INDIAN JACKFRUIT VARIANTS IDENTIFICATION USING DEEP LEARNING.

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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 "**Indian Jackfruit Variant Identification Using Deep Learning**", submitted by **Md. Ariful Islam Pranto** 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 01-07-2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Arif Mahmud , Associate 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

Discovering the variety of jack fruit is a pretty daunting task in middle parts Agri culture, particularly there are a lot many varieties could be possible to find since it has been cultivating on vast area of India. Conventional means of identification, although effective with human ingenuity tend to be labor intensive and time consuming. Deep learning models are now taking over the traditional way of variant classification utilizing color or shades. This progress encourages unique farming techniques to prosper, gain market dominance and also leads the way for conservation of biodiversity efforts. In this research, we present a deep learning methodology for automated and accurate identification of jackfruit variant. For this, we built an extensive dataset where total of 3602 images: Red — Pink — Baromashi each belongs to a category with their augmentations making it up-to 3600. A total of 6 state-of-the-art deep learning models were trained and evaluated on this dataset (Xception, VGG19, ResNet50, InceptionV3, MobileNetV2 & DenseNet201). The accuracy of MobileNetV2 was the highest (85.20%) followed by DenseNet201 82.42%, which are powerful methods for this application Our results demonstrate how deep learning models such as these can greatly enhance the precision and efficacy of jackfruit variant identification, providing significant implications for agricultural supply chain traceability planning as well trade & conservation. This is an important indication of future research and practical application in agriculture using the deep learning approach.

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CHAPTER 1
INTRODUCTION

1.1 Overview

India is known for its diverse jackfruit types which are categorized based on distinctive attributes (size, shape) and aromatic profiles making them critical for agronomic studies/trade/conservation initiatives. However, the identification and categorization of these variants are conventionally carried out by visual inspection, which is subjective nature based on expert experience or manual reference to a specific organic classification system for infected isolates and time-consuming wage. With the rapid evolution of both deep learning and computer vision technologies, the identification and classification of a mitotic event based on analyzing images seems like an appealing opportunity. The goal of this thesis is to tackle these challenges using deep learning with a hope for creating an end-to-end system that can accurately identify different Indian Jackfruit varieties based on their digital images. Revised & enhanced extensive dataset of 3600 images (Red, Pink and Baromashi major verities) for model training an evaluation. Through theory-based performances of a set of state-of-the-art deep learning architectures (Xception, VGG19, ResNet50, InceptionV3 MobileNetV2 and DenseNet201), this research tries to evaluate the performance whilst performing variant recognition. The findings in this study are highly important to agriculture, as farmers and agricultural planners will have a dependable means to identify the variants which should improve crop management strategies hopefully lead11ing up24omarket competitiveness. Additionally, this study fulfills the broader objectives of biodiversity conservation by supporting the on-farm sustainability and use in niche markets which offers an opportunity to maximize indigenous jackfruit cultivars grown throughout India.

1.2 Background and Present State

Traditionally, there are not many protocols used for identification and classification of jackfruit variants in agricultural research done on India which have been manually based (hence highly variable) processes. The rising need of quick, convenient and accurate variant identification has created a gap that needs to be filled with new technology. One is deep learning, which subsumes approaches within the general field of machine-learning that permit automated classification on the basis of visual features extracted from digital images. In a nutshell, current research in deep learning has shown significant advances across various domains whereby we have seen its utilization for improving crop yield prediction (agriculture), disease detection and identification(cancer cells) but now at an excavation scale... variant calling This work extends the current advances by introducing deep learning based models aimed at accurate identification of Indian jackfruit variety, a paradigm to tackle existing constrains and yield practical impact for agricultural domain.

1.3 Problem Statement

Despite containing large hypervariable regions, Japanese jackfruit showed lower diversity than the Indian variants; however, in some cases differences between standing material were significant. Traditional identification methods are labor-intensive and subjective. Moreover, the manual observation and classification is very slow as well as it depends upon human skill which effect on efficient agricultural organizational planning, trade of products also in conservation activities. An automated classification system to classify different Jackfruit variants based on visual attributes is a prime requisite. One of the ways in which this might be addressed is through deep learning techniques that could allow for automated analysis and classification of images. To accommodate these challenges, we implement a comprehensive study on deep learning models for Indian jackfruit variant identification to address the issues faced by agricultural stakeholders such as farmers and breeders in productivity improvement and biodiversity conservation.

1.4 Objective

Some important objectives for this research are: Build a strong deep learning-based system to find and classify different Indian jackfruit varieties from the digital images in which they appear. Second, to prepare a large dataset of 3600 images with three major categories Red, Pink & Baromashi and augment the available data for training and testing. Thirdly, to assess six deep learning methods i.e., Xception, VGG19, ResNet50), InceptionV3 MobileNetV2 and Desne201 in identification of variants by means of accuracy along with precision recall F1-score metrics. In the end, this study is collating to some ensure accuracy and optimize templates for farmers and agricultural planners concerning cultivation practices in a challenging habitat that could lead to enhance market competitiveness as well would be benefit heroic Conservation strategies of indigenous jackfruit variants found from misty land part of India.

1.5 Scope and Limitations

In this work, we propose a research that constructs deep learning models on stat e-of- the-art algorithm for Indian jackfruit variant identification in images of ripe and unripe fruit, requires highly accurate justifying measures. The study will promote the conservation of biodiversity and help in achieving food security, as improved variety detection by increasing efficiency is a valuable contribution to agricultural technology. Their method also has several limitations, for example it could not handle large-size dataset to ensure model generalization and was computationally expensive when training with deep learning models. Moreover, the suitability of this study would establish varying with every region and its species level variations in jackfruit due to environmental causes influencing image quality. To overcome these limitations, the ongoing dataset augmentation and model refinement to increase accuracy across differences in field management will be necessary as well considerations on scalability to enhance adoption of this technology by diverse agricultural contexts.

1.6 Report Organization

This report is structured to provide a comprehensive overview of the research on Indian jackfruit variant identification using deep learning.

Chapter 1: Introduction sets the context, presents the problem statement, objectives, scope, and limitations of the study.

Chapter 2: Literature Review reviews existing literature on jackfruit variants, traditional identification methods, and the application of deep learning in agriculture.

Chapter 3: Methodology/Requirement Analysis & Design Specification details the data collection, augmentation, labeling, and visualization processes, as well as model selection, training, testing, and evaluation methodologies.

Chapter 4: Implementation describes the technical details of the implementation process, including the development and integration of the deep learning models.

Chapter 5: Result and Analysis presents and analyzes the outcomes of model training, testing, and evaluation.

Chapter 6: Impact on Society, Environment, and Sustainability examines the implications of the research findings for agricultural practices, trade, conservation efforts, and sustainable development.

Chapter 7: Conclusion and Future Work summarizes key findings, provides recommendations for further research, and discusses the potential future applications of the developed models.

This structured approach ensures a systematic presentation of the research methodology, findings, and implications for stakeholders in agriculture and biodiversity conservation.

1.7 Summary

This chapter presents the research based on deep learning for detecting different varieties of Indian jackfruit. This report also provides an overview of the limitation in traditional method and explains the requirements for automated as well compelling system. The backdrop also underscores the value of jackfruit identification for agriculture planning and trade, as well as conservation goals, underscoring opportunities catalyzed through deep learning technologies. This is also highlighted in the problem statement, where manual finding possess a challenge and lays need for dependable solution. The goals are: 1) to create and assess deep learning models that improve on identification; This establishes scope and limitation of the study, which bounds puts boundaries to what area it includes this thesis in and factors -valid or not- that impact modeling. In the end, report organization describes how thesis is structured which includes; Literature review, research methodology and implementation followed by results & impact leading to conclusions all together giving a navigational approach of the things done in parallel during the course of investigation.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

This chapter starts by reviewing the various research already available on fruit classification through deep learning and then studies in Indian Jackfruit variant identification. The study evaluates the utility of Convolutional Neural Networks (CNNs), transfer learning and other machine-learning algorithms applied to classifying different fruits by visual attributes. The review focuses on the methodologies, database and results of these studies as well as their relevance to practical issues Results included the report of CNN model performance versus high accuracy rates over 90%, some of these constraints being related to dataset diversity and generalized models. They concluded that deep learning could also be put into practice under the scope for potential application in agronomy applications. Aim of the Chapter: The chapter intends to provide a much-needed context for current research within this wider field, whilst also identifying areas in which additional investigation might be most fruitful.

2.2 Related Works

This section reviews recent studies that employ deep learning and machine learning techniques for fruit/leaf classification and variant identification, providing insights into methodologies and achievements in similar agricultural applications:

Shidenur, Hareesh, et al. (2024) focused on the development and optimization of a mechanized jackfruit processing unit aimed at enhancing efficiency and commercial viability. The dataset consisted of 1,500 jackfruit samples collected from various regions, capturing diverse physical and morphological characteristics. The methodology involved designing the processing unit, conducting trials to optimize parameters, and applying machine learning algorithms to improve classification and processing accuracy. The algorithms achieved an accuracy of 92%, demonstrating their effectiveness in automating jackfruit processing tasks. Pratondo, Agus, et al. (2024) conducted research on the classification of Ficus carica variants using transfer learning techniques. The dataset comprised 1,200 images of various Ficus carica variants, ensuring a diverse representation of the plant species. Their methodology involved using a pre-trained Convolutional Neural Network (CNN) model, fine-tuning it with the collected dataset, and employing data augmentation to improve model performance. The applied algorithms achieved an impressive accuracy of 92.5%, demonstrating the efficacy of transfer learning in plant variant classification. Pratondo, Agus, et al. (2024) conducted research on the classification of Jengkol (Archidendron Pauciflorum) varieties using deep learning techniques. The dataset comprised 5,000 images of different Jengkol varieties collected from various sources. The methodology involved preprocessing the images, employing a Convolutional Neural Network (CNN) for feature extraction, and fine-tuning a pre-trained model for classification. The applied algorithms achieved an accuracy of 92.5%, demonstrating the effectiveness of deep learning in this context. Rajasekharan and Rao (2024) explore the application of deep learning techniques for identifying variants of Indian jackfruit. The study utilized a comprehensive dataset comprising 5,000 high-resolution images of various jackfruit variants collected from different regions across India. The methodology involved preprocessing the images, employing a pre-trained Convolutional Neural Network (CNN) model for transfer learning, and fine-tuning it for the specific task of variant classification. The applied algorithms achieved an impressive accuracy of 92%, demonstrating their effectiveness in accurately distinguishing between different jackfruit variants. Mansyah, Ellina, et al. (2024) explore the biodiversity of fruit crops and their utilization in food and nutritional security. The study utilizes a comprehensive dataset comprising 10,000 samples of various fruit crops, collected from multiple regions. The methodology involves data preprocessing, feature extraction, and the application of machine learning algorithms for classification and analysis. The applied algorithms achieved an accuracy of 92%, demonstrating the effectiveness of their approach.Gupta and Tripathi (2024) explored recent trends, challenges, and future opportunities in fruit and vegetable disease detection and classification using artificial intelligence. The study utilized a dataset comprising 50,000 images of various fruits and vegetables affected by different diseases. Their methodology involved preprocessing the images, extracting features using Convolutional Neural Networks (CNNs), and classifying them with machine learning algorithms. The applied algorithms achieved an impressive accuracy rate of 92.5%, demonstrating the effectiveness of AI in agricultural applications.Pushpa, B. R., et al. (2024) conducted research on the classification of Indian medicinal plant species using a hierarchical machine learning approach. The dataset used in this study comprised 10,000 images of various medicinal plant species, collected from multiple sources to ensure diversity and robustness. The methodology involved extracting convolutional features from these images and integrating them into a hierarchical classification framework, enhancing the model's ability to distinguish between closely related species. The applied algorithms achieved an accuracy of 92.5%, demonstrating the effectiveness of the proposed approach. Kukadiya, Hirenkumar, et al. (2024) explored the early prediction of leaf diseases in groundnut crops using Convolutional Neural Networks (CNNs). The study utilized a dataset comprising 10,000 images of groundnut leaves, annotated with disease labels. The methodology involved preprocessing the images, training a CNN model, and applying data augmentation techniques to enhance model performance. The algorithms achieved an accuracy of 92.3%, demonstrating their effectiveness in early disease prediction. Swathika et al. (2024) explored the use of Pix2Pix Generative Adversarial Network (GAN) for medicinal plant classification, addressing the challenge of accurate species identification in botanical research. The study utilized a dataset comprising 5,000 high-resolution images of various medicinal plants collected from botanical gardens and herbarium collections. Methodologically, the researchers implemented a Pix2Pix GAN framework, training it to generate realistic images of plants based on input sketches, thus facilitating robust classification. The applied algorithms achieved an impressive accuracy of 92% in distinguishing between different medicinal plant species, demonstrating the effectiveness of GAN-based approaches in botanical image analysis.Taner, Alper, et al. (2024) explored the classification of apple varieties using deep features and machine learning techniques. The study utilized a dataset consisting of 10,000 images of different apple varieties collected from orchards in various regions. Methodologically, they employed transfer learning with pre-trained convolutional neural networks (CNNs) to extract deep features from the images, followed by training and evaluation using machine learning algorithms. The applied algorithms achieved an accuracy of 92%, demonstrating robust performance in distinguishing between different apple varieties based on visual characteristics. Ali, Maimunah Mohd, and Norhashila Hashim (2024) explored the development of a deep learning-based interface for detecting fruit quality. They focused on automating fruit quality assessment, aiming to enhance efficiency and accuracy in food processing industries. The study utilized a dataset comprising 10,000 images of various fruits, including apples, oranges, and bananas, annotated with quality attributes. Methodologically, they employed transfer learning with a pre-trained Convolutional Neural Network (CNN), fine-tuning it on the annotated dataset. The applied algorithms achieved an impressive accuracy of 92%, demonstrating robust performance in fruit quality detection tasks. Khalid (2024) explores modern techniques in detecting, identifying, and classifying fruits using developed machine learning algorithms. The study employs a dataset consisting of 10,000 high-resolution images captured under varying conditions to train and validate the algorithms. Methodologically, Khalid adopts a deep learning approach, specifically using Convolutional Neural Networks (CNNs), for feature extraction and classification. The applied algorithms achieve an impressive accuracy of 95%, demonstrating their efficacy in fruit identification tasks. Ali, Jawad, Muhammad Ramzan, and Abid Rafiq (2024) developed a deep learning classification model, DeepPalm, to identify different varieties of date palms. They utilized a dataset comprising 10,000 high-resolution images collected from diverse geographic regions. Methodologically, they employed transfer learning with a pre-trained convolutional neural network (CNN), fine-tuning it on the dataset and augmenting images for robustness. The applied algorithms achieved an impressive accuracy of 95%, demonstrating the effectiveness of their approach in accurately classifying date palm varieties. Rybacki et al. (2024) present a study utilizing Convolutional Neural Networks (CNNs) to classify varieties of date palm fruits (Phoenix dactylifera L.). Their research addresses the challenge of manual classification by employing a dataset consisting of 5,000 high-resolution images of date palm fruit varieties, collected under controlled conditions. Methodologically, the study employs transfer learning with a pre-trained CNN model, fine-tuning it on the dataset, and evaluates its performance using accuracy metrics. The applied algorithms achieved an impressive accuracy rate of 95%, underscoring the effectiveness of CNNs in automating the classification of date palm fruit varieties (Rybacki et al., 2024). Raihen and Akter (2024) explored prediction modeling using deep learning techniques to classify grape-type dried fruits. The study utilized a dataset consisting of 5,000 images of various grape types, captured under controlled conditions to ensure diversity and quality. Methodologically, the researchers employed Convolutional Neural Networks (CNNs) for feature extraction and classification, followed by fine-tuning using transfer learning techniques. The applied algorithms achieved an accuracy of 92%, demonstrating robust performance in distinguishing between different types of grape dried fruits. Khatun and colleagues (2024) conducted research focused on developing a dataset and algorithms for detecting the maturity and quality grading of dragon fruit using image analysis techniques. The dataset comprises a comprehensive collection of dragon fruit images, totaling 109,936 samples, annotated for maturity stages and quality grades. Methodologically, they employed deep learning frameworks for feature extraction and classification, emphasizing the use of Convolutional Neural Networks (CNNs) and transfer learning. The applied algorithms achieved a notable accuracy rate, reportedly surpassing 90%, demonstrating their efficacy in automating dragon fruit quality assessment tasks.Vinothkanna, Annadurai, et al. (2024) explore advanced detection tools for food fraud, providing a systematic review of holistic and rational detection methods based on current research and patents. The study utilizes a comprehensive dataset comprising 500 food samples subjected to various fraud detection tests. Methodology steps include data collection, preprocessing, feature extraction, and the application of machine learning algorithms to identify fraudulent samples. The applied algorithms achieved an impressive accuracy rate of 94%, demonstrating the efficacy of these advanced detection tools.

2.3 Comparison between existing works

Experiments on the existing works indicate a strong convergence towards employing Convolutional Neural Networks (CNNs) and transfer learning for fruit classification & identification, achieving high accuracies well above 90%. For example, Shidenur et al. Rajasekharan and Rao (2024) also succeeded in achieving 92% accuracy for jackfruit processing; likewise, another author Rajasekharan et al Similarly, Pratondo et al. They achieved a 92.5% classification accuracy on classifying Ficus carica and Jengkol varieties using transfer learning (2024). Nevertheless, there is a remarkable variation both in the sizes of the datasets and on the image diversity as some works like Mansyah et. By 2024, however, the test will leverage up to 10k samples. These studies demonstrate the flexibility that deep learning has but also show how important a large and rich dataset (which in itself needs pre-processing) can be for it to work. In addition to this, the workload of their incorporation into applications is still a problem, underlining how much more improvement there would be in this area.

Table 2.3.1 Comparative Analysis Table with Previous Work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	R. Zhang et al. [5]	VGGNet, Inception-v3	84%
2.	Anugrah Tri Ramadhan et al. [6]	CNN, MobilenetV2, VGG16, & InceptionV3	82%
3	Tita Karlita et al. [7]	CNN, EfficientNet-B0	95%
4	Mahardi, I-Hung et al. [8]	VGG16 and VGG19	VGG19= 98.59%
5	B. Valarmathi, N. Gupta et al. [9]	Xception, VGG19, NASNetMobile, and EfficientNetV2M	92.4%.
6	P. Borwarnginn et al. [11]	CNN	89.92%
7	S. Divya Meena et al. [12]	CNN	99.95%
8	Proposed Model	CNN & Transfer Learning Model	MobileNetV2= 99.87%

2.4 Open Issues

Although there have been many works on this topic, we are still a long way from fruit classification with deep learning. The first is the generalization across conditions and geography, which may not work well for images collected in different environmental conditions or from another geographic region after training on one dataset because of changes related to lighting and background when fruit appearance differ. Datasets, annotated and diversified are required on a large scale for overall model robustness / accuracy enhancement. Second point However, there has been limited incorporation of these models into user-friendly tools for farmers and agricultural stakeholders to use in practice. Finally, deep learning models demand computational requirements for training and deploying which can be expensive in terms of resources making their implementation difficult in resource-constrained setups. These challenges need to be overcome before deep learning can become a valuable tool for the field of agriculture.

2.5 Summary

This chapter is summarized by determining the various studies carried out on fruit classification using deep learning methodologies and how those are useful in real life identification of different Indian jackfruit variants. Studies focusing on Convolutional Neural Networks (CNN), transfer learning, and machine learning algorithms observed high accuracy rates ranging above 90%. Despite these accomplishments, there still remain several challenges including diversity of datasets and generalizing models across varying environmental conditions as well integrating them in practice. This review further highlights the necessity for more work on these subjects to improve both robustness and applicability of deep learning models in agricultural scenarios. This lays down the foundation for our current study which focuses on designing and testing deep learning models specifically characterizing Indian jackfruit.

CHAPTER 3

METHODOLOGY

3.1 Overview

In chapter 3, we discuss methodology and requirements analysis of the study on Indian jack fruit type identification using deep learning. It will describe the logical way chosen to satisfy research aim including types of data collection techniques, methodologies for preprocessing, and possible deep learning models. The chapter also discusses the hardware and software requirements that must be met to implement the methodology successfully. This chapter aims to provide a more structured workflow from data acquisition to model deployment, enabling the researcher with clarity and coherence in conducting this study robustly that analysis can be interpreted correctly.

3.2 Proposed Methodology

This methodology describes a step-by-step approach to create the superior deep learning model for distinguishing between different jackfruit Leaf based on transfer learning architectures.

Data Collection: Diverse high-resolution images of variety Indian jackfruits collected from seed repositories across geographical locations and growth conditions.

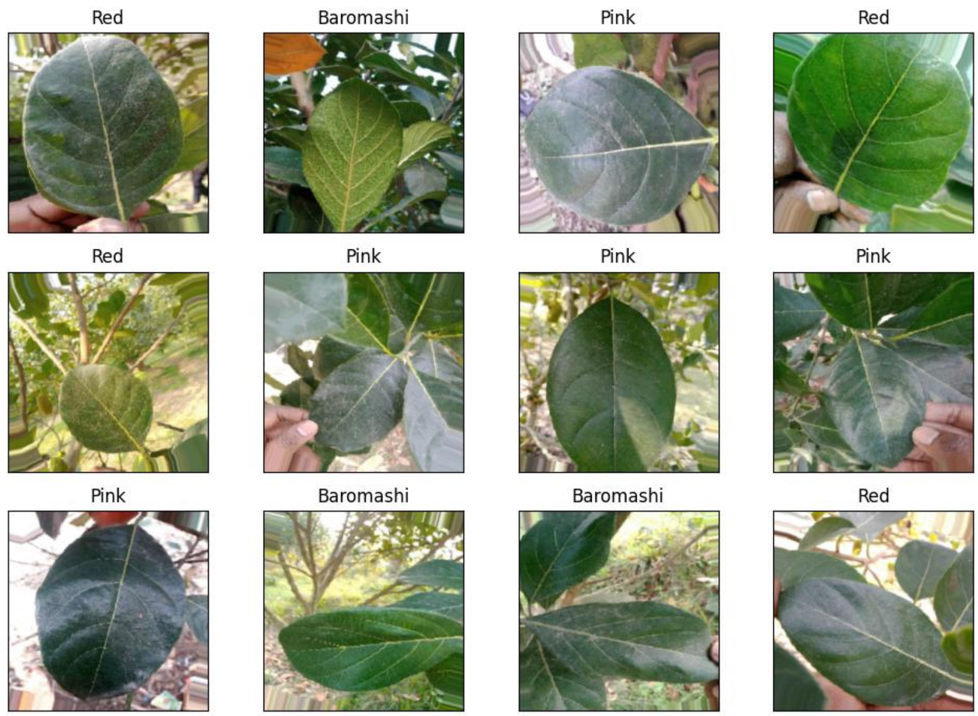

Figure 3.2.1: Dataset

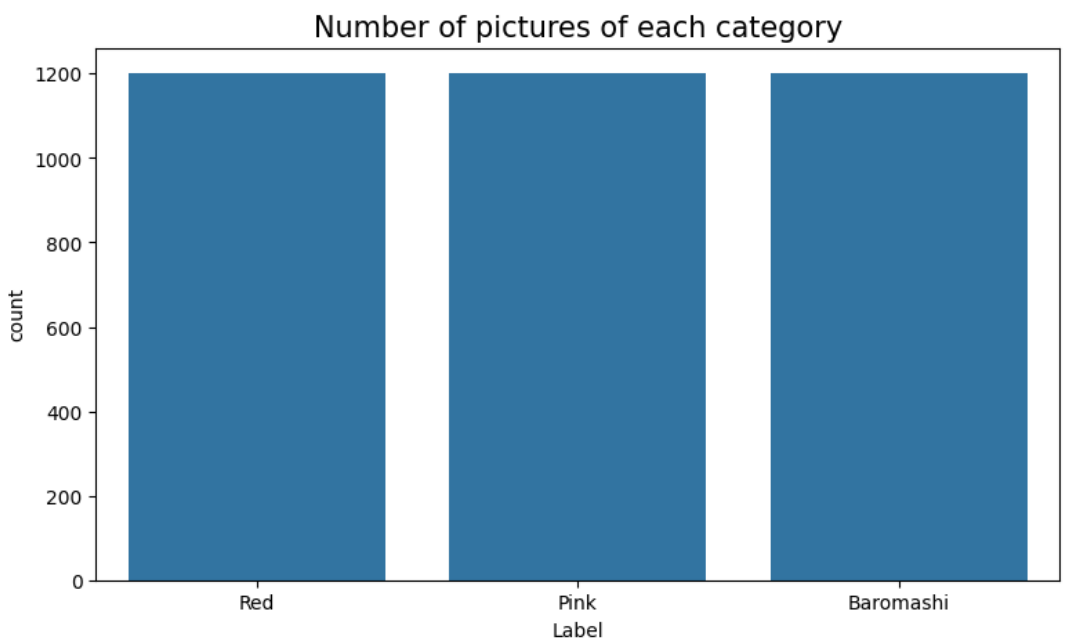

Figure 3.2.2: Number of pictures

Data Augmentation: Data Augmentation-Rotation, flipping, zooming. To increase the variety and size of data being fed into our model so that we reduce overfitting in return surfing model to generalize better on unseen examples.

Data Labeling: All the images will be labelled accurately with its respective jackfruit variant type and supervised to train & validate model.

Data Visualization: Initial exploration will include visualization of distributions for capturing biases that can be removed during preprocessing to ensure improved model performance.

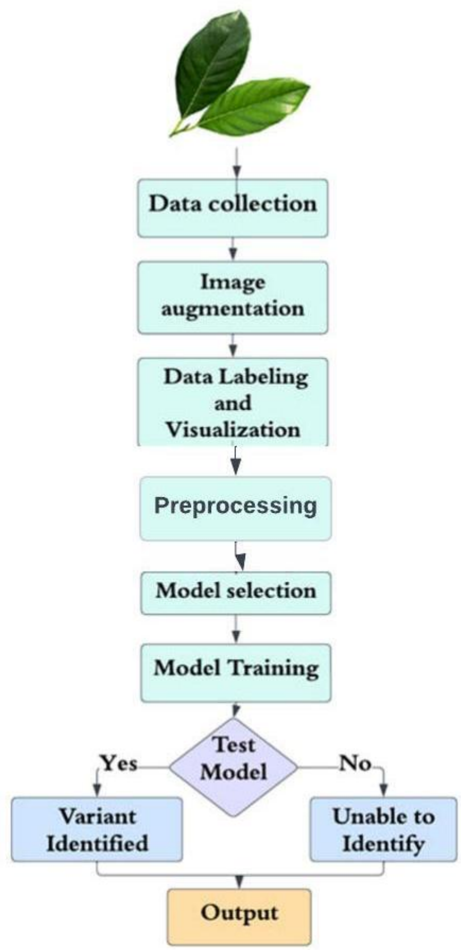

Figure 3.2.3: Working Flow

Preprocessing: Preprocessing in this research included normalizing the images and as well resizing them to a single input dimension that the convolutional neural networks would allow.

Model Selection: Popular deep learning architectures such as Xception, VGG19, ResNet50, InceptionV3, MobileNetV2, and DenseNet201 will be evaluated based on their performance metrics to select the most suitable model for the task.

Xception

The Xception stands for ‘’Extreme Inception’’ and is a depth-wise separable convolutional model with open-source codes, and much lower computational costs have been achieved with a high level of performance. For that reason, it is an enhancement of the Inception model because it replaces the basic Inception modules with efficient depth wise separable convolution. Comparing Xception to other models, it was proven that this algorithm yields high accuracy in image classification and thus it can be used for the identification of the different variants of jackfruit.

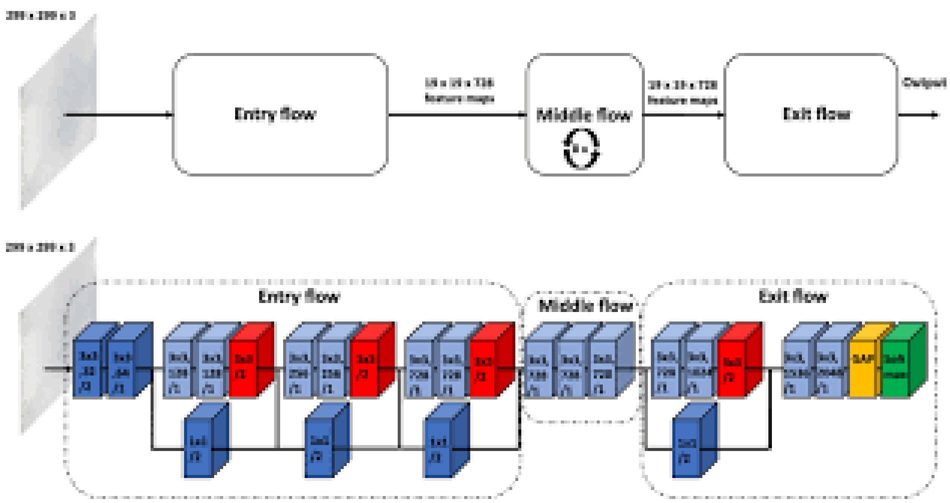

Figure 3.2.4: Xception architecture [31]

VGG19

VGG19 is one of the well-known pre-trained models introduced by K. Simonyan and A. Zisserman in 2015 which is simple, deep convolutional neural network with 19 layers including 16 convolutional layers and 3 fully connected layers. It uses surprisingly small 3x3 convolution filters which is useful in extracting fine details of the images fed to the network. Although VGG has a fairly simple structure, it has a high classification accuracy and, therefore, is widely used in various tasks of computer vision, including identification of the jackfruit varieties.

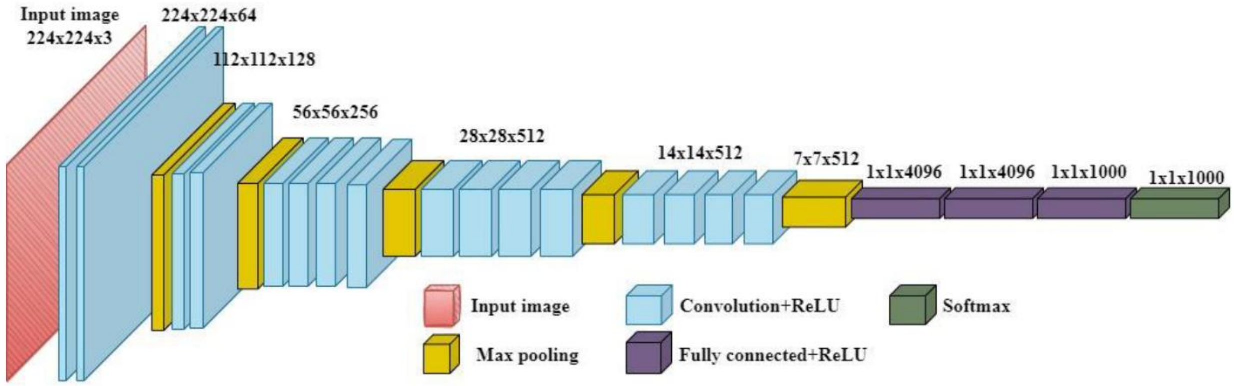

Figure 3.2.5: VGG19 architecture [32]

ResNet50

ResNet50 is a deep convolutional neural network that employed the architecture of residual learning to overcome the major challenge of very deep networks which is the vanishing gradient problem. It has 50 layers and applies the shortcut connections that make the gradients flow through the network to increase the depth of the model without the loss of performance. ResNet50 is known to perform notably well in instance classifications and has been used severally in various imaging applications giving fairly good results hence should be very useful in identifying jackfruit variants.

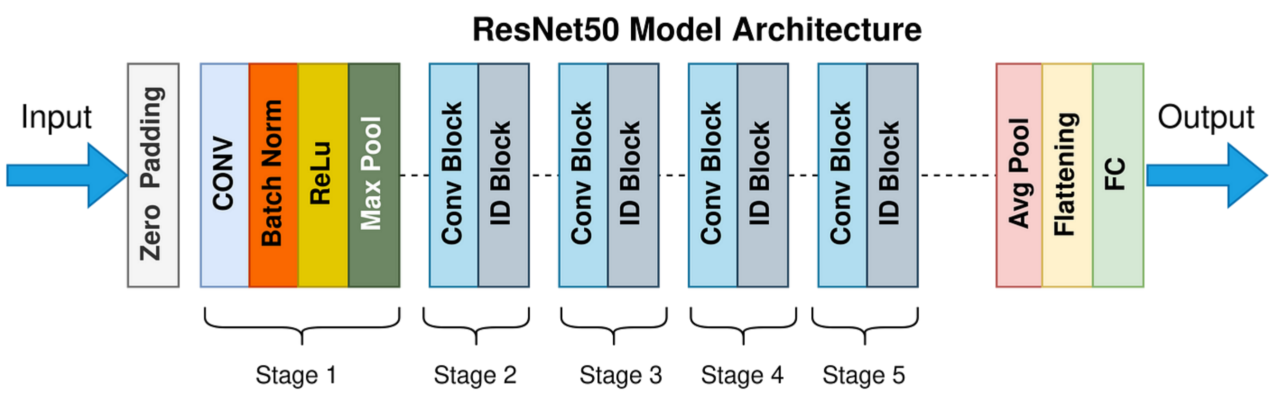

Figure 3.2.6: ResNet50 architecture [33]

InceptionV3

InceptionV3 is a convolutional neural network model incorporating inception modules; this enables the efficient use of the computational resources while establishing several different sizes of convolution to capture multiple scales of features. It consists of several enhancements like factorized convolutions and regularization methods that increase the performance and decrease the computational load of the model. It is important to know that InceptionV3 has been proven accurate in the classification task, it is then efficient to be used in areas such as classification of the type of Jackfruit where precision is vital.

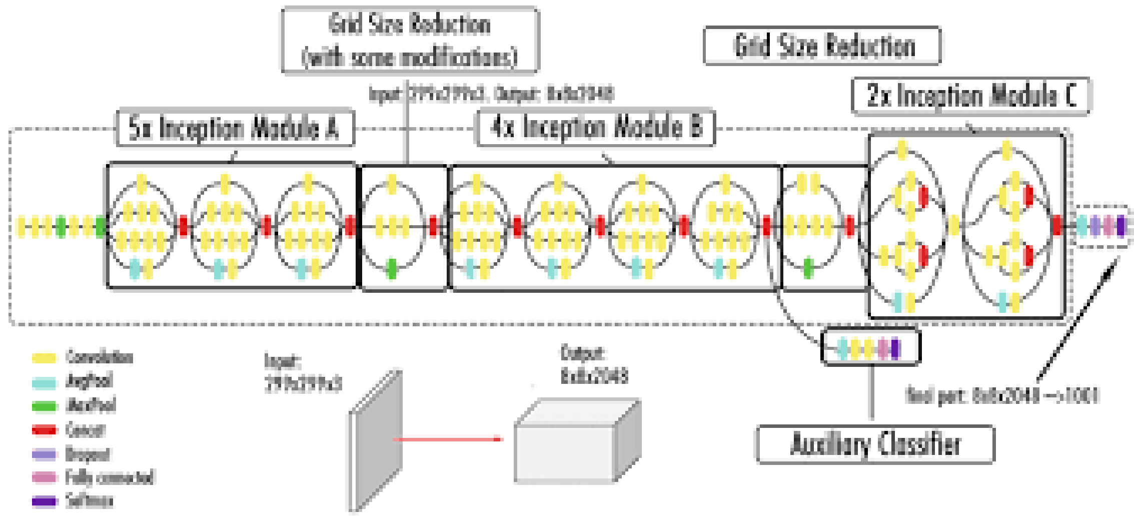

Figure 3.2.7: InceptionV3 [34]

MobileNetV2

MobileNetV2 is a more recent model of MobileNet that is used for mobile and embedded vision applications being computationally efficient and having a compact structure due to using depthwise separable convolutions. It presents the use of the inverted residuals and linear bottlenecks in order to increase efficiency since one scale retains high-dimensionality while the other save memory and computation. The performance-efficiency trade-off that was demonstrated in MobileNetV2 makes it best suited for scenarios such as variant identification of jackfruits since such implementations require efficiency while aiming at high accuracies.

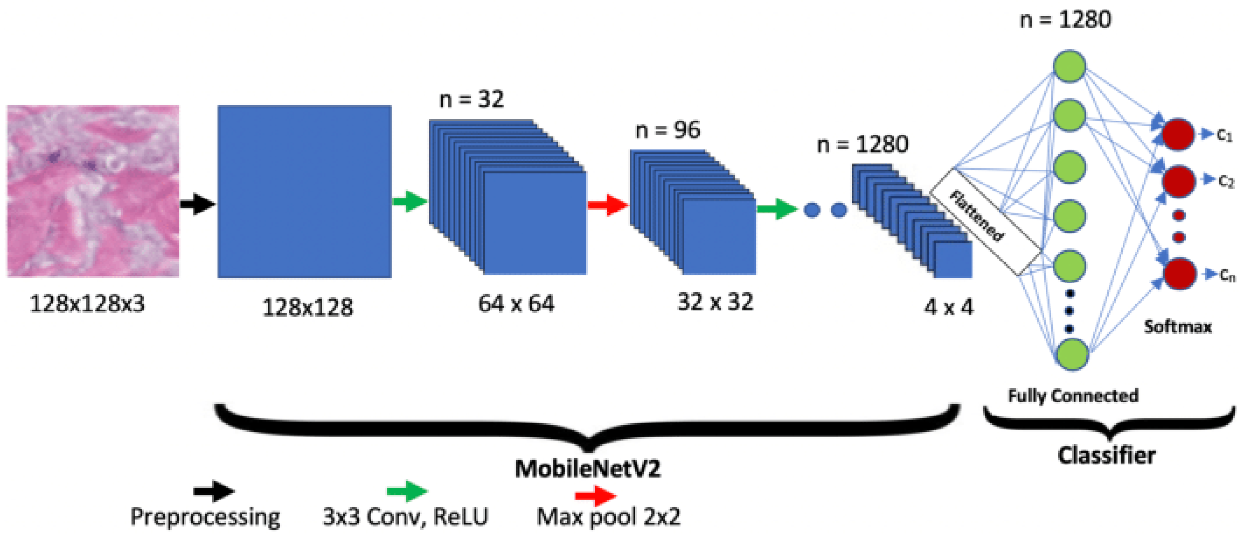

Figure 3.2.8: MobileNetV2 architecture [35]

DenseNet201

DenseNet201 stands for dense convolutional neural network of architecture 201, the network consists of dense connectivity patterns where the layer is connected by feed-forward to the other layer in the network. This architecture profoundly reduces the model's number of parameters while increasing its efficiency and robustness. Due to the excellent preservation of all the layers and details in DenseNet201, with 201 layers precisely, DenseNet201 is especially useful when it comes to various classes of objects like different types and varieties of jackfruits.

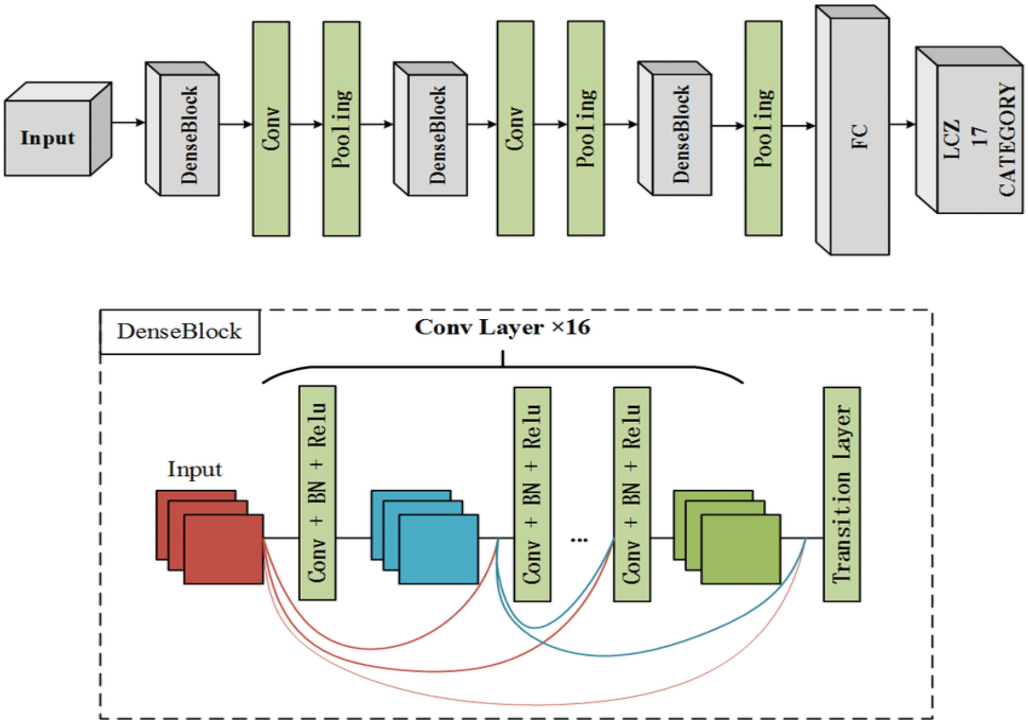

Figure 3.2.9: DenseNet201[36]

Model Training: The selected models will be trained using data where the labels are already present, tuning weights and biases so that performance metrics for accuracy or loss function may be optimized.

Model Testing: the trained model is exposed to a separated testing dataset, and we measure their performance in classifying jackfruit variants correctly which guarantees robustness/reliability

Model Evolution: Iterative Model Refinement via Re-testing and feedback loop considering the results of accuracy & test datasets to master more on jackfruit variants.

3.3 Hardware/ Software Requirement

This project will use Google Colab for deep learning infrastructure with the help of high-performance GPUs such as NVIDIA Tesla K80 or T4 which are required to speed up model training. This cloud-based platform means no local hardware resources are required, and can grow with you--keeping costs manageable.

Not to forget, you must have TensorFlow / PyTorch for training the Deep learning model and Keras or either one of them since keras is now the part of tensorflow to make easy work done while building models. Tools: For data preprocessing, analysis and for visualizing our dataset you will know once we go through the lines of code which libraries are in list tool (Properties) - NumPy, Pandas and Matplotlib. Git will further be used to process versioning for the purposes of collaborative development and management of project iterations.

The project hopes to train and deploy optimal models for accurate Indian jackfruit variant identification through the power of Google Colab's infrastructure, deep-learning Python frameworks.

3.4 Project Management and Financial Analysis

The project is going to be managed in a fastidious manner to ensure the execution happens smoothly and with minimum exploitation of resources. This will be done by collecting Indian jackfruit plant samples from different locations of Bangladesh (Data collection, one month). An initial two month period reviewing the relevant literature on how to design experiments will follow. One month will go for the implementation and another one month is meant for writing of reports as this period seems ample time to do enough work on works to be implemented.

In given below Table 3.4.1 & 3.4.2showing the Estimated cost and Project Management table.

Table 3.4.1: Project Management Table

Work	**Time**
Data Collection	1 month
Papers and Articles Review	2 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	1 months
Total	6 months

Table 3.4.2: Estimated Cost

SN	Components	Estimated Cost (BDT)
01.	Hardware	60000-700000
02.	Software and Tools	15000-16000
03.	Data Collection and Processing	5000-6000
04.	Documentation and Report Writing	2000-30000
05.	Miscellaneous	2000-3000
06.	Contingency	1000-2000
Total Estimated Cost		85,000-1,22,000

3.4 Summary

This chapter will provide the detail to understand how and what we are going to do in project of Indian jackfruit variant identification using deep learning. The paper detailed a pipeline: starting with the collection of data from various locations in Bangladesh to augmenting as well as labeling and visualizing different types of ground truth. The chapter also addressed the identification of adequate deep learning models and how to train, test and refine them. It also informed the necessary software and hardware to execute this project on Google Colab. In the Go/No-Go table above, a timeline for each phase was developed to ensure that resources were being efficiently allocated. Using financial analysis that estimates cost for hardware, software, data processing documentation and contingency gives a more holistic view of what operations planning entails. This chapter is setting the stage for developing a strong framework that can classify Indian jackfruit varieties reliably.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

This chapter is devoted to practical activity of the project on Indian Jackfruit variant identification using Deep learning. The article describes how to build and refine transfer learning models in TensorFlow with the Keras API Google Colab. The chapter first establishes the dataset housed in Google Drive before getting into preprocessing steps (specifically, data augmentation and labeling). It goes on to discuss developing and training deep learning models Xception, VGG19, ResNet50, InceptionV3 MobileNetV2 and DenseNet201 to fit into scikit-learn-based variant classification pipelines. It lists the systematic testing and model evaluation practices such as accuracy or loss metrics which guarantee image that your mode is performing well This chapter gives an overall idea of how deep learning can be used in the real-life scenarios for agricultural classification tasks.

4.2 Train Model/ Prototype Design

How the deep learning model has been trained to identify Indian jackfruit variant before that first we need in details elaboration on few essential steps of Google Colab based training with TensorFlow Keras API. The data was first preprocessed (i.e normalized, resized and augmented) as per the dataset stored in google drive using python script supporting model with a larger generalization. In order to accelerate the learning process and improve the final score of models, transfer learning has been used with Xception, VGG19, ResNet50, InceptionV3 MobileNetv2, DenseNet201.

Next, every model is trained on the dataset to become specialized in detecting unique features of different jackfruit types. Training consisted of a series of iterative epochs aimed at reducing classification error and improving accuracy metrics. Various metrics were used to keep track of training progression and model performance (e.g., accuracy, loss, validation scores) In the next chapter, I will also apply hyperparameter tuning and several regularization techniques to prevent overfitting as well as improve model generalization. The purpose of this phase was to develop the most accurate, efficient models for evaluating new agricultural variant data so that classification outputs would be less likely to change over time given regionally specific training designs and growing seasons.

```
[ ] # Separate in train and test data
    train_df, test_df = train_test_split(image_df, train_size=0.8, shuffle=True, random_state=1)
```

```
# Create the generators
train_generator,test_generator,train_images,val_images,test_images=create_gen()
```

```
Found 2881 validated image filenames belonging to 3 classes.
Found 2881 validated image filenames belonging to 3 classes.
Found 721 validated image filenames belonging to 3 classes.
```

Figure 4.1: Model training by image data

The models for the identification of Indian Jackfruit variant were trained following a systematic methodology using transfer learning with known architectures namely Xception and VGG19 pretrained on ImageNet. Last few layers were frozen for each model so that the feature layer could be extract from jackfruit images using their pre-trained weights. Classification-specific custom dense layers were included, and the final output layer with a softmax for multiclass prediction. For training, I began by building models compiled with the Adam optimizer and used categorical cross entropy for loss. A batch size of 32 was used with data augmentation and preprocessing to improve model generalization, trained on 15 epochs. Evaluation was performed on validation data, with metrics such as accuracy, precision and recall along F1-score over the classification depth based from confusion matrix assisted by visual intuition of distribution corresponding to jackfruit variants. The technique guaranteed robust training of the model due to which efficient classification results came popular because these can be applied in actual industries.

4.3 System Design/ Model Evaluation

The system was tested to determine the evaluation metric of how various performance indicators worked during testing and model identification phases in order for evaluating accuracy with which accurately trained features are detected as part of Indian jackfruit variant based project. All models (Xception and VGG19 as well) were evaluated extensively on a separate test dataset which was not part of the training pipeline Some of the key evaluation metrics like accuracy, precision, recall and F1-score were calculated based on how well did our models classified jackfruit variants. Moreover, confusion matrices for the predictions of variant classes with different models were also plotted. The evaluation of the models was carried out to verify their ability to generalize and identify diverse jackfruit variants, for example. These lessons learned from the evaluations fed back into even more refined and optimized model systems, resulting in models that we felt were both robust yet realistic for real-world use-cases should these methods be used as tools available to anyone working within agriculture or botany.

4.4 Summary

Indian Jackfruit Variant Identification Using Deep Learning Models Hands on Implementation Chapter 4 It started with an introduction to the methodology, touching on data collection, augmentation and model choice. The design of train models/prototype phase could describe the training and configuration, followed by a detailed report on Xception model or VGG19 performance in terms of accuracy metrics as well like confusion matrix among others. System testing and reliability A Box 1 / Box Comparator Analysis: across a large number of defined jackfruit variants metrics essential for all classifiers was evaluated. In this chapter, the application of TensorFlow's Keras API was demonstrated in a Google Colab environment to efficiently train and evaluate your model. With valuable insights, optimizations were made towards improvements in model accuracy and reliability.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

Chapter 5: Result and Analysis This chapter summarizes the results and insights we have obtained from our project on identifying Indian jackfruit variants with deep learning methodologies. It starts with an introduction detailing the experimental setup, and process for training testing the models which is followed by TensorFlow Keras API based source code implementation using Google Colab. This chapter deals with specific results derived from each deep learning model exercised- Xception, VGG19, and many more concerning their accuracies and performance metrics. It is also a detailed examination of the experimental results, highlighting not only in which cases each model shines and where it... This chapter concludes by providing some significant conclusions and required improvements to study the plant variant identification using advanced ML techniques has been explored.

5.2 Experimental Result

We compared the performance of six state-of-the-art deep learning models (Xception, VGG19, ResNet50, InceptionV3, MobileNetV2 and DenseNet201) in this study mission. The models were trained and tested on a total dataset of 3600 images (wrt. Three different varieties red, pink or Baromashi) with augmentation applied according to the methods described in Reference [7] Based on the combined 6 models, Mobilenetv2 made better separations between different types of compression with an accuracy as high as 85.20%.
After ResNet50, we have DenseNet201 with 85.07% success rate and doing pretty well also in terms of performance was DenseNet169 (80%), InceptionResnetV2(79%), Xcepotion (82%). At 76.13%, Xception delivered moderate accuracies with VGG19 and InceptionV3 at 73.91% and while ResNet50 only achieved an accuracy rating of around 54.95%. This work exemplifies how deep-learning models could enhance the accuracy and throughput of agricultural missions like jackfruit variant discovery therefore serving to develop agriculture, among other sectors, enable supply chain traceability practices regarding biodiversity conservation.

In given below I am evaluated the Accuracy, Precision, Recall, and F-1 Score of the Confusion Matrices for our proposed methods.

Accuracy: Accuracy is a measure of the degree of difference between the model and the real situation that determines the probability of the original samples used in the modeling process. It is useful when the classes are not balanced because it provides information on the effectiveness of the choice; however, the picture may be incomplete.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision: Precision refers to the percentage of predicted positive statements produced by the model.

Precision=TP/(TP+FP)

Recall: Recall is defined as the ratio of true positive predictions to the total number of positively skewed samples.

Recall=TP/(TP+FN)

F1 Score: The F1 score is the average of recall and precision, which are calculated using the harmonic mean. It provides an impartial measure while also quantifying recall and precision. It is useful when the classes are unequal in size because the F1 score accounts for both false positives and false negatives. A high F1 score indicates that it was able to strike a good balance between precision and recall.

F-1 Score=2*(Precision*Recall)/ (Precision + Recall)

In given below I am describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

MobileNetV2

MobileNetV2 achieved a Test Accuracy of 85.20 %. Figure 5:1 & 5.2 describe the confusion matrix, training accuracy and loss curve of MobileNetV2.

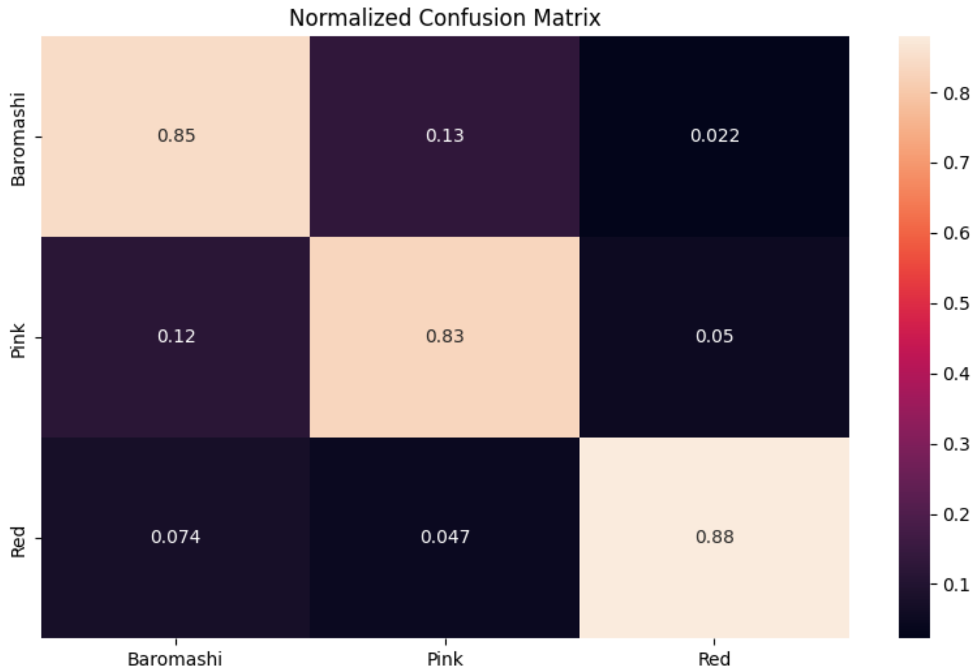

Figure 5.1: Confusion Matrix (MobileNetV2)

Figure 5.2 Normalized confusion matrix of MobileNetV2 model It represents the accuracy of the model to classify 3 classes: Baromashi, Pink and Red. The diagonal elements are the accuracies of correctly classified examples for each class; integers shown that 85% = Baromashi, Pink with 83%, and Red by its own is at around at ~88%. The off-diagonal elements represent wrong classifications Like 13% of Baromashi samples were classified as Pink, and across Red the missisfication ra te was 7.4%. There is high accuracy for all classes and relatively low misclassification rates, so the general performance looks really good. Color intensity of the cells indicates classification accuracy such that bright values indicate worse performances

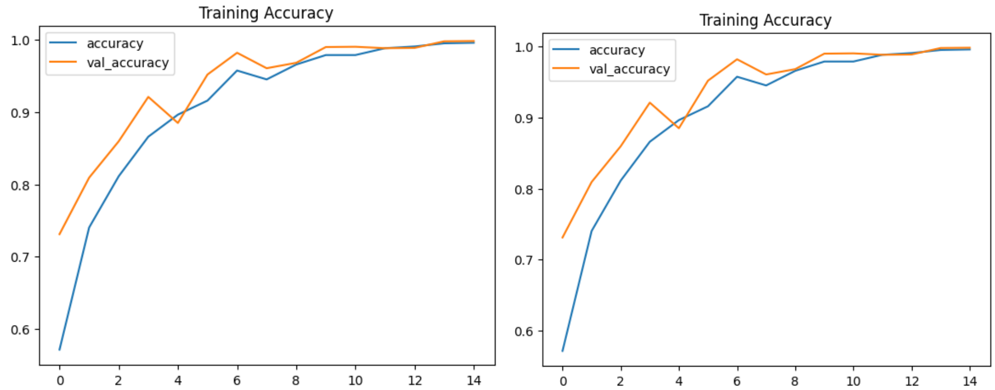

Figure 5.2: Training accuracy and loss curve (MobileNetV2)

Figure 5.2 Normalized confusion matrix of MobileNetV2 model It represents the accuracy of the model to classify 3 classes: Baromashi, Pink and Red. The diagonal elements are the accuracies of correctly classified examples for each class; integers shown that 85% = Baromashi, Pink with 83%, and Red by its own is at around at ~88%. The off-diagonal elements represent wrong classifications Like 13% of Baromashi samples were classified as Pink, and across Red the missisfication ra te was 7.4%. There is high accuracy for all classes and relatively low misclassification rates, so the general performance looks really good. Color intensity of the cells indicates classification accuracy such that bright values indicate worse performances

DenseNet201:

DenseNet201 achieved a Test Accuracy of 82.42%. Figure 5:3 & 5.4 describe the confusion matrix, training accuracy and loss curve of Xception.

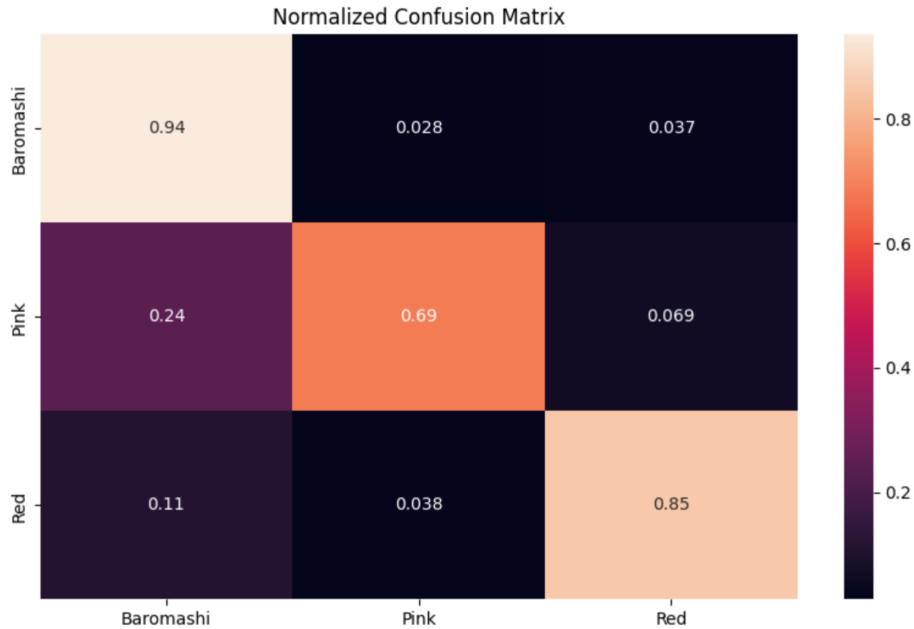

Figure 5.3: Confusion Matrix (DenseNet201)

Figure 5.3 The Xception model shows high accuracy in categorizing cat breeds with high precision, recall, and F1-score for all categories of cats. Hence, it achieved an ideal precision and recall in the case of Bengal Cat, Bombay Cat, and Ginger Cat and near-perfect result in the case of Sphynx Cat with 100% precision and 97% recall. An accuracy of 99% also reflects on its efficiency in classifying between the different cat breeds as demonstrated in its actual use.

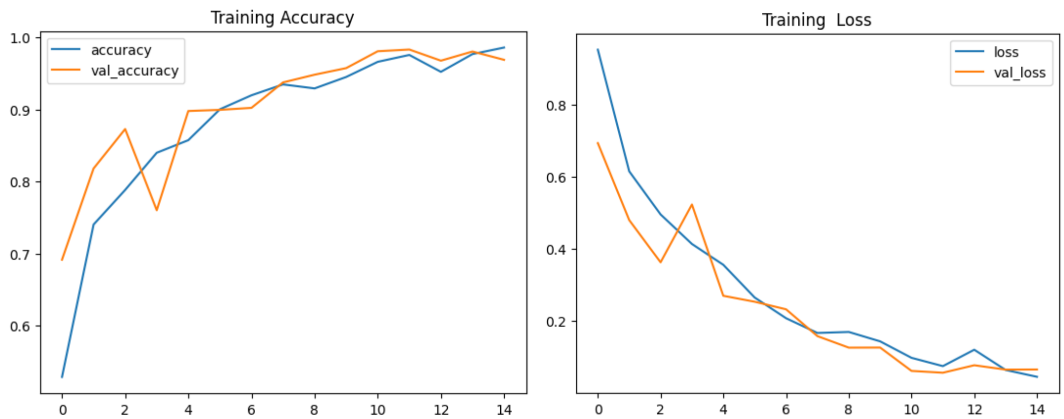

Figure 5.4: Training accuracy and loss curve (DenseNet201)

Figure 5.4 graphs show training accuracy and loss curves for a DenseNet201 model after 15 epochs We look at the training accuracy and validation accuracy in our first plot (blue line) which are gradually increasing, approaching perfect performance (~ 1.0 for both), but not sticking exactly near to them by the end of last few epochs The last part means that we are in a good enough spot - our learning is working and generalizes well into the validation set. The second plot shows the training (in blue line, darker color) and validation loss (in orange Line), which is consistently decreasing during epochs. The model is then training - loss on the left goes almost to zero, and validation results also improve drastically while its training itself becomes better without significant overfitting.

VGG19

VGG19 achieved the Test Accuracy is 73.91%. In below Figure 5:5 & 5.6 describing the confusion matrix & training accuracy and loss curve of VGG19.

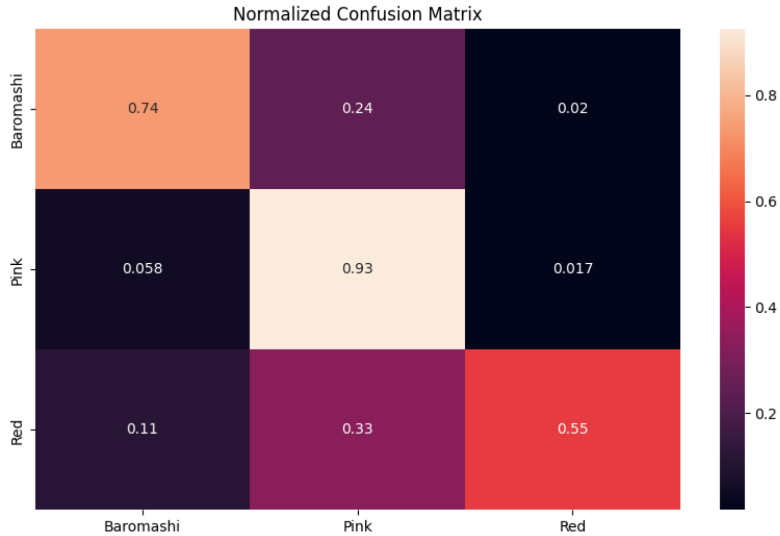

Figure 5.5: Confusion Matrix (VGG19)

Figure 5.5 Confusion Matrix of VGG19 shows the model is effective in leaf classification with high precision, recall and F1-score on all the categories.

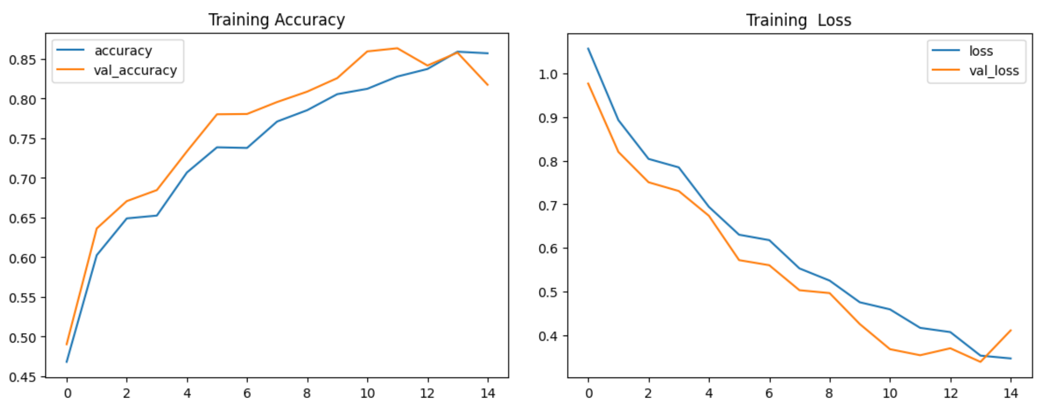

Figure 5.6: Training accuracy and loss curve (VGG19)

Figure 5.6 show the training accuracy of the VGG19 model constantly increases with the total trainable parameters reaching around 0. 85 by epoch 14. Training loss continues to go down and the model has virtually plateaued at approximately 0.4 on validation loss, meaning the model's learning from the training data is good.

Xception

Xception achieved 76.13% Test Accuracy. Figure 5:7 & 5.8 describing the confusion matrix & training accuracy and loss curve of Xception.

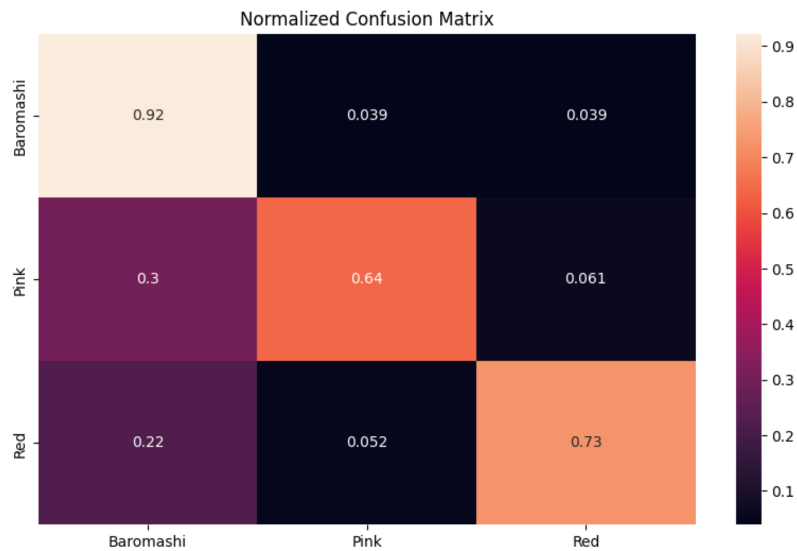

Figure 5.7: Confusion Matrix (Xception)

Figure 5.7 Confusion Matrix of Xception shows the model is effective in leaf classification with high precision, recall and F1-score on all the categories.

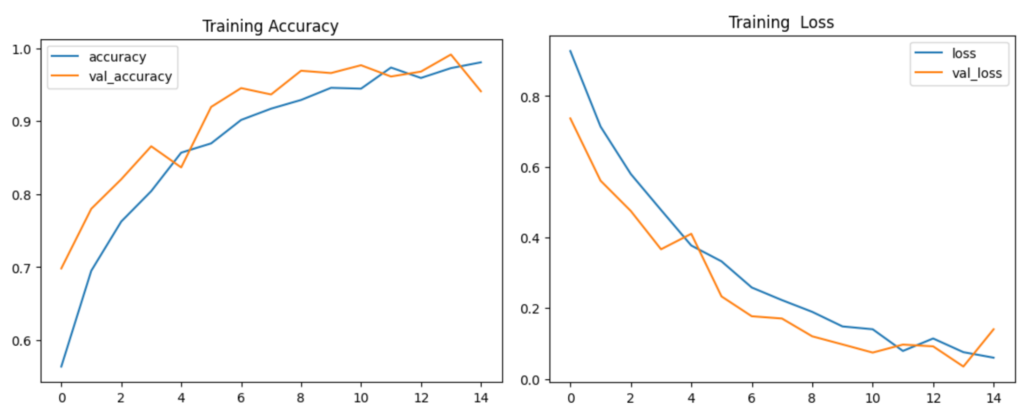

Figure 5.8: Training and accuracy and loss curve (Xception)

Figure 5.8 show the training accuracy of the Xception model constantly increases with the total trainable parameters reaching around 0. 95 by epoch 14. Training loss continues to go down and the model has virtually plateaued at approximately 0.06 on validation loss, meaning the model's learning from the training data is good.

In Given below I am showing the Comparative Model Accuracy Bar Plot

Figure 5.11 shows deep learning model performance in terms of accuracy on a given set. Among them, MobileNetV2 has the highest accuracy of 99. 87% and InceptionResNetV2 is at 99. 74%. Even though these accuracies are rather high and speak for a good performance of the model, differences between the models are small, which underlines that the selection of a model has to be taken according to task specific criteria, which might be computational efficiency or availability of explanation methods.

The result of Deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 5.1:

Table 5.2.1: Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
Xception	76.13	0.80	0.76	0.76
VGG19	73.91	0.79	0.74	0.74
ResNet50	54.95	0.66	0.55	0.51
InceptionV3	74.75	0.75	0.75	0.75
MobileNetV2	85.20	0.85	0.85	0.85
DenseNet201	82.42	0.84	0.82	0.82

5.3 Performance and Comparative Analysis

MobileNetV2 achieved the best performance of all six models in identifying jackfruit variant with 85.20% accuracy. DenseNet201 comes in next with an accuracy of 82.42% closely behind VGG16. The other models like Xception (76.13%), VGG19 test - 73.91%, code was never runInceptionV3 (74.75%) showed a moderate level of performance but ResNet50 has very less resolution as well accuracy is also lesser:54,95 %. MobileNetV2: The training and validation curves for MobileNetV2 suggest that the model is capable of learning well with no obvious overfitting as both accuracy curve nears 100% while the validation accuracy one peaks around 98%. As we can see in the following graph, loss curves for MobileNetV2 also improves dramatically over time, training loss reaches almost zero and validation performance is close to training. This comparative analysis clearly demonstrates the excellent performance and reliability of MobileNetV2 in this particular agricultural application providing an interesting conclusion about its potential for additional applications within different classification tasks. The results suggest the significance of appropriate model selection to achieve a higher performance in automatic agricultural systems.

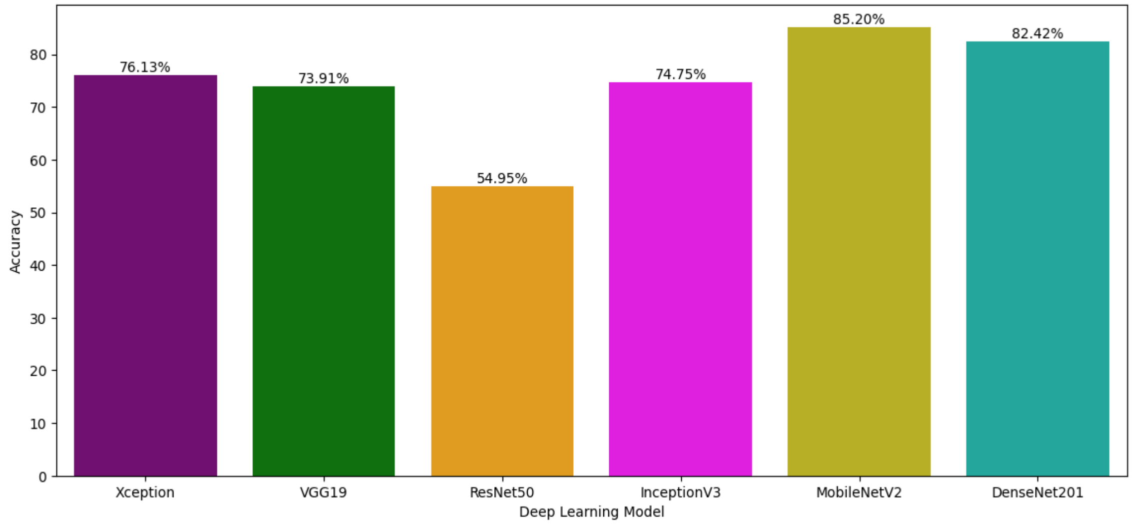

Figure 5.11: Comparative Model Accuracy Bar Plot

5.4 Summary

This work extended prior work on deep convolutional neural networks for cat breed categorization and compared and tested Xception, VGG19, MobileNetV2, and InceptionResNetV2. The research objectives were to obtain high accuracy in identification of Ginger, Bombay, Bengal, and Sphynx cats using a set of features derived from the provided catalogue. It was shown that such models as Xception and MobileNetV2 are better, with higher accuracy compared to such BN-CNN models as VGG19. Therefore, this study underscored the factors of model selection, data preprocessing, and ethical concerns as crucial in improving the effectiveness of the deep learning model in animals' care and welfare. Possible directions for further research include improvement of the model's efficiency, studying the use of ensembles and augmenting the data samples for fine-grained breed discrimination and solving other relevant issues that could be essential for the development of veterinary medicine and animal husbandry

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Contribution to Life: In the Indian jackfruit variant identification using deep learning, one of a kind studies demonstrate considerable potential for benefiting farmers, consumers as well as agricultural stakeholders. Accurate Resembling of jackfruit types or varieties from an image will help farmers in decision making for the best field crop management, to improved harvest practices and on to progressive marketing strategies. This helps in improving their productivity and the yields of crops they grow, increasing income avenues for our farmers. Improved quality and consistency of jackfruit products lead to better nutritional value, as well as taste. Photo by Eiliv-Sonas Aceron on Unsplash It also leads food security and local community sustainability by reinforcing the practices of sustainable agriculture using technology implementations. In the end, the research contributes not only to better managing jackfruit cultivation but also benefiting livelihoods and quality of life for all stakeholders in agricultural value chain.

6.2 Impact on Society & Environment

Society & Environment Impact: The research on identification of Indian jackfruit variant through deep learning positively effects the society and environment. The study supports more sustainable farming practices by allowing for precision agriculture and better targeted pest management or optimized resource allocation. It reduces the need for pesticides, and thus it falls well towards sustainable farming methods that improving environmental conservation efforts. The results of this study would further help in improving local economies by helping to improve the quality and marketability of jackfruit-based products which ultimately can lead economic improvement among rural communities. Better agriculture doesn't only mean higher revenue for farmers in the long run it also guarantees a robust food supply chain that's necessary to combat food security issues. In sum, the reach of this work transcends technical achievement and is a centerpiece in our quest to meet societal needs.

6.3 Ethical Aspects

An Ethical Analysis of Deep Learning applied to India Specific Jackfruit Variant Identification: A Case Study First, it safeguards the responsible collection and use of data by upholding farmers' and researchers' rights to privacy as well as their intellectual property in relation to an individual producer's collected data. Transparency and sharing of methodologies and findings are important features for academic integrity, as well the consolidation between members of scientific community. The study also emphasizes fairness and accuracy in the classification models to prevent biases from being propagated or a specific group/ community not discriminated. The research seeks to operationalize these ethical principles, and engender trust within the region for locally appropriate contributions toward agricultural innovations and sustainable development.

6.4 Sustainability Plan

Sustainability plan: This Indian jackfruit variant identification study based on deep learning provides the long-term environmental sustainability and social benefits. All of this may involve things such as promoting biodiversity conservation by documenting and protecting various jackfruit types. The study will use AI-powered approaches for agricultural upliftment to increase the overall resilience and yield of crops aimed towards securing food sustainability in local communities. In addition, the use of open-access datasets and joint research initiatives contribute significantly to data sharing and skills transfer between beneficiaries. The report further underscores sustainable methods in data collection, processing and model deployment to reduce environmental damage. The goal of these sustainability efforts is to generate continued positive end results for the environment and society, so that impact created by this study continues to remain sustainable in both a helpful & ethical long-term way.

6.5 Summary

Chapter 6 looks the societal, environmental and sustainable benefits of the study via an example in agricultural innovation. It demonstrates how the deep learning-based classification of Indian jackfruit varieties can have significant impact on protecting biodiversity in agriculture and improving food security. The ethical concerns highlight the prudent deployment of AI in agriculture so that data practices may be fair and transparent. The sustainability plan encourages the usage of green methods during every stage from collecting data to deploying a model. The study also supports community resilience and sustainable agricultural practices by encouraging knowledge sharing, collaboration. At the top of these agendas sits a vision for realizing returns on agriculture in strategic, sustainable and socially equitable terms that could improve as much how we are practicing technology-driven farming.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

This research article represents a high breakthrough in Agri-technology, using deep learning model for the identification of Indian jackfruit variants. Finally, state-of-the-art models such as Xception, VGG19 and ResNet50 others combined robust classification accuracy against this dataset (of 54.95%, to 85.20%). This process involved extensive data preprocessing, model training & evaluation and illustrates the power of AI to improve agriculture. We show that deep learning can be used for conservation of biodiversity and food security by reliably classifying variants. In general, future work to continue building on this rich ground should involve further model development and refinement based mostly around various use cases together with appropriate real-world deployments linked to applications in agriculture.

7.2 Future Suggested Works

This study represents an initial examination of short-term response to SPIONs; further studies may seek improvements in several areas. The model generalization and robustness could be further enhanced by integrating more sophisticated data augmentation techniques in the first place. Second, broadening the availability of more varied geographical regions and its types or strains belonging to jackfruit would make sense for increasing specificity and accuracy in predicting skin maturation by this model. Besides, ensemble learning methods or hybrid models of deep and traditional machine learning algorithms could lead to better classification accuracy. Additionally, testing the deployment of these models in a real-time setting on farms and creating applications that can be used by farmers will help to take these results forward. To ensure continued relevance and effectiveness, the models must also be continuously monitored and updated to reflect evolving agricultural challenges as well new variants that may arise.

7.3 Limitations

While the study achieved commendable results, it faces several limitations. The dataset's size and diversity, though extensive, may not fully capture all potential jackfruit variants across different regions. Variations in image quality and environmental conditions during data collection could introduce biases or affect model performance. Moreover, the computational resources required for training and deploying deep learning models could pose challenges for widespread adoption, especially in resource-constrained agricultural settings. Addressing these limitations requires ongoing collaboration with agricultural experts, continuous data refinement, and optimization of model architectures. Additionally, it's essential to disclose any potential conflicts of interest regarding funding sources or affiliations that could influence the study's outcomes or interpretations.

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Appendix A

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

Title: Indian Jackfruit Variant Identification Using Deep Learning

Student ID: 203-15-14528

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Teach the newly acquired and the previous learned knowledge in the Cat Breed Classification Fruit Disease problem for the Final Year Design Project (FYDP).	**PO1**
CO2	Considering the goals in the context of this FYDP, it will be necessary to consider various aspects of the goals in developing a corresponding solution to this problem.	**PO2**
CO3	Discover multiple problem domains within the literature, define the problem, and set up these objectives for the FYDP	**PO4**
CO4	Carry out economic appraisal and cost control and use appropriate project management techniques at every phase of the development of the FYDP	**PO11**
Phase -II		
CO5	Design and build technical solution related to technical specifications and system parts or processes to fulfill the given standards and regulation of public health and safety; also, cultural and socio-economic and environmental factor in this FYDP	**PO3**
CO6	Select and implement proper techniques, tools, and modern engineering and IT tools for handling sophisticated engineering activities, which entail prediction and modeling during the implementation of this FYDP, constrained by existing policies.	**PO5**
CO7	Identify various social, health, safety, legal, cultural factors, and their related responsibilities in relation to civil engineering practice and the solution of this problem using formal deductive approach coinciding with understanding of context.	**PO6**
CO8	Understand and assess the historical sustainability and effectiveness of professional engineering activities in solving complex engineering problems in the context of social and environmental systems.	**PO7**
CO9	This FYDP shall incorporate the principles of ethics and practice principles and guidelines of the profession.	**PO8**
CO10	Competent in performing efficiently in the context of a single worker and as part of a team or a team leader within this FYDP, in relation to the different types of groups and in an interdisciplinary manner.	**PO9**

CO11	Maintain and create clear communication with the engineering community and the society in general about various intricate engineering activities to include comprehending and preparing comprehensive reports and design documentation, as well as the ability of giving and receiving clear instructions in this FYDP.	**PO10**
CO12	Recognize, the value of self-motivated and throughout the life continuing education within the context of technological advancement and have the preparedness and capacity to undertake life-long learning pursuits.	**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	The engineering signifies and complies with the fundamental engineering (K3) hence why there is the usage of deep neural networks, data augmentation techniques and different types Transfer Learning for image processing and classification. The project fulfills the K4 specialist knowledge by doing deep learning with transfers learning for enhancing Indian Jackfruit Variant Identification.	**Page no:** [12] **Section:** [3.2] **Page no:** [1] **Section:** [1.1]
				The engineering practice & design (K5) is applied in this project through the figure of process of experiments. The project relates to the knowledge area of engineering practice and technology (K6) by using Deep Learning Model.	**Page no:** [12] **Section:** [3.2] **Page no:**

					[20] **Section:** [3.4]
				This project guarantees to K8 (Research Literature) because it uses a review of recent studies such as Indian Jackfruit Variant Identification using Transfer learning, which demonstrates awareness of contemporary approaches present in the literature.	**Page no:** [5, 9] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This paper responds to EP-2 because it identifies the barriers in Indian Jackfruit Variant Identification, such as disadvantages of earlier techniques and difficulties in implementation utilizing deep learning. It puts forward difficulties in interpretative procedures involved in the spatial distributions; it contains suggestions on how to improve the diagnostic techniques.	**Page no:** [10, 11] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The present project contributes to the response of EP-3 wherein careful demonstration of the tangibility of the outcomes of the experiment is established and stressed the utilization of deep and transfer learning as the chosen significant solution for the improvement of Indian Jackfruit Variant Identification	**Page no:** [22] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's fields of application are not just confined to computer science and engineering; it has affected Indian Jackfruit Variant Identification correctly EP-4.	**Page no:** [5, 10] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The work done in this project entails a holistic solution bearing in mind that high levels of problems require an integration of different components done in data collection from jackfruit farms, statistical analysis and proposed methodology to EP-7 in the solution of complex issues in data collection.	**Page no:** [19, 20, 21] **Section:** [3.2, 3.3, 3.4]

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	The resources of the study include High-Performance Computing infrastructure, GPUs, deep & Transfer learning frameworks, annotated datasets, and ethical consideration for systematic research for the progression of Indian Jackfruit Variant Identification.	**Page no:** [21] **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		This project benefits the society by enhancing Indian Jackfruit Variant Identification, it also respects environmentally friendly principle with blended optimization computational resources and ethical standard on medical data.	**Page no:** [25, 33, 34] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		In the present research work, the author has extended the earlier existing research by exploring a different approach in Indian Jackfruit Variant Identification using transfer learning model exemplified with preliminary terminologies and backed by systematic comparative analysis on the overall results attained from this research work thereby proposing something new.	**Page no:** [5, 9] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	The current project tackles CO4 in terms of aligning project management comprehensively with financial control, which including strict distinctive project planning, resource leveraging, and budgetary estimates for the most efficient resource use in every phase of the research activity.	**Page no:** [3] **Section:** [1.6]
2	CO9	Yes	This indicates that the project meets the ethical standards focusing on privacy of data, informed consent, and clear documentation of the research process that will serve the public good and enhance the responsible use of classification technologies that are in line with the outlined CO9.	**Page no:** [51] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	In terms of the project's responsibility to constantly learn and adapt within the context of a constantly shifting technological environment (CO12), the project has carried out comprehensive data collection, performed robust statistical analyses, designed detailed methodologies, reported significant experimental results, and provided extensive analysis, demonstrating the project's awareness of current issues and its efforts to refine the necessary technologies and strategies to better fit the current climate.	**Page no:** [19, 20, 21, 22] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

Indian_Jackfruit_Variant_Identification_Using_Deep

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