix. The efficiency of a regulated learning process is demonstrated by deep learning using a table structure called a confusion matrix, often referred to as an error matrix. We determine True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) using a confusion matrix.

4.2.1 Accuracy

Accuracy is the most evident performance metric. In simple terms, it is the percentage of experimental data that was correctly predicted from all observations.

$$Accuracy = (TP + TN) \ / \ (TP + FP + FN + TN) \qquad (1)$$

4.2.2 Precision

The accuracy ratio examines how well each expected positive research agrees with the measurements that were successfully predicted as positive. How many individuals have avoided harm as a result of these measures?

$$Precision = TP / (TP + FP) \tag{2}$$

4.2.3 Recall

Remember the ratio of true good result predictions to all valid class observations. What proportion of the articles were marked as providing real information?

$$Recall = TP / (TP + FN) \tag{3}$$

4.2.4 F_1-Score

The weighted F_1 Ranking is accurate and easy to memorize. False positives and false negatives are factored into the score calculation. F_1 is frequently more valuable than accuracy, while appearing to be more difficult to explain, particularly when the classification is asymmetrical.

$$F_1\text{-}Score = 2 \times (Recall \times Precision) / (Recall \times Precision) \tag{4}$$

4.2.5 Sensitivity

The real positive rate, also known as sensitivity, is the proportion of positive cases that provide a positive result when a specific testing is included in a model without changing the data.

$$\text{Sensitivity} = TP / (TP + FN) \tag{5}$$

4.2.6 Specificity

In the case of an unaffectedly negative model, the actual negative rate, also known as specificity, is the number of specimens that test negatively when the test is conducted.

$$\text{Specificity} = TN / (TN + FP) \quad (6)$$

We employed deep learning algorithms to create the most accurate models for recognizing nut breeds.

The frequency of pictures in each class, the range of augmentation, and the quantity of data after augmentation that will be sent to the models for training, testing, and validation are all displayed in Table 4.2.1.

Table 4.2.1 Statistical details of the nut dataset

Variety name	Captured image	After augmentation	Training data	Validation data	Test data	Total training data	Total test data	Total Validation data
Almond	200	800	640	80	80	3840	480	480
Cashew	200	800	640	80	80			
Peanuts	200	800	640	80	80			
Pistachio	200	800	640	80	80			
Walnuts	200	800	640	80	80			
Wild Almond	200	800	640	80	80			

The model analysis's efficacy is shown in Table 4.2.2. It is clear that using our dataset improved the performance of transfer learning approaches. Their accuracy ranges from 36.45% to 95.83%. Out of the several models that are now accessible, we must select the best one.

Table 4.2.2 Performance Analysis Metrics

Serial	Algorithm	Test Accuracy (%)	Test Loss	F_1-Score	Precision	Recall
1	VGG16	91.25	0.3233	0.91	0.91	0.91
2	ResNet50	36.45	1.539	0.36	0.36	0.25
3	MobileNet	95.83	0.1623	0.96	0.96	0.96
4	Inception V3	92.70	0.5097	0.93	0.93	0.93
5	Xception	88.33	0.5086	0.90	0.88	0.88

The ratings of the five CNN-based architectures used were as follows: VGG16, ResNet50, MobileNet, Inception V3, and Xception. The algorithm's rating depended on F_1-score, precision, recall, and testing accuracy. The accuracy, recall, precision, and F_1-score were computed using equations 3, 4, 5, and 6, and the results are displayed in table 4.3.3. It is clear that MobileNet performs the best, with the highest accuracy (95.83%). MobileNet is superior to Inception V3 and VGG16 in object recognition, with a 3.13 percent accuracy difference between the top two models. The other algorithms can also recognize objects that closely resemble the MobileNet, with accuracy rates of 91.25%, 36.45%, 92.70%, and 88.33% for VGG16, ResNet50, Inception V3, and Xception, respectively.

4.3 Results and Discussion

The work receives a sequential accuracy rate when the classification accuracy terms are completed. The accuracy and confusion matrix produced by this work indicate that the proposed model is appropriate for the road damage recognition employment. This work has been done in this way.

4.3.1 VGG16:

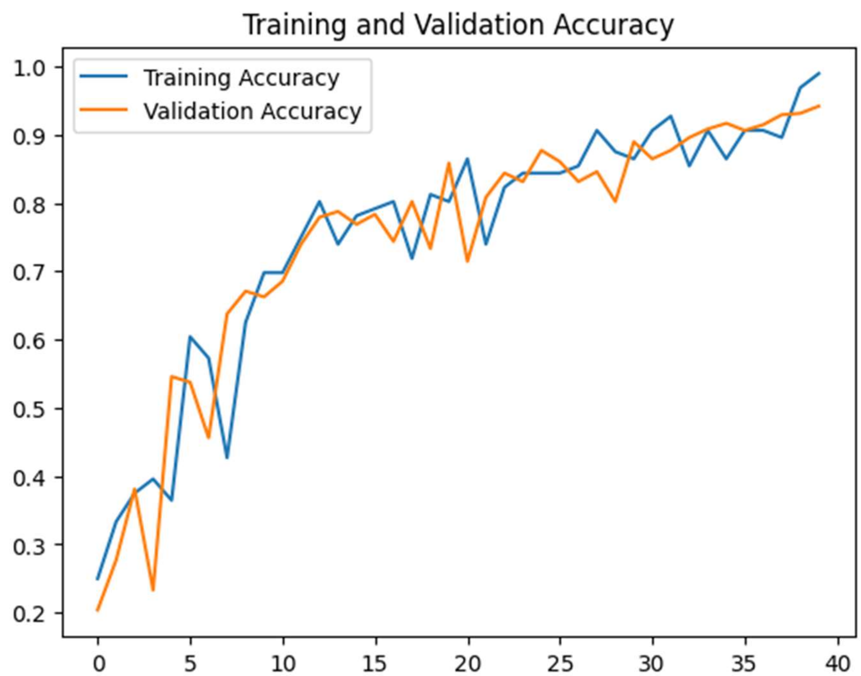


Figure 4.3.1.1 VGG16 Training vs Validation accuracy

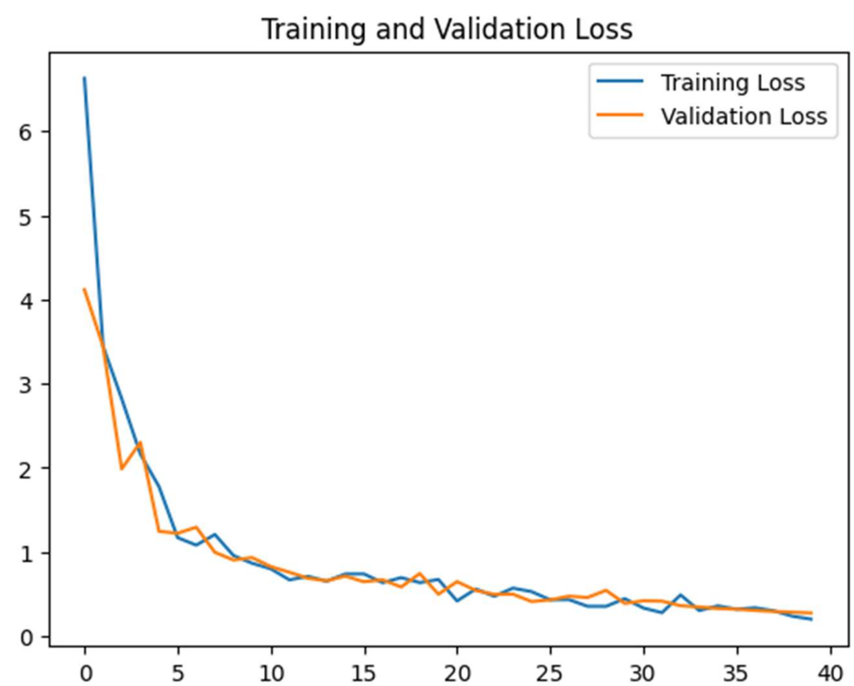


Figure 4.3.1.2 VGG16 Training vs Validation Loss

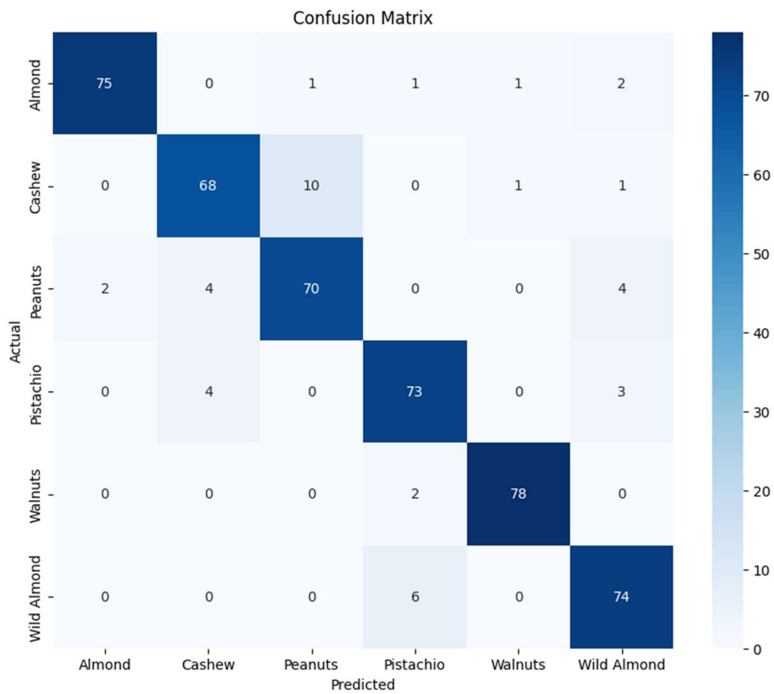


Figure 4.3.1.3 VGG16 Confusion Matrix

Figure 4.4.1.4 VGG16 demonstration of correct and incorrect recognition of nut breed images

4.3.2 ResNet50:

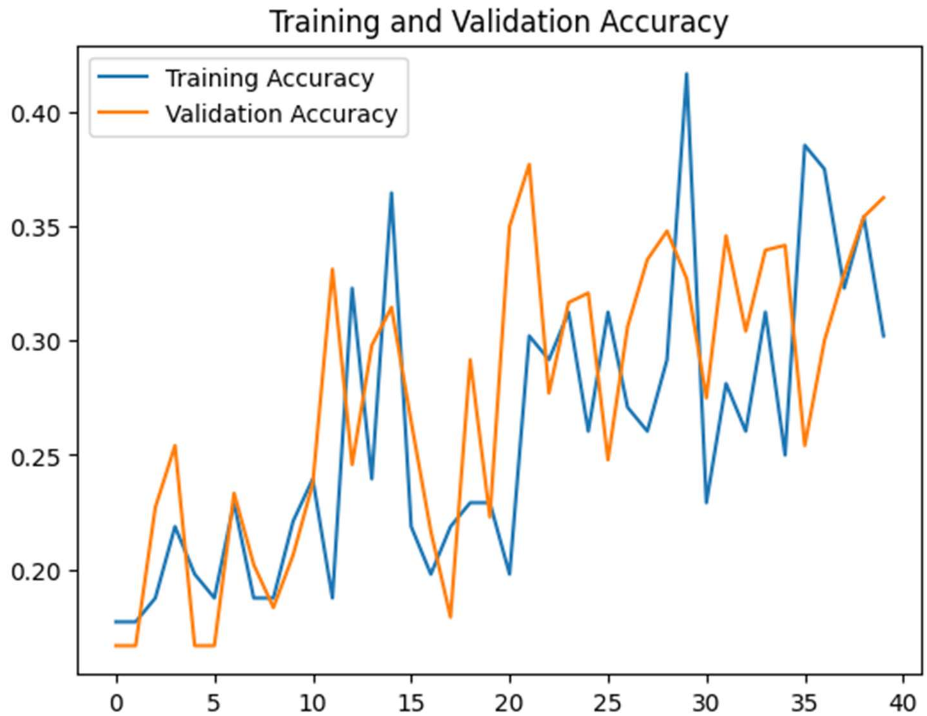


Figure 4.3.2.1 ResNet50 Training vs Validation Accuracy

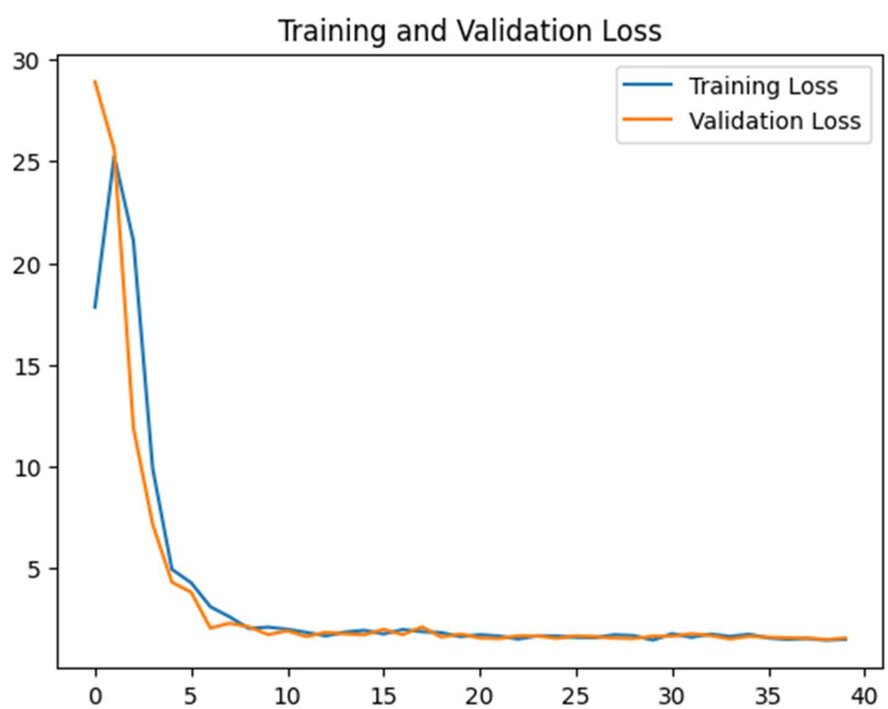


Figure 4.3.2.2 ResNet50 Training vs Validation Loss

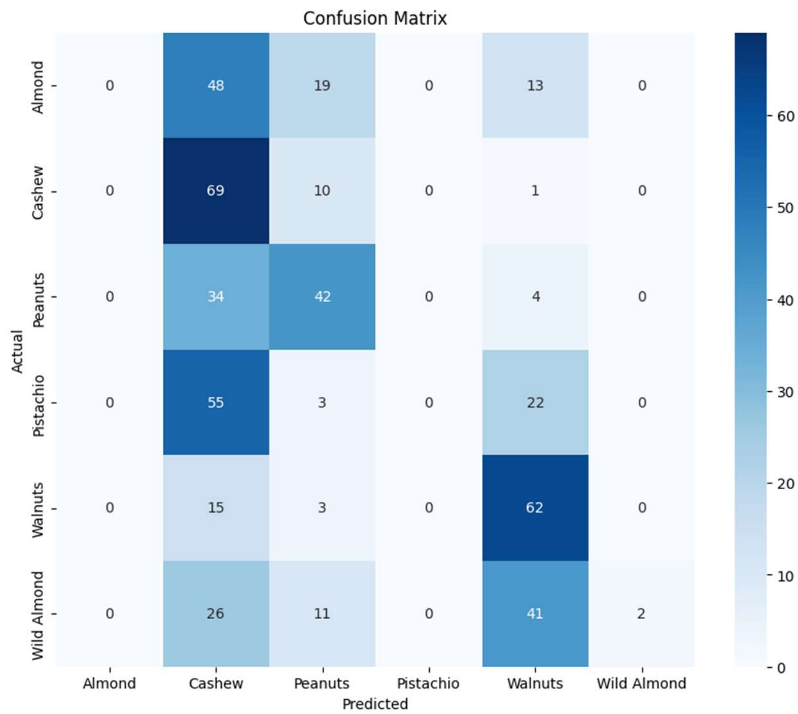


Figure 4.3.2.3 ResNet50 Confusion Metrics

Figure 4.3.2.4 ResNet50 demonstration of correct and incorrect recognition of nut breed images

4.3.3 MobileNet:

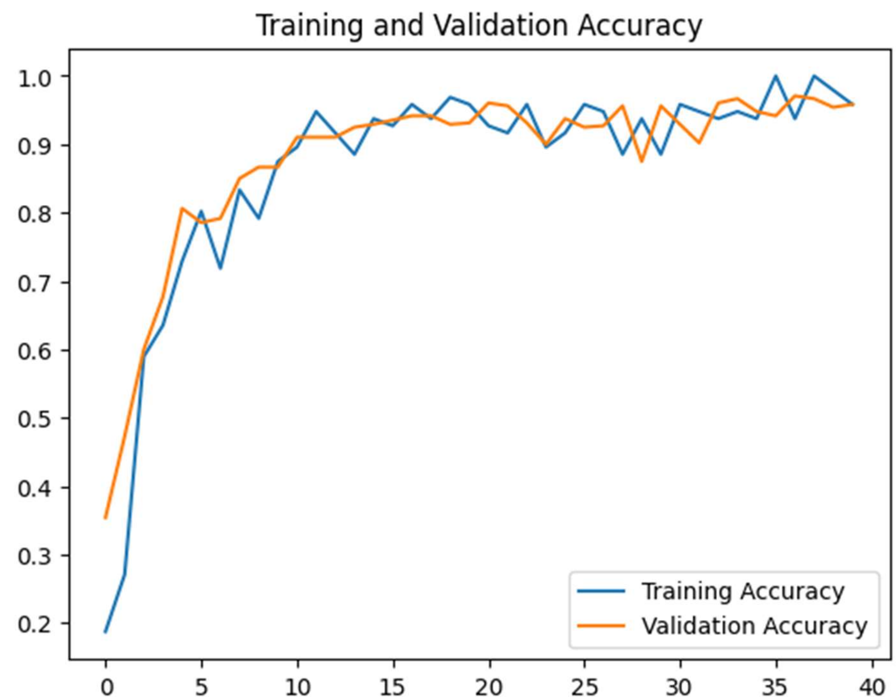


Figure 4.3.3.1 MobileNet Training vs Validation accuracy

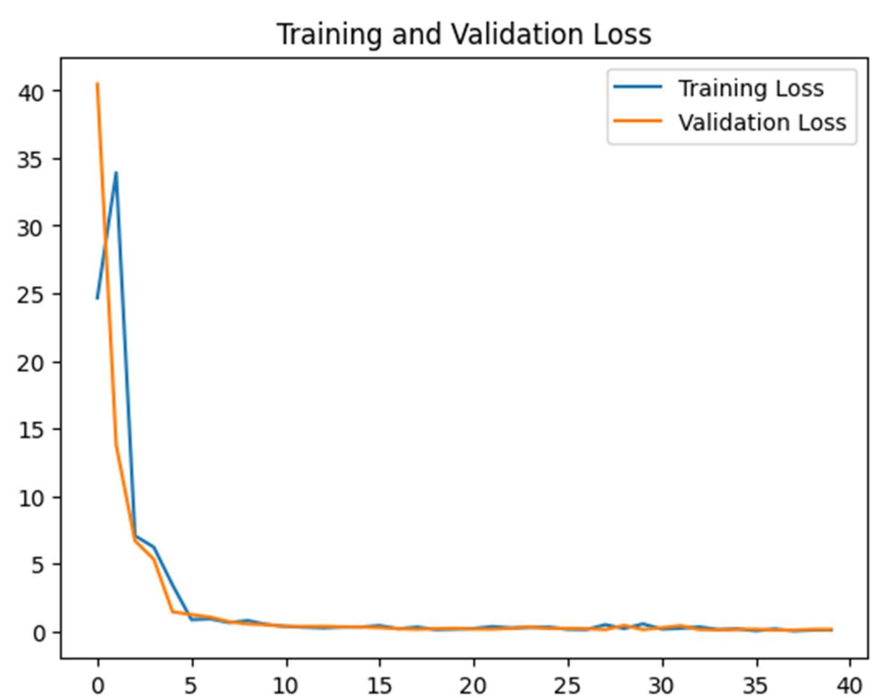


Figure 4.3.3.2 MobileNet Training vs Validation Loss

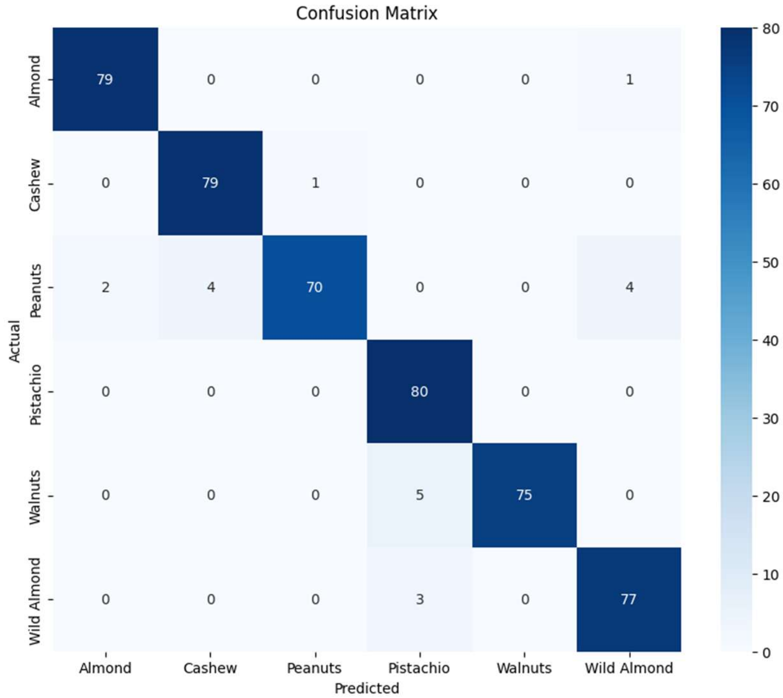


Figure 4.3.3.3 MobileNet Confusion Matric

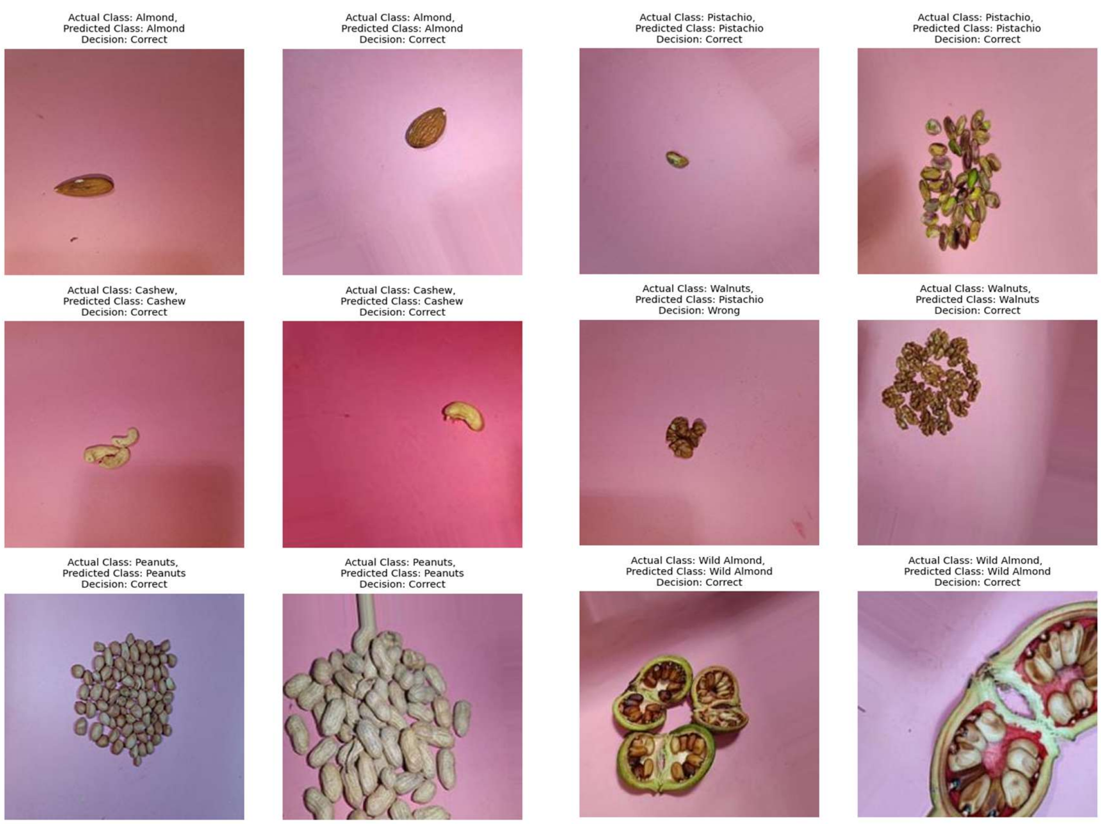


Figure 4.3.3.4 MobileNet demonstration of correct and incorrect recognition of nut breed images

4.3.4 Inception V3:

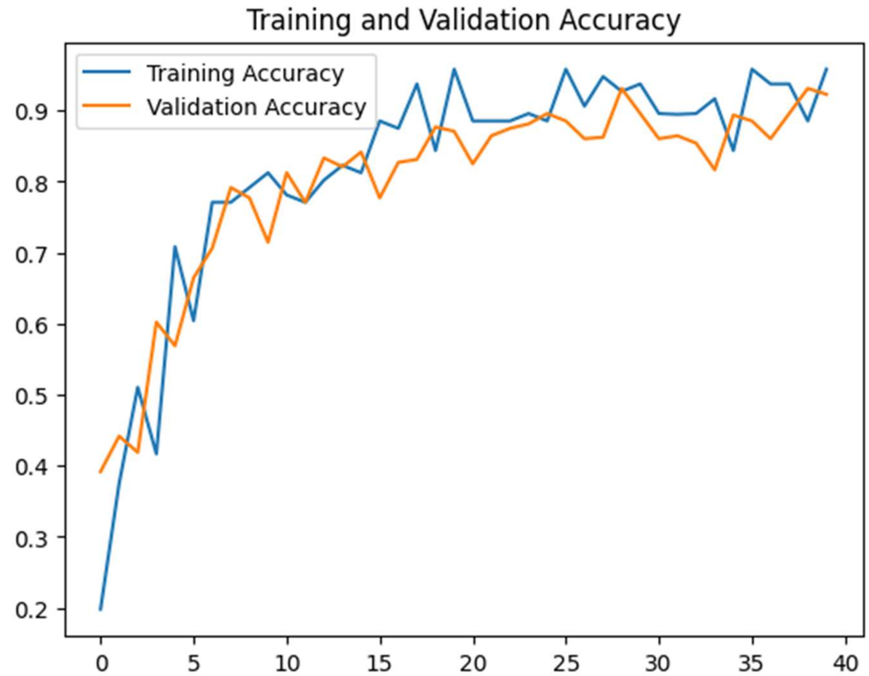


Figure 4.3.4.1 Inception V3 Training vs Validation Accuracy

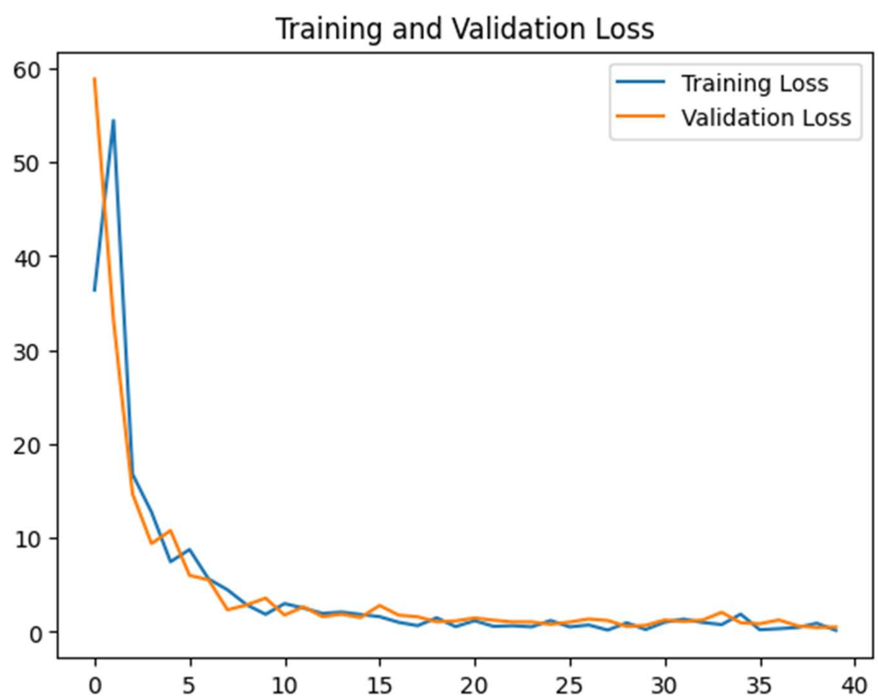


Figure 4.3.4.2 Inception V3 Training vs Validation Loss

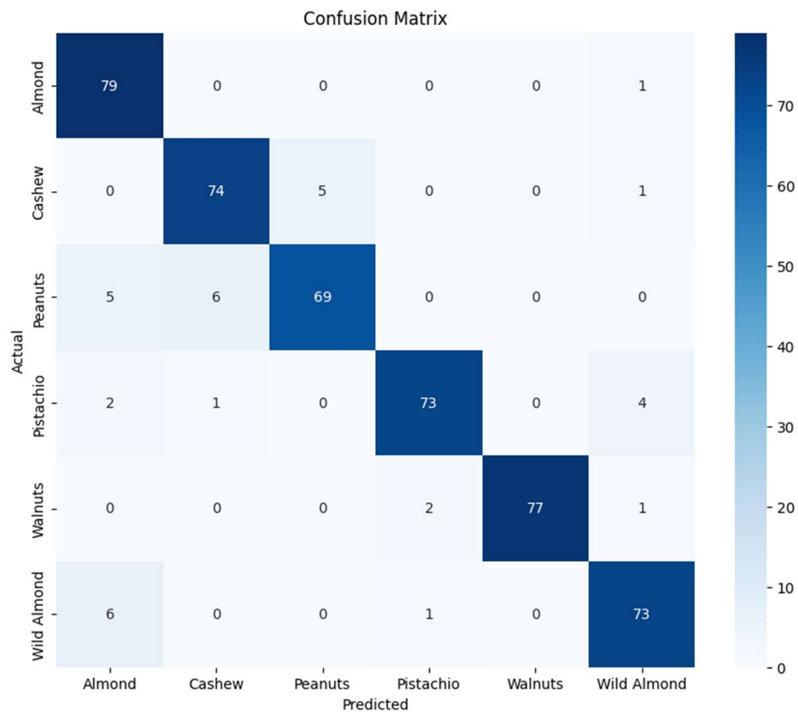


Figure 4.3.4.3 Inception V3 Confusion Matric

Figure 4.3.4.4 Inception V3 demonstration of correct and incorrect recognition of nut breed images

4.3.5 Xception:

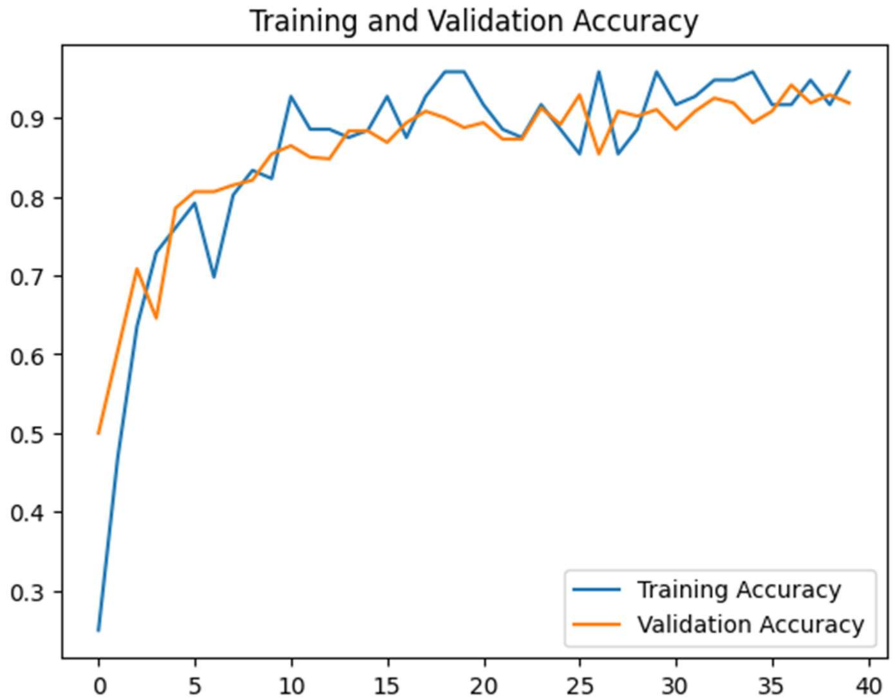


Figure 4.3.5.1 Xception Training vs Validation Accuracy

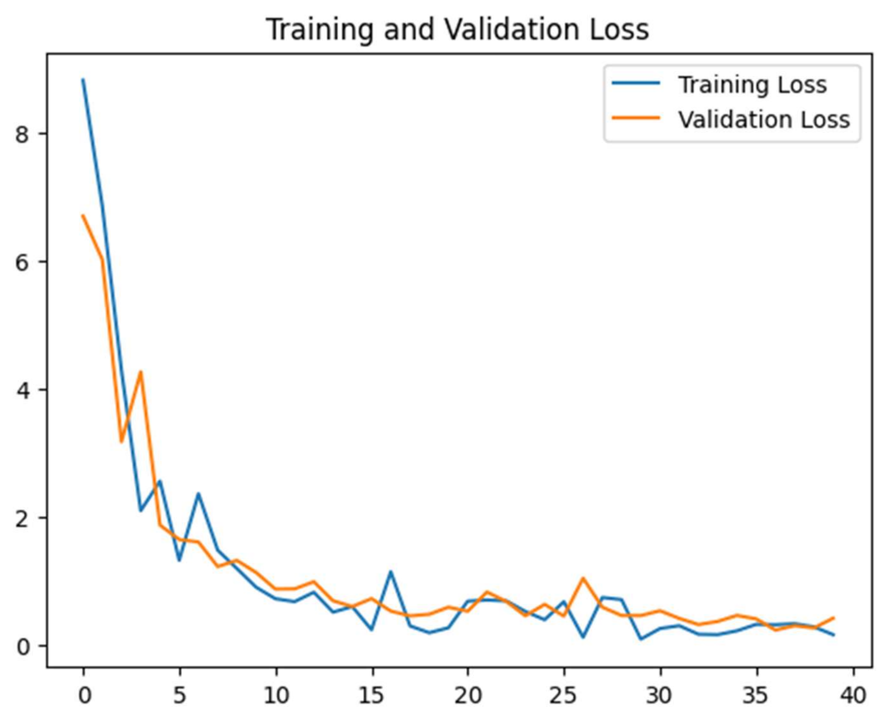


Figure 4.3.5.2 Xception Training vs Validation Loss

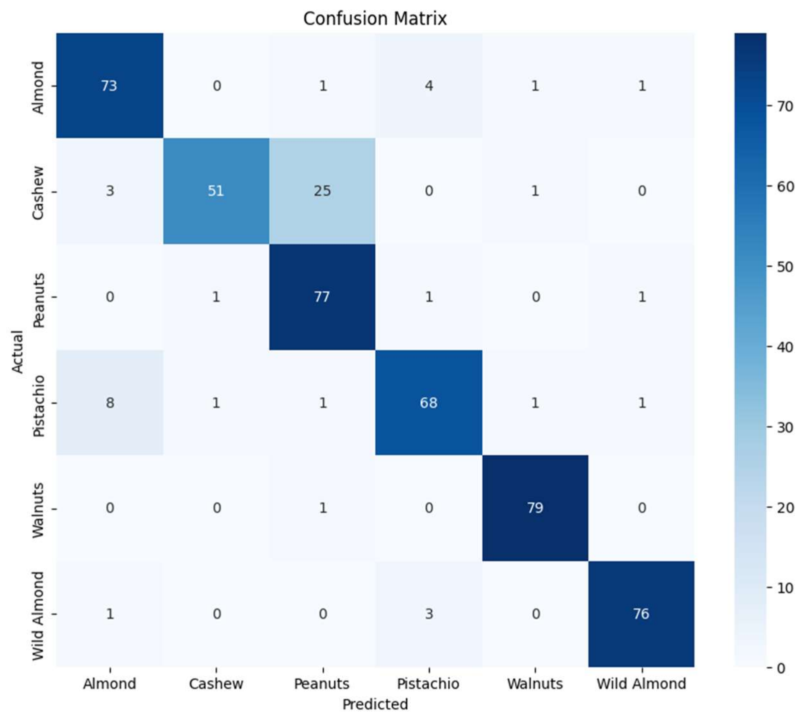


Figure 4.3.5.3 Xception Confusion Matric

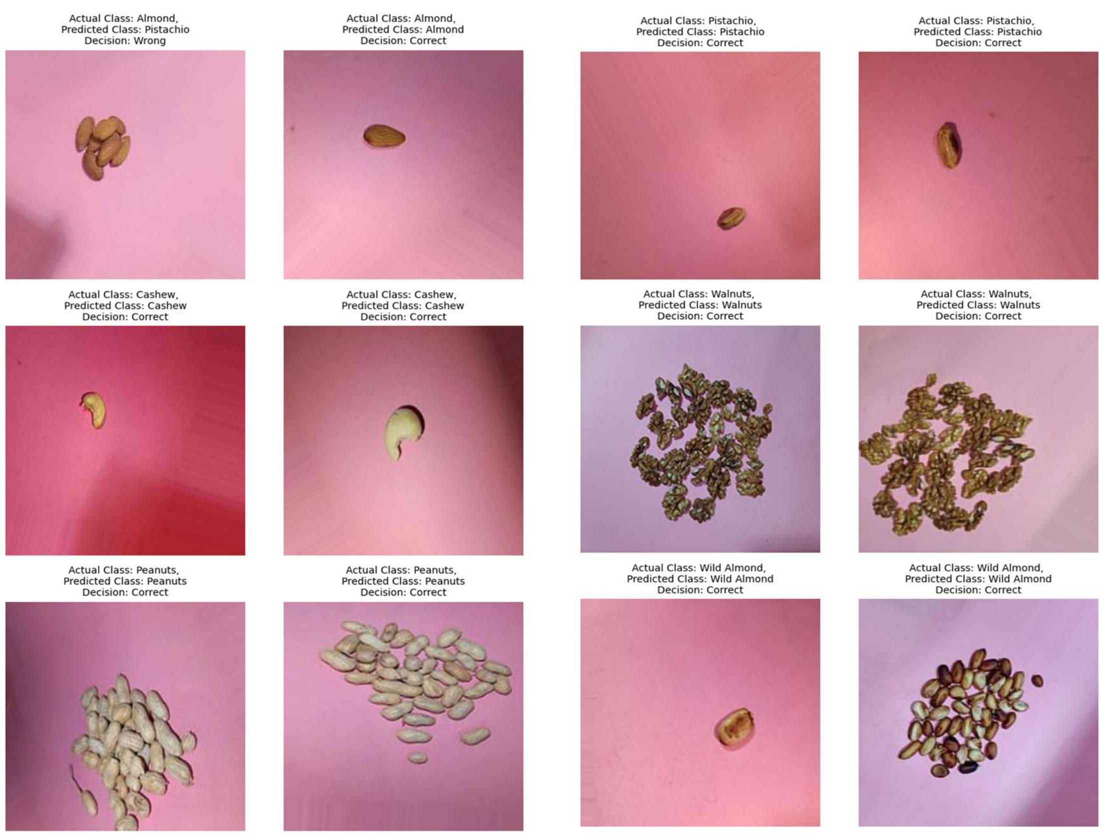


Figure 4.3.5.4 Xception demonstration of correct and incorrect recognition of nut breed images

In this paper, the performance of five CNN-based architectures (VGG16, ResNet50, MobileNet, Inception V3, and Xception) is tested. The performance is measured using F1-score, precision, recall and accuracy. Of them, MobileNet outperformed all of the models with the highest accuracy of 95.83% and enhanced sensitivity and specificity ratings as well. MobileNet performed better in object recognition and was 3.13% better than the second-best model, Inception V3. The accuracy rates for other models were (VGG16), 36.45% (ResNet50), 92.70% (Inception V3), and 88.33% (Xception). Given these results, MobileNet is the best-performing model to use for nut breed recognition.

4.4 Comparative Analysis

Table 4.4.1 Comparative Analysis

Aspect	Existing Works	Our Work
Dataset Size	Small datasets (e.g., 303 - 3,000 images).	4,800 raw images collected and organized into six nut breed categories.
Number of Classes	Ranges from 4 to 18.	6 nut breeds: Almond, Cashew, Peanuts, Pistachio, Walnuts, and Wild Almond.
Models Evaluated	Limited models like Inception V3, Xception, EfficientNet, or customized CNNs.	Comprehensive evaluation of 5 CNNs: VGG16, ResNet50, MobileNet, Inception V3, and Xception.
Dataset Diversity	Often limited to specific nut types or regions.	Dataset created with raw images from local shops to ensure diversity and applicability.
Generalization	Focused on specific nuts or regions with limited multimodal data integration.	Generalized approach with diverse nut breeds, addressing dataset diversity gaps.
Image Augmentation	Basic techniques like flipping and rotation used occasionally.	Advanced augmentation (rotation, shifting, flipping) expanded dataset from 200 to 800 images per class.
User Interface	No user interface for real-world application.	Web-based interface developed using Python Flask and React for real-time user interaction.
Real-World Application	Limited focus on real-time and industrial applications.	Designed a scalable system applicable for supply chain, quality control, and agricultural research.

Table 4.4.1 highlights how our work addresses gaps in dataset diversity, comprehensive evaluation, and real-world applicability compared to existing research

4. Summary

The current work evaluates the performance of five CNN models, namely VGG16, ResNet50, MobileNet, Inception V3, and Xception for nut types classification. F1-score, precision, recall, and accuracy were used to evaluate models. MobileNet achieved the highest accuracy of 95.83%, 3.13% higher than Inception V3 — the second-best model. It showed increased sensitivity and specificity, making it the best model for nut breed determination. The rest of the models achieved the accuracy of 91.25%(VGG16), 36.45%(ResNet50), 92.70% (Inception V3) and 88.33%(Xception) showing how clearly MobileNet is better than all other models in this competition.

Chapter 5

Engineering Standards and Design Challenges

This chapter analyzes the engineering standards adhered to and the obstacles faced during the system's design and development. It examines the strategies implemented to tackle these difficulties.

5.1 Compliance with the Standards

The generation and implementation of nut breed recognition system was followed with engineering and design standards. It covers compliance with standards-set criteria in the industry with respect to machine learning framework/application use, dataset pretreatment protocols, and evaluation metrics. This guarantees the system's reliability, correctness, and scalability as well as adherence to ethical and professional principles in the realms of artificial intelligence and computer vision.

5.1.1 Communication Standards

The communication protocols adopted in the current project enabled easy collaboration and data collection. Conversations with local nut store owners were formal and businesslike, demanding quick and clear agreement to use data. Regular meetings on Google Meet and face-to-face conversations enhanced teamwork, ensuring constant updates and alignment. They emphasized on active listening and providing feedback to improve decision-making. Coordination was done using appropriate communication channels like email and casual chat. We maintained confidentiality and data security during this process to protect sensitive information. These guidelines enabled effective communication both for team members and those outside who needed to communicate with the project team.

5.2 Impact on Society, Environment and Sustainability

Sustainability, the environment, and society are all greatly impacted by deep learning for nut breed recognition. Accurate nut breed recognition and categorization made possible by this technology can improve agricultural productivity by assisting farmers in maintaining quality control and optimizing production methods. It promotes sustainable farming methods by minimizing mistakes and resource waste by decreasing reliance on manual procedures. In terms of the environment, improved breed recognition can help recognize and endangered nut breeds, guiding biodiversity preservation. Additionally, it promotes supply chain transparency, guaranteeing that customers get premium goods with genuine labels. Reduced resource waste also leads to reducing carbon emissions from agriculture. Societally, this invention has the potential to empower farmers, particularly in poor countries, by giving easily available tools for increasing production and profitability. Thus, deep learning applications in nut breed detection coincide with global sustainability goals, supporting economic growth while protecting the environment and social well-being.

5.2.1 Impact on Life

Nut breed recognition using deep learning has a significant positive influence on living quality by transforming food production and agriculture. It makes it possible to accurately recognize different types of nuts, guaranteeing authenticity and quality throughout the supply chain, which is useful to both producers and consumers. It increases farmers' productivity and profitability by reducing their reliance on manual recognition. This technique also contributes to biodiversity conservation by recognizing and safeguarding unusual nut breeds. It also gives the food industry the ability to uphold uniform standards, enhancing customer confidence and health. Overall, it brings technology and agriculture together to produce a more efficient and sustainable environment that benefits people all over the world.

5.2.2 Impact on Society, Environment

The recognition of nut breeds has wide and complex social implications. Proper nut breed recognition and classification could revolutionize agriculture through improving crop management procedures, increasing food security, and supporting sustainable farming. It gives farmers the ability to make wise resource decisions, manage pests and diseases, and select cropping techniques, all of which increase output potential and production. Additionally, recognizing the right breeds of nut enables the preservation of genetic variety, which is necessary for upcoming breeding programs and the ability of nuts to adapt to changing environmental conditions. Customers benefit from this accreditation as well since it ensures continuous quality and increases their trust in the goods they purchase. Furthermore, it promotes the sharing of knowledge between farmers and scholars and creates chances for the nut industry to expand, facilitate trade, and innovate. Overall, the advantages of recognizing different breeds of nuts extend beyond agriculture and help society by promoting economic growth, ecologically friendly practices, and improved food production.

5.2.3 Ethical Aspects

The ethical elements of deep learning for nut breed recognition include justice, inclusiveness, and equal access. Algorithms must be unbiased to ensure reliable identification across various nut breeds and geographies. Protecting data privacy and remaining transparent about how models are developed and implemented are critical for trust. Furthermore, offering access to small-scale farmers helps to prevent a digital gap and promotes equitable technology adoption. Ethical implementation guarantees that this invention benefits all stakeholders in a sustainable and responsible manner.

5.2.4 Sustainability Plan

Our research aims to help farmers make without mistakes nut breed selections. The capacity to support environmentally and resource-conscious farming methods that will enable sustained recognition of nut breeds. Farmers will be able to use pesticides, fertilizers, and water more efficiently if nuts are recognized and classified differently. This focused approach will increase output while reducing the environmental effect of nut farming. Furthermore, recognizing and protecting unique and uncommon nut breeds will contribute to the preservation of genetic variety and biodiversity, both of which are essential for the long-term viability of nut crops. We can encourage agriculture that is sustainable.

5.3 Project Management and Financial Analysis

For the purpose of this project, research and development are being conducted for a deep learning model that can recognize different types of nuts. Hardware, software, dataset acquisition and miscellaneous expenditures are the key components that are broken down into the budget's primary categories in table 5.3.1. Further, in order to guarantee cost-effectiveness, an alternative budget is supplied in table 5.3.2.

Primary Budget:

Table 5.3.1 Primary Budget

Category	Details	Cost (Taka)
Hardware	High-performance GPU-enabled laptop/PC or cloud services like Google Colab Pro	1500
Software	Paid DL libraries, IDE licenses, cloud storage, writing tools	2500
Dataset Acquisition	Image collection services	2500
Miscellaneous	Internet, utilities, etc.	1500
Total		**8000**

Alternate Budget:

Table 5.3.2 Alternate Budget

Category	Details	Cost (Taka)
Hardware	Free-tier cloud computing (Google Colab free plan)	0
Software	Open-source tools like TensorFlow, PyTorch	0
Dataset Acquisition	Open-access datasets like ImageNet, NutsDB	0
Human Resources	Self-conducted research	0
Miscellaneous	Internet (personal use)	1000
Total		**1000**

5.4 Complex Engineering Problem

Complex engineering challenges involve a variety of related problems that require high-level technical knowledge, multidisciplinary collaboration, and innovative solutions. Such problems often yield unexpected findings and require rigorous research, design, and validation. This is the first attempted deep learning-based agriculture application in nut breed identification integrating with image processing and agricultural expertise to address real-world issues.

5.4.1 Complex Problem Solving

Table 5.4.1.1 Mapping with complex problem solving.

EP1 Depth of Knowledge	**EP2** Range of Conflicting Requirements	**EP3** Depth of Analysis	**EP4** Familiarity of Issues	**EP5** Extent of Applicable Codes	**EP6** Extent of Stakeholder Involvement	**EP7** Interdependence
✔		✔				✔

Mapping with Knowledge Profile for EP1

Table 5.4.1.2 Mapping with knowledge Profile (EP1)

K1 Natural Sciences	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
		✔	✔	✔	✔		✔

K3 (Engineering Fundamentals): Understanding of basic engineering principles like algorithms and data structures relevant to deep learning.

K4 (Specialist Knowledge): Expertise in deep learning frameworks, including CNNs and transfer learning as well as their application to image recognition.

K5(Engineering Design): Creating and implementing a competent deep learning model for the niche task of nut breed detection.

K6 (Engineering practice): Applying engineering principles to real-world problems, such as using cloud services and hardware to model training.

K8 (Research Literature): We conducted a detailed research of the literature, to determine the best-suited model and approaches for the project.

Mapping with Knowledge Profile for EP3

Table 5.4.1.3 Mapping with knowledge Profile (EP3)

K1 Natural Sciences	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
	✔	✔	✔	✔			

K2 (Mathematics): Understanding and applying concepts of optimization, loss functions, and performance measures.

K3 (Engineering Fundamentals): Assess key deep learning principles of determining the architectures that are most suited to detect nut breeds.

K4 (Specialist Knowledge): Detailed assessment of the selected CNN models to use (MobileNet, Inception V3, etc.) and their suitability to the task in question.

K5 (Engineering Design): Evaluating and improving the design of a model based on its success and limitations in the quality of the desired outcome.

Mapping with Knowledge Profile for EP7

Table 5.4.1.4 Mapping with knowledge Profile (EP7)

K1 Natural Sciences	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔	✔	✔	✔	✔	✔

K1 (Natural Sciences): Understanding the Biological and Taxonomical Features of Nut Types through Photographic Documentation.

K2 (Mathematics): Application of Mathematical modeling, Optimization and Statistical Analysis to Deep Learning Algorithms.

K3 (Engineering Fundamentals): Application of engineering concepts in the building and training of the deep learning model.

K4 (Specialist Knowledge): Using domain knowledge such as machine learning, image recognition, and data science to build models.

K5 (Engineering Design): Applying design principles to improve the architecture of models and maximize performance.

K6 (Engineering practice): How engineering practice can be used to operationalize models. (e.g. in the 'cloud' or on high-performance hardware)

K8 (Research Literature): using them to improve the model and increase classification accuracy.

5.4.2 Engineering Activities

Table 5.4.2.1 Mapping with complex engineering activities

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔	✔	✔	✔	✔

EA1: This project has access to all sorts of resources, including researchers, GPUs, datasets, and CNN-based technologies.

EA2: This project deals with issues related to dataset balance, model optimization, and the necessity of interdisciplinary cooperation between agriculture and technology.

EA3: a novel use in agriculture using CNNs and transfer learning for nut identification.

EA4: It encourages sustainable agriculture, diminishes human labor, and enhances food security and the livelihood of farmers.

EA5: Applies the concepts of deep learning in a specific field thereby contributing to the development of applications in agricultural technology.

5.5 Summary

The deep learning-based nut breed detection project impacts in the fields of society, environment, and sustainability. So, it increases agricultural production, it encourages us to utilize sustainable agriculture and helps us saving biodiversity as well. This initiative makes clear the flow of a goods supply chain and puts power back in the hands of farmers, especially in developing countries. Ethics ensures that technology is comprehensive and universal. The decomposition of study financing to primary and alternative plans allows for more effective use of resources. This project is a multi-faceted technical challenge, combining multiple disciplines from deep learning, image processing and farming knowledge. It includes a multitude of resources, cross-didactic collaboration, as well as innovative approaches to solving real-world problems.

Chapter 6
Conclusion

This chapter encapsulates the study findings, emphasizing its contributions and consequences. It delineates prospective future endeavors and enhancements in the domain of nut breed recognition by deep learning.

6.1 Summary

The use of deep learning techniques for nut breed recognition shows significant potential for accurately recognizing different nut breeds. Deep learning demonstrates the ability to learn complex patterns and properties in nut images, allowing for robust classification through the examination of large datasets and the use of powerful neural network models. Nut recognition has been successfully applied to deep learning models such as VGG16, ResNet50, MobileNet, Inception V3, and Xception. These algorithms were trained on images of various nuts to differentiate between multiple nut breeds based on their different visual properties, including as size, shape, color, texture, and skin pattern. Among deep learning models, the MobileNet has the highest accuracy. The MobileNet model accuracy was 95.83%. This technology has various advantages, including non-destructive and quick nut breed registration, support with quality assurance and labeling, and disease and pest management in nut crops. It is essential to address concerns such as the availability of different datasets and the interpretability of deep learning models. More study and collaboration in this field will result in improvements to nut categorization systems as well as developments in nut production, breeding, and trade.

6.2 Limitation

Even though we may use these trained models to get the highest accuracy, we might have achieved significantly better outcomes if we had access to additional data. It may be challenging to obtain accurate and representative training data, especially for rare or local nut breeds. It can be expensive and technically difficult to establish and maintain the infrastructure and expertise needed to recognize nut breeds for small-scale growers in areas with limited resources.

6.3 Future Work

Nowadays, it is important to select a nut breed when it is still in the budding stage in order to optimize production and productivity. Since it takes a lot of expertise to recognize different nut breeds, it will be very helpful to install this system on cellphones. Farmers would be able to snap a picture of a nut and send it to the server. Once the nut breed has been recognized, the server will automatically provide the information.

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