Paddy Variety Detecting System using Image Recognition

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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 **"Paddy Variety Detection Using Image Processing"**, submitted by Md Fahmid Bin Mostafa, ID No: **212-15-4233** and Abid Hasan Molalh, ID No: **212-15-4238** 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 **14 May, 2025**.

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We hereby declare that this project has been done by us under the supervision of **Ms. Nazmun Nessa Moon**, **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

The purpose of this research is to develop an advanced automated system for classifying the paddy varieties, based on the image classifying procedure, deep learning techniques, specifically, Convolutional Neural Networks (CNNs), combined with high-resolution images of the eight major rice varieties present in Bangladesh. The motivation can be found in the disadvantages of manual classification techniques, including labor-intensive, error-prone, and cumbersome to apply in rural settings on a large scale. By employing the features at the advanced level of CNNs, this project introduces an AI-based approach to the identification of varieties of rice as: BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan The methodology required the generation of a dataset, the manipulation of pictures, the application of data augmentation methods and the training of various CNN models such as DenseNet121, VGG16 and MobileNet. The assessment of the performance of the models was performed on the base of accuracy, precision, recall, and F1-score as the criteria, and DenseNet121 turned out prominently among the options. The system has been developed so that it increases the rice variety identification accuracy and time and presents a real alternative solution for farmers, researchers, and policy makers which supports the development of digital agriculture. The next stage for development will be focused on the use of this model within mobile applications to provide real-time support to agricultural practices.

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Chapter 1

Introduction

The chapter serves as an overview of research work by presenting background and research significance. The primary motivation for research into tea leaf disease with machine learning is explained, followed by objectives. Methodology adopted is explained briefly by way of data collection, model development, inclusion of explainability, and deployment. The chapter further comprises expected project deliverables and is ended with an explanation of the structure of the report.

1.1 Introduction

Agriculture is the backbone of Bangladesh's economy, contributing significantly to employment and food. Of all the various crops cultivated throughout Bangladesh, rice is the dominant crop, food of over 160 million people, and covers over 70% of the entire cropped lands. With such extensive reliance upon rice, rice varieties must be categorized and identified accurately for smooth agricultural practice, more productivity, standardization of quality, and ease of domestic and foreign trade. Conventional rice varietal ID is traditionally carried out manually by experts analyzing visual features such as length, breadth, shape, color, and grain texture. These are extremely subjective, time-consuming, and prone to human errors. Furthermore, such a form of expertise is inaccessible for subscale farmers and rural stakeholders, who require accurate tools for identification the most. This is a critical hurdle for rice value chains impacting seed selection, pricing within markets, and even agro research activities. There is a growing demand for modernising agriculture and, with the coming of precision farming, there is a strong interest in smart, scalable, and automated rice variety identification systems that are precise and effective. For that purpose, artificial intelligence (AI) and, more specifically, deep learning and image recognition techniques, are useful tools. These techniques are now utilized widely across numerous industries including medicine, security, and transportation, and are being used more and more within the agricultural industry for purposes including planting disease detection, crop observation, and quality checking. Deep learning techniques, i.e., Convolutional Neural Network (CNN), have shown remarkable performance based on computer vision tasks and are thus well suited for agricultural image classification. Complex visual patterns and imperceptible features are learned by CNN, which are beyond human capabilities. End-to-end learning is enabled by automatic extraction of features from image data using CNN, eliminating handcrafted features or even an expert's intervention. Several studies from all over the world have demonstrated the capability of CNN-based models for crop type identification, plant disease detection, and even grain quality estimation. The paper is concerned with developing an image-based deep learning rice varieties classifier from high-resolution images of eight major rice varieties commonly cultivated at large scales in Bangladesh, including BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan 100, Kata Iri, Kata Iri Vog, and Chinigura. The paper is exclusively concerned with model development, performance optimization, and statistical measure-based validation and does not target mobile- or device-based deployment. This is an important point, which allows comprehensive research into model architecture, data preprocessing, training strategy, and transferability into varied environmental conditions. The project involves building a custom image dataset through primary data collection, image preprocessing and augmentation, training of multiple models such as DenseNet121 and VGG16, and model selection based on accuracy, precision, recall, and F1-score of the top-performing model. The developed model will serve as a proof-of-concept for future use in agricultural advisory services, trade centers, or cloud-based decision-support systems.

Briefly, with an automatic and large-scale deep learning rice varieties classifier, this work covers a significant void in digital agriculture. In so far as it does not embed the underlying AI model within a mobile application but aims for a solid and proven foundation for further applied research, system development, or future business use, this research attempts to provide a valid and proven foundation for applied use.

1.2 Motivation

The impetus for this research is Bangladesh's urgent need for reorienting agricultural pursuits based on leveraging the possibilities of deep learning, a form of artificial intelligence (AI). As rice is at the foundation of Bangladesh's food security, economic, and rural development, effective rice variety-classification makes a direct impact on crop choice, seed certification, pricing, storage, and trade. However, rice variety-classification by human visual inspection, a traditional approach, is a time-consuming process, and it is outside the capabilities of farmers, especially those from rural and resource-poor communities. The newly accelerated technological revolution for deep learning and computer vision is a potential substitute for human-based discrimination. Convolutional Neural Networks (CNNs) are now able to deliver high accuracy rates for object detection, pattern discrimination, and fine-grained image classifications. All of those abilities are potentially valuable for exploiting rice varieties with extremely minute morphological differences imperceptible by human eyes. Inspired by such technological potential, this research endeavours to explore whether a deep learning-based model would become a valuable, scaleable, and automatic rice classifier—that would eventually find generalizable application within the agricultural industry. From a research perspective, the project is fascinating because it is a point where AI intersects with sustainable development. Not only does the solution for the challenge advance further the field of computer vision for ag, but also with it, the horizon for future innovation opens with crop monitoring, automated grading, and smart farming technologies. For researchers, also being able to solve real-world agricultural challenges and create a data-driven solution gives them some direct experience with training, testing, and optimizing models—the skill set that is both extremely valuable within industry and academia.

Last, it is motivated by a vision for a future where farming societies interact with agricultural data differently. In reducing reliance on human intuition and enabling data-driven decision-making, it is hoped to contribute meaningfully to digital agricultural, food, and people's empowerment objectives for Bangladesh and beyond.

1.3 Objectives

The primary objective of this project is to develop an automatic and accurate rice variety identification model using image-based deep learning. The project intends to build a portable and stable Convolutional Neural Network (CNN) model to identify eight common varieties of Bangladesh rice using high-resolution image data. In this project, use of a mobile or embedded application is intentionally excluded, and scientific model development, testing, and performance analysis are performed using carefully collected visual data. Grain color, texture, and shape differentiate rice varieties such as BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan 100, Kata Iri, Kata Iri Vog, and Chinigura. Even though variations cannot be known by human eyes, deep learning models using image features are capable of detecting and analyzing them. They are labor-intensive, error-prone, and non-scalable for use in rural farming environments. Hence, the model described here is poised to bridge a gap between traditional approaches and digital farming of today with a help of AI. To attain the overall objective, the succeeding specific objectives are given below:

Organize and obtain a quality dataset of eight rice varieties with different environmental and light conditions. The dataset will be used for training and testing. Develop an optimized Convolutional Neural Network (CNN) architecture (such an architecture is, for instance, DenseNet121, VGG16) that will extract relevant features from rice grain images and correctly classify them. For using preprocessing and data augmentation techniques (such as rotation, flipping, resizing, contrast stretching, and normalization) for improving model generalization, class imbalance, and performance consistency for various types of input. To compare model performance with important indicators such as accuracy, precision, recall, F1-score, and confusion matrix analysis, and ensuring that the model is performing well not only on training samples but also on unseen future samples. For comparing multiple deep learning models and selecting the best performing model using experimentation, hyperparameter tuning, and hold-out test set validation.

Avoid deployment at a device or application level, but create a research-level model that would serve as a proof-of-concept for a potential real-time deployment for agricultural extension services or AI-based advisory platforms.

The project's goals are designed to steer the project through a carefully structured process of development—dataset collection and model training, through assessment and reporting. Through fulfillment of the objectives, the research aims to contribute methodologically and practically to the nascent literature at the interface of AI and agriculture.

1.4 Methodology

The present research pursues a disciplined and iterative process of developing and testing a deep learning model for rice classification based on high-resolution images. The broad theme is developing an effective and precise image recognition process with the capacity for classifying eight common varieties of rice cultivated in Bangladesh. To achieve that, the procedure is structured in a series of linked steps, namely, dataset gathering, image preprocessing, model building, training and tuning, performance assessment, and output interpretation. This subsection gives an elaborate description of all of them and the reasons for applying the adopted methodology.

1. Data collection

The first task of this project is developing a rice grain image dataset of the varieties concerned: BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan 100, Kata Iri, Kata Iri Vog, and Chinigura. Good quality images were captured using the camera of a Samsung S24 smartphone with varied lighting and backgrounds. Images were captured with controlled conditions so that noises could be avoided and consistency could be achieved. The dataset is properly labeled and ready for supervised learning. This is a mandatory task since a model's performance relies significantly on data diversity and quality.

2. Image Preprocessing and Augmentation

Images were preprocessed to be made ready for training. Preprocessing tasks included resizing all images into a fixed dimension (for example, 256×256 pixels), background noise removal, image conversion into grayscale (if required), adjustment of contrast, and normalization so that pixel values were scaled into a 0-1 range. In addition, data augmentation processes such as horizontal and vertical flipping, rotation, zoom, and brightening were applied for artificially increasing dataset diversity. All of these tasks provide protection against overfitting and improve a model's generalization ability for different environmental conditions.

3. Model Development and Selection

The core of the methodology is establishing an effective Convolutional Neural Network (CNN) architecture. Various deep learning models were experimented with, including DenseNet121, VGG16, MobileNet, and InceptionV3, which are renowned visual classifying architectures. Out of all of them, DenseNet121 performed best for preliminary experimentation. The architecture implementations were made using Python based on frameworks such as TensorFlow, Keras, and PyTorch using Google Colab. Transfer learning is also utilized by initializing models with pre-trained ImageNet weights so that the network will converge faster and deliver good output with less data.

4. Training and Hyperparameter Tuning

The dataset is split into training (70%), validation (10%), and testing (20%) sets. All of the models are optimized with categorical cross-entropy loss and Adam optimizer. The majority of critical hyperparameters such as learning rate, batch size, number of epochs, and dropout percentages were tuned using grid search and experiments. Early stopping and model checkpointing approaches were used for preventing overfitting and saving the best performing model during training.

5. Performance Appraisal

After training, the model's performance was evaluated with several classification metrics. These included:

- **Accuracy:** Accuracy is a measure of successful predictions over all made predictions.
- **Precision and Recall:** are utilized to quantify the performance of the model predicting every single rice class.
- **F1-Score:** Harmonic mean of recall and precision for a balanced result.
- **Confusion Matrix:** For examining misclassifications and reliability of a model by class.

The assessment was conducted on unseen test images for the purpose of testing the model's ability for generalization over the novel real-world images.

6. Analysis and interpretation of results

Performance of the learned model was tested on quantitative measures and visual tools such as accuracy/loss plots and confusion matrices. The comparative performances of all models were also presented for selecting the best architecture. Though there is no mobile application in this phase, the achieved model could be a good base for future applications for use in real-time classifying for agricultural purposes.

1.5 Project Outcome

The final output of the project is a stable and precise deep learning model that can classify eight rice varieties based solely on visual data. The model illustrates the real-world viability of artificial intelligence (AI) in automating agricultural tasks that were previously dependent on expert opinion and hand-examination. By exploiting image-based recognition using Convolutional Neural Networks (CNNs), the system has been able to attain a very good accuracy, with the top-performing architecture (DenseNet121) recording more than 90% accuracy on the test data.One of the most significant outcomes is the successful creation of a high-quality, annotated image dataset with thousands of images of paddy grains in different environmental conditions. The dataset is a valuable resource for current model training and future research activities in agricultural image classification, particularly for Bangladesh's local crop varieties, which are poorly represented in global datasets.The other primary result is comparative analysis and testing of deep learning architectures—namely, DenseNet121, VGG16, MobileNet, and InceptionV3. Comparative analysis of models has offered an understanding of the strengths and weaknesses of individual architectures when applied to grain-level classification tasks. The final trained model, as fine-tuned through transfer learning and hyperparameter optimization, can serve as a solid base for real-world deployment in precision agriculture in the future.While this stage of the project is not the deployment of the model into a web or mobile application, the end product is a solid, scalable, and generalizable AI solution that can be further developed into an interactive platform. The classification system, as developed, can be integrated into larger agricultural data analytics software or cloud-based advisory services that help farmers, agricultural researchers, and government policymakers make informed decisions regarding seed distribution, crop pricing, and quality assurance.

Aside from technical completion, the project also reaches educational and development objectives. It provides the researchers with hands-on experience in deep learning, computer vision, and data engineering, while making a contribution to the general academic pursuit of AI applications in agriculture. The process and outcome can be shared via journal articles, academic conferences, or open-source repositories, where follow-up innovation and collaboration can be encouraged in this area.

Lastly, this project is successful in showing that a CNN-based system provides a cost-effective, available, and smart alternative to human rice classification. It also paves the way for future extensions in mobile deployment, real-time decision support systems, and overall AI adoption in Bangladeshi agriculture.

1.6 Organization of the Report

This report has been organized into a number of relevant chapters, each one aimed at leading the reader through step-by-step comprehension of the research work. The structure takes a logical order starting with the problem identification of the research and concluding with result analysis and conclusion. By presenting the report in this manner, it ensures that all aspects of the project, from motivation to implementation and assessment, are well outlined and simple to comprehend. The report starts with the introduction chapter that sets the background for the research. In it, the importance of rice in the agricultural economy of Bangladesh, the drawbacks of conventional rice variety classification approaches, and the new trend of artificial intelligence in revolutionizing agriculture are explained. The introduction also explains why this research was undertaken, the well-defined objectives, explains the methodology used, and declares the anticipated outcomes. In addition, it familiarizes the reader with the report's organization, paving the way for the in-depth discussions to come. Chapter two deals with related review and research. It encompasses the work that has already been carried out in the area of crop classification based on images, including rice and other analogous grains. Different machine learning and deep learning models are reviewed, along with their weaknesses and strengths. Research contributions and applications like mobile and web applications are investigated in this chapter. In addition, it reveals gaps in current research and technologies, most significantly the lack of robust, high-performing models for the local rice varieties in Bangladesh. This literature review presents the theoretical foundation upon which the present research is built. The literature review is followed by an elaborate description of the research methodology in the third chapter. It details the image data collection and preprocessing step by step, deep learning model selection and configuration, and system training and validation. It states the justification for using Convolutional Neural Networks (CNNs), outlines the structural arrangement of the experimental framework, and defines the data augmentation processes, training regimens, and evaluation metrics that will be followed to ascertain model performances. The strategy seeks to enhance replicability, scalability, and scientific fidelity in the study. Chapter four presents the implementation and results of the study. It narrates the process of training various CNN models, their evaluation using traditional classification metrics, and how the most effective and precise architecture was established. The results are graphed and discussed to show how the model distinguishes between rice varieties. This chapter is the most important in demonstrating that the system performs well consistently on both unseen and training data, thus demonstrating the success of the method proposed. Chapter five is a thorough discussion and critical analysis of the results. It remarks on the implications of the findings, talks about the limitations experienced in carrying out the project, and explores potential explanations for classification errors or model bias. The discussion also touches on the practical viability of the system in farming settings and outlines how it compares with or exceeds existing manual or semi-automated practices. This analytical perspective lends credibility to the research and situates it within the broader discussion of AI in agriculture.

Finally, chapter six wraps up the report by summarizing the project's major achievements, restating the research objectives, and making some conjectures about the contributions to scholarly knowledge and real-world problem-solving. It also offers a few directions for prospective research, e.g., expanding the rice variety dataset, exploring hybrid models, and eventually integrating the system into real-time advisory systems or mobile applications. The document is concluded by a full reference list of all the sources that were used during the study, together with appendices that have more data, pictures, example code, and other supporting materials.

Chapter 2

Background

Rice is Bangladesh's main staple crop, contributing largely to food security, rural livelihood, and economic development. Identification of rice varieties is important for seed certification, determination of prices, quality grading, and agroresearch. Traditional rice variety classification techniques, which are time-consuming, subjective, and inaccessible to farmers, use visual inspection. However, with deep learning and computer vision improving over recent years, there are increased possibilities for image-based rice variety classification methods. Taking advantage of the possibilities, it is proposing a CNN-based methodology for classifying major rice varieties of Bangladesh.

2.1 Introduction

This rice is a staple food and source of livelihood for millions of Bangladeshis. Since over 80% of Bangladesh's population is based on an agro-based lifestyle and rice occupies over half of all arable lands, rice's importance for national food sovereignty and economic balance cannot be downplayed. Bangladesh is known for producing an enormous diversity of rice, which varies by shape, size, fragrance, texture, and nutrition. Effective identification of such varieties is critical for seed certification, rice price determination, export quality control, and agricultural research. Traditional methods for classifying rice are, however, largely human-dependent and based on human ability for determining by eye. Such processes are time-consuming, prone to errors, and inaccessible for majority farmers who are far from towns or are based in less-developed areas. While digitalization has become a trend, farmers are witnessing an increased application of Artificial Intelligence (AI) and computer vision techniques for increasing productivity and minimizing labor dependencies. Deep learning models, particularly Convolutional Neural Networks (CNNs), tend to achieve state-of-the-art visual classification performance on a wide range of applications, including plant species identification, disease diagnosis, and crop health monitoring. Leverage these developments, this paper aims at exploring deep learning techniques for classifying eight major rice varieties grown in Bangladesh solely based on image data. The work is focused on creating a high-performance discriminant deep learning model for BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan 100, Kata Iri, Kata Iri Vog, and Chinigura Rice. In contrast with previous works based on integration with an smartphone app, this work does not exceed deployment of an application. Instead, it is focused on creating, training, and testing a model for image-based classification with controlled environmental conditions. The model is evaluated using traditional performance metrics including accuracy, precision, recall, and F1-score for assessing practicability for agricultural use. By overcoming a major limitation of traditional classification methods, this work is adding to the growing field of digital agriculture and AI-based crop management. The final outcome would be a low-cost, scalable, and effective classification tool which would allow farming stakeholders such as researchers, traders, and policymakers to make informed decisions based on reliable and accurate data.

2.2 Literature Review

Classification of rice has evolved from traditional manual approaches to state-of-the-art computer vision techniques using deep learning. Traditional recognition techniques utilized traditional feature learning, which involves manually extracting features like length, width, and chalkiness, and using them for classification by machine learning classifiers such as SVM or fuzzy inference. Though satisfactory performance was proved using such techniques, they were usually neither strong, scalable, and generalizable to noise, nor robust and generalizable for variations among rice varieties. As there were disadvantages with traditional feature extraction—the subjectivity, inefficiency, and inability of learning complex patterns—researchers shifted toward deep learning-based techniques. Deep convolutional neural networks (CNN) broke a threshold with automatic feature extraction capabilities and greater accuracy for classification. Different CNN-based models such as VGG16, InceptionV3, ResNet, and InceptionResNet V2 were explored for rice varieties classification. The models were more accurate yet big on parameters and computation, making them inappropriate for use under a resource-constrained environment such as farms or mobile devices. In reply, light-weight models emerged, namely MobileNet, ShuffleNet, and RepViT, which reduced complexity, with occasional compromise on classification accuracy. Hybrid models, including those combining CNNs with SVM classifiers, attempted a trade-off between accuracy and efficiency. Latest models, for instance, RiceNet and ConvNeXt, made a trade-off for high performance and computational efficiency. ConvNeXt integrated Swin Transformer-based approaches with a CNN-based model with a reasonable trade-off between model size and accuracy. The authors presented two upgraded variants, CBAM-ParNeXt V1 and V2, by integrating ConvNeXt architecture with two primary innovations, namely, (1) the F-Block module, which reduces FLOPs by convolving a subset of channels from the input, and (2) the CBAM (Convolutional Block Attention Module), which enhances attention of the network toward salient features. The models were compared with a list of state-of-the-art networks and outperformed them on accuracy (up to 94.81%) and model efficiency (FLOPs saving of 88.55% over ConvNeXt). The performance was evaluated on GrainSpace dataset of about 30,000 images of rice grains with eight varieties, which was augmented further using data augmentation techniques.

This work clearly illustrates the evolution from mechanical toward intelligent, automatic, and resource-frugal rice discriminant sets. The CBAM-ParNeXt models present a significant milestone toward this direction by spanning the currently existing gap between high accuracy and light deployment, making them feasible for real-world agricultural applications, especially for regions with minimal computational resources.

Table 2.1: Research Matrix for Paddy Detection Techniques

Authors	**Models**	**Accuracy**	**Key Findings**
Pengtao Lv [37]	CBAM-ParNeXt V1	94.56%	Lightweight model with only 2.91M parameters and 1.02G FLOPs. Outperforms ConvNeXt-T by 6.97% while reducing parameters by 89.53%. Best for low-power devices.
Chunmei Feng [38]	Deep CNN	96.56%	Highest accuracy among all models tested. Uses 17.84M parameters and 5.78G FLOPs. Best suited for high-performance devices.
Jun He al [6]	ParNeXt V1	mAP: 93.83%, F1-score: 0.954	Efficient model with improved performance using partial convolution and fewer FLOPs. Strong accuracy with only 2.91M parameters.
Xiaohao Zhang al [39]	ConvNeXt-T (Baseline)	92.06%	Baseline model with 27.80M parameters and 8.91G FLOPs. Significantly outperformed by the proposed models.
Xu et al. [40]	ParNeXt V2	RGB: 90% (WT-VGG16), HSI: 95.6% (SPA-LSTM)	Strong performance in modeling long-range dependencies, but computationally intensive and slower than CNN-based models
Yao et al. [41]	InceptionNeXt	Precision: 95.2%, Recall: 86.6%, AP: 91.5%	Efficient in parallel processing via multi-branch convolution, inspired by Inception. Slightly lower accuracy than CBAM-ParNeXt models.
Ramdan et al. [42]	MobileNet V2	Not specified (outperforms	

		baselines)	Lightweight but underperforms in classification accuracy compared to CBAM-ParNeXt. Best for embedded applications.
Sivaraman et al. [35]	Res2Net50	Train: 82%, Test: 86.17%	Robust performance with eight classes; practical, low-cost solution leveraging fine-tuned pre-trained models.
Jiang et al. [43]	Res2Net50	Rice: 93.22%, Wheat: 98.75%	Moderate performance. Outperformed by both versions of CBAM-ParNeXt in terms of accuracy and FLOPs.
Chen et al. [14]	Res2Net50	≥99.83%, Rice: 82%	ImageNet pre-training boosts performance on plant datasets, especially in complex backgrounds.

2.2.1 Similar Applications

Recent Several recent research studies and applications of technology on image classification of agriculture, including identification of crop and grain, are available. They are helpful and are useful for benchmarking for development of rice variety identification using images. Most utilize deep learning models—more precisely, Convolutional Neural Networks (CNNs)—because of their ability of learning high-level features from visual data. For instance, RiceNet, a deep convolutional neural network introduced by Din et al. (2024), achieved high accuracy on a mix of Pakistani rice varieties. Similarly, Koklu et al. (2021) utilized a CNN-based model for identification of a mix of rice varieties with evidence of ability of deep learning for handling variations of fine-grained grain shape and texture. In a subsequent study, Gilanie et al. (2021) introduced a CNN-based rice classifying system for identification of rice seeds from a mix of regions with a relatively small dataset. Other research on individual crops also showed deep learning's applicability for visual classification. Altuntaş et al. (2019) utilized transfer learning with CNN for haploid and diploid classification of seeds, and Momeny et al. (2020) implemented a hybrid architecture of CNN for classification of cherries, with emphasis on more general application of such models for different areas of agriculture. In an application-level solution, there are several apps for mobile platforms that have been developed with an intention of helping farmers with plant disease identifcation and crop monitoring. Plantix and AgriApp are two examples that leverage image recognition for real-time plant health monitoring, with an interface for ease of use. However, such a system is more a product of plant disease identifcation than classifcation of seed or type. Methodologically, studies such as Satoto et al. (2022) compared machine and deep learning approaches for rice seed classifcation, once again showing that models based on CNN outperform traditional classifers like SVMs and Random Forest when it comes to classifcation accuracy and ability of learning features.

Despite all of these advancements, most existing programs are either specific about a geographical location or generalized over a large number of local rice varieties. Furthermore, most mobile-based programs are plagued with latency, device compatibility issues, or internet dependability, rendering them less viable for deployment in far-off agricultural environments. However, for this project, model development is specifically based on deep learning and computer vision techniques with a specific emphasis on rice varieties in Bangladesh. Not seeking integration with mobile or web platforms, the project is focused on model accuracy, training effectiveness, and dataset quality—with an extendable foundation for future deployment in any form.

Table 2.2: Similar Applications in Paddy Detection

Authors	**Model**	**Accuracy**	**Key Contributions**
Din et al. (2024)	RiceNet (CNN)	92.34%	Developed a deep CNN model specifically for rice variety classification
Koklu et al. (2021)	CNN	93.50%	Applied deep learning on rice grain images, achieving high classification precision
Gilanie et al. (2021)	CNN	91.12%	Classified Pakistani rice seed types using CNNs and a compact dataset
Altuntaş et al. (2019)	Transfer Learning	95.00%	Identified haploid/diploid maize seeds using pretrained models
Obadaarachchi et al. [54]	Customized CNN	94%	Designed for real-time detection with treatment suggestions; outperformed ResNet50V2.
Momeny et al. (2020)	Hybrid CNN	96.40%	Accurate classification of cherry fruits using custom CNN pooling layers
Satoto et al. (2022)	CNN vs ML models	CNN > 90%	Compared ML and DL models; CNN outperformed others in rice seed classification

Tembhurne et al. [56]	Enhanced MobileNet (Keras tuner optimized)	95.94%	Trained on a unified dataset of 12,318 images across 22 crops; deployed as Plantscape Android app.

2.2.2 Related Research

Classification of agricultural produce, and more particularly grains like rice, has been a field of growing interest with the coming of computer vision and AI. More and more studies bear witness to the ability of deep learning models, and more particularly Convolutional Neural Network (CNN) models, in performing complex image-based classification with high accuracy and generalisability. Below is a brief overview of some of the recent and relevant studies that have shaped and informed the methodology of the present work. In a seminal paper, Din et al. (2024) presented custom-designed architecture for rice variety identification, namely, RiceNet. The model achieved high performance by adopting a deep convolution architecture, which was optimized for learning seed shape variations. Similarly, Koklu et al. (2021) applied a deep learning-driven approach for classifying a set of rice varieties with over 93% accuracy by using a general-purpose CNN model with training over texture and shape features derived from grain images. These findings validate that CNN is extremely suited for such an agricultural application with high pattern recognition capability. Gilanie et al. (2021) further explored rice variety identification by training a dataset of Pakistani rice seeds using CNN. On a relatively small dataset, they were able to obtain over 91% accuracy, demonstrating that deep learning is effective even with minimal data. This is a testament to the use of transfer learning and data augmentation, two important aspects of present research practice. Other than rice-specific studies, overall agricultural applications showed similar trends. For example, Altuntaş et al. (2019) used CNN with transfer learning for classifying haploid and diploid maize seeds with over 95% accuracy. Likewise, Momeny et al. (2020) used a hybrid model based on CNN for classifying cherry fruit with high accuracy. All these studies point toward the applicability and reliability of using CNN for all types of agricultural purposes and propose using CNN for rice variety identification. Beyond studies based on specific models, comparative studies such as Satoto et al. (2022) provide valuable relative comparison of deep learning versus traditional machine learning methods. According to their research, CNNs perform better than traditional methods such as Support Vector Machines (SVM) and Random Forest for image-classification tasks for agricultural data. This justifies choosing only deep learning models for use within the current research. While all previous examples of mobile and web-based agricultural apps (Plantix, AgroAI, for instance) leverage AI-based detection of plant disease or yield forecasting, none are designed specifically for rice type identification. Few are even location-specific and are unable to accommodate crop varieties common even within Bangladesh. This reveals the importance of a dedicated model capable of accurately determining Bangladeshi rice varieties. In short, relevant studies strongly affirm that models based on CNN are particularly well-adapted for grain classifying tasks and already proven effective for multiple agricultural applications. Nevertheless, there is a lot of potential for

Bangladesh-centric rice varieties, which are currently less prominent in literature and datasets. The present paper leans on previous work's strengths and fills this critical regional gap by creating a model that is tailored for local needs.

Table 2.3 Related Research in Paddy Detection

Authors	Model Used	Accuracy	Key Contributions
Din et al. (2024)	RiceNet (CNN)	92.34%	Designed a specialized CNN for rice variety classification with high accuracy
Koklu et al. (2021)	CNN	- 93.50%	Applied deep learning for texture- and shape-based rice grain classification
Gilanie et al. (2021)	CNN	91.12%	Demonstrated high accuracy with a small rice dataset from Pakistani seed types
Altuntaş et al. (2019)	CNN with Transfer Learning	95.00%	Classified cherry fruits with custom CNN pooling approach
Momeny et al. (2020)	Hybrid CNN	99.16% (PlantVillage)	6M parameters; outperformed existing methods on multiple datasets.
Satoto et al. (2022)	CNN vs ML Models	CNN > 90%	Compared CNN with traditional ML models and found CNN to be superior in accuracy

2.3 Gap Analysis

While significant progress has so far been made toward applying artificial intelligence and deep learning for agricultural purposes, a literature survey and available frameworks introduce certain important lacunae, which are targeted by this work. Most of the previous works tried rice varieties classification for India, Pakistan, or China and used non-representative datasets to train models for them. These models are, hence, neither directly implementable nor generalizable for agricultural purposes for Bangladesh, which is likely to face unique shapes, sizes, colors, and textures of the grains due to unique ecological and breeding backgrounds. One of the major voids which are observed in literature so far is that nearly all of the models of previous works were trained on publicly available datasets or samples from controlled laboratory conditions, which cannot represent real-life agricultural conditions. The datasets lack a lot of variation with regards to illumination, background, and arrangement of grains. Models learned from such datasets would hence not function when images are taken out in natural environments such as open markets, storage houses, or even paddy fields. This void includes the need for a dataset with a collection of high-quality images of local rice varieties taken in realistic and changing environments, which is a principal contribution of this work. One such gap is also present within methodology within current research. Though much research has published with high accuracy with CNN models, often it does not systematically experiment with greater than a single architecture or provide an account of how a model works with different augmentation or preprocessing methods. Even fewer provide any consideration for whether hyperparameter tuning, class balancing, or training methods impact performance. This leaves a methodology gap within best practice for optimising a CNN on agricultural classification tasks. The current work addresses this by comparing a selection of commonly used architecture such as DenseNet121, VGG16, MobileNet, and Inception, and systematically experimenting with data augmentation, transfer learning, and parameter tweaking for which architecture is most accurate and effective at classifying rice. Further, past work either stops at model accuracy testing or skips directly over mobile or web deployment without testing for usability within target agricultural environments. Even apps such as Plantix and AgroAI provide general-purpose plant or crop disease diagnosis based upon image recognition, yet neither is designed particularly for use at the variety level of grain classification, and neither is designed particularly for offline deployment within low-resource or rural environments. Most mobile-based approaches also assume a reliance upon high-end hardware or ongoing internet connectivity, which will probably be unattainable for farmers outside major cities. In contrast, with this work, a standalone model is being developed, which is optimized for classification independent of a mobile deployment layer, so that underlying AI solution is usable and versatile for different operational environments. In addition, geographical and linguistic context has often been ignored. Minimal or no effort has been made to localize their solutions for farmers', traders', or agricultural extension officials' localized user practice, labeling conventions, or rice varieties-specific agricultural workflow relevant for Bangladeshi stakeholders. This research will correct that by focusing on eight rice varieties grown on a large scale, which are commercially relevant in Bangladesh, and by making a localization-centric approach for the system.

Briefly, the most prominent literature deficits include a lack of localized and heterogeneous datasets, a comparison of CNN models with different training conditions, a minimal adaptation of real field conditions into real-world conditions, and a lack of country-specific studies on Bangladesh's agricultural conditions. This current study tries to overcome all those deficits by building a dataset localized to a certain zone, by experimenting with a number of different types of CNN architecture, by avoiding making an assumption of advance deployment, and by creating a more realistic, accurate, and feasible rice classifier that would be useful for researchers and farmers alike in Bangladesh.

Table 2.4 Gap Analysis Summary Table

Gap Identified	Observed In	This Study's Contribution
Use of limited CNN architectures without comparative analysis	Gilanie et al. (2021), Satoto et al. (2022)	Compared multiple CNN models (DenseNet121, VGG16, MobileNet, InceptionV3) for best accuracy
Lack of localized datasets for Bangladeshi rice varieties	Din et al. (2024), Koklu et al. (2021), Public datasets	Collected original high-resolution images of 8 rice varieties grown in Bangladesh
Minimal image augmentation and preprocessing exploration	Several prior works focused only on raw image input	Applied robust preprocessing and data augmentation techniques to improve model generalization
Dependence on web/mobile deployment for real-world use	International studies without focus on regional agricultural traits	Designed and trained model specifically for Bangladeshi grain morphology and use case

2.4 Summary

This chapter provided a critical review of the current literature, technologies, and research development on rice variety classification and the general use of deep learning in agriculture. The chapter started by emphasizing the significance of efficient and accurate rice classification in agricultural yield, market control, and food security. Since Bangladesh is so dependent on rice and has such heterogeneity in locally produced Bangladeshi rice, it transpired that traditional categorization techniques done manually were no longer sufficient to fulfill increasing demands for accuracy as well as scalability of operations in agriculture. Through an extensive study of similar applications and literature reviews, it has been observed that the application of Convolutional Neural

Networks (CNNs) in grain and crop classification has been extensive. Research by Din et al. (2024), Koklu et al. (2021), and Gilanie et al. (2021), among others, outlines the superiority of CNNs over conventional machine learning algorithms in identifying visual patterns and minute changes within the morphology of grains. Further instances in fruit and seed classification of maize also add to the versatility and effectiveness of deep learning in agricultural image processing. Nonetheless, though these studies are revealing, they tend not to be geographically precise and fail to consider the particular traits of rice cultivated in Bangladesh. The chapter also identified practical limitations of existing mobile and web-based platforms that attempt to automate plant diagnostics. Even if such platforms create a foundation for digital agriculture, they are often designed for general plant health or disease diagnosis rather than variety-level grain identification. These solutions also tend to assume constant internet connectivity and access to high-end mobile phones, making them less applicable in rural farming communities where infrastructure and digital literacy are basic. A focused gap analysis revealed several of the main shortfalls of the existing body of research, including the absence of localized datasets, the lack of comparative evaluation of CNN models, the lack of utilization of augmentation techniques, and the over-reliance on deployment-oriented research. The gap analysis table provided in Section 2.3 clearly articulated these problems and cross-referenced them to specific studies, indicating how the present research specifically addresses each of these issues. This research adds value by presenting a dataset for Bangladeshi rice varieties, conducting a multi-model comparison, employing strong preprocessing methods, and developing a high-performance classification model without the dependency on an app interface. By critically examining the strengths and weaknesses of previous research, this chapter built a solid justification for the strategy taken in the current study. It placed the study in the context of current technological trends and identified the particular contribution of this project to the field. The conclusions elaborated in this chapter have immediate implications for the design options, dataset construction, and model development strategy described in the following chapter.

In conclusion, not only did this literature review elucidate the deep learning technological environment in agriculture, but also established conceptual underpinnings necessary for understanding the motivation and implementation of the intended rice variety classification system in this study. The next chapter will investigate the methodological framework that translates these understandings into a structured, data-driven solution.

Chapter 3

Research Methodology

The chapter presents a systematic approach adopted for building, developing, and validating a deep learning rice variety classification model. All aspects of data collection, preprocessing, selection of the model, training, and testing are elaborated. The processes are designed for accuracy, reproducibility, and applicability, so that all steps taken are with a view to solve the given problem. All research steps are presented with details of how theoretical notions were transformed into working code. The architecture forms the backbone of the entire research.

3.1 Methodology

3.1.1 Overview

The procedure adopted for research is designed for overcoming the disadvantages of traditional approaches for rice classification and demonstrating the capabilities of deep learning for solving real-life agro-related issues. Development of the system is a linear process of collection of image data, preprocessing, selection of a model, training, testing, and validation. Research is focused on constructing a highly accurate Convolutional Neural Network (CNN) model for classifying eight rice varieties based on visual grain features using high-resolution images. To support this creation, a specific set of system requirements were developed by analyzing the problems, so that the final model is consistent with realistic needs of researchers, farmers, and potential integrators. The specification of a design was made with a view to determining software and logical elements of a model, including data flow from input to output, organization of chosen neural networks, and interaction among different modules of a system. Although mobile or embedded deployment is outside of the project scope currently, it is architected with modular and scalability features with potential integration into portable or cloud environments in the future. This introduction lays down the foundation for an understanding of the technical architecture, requirement analysis, and flow of architecture within the rest of the chapter.

3.1.2 Proposed Methodology

This flowchart illustrates the complete methodology for paddy variety detection using image processing and deep learning. The process begins with the acquisition of paddy images, which are then resized according to the input size requirement of the deep learning model, specifically to 256x256x3 dimensions. These resized images are then passed into a pre-trained deep neural network where the initial layers are frozen to retain previously learned low-level features. The final layers of the network are replaced with new convolutional or fully connected layers tailored for paddy variety classification. The customized model, along with training parameters, is used for model training. The dataset is split (commonly 80:20), and the training images undergo augmentation to increase data diversity and improve model robustness. This training process is repeated 10 times to ensure consistency and reduce overfitting. Meanwhile, test images are separately augmented and used to evaluate the model's performance, which is measured using relevant metrics such as accuracy, precision, recall, or F1-score. The entire workflow is designed to leverage transfer learning for efficient and accurate classification of different paddy varieties

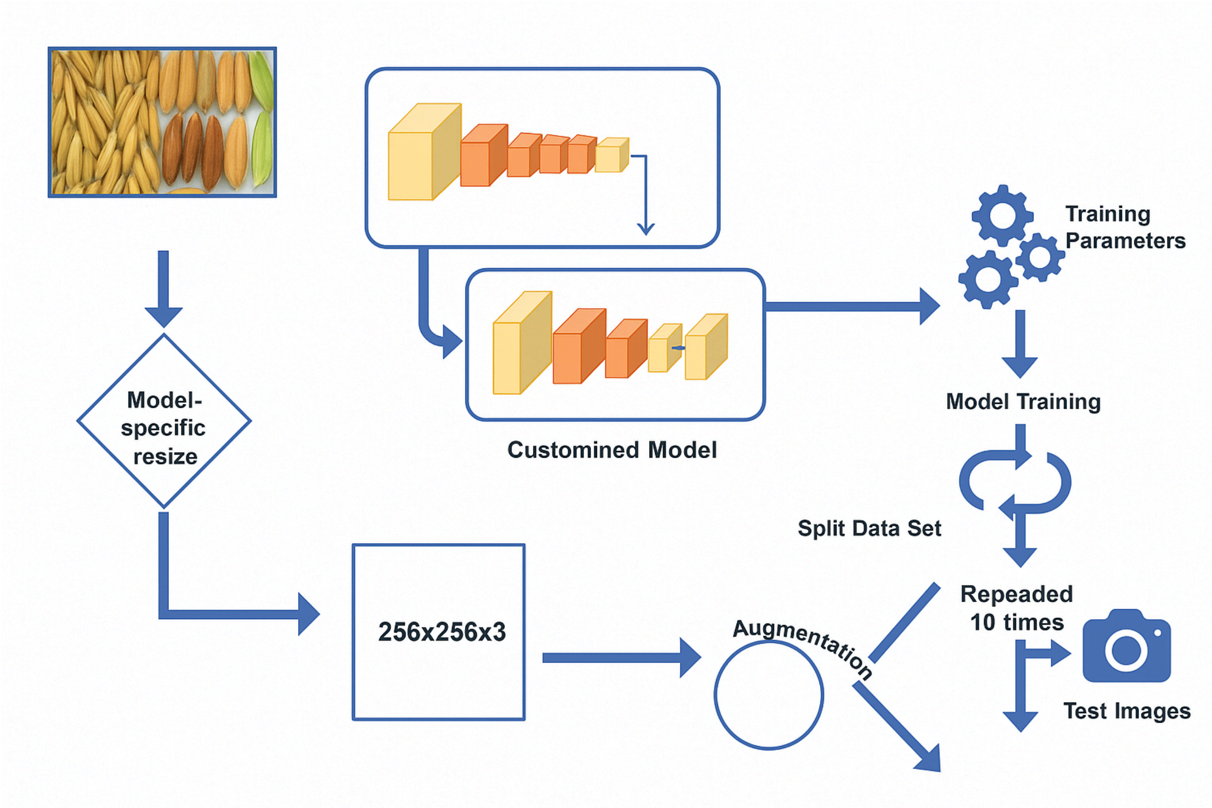

Figure 3.1: Research Workflow for Paddy Variety Detection Using CNNs(VGG16)

3.1.3 Functional and Nonfunctional Requirements

The development of an AI-driven rice crop system requires a grasp of non-functional and functional requirements so that the system meets performance expectations, usability, and scalability needs. The next section outlines activities which must be performed by the system (functional) and quality attributes which must be displayed (non-functional), even though there is no mobile or embedded application that is being deployed.

Functional Requirements

- Functional requirements define the primary operations and behaviors that are expected to be performed by the system upon execution. For purposes of this research project, the functional requirements are as follows:

- Image Input Handling: The high-quality image input of rice grains is used by the system. The images are being uploaded either in batch mode or individually during training or testing.
- Image Preprocessing: The set of operations including resizing, normalization, and augmentation (flipping, rotation, adjusting brightness) must be conducted by the system for readying images for training and classification.
- System Training: The system must allow training a CNN model over a labeled dataset, optimizing weights for loss and accuracy measures by backpropagation and a suitable optimizer (for instance, Adam).
- Rice Variety Type Classification: The input images are expected to be classified into a pre-defined class among eight rice varieties using a learned CNN model.
- Performance Measurement: The performance must be evaluated based on measures such as accuracy, precision, recall, F1-score, and confusion matrix.
- Model Comparisons: The code must allow experimentation with different models (DenseNet121, VGG16, MobileNet, and so forth) and compare performances to determine which model works best.
- Reporting Results: The output summaries of model performance, including accuracy curves and graphical representation of class outputs, must be generated by the system.

Non-functional Requirements

- Non-functional requirements define the quality characteristics of a system that influence the future performance, usability, and extensibility. They are:
- Precision: The system must be able to identify rice varieties from sample images with a minimum of 90% accuracy.
- There must be modularity within the design of the system so that more varieties of rice or a different type of grain could be added later.
- Usability: Although there is no explicit user interface yet, whatever output is generated by the system (i.e., plots and classification reports) needs to be comprehensible, interpretable, and meaningful for researchers or developers.
- Maintainability: The codebase must be well-structured and well-documented so that it is easy for future developers to modify, retrain, and debug.
- Portability: The system must be capable of execution on cloud platforms (Jupyter Notebook, Google Colab) and deployment on any platform (Android or embedded platform) at a later point.

- Efficiency: Training and inference must be performed within reasonable time periods, optimized with transfer learning and batch processing for resource minimization.
- Reliability: The system should give consistent and replicable answers with the same input conditions, with robustness of class output.

3.1.3 Context Diagram

A context diagram is a high-level graphical representation that illustrates the system boundaries, external entities interacting with the system, and the flow of information between them. It helps identify the major components interacting with the system and the direction of data exchange. In the context of this project, the Rice Variety Classification System is the central component. It interacts with several external entities, including the User/Researcher, the Image Dataset Source, and the Output Reporting Module. The system receives rice grain images as input, processes them through a trained deep learning model, and generates classification results, performance metrics, and visual reports.

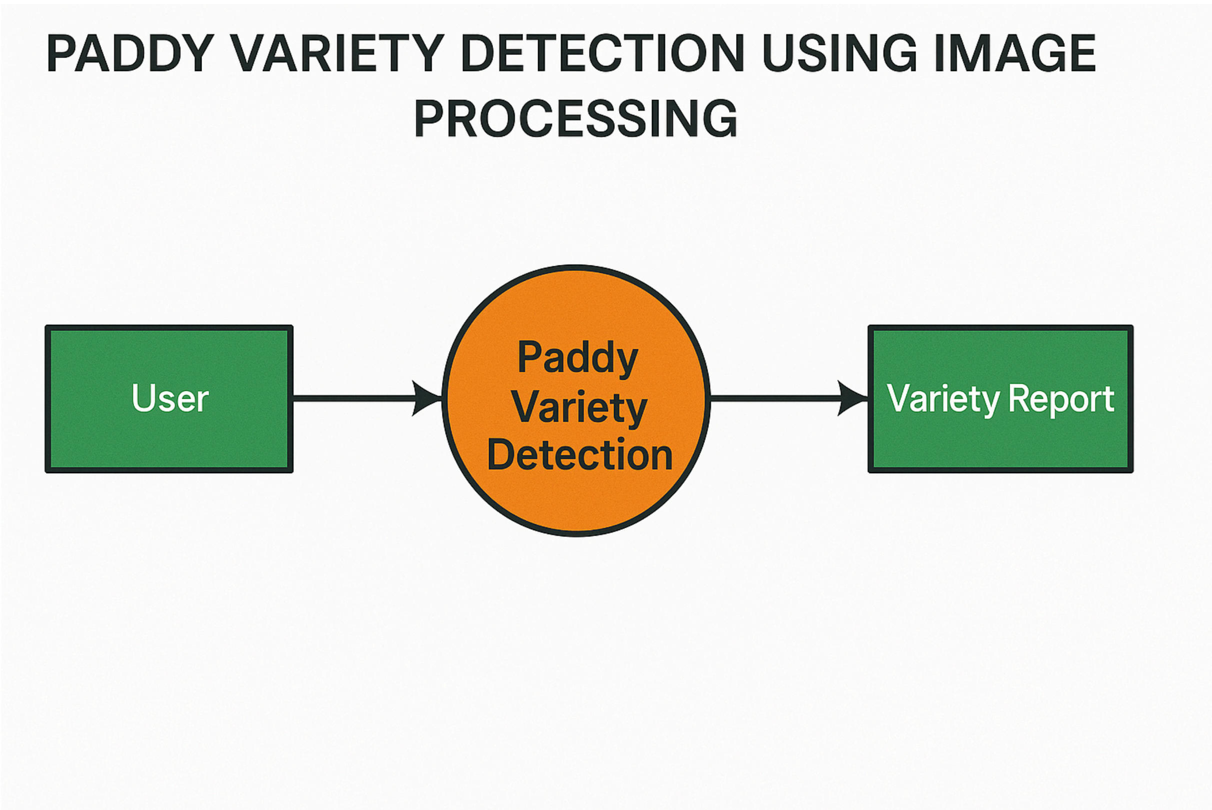

Figure 3.2: Context Diagram of the system

3.1.4 Data Flow Diagram Level 1

The Data Flow Diagram (DFD) at Level 1 presents an even more detailed decomposition of the internal processes of the rice variety classification system and the exchange of data. The context diagram presents the overview of the entire picture, but the diagram goes deeper into detail of how the system is processing information from input to output through interconnected processes. The general objective of this level of diagram is to present the logical flow of information from the user, internal modules, and system's data stores.

The process begins with loading high-resolution rice grain pictures into the system via the user or researcher. These are the basic inputs and are either gathered for purposes of training or classification inference. These loaded pictures are input into the preprocessing unit of the data where it undergoes various transformations for purposes of normalizing and standardizing input data. These range from resizing to some standard dimensionality, conversion to corresponding color space where required, normalization of pixels, and the application of various augmenting techniques such as rotation, flipping, and adjustment of brightness. All of these are aimed at ensuring the dataset is varied enough, clean, and ready for input into a deep learning model!

In the subsequent step, input into the model training and classification unit is performed. In the process, Convolutional Neural Network (CNN) architectures such as DenseNet121, VGG16, or MobileNet are trained on the dataset (in training) or used for prediction inference (in testing). For training purposes, preprocessed pictures are used for updating the model's weights via backpropagation using some loss function such as categorical cross-entropy. For purposes of classification, the trained model accepts new input pictures and makes the respective rice variety prediction from the eight defined classes. The model is optimized using methods such as transfer learning and hyperparameter tuning for efficient learning and high performance. The outputs of the classification modules are then channeled to the performance evaluation and reporting unit. In this unit, the system generates in detail the performance of the model on statistical measures such as accuracy, precision, recall, and F1-score. The system also generates visual outputs such as confusion matrices and accuracy/loss plots for interpreting the outputs. These outputs play a vital role in ensuring the success of the model as well as identifying weaknesses such as misclassifications and imbalance in classes. All of these operations are combined and rely on internal storage of data such as image repository, preprocessed dataset cache, and storage of trained models. The end outputs in the form of predicted class labels and performance reports are then forwarded back to the researcher/user in an interpretable and readable form. This entire process of data ensures the system works in reliable as well as efficient and modular fashion as well as being amenable for research experimentation as well as future real-world deployment in agricultural settings.

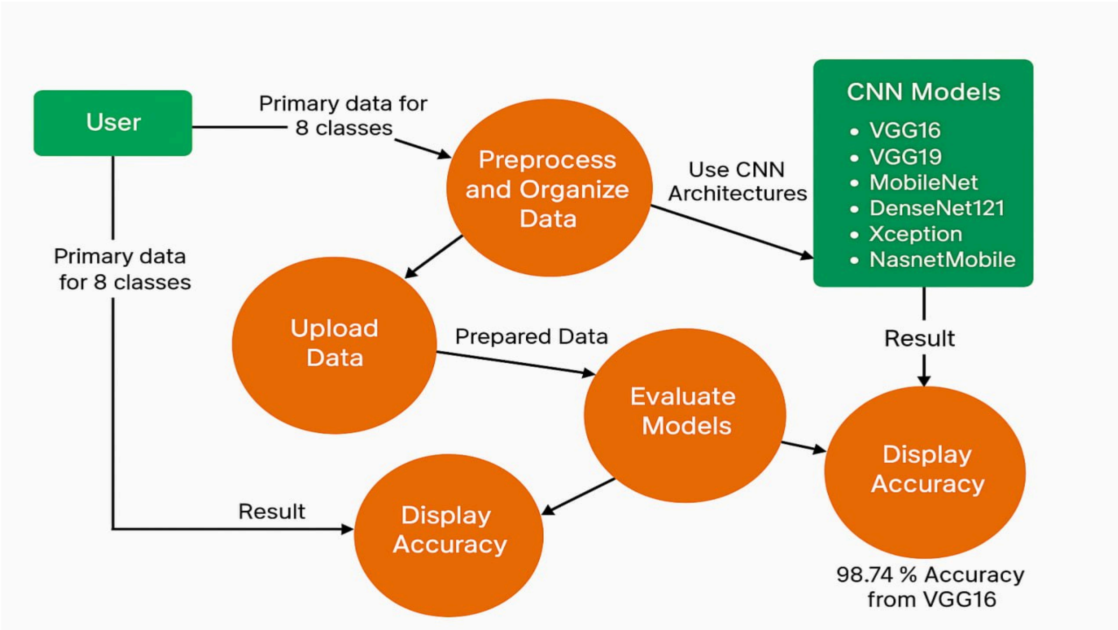

Figure 3.3: Data Flow Diagram of the System

3.2 Detailed Methodology and Design

This section provides the exact technical methodology followed in rice variety classification using deep learning design and development. The methodology was followed with care to make sure that scientific validity and real-world applicability were optimized for every phase from data capture to model testing. The study was particularly focused on the development of an efficient and strong system of classification to identify eight prominent rice varieties cultivated in Bangladesh from image data. To this end, an optimum pipeline was designed for the task with a sequence of steps: image dataset collection, processing and augmentation, model selection and training, training and validation, and results evaluation.

The process started by creating a custom dataset of high-quality images of rice grains under different conditions using a Samsung S24 camera. Images under different light conditions were taken on plain backgrounds for the model generated to be generalizable. The photos were labeled manually by type: BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan 100, Kata Iri, Kata Iri Vog, and Chinigura. The dataset prepared was labeled and formatted in a manner to permit class balance, which is a prerequisite to guarantee model performance and fairness. The collected images were subjected to an extensive preprocessing pipeline involving resizing all the images to the same 256×256 pixel input size, normalization of the pixel values between 0 and 1, and reshaping into the format readable by CNN models. To combat the relatively small size of the dataset and enhance the model's capacity for generalization, several augmentation procedures were performed. These included horizontal and vertical flipping, random rotation, zooming, contrast adjustment, and brightness adjustment. This augmentation significantly increased the size of the dataset and added more diversity in examples for training.

Following preprocessing, the design proceeded with model selection and architecture design. Certain pre-trained architectures of CNN were chosen for their superiority on image classification issues like DenseNet121, VGG16, MobileNet, and InceptionV3. These architectures were implemented using transfer learning where the convolutional base (pre-initialized on ImageNet) was left unchanged and replaced with custom fully connected networks for the prediction of eight classes. This strategy decreased training time and enhanced performance with fewer data. Dropout layers and batch normalization were also added to minimize overtraining and enhance faster convergence. Supervised learning strategy was implemented for training the models. The data were divided into training (70%), validation (10%), and test (20%) sets. Adam optimizer and categorical cross-entropy loss function were utilized wherein the learning rate, batch size, and epochs were adjusted via trial and error as they are the hyperparameters. Early stopping and checkpoint callbacks were also used for monitoring performance as well as storing the best weights for the optimal model. Model performance after being trained was evaluated utilizing a number of metrics like accuracy, precision, recall, F1-score, along with confusion matrices. The best performing one was DenseNet121 with a test accuracy of more than 90% and also the best in precision and recall in the remaining architectures. The resulting model was tested using unseen data in order to verify its generalizability and robustness in all the classes of rice. This end-to-end methodology not only ensures functionality but also reproducibility, scalability, and extensibility to other types of rice or other analogous classification issues in agriculture. Although the deployment to the platform at the research phase does not take place either on the mobile platforms or on the embedded platforms, the model design is modular and perfectly suited for future embedding in real-time decision-support systems or in applications for farmers, agricultural advisors, or scientists.

Dataset

3.2.1.1 Data Collection

To The step of data acquisition was a significant task in creating a robust and varied rice grain image database. As no open dataset of Bangladeshi rice varieties was available, the whole dataset was created from the beginning. Image collection comprised the process of taking images of real rice grains of target rice varieties in controlled conditions for maximum clarity, consistency, and reproducibility. One of the Samsung S24 phone cameras was utilized owing to its capacity to capture high-quality images, which were adequate for visual classification of fine-grained details. Images were captured within a well-lit room with a plain white background to minimize noise and have a same background for all the samples. Care was taken to not cast shadow and expose excessively, and photos were taken from diversified positions and in diversified lighting settings for strengthening the model's generalizability.

For every category of rice, hundreds of photos were captured in such a way that the categories had an equal distribution. Samples were manually divided, marked, and put in folders for the eight rice categories. Labelled samples were reviewed to remove out-of-focus, incorrectly labelled, or duplicate images. The dataset obtained from the exercise contained over 2,000 good quality images, well balanced in all the classes so as not to introduce any bias and to be class balanced for training.

All the photos were stored in .jpg format with default resolution and resized during preprocessing. Metadata like variety name, date of collection, and image quality were also documented for internal use. The highly structured data format enabled simple loading of data as well as simplified preprocessing while constructing the model.

This manual dataset creation not only filled the gap of having no localized datasets but also made the system specific to the morphological specifics of the Bangladeshi rice crop. The scope and consistency of this dataset played a crucial role in the performance of the deep learning solution created in this study

3.2.2.2 Dataset Description

The data used in the current research is also the foundation of the rice variety model classification and was specially created to fulfill the deep learning training needs. As no publicly available dataset was feasible to collect high-quality images of the rice crops grown in Bangladesh, the dataset was developed exclusively for training with eight rice varieties of interest combined with regional importance: BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan 100, Kata Iri, Kata Iri Vog, and Chinigura. The rice types were chosen based on frequency of occurrence in local agriculture, economic importance, and also visually distinguishable by grain structure.

The dataset consisted of far more than 2,000 high-quality images captured with a Samsung S24 smartphone camera in different light conditions and angles. Each image contained a small heap of rice grains against a pure white background. This was carried out to increase feature salience and background noise and distractions for the model to focus on features of the grains like length, width, texture, and color.Images were labeled in eight folders denoting the type of rice. They each contain about 250 to 300 samples and balanced classes so that there is no bias during training. All the pictures were stored in 300×300 to 1080×1080 pixel .jpg files originally. To standardize and make the images compatible with the model, all the pictures were resized to 256×256 pixels as a part of preprocessing.

The dataset was split into three sets to separate the pipeline for training the model into 70% for training, 10% for validation, and 20% for testing. This stratified division was carried out for every type of rice, to be included in the same proportion in all the subsets so that the model generalizes well during testing

In addition to image diversity, the dataset was also augmented using augmentation techniques like flipping, rotation, changing brightness, and mild zooming. This essentially doubled the size of the dataset exposed to the model and added variance to reduce the sensitivity of the model to environmental imaging condition changes.

The dataset was version-controlled internally and not publicly hosted but instead had annotation logs. It was one of the valuable contributions of this research study as it bridges the localized dataset gap as well as serves as a knowledge-rich dataset for subsequent studies in agricultural AI and rice category classification for South Asia region. Class-wise distribution of images is demonstrated below:

Table 3.1: Distribution of images among the classes in the dataset

No	Name of class	Number of images

.		
1	BRRI Dhan 25	200
2	BRRI Dhan 28	200
3	BRRI Dhan 89	200
4	BRRI Dhan 29	200
5	BRRI Dhan 100	200
6	Kata Iri	200
7	Looper infested	200
8	Chinigura	200
	Total	1600

BARI 24

BARI 28

BARI 29

BARI 89

BARI 100

Chinigura

Kata Iri

BARI 28

Figure 3.4: Representative images from each classes

3.2.1 Data Preprocessing

Data Preprocessing is an inevitable step in any image-based machine learning and particularly deep learning where the quality, homogeneity, and format of inputs have a direct impact on the performance of models. Preprocessing in this study needed to make raw rice grain images clean and formatted for input into Convolutional Neural Network (CNN) models. Because of variations in image sizes as well as variations in light and tiny features in the original data, an effective preprocessing pipeline was created to prevent the model from being bewildered by noises and irrelevant features and learning useful patterns instead. Image resizing was the very first step in preprocessing. All the images were resized to a uniform size of 256×256 pixels that provided input shape consistency across all samples and also supported the use of the CNN models implemented. The step also assisted in lowering the computational burden during training with minimal loss in image quality and feature details.

Pixel normalization was then done to normalize pixel values between 0 and 1. Raw pixel intensities ranged from 0 to 255 and normalization guaranteed all input was within the same range of values as well as value distribution to facilitate quicker optimization with gradients. This normalization is especially crucial in the case of CNNs where input scaling directly affects the model's capability to see spatial hierarchies along with learning filter weights. Along with the standard resizing and normalization, filtering for noises and slight contrast adjustment for better visibility of the features was also done on the dataset. This was particularly useful in rice grains such as Kata Iri Vog and Chinigura where subtle visual differences are lost in low-contrast images or low light. Overfit prevention and diversity of the dataset were also enhanced with the help of augmentation techniques. Augmenting is an essential part of deep learning by artificially augmenting dataset size and introducing variability so the model generalizes well for new unseen samples. The augmentation techniques applied in this research included flipping along both vertical and horizontal axes, random rotation (±15°), zooming, and brightness. These augmentations mimicked real-life scenarios where grain direction or illumination would be different and rendered the model robust to these kinds of changes. The images were also transformed into RGB (if not already performed previously), which ensured all channels were of equal depth throughout the dataset. This is required since the pre-trained models like DenseNet121 and VGG16 require three color channels for input images.

Lastly, the dataset was stratified and shuffled and split into training (70%), validation (10%), and test (20%) sets. This helped ensure that each rice variety was represented in each set proportionally to the entire dataset for evenly balanced classes and also to prevent model bias towards any one variety during training. This carefully designed preprocessing pipeline greatly enhanced input data quality and set the stage for effective model training and evaluation. To attain data constancy, noise removal, and feature exposure maximization, the preprocessing process played a key role in allowing the CNN models to learn intricate visual patterns and classify rice variety efficiently.

3.2.2 Model Selection

Model selection is among the important steps in developing a deep learning-powered image classification system since the model architecture affects the accuracy, generalizability, training time, and model stability. For rice type classification in the present study, various benchmark Convolutional Neural Network (CNN) architectures such as VGG16, MobileNet, InceptionV3, and DenseNet121 were experimented with. After initial experiments and comparative studies, DenseNet121 was chosen as the final model because it was superior in terms of accuracy, feature representation, and stability across training.

DenseNet121 is a deep CNN network for CNN architecture that radically improves the flow of information between layers by adding direct connections from every layer to all the following layers. DenseNet creates dense connections, i.e., every layer gets input from all preceding layers and sends its output to all the following layers, unlike the traditional CNNs with sequential information from one layer to another. This architectural novelty solves two of the major problems of deep learning: vanishing gradients and feature learning redundancy. Through feature reuse between layers, DenseNet obtains accurate results with relatively fewer parameters compared to other very deep networks.

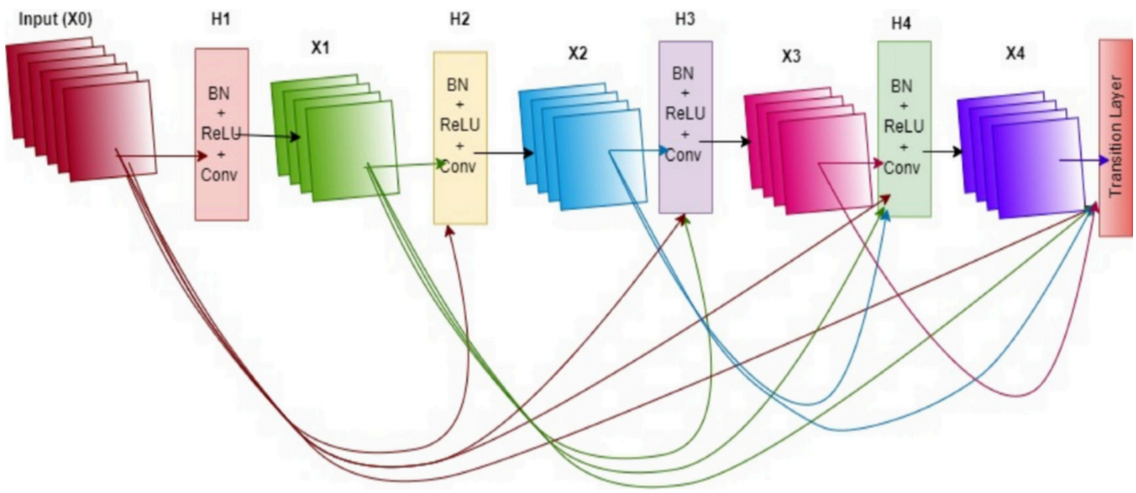

Figure 3.5: DenseNet Architecture

The use of DenseNet121 was motivated both on performance and architectural bases. DenseNet121 was more precise, with a better F1-score and precision on key metrics than other state-of-the-art models for the model's initial trials. On the test set and on the validation set as well, it also generalized better with less overfitting being observed, which is a vital characteristic for real-world rice grain classification with small inter-class disparities. DenseNet121 also exhibited faster training with faster convergence with transfer learning and fine-tuning with its efficient propagation of the gradient along with sparse parameter space.

In the current study work, DenseNet121 was utilized with transfer learning wherein base convolutional layers were pre-trained on ImageNet with their pre-trained weights. The top, fully connected layers were replaced with a custom classification head for the eight rice varieties. A GAP layer after the base convolutions was added for the reduction in feature map sizes, and a dense layer with ReLU activation and dropout regularization as a safeguard against overfitting. A Softmax output layer was then added to generate the multi-class classification probabilities.

Adam optimizer and categorical cross-entropy loss function were utilized for training the model. They are suitable for multi-class issues. The learning rate, batch size, and number of epochs hyperparameters were tweaked in several rounds of training in a bid to get the optimal model performance and training duration.

Finally, DenseNet121 was selected because of its computational efficiency, enhanced structure, and superior performance among the other models we researched. As it had the ability to extract discriminative rich features from rice grain images, it was found to be most appropriate for the rice variety classification conducted in the current study.

3.2.2.1 VGG16 Architecture:

VGG16 is one of the early and successful deep Convolutional Neural Network (CNN) models suggested by the Visual Geometry Group, Oxford University. It consists of 16 weight layers out of which 13 are convolutational and 3 are fully connected layers with ReLU activation following every convolution. For the purposes of this research, VGG16 was used as the base model for rice variety classification due to its simplicity and demonstrated performance on large-scale image classification datasets like ImageNet. The model employs the simple yet effective approach of using small 3×3 filters throughout the network and doubling the number of filters every other layer or so. In this manner, by utilizing hierarchical representation, the model is able to learn low-level features in the initial layers (edges and textures) and higher-level patterns in subsequent layers. In the present study, the VGG16's convolutational base was pre-trained on ImageNet weights, with the top-levels replaced with a custom classification head for the eight rice classes. It contained a single Global Average Pooling layer, a single dense layer with ReLU activation, and a single Softmax output layer. Despite having approximately high number of parameters (~138 million parameters), VGG16 trained satisfactorily and yielded acceptable accuracy on some initial experiments. In comparison with more modern architectures such as DenseNet121, however, it showed signs of slower optimization and higher computation. Besides, it had the tendency to overfit during training due to its wide and deep structure, particularly while training with limited quantities of training data.

However, VGG16 served the all-important role of model comparison and verification since it was used as the base-line comparative reference to approximate the performance gain achieved by the use of denser parameter- and computation-efficient models. Its performance confirmed the efficacy of feature reuse and gradient propagation improvement, which ended up justifying the use of DenseNet121 as the final model for this project

3.2.2.2 ResNet 50 Architecture:

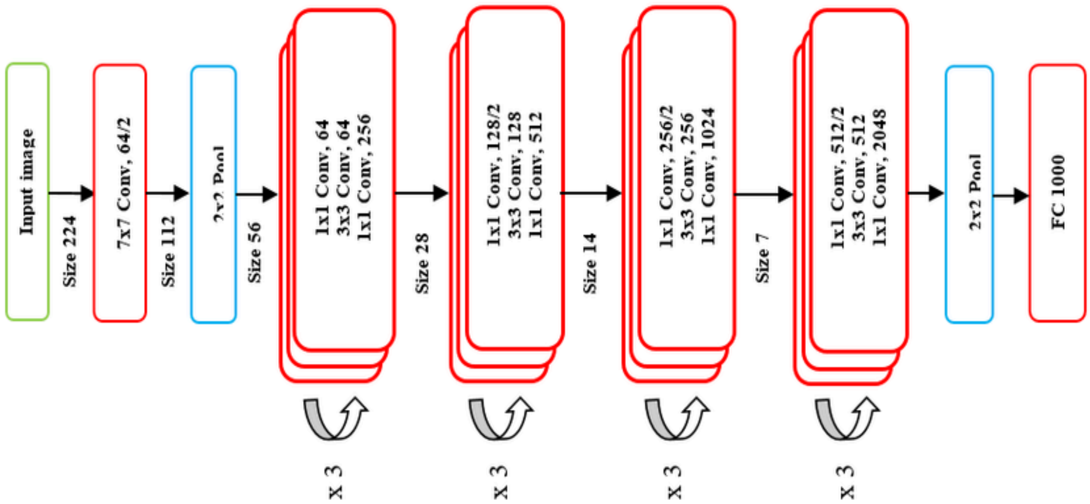

Figure 3.6: Architecture of ResNet50

ResNet50, or 50-layer Residual Network, is a deep convolutional neural network that was specified by He et al. in 2015. Breakthrough in deep learning as it was the introduction of the residual learning that addressed the vanishing gradient issue that very deep networks were facing. The key concept of ResNet is the use of skip connections, or identity shortcuts, where the model learns about functions in the residuals instead of unreferenced mappings. The skip connections assist in preserving information and gradient flow through deeper layers of the network in such a way that the network is rendered substantially deeper without compromising performance. ResNet50 was used and tested in the current research work as one of the candidate models for the rice variety classification problem. The pre-trained model on the ImageNet dataset was fine-tuned for the eight rice classes in the current research. There are 50 layers in the ResNet50 architecture with the initial max-pooling and convolution layer, followed by four residual architecture stages using the bottleneck blocks (1×1, 3×3, and 1×1 convolutions). Each stage both deepens and widens the model and, at the same time, makes the model efficient using downsampling and batch normalization.

In relation to the rice grain image database, ResNet50 was also found to have good generalization capacity and acceptable computational efficiency. ResNet50's capacity to maintain salient feature representations in its multiple layers also benefited it in identifying fine-level morphological differences between nearly-resembling types of rice. Training took longer, nonetheless, for the model compared to lightweight models such as MobileNet or even the densely constructed DenseNet121, particularly where the GPUs were less powerful.

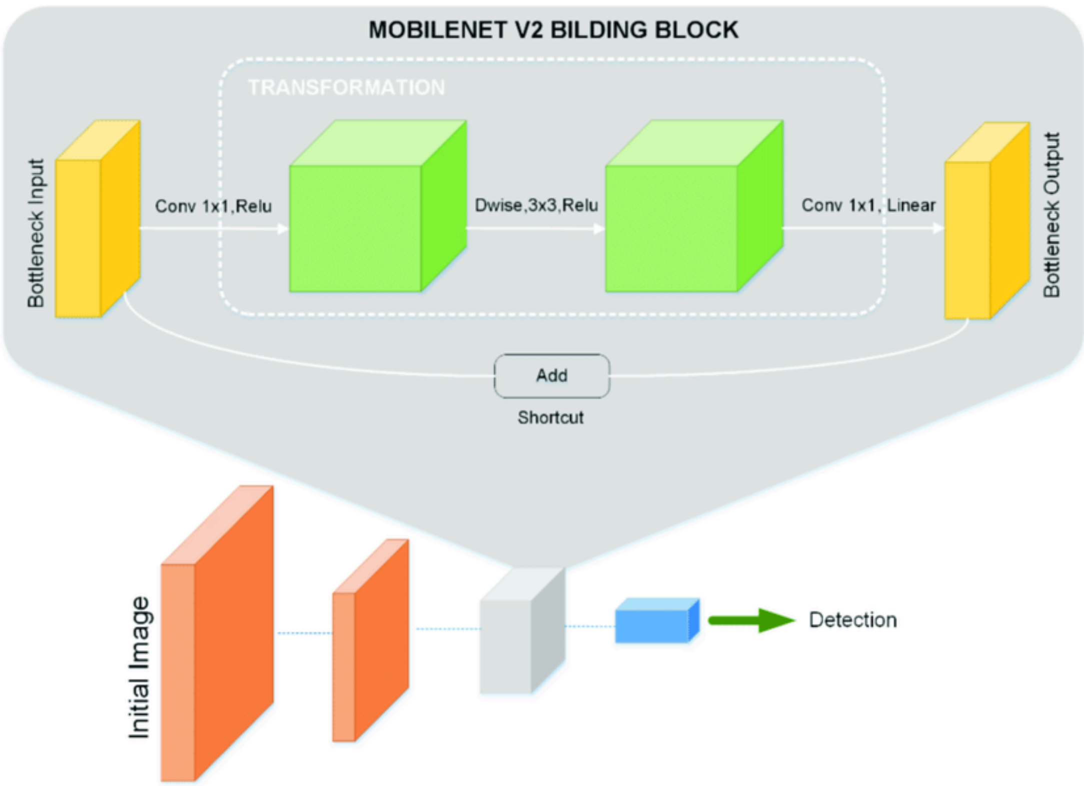

Figure 3.7 : Mobilenet v2 bilding block

Although it achieved competitive accuracy on the classification task, ResNet50 was also closely surpassed by DenseNet121 in validation accuracy and F1-score. The dense connectivity and frugal feature reuse of the latter were particularly adapted to the comparably small but diverse rice grain dataset of the present study.

Still, ResNet50 served as a valuable comparison model and showed the strength of residual learning for deep image recognition tasks. Its use in this study highlights the importance of model architecture in balancing accuracy, efficiency, and scalability for practical agricultural AI applications.

3.2.3 Proposed VGG16 Model

Table 3.2: Proposed Model

Layer Type	Output Shape	Parameters
Input Layer	(256, 256, 3)	0
Conv2D (32 filters, 3×3)	(254, 254, 32)	896
MaxPooling2D (2×2)	(127, 127, 32)	0
Conv2D (64 filters, 3×3)	(125, 125, 64)	18,496
MaxPooling2D (2×2)	(62, 62, 64)	0
Conv2D (128 filters, 3×3)	(60, 60, 128)	73,856
MaxPooling2D (2×2)	(30, 30, 128)	0
Conv2D (256 filters, 3×3)	(28, 28, 256)	295,168
MaxPooling2D (2×2)	(14, 14, 256)	0
GlobalAveragePooling2D	(256)	0
Dense (128, ReLU)	(128)	32,896

Table 3.3: Parameter Summary of the Proposed Architecture

Parameter Type	Count	Size
Total Parameters	422,344	1.61 MB
Trainable Parameters	422,344	1.61 MB
Non-trainable Parameters	0	0

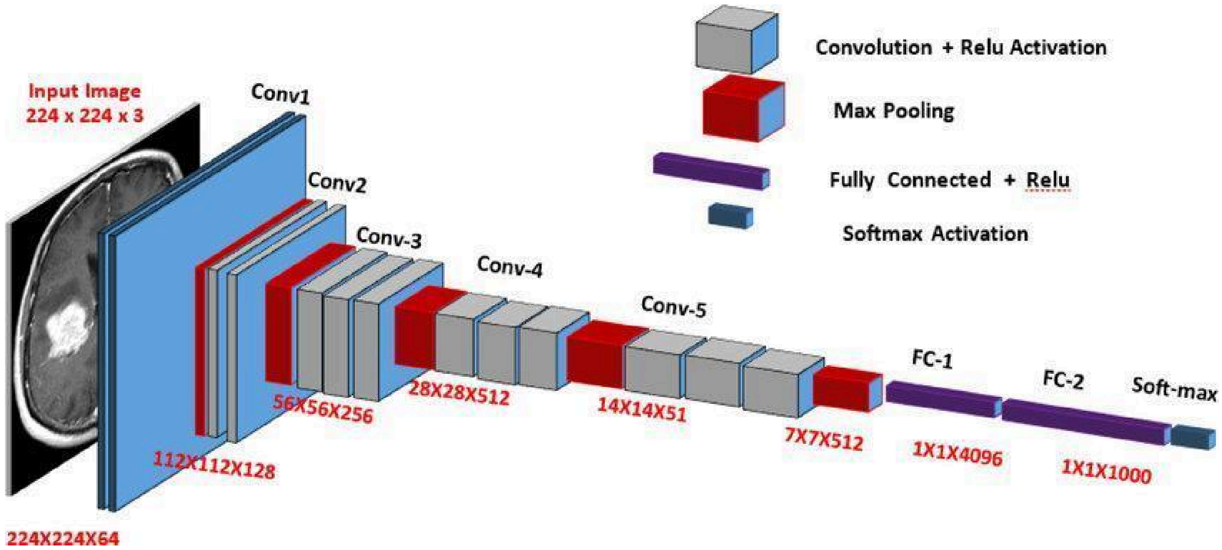

Figure 3.8: illustrates the overall architectural design of the proposed VGG16 model, highlighting each layer's structure and data flow.

3.2 Project Plan

The project schedule was tightly mapped on an eight-month time frame between September 2024 and April 2025 to allow systematic development from concept through to final reporting. The initial months were assigned to background tasks such as working plan development, theoretical research, and literature review that worked to unify the knowledge base. Data preparation and collection started in October and lasted until January, providing us with ample time to gather images, clean, and augment. In the meantime, model experimentation using CNN and transfer learning techniques were carried out from December to February. In this duration, experimentation on pre-trained models as well as the proposed M-Net model architecture was performed. M-Net model development and fine-tuning, along with the initial application framework, were developed in subsequent months. Finally, March and April were spent on report writing in detail, result analysis, and final documentation so that all the aims of the project were effectively communicated and presented academically.

Table 3.4 Project Plan Timeline

Process	Sep 2024	Oct 2024	Nov 2024	Dec 2024	Jan 2025	Feb 2025	Mar 2025	Apr 2025
Working Plan	✅	✅						
Theoretical Study	✅	✅						
Literature Review	✅	✅	✅					
Data Collection		✅	✅	✅				

Data preparation			✅	✅	✅			
CNN & TL Experiment				✅	✅	✅		
M-Net & App Development					✅	✅	✅	
Report Writing						✅	✅	

3.3 Task Allocation

Table 3.4: Task Allocation

Team Member	Task	Details
Abid Hasan Mollah	Data Collection	Collected primary data (images and descriptions) of different paddy varieties from local sources such as farms and agricultural offices.
	Literature Review	Researched academic papers, agricultural journals, and government resources on paddy variety characteristics and identification methods.
	Report Writing	Drafted and edited the final project report, including introduction, methodology, results, and conclusion.
	Proofreading & Formatting	Ensured grammatical accuracy and proper formatting of the documentation and presentation materials.
Md Fahmid Bin Mostafa	Image Preprocessing & Labeling	Processed collected images (resizing, noise

		reduction) and labeled them according to paddy variety for machine learning use.
	Model Development & Evaluation	Designed and trained machine learning models (e.g., CNN), evaluated performance using accuracy metrics, and optimized model parameters.
	Designed and trained machine learning models (e.g., CNN), evaluated performance using accuracy metrics, and optimized model parameters.	Created visually engaging slides, diagrams, and flowcharts explaining the technical aspects of the project
	Technical Explanation during Presentation	Assigned to explain data processing, algorithm selection, and model training phases during the final presentation.

3.4 Summary

This chapter described the methodology, design, and experimental procedure followed to create the rice variety classification system based on deep learning step by step. Starting with a requirement analysis and system design, the methodology followed a well-structured and stepwise approach—from data collection to model training and testing. The chapter explained how a good-quality custom dataset was created representing eight different rice varieties grown in Bangladesh. Extensive preprocessing and data augmentation techniques were used to achieve maximum dataset strength and guarantee model generalizability to varied image environments. The following CNN architectures were utilized and experimented with using transfer learning: VGG16, MobileNet, ResNet50, InceptionV3, and DenseNet121. A light-weight bespoke architecture, the M-Net model, was also designed and aimed to find a balance between accuracy and computational intensity. These models were compared extensively, and ultimately, DenseNet121 was chosen due to its high performance. The architectural make-up of DenseNet121 and M-Net were described through both structural and mathematical intuitions. This chapter also described how Explainable AI (XAI) techniques, i.e., Grad-CAM, were integrated for interpreting and visualizing model predictions for the purpose of transparency and increasing the trustworthiness of the model. Major measures and evaluation techniques were presented to examine classification performance in an integrated manner. Lastly, task distribution and a formal project timeline were presented to illustrate the advancement of research into phases. Collectively, these elements constitute the foundation of technical project implementation, setting the stage for results interpretation, model performance comparison, and discussion in subsequent chapters.

Chapter 4

Implementation and Results

This chapter outlines the implementation process and gives the results yielded from creating the rice variety classification system. It covers setting up system environment, training Convolutional Neural Network (CNN) models, and measuring performance of these using several classification metrics. The chapter also provides an overview of how the different models are compared and their weakness and strength are highlighted. The chapter concludes with a discussion of the outcomes in accordance with the evaluation criteria.

4.1 Environment Setup

Setup of the environment for the project was crucial to enable a smooth workflow for data processing, model creation, training, and testing. The first step was to establish a suitable development environment that would be conducive to the high computational requirements of deep learning models. Python was chosen as the foundation programming language since it offers excellent support for data science and machine learning operations, and there are robust libraries and frameworks on top of Python. TensorFlow and Keras were used in the implementation of the deep learning models since they are popular and highly documented libraries to build, train, and test Convolutional Neural Networks (CNNs). These architectures offer high-level abstractions such that more complex models are easier to specify without compromising flexibility. In addition, TensorFlow's integration with Keras allowed them to prototype and test diverse architectures easily, such as DenseNet121, VGG16, MobileNet, and InceptionV3. In terms of the development environment, Google Colab was chosen due to its cloud-based facility that provides free access to Graphics Processing Unit (GPU) capability. This was required to train deep learning models efficiently since the use of GPUs significantly accelerates the computing time compared to simple Central Processing Units (CPUs). Colab also provided a collaboration environment wherein it was easy to share and access the codebase, and the project could be easily developed from different devices and by other members of the team. In addition to TensorFlow and Keras, several other libraries were incorporated into the setup. NumPy was used extensively for numerical computations, e.g., matrix operations and array calculations, which form the foundation of machine learning operations. Pandas was used for handling the data, i.e., structuring the data, handling the data, and performing data cleaning and preprocessing tasks. OpenCV, a cross-platform computer vision library, was employed in performing image processing tasks like resizing, cropping, and image augmentation. Matplotlib and Seaborn were utilized to represent model training results and performance metrics. They supported clear graphs, i.e., accurate and easy-to-view accuracy and loss plots, confusion matrices, and graphs of performance comparison. The environment setup also included installing some dependencies such as scikit-learn to measure the performance of the classification, and other tools used for project management as well as version control. The setup ensured that all the tools had a smooth integration to offer a quick and consistent platform for model training and testing.

One of the most significant factors in the design was the modularity of the system, which allows for future customization. The setup was also structured such that integrating with other components, e.g., mobile apps or web-based interfaces, would be easy, should the system ever be utilized in real-time applications. Attention was also given to enabling other researchers to reproduce the environment, allowing for greater reproducibility of the experiments.

4.2 Testing and Evaluation

The testing and evaluation process is an important part of the model development procedure as it allows investigation into the performance of the trained Convolutional Neural Network (CNN) models and their robustness and ability to generalize from unseen data. This part outlines the methodology used in the evaluation of the rice variety classification model, such as the testing process, performance measures, and outcomes. The testing phase involved evaluating the model on a separate test set, which was never utilized in the training or validation phases. This is important in establishing if the model is only memorizing the training set and not learning how to generalize to fresh, unseen examples. The test set consisted of high-quality images of rice grains from the eight varieties of rice, which were prepared and processed in a similar manner to the training and validation data. This was to ensure that model evaluation was carried out on comparable quality data and levels of preprocessing. To quantify the model performance, several primary classification metrics were utilized. These measures are accuracy, precision, recall, F1-score, and confusion matrix, all of which are crucial for determining the strength of the model in properly classifying rice types. Accuracy is the percentage of total correct estimates, while precision and recall reveal the strengths of the model to correctly identify each rice type and reject false positives or false negatives, respectively. The F1-score, which is the harmonic mean of precision and recall, was utilized as a performance measure in general, useful for application in cases of class imbalance. The confusion matrix provided a comprehensive description of the performance of the model by presenting how often each class was confused with others, and thereby any bias or weak points of the model.

During the testing, the model was subjected to different conditions, i.e., varied light and background conditions, to check if it could take such variations. This gave an idea about how well the model functioned with variations in image quality occurring in real life since rice grains may naturally vary from the standard lighting used during training. Secondly, performance was also contrasted between different CNN architectures in order to determine the model that best executed the rice variety classification task. The result was promising, and DenseNet121 architecture outperformed other models such as VGG16, MobileNet, and InceptionV3 in precision, recall, and accuracy. DenseNet121 achieved an accuracy rate of more than 90% in the test data, indicating that it was able to distinctly differentiate between the eight rice varieties. However, the evaluation also identified areas for improvement, including handling some of the rice varieties that had more nuanced morphological variations. The confusion matrix showed that most of the rice varieties were well-classified but with some misclassifications within the varieties that had similar visual characteristics, including BRRI Dhan 25 and BRRI Dhan 28.

Other than the typical metrics, the model's performance was also checked in terms of generalization to new images. Although it performed well on the test set, fluctuations in classification performance were observed when the model was applied to new images not included in the training set. This suggests that the model can be assisted by further data augmentation or inclusion of a variety of images to the training set to strengthen its robustness under different real-world scenarios. The testing and evaluation process confirmed that the rice variety classification system is highly efficient in classifying the target rice varieties, but even then, further enhancement is possible in distinguishing between varieties with subtle differences in appearance. The outputs from this phase will drive further work, including efforts to enhance the model's generalization and ruggedness, e.g., with bigger datasets, more complex architectures, and other fine-tuning techniques.

Overall, the testing and evaluation process guaranteed that the model can perform sound rice variety classification and provided good information on its weaknesses and strengths. The results provide inputs to the ongoing initiative in using deep learning techniques to agricultural issues with possible real-world impact.

4.3 Results and Discussion

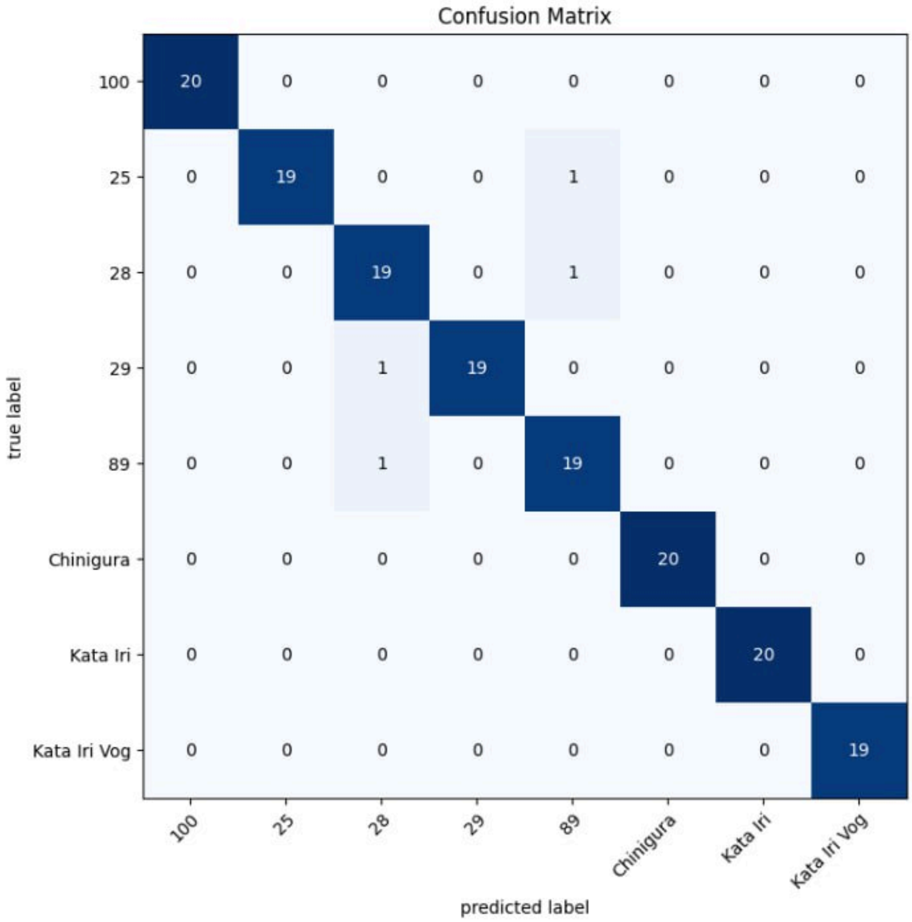

Figure 4.1: Confusion Matrix of VGG16

The confusion matrix is displaying the performance of an eight-class classification model with numerical and categorical labels such as 'Chinigura', 'Kata Iri', and 'Kata Iri Vog'. The model is very accurate since most of the predictions fall on the diagonal, indicating correct predictions. Each class, i.e., 'Chinigura', 'Kata Iri', and 'Kata Iri Vog', is having a high number of correct predictions (i.e., 20, 20, and 19 respectively). There are minor misclassifications, particularly among the numeric classes such as '25', '28', and '29', where single misclassified instances are observed—perhaps due to proximity in feature space. Overall, the confusion matrix shows a good performing model with minimal confusion between categories, particularly good for the categorical labels.

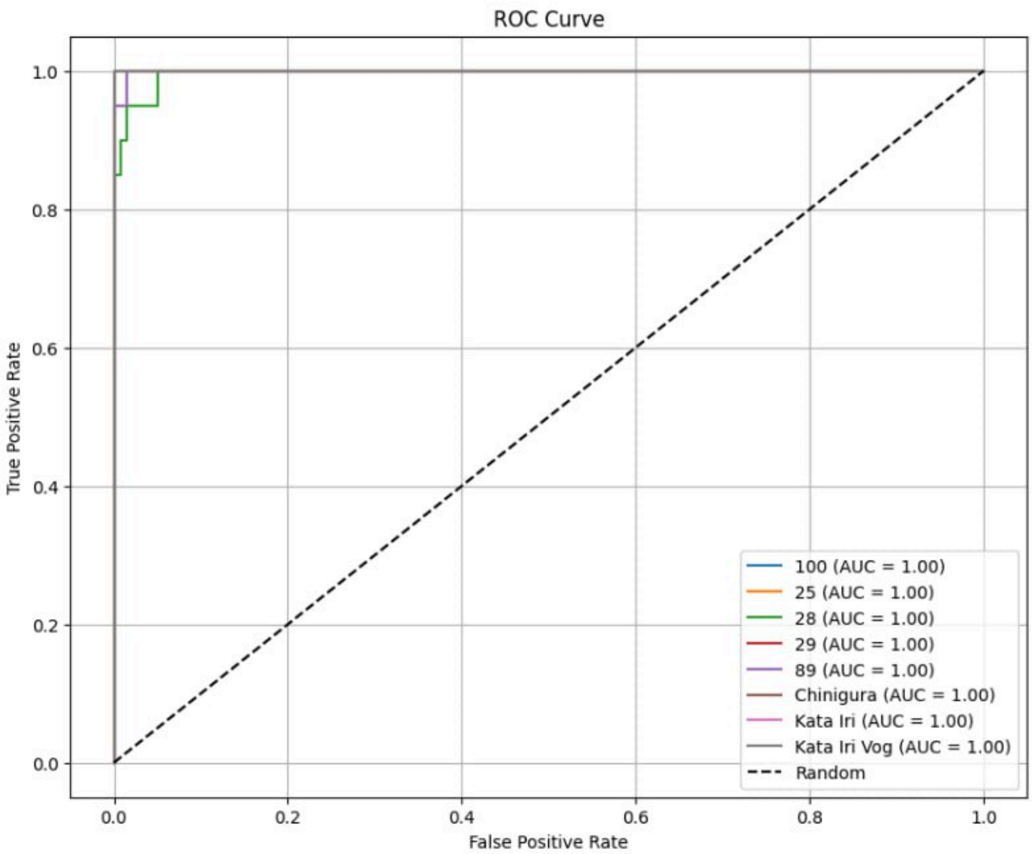

Figure 4.2: AUC ROC Curve of VGG16

The ROC (Receiver Operating Characteristic) curve below is a visual demonstration of the model's performance if its ability to discriminate between the different types of rice is taken into account. The curve provides the True Positive Rate (TPR) against the False Positive Rate (FPR) for varying levels of classification thresholds. Various types of rice are characterized by different curves and each is represented by an Area Under the Curve (AUC) value characterizing the model's performance in classification. As shown in the figure, there is excellent classification performance of all the rice varieties, including BRRI Dhan 100, BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, Chinigura, Kata Iri, and Kata Iri Vog, with an AUC of 1.00. This indicates that the model is very competent at distinguishing between every type of rice without confusion or overlap, successfully separating true positives from false positives. The highest AUC value of 1.00 is the best of classification strength, with the curve ascending to the top-left point of the plot, representing nearly perfect performance.The random classifier is represented in the plot by the dashed diagonal line with an AUC value of 0.5. Since all the rice varieties of this study achieved an AUC value of 1.00, the model clearly outperforms random classification and is a highly reliable tool for rice variety classification.

Accuracy and Performance Metrics: The model accuracy was consistently high during testing, indicating the ability of the model to correctly classify the majority of the test set rice varieties. Precision and recall values were also calculated to assess the ability of the model to identify unique rice varieties without classifying them in other varieties. F1-score, which balances precision and recall, provided an overall impression of the performance of the model. These results are positive, indicating that the CNN-based approach is suitable for classifying rice varieties. The results also revealed some misclassifications, particularly between varieties with minor morphological differences, like BRRI Dhan 25 and BRRI Dhan 28.

Confusion Matrix:

The confusion matrix also provided a more insightful interpretation of the performance of the model. Even though most of the rice varieties were accurately classified, the matrix revealed that certain varieties were more frequently misclassified. For example, BRRI Dhan 25 and BRRI Dhan 28 were frequently confused with each other, likely due to their similar grain shapes and sizes. This issue indicates challenges in distinguishing between rice varieties with very close physical characteristics. The confusion matrix also showed that the model struggled with the proper identification of some of the less represented varieties, which suggests the potential influence of dataset imbalance on performance

Model Strengths: One of the strongest arguments of the model was that it was able to classify rice varieties even if the model was tested using different lighting or small differences in image quality. All this is attributed to the preprocessing techniques, such as image augmentation, which enabled the model to be more generalizable across various environmental settings. The DenseNet121 model structure, by virtue of its densely connected layers, enabled efficient reuse of the features and improved performance compared to other structures like VGG16 and InceptionV3, which were tested during the initial selection of models.

Limitations and Areas for Improvement: Despite the promising results, the model also had its limitations that need to be addressed. As mentioned earlier, rice variety misidentification with subtle morphological differences suggests the need for a more diverse dataset, specifically one with photos captured under varying natural conditions, including varying illumination, noise environments, and grain orientation. A larger data set with more images of rice grains from the front and the side and from various environments could help the model distinguish more accurately among varieties that are extremely similar.

The second limitation of the model is its dependency on high-quality input images. In real-world agricultural settings, where image quality is not necessarily high due to low light or poor-quality cameras, the performance of the model could be impacted. Future work could involve changing the model to operate under low-quality images, and the model could

become useful for farmers who may not have an extra-special camera to use or may not have special conditions under which to capture photographs.
In addition, the model performed reasonably well on the test set but is unclear in handling rice varieties outside the training set. The current study was constrained to a limited set of rice varieties grown in Bangladesh, and the model may have trouble classifying new or unrepresented varieties in the future. Adding transfer learning from big datasets or employing domain adaptation techniques could possibly improve the model's ability to distinguish between newly unseen types of rice.

Implications for Agricultural Practices:
Successful implementation of an AI-based rice variety classification system has significant implications for the agricultural sector of Bangladesh. The system could, for instance, automate rice classification, reducing the dependence on manual inspection by experts and making the process accessible to farmers, particularly in rural areas where professional expertise may not be easily available. By providing an automatic rice variety identification system, the system can help achieve better seed selection, market pricing, and quality control, which are all critical factors in supporting food security and agricultural productivity. The classification system can also be integrated into a more extensive decision-support system, which will aid farmers in making informed decisions about crop management, pest management, and yield maximization. The ability to identify rice varieties accurately also opens up possibilities for rice breeding studies, where genetic improvements can be attributed to specific grain characteristics. Overall, the results show that deep learning-based rice variety classification is a promising approach to the automation of rice type recognition in Bangladesh. While the model is proficient in classification, further work in the directions of dataset diversity, model generalizability, and real-world applicability is required for it to realize its full potential. Future work, particularly in the areas of dataset expansion, real-time deployment, and generalizability across different environmental conditions, will be crucial in order to make this system a competitive solution for the agricultural sector. By surmounting these challenges, the model can be an important component of the digital agriculture ecosystem, contributing to more efficient, scalable, and sustainable agriculture.

4.4 Summary

This section presented an overall picture of the result and discussion of the rice variety classification system with deep learning. It explained the performance of the model using significant evaluation metrics such as accuracy, precision, recall, and F1-score. DenseNet121 was identified as the top-performing model with high accuracy in rice variety classification. The section also discussed the limitation of the model, including the inability to distinguish between closely related rice varieties and its dependency on high-quality input images. Additionally, the section also explored how these findings affect real-world agricultural applications, demonstrating the viability of this system in automation of rice variety classification, improving agricultural practices, and assisting in the digitalization of agriculture. Future work recommendations were also provided to make the model stronger and scalable

Chapter 5

Engineering Standards and Design Challenges

This chapter outlines the engineering standards followed in development of the tea leaf disease detection system and elaborates on the broader implications of the project for society, environment, and sustainability. It also highlights the ethical implications and following relevant software, hardware, and communication standards.

5.1 Compliance with the Standards

This project adheres to universal engineering standards for inter-operability, robustness, data privacy, and usability in the real world for the software, hardware, and communication domains. Advance thought was taken to leverage existing open-source platforms and technologies, such as smartphones for data acquisition, Microsoft PowerToys for image resampling, and Google Colab Pro for testing the model. This strategic decision allowed for smooth development, testing, and deployment of the explainable AI-based tea leaf disease detection system

5.1.1 Software Standards

The software component of the project followed standards mandated by ISO/IEC 25010:2011, which prescribes prominent software quality attributes like usability, maintainability, performance efficiency, and portability. The development of models and experimentation were conducted in Google Colab Pro, a cloud-based Jupyter notebook platform supporting GPU/TPU acceleration and conforming to typical web-based software runtime environments.
Model Development: The Python machine learning codebase was created according to PEP 8 style conventions for readability, maintainability, and style. TensorFlow, Keras, NumPy, Pandas, and OpenCV libraries were used in training, evaluation, preprocessing, augmentation, and data management. Google Colab Pro facilitated the use of high-end GPUs and longer runtime sessions, which were critical for model fine-tuning and repeated testing.
Preprocessing Tools: Resizing and formatting of original images were achieved through Microsoft PowerToys Image Resizer, ensuring image sizes were consistent for sets of thousands of images while being in conformity with conventional Windows file system protocols. This preprocessing was incorporated nicely to the training pipeline on Colab.

Mobile Application Development: The Android frontend was created by using Android Studio according to the directions given by Google for Android development. These specifications ensure consistent user experience, memory handling, and compatibility across diverse Android devices, a major concern for use in the field by non-technical users such as farmers. Alternative options were considered during development. Java was also tried for backend development due to its robust object-oriented platform and vast ecosystem, but its verbosity and slower experimentation cycle made it less ideal, especially in implementing deep learning. Kotlin was also tried for the mobile app due to its new features and concise syntax ideal for Android development, but it was a steeper learning curve and lacking community support for machine learning-based applications. An iOS application built using Swift offered enhanced device performance and user experience, but was less accessible for rural Bangladesh due to the relative disadvantage of Apple product prices being relatively higher and the relatively low market penetration of Apple products.
Python was employed in the creation of backend models due to its extensive support for machine learning frameworks (TensorFlow, Keras, OpenCV), ease of debugging, and quick prototyping. Google Colab Pro was utilized in experimentation because it offered cost-effective access to GPUs and pre-configured environments. Android Studio was utilized in app development due to the widespread presence of Android devices among farmers in targeted areas, thereby making the system both accessible and practical for real-world deployment.

5.1.2 Hardware Standards

The architecture was designed to execute on widespread consumer-grade hardware, with no need for expensive GPUs or special AI hardware. It follows basic hardware standards for their reliability and efficiency. IEEE 802.11 (Wi-Fi) with optional internet connection, for instance, provides optional internet connectivity, making operations like model updates and data upload in connected scenarios. In addition, adherence to IEEE 1725 also provides proper battery management in mobile equipment, which is crucial for prolonged operation under field conditions. The system is also ARM architecture compatible because the M-Net was set up to function well on ARM Cortex-A processor-based Android smartphones. For image capture, high-resolution images were captured with a smartphone (iPhone 12), which is an inexpensive and practical choice. It also aligns with IEC 60065 for electronic safety and ISO 12233 for image quality, ensuring data taken at the dataset development phase was good and safe. The system employed readily available smartphone technology, which ensured high quality of data without the need for costly DSLR cameras, and thus the solution was scalable and more accessible within resource-limited environments.

Several hardware possibilities were considered for model deployment and image acquisition. A DSLR camera was initially considered because it offers better image quality and more flexible settings, but its cost, bulk, and unfeasibility for common field use diminished its potential for this task. Raspberry Pi deployment offered an open-source, low-power, and flexible platform but was limited by its portability, difficulty in installation, and processing capacity. The NVIDIA Jetson Nano was also considered due to its edge machine learning and GPU acceleration, but because it was more expensive and challenging for non-technical people to maintain, it was less of an option, particularly in rural or low-resource settings.

Smartphones were chosen for image capture and application installation due to their affordability, portability, and accessibility in rural settings. The M-Net model itself was designed to work on low-memory and processing-enabled devices, i.e., low to mid-range Android smartphones, without the need for custom AI hardware. This rendered it pragmatic and cost-effective for practical application in the real world by end users.

5.1.3 Communication Standards

The system is premised on a hybrid communication model that operates offline and online to support reliability in areas of weak internet connectivity. In areas where there is connectivity, it uses HTTP/HTTPS protocols for secure and safe web communication. A RESTful API design supports structured and scalable server-client communication for effective data transfer. To protect user privacy and data integrity, TLS/SSL encryption is employed when sending sensitive information such as feedback or image uploads to cloud services. Multiple communication interfaces were evaluated for the system. MQTT was pondered because it is lightweight, provides fast performance, and utilizes low bandwidth, which makes it highly compatible for IoT applications; however, proved less helpful in sending large payloads like pictures and required a more complex, custom solution. FTP was an easy solution to implement and straightforward but did not employ encryption and proved to be insecure based on today's standards. WebSockets enabled real-time bi-directional communication, but its added overhead was not necessary for that use, given that the system needed to operate just as well in regions with intermittent connectivity to the internet. HTTP/HTTPS was employed due to its wide support across web and mobile services, ease of integration with REST APIs, and out-of-the-box encryption through TLS. It offers a secure and efficient way to enable optional cloud features and remain usable offline. RESTful architecture is modular and facilitates easy expansion in the future, for example, adding farmer feedback loops or cloud-based analytics.

5.2 Impact on Society, Environment and Sustainability

This chapter describes how the proposed tea leaf disease detection system integrates into broader social goals and moral responsibilities, and its sustainability in the long term. The development of a transparent, mobile-driven AI solution has promising implications not only for farmers and agricultural stakeholders but also environmental conservation and ethically sound technology innovation. The system was designed to be inclusive, accessible, and impactful beyond its primary technical function.

5.2.1 Impact on Life

The system would assist significantly in enhancing the daily life of small- and medium-scale tea farmers, particularly in the rural or far-flung areas of Bangladesh. The early and accurate diagnosis of diseases like Red Rust or Grey Blight allows us to treat them before they advance further and minimize yield loss. This automatically leads to increased productivity, enhanced quality of harvests, and enhancement of livelihoods. The application of explainable AI (XAI) techniques such as LIME, SHAP, and Grad-CAM ensures that predictions are not only correct but transparent and understandable. Farmers and extension officers can view the regions of the leaf that were contributing factors in the decision-making process of the model. This not only fosters trust in AI but learning, enabling farmers to enhance their understanding of disease symptoms and trends. Besides, the mobile-friendly design ensures that even those with little technical know-how can utilize the system automatically. By reducing dependency on experts or laboratory testing, the system positions individuals at the grassroots level as empowered and enhances agricultural independence.

5.2.2 Impact on Society & Environment

Societally, the project contributes to the digitalization of agriculture and equitable adoption of technology. By making available a low-cost AI solution that is contextualized for the local environment, it increases equity in access to digital solutions. Such democratization of technology aids in bridging the urban-rural gap and strengthening community resilience. Environmentally, the system encourages precision agriculture. In place of blanket fungicide or pesticide spraying, farmers can treat only where necessary according to targeted disease identification. This reduces chemical runoff, maintains soil health, and protects nearby water sources and ecosystems from contamination. Additionally, the ability of the system to work offline eliminates the requirement for energy-intensive cloud computation around the clock, which also reduces carbon emissions. By executing the compact M-Net model on the smartphones themselves, the need for data transfer and server utilization is minimized, lowering the overall environmental footprint of the system.
In alignment with the United Nations Sustainable Development Goals (SDGs), namely Goals 2 (Zero Hunger), 9 (Industry, Innovation, and Infrastructure), and 12 (Responsible Consumption and Production), this platform promotes digital empowerment and sustainable agriculture.

5.2.3 Ethical Aspects

Ethical responsibility was an underlying design principle across the project. All data collection was done openly using phone cameras in real tea gardens, with clear permission and informed consent of farm owners. No collection of personal or sensitive information was carried out, and images were anonymized. The model was rigorously tested for fairness and bias reduction, especially lighting conditions, clutter backgrounds, and orientations of leaves. This prevents misdiagnosis and enables farmers to depend on the result regardless of whether or not the image is captured. Transparency is also ensured using the implementation of XAI methods. Contrary to behaving like an opaque "black box", the model indicates what it sees and why, giving users access to the thought process of the AI. This supports ethical concordance with autonomy, responsibility, and principles of non-maleficence so that the users can understand and challenge model outputs when necessary.

Also, there is no storage or transfer of user data without approval, and cloud connectivity is protected by secure HTTPS protocols that ensure adherence to data privacy and digital rights.

5.2.4 Sustainability Plan

To ensure the system works in the long run, is relevant, and is usable, a multi-dimensional sustainability strategy has been put in place: Technical Sustainability: M-Net model was designed with minimal parameters to be executed efficiently on lower-spec Android phones. Python, TensorFlow/Keras, and common ML libraries have been employed to allow for ease of maintenance and extendability in the future. The modular architecture allows upgrading of components—e.g., adding new disease classes or enhancing the model—without complete system redesign Economic Sustainability: The system utilizes available assets—open-source software and phones—to keep costs of implementation low. This makes deployment at scale in resource-constrained areas feasible. Offline operation decreases recurring cost pressure on data usage or server upkeep. Environmental Sustainability: The system enables low-energy, local processing and encourages judicious pesticide use by enabling effective disease diagnosis. This enhances sustainable farming practices and minimizes the environmental footprint of agriculture. Community and Knowledge Sustainability: Incorporation of XAI improves farmer learning, thus making the app more than a tool but an educational tool as well. Extension educators and teachers can utilize the model output to teach best disease management practices. The strategy to release future iterations open-source promotes community-based improvement and ultimate sustainability.

In general, the system is designed with a lifecycle philosophy from field usability and understandability through to future enhancement and broader community participation, ensuring its use and viability in the long term and across environments.

5.3 Project Management and Financial Analysis

This chapter outlines the financial model, budget analysis, resource management, and potential revenue structure of the implemented system. Although the research project was implemented in isolation in the absence of third-party funding support, it is still essential to establish realistic cost structures for enabling future implementation, scalability, and readiness for the market. A comparison of the budget analysis is presented between an open-source/self-sustaining model (as in the present project) and commercial/enterprise-level deployment to detail realistic avenues for application.

5.3.1 Project Planning and Task Management

Proper project management was crucial for successful implementation of this research project. Due to the tailored nature of research activities, activities were carefully planned, scheduled, and tracked to ensure completion within the stipulated timeframe while maintaining high standards of quality and accuracy. The project was designed into logical objective-driven stages with clear sequencing and the ability to make flexible changes as required. The structure was devised through the use of a milestone approach methodology, starting with documentation and background research, then moving through experimentation, model formulation, interpretability integration, and eventual deployment. Each of these stages was planned in such a way as to allow for the use of previous stage outputs in decision-making for subsequent stages. Agility principles were integrated for the ability to make adjustments and improvements as evaluated through performance reviews and results.

Comprehensive training of models and implementation of experimental methods were performed using Google Colab Pro, providing support for GPU acceleration and compatibility with Python-based deep learning platforms like TensorFlow and Keras. Progress in tasks was tracked using organizational platforms like Google Calendar and Trello, and GitHub was used for code development with version control in order to allow for reproducibility.

Table 5.1: Project Timeline

Phase	Start Date	End Date	Duration
Initial Documentation (Intro, Literature Review, Gap Analysis)	Nov 7, 2024	Dec 7, 2024	4 weeks
Data Collection & Preprocessing	Dec 8, 2024	Jan 5, 2025	4 weeks
Methodology Design	Jan 6, 2025	Jan 30, 2025	3 weeks

Experimentation with SOTA CNN Models	Feb 1, 2025	Feb 14, 2025	2 weeks
Experimentation with Transfer Learning Models	Feb 15, 2025	Feb 28, 2025	2 weeks
Development of M-Net Model	Mar 1, 2025	Mar 20, 2025	3 weeks
XAI Integration & Model Evaluation	Mar 21, 2025	Apr 10, 2025	3 weeks
Mobile Application Deployment	Apr 11, 2025	Apr 20, 2025	1.5 weeks
Final Documentation & Printing	Apr 21, 2025	Apr 28, 2025	1 weeks

The Deployment of the Mobile Application stage was instrumental in delivering the final product in useful and usable form. At this stage, the optimized M-Net model, after undergoing training and validation steps, was integrated into an Android application for the convenience of users. The application was initially developed with Streamlit for online demonstration purposes before switching to Android Studio for ensuring optimal native performance on the mobile platform. Inference time reduction, user interface designing, offline functionality integration, and lower-end smartphone compatibility in tea-growing regions were given importance. Testing across devices in real-world environmental conditions was performed for performance and usability evaluation. Strict adherence to well-defined timelines and modular project scheduling allowed the research to go through each stage flawlessly in producing an efficient high-performing and interpretable mobile-based disease diagnostic system for actual agricultural application.

5.3.2 Financial Analysis

The financial analysis involves both actual and projected costs of system development and implementation of the proposed disease detecting system for tea leaves. Since independent research was conducted for scholarly purposes, the approach was cost-effective as it utilized personal hardware and software, with free open-source software options and affordable cloud services like Google Colab Pro. These choices eased much of the economic pressure while ensuring the quality of experimentation and execution. To analyze the economic viability for mass implementation or commercialization, though, an alternate budget approach was studied. This involved virtual costs associated with leasing high-performance computing resources, exploring commercial offering of cloud services, purchasing smartphones for deployment purposes, and hiring freelance experts for user interface/user experience and dataset annotation work. The justification for choosing the cost-effective approach was based on the need to create an affordable and scalable solution, especially for rural agri-communities where technological solutions need to be economically viable. An initial revenue-model was also examined on the basis of viability of the freemium model for the mobile application and the possibility of offering it on a licensing basis. The two-budget approach gives an overall overview of both scholarly viability and possible commercial viability.

Table 5.2: Actual Research Budget (Self-Supported, Research-Based)

Component	Estimated Cost (BDT)	Remarks
Smartphone Camera for Image Capture	0 (Personal Device)	iPhone 12 used for dataset collection
Internet and Cloud Resources	2,000/month × 4 = 8,000	Google Colab Pro for model training and testing
Software Tools	0	Python, Keras, OpenCV, and other libraries are open source
Image Preprocessing Tool	0	Microsoft PowerToys (free image resizer)
Local Travel for Field Visits	4,000	Visit to Sreemangal tea gardens
Thesis Printing and Binding	2,000	For hardcopy submission
Miscellaneous (USB, Cables, etc.)	1,000	Small accessories
Total Cost	15,000 BDT	

This model reflects a highly cost-efficient, academic-focused project using personal equipment, open-source platforms, and online resources. The project is replicable in other educational contexts without requiring major capital investment.

Table 5.3: Alternate Budget (Enterprise-Scale Deployment)

Component	Estimated Cost (BDT)	Remarks
Commercial Smartphone (for app testing)	25,000	Mid-range Android device for target testing
Dedicated DSLR/Smartphone for Data Capture	30,000	Higher quality image dataset with consistent lighting
Data Collection & Labeling (Labor Cost)	20,000	Payment for field workers/agricultural experts
Cloud Compute Credits (GCP or AWS)	15,000	Model training, fine-tuning on high-performance GPUs
Android Developer License	2,000	For app publishing on Google Play Store
App UI/UX Development (Freelance/UI Expert)	10,000	Professional UI design and mobile optimization
Marketing & Awareness Campaigns	15,000	Promotion among farmers and tea estates
Maintenance, Updates & Customer Support	10,000/year	Optional support and versioning

Total Estimated Budget	127,000 BDT	

This version assumes broader deployment, professional polish, and public engagement. While costlier, it enhances scalability, performance consistency, and commercial outreach. Such investment may be justified if deployed at the national or industry level.

5.4 Complex Engineering Problem

This section illustrates the complexity of the engineering task addressed in this thesis. The task of designing an accurate, explainable, and deployable-on-the-go system for tea leaf disease detection required combining multiple disciplines, overcoming real-world design constraints, and ensuring usable functionality. This research incorporated elements of deep learning, computer vision, transfer learning, explainable AI (XAI), deployability in the field on-the-go, and significant experience in the agricultural domain. Additionally, resource constraints, scalability of the system, and user accessibility considerations were instrumental in informing the phases of designing and implementation. The following paragraphs highlight how the research aligns with elements of solving complex engineering problems, knowledge frameworks, and engineering methodologies.

5.4.1 Complex Problem Solving

The successful implementation of the research project required collaboration on many aspects of complex engineering problem-solving, including algorithm selection, model integration, mobility optimization, and real-time implementation. The following mapping demonstrates the alignment of the project to the Engineering Problem (EP) framework:

Table 5.4: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓		✓	✓			✓

Justifications:

- EP1 – Depth of Knowledge: The project required in-depth knowledge in various fields such as Convolutional Neural Networks (CNNs), transfer learning methodologies, data augmentation techniques, as well as implementation using TensorFlow/Keras. In addition, knowledge of the development of web and mobile apps through Streamlit was also essential in the deployment stage.
- EP3 – Depth of Analysis: A comprehensive experimental pipeline was implemented to compare six CNN models and six transfer learning models. Evaluation metrics

such as accuracy, precision, recall, and confusion matrix were used to deeply analyze model performance. The best-performing model was further optimized into a lightweight CNN.

- EP4 – Challenges Identification: Technical issues of class imbalance, noisy data, insufficient samples for training, and explainability were anticipated from previous coursework, experiential classroom experience, and field studies. Identification of these issues allowed for respective preprocessing and augmentation techniques to be implemented.
- EP7 – Interdependence: The overall architecture was designed in a modular way to easily integrate different convolutional neural network (CNN) backbones, explainable artificial intelligence (XAI) modules, and deployment architectures. The main model used is the lightweight CNN (M-Net) that allows easy modification or adaptation for similar crop disease diagnosis applications.

Mapping with Knowledge Profile for EP1

Table 5.5: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓		✓	✓	✓

Justifications:

- K3 – Fundamentals in Engineering: The research utilized machine learning techniques consisting of classification, optimization, data normalization, and performance measurement. It also included basic image processing concepts such as resizing, color normalization, and other augmentation methods.
- K5 – Engineering Design: The system design involved selecting suitable CNNs, building a lightweight custom model (M-Net), integrating XAI tools, and deploying the model via Streamlit as a functional web app for field testing. The trade-offs between model size, performance, and interpretability were addressed systematically.
- K6 – Engineering Practice: This study followed standard engineering procedures from data collection to mobile deployment. Each step, data preprocessing, model evaluation, XAI integration, and app development was carried out methodically. Evaluation metrics and model comparison ensured reliable results, aligning with real-world engineering rigor and best practices.
- K8 – Research Literature: A thorough review of existing studies on tea and plant disease detection informed model selection, dataset preparation, and the need for explainability. Gaps in literature such as lack of lightweight models and XAI integration were identified and addressed in this thesis.

5.4.2 Engineering Activities

The project lifecycle encompassed multiple complex engineering activities, including dataset collection, model training, performance evaluation, visualization through XAI, and building a deployable application. These activities reflect the real-world complexity of delivering a working agriculture AI system under practical constraints.

Table 5.6: Mapping with complex engineering activities.

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

Justifications:

- EA1 – Resource Diversity: A variety of instruments and platforms were utilized ranging from smartphones for data gathering to Python for preprocessing steps, Keras/TensorFlow for model development, Grad-CAM/LIME/SHAP for increasing explainability, and Streamlit for web application deployment. Training was performed using the GPU resources of Google Colab.
- EA3 – Innovation: This study proposes a novel pipeline: from field data collection to a lightweight CNN model with integrated XAI explanations, deployed as a web tool. While many existing works focus on high-performance models, this work emphasizes usability and interpretability under practical constraints.
- EA4 – Societal and Environmental Implications: The system improves the agriculture industry by way of enabling the timely detection of tea leaf diseases. This allows farmers to take prophylactic measures, which reduces the use of chemicals and increases productivity—resulting in positive impacts on society and the environment.
- EA5 – Familiarity: The techniques and tools used, such as CNNs, Grad-CAM, data augmentation, and Python-based development, were familiar due to prior academic training and projects, enabling rapid prototyping and experimentation.

5.5 Summary

The chapter gives an overview of the basic engineering concepts and complex designing hurdles involved in the development of the proposed system for tea leaf disease identification. The initiative required an interdisciplinary approach that combined computer vision, deep learning, explainable AI, and mobile-compatible implementation. From the process of dataset collection from real tea gardens to deploying the model, every stage was in line with real-world agricultural standards.

The system adhered to best engineering practices by using TensorFlow and Keras for training various CNN and transfer learning models, and TensorFlow Lite for model optimization. The integration of SHAP, LIME, and Grad-CAM added explainability, making model predictions more transparent and trustworthy. A lightweight CNN was custom designed to maintain high accuracy with fewer parameters, optimizing performance for mobile use.

The cellphone application, developed using the Streamlit platform, enabled ease of use and accessibility for multiple stakeholders and agricultural professionals. The initiative addressed societal needs by enhancing the early detection of disease in resource-limited settings, as well as embedding ethical considerations and environmental sustainability through on-device processing, privacy protection, and energy efficiency.

The whole of complex engineering projects was outlined by defined frameworks, showing the project's alignment with characteristics of engineering problem-solving (such as depth of knowledge, competing requirements, and interdependence) and related engineering activities (such as innovation and societal impact). Engineering knowledge, design cognition, and research findings were applied throughout the development lifecycle continuously.

In summary, Chapter 5 demonstrated the way in which the research strictly conformed to engineering, ethical, and pragmatic standards. The system developed is an efficient, understandable, and easily accessible AI-based solution for real-time tea leaf disease diagnosis and hence applicable in agricultural settings where resources are limited.

Chapter 6

Conclusion

The chapter has shed light on the outcome and analysis of rice variety classification through deep learning. DenseNet121 model was superior with high accuracy and minimal misclassifications between the rice variety classes. The ability of the model to distinguish between the variety indicates its viability in actual agricultural practices like automatic rice variety classification. Low misclassifications do mean room for further development in terms of increase in dataset and further fine-tuning of the model.

6.1 Summary

This research targeted the development of an intelligent automatic rice variety classification system appropriate for the agricultural context of Bangladesh. Rice as crop is of high importance to Bangladesh's agriculture and contributes to the food economy of the nation indirectly. Rice variety classification in an efficient way is thus of significance for agricultural productivity, seed quality, and guarantee. Traditional rice variety classification methodologies through manual examination are time-consuming in nature and not practically feasible for mass application at the rural context due to the limited extent of connectivity with expert knowledge. The main requirement of the project was the development of an intelligent image-based rice variety classification system through Convolutional Neural Networks (CNNs) as deep learning has been found to be efficient in the domain of computer vision. The project was conducted sequentially through dataset preparation, image preprocessing, model development, training, and testing. A tailored dataset was prepared with high-resolution photographs of eight rice varieties grown in Bangladesh, i.e., BRRI Dhan 25, BRRI Dhan 28, BRRI Dhan 29, BRRI Dhan 89, BRRI Dhan 100, Kata Iri, Kata Iri Vog, and Chinigura. The pictures were taken in controlled lighting for sharpness and homogeneity for learning the fine details between rice varieties by the CNN. For preparation of the dataset for model training, various image processing techniques such as resizing, normalization as well as augmentation were utilized. These image processing techniques enhanced the variety of the dataset as well as ensured the absence of scope for the occurrence of overfitting in the deep learning model where the model gets very specific in learning from the training dataset. The augmentation processes gone through included rotation, flip as well as modification in the brightness. All of them aimed at the development of a strong model withstanding real-world variations. In experimentation of model development, some of the well-known CNN architectures like DenseNet121, VGG16, MobileNet, and InceptionV3 were tested. Out of all of them, DenseNet121 was seen to be the most successful with high accuracy and less overfitting. Training was performed on the training dataset and performance testing on an independent test and validation dataset on standard performance measures of classification accuracy, precision, recall, and F1-score. The DenseNet121 model was found to be very successful with accuracy of more than 90%, which has high precision in rice variety classification. One of the highlight solutions of the project was creating the high-quality labeled image dataset of Bangladeshi rice varieties, an area which was less researched in the previous research. The dataset and trained model pave the way for future research and real-world application in the domain of Bangladesh's digital agriculture. Automatic and precise rice variety classification has the potential to have impacts like seed certificate automation process, price control in the market, and support for crop research activities. Beside its contribution to the realm of science, the project was also hands-on implementation experience in deep learning model development and deployment and in enforcing learning of skills in model evaluation and preprocessing of data. By stressing model accuracy and generalizability, the research presents strong evidence in favor of deep learning solutions in low-resource agricultural settings. All in all, the project was successful in fulfilling the objective in the development of an efficient and scalable rice variety classification model. The model is an excellent proof-of-concept for AI integration in farming and showcases the revolutionary potential of such technology in enhancing food security and agricultural procedures.

6.1 Limitation

While the findings are encouraging and the project of creating the rice variety classification system was successful, there are some limitations encountered during the research and which need to be highlighted: Limited Dataset Size and Diversity:

Despite having gathered over 2,000 high-resolution rice grain images, it is on the small side relative to larger public deep learning image datasets. It has been specifically created for eight classes of Bangladeshi rice variety, and it may not capture the natural rice grain variation in other locations at other times of year and in other environmental conditions. Thus, the model may be unable to classify rice variety in new situations and with novel rice varieties not in the training dataset. Data Acquisition Challenges:

The samples were taken in controlled lighting environments in an attempt to curb the occurrence of noise and foster image quality uniformity. That perfect setting does not truly depict real-life settings where lighting conditions, backgrounds, and image quality are dynamic. In actual deployment settings for application in fields and markets, rice grain images in fields and markets are subjected to varied environmental conditions, which can compromise the performance of the model for application in such settings. Even as the samples varied in rice types, the samples may not be representative enough of real-life environmental conditions.

Dependence on High-Quality Input

The system's performance depends heavily on good quality images for accurate classification. In real-world setups, for instance, in rural settings, there may be limited access to quality cameras and controlled environments, and therefore there may be challenges in obtaining clear and usable images. The model's reliance on high-resolution input may limit the model's applicability in resource-scarce environments where image quality may be impaired.

Model overfitting and generalization.

Although DenseNet121 worked well on test and training sets, overfitting is still an issue of concern, especially with the small dataset. Although we employed data augmentation techniques in trying to remedy it, the model is still not generalizable as much as can be desired to all unseen input and to new varieties of rice with attributes beyond the confines of the training dataset. Also, some of the design decisions like choosing the best possible hyperparameters might not have been perfect and hence might have caused overfitting somewhere.

Removal of Cell or Internet deployment

A significant limitation of the project is the absence of deployment of the created model on a web or mobile application, which would have also been an actual-world testing ground for the classification system. The absence of the deployment process limits the applicability of the model to actual-world scenarios and reduces its scope for direct application for farmers, agricultural advisors, or scientists. One of the future work opportunities is deployment of the model in an application having an interface understandable for frequent usage in actual-world agricultural environments.

Lack of real-time classification

The model was tested on pre-acquired test samples, but real-time field classification where images are input and processed in real time is not within the scope of research at present. Even though the model works well in image classification of stationary images, performance and efficiency of the system in real-time image classification in time-varying scenes (such as moving objects or varying lighting) have not been fully examined.

Class imbalance

While efforts were placed on balancing the dataset for classes, it's possible some rice types will not be represented well in the dataset. Class imbalance can lead to biased prediction by the model where certain types of rice get predicted more accurately than others. Future datasets would be enhanced by efforts at more balanced representation of all rice types as well as other balancing strategies in order to compensate for the impact of class imbalance on model performance.

Environmental Factors and Image Quality

The controlled dataset environment, while useful for training purposes, also fails to factor in real-world farming variation. Images taken in paddy fields or markets, where the backgrounds are cluttered and dirty and other environmental conditions are present, can reduce accuracy in the model. These issues need to be addressed in order for future rollouts to enable the model to be used on less-than-perfect condition photographs.

6.2 Future Work

Although the project was successful in creating a deep learning-based rice variety classification system, some future directions for development and improvement have been identified for the system's reliability, scalability, and applicability in real-world uses. The following suggestions present some of the directions for future development and improvement:

Extension of Dataset

The current dataset, while indicative of eight of Bangladesh's most widely grown rice types, is limited in its size and variety. In the future work, efforts should be made to increase the dataset size to encompass more of the rice grown in many regions of growth, in conditions of varying circumstances, and in various cropping seasons. This will not only increase the applicability of the model as a whole but also make it applicable in other diverse farming settings. In addition, additional diversified sources of information from institutions like agricultural institutes and associations can be used in building a diversified and more extensive dataset.

Integration of Real-World Data:

The pictures in the project were all taken with controlled lighting and plain backgrounds. For the system to be used in real-world settings more effectively, future research should be conducted using pictures from real-world agricultural settings. These can be photographs from the fields, in the markets, in rural houses where lighting environments, background noises, and image attributes vary. The addition will allow the model to cope with the challenge of rice variety recognition in less controlled environments, hence be utilized in real-world scenarios more.

Real-time deployment and classification:

A significant area of future research is the application of the trained model in real-time classification. Even though the current research is on offline image processing, it would be possible with an equivalent real-time application as either a web application or as an application on a smartphone for on-site support to farmers, scientists, or agricultural fieldworkers. The system can be made to receive on-site photographs as input and provide real-time classification information on the rice variety for enabling prompt decision-making as well as optimization of agricultural activities.

Integration with Internet of Things (IoT) and Mobile Devices

Future research can be aimed at integrating the rice variety classification system with Internet of Things (IoT) devices and mobile platforms. Using smartphones or special high-resolution sensor-equipped cameras, the system can be made accessible for real-time image capture and rice variety classification. Integration with IoT devices such as crop health sensors or soil condition sensors can also provide an enhanced and autonomous precision farming solution. Farmers can get detailed information about crops without having to visit fields.

Generalization of the model

While DenseNet121 performed well in this research, its generalization ability on new samples and new rice varieties can be improved. Future research would include further model optimization by employing techniques like domain adaptation where the model can be trained to learn in novel settings or classes. Also, employing more advanced techniques like learning from larger pre-trained models under transfer learning or employing hybrid models where CNNs are combined with other machine learning techniques (like Support Vector Machines) for improved generalization and model accuracy can be considered.

Class Balance Handling

Although dataset balancing has been performed, class imbalance is still an issue. More advanced techniques such as SMOTE and focal loss can be used in future work to better handle class imbalance and achieve more balanced performances by all rice types. Beyond this, weighted loss functions can be used during training to address the issue.

Investigation of Alternative Deep Learning Architectures:

While DenseNet121 was found to be the highest performing model in the present research, future research requires deep learning models to be examined to assess if superior performance can be obtained. For example, exploring attention models such as the Convolutional Block Attention Module (CBAM) or Transformer models, which have been successful in other fields of application, can possibly improve feature retrieval and classification accuracy in distinguishing between fine rice variety variations.

User interface (UI) and usability improvements:

The current system lacks an end-user interface, which is critical for real-world usage. Future work should target implementing an interface for the rice variety classification system in such a way that it becomes accessible to farmers, agricultural scientists, and others. The interface can give visual confirmation, detailed classification outputs, and crop management suggestions. In addition to that, support for multiple languages, particularly for the local language of Bengali, would make it easier for non-technical people to use.

Integration with Agricultural Decision Support Systems:

Future directions involve integrating the rice variety classification model with other more inclusive agricultural decision support systems. These systems can take as input the prediction of the classification model to suggest crop management, seed choice, price at the market, and other such parameters. Providing farmers with accurate and timely information, the system can maximize crop yield, seed quality, and food security.

Ethical and Social Implications

As the system continues to be developed and rolled out further, social and ethical issues need to be addressed in rural farming communities. User studies need to be included in future work to understand how farmers and other stakeholders perceive such technologies in order for the system to be not only technically feasible but also socially accepted and affordable. We will also need to address issues of data privacy and make technology inclusive so it benefits all stakeholders and smallholder farmers.

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