Sylhet Engineering college

(Shahjalal University of Science and Technology)

Department of Computer Science and Engineering

CSE800

Bangladeshi rice grain types classification and quality grading using computer vision

Abdullah Al Naseeh Chowdhury	**Khalilur Rahman**	**Syme Al-Azad Shuvo**
2018331501	**2018331518**	**2017331554**

Department of Computer Science and Engineering

Supervisior

Md. Abu Naser Mojumder

Assistant Professor & Head

Department of computer Science and Engineering

Sylhet Engineering College,Tilaghor,Sylhet

13 March 2024

Recommendation Letter from Thesis Supervisor

The thesis entitled "Bangladeshi rice grain types classification and quality grading using computer vision" submitted by the students:

1. Abdullah Al Naseeh Chowdhury
2. khalilur Rahman
3. Syme Al-Azad Shuvo

is a record of research work carried out under my supervision and I, hereby, approve that the report is submitted in partial fulfillment of the requirement for the award of their Bachelor's Degree

.....
(Signature of Supervisor)
Md. Abu Naser Mojumder
Professor and Head
Assistant professor & Head
Department of Computer Science and Engineering
Sylhet Engineering College,Tilaghor,Sylhet

Certificate of Acceptance of the Thesis

The thesis entitled "Bangladeshi rice grain types classification and quality grading using computer vision"

submitted by the students:

1.Abdullah Al Naseeh Chowdhury

2.Khalilur Rahman

3.Syme Al-Azad Shuvo

as part of the requirements of the course CSE-800, is being approved by the Department of Computer Science and Engineering as a partial fulfillment of the B.Sc. (Engg.) degree of the above students.

.....	.....	.....	.....
Supervisor	Internal	Internal	Internal
Md. Abu Naser Mojumder	**Nayan Kumar Nath**	**Md Lysuzzaman**	**Abdur Rouf**
Assistannt Professor & Head	Lecturer	Lecturer	Associate Professor & Principle(In Charge)
Dept. of CSE,SEC	Dept. of CSE,SEC	Dept. of CSE,SEC	Dept. of CSE,SEC

.....	.....
Chairman,Exam committe	External
Md. Abu Naser Mojumder	**Mohammad Shahidur Rahman ,Phd,SMIEEE**
Assistannt Professor & Head	Professor
Dept. of CSE,SEC	Dept. of CSE,SUST

Abstract

Rice, which is among the most widely produced grain products worldwide. The type of rice grain is essential for export and import. Therefore, it becomes necessary to distinguish rice types to avoid fraudulent labelling.This study analyzes the classification of five rice types in Bangladesh using six different models: VGG16, ResNet50, Inception, EfficientNetB7, and YOLOv5. EfficientNetB7 has the highest accuracy of 96% among the models. We used EfficientNetB7 for classification and YOLOv5 for detecting numerous rice photos. Additionally, the EfficientNetB7 model was fine-tuned to improve its performance. Our research helps to improve rice classification accuracy, which is important for agricultural practices and food security in Bangladesh. This hybrid approach combines classification and detection algorithms to provide a comprehensive solution for rice quality assessment. Additional developments and optimizations in model training and data augmentation approaches could significantly improve the accuracy and usability of the proposed methodology.

Acknowledgement

We would like to thank the Department of Computer Science and Engineering, Sylhet Engineering College, Sylhet, Bangladesh, for supporting this research.

We are very thankful to our honorable supervisor **Md. Abu Naser Mojumder** for his worthy supports and directions.

We are also very grateful to the authors and researchers for their previous works which played a very important role in our thesis.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

Contents

Abstract **i**

Acknowledgement **ii**

List of Figures **v**

List of Tables **vi**

1 Introduction **1**

1.1 Contextual Background 1

1.2 Problem Statement and Motivation 2

1.3 Research Aims and Objectives 2

1.4 Methodology 2

1.5 Contribution 3

1.6 Thesis Organization 3

2 Literature Review **5**

2.1 Traditional Approaches for Crop Classification 5

2.2 Deep Learning Algorithms for Crop Classification 6

2.3 Research Gap 8

3 Dataset **9**

3.1 Dataset 9

3.2 Data Preprocessing 10

3.2.1 Image Acquisition 10

3.2.2 Background Removal 10

3.2.3 Image Resizing 11

3.2.4 Noise Reduction 11

3.2.5 Image Enhancement 11
3.2.6 Data Labeling 11
3.2.7 Annotation Guidelines 12
3.2.8 Annotation Process 12
3.2.9 Documentation and Metadata 12
3.3 Train Test split 12
3.4 Data Augmentation 13

4 Methodology Description 14
4.1 Chapter summary 14
4.2 Applied Models 16
4.2.1 Deeplearning Model Architecture 16
4.2.2 Xception 16
4.2.3 VGG16 17
4.2.4 VGG19 18
4.2.5 ResNet50 19
4.2.6 EfficientNetB7 20
4.2.7 Yolov5 21
4.3 Experimental Setup 22
4.4 Evaluation Matrix 22
4.4.1 Confusion Matrix: 23
4.4.2 Accuracy 23
4.4.3 Precision: 23
4.4.4 Recall (Sensitivity): 23
4.4.5 F1 Score: 24
4.5 Model Selection 24
4.6 Proposed Model 25
4.6.1 Abluation study 25

5 Experimental Results and Discussion 27
5.1 Our deployed output result 30

6 Future Work and Conclusion 32

References 33

List of Figures

1.1 Overall Methodolgy 3

3.1 Five categories sample image 9

4.1 Classification methodology 15

4.2 The architecture of the deep learning model used for improving rice Classification 16

4.8 result of yolov5 model 22

5.1 Confusion matrix of EfficientB7 and Xception 27

5.2 Confusion matrix of VGG16 and VGG19 28

5.3 Resnet50 28

5.4 Multi-class ROC AUC Curve demonstrating the ideal classification performance of the EfficientNetB7 model across fice cateries rice classes using Adam optimizers 29

5.5 Multi-class ROC AUC Curve demonstrating the ideal classification performance of the Yolov5 model across fice cateries rice classes using Adam optimizers 30

List of Tables

4.1 Xception fine-tuned parameter description in summary 17
4.2 VGG16 fine-tuned parameter description in summary 18
4.3 VGG19 fine-tuned parameter description in summary 19
4.4 ResNet50's fine-tuned parameter description in summary 19
4.5 Summarized performance description of all models with loss matrix binary cross entropy 25
4.6 Summarized performance description of EfficientNetB7 models with Optimizer 26

Chapter 1

Introduction

1.1 Contextual Background

For most people worldwide, including those in Bangladesh, rice is one of the most important foods [1]. The cultivation, importation, and exportation of several types of rice have occurred worldwide. In addition, rice, or Oryza Sativa in Latin, is a great source of particles, protein amino acids, and carbohydrates. As a medicine, it can treat diabetes, decrease cholesterol, lessen cancer risk, and enhance digestion. As a result, ensuring the quality of the rice grains is one of the most crucial requirements [2]. It is estimated that around 120 countries have a total output capacity of 513 million tons of rice in 2022 [3]. Identifying rice varieties based only on eye observation is difficult as rice varieties present few visible differences, especially for people with expertise in the field. In the food sector, traditional evaluations are conducted by many operators (trained instructors) utilizing visual perception. With the advancement of technology, humans can assess the quality of food grains by analyzing images of the issues [4, 5]. Recent advancements in Machine Vision present an opportunity for agricultural companies and rice suppliers to utilize this technology as an effective solution. These innovative methods could bring significant advantages to the sector, including improved quality control, cost optimization, and streamlined supply chain management.

1.2 Problem Statement and Motivation

The rice organization in Bangladesh faces difficulties in accurately distinguishing various varieties of rice grains and evaluating their quality due to its dependence on labour-intensive inspection techniques, which are time-consuming, subjective, and sensitive to human error. The majority of the current rice grading techniques rely on personal, time-consuming visual inspections, and the operators' expertise and health have a significant influence on the classification outcomes. Regarding rice quality, machine vision may be a quicker and more objective way to assess it. This might help people verify and improve the detection findings.

The purpose of the work is to use computer vision technology to upgrade and enhance Bangladesh's rice sector, resulting in higher levels of profitability, sustainability, and productivity in the trading and production of rice.

1.3 Research Aims and Objectives

The research's goal is to develop and use a computer vision-based system that can automatically find different kinds of rice grains and rate their grade in Bangladesh.

objectives:

- To review existing state-of-art deep learning algorithms for rice classification
- To implement and optimize the performance of the chosen architectures
- To evaluate the performance of classification models using performance metrics and validate their performance with reference to the existing works.

1.4 Methodology

Our overall methodology is given below.

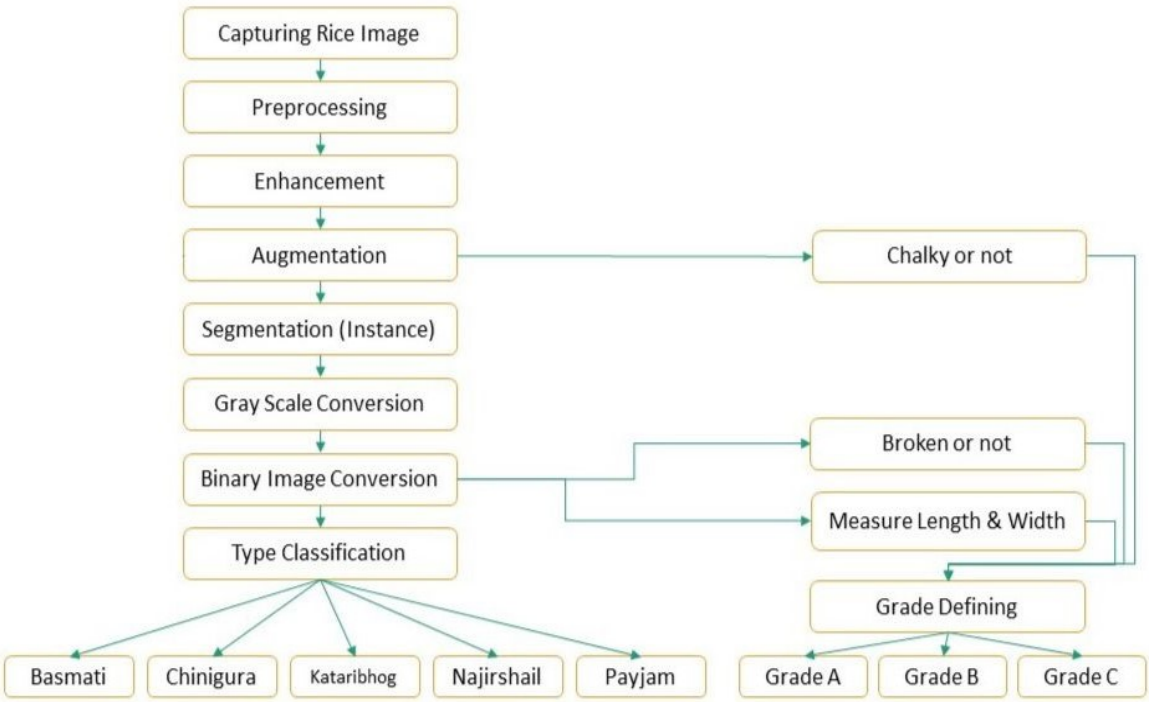


Figure 1.1: Overall Methodolgy

1.5 Contribution

Our paper makes a significant contribution to the field of rice classification using DL models. Comparison of chosen CNN architectures and finding the best performing model in the study area. To the best of our knowledge, this is the first study to examine the performance of multiple DL models, including ResNet50, Xception, VGG16, VGG19 EfficientNet, and Yolov5, on this classification task.Besides we develop unique dataset ”Riceclssify5Bd” . Through a comprehensive evaluation, we provide insights into these models’ performance and running time, which can inform future research in this area. Furthermore, our study contributes to advancing the state-of-the-art in rice classification, with implications for agricultural productivity, food logistics management, and food security.

1.6 Thesis Organization

This thesis is divided into seven chapters. Chapter 1 introduces the contextual background of the thesis, states the problem and motivation behind the work, aims and

objectives and highlights the contribution of the work. Chapter 2 reviews the related works on the existing methods for crop classification. Also, this chapter deals with the selected CNN architectures to be implemented to fulfil the objective of the study. Chapter 3 provides the theoretical background of the convolutional neural network architecture along with the baseline algorithms. Chapter 4 familiarizes the reader with the study area and presents the datasets used as input for CNN architectures. Chapter 5 presents the methodological description of the implementation, training, experimental settings and performance evaluation of chosen CNN-based classifiers for classification and yield estimation purposes. In Chapter 6, the results of the experiments are shown, interpreted and discussed. Finally, the thesis ends with the conclusion and future directions of the work in Chapter 7.

Chapter 2

Literature Review

2.1 Traditional Approaches for Crop Classification

Traditional methods for classifying crops include a range of techniques that have been widely used in agricultural fields of study. A variety of and hyperspectral technology are two examples of remote sensing methods that have proved instrumental in gathering useful data from the many light wavelengths reflected by crops [6]. Various categorization techniques and data sources have been employed in previous multi-temporal remote sensing research for crop mapping, particularly rice crop mapping. Generally speaking, there are two categories of methodologies for classifying rice crops: supervised and unsupervised categorization [7].

These traditional approaches are essential parts of decision support systems that integrate domain knowledge, machine learning algorithms, and remote sensing data to offer complete crop classification solutions and help farmers and decision-makers make wise agricultural decisions [8]. It takes a lot of time and requires adjustment when data sets change when using standard methodologies for image classification. This makes information unavailable in a timely manner, which is important for monitoring and decision-making. If sufficient training data are available, sophisticated and clever classification algorithms are also necessary to achieve high classification accuracy in addition to high-quality remote sensing data. Crop classification has seen the effective use of traditional classification techniques as SVM [9], Random Forest (RF) [10], and Decision Trees (DTL) [11–13]. Despite the fact that a lot of work has gone into classifying crops using these methods, the algorithms that extract features from raw data require extensive domain expertise and accurate analysis of features

[9][20].

2.2 Deep Learning Algorithms for Crop Classification

Farahnakian et al. [14] conducted a study employing a dataset comprising 75,000 rice images. They tested multiple deep learning architectures, including ResNet, VGG, EfficientNet, and MobileNet, achieving an exceptional accuracy of 99.67% with the EfficientNet model. Building upon this, Ibrahim et al. [15] focused on a smaller dataset of 90 testing images, exploring the classification of three rice grain types—Ponni, Basmati, and Brown rice—utilizing support vector machines (SVM) and artificial neural networks (ANN), where ANN, particularly employing the Level Sweep image transformation technique, yielded a noteworthy accuracy of 93.34%. In a separate study, Sumaryanti et al. [16] showcased varying classification accuracies for different rice varieties. Mentik Wangi achieved the highest at 96.6% and Cilosari, the lowest at 30%, indicating the diverse challenges in rice grain classification. Transitioning to spectral analysis, Chatnuntawech et al. [17] employed hyperspectral imaging to capture spatio-spectral data of rice seeds, using a modified ResNet-B deep convolutional neural network (CNN) for classification, expanding the scope of classification techniques in rice research. Furthermore, Gujjar and Siddappa [18] delved into edge detection methods for rice grain identification, applying Canny, Sobel, and Laplacian Gaussian filter techniques to enhance images and detect grain edges, highlighting the significance of preprocessing techniques in image analysis. Finally, Tasci et al. [19] utilized a dataset comprising 75,000-grain images of various rice varieties. They introduced a Lenet-5-based QNN network, achieving a remarkable classification accuracy of 99.87% at the W3A3 quantization level, demonstrating advancements in model architectures and quantization techniques for efficient rice grain classification. Building upon these diverse methodologies, Kim et al. [20] study incorporated ANN and CNN models for classifying 17 rice grain varieties, showcasing notable accuracies with modified VGG16 and ResNet50 models and emphasizing the continuous refinement and exploration of neural network architectures in rice research.

Uddin et al. [21] explored a dataset comprising 4748 rice images and tested various deep learning architectures. They achieved accuracies of 66.0%, 65.33%, 62.67%, 65.0%, 54.0%, and 52.0% with models such as SIFT-SVM, HOG-LR, SIFT-LR, HOG-

KNN, and SIFT-KNN, respectively. The highest prediction accuracies were obtained with RiceNet (94%), InceptionV3 (84%), and ResNetInceptionV2 (81.333%).

Xiong et al. [22] analyzed 10575 rice images to detect chalky and broken rice kernels. Using a support vector machine (SVM) classifier, they achieved recognition accuracies of 99.3% for broken kernels, 96.3% for chalkiness, and 93.6% for damaged and spotted areas. Koklu et al. [23] investigated the classification of five different rice varieties: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. They utilized a dataset of 75,000 grain images, achieving classification accuracies of 99.87% for ANN, 99.95% for DNN, and 100% for CNN. Chen et al. [24] examined a dataset of 40,000 rice grains comprising three varieties: medium-grain Japonica rice, round-grain Glutinous rice, and long-grain Indica rice. Their convolutional neural network detectors achieved an overall average accuracy of 99.52%.

Trivedi et al. [25] focused on a dataset of 7424 rice grain images encompassing five types of rice often grown in Turkey: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. They achieved classification success rates of 99.7% using VGG16 CNN with logistic regression classifier. Qadri et al. [26] investigated the classification of six Asian rice varieties using a dataset of 10,800 grain samples. They deployed five MV classifiers and achieved classification accuracies of 97.4%, 97.0%, 96.3%, 95.74%, and 95.2% with LMT Tree, Meta Classifier via Regression, Meta Bagging, Tree J48, and Meta Attribute Select Classifier, respectively. The highest overall accuracy observed was 97.4% with LMT-Tree.

Tin et al. [27] investigated a dataset containing 76 rice images representing five types of rice grains in Myanmar: Pawan Hmwe, Lone Thwe Hmwe, Ayeyarmin, Kauk-Nyinn-Thwe, and Kauk-Nyinn-Pu. They developed a machine learning model that achieved an 80% accuracy rate for Myanmar rice samples using extracted features. Biren Arora et al. [28] demonstrated techniques for classifying surti kolam, idli rice, long-grain basmati, and boiled rice. Their classification algorithms included Logistic Regression, Decision Tree Classifier, K-Neighbor Classifier, Linear Discriminant Analysis, and Random Forest Classifier. Logistic regression achieved the highest overall accuracy of 96Ghulam Gilanie et al. [29] analyzed a dataset comprising 1000 rice grains, including varieties like Basmati 2000, Chenab basmati, KSK 133, Kissan basmati, KSK 434, PK 1121 aromatic, and Punjab basmati, commonly cultivated in Pakistan. They designed a new convolutional neural network (CNN) model with 18

layers for rice seed classification, achieving 100% accuracy.

2.3 Research Gap

There is no information on the various strains of rice grown in Bangladesh as a result of the lack of previous research on rice varieties in the country. Similar to this, the analysis of rice datasets has not yet made use of the state-of-the-art convolutional neural network architecture EfficientNetB7, demonstrating the need for contemporary methods in agricultural research. Moreover, there has never been any research done on the combination of quality grading and categorization in rice assessment, therefore this is a new field to examine. By filling in these gaps, researchers will be able to better understand the different strains of rice that are grown in Bangladesh, increase the effectiveness of analyzing rice datasets with the use of cutting-edge neural network architectures such as EfficientNetB7, and create all-encompassing techniques for simultaneously quality grading and classification. These initiatives could result in important breakthroughs in agricultural research, which would benefit farmers and consumers alike.

Chapter 3

Dataset

3.1 Dataset

For any research work, the dataset plays the most vital role, and it is so challenging to collect suitable data for corresponding works. Our dataset is a comprehensive collection of images aimed at facilitating research in the field of rice grain classification and quality assessment. This dataset is specifically tailored to the unique varieties of rice prevalent in Bangladesh, focusing on five distinct types: Payjam, Najirshail, Jirashail, Chinigura, and Basmati which have been collected from local market.Our sample image is given bellow figure 3.1

Figure 3.1: Five categories sample image

Additionally, the dataset includes images of broken and chalky rice to support quality grading endeavors.

Rice grain is a delicate object, and it's a subtly difficult job to capture a detailed image of rice grain. So, for capturing first, we have used a camera device containing macro lenses to emphasize the rice grain structure. Because the color of rice grain is nearly white, we have used a black background beneath the rice grain and a precise lighting condition to capture rice grain images with a detailed texture. There is a

portion of our research dedicated to grading the quality of the rice grain. For this, we need to measure the height and width of the rice grains through the captured image. Since the computer was programmed to measure this by pixel count, we needed to build a platform by which we could capture all images from a specific distance to assess measurement. And that's how we gather a suitable dataset.

This comprehensive dataset serves as a catalyst for innovation across diverse domains, enabling researchers and practitioners to:

- Develop and fine-tune classification algorithms adept at discerning various rice grain types prevalent in Bangladesh.
- Pioneering novel methodologies for quality grading systems, leveraging visual attributes such as broken and chalky grains.
- Expanding the horizons of image augmentation and data preprocessing techniques, particularly within agricultural datasets.

3.2 Data Preprocessing

The data preprocessing steps aim to enhance the quality and suitability of the input images for subsequent classification tasks. In this section, we outline the data preprocessing pipeline adopted in our research.

3.2.1 Image Acquisition

Initially, high-resolution images of Bangladeshi rice grains were acquired using suitable imaging equipment. These images serve as the raw input data for our classification model.

3.2.2 Background Removal

To isolate the rice grains and minimize the influence of background elements, we employed background removal techniques. This step involves segmenting the rice grains from their surroundings using algorithms such as chroma keying or image segmentation based on color thresholds.

3.2.3 Image Resizing

The original images, often captured at high resolutions such as 1980x1980 pixels, were resized to a standardized dimension of 300x300 pixels. Resizing the images not only reduces computational complexity but also ensures uniformity in the input data size across all samples.

3.2.4 Noise Reduction

Images captured under varying conditions may contain noise, which can distort features crucial for classification. In our preprocessing pipeline, we employed salt-pepper noise reduction techniques to mitigate the impact of noise on image quality. This process involves the application of filters or algorithms designed to suppress noise while preserving important features of the rice grains.

3.2.5 Image Enhancement

Enhancing the quality of the images is vital for extracting meaningful features during the classification process. We utilized image enhancement techniques to improve the clarity, contrast, and overall visual appearance of the rice grain images. Enhancement algorithms adjust brightness, contrast, and sharpness to highlight relevant details and textures present in the grains. By meticulously executing these preprocessing steps, we ensure that the input data is optimized for subsequent classification and grading tasks. The preprocessed images serve as the foundation for feature extraction and model training, facilitating the development of robust and accurate classification models tailored to Bangladeshi rice varieties.

3.2.6 Data Labeling

In the process of developing a robust classification system for Bangladeshi rice grains and quality grading, accurate data labeling is essential to establish ground truth annotations for model training and evaluation. In collaboration with experts from Sylhet Agriculture University, a meticulous data labeling procedure was devised to ensure the integrity and relevance of the labeled dataset. This section outlines the data labeling methodology employed in our research:

Expert Consultation: To ensure precision and consistency in labeling, we engaged experts specializing in rice grain taxonomy and quality assessment from Sylhet Agriculture University. These experts possess in-depth knowledge of Bangladeshi rice varieties and are adept at discerning subtle characteristics indicative of grain quality.

3.2.7 Annotation Guidelines

: Comprehensive annotation guidelines were developed in consultation with the domain experts to define the criteria for classifying rice grains and assigning quality grades. These guidelines encompassed various attributes such as grain size, shape, color, texture, and any visible defects or anomalies.

3.2.8 Annotation Process

: The labeling process involved meticulously examining each preprocessed image and assigning appropriate labels based on the established guidelines. Experts scrutinized the images to identify distinctive features and characteristics indicative of specific rice varieties and quality grades.

3.2.9 Documentation and Metadata

Detailed documentation of the labeling process, including metadata such as sample identifiers, labels, and associated attributes, was maintained to facilitate traceability and reproducibility of the dataset. By adhering to rigorous labeling standards and leveraging the expertise of domain specialists, we established a meticulously annotated dataset tailored to the classification of Bangladeshi rice grains and quality grading. The labeled dataset serves as a valuable resource for training and evaluating machine learning models, enabling accurate and reliable classification outcomes essential for agricultural research and quality assessment initiatives.

3.3 Train Test split

We have collected a total of 12,500 images of five types of rice for classification. Each type contains a dataset of 2500 images. Along with these, we have also collected 500 images of broken rice and 500 images of chalky rice for our quality grading process.

To ensure the integrity and reliability of model training and evaluation, the dataset was meticulously partitioned into three subsets: Train Data: 80% of the dataset (10,000 images) Validation Data: 10% of the dataset (1,250 images) Test Data: 10% of the dataset (1,250 images)

3.4 Data Augmentation

Augmenting the training data was paramount to enhancing its diversity and robustness. Employing cutting-edge techniques, the original 10,000 images were expanded into a vast repository of 30,000 augmented images. This augmentation process imbued the dataset with a wealth of variations in perspectives, orientations, and lighting conditions, ensuring the trained models' resilience and adaptability.

Our dataset serves as a valuable resource for advancing research and innovation in rice cultivation, processing, and quality control. By providing a standardized and comprehensive collection of images, this dataset empowers researchers to develop robust solutions that address the unique challenges of rice grain classification and quality assessment in the context of Bangladesh's agricultural landscape.

Chapter 4

Methodology Description

4.1 Chapter summary

This chapter covers the essential section followed to accomplish the study. The 'Data Collection' section includes a detailed explanation of the dataset. Furthermore, the data set's provenance has been thoroughly analyzed. The 'Data Preprocessing' section describes how several picture preparation procedures were used to improve the dataset's overall image quality. In the 'Train Test Split' section, the dataset is partitioned into train and test sets for the experiment. In the 'Data Augmentation' section, data augmentation was implemented to prevent model overfitting. The 'Applied Model' section includes six unique models used to analyze the dataset. After assessing all models in the 'Select Best Model' area, we decided on the one with the best overall performance. Finally, In the "Proposed Model" Section, we analyzed the model by using different kinds of evaluation matrices such as Precision, Recall, F1-score, and Accuracy.

our overall methodology :

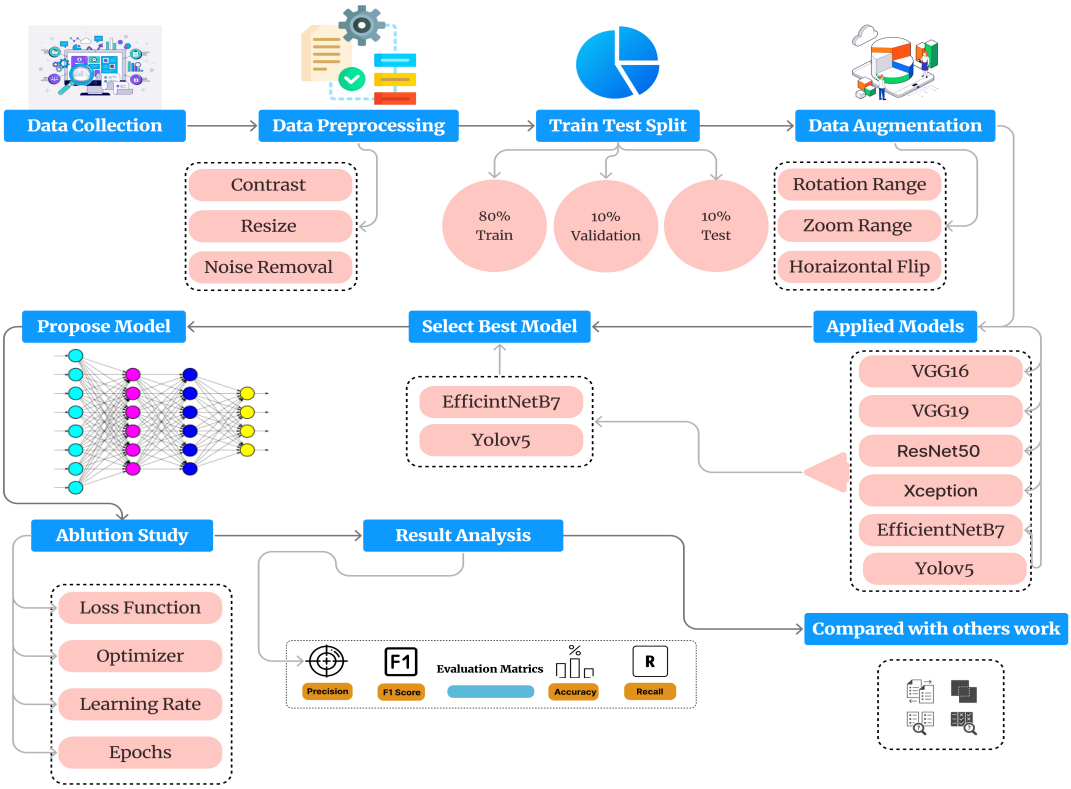


Figure 4.1: Classification methodology

4.2 Applied Models

4.2.1 Deeplearning Model Architecture

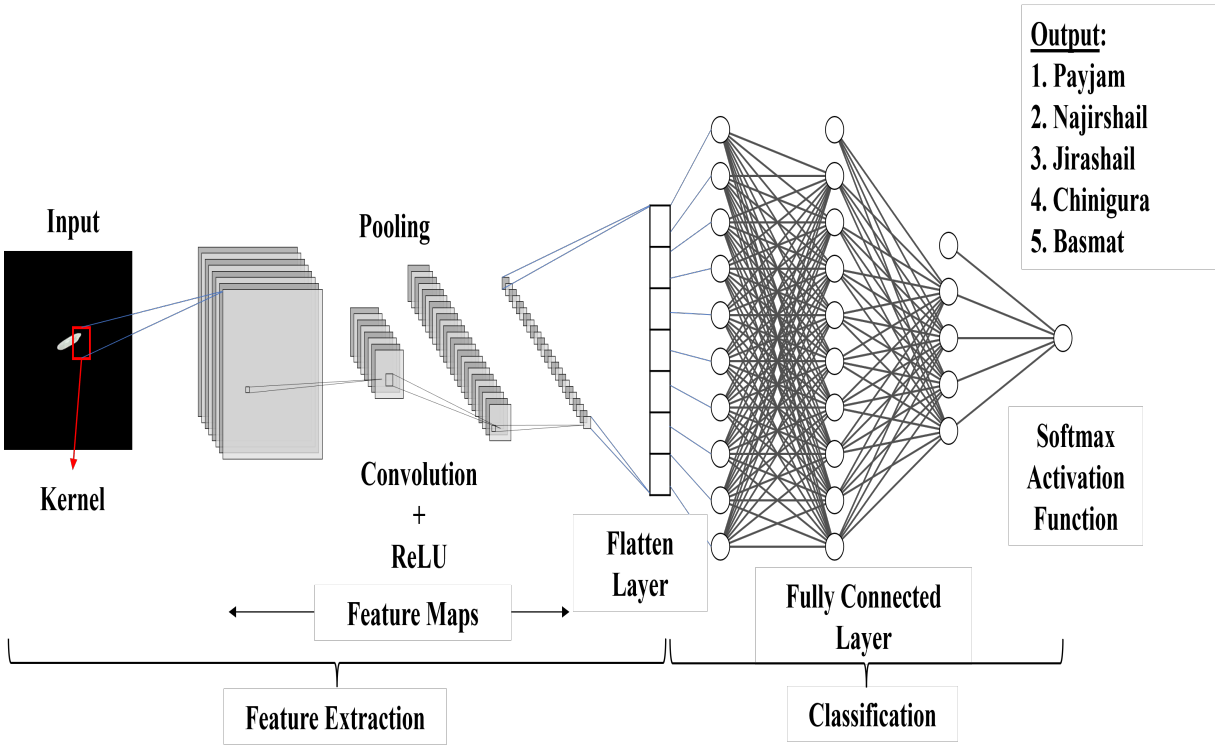


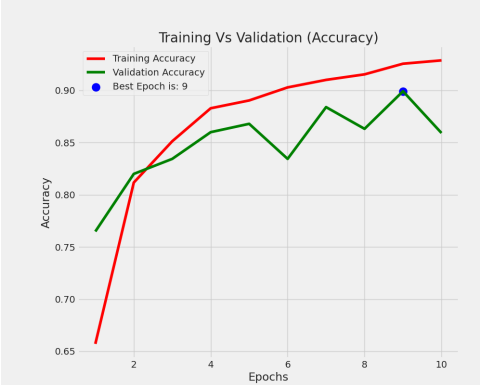
Figure 4.2: The architecture of the deep learning model used for improving rice Classification

4.2.2 Xception

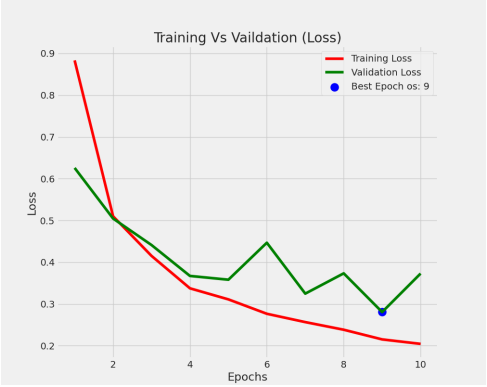
Deep convolutional neural networks (CNNs) like the Xception model architecture are made specifically for image categorization applications. It uses depthwise separable convolutions to minimize computational complexity without reducing model performance, thus being an extreme version of inception modules. By separating the spatial and channel-wise information, Xception, in contrast to conventional CNNs, enables more effective feature extraction. This design includes of max-pooling layers after repeated convolutional blocks, which result in fully linked layers for classification [30].

Name	Description
Loss	categorical-crossentropy
Optimizer	Adam
Learning Rate	0.001
epochs	10

Table 4.1: Xception fine-tuned parameter description in summary



(a) Accuracy graph of Xception



(b) Loss graph of Xception

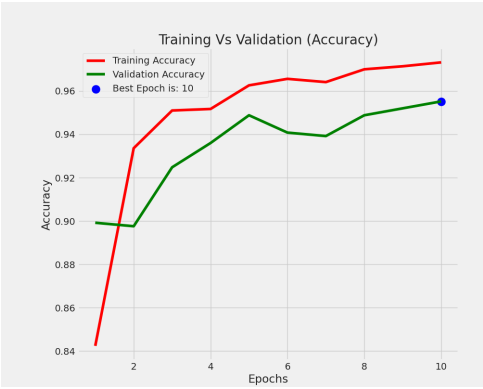
Figures 4.3a and 4.3b show, respectively, accuracy and loss of Xception.

4.2.3 VGG16

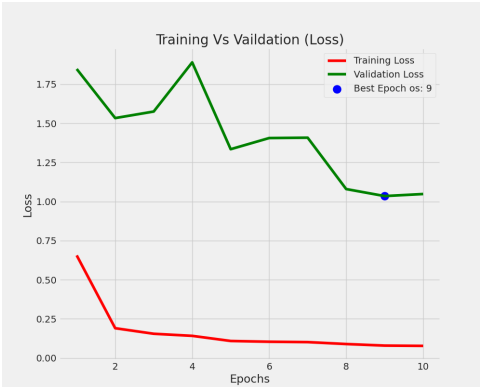
A convolutional neural network with 16 layers is called VGG16.VGG16 is avconvolutional neural network models designed for image classification tasks. VGG stands for Visual Geometry Group. They are architecturally identical (16 layers). Throughout the network, both models employ simple 3x3 convolutional filters to learn a hierarchical representation of the input picture. The last fully connected layers provide the final outputs, which are probability distributions over the many classes of objects recognized by the network [31].The tables that follow provide further details and additional information about these revisions. Table 14's data reveals that the VGG16 model's initial loss function was categorical-crossentropy. Adam was designated as the optimizer, and the learning rate was set to 0.001. The epochs were set by the number 10.Adam as the optimizer, and a learning rate of 0.001 were then added to the VGG16 model. The epoch was determined to be 10 as shown in Table 15

Name	Description
Loss	categorical-crossentropy
Optimizer	Adam
Learning Rate	0.001
epochs	10

Table 4.2: VGG16 fine-tuned parameter description in summary



(a) Accuracy graph of VGG16



(b) Loss graph of VGG16

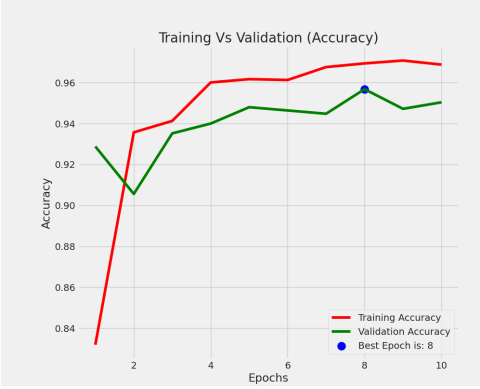
Figures 4.4a and 4.4b show, respectively, accuracy and loss of VGG16.

4.2.4 VGG19

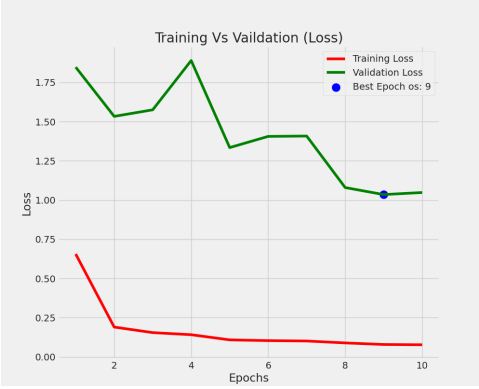
A convolutional neural network with 19 layers is called VGG19.VGG19 is avconvolutional neural network models designed for image classification tasks. VGG stands for Visual Geometry Group. They are architecturally identical (19 layers). Throughout the network, both models employ simple 3x3 convolutional filters to learn a hierarchical representation of the input picture. The last fully connected layers provide the final outputs, which are probability distributions over the many classes of objects recognized by the network [31].The tables that follow provide further details and additional information about these revisions. Table 14's data reveals that the VGG19 model's initial loss function was categorical-crossentropy. Adam was designated as the optimizer, and the learning rate was set to 0.001. The epochs were set by the number 10. The Binarycrossentropy loss function with Adam as the optimizer, and a learning rate of 0.001 were then added to the VGG19 model. The epoch was determined to be 10 as shown in Table 15

Name	Description
Loss	categorical-crossentropy
Optimizer	Adam
Learning Rate	0.001
epochs	10

Table 4.3: VGG19 fine-tuned parameter description in summary



(a) Accuracy graph of VGG19



(b) Loss graph of VGG19

Figures 4.5a and 4.5b show, respectively, accuracy and loss of VGG19.

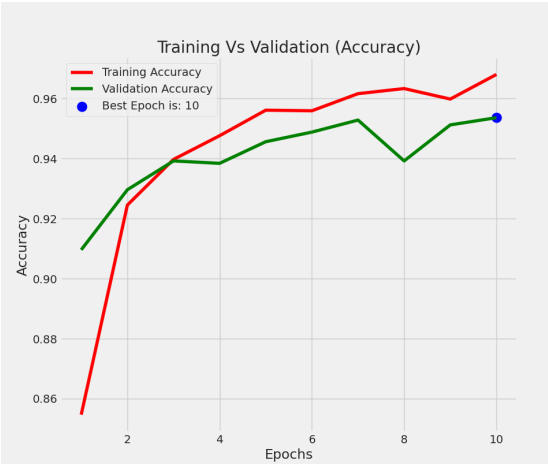
4.2.5 ResNet50

A 50-layer version of the ResNet model architecture is called ResNet50. It is a deep neural network for several computer vision tasks like object recognition, semantic segmentation, and picture classification.The pre-trained network can categorize images into thousands of distinct object categories [32]. Brief descriptions of the parameters for binary cross entropy is given in Tables 4.4. The tables that follow provide further details and other information about these changes. Table 4.4 data revels that the loss function for the ResNet50 model was categorical-crossentropy.The optimizer job was given to Adam,and the learning rate was set to 0.001. The number of 10 was selected as the epoch.

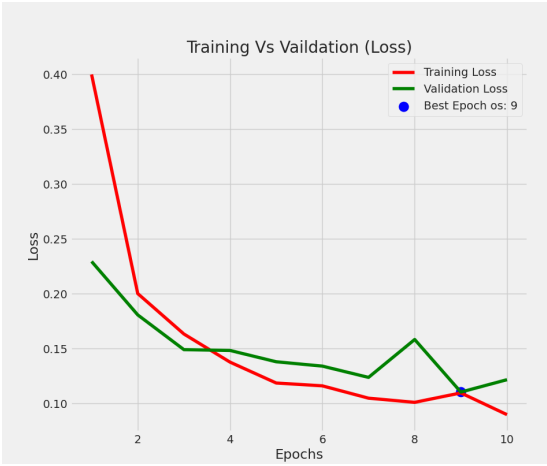
Name	Description
Loss	categorical-crossentropy
Optimizer	Adam
Learning Rate	0.001
epochs	10

Table 4.4: ResNet50's fine-tuned parameter description in summary

Figures 4.6a and 4.6b show, respectively, accuracy and loss of Resnet 50.



(a) Accuracy graph of ResNet50

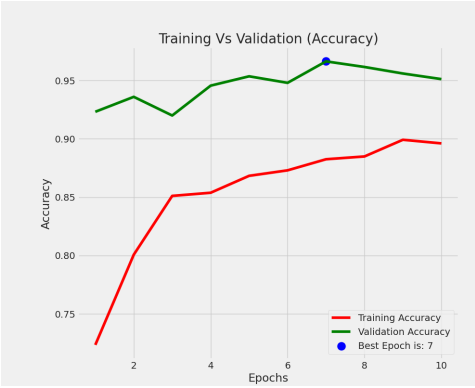


(b) Loss graph of ResNet50

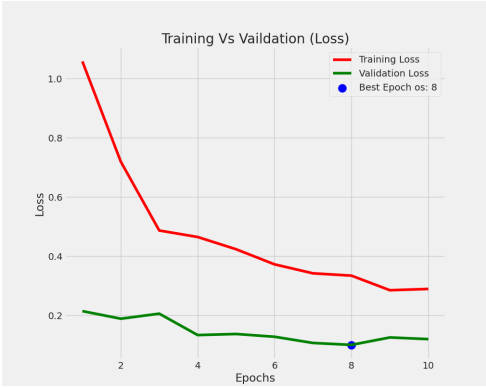
4.2.6 EfficientNetB7

The method for convolutional neural network building and scaling is referred to as EfficientNet [33]. EfficientNet is a CNN design that aims to attain cutting-edge performance while ensuring efficiency in computing resources. Tan and Lee [34] introduced a proposal that utilizes a compound scaling mechanism to scale the network's depth, breadth, and resolution equally. The fundamental concept underlying EfficientNet is carefully scaling up the network to achieve a balanced compromise between model size and accuracy.This study's dataset was split into five categories. using a modern pre-trained version of the neural network. In Tables **??** the settings for binary cross entropy . The tables that follow include further information and specifics about these adjustments.The number of 10 was selected as the epoch.

Name	Description
Loss	categorical-crossentropy
Optimizer	Adam
Learning Rate	0.001
epochs	10



(a) Accuracy graph of EfficientNetB7



(b) Loss graph of EfficientNetB7

Figures 4.7a and 4.7b show, respectively, accuracy and loss of EfficietNetB7.

4.2.7 Yolov5

Ultralytics created YOLOv5, an improved algorithm for object identification and classification. The focus is on a convolutional neural network that scans an image in a single pass, producing predicted class labels and bounding boxes for each object. The architecture includes a backbone network to extract visual information and a detection head for object recognition and classification. YOLOv5 enhances accuracy and speed using techniques like multi-scale training, data augmentation, and anchor box clustering. Multiscale training enables the network to detect objects at various image sizes. Data augmentation creates new training images using modifications such as rotation and scaling. Anchor box clustering joins related objects to generate more appropriate anchor boxes based on their size and form distribution.

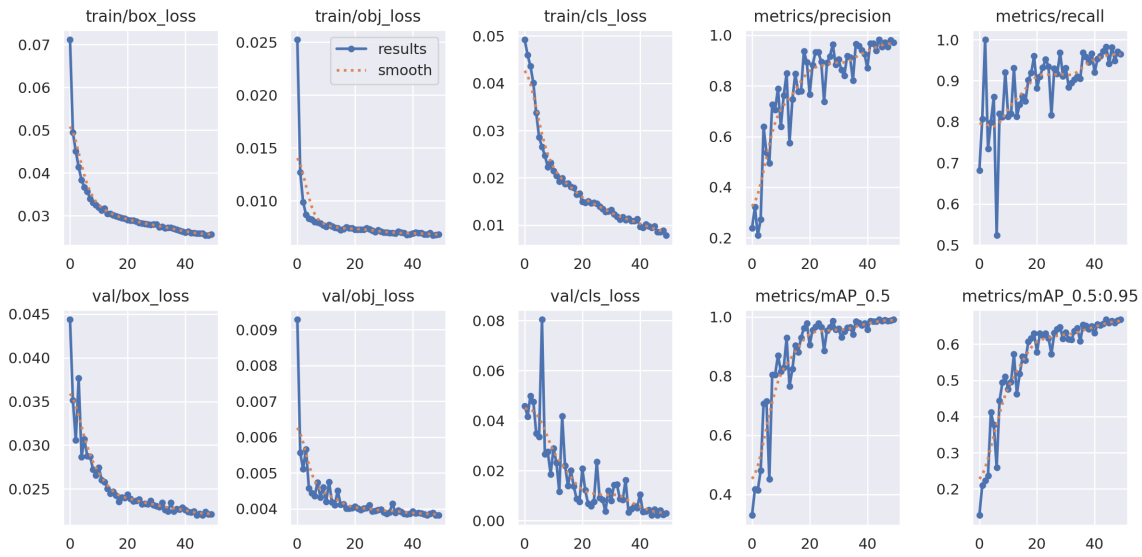


Figure 4.8: result of yolov5 model

4.3 Experimental Setup

The experimental setup for training deep learning models is crucial as it impacts the performance and the efficiency of the training process. Our experimental configuration (both Hardware and software configurations) is as follows: Our experimental setup for running the machine learning program was configured on Kaggle, an online platform that provides access to computational environments for data science and machine learning. We utilized a GPU-accelerated environment powered by a Nvidia Tesla P100 GPU, which significantly speeds up the training process. The programming was conducted in Python, chosen for its extensive support and libraries in the data science domain. For the implementation of the machine learning pipeline, we leveraged Scikit-learn, a versatile Python library that offers efficient tools for data mining and data analysis, including functionalities for preprocessing data, implementing various machine learning algorithms, and evaluating model performance.

4.4 Evaluation Matrix

Evaluation metrics are quantitative indicators utilized to evaluate the performance of DL and ML algorithms. In the following section, I will explain some standard evaluation metrics used for classification problems employing mathematical expressions.

4.4.1 Confusion Matrix:

The confusion matrix is a tabular representation that facilitates the observation of an algorithm's performance. Ordinarily, it consists of two dimensions—"Actual" and "Predicted"—with "Positive" and "Negative" values in each. True positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are contained in this matrix. It is highly beneficial for conducting an exhaustive assessment of the performance of a classification model and gaining insight into the various types of errors it generates.

4.4.2 Accuracy

Accuracy is a metric that quantifies the ratio of accurate predictions (both true positives and true negatives) to the total number of predictions. Accuracy can be defined as

$$Accuracy = \frac{\sum_{i=1}^{k} \text{Correction prediction}_i}{N}$$

4.4.3 Precision:

The precision metric quantifies the percentage of accurate positive predictions among all the positive predictions generated by the model. High precision indicates a low rate of false positives. Mathematically,

$$Precision = \frac{TP}{TP + FP}$$

Where TP is True Positives and FP is False Positives.

4.4.4 Recall (Sensitivity):

Recall quantifies the model's capability to accurately detect and identify all relevant instances. A high recall indicates that the model accurately identifies most of the true positives. Mathematically,

$$Recall = \frac{TP}{TP + FN}$$

Where FN is the False Negatives.

4.4.5 F1 Score:

The harmonic mean of precision and recall constitutes the F1-Score. It achieves a harmonious equilibrium between recall and precision by incorporating false positives and negatives into a single metric. The maximum value of an F1-Score (perfect precision and recall) is 1, and the minimum value is 0. Mathematically,

$$F1 = 2 * \frac{Precision * Recall}{Precison + Recall}$$

Accuracy in terms of multi-class classification is calculated as the ratio of correct predictions (true positives and true negatives) to the total number of predictions, regardless of the class.In comparison, precision, recall, and F1 are considered in the form of weighted averages for multi-class classification.Weighted averaging gives each class a weight based on its proportion in the dataset. To obtain weighted metrics, the precision, recall, and F1 score for each class are multiplied by their corresponding weights, and the results are then totaled and divided by the total weight. This method accounts for the dataset's class imbalance.

4.5 Model Selection

When utilizing the categorical cross-entropy loss matrix, the performance metrics of the EfficientNetB7 model reached optimal scores across all categories, achieving accuracy, precision, recall, and f1 score for five categories of rice. Additionally, VGG16 model achieved 95%,VGG19 is 94% accuracy, precision, recall and f1 score. The ResNet model also achieved 93% accuracy. On the other hand, Xception model achieved the lowest accuracy, precision, recall and f1 score for five categories rice. According to Table 3.8, EfficientNetB7 model outperforms all other models with accuracy, precision, recall and f1 score.

Model Name	Accuracy	Precision	Recall	F1 score
VGG16	95%	95%	95%	95%
VGG19	94%	94%	94%	94%
ResNet50	93%	93%	92%	93%
Xception	89%	89%	89%	89%
EfficientNetB7	**96%**	**96%**	**96%**	**96%**

Table 4.5: Summarized performance description of all models with loss matrix binary cross entropy

4.6 Proposed Model

4.6.1 Abluation study

The ablution study explores the impact of different optimization algorithms and epochs on the accuracy of a model. Three optimizers, namely Adam, SGD, and RMSprop, were compared over 10 and 15 epochs. Among these, the Adam optimizer yielded the highest accuracy of 94% when trained with a learning rate of 0.001 over 15 epochs.

The study demonstrates the significance of optimization algorithms in training deep learning models. Adam, known for its adaptive learning rate, outperformed SGD and RMSprop in terms of convergence speed and final accuracy. Additionally, extending the training duration to 15 epochs resulted in improved performance, particularly with Adam.

These findings underscore the importance of selecting appropriate optimization techniques and training durations to achieve optimal model performance. Further experimentation and analysis could delve deeper into the intricacies of optimization algorithms and their interactions with other hyperparameters to enhance model training and performance in various domains.

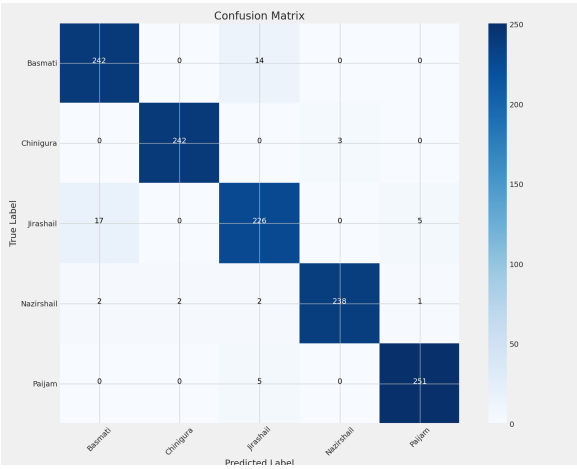
Optimizer	Learning Rate	Epochs	Accuracy	Loss
Adam	0.001	10	96%	10%
	0.01	10	94%	16%
Adam	0.001	15	94%	19%
	0.01	15	94%	17%
SGD	0.001	10	93%	17%
	0.01	10	93%	17%
SGD	0.001	15	92%	15%
	0.01	15	93%	17%
RMSprop	0.001	10	87%	34%
	0.01	10	88%	20%
RMSprop	0.001	15	88%	25%
	0.01	15	89%	26%

Table 4.6: Summarized performance description of EfficientNetB7 models with Optimizer

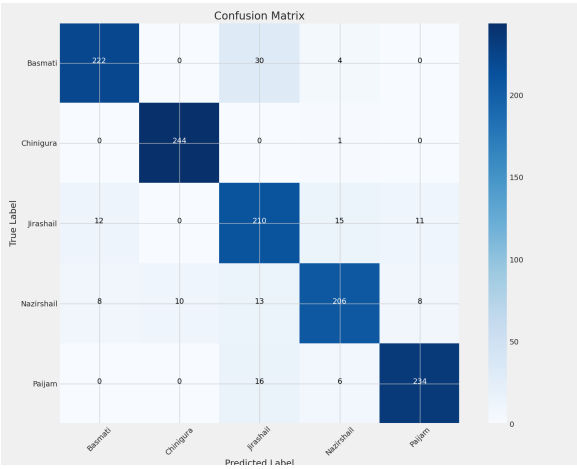
Chapter 5

Experimental Results and Discussion

The confusion matrix for five of the models that we used to categorize the rice grains is depicted in the pictures that follow. The confusion matrix produced by EfficientNetB7 is displayed in Figure 5.1a. The Xception-generated confusion matrix is displayed in Figure5.1b. Figure 5.2a displays the confusion matrix that VGG16 produced.Figure 5.2b displays the confusion matrix that was produced using VGG19.The confusion matrix produced by ResNet50 is displayed in Figure **??**. We can determine that EfficientNetB7 is the optimal model for our dataset in terms of accuracy based on the matrices that are displayed above.

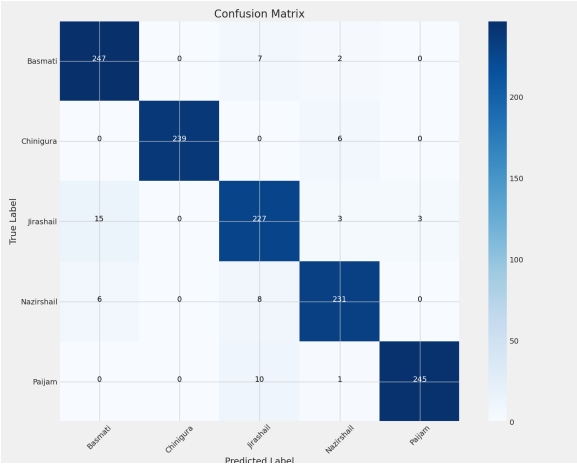


(a) EfficientNetB7

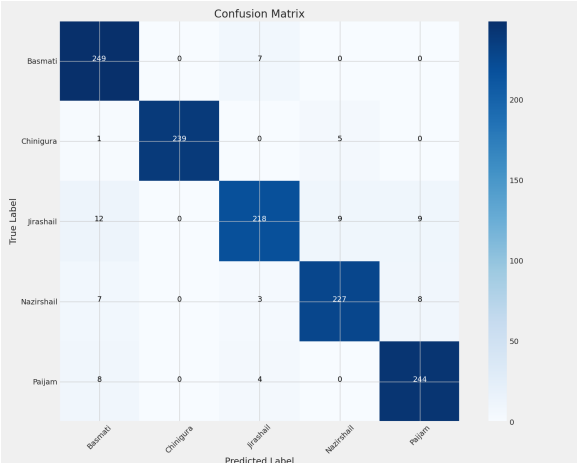


(b) Xception

Figure 5.1: Confusion matrix of EfficientB7 and Xception



(a) VGG16



(b) VGG19

Figure 5.2: Confusion matrix of VGG16 and VGG19

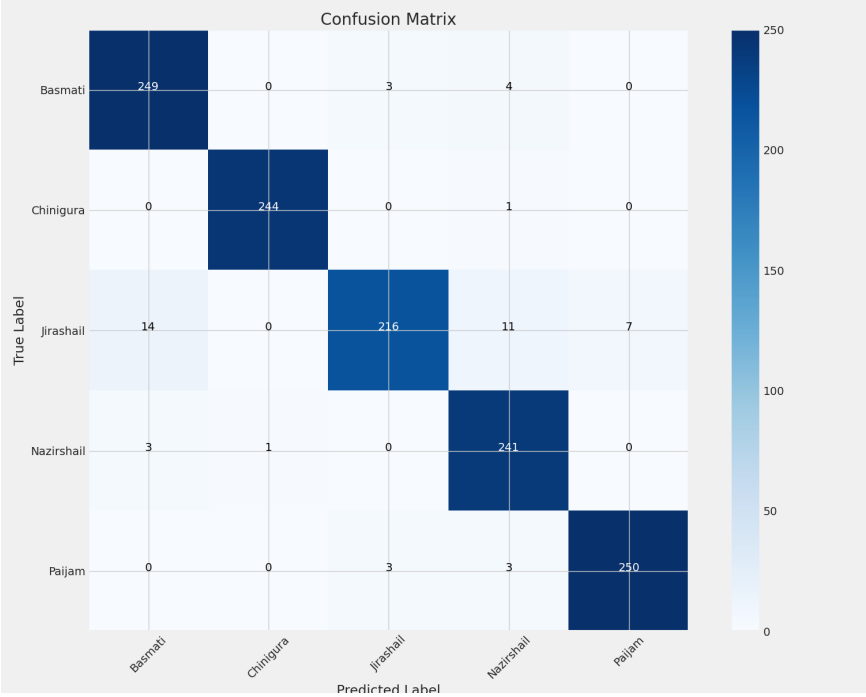


Figure 5.3: Resnet50

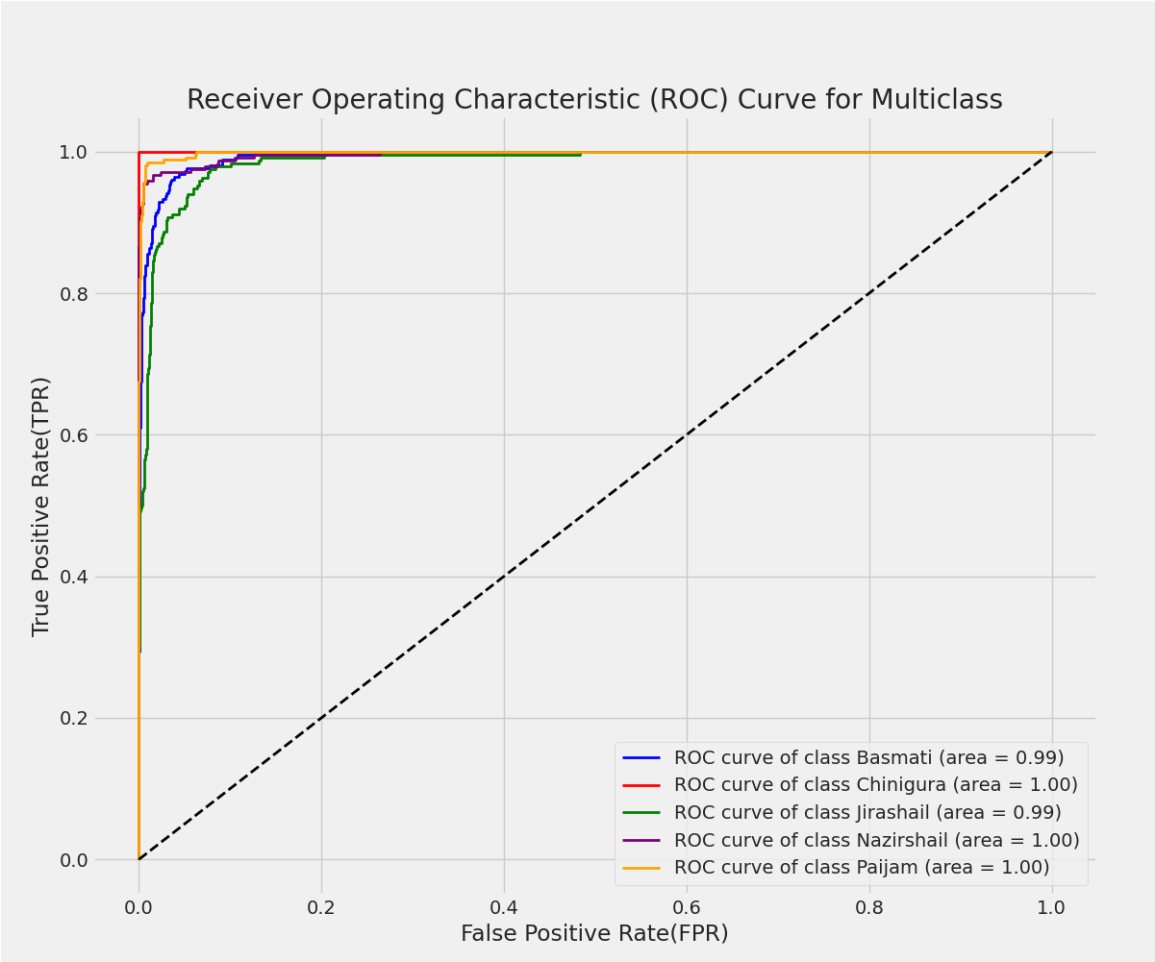


Figure 5.4: Multi-class ROC AUC Curve demonstrating the ideal classification performance of the EfficientNetB7 model across fice cateries rice classes using Adam optimizers

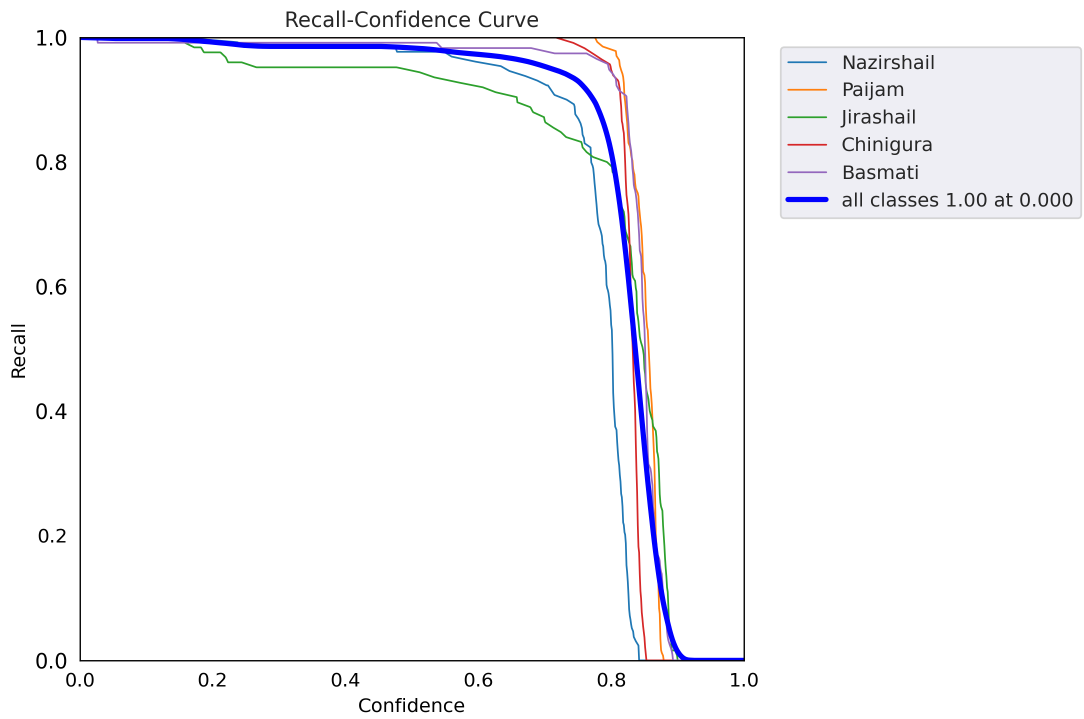
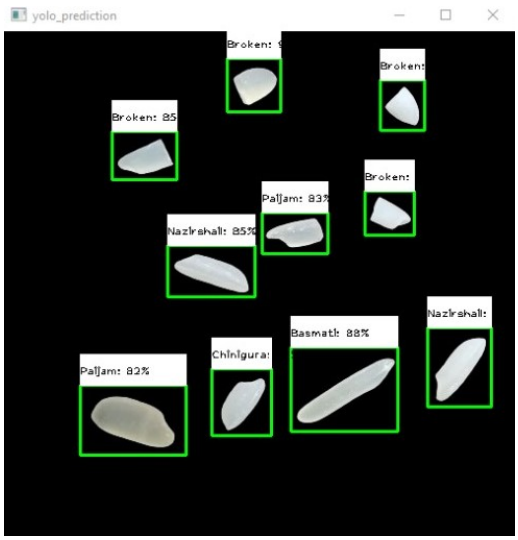


Figure 5.5: Multi-class ROC AUC Curve demonstrating the ideal classification performance of the Yolov5 model across fice cateries rice classes using Adam optimizers

(a) Multiple rice grain test data

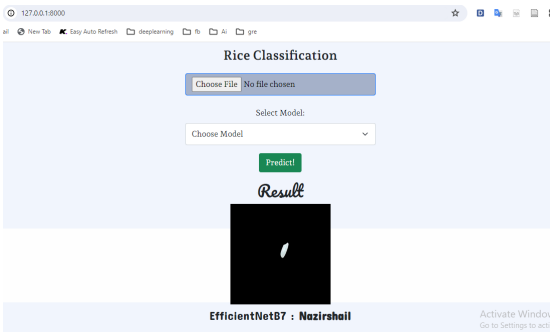


(b) Detected multiple rice grain test data

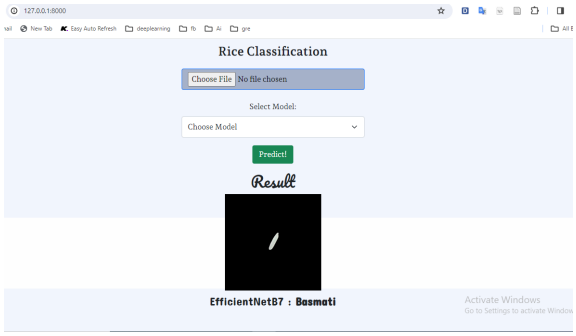
5.1 Our deployed output result

We created and implemented a user-friendly web application after our transfer learning model for rice categorization was trained and tested. Using the learned model, this application allows users to categorise different rice types easily. Anyone can enter

remote sensing information or photos by employing the system, facilitating prompt and precise rice categorization. By streamlining the rice categorization process, our online application makes agricultural management and decision-making more accessible. The basic user interface of the application is shown in figure 5.7a and 5.7b



(a) Najirshail rice



(b) Basmati rice

Chapter 6

Future Work and Conclusion

Through the research project we worked on, our team was able to properly classify various rice grain categories that cultivated in our territory. We have collected each single rice grain and having image acquisition and preprocessing, later on the inputs were fed to different classification models. We got the best promising result from EfficientNetB7.From YOLO detection model, we successfully been able to detect multiple rice types along with broken and chalky rice from a single image. We also set up a script that aims to measure length and width of rice grains and store the values into our database so that we can establish a quality grading statement.

We're aiming to make our rice grain classification and grading system available in mobile app stores, which will allow users to easily detect different types of rice and understand their quality grades. We're considering using X-ray or infrared imaging technology to capture rice grain images that will help us extract more detailed features, leading to improved accuracy in classification and grading. We're looking into developing IoT-based applications for industries involved in rice processing in the near future. These applications will help in automatically removing unwanted particles from rice batches.

References

[1] FPMU, "Research report.pdf," https://mofood.portal.gov.bd/sites/default/files/files/mofood.portal.gov.bd/miscellaneous_info/a9ddc474_c297_4cce_9dad_43b9104ac357/Research%20report.pdf, May 2023, (Accessed on 02/11/2024).

[2] R. A. Dar, D. M. Bhat, A. Assad, Z. U. Islam, W. Gulzar, A. Yaseen *et al.*, "Classification of rice grain varieties using deep convolutional neural network architectures," *Muzafar and Bhat, Dr. Muzafar and Assad, Assif and Islam, Zahir Ul and Gulzar, Wahid and Yaseen, Aamir, Classification of Rice Grain Varieties Using Deep Convolutional Neural Network Architectures*, 2022.

[3] FAO, "Fao cereal supply and demand brief — food and agriculture organization of the united nations," https://www.fao.org/worldfoodsituation/csdb/en, (Accessed on 02/11/2024).

[4] S. Abirami, P. Neelamegam, and H. Kala, "Analysis of rice granules using image processing and neural network pattern recognition tool," *International Journal of Computer Applications*, vol. 96, no. 7, 2014.

[5] A. Tahir, S. Neethirajan, D. Jayas, M. Shahin, S. Symons, and N. White, "Evaluation of the effect of moisture content on cereal grains by digital image analysis," *Food Research International*, vol. 40, no. 9, pp. 1140–1145, 2007.

[6] R. K. Dhumal, K. YogeshRajendra, and S. Mehrotra, "Classification of crops from remotely sensed images: Anoverview," *International Journal of Engineering Research and Applications (IJERA)*, vol. 3, no. 3, pp. 758–761, 2013.

[7] H. Tian, M. Wu, L. Wang, and Z. Niu, "Mapping early, middle and late rice extent using sentinel-1a and landsat-8 data in the poyang lake plain, china," *Sensors*, vol. 18, no. 1, p. 185, 2018.

[8] P. J. Drohan, M. Bechmann, A. Buda, F. Djodjic, D. Doody, J. M. Duncan, A. Iho, P. Jordan, P. J. Kleinman, R. McDowell *et al.*, "A global perspective on phosphorus management decision support in agriculture: Lessons learned and future directions," *Journal of Environmental Quality*, vol. 48, no. 5, pp. 1218–1233, 2019.

[9] K. Uddin, H. L. Shrestha, M. Murthy, B. Bajracharya, B. Shrestha, H. Gilani, S. Pradhan, and B. Dangol, "Development of 2010 national land cover database for the nepal," *Journal of environmental management*, vol. 148, pp. 82–90, 2015.

[10] N. Torbick, D. Chowdhury, W. Salas, and J. Qi, "Monitoring rice agriculture across myanmar using time series sentinel-1 assisted by landsat-8 and palsar-2," *Remote Sensing*, vol. 9, no. 2, p. 119, 2017.

[11] A. O. Onojeghuo, G. A. Blackburn, Q. Wang, P. M. Atkinson, D. Kindred, and Y. Miao, "Mapping paddy rice fields by applying machine learning algorithms to multi-temporal sentinel-1a and landsat data," *International journal of remote sensing*, vol. 39, no. 4, pp. 1042–1067, 2018.

[12] N. Gandhi, L. J. Armstrong, O. Petkar, and A. K. Tripathy, "Rice crop yield prediction in india using support vector machines," in *2016 13th International Joint Conference on Computer Science and Software Engineering (JCSSE)*. IEEE, 2016, pp. 1–5.

[13] N.-T. Son, C.-F. Chen, C.-R. Chen, and V.-Q. Minh, "Assessment of sentinel-1a data for rice crop classification using random forests and support vector machines," *Geocarto international*, vol. 33, no. 6, pp. 587–601, 2018.

[14] F. Farahnakian, J. Sheikh, F. Farahnakian, and J. Heikkonen, "A comparative study of state-of-the-art deep learning architectures for rice grain classification," *Journal of Agriculture and Food Research*, vol. 15, p. 100890, 2024.

[15] S. Ibrahim, S. B. A. Kamaruddin, A. Zabidi, and N. A. M. Ghani, "Contrastive analysis of rice grain classification techniques: multi-class support vector machine vs artificial neural network," *IAES International Journal of Artificial Intelligence*, vol. 9, no. 4, p. 616, 2020.

[16] L. Sumaryanti, A. Musdholifah, and S. Hartati, "Digital image based identification of rice variety using image processing and neural network," *TELKOMNIKA Indonesian Journal of Electrical Engineering*, vol. 16, no. 1, pp. 182–190, 2015.

[17] I. Chatnuntawech, K. Tantisantisom, P. Khanchaitit, T. Boonkoom, B. Bilgic, and E. Chuangsuwanich, "Rice classification using spatio-spectral deep convolutional neural network," *arXiv preprint arXiv:1805.11491*, 2018.

[18] H. S. Gujjar and D. M. Siddappa, "A method for identification of basmati rice grain of india and its quality using pattern classification," *International Journal of Engineering Research and Applications*, vol. 3, no. 1, pp. 268–273, 2013.

[19] M. Tasci, A. Istanbullu, S. Kosunalp, T. Iliev, I. Stoyanov, and I. Beloev, "An efficient classification of rice variety with quantized neural networks," *Electronics*, vol. 12, no. 10, p. 2285, 2023.

[20] N. Tran-Thi-Kim, T. Pham-Viet, I. Koo, V. Mariano, and T. Do-Hong, "Enhancing the classification accuracy of rice varieties by using convolutional neural networks," *International Journal of Electrical and Electronic Engineering & Telecommunications*, vol. 12, no. 2, pp. 150–160, 2023.

[21] N. M. U. Din, A. Assad, R. A. Dar, M. Rasool, S. U. Sabha, T. Majeed, Z. U. Islam, W. Gulzar, and A. Yaseen, "Ricenet: A deep convolutional neural network approach for classification of rice varieties," *Expert Systems with Applications*, vol. 235, p. 121214, 2024.

[22] S. Chen, J. Xiong, W. Guo, R. Bu, Z. Zheng, Y. Chen, Z. Yang, and R. Lin, "Colored rice quality inspection system using machine vision," *Journal of cereal science*, vol. 88, pp. 87–95, 2019.

[23] M. Koklu, I. Cinar, and Y. S. Taspinar, "Classification of rice varieties with deep learning methods," *Computers and electronics in agriculture*, vol. 187, p. 106285, 2021.

[24] P. Lin, Y. Chen, J. He, and X. Fu, "Determination of the varieties of rice kernels based on machine vision and deep learning technology," in *2017 10th*

international symposium on computational intelligence and design (ISCID), vol. 1. IEEE, 2017, pp. 169–172.

[25] I. Cinar and M. Koklu, "Identification of rice varieties using machine learning algorithms," *Journal of Agricultural Sciences*, pp. 9–9, 2022.

[26] S. Qadri, T. Aslam, S. A. Nawaz, N. Saher, A. Razzaq, M. Ur Rehman, N. Ahmad, F. Shahzad, and S. Furqan Qadri, "Machine vision approach for classification of rice varieties using texture features," *International Journal of Food Properties*, vol. 24, no. 1, pp. 1615–1630, 2021.

[27] M. M. Tin, K. L. Mon, E. P. Win, and S. S. Hlaing, "Myanmar rice grain classification using image processing techniques," in *Big Data Analysis and Deep Learning Applications: Proceedings of the First International Conference on Big Data Analysis and Deep Learning 1st*. Springer, 2019, pp. 324–332.

[28] B. Arora, N. Bhagat, L. Saritha, and S. Arcot, "Rice grain classification using image processing & machine learning techniques," in *2020 International Conference on Inventive Computation Technologies (ICICT)*. IEEE, 2020, pp. 205–208.

[29] G. Gilanie, N. Nasir, U. I. Bajwa, and H. Ullah, "Ricenet: convolutional neural networks-based model to classify pakistani grown rice seed types," *Multimedia Systems*, pp. 1–9, 2021.

[30] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 1251–1258.

[31] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[32] X. Zhao, K. Li, Y. Li, J. Ma, and L. Zhang, "Identification method of vegetable diseases based on transfer learning and attention mechanism," *Computers and Electronics in Agriculture*, vol. 193, p. 106703, 2022.

[33] D. Attota, D. N. Tadikonda, S. Pethe, and M. A. A. H. Khan, "An ensembled method for diabetic retinopathy classification using transfer learning," in

2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC). IEEE, 2022, pp. 1444–1449.

[34] M. Tan and Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," in *International conference on machine learning*. PMLR, 2019, pp. 6105–6114.