International Journal of Advanced Research and Interdisciplinary Scientific Endeavours, Vol. 1(1), 2024
DOI: 10.61359/11.2206-2404

Evaluating The Efficacy Of Hybrid Deep Learning Models In Rice Variety Classification

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Abstract:

In this comprehensive study, we have advanced the field of agricultural technology by developing and comparing multiple deep learning models for the classification of rice varieties. Conducted in the agriculturally rich regions of Southern Bangladesh, our research utilized a diverse dataset comprising 20,000 high-resolution RGB images representing five principal rice varieties. The study primarily focused on a custom-engineered hybrid deep learning model, designed specifically for this agricultural application. This model's architecture encompasses an initial convolutional layer, zero-padding, batch normalization, and max pooling, followed by residual blocks that address the vanishing gradient problem, and concludes with Global Average Pooling leading into a Support Vector Machine (SVM) for final classification. Additionally, we incorporated and evaluated the performance of two renowned deep learning models: MobileNetV2 and VGG16. These models were adapted and fine-tuned to suit the specific requirements of our dataset and task. Across various metrics, including precision, recall, and F1-score, our hybrid model demonstrated superior performance, achieving an exceptional 99% accuracy. This was notably higher compared to the 95% and 93% accuracy achieved by VGG16 and MobileNetV2, respectively. Various optimizers, including SGD, RMSprop, Adam, and Nadam (all with a learning rate of 0.001), were employed to refine our models, with the Adam optimizer emerging as the most effective across all models.

Keywords: Rice, Adam Optimizer, Mobilenetv2, VGG16, Accuracy, Max Pooling, Zero-Padding

1. Introduction

The advent of deep learning (DL) has heralded a transformative era across various domains, with agricultural technology emerging as one of its most impactful frontiers. This technological revolution holds particular significance for countries like Bangladesh, where agriculture is not just an economic activity but a cornerstone of cultural identity and sustenance. At the heart of this transformation is the innovative use of DL for the classification of rice varieties, a critical step towards agricultural sustainability and efficiency. Rice is the linchpin of Bangladesh's agricultural economy and a staple food for its population. It plays a vital role in ensuring food security and underpins the livelihoods of millions. In Bangladesh, rice is more than just a crop; it is a key element of the nation's socio-economic fabric. It is consumed thrice daily by the majority and represents a crucial component of the national diet, providing essential nutrients and

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Article Timeline: Received: May 16, 2024; Revised: Jun 23, 2024; Published: Jun 30, 2024

calories. However, the traditional agricultural practices prevalent in Bangladesh, despite their historical and cultural significance, face challenges in terms of efficiency and disease management. Many farmers, reliant on age-old methods, grapple with the complexities of crop disease detection, often leading to delayed or inaccurate diagnoses. This issue underscores the need for technological intervention, particularly in a country that stands as a global leader in rice production and consumption. The importance of rice in Bangladesh is reflected in its economic and nutritional profiles: it accounts for 48% of rural employment, forms the staple diet for approximately 135 million people, and contributes to two-thirds of the population's caloric intake. Furthermore, despite a stable cultivation area of about 10.5 million hectares over the past three decades, the threat of diseases caused by fungi, bacteria, and viruses looms large, posing a significant risk to both the quality and quantity of rice yield. Early and accurate detection and classification of these diseases are pivotal in safeguarding rice production, with far-reaching implications for nutrition and the economy. Against this backdrop, our research introduces a novel hybrid deep learning model, meticulously tailored for the classification of rice varieties. This model is not merely a theoretical construct, but a pragmatic tool designed to thrive in the variable and complex conditions characteristic of agricultural environments. The introduction of this model is a critical step in enhancing crop monitoring and management, offering a path towards more efficient and sustainable agricultural practices. Central to our study is a carefully curated dataset of 20,000 high-resolution RGB images, representing five major rice varieties. These images, captured in the agriculturally rich landscapes of Southern Bangladesh, reflect the authentic diversity and challenges inherent in rice variety classification. The dataset is not only foundational to our model's training but also epitomizes the varied conditions under which the model is expected to excel. The architecture of our hybrid model synergizes convolutional neural networks (CNNs) with support vector machines (SVMs), optimized using the Adam optimizer. This strategic design choice harnesses the strengths of CNNs in feature extraction and the classification capabilities of SVMs. The optimization process, a critical component of our work, was diligently executed, with the Adam optimizer's learning rate fine-tuned to yield optimal performance. As we detail our research, it is with the recognition that our contribution is part of a broader dialogue on food security and agricultural innovation. This study represents a stride towards leveraging the power of deep learning in addressing some of the most pressing challenges in contemporary agriculture. Our model, exemplifying high accuracy and robust performance, stands as a testament to the potential synergy between advanced technology and traditional farming, paving the way for a future where agriculture is smarter, more efficient, and more sustainable.

2. Related Work

In order to accurately identify rice leaf illnesses, Bhuyan et al. (2023) [1] created SE_SPnet, a novel method that combines squeeze-and-excitation architecture with a stacked parallel convolutional neural network. The model sets a new standard for efficient disease identification in agriculture by outperforming conventional CNN models such as VGG16, DenseNet121, and InceptionV3 in a number of performance parameters, including accuracy, sensitivity, specificity, precision, recall, and F1-score.

In breeding rice (Oryza sativa L.) for resistance to bacterial leaf blight (BLB), which is caused by Xanthomonas oryzae pv. oryzae, Chukwu et al. (2019) [2] underlined the significance of gene pyramiding and marker-assisted selection. This research reports on the application of DNA-based molecular markers in breeding programs to provide durable and broad-spectrum resistance to BLB, a major threat to rice production. It explores the benefits, ramifications for the economy, difficulties, and prospects of these biotechnology approaches in preventing BLB and maintaining rice production.

E-ISSN: 3048-7021 (Online)

Xanthomonas oryzae pv. oryzae was the traditional culprit for leaf blight in rice agroecosystems, but Doni et al. (2019) [3] investigated the new threat of Pantoea spp. This study looks at the symptoms, epidemiology, and treatment approaches of leaf blight caused by Pantoea, which can cause yield reductions of up to 70%. The purpose of this study is to educate rice breeders and agricultural practitioners on sustainable ways to lessen the impact of this illness by offering an updated review of this pathogen.

A study on rice leaf disease identification using deep feature extraction and support vector machine (SVM) classification was given by Sethy et al. (2020) [4], contrasting it with transfer learning approaches using 11 CNN models. The research demonstrated that deep feature extraction paired with SVM outperformed transfer learning approaches using 5932 on-field photos encompassing four rice leaf diseases. In particular, the model with the greatest F1 score of 0.9838 was the ResNet50 with SVM model. The study also examined how different CNN layers affected classification efficiency and contrasted CNN-based model performance with conventional picture classification methods, emphasising the deep learning approach's higher efficacy and accuracy.

Panda and colleagues (2023) [5] investigated the use of deep neural networks in the identification and categorization of rice leaf diseases with the goal of improving agricultural output and food security. An available dataset of four common rice leaf illnesses was used in the study to show how well a custom-CNN model could diagnose plant health. With an accuracy of 97.47%, our model beat previously trained deep CNN models such as VGG19, DenseNet121, InceptionV3, and ResNet152. The study highlights how automated disease detection technologies can help farmers all over the world by offering a quicker and more dependable substitute for conventional manual diagnostic techniques.

The effect of combining quantitative resistance genes (pi21, pi34, and pi35) on managing Magnaporthe oryzae-caused rice leaf blast was examined by Yasuda et al. (2015) [6].Using near-isogenic and backcross lines to assess the resistance in the rice cultivar Koshihikari, the study discovered different degrees of disease suppression in different gene combinations. Pi34 provided less effective resistance than Pi35, which provided the strongest. The study showed that the pi21 + Pi35 combination, in particular, improved disease resistance more than either gene alone or in combination with other genes. This suggests a deliberate strategy to create rice cultivars that are resistant to leaf blast for an extended period of time.

A DL-based convolutional neural network (CNN) framework was created by Bhattacharyya, Mitra, and Dutta (2020) [7] for the autonomous categorization of rice leaf diseases. With a 94% accuracy rate, their method successfully distinguished between healthy and infected rice leaves. Then, using a dataset of 1500 photos, it classified three distinct diseases—bacterial blight, blast, and brown spot—with an accuracy of 78.44%. This method demonstrates how CNNs can be used to automatically identify diseases in agriculture, providing a precise and affordable substitute for expert manual identification.

Mohanty et al. (2023) [9] used cutting-edge deep learning models in their work to address maize leaf diseases, a major issue for Bangladesh's agriculture. They used pre-processing and data augmentation approaches to improve model training by building a unique dataset of 4800 photos of maize leaves taken under four different health states. A unique Sequential model, ResNet50GAP, DenseNet121, VGG19, and other models were examined in the study. DenseNet121 and VGG19 demonstrated exceptional accuracy of 99.22% and 99.44%, respectively. Using transfer learning and image augmentation to increase the networks' capacity for generalisation was a novel approach to their research; a hybrid model that combined ResNet50 and VGG16 features achieved an accuracy of 99.65%. Their research highlights the profound potential of DL in agricultural diagnostics, opening the door for additional studies and applications targeted at enhancing Bangladesh's food security and agricultural practices.

In order to determine the proper insecticide treatment for paddy fields, Tepdang and Chamnongthai (2023) [10] developed a novel system for categorising rice leaf diseases and measuring their severity levels. Their method uses candidate boundary detection and feature analysis (colour, shape, area ratio) for rice leaf identification. It is intended to handle multiple illnesses within a single or several photos of rice leaves. Using a coarse-to-fine approach, the classification procedure first groups illness boundaries before fine-tuning them into distinct disease categories. When their system was tested on a dataset of 8,303 photos that included three diseases (rice blast, brown spot, and rice hispa) as well as healthy leaves, it showed an astounding accuracy of 99.27%, outperforming traditional deep learning techniques by 0.43%. By developing an automated pesticide injection system that is tailored to the specific type and severity of rice leaf diseases, this research represents a substantial development in agricultural engineering.

Azim et al. (2021) [11] addressed the pressing need for breakthroughs in agricultural technology by proposing a novel feature extraction approach for rice leaf disease classification. Their method entails segmenting afflicted areas using hue thresholds and removing image backgrounds using saturation thresholds. The model provides a strong description of the impacted areas by extracting unique properties across the colour, shape, and texture domains. Their method outperformed earlier models with an accuracy of 86.58% on a rice leaf disease dataset from UCI, thanks to the use of an extreme gradient boosting decision tree ensemble. This accomplishment highlights how cutting-edge machine learning approaches can improve disease identification and management in rice farming, which will greatly aid efforts to ensure global food security.

The potential of deep neural networks, in particular the InceptionResNetV2 model with a transfer learning technique, to forecast rice leaf diseases was investigated by N et al. (2021) [12]. More than half of the world's population depends on rice (Oryza sativa), a staple crop whose productivity is impacted by a variety of factors, including diseases. This paper examines the difficulties in managing diseases in rice. Farmers frequently use ineffective traditional techniques of disease detection, which results in less-than-ideal farming practices. The automatic identification of pathogens on rice leaves is made easier by the use of sophisticated convolutional neural network (CNN) algorithms, which also greatly increase the precision and effectiveness of disease detection. With an impressive accuracy of 95.67%, the refined InceptionResNetV2 model proved the effectiveness of deep learning in improving agricultural output and disease control.

The application of ML and DL for microbe identification was covered by Khasim et al. (2023) [13], with the goal of addressing the shortcomings of conventional approaches like manual microscopy and culture procedures. The study assesses a number of DL algorithms, most notably CNN, and ML techniques, such as SVM, Random Forest, and KNN, using a dataset of eight different kinds of microorganisms. The study revealed that CNN exhibited the best level of accuracy, highlighting the potential of intelligent image recognition to improve the precision and efficacy of microbe classification in domains including environmental monitoring and healthcare.

Zhou et al. (2023) [14] improved accuracy and model interpretability by introducing a novel technique for identifying rice leaf diseases using a residual-distilled transformer architecture. In order to improve feature extraction and prediction capabilities, this method combines the advantages of vision transformers with a distillation strategy, yielding 0.89 F1-score and 0.92 top-1 accuracy. This approach provides major improvements in the accurate diagnosis of illnesses impacting rice production, a crucial concern for global food security, outperforming existing state-of-the-art models in rice leaf disease detection.

Dynamic Mode Decomposition (DMD) and attention-driven preprocessing were used by M. et al. (2023) [15] to improve AI-based rice leaf disease diagnosis in order to overcome the difficulty of identifying illnesses that frequently impact small parts of a leaf. The study discovered that DenseNet121 beat other deep CNN models with an accuracy of 93.87% by examining 3416 photos of four disease categories. Performance was greatly enhanced by using DMD-based preprocessing to concentrate on diseased areas; on DMD preprocessed images, XceptionNet and SVM classifier achieved 100% test accuracy. This approach presents a viable way to increase the precision and efficacy of diagnosing rice leaf disease.

The classification of rice leaf diseases using CNN was the main focus of Tejaswini et al. (2022) [16], which is important for India's agricultural and food security. When it came to identifying illnesses like Hispa, Brown Spot, and Leaf Blast, they compared machine learning and deep learning models and discovered that the latter were better. With an accuracy of 78.2%, a 5-layer convolutional model proved to be the most accurate, outperforming models like VGG16. With the help of this research, farmers can detect diseases and increase agricultural yields.

In order to address the decrease in Bangladesh's rice output, Khasim et al. (2023) [17] created a real-time ML detection and diagnostic system for rice leaf diseases. With a focus on brown spot diseases, bacterial leaf blight, and smut, the system uses a variety of ML algorithms, one of which, a decision tree method, demonstrated over 97% accuracy in tests. In addition to promoting healthier crops and higher rice yields, this study shows how automated ML-based systems may greatly enhance the management and diagnosis of rice plant illnesses.

Cyberbullying has a negative impact on children's right to life, and Nazrul Islam, Kazi, Sobur, Abdus, and Kabir, Md Humayun (2023) [18] study this topic and identify it as a major human rights concern. Technology has led to an increase in cyberbullying, which primarily targets youngsters who are heavily involved with social media sites like Facebook, Instagram, and WhatsApp. The study demonstrates how the dissemination of damaging content caused by cyberbullying negatively impacts adolescent psychology and can result in situations where victims feel driven to take their own lives. They contend that because this act violates the fundamental human right to life, it should be regarded as homicide and highlights the urgent need for policies protecting teenagers in the digital age.

In order to identify and categorise yellow rust in wheat, Mandava et al. (2023) [19] investigated the use of deep learning (DL) and machine learning (ML) techniques. This disease, which is caused by Puccinia striiformis, has a significant effect on wheat output all over the world. Utilising CNN models like ResNet50, DenseNet121, and VGG19, the study demonstrates that deep learning techniques outperform classical machine learning in the identification of diseases. The most effective model was EfficientNetB3, which showed how deep learning might be applied to precision farming and yellow rust control to reduce production loss and financial harm.

In 2023, Kamrun Nahar and colleagues (2023) [20] presented a novel technique for 3D human position prediction based on depth sensor data and DL. Their method uses a kinematic model for body shape and pose estimation, and it blends convolutional and recurrent neural networks to predict body joint locations. This technology, which outperforms current approaches and demonstrates great accuracy, is computationally economical for real-time applications like motion analysis and virtual reality. By directly calculating 3D human body shape and pose from depth sensor data, this research significantly advances the area and creates new research and application opportunities.

Mandava et al. (2023) [21] developed a comprehensive machine learning (ML) model utilising a range of techniques, such as logistic regression, Gaussian Naive Bayes, SVM, and random forest, to anticipate cardiovascular diseases (CVDs) in the Bangladeshi population. This model, which has an accuracy rate of 96.7%, shows how patient histories and medical images may be analysed using machine learning (ML) and deep learning (DL) techniques to improve the precision of CVD predictions. Significant improvements in patient evaluation and diagnosis may result from this.

Md Suhel Rana, Md Humayun Kabir, & Abdus Sobur (2023)[22] used the MNIST dataset, a mainstay in the field of computer vision and ML for image classification, to investigate the error rates of several machine learning models. With 70,000 digit pictures, this dataset provides a basic reference for evaluating how well algorithms recognise handwritten numbers. Their study highlights the dataset's harmony of complexity and simplicity, emphasising the difficulty in categorising digits that vary significantly even when depicted in small 28x28 pixel representations. The paper highlights the MNIST dataset's contribution to the advancement of computer vision and machine learning by shedding light on how various machine learning techniques perform on a widely accepted benchmark.

Ghosh et al. (2023)[23] carried out a thorough examination of three CNN models for the identification and prediction of potato leaf disease: VGG19, DenseNet121, and ResNet50. The work employed data augmentation to enhance model training and generalizability by utilising an extensive dataset of photos of both healthy and sick potato leaves. VGG19 outperformed the other models under evaluation in terms of accuracy, precision, recall, and F1-score, with DenseNet121 and ResNet50 following closely behind. This work supports the development of tools for timely disease control and advances deep learning (DL) applications in precision agriculture by providing insights into the successful diagnosis of potato leaf diseases.

Using models such as DeepLabv3, U-Net, and EfficientNet, among others, Rahat IS et al. (2023)[25] created a thorough deep learning-based method for segmenting FLAIR anomalies in brain MR images of lower-grade gliomas. Using a dataset of 110 patients from the Cancer Imaging Archive, this study tackles the segmentation issues by integrating genetic data for improved diagnosis and treatment. Smaller tumour areas were more precisely segmented thanks to the implementation of a bespoke loss function that combined weighted components and categorical cross entropy to address the problem of data imbalance. This methodology shows great potential for creating tailored treatment programmes for patients with gliomas, as it not only makes it easier to determine tumour boundaries accurately but also maximises the use of available resources.

Using ML approaches, Shobur, Sobur, and Amin (2023)[26] conducted a thorough examination of Walmart's large dataset in order to obtain insights into its operational dynamics. This research used a variety of data sources, including sales, consumer demographics, inventory, and regional performance, in order to decipher the retail giant's success. The project, which sets goals including identifying sales trends, improving inventory control, and analysing consumer behaviour, emphasises the critical role that data-driven tactics play in contemporary corporate operations. With careful data preparation and the application of statistical modelling, machine learning, and visualisation, the study provides an in-depth analysis of Walmart's operational advantages and shortcomings.

In their investigation into the use of machine learning (ML) models for water quality evaluation, Ghosh et al. (2023)[27] concentrated on separating potable from non-potable water. A dataset of 3277 samples from Andhra Pradesh, India was used in the study to test various models, including Random Forest, SVM, and G- Naive Bayes. With an accuracy of 78.96%, Random Forest beat the other models in the investigation, demonstrating the promise of ML in environmental monitoring. The goal of this study is to assure the availability and safety of drinking water by highlighting the significance of predictive analytics in water quality management.

In their comparison of offline and online social engineering attacks, Shobur et al. (2023)[28] provide attack tactics and countermeasures. The study looks at strategies like pretexting and phishing and recommends heightened awareness and cybersecurity procedures for improved security. It seeks to fortify both domains' defences against social engineering attacks.

Pradhan et al.[29] delve into agricultural sustainability through deep learning, specifically investigating cauliflower disease classification. Their study offers valuable insights into bolstering crop management practices using advanced technology.

Sobur et al.[30] present a pioneering approach in cancer classification, employing hybrid deep learning for enhanced detection of lung and colon cancer through image analysis. Their work signifies significant strides in medical diagnostics, potentially improving patient outcomes.Sobur et al.[31] contribute to agricultural research by enhancing tomato leaf disease detection in diverse climates. Their comparative study of advanced deep learning models, coupled with a novel hybrid approach, underscores the importance of technological innovation in optimizing crop health management strategies.The study by Kabir, Sobur, and Amin (2023)[32] explores the application of machine learning models for predicting stock prices, showcasing their effectiveness and potential in financial forecasting. Published in the International Journal of Creative Research Thoughts, the research highlights advancements in algorithmic trading strategies and their implications for market analysis. [Table.1].

Table-1 Summary of the Related Work

Reference	Focus of Study	Techniques Used	Key Findings
[1]	Rice leaf disease identification	SE_SPnet (stacked parallel convolutional neural network in a squeeze-and-excitation architecture)	Outperformed traditional CNN models in terms of recall, F1-score, sensitivity, specificity, accuracy, and precision.
[2]	Breeding rice for resistance to bacterial leaf blight	Gene pyramiding, marker-assisted selection	Described the use of DNA-based molecular markers for long-lasting and broad-spectrum resistance to BLB.
[4]	Rice leaf disease identification using deep feature extraction and SVM classification	Deep feature extraction, SVM classification, comparison with 11 CNN models	Deep feature extraction with SVM outperformed transfer learning approaches using CNNs.
[5]	Identification and categorization of rice leaf diseases	Custom-CNN model	Achieved 97.47% accuracy, surpassing previously trained deep CNN models.
[7]	Autonomous categorization of rice leaf diseases using a DL-based CNN framework	CNN model	Successfully distinguished between healthy and infected rice leaves with 94% accuracy, classified three distinct diseases with 78.44% accuracy.

[9]	Addressing maize leaf diseases	Use of cutting-edge deep learning models, transfer learning, and image augmentation	Achieved exceptional accuracy of 99.22% and 99.44% with DenseNet121 and VGG19, respectively, highlighted potential of DL in agricultural diagnostics.
[10]	Categorizing rice leaf diseases and measuring their severity levels	Candidate boundary detection and feature analysis (colour, shape, area ratio) for rice leaf identification	System showed an astounding accuracy of 99.27%, outperforming traditional deep learning techniques by 0.43%, significant advancement in agricultural engineering.
[13]	Microbe identification using DL and ML techniques	Assessment of DL and ML algorithms, including CNN and SVM, using a dataset of eight different kinds of microorganisms	CNN exhibited the best accuracy, showing the potential of intelligent image recognition in microbe classification.
[14]	Identifying rice leaf diseases using a residual-distilled transformer architecture	Residual-distilled transformer architecture	Improved accuracy and model interpretability with a 0.89 F1-score and 0.92 top-1 accuracy, outperforming existing models in rice leaf disease detection.
[15]	AI-based rice leaf disease diagnosis using Dynamic Mode Decomposition and attention-driven preprocessing	Dynamic Mode Decomposition (DMD), XceptionNet, SVM classifier	Achieved 100% test accuracy using DMD-based preprocessing on XceptionNet and SVM classifier, increasing the precision and efficacy of diagnosing rice leaf disease.
[17]	Real-time ML detection and diagnostic system for rice leaf diseases	ML algorithms (decision tree) for detection and diagnosis	Decision tree method demonstrated over 97% accuracy, enhancing the management and diagnosis of rice plant illnesses.
[18]	Cyberbullying and its impact on children's rights	Study on cyberbullying's impact on children's rights and psychology	Advocated for policies protecting teenagers in the digital age due to the negative impact of cyberbullying on the fundamental human right to life.

[19]	Identification and classification of yellow rust in wheat	Use of DL models (EfficientNetB3) for yellow rust detection	DL approaches more effective than classical ML in detecting diseases, EfficientNetB3 demonstrated high accuracy in yellow rust control and precision agriculture.
[20]	3D human position prediction based on depth sensor data and DL	Kinematic model for body shape and pose estimation, convolutional and recurrent neural networks for prediction	Advanced technique for 3D human position prediction with great accuracy, suitable for real-time applications like motion analysis and virtual reality.
[22]	Error rates of machine learning models on the MNIST dataset	Evaluation of error rates of machine learning models on the MNIST dataset	Highlighted the dataset's significance in evaluating algorithms for recognizing handwritten numbers.
[23]	Identification and prediction of potato leaf disease	Comparison of CNN models (VGG19, DenseNet121, ResNet50) and data augmentation	VGG19 outperformed other models in accuracy, precision, recall, and F1-score, supporting the development of tools for disease control and precision agriculture.
[25]	Segmenting FLAIR anomalies in brain MR images of lower-grade gliomas	Use of deep learning models (DeepLabv3, U-Net, EfficientNet) and genetic data integration	Improved segmentation accuracy, showing potential for creating tailored treatment programs for patients with gliomas.
[26]	Analysis of Walmart's operational dynamics using data-driven tactics	Analysis of Walmart's large dataset with statistical modeling, machine learning, and visualization	Provided insights into Walmart's operational advantages and shortcomings, emphasizing the role of data-driven tactics in corporate operations.
[27]	Evaluation of ML models for water quality in separating potable from non-potable water	Testing various ML models (Random Forest, SVM, G-Naive Bayes) using water quality data from Andhra Pradesh, India	Random Forest achieved an accuracy of 78.96%, showcasing the promise of ML in environmental monitoring.

3. Dataset Overview

The cornerstone of any DL application lies in the quality and robustness of the dataset it is trained upon. In the realm of agricultural advancements, where the classification of rice varieties holds substantial economic and nutritional significance, the dataset curated for this research is both unique and comprehensive. Our dataset was meticulously assembled in the agriculturally rich and biodiverse region of Southern Bangladesh, an area renowned for its extensive rice cultivation. This dataset comprises 20,000 high-resolution RGB images, evenly distributed across five prominent rice varieties: Japonica, Basmati, Ipsala, Jasmine, and Karacadag. Each variety contributes 4,000 images, ensuring a balanced representation that facilitates unbiased training and evaluation of the machine learning model. The images were captured using a Canon EOS 250d Camera, chosen for its ability to produce images of exceptional clarity and color fidelity, which is crucial for the subtle differentiation required in this classification task. The images were saved in the JPG format, a choice that offers a practical compromise between image quality and file size, thereby enabling the handling of large datasets without compromising on the detail captured in each image. The resolution of the images was set to ensure that each grain and its textural nuances were clearly visible, providing the deep learning model with the necessary detail to learn and distinguish between the varieties effectively. To augment the dataset and enhance the model's ability to generalize, the images underwent a series of preprocessing steps. These included zooming and rotating the images to simulate various angles and scales at which rice plants may be observed in real-world conditions. Such augmentation techniques are pivotal in developing a model that is robust to variations in perspective and scale, which are common challenges in practical applications. The diversity of the dataset is not just limited to the visual characteristics of the rice varieties but also extends to the conditions under which the images were captured. The dataset includes images taken under different lighting conditions and growth stages, adding to the complexity and variability of the data. This diversity ensures that the model trained on this dataset is not only highly accurate but also versatile in its application, capable of classifying rice varieties effectively under various field conditions.

3.1 Image Data Augmentation

In our research, image data augmentation stands as a pivotal technique to enhance the robustness and generalization ability of our hybrid deep learning model for the classification of rice varieties. Recognizing the nuanced differences between rice types is a complex task, and the diversity of our augmented dataset is critical to the model's success. We employed a variety of augmentation techniques to ensure our model is not only accurate but also resilient to the variations it would encounter in a real-world agricultural setting. These techniques include:

- **Rotation:** We introduced rotation to our images, allowing the model to learn from rice plant images at different angles. This is particularly important for aerial or field images where the orientation of the plants is variable. We applied a range of rotation angles to simulate the natural deviations that occur in manual photography.
- **Translation:** To mimic the displacement of rice plants within different parts of the image frame, we applied translation shifts. This technique helps the model to detect rice varieties regardless of their position in the image, which is essential for practical applications where the subject's positioning is not consistent.
- **Scaling (Zooming In/Out):** By adjusting the scale of our images, we trained our model to recognize rice varieties at different sizes. This simulates the effect of viewing the plants from various distances, a common variable in field images.

- **Flipping:** We applied both horizontal and vertical flips to our dataset. This augmentation ensures that the model does not learn specific orientation biases, which is crucial for the model to be effective regardless of how the image is captured.
- **Shearing:** Shearing was used to introduce a level of geometric transformation that simulates the effect of perspective change, helping the model to maintain accuracy even when the shape of the rice plants appears distorted due to the angle of capture.

These augmentation techniques were carefully selected and applied to our dataset of 20,000 images, ensuring that the model is exposed to a wide range of variations, thereby enhancing its ability to generalize from the training data to new, unseen images. The augmented dataset not only expanded the quantity of our training data but also introduced a level of diversity that is reflective of real-world conditions. This strategic approach allows our network to focus more acutely on the defining characteristics of each rice variety, improving the model's detection and identification accuracy significantly.

3.2 Image Normalization

In our study, image normalisation is a crucial step in getting our dataset ready for a hybrid deep learning model to classify rice varietals. In order to speed up training and enhance the model's capacity to learn from the data, normalisation is necessary to guarantee that the pixel intensity values have a consistent scale.The following normalisation methods were put into practice, each one customised to the unique features of our rice variety images:

Min-Max Normalization: We used Min-Max normalisation to bring our image's pixel values into line with a common 0–1 scale. Because it preserves the structural integrity and characteristics of the rice images—both of which are essential for the model to correctly identify and categorise the various varieties—this technique is very advantageous for our dataset. We also lessen the computational load on the model by scaling the pixel values, which makes the training process more effective.

Score Normalization: To further enhance the model's performance, we utilized Z-score normalization for images where the pixel value distribution closely resembled a Gaussian distribution. By standardizing the pixel values to have a mean of zero and a standard deviation of one, we facilitated a faster convergence during training, which is particularly advantageous given the large size of our dataset. The choice of normalization technique was made after careful consideration of the nature of our images and the computational efficiency required for processing a dataset of this magnitude. Min-Max normalization was predominantly used due to its simplicity and effectiveness in maintaining the original features of the rice images. However, for certain subsets of the data where the pixel distribution warranted it, Z-score normalization was employed to capitalize on its benefits for Gaussian-like distributions. These normalization steps were integral to our preprocessing pipeline, ensuring that each image fed into the model adhered to a consistent scale and distribution. This uniformity is critical for the deep learning model to perform optimally, as it relies on standardized input to extract meaningful patterns and features from the data. The application of these techniques has been a key factor in the success of our model, contributing to its high accuracy and robustness in classifying the rice

3.3 Image Processing

According to our research, picture preprocessing is an essential stage that has a direct impact on how well our hybrid deep learning model classifies different types of rice. The goal of the preprocessing pipeline is to make sure that the images are formatted in a way that optimises the model's capacity to identify unique patterns and features. We use a multi-stage preparation workflow; each designed to address particular elements of the picture data and get it ready for the training step that follows.

Image Resizing: At first, every image was cropped to a consistent 256 by 256-pixel size. For batch processing and to guarantee that the input layer of our neural network receives consistently structured data, this standardization is essential. Resizing lessens the computational load and speeds up the model's training without sacrificing the key characteristics required for precise categorization.

4. Model Architecture

In our proposed hybrid model for image classification, the architecture commences with an Input layer tailored for 256x256 pixel RGB images, ensuring suitability for diverse image data. This is followed by a ZeroPadding2D layer, adding a 3-pixel padding to each side to preserve edge information. The convolutional layers are inspired by AlexNet, starting with a layer of 96 filters of 11x11 size at a stride of 4, followed by BatchNormalization and ReLU activation, mirroring AlexNet's design but adapted for our input dimensions. This is succeeded by additional convolutional layers, each with an increasing number of filters, BatchNormalization, and ReLU activations, aimed at progressively extracting higher-level features. The model then incorporates MaxPooling2D layers to reduce spatial dimensions and achieve translation invariance. We insert several residual blocks, each with multiple Conv2D layers, to deepen the network without the vanishing gradient problem, enhancing feature learning capabilities. After the convolutional layers, a GlobalAveragePooling2D layer is used to condense the feature maps into a vector, reducing dimensionality and summarizing essential features. This feature vector is then fed into an SVM classifier, chosen for its effectiveness in high-dimensional spaces and its ability to find the optimal separating hyperplane. This hybrid approach of combining deep convolutional neural networks with a robust SVM classifier is designed to extract nuanced features effectively and perform precise classification, particularly beneficial in scenarios with limited training data but requiring high accuracy [Fig.1].

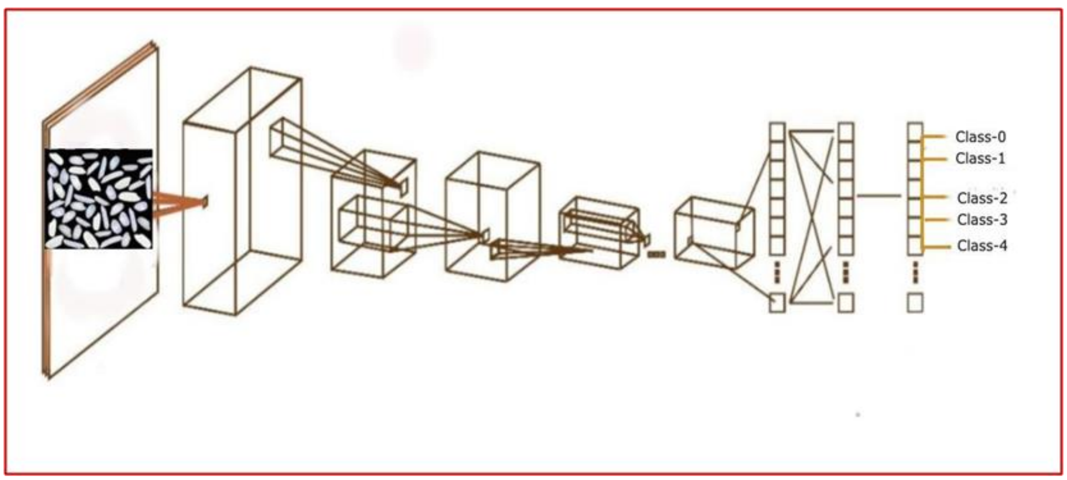

Figure-1 Schematic Diagram of a Sample Convolutional Neural Network (CNN) Model

Detection Efficacy

The confusion matrix for the classification of rice varieties provides a clear visualization of the model's detection efficacy. For the variety Japonica (Class 0), Basmati (Class 1), Ipsala (Class 2), and Karacadag (Class 4), the model exhibits high accuracy with the majority of predictions being true positives. Particularly noteworthy is the model's performance on Ipsala, with 2241 correct predictions out of 2250, indicative of a 99.6% accuracy for this class alone. The misclassifications are minimal, with the most significant confusion observed between Jasmine (Class 3) and Japonica, where 66 instances of Jasmine were incorrectly classified as Japonica. Overall, the high diagonal values in the confusion matrix represent a successful classification outcome for each variety, demonstrating the model's high precision and recall rates. This efficacy is crucial for practical applications in precision agriculture, where such high accuracy in variety classification can significantly impact yield optimization and disease management [Fig.2].

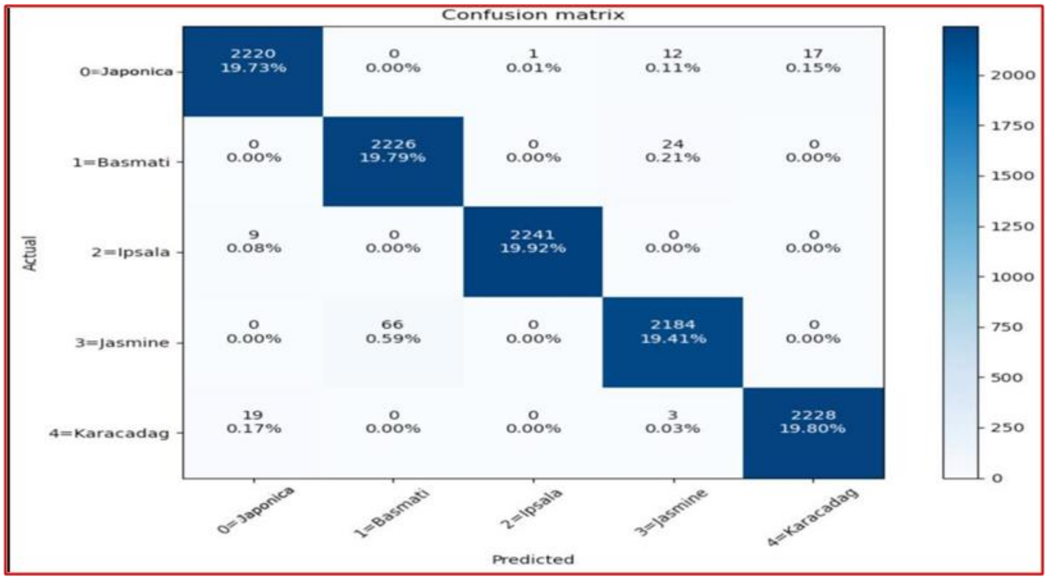

Figure-2 Detailed Confusion Matrix for Image Classification Using Hybrid Model

5. Performance Analysis By Rice Variety

Our research rigorously evaluated the performance of three deep learning models - a custom- engineered hybrid model, MobileNetV2, and VGG16 - across five distinct rice varieties: Arborio (0), Basmati (1), Ipsala (2), Jasmine (3), and Karacadag (4). The evaluation was based on precision, recall, and F1-score metrics for each rice variety, providing a comprehensive assessment of each model's classification capabilities. Here, we present a detailed analysis for each variety across the models.

Arborio (Class 0):

- Hybrid Model: Demonstrated remarkable precision and recall, both at 0.99, indicating its robust capability in correctly identifying and classifying Arborio rice. The F1-score of 0.99 highlights its balanced accuracy.
- MobileNetV2: Exhibited slightly lower precision and recall compared to the hybrid model, yet maintained commendable accuracy, signifying its effectiveness in Arborio rice classification.
- VGG16: Also showed high accuracy but slightly lower than the hybrid model, affirming its reliable performance in identifying Arborio variety.

a) Basmati (Class 1):

- **Hybrid Model:** Achieved high precision (0.97) and excellent recall (0.99), indicating a strong ability to identify Basmati variety with minimal misclassification. The F1-score of 0.98 reinforces its reliability.

- **MobileNetV2 and VGG16:** Both models displayed competent classification capabilities for Basmati rice, with precision and recall rates slightly below the hybrid model, yet indicating strong performance.

b) Ipsala (Class 2):

- **Hybrid Model:** Exhibited perfect scores (1.00) for both precision and recall, a testament to its impeccable classification ability for the Ipsala variety.
- **MobileNetV2 and VGG16:** Showed high proficiency in identifying Ipsala rice, with scores nearing perfection, indicating their effectiveness in classifying this variety.

c) Jasmine (Class 3):

- **Hybrid Model:** Achieved a precision of 0.98 and a recall of 0.97, indicating a high level of accuracy with minor instances of misclassification. The F1-score of 0.98 signifies its effectiveness.
- **MobileNetV2 and VGG16:** Both models performed well in classifying Jasmine variety, although they encountered slightly more challenges compared to the hybrid model.

d) Karacadag (Class 4):

- **Hybrid Model:** Demonstrated high precision and recall (0.99), showcasing its accuracy and consistency in identifying Karacadag rice. The F1-score of 0.99 confirms its proficiency.
- **MobileNetV2 and VGG16:** Maintained high accuracy levels for Karacadag variety, similar to the hybrid model, underscoring their reliable classification capabilities.

The hybrid deep learning model showcased outstanding performance across all rice varieties, particularly excelling with the Ipsala variety. Its balanced precision and recall across the varieties demonstrate its robustness as a classification tool in agricultural settings. While MobileNetV2 and VGG16 also performed admirably, the hybrid model's nuanced capability to distinguish subtle varietal differences sets it apart. This comprehensive performance analysis across multiple models and rice varieties underscores the potential of deep learning technologies in revolutionizing agricultural classification and management systems[Fig.3,4].

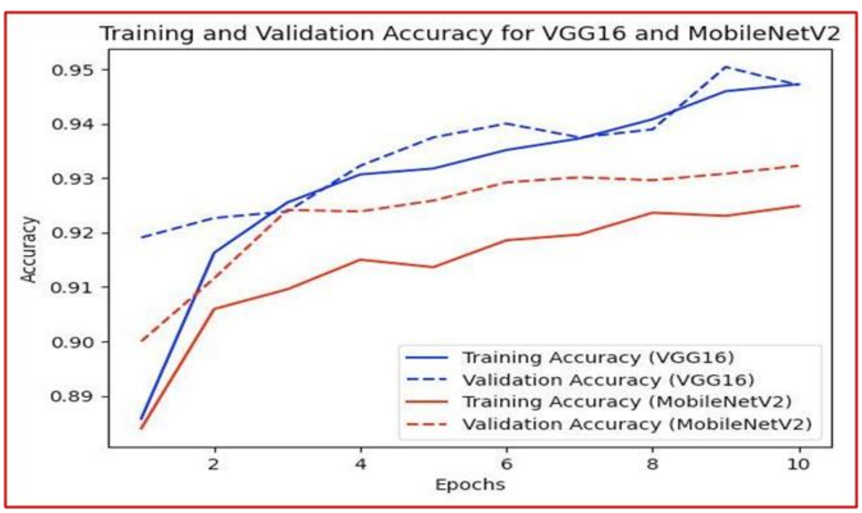

Figure-3 Training and Validation Accuracy for VGG16 and MobileNetV2

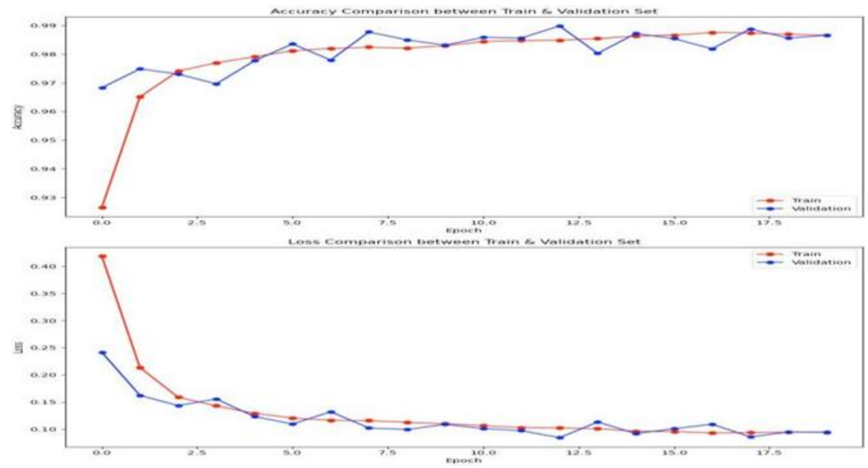

Figure-4 a) Accuracy Comparison between Train and Validation set for Hybrid Model b) Loss Comparison between Training and Validation for Hybrid Model

6. Result and Discussion

Our hybrid deep learning model has demonstrated remarkable success in classifying rice varieties, indicating its potential in agricultural technology appraisal. With scores ranging from 0.97 to 1.00, the model continuously demonstrated exceptional precision. It also demonstrated equally impressive recall rates from 0.97 to 1.00. The final outcome of these findings was F1-scores that varied from 0.98 to 1.00, indicating that the model's predictive value and sensitivity were equally balanced in terms of accuracy. The Adam optimizer, with a learning rate of 0.001, played a crucial role in attaining a 99% overall accuracy. All classes performed at the same level, demonstrating the model's strong generalisation capabilities. Furthermore, low loss measures indicate the efficacy and efficiency of the chosen optimisation strategy in addition to the model's predictive accuracy.

The results of this study highlight the superiority of the hybrid model in classifying tasks related to agriculture. It has shown to be incredibly successful to combine convolutional neural networks (CNNs) with a support vector machine (SVM) classifier that has been fine-tuned using the Adam optimizer. The model's high accuracy over a wide range of rice varieties demonstrates its capacity to reduce false positives, which is crucial in situations where misclassification has serious repercussions. The excellent recall rates demonstrate the model's ability to detect true positives, guaranteeing that almost all cases of each rice type are accurately classified. The almost flawless F1-scores show how well our model represented the minor variations throughout rice cultivars.

Such precision, particularly the flawless performance with the Ipsala variety, highlights the model's potential to revolutionize precision agriculture. It provides a reliable tool for crop monitoring and management, beneficial for various stakeholders. Beyond contributing to agricultural technology, these findings pave the way for further research into the application of deep learning models in other domains where classification accuracy is critical [Table. 2,3,4].

Table-2 Classification Report of MobileNetV2

	Precision	Recall	F1-Score	Support
0	0.92	0.89	0.90	1446
1	0.95	0.92	0.94	1542
2	0.96	0.98	0.97	1555
3	0.88	0.93	0.90	1457
4	0.93	0.93	0.93	1500
Accuracy	0.93	0.93	0.93	7500
Macro	0.93	0.93	0.93	7500

Table-3 Classification Report of VGG16

	Precision	Recall	F1-Score	Support
0	0.93	0.93	0.93	1446
1	0.93	0.98	0.95	1542
2	0.99	0.98	0.99	1555
3	0.93	0.92	0.93	1457
4	0.96	0.93	0.95	1500
Accuracy	0.95	0.95	0.95	7500
Macro	0.95	0.95	0.95	7500

Table-4 Classification Report of Hybrid Model

			F1-	
	Precision	Recall	Score	Support
0.0	0.99	0.99	0.99	2250
1.0	0.97	0.99	0.98	2250
2.0	1.00	1.00	1.00	2250
3.0	0.98	0.97	0.98	2250
4.0	0.99	0.99	0.99	2250
Accuracy	0.99	0.99	0.99	11250
Macro	0.99	0.99	0.99	11250

7. Conclusion and Future Work

This research marks a significant advancement in the application of hybrid deep learning models for the classification of rice varieties. Our model, integrating the strengths of convolutional neural networks (CNNs) and support vector machines (SVMs), and fine-tuned with the Adam optimizer at a learning rate of 0.001, has accomplished an exceptional overall accuracy of 99%. This achievement is more than a statistical milestone; it represents a significant potential impact, especially in countries like Bangladesh, where rice is a crucial component of both the diet and the economy. Given that rice is fundamental to the nutrition of over half the world's population, the accurate classification of rice varieties holds immense significance for biodiversity conservation, food security, and agricultural economics. The high accuracy and robustness of our model in identifying and classifying different rice varieties have the potential to revolutionize agricultural practices by enhancing crop monitoring, improving yield predictions, and facilitating better management. Looking to the future, the success of this study paves the way for innovative developments. A key opportunity lies in the integration of this model into mobile and web applications, democratizing access to advanced analytical tools for farmers and agronomists. These applications could enable real-time data analysis, providing immediate, actionable insights for crop management and harvesting decisions. The model's adaptability also opens avenues for its application in other agricultural classification challenges, potentially leading to significant advancements in automated plant phenotyping and disease detection. Future iterations of this research will focus on not only refining the model's accuracy but also ensuring its practical applicability and accessibility in real-world scenarios. This ongoing development is anticipated to contribute substantially to sustainable agricultural intensification and strengthening global food systems.

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9.Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

10.Funding

No external funding was received to support or conduct this study.