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Research Article

Enhancing Agricultural Diagnostics: Advanced Training of Pre-Trained CNN Models for Paddy Leaf Disease Detection

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Abstract

Timely and precise identification of foliar diseases is essential in contemporary agriculture to avert crop loss, enhance productivity, and guarantee food security. Paddy, being one of the most extensively farmed and consumed staple crops globally, is especially vulnerable to several leaf diseases that can markedly diminish yield. Conventional illness detection techniques, which depend significantly on manual observation and expert evaluation, are frequently time-consuming, labor-intensive, and susceptible to discrepancies. These constraints need the implementation of automated and efficient disease detection technologies. This research investigates the utilization of a pre-trained EfficientNetB3 convolutional neural network for the identification and categorization of paddy leaf diseases. The model was trained and assessed on a rich and diverse dataset comprising annotated pictures of healthy and sick paddy leaves. The performance evaluation included conventional classification criteria like as accuracy, precision, recall, and F1-score to ensure a comprehensive assessment of the model's efficacy. The EfficientNetB3 model exhibited exceptional performance, with an overall accuracy of 96% in the detection and classification of prevalent paddy leaf diseases. This elevated accuracy signifies the model's proficiency in generalizing effectively across diverse illness categories and imaging settings. The findings underscore the capability of deep learning and computer vision methodologies to revolutionize agricultural operations by offering scalable, dependable, and instantaneous solutions for disease identification. The suggested approach facilitates early diagnosis, aiding farmers and agronomists in executing timely and precise treatments, hence minimizing crop loss and enhancing production. Moreover, the incorporation of AI-driven technologies into current agricultural frameworks fosters sustainable farming and strengthens the resilience of food production systems. The research highlights the significant influence of artificial intelligence on precision agriculture and establishes a basis for additional investigation into intelligent crop monitoring systems.

Keywords

EfficientNet, Convolutional Neural Network, CNN, Leaf Disease Detection, Paddy, Deep Learning

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1. Introduction

The advent of deep learning in disease detection for agriculture is undoubtedly a transformative technological breakthrough. This revolutionary technology has significantly impacted various industries, including agriculture, by providing advanced solutions for energy and architecture. One crucial advantage of deep learning is its ability to detect crop diseases, which can have a substantial impact on yield and quality. Paddy, being a major food crop, is particularly susceptible to various diseases that can significantly diminish yield and pose a threat to food security. Traditional disease detection methods relying on human skills are time-consuming and error-prone. In contrast, utilizing pre-trained CNN models offers an innovative and efficient alternative. These models have already shown their effectiveness in various image recognition tasks, providing a promising solution to improve the automation and accuracy of rice leaf disease diagnosis.

In this study, we focused on the performance of the EfficientNetB3 architecture in detecting and classifying common paddy leaf diseases. Through rigorous training and optimization, the EfficientNetB3 model achieved an impressive accuracy of 96%. This result highlights the model's effectiveness in early diagnosis of paddy leaf disease, which is necessary for protecting the health and productivity of paddy crops. The research underscores the potential of artificial intelligence-powered (AI) systems in revolutionizing paddy farming and ensuring the stability of global paddy production. Thus, this study unequivocally emphasizes the critical role of deep learning in advancing agricultural practices [16].

2. Literature Review

Recent research highlights the effectiveness of the Mask R-CNN instance segmentation model in ArcGIS Pro for detecting and segmenting paddy fields from aerial images and enhancing rice production management. The study found that the ResNet-50 backbone performed better than ResNet-101 for this task. The RGB + DVI image dataset achieved the highest mean average precision of 74.01%. Utilizing aerial images and labeled data, the Mask R-CNN model proved crucial for accurate paddy field detection and segmentation, demonstrating the potential of advanced image analysis in agricultural monitoring [1].

In their study on rice disease detection, the authors highlighted that ResNet-50 achieved the highest accuracy of 99.75%, with a validation accuracy of 99.69%. The ResNet-50 model's connection-skipping design contributed to its superior performance. Transfer learning with pre-trained models, including Inception V3, VGG16, VGG19, and ResNet-50, significantly improved disease detection accuracy. Wang et al., as discussed by the authors, developed an automated rice blast disease diagnosis technique leveraging deep learning, image processing, and transfer learning with these pre-trained models, demonstrating the effectiveness of these advanced techniques in enhancing agricultural disease management [2].

Recent advancements in paddy leaf disease detection have seen CNN models achieving high accuracy. Notably, Zhang et al., as discussed by the authors, developed a hybrid model named MSCVT, which leverages the strengths of CNNs for extracting local disease information and Vision Transformers (ViT) for capturing global receptive fields. This model integrates multiscale convolution and self-attention mechanisms, enabling the fusion of local and global features at both the shallow and deep levels. The MSCVT model demonstrated exceptional performance, achieving a recognition accuracy of 99.86% on the PlantVillage dataset and 97.50% on the Apple Leaf Pathology dataset. This hybrid approach showcases the potential of combining CNN and ViT technologies for advanced crop disease recognition [3].

In a recent investigation concerning the detection of diseases in rice crops, a YOLO v5 detection network operating at multiple scales was introduced, resulting in superior performance. The network was founded on DenseNet-201 and featured a Bidirectional Feature Attention Pyramid Network (Bi-FAPN) module to improve the precision of detection. The proposed methodology encompasses preprocessing, segmentation, feature extraction, and detection stages. This sophisticated strategy yielded an average precision rate of 82.8 and an accuracy level of 94.87%, underscoring its efficacy in the identification and categorization of diseases in rice crops at an early stage. The integration of DenseNet-201 and Bi-FAPN in the YOLO v5 framework significantly contributed to these high-performance metrics [4].

In a recent study, a stacking- based integrated learning model was developed for rice disease recognition, incorporating four convolutional neural networks: an improved AlexNet, improved GoogLeNet, ResNet50, and MobileNetV3as base learners, and a support vector machine (SVM) as the sublearner. This model achieved a high recognition rate of 99.69% on the rice dataset. The stacking-based model outperformed the individual models, demonstrating superior performance on the plant dataset. The study employed precision, recall, accuracy, and F1 metrics for a comprehensive evaluation of the model's performance. This integrated approach highlights the effectiveness of combining multiple neural networks with an SVM for advanced plant disease detection [5].

In a recent study, Huang et al. proposed a high-quality image augmentation (HQIA) method for generating high-quality rice leaf disease images using a dual generative adversarial network (GAN) approach. This method integrates Improved Training of Wasserstein GANs (WGAN- GP) and Optimized-Real-ESRGAN (Opt-Real-ESRGAN) to produce enhanced images. The HQIA method significantly improved the recognition accuracy of rice leaf diseases compared to using the original training set alone. The high- quality images generated through this augmentation technique led to better training outcomes, demonstrating the efficacy of HQIA in enhancing model performance for plant disease detection [6].

Alam et al. (2024) demonstrated the remarkable accuracy of EfficientNetB3, along with other models, in their study on leaf disease detection. Notably, EfficientNetB3 achieved an accuracy of nearly 99% in identifying paddy leaf diseases. This impressive performance underscores the potential of this model in revolutionizing agricultural disease detection [7].

In a recent study focused on plant disease detection, four pre-trained CNN deep learning modelsaˆAlexNet, VGG16, ResNet50, and DenseNet121aˆwere utilized as edge solutions. Among these, DenseNet121 demonstrated the highest accuracy at 96.4%. The model maintained high recall, precision, and F1 scores when deployed on a Vision Processing Unit (VPU) device. The study also incorporated image transformation techniques and down sampling to address class distribution. Testing was conducted on various hardware platforms, including CPU, GPU, and VPU, using PyTorch and OpenVINO frameworks, ensuring robust performance across different processing environments [8].

Similarly, Abhijit Pathak et al. (2024) [9] showcased a comparable approach using the VGG16 model, which achieved an impressive 99.6% accuracy in detecting tomato leaf diseases. These findings underscore the significant potential of deep learning models to revolutionize agricultural disease detection [9].

This paper presents a Deep Convolutional Neural Network (CNN) transfer learning-based approach using a modified VGG19 model for the accurate detection and classification of rice leaf diseases. The model underwent two levels of fine-tuning to enhance the classification accuracy. Compared to previous models that achieved 93% accuracy in predicting five diseases, the improved model attained a significantly higher accuracy of 98.7% in predicting ten disease classes. The study also analyzed the model architecture and common computer vision techniques, emphasizing smaller model sizes, minimal GPU usage, and shorter training times, thereby optimizing efficiency and performance in practical applications [10].

This paper proposes a deep convolutional neural network aimed at enhancing performance more effectively than other pretrained models. Several hyperparameters were meticulously adjusted to achieve improved accuracy. [11].

The research utilized deep learning algorithms, particularly tailored CNN models, for the classification of rice leaf diseases, resulting in a test accuracy of 98%. This study underscores the efficacy of sophisticated neural network architectures in improving the detection of paddy leaf diseases, thereby providing advantages to farmers and agricultural methodologies [12].

This study introduces a convolutional neural network model tailored for the classification of rice leaf diseases, attaining an accuracy rate of 99.99%. The study highlights the efficacy of deep learning methodologies in the diagnosis of bacterial blight, blast, brown spot, and tungro in rice crops [13].

This study examines the application of a Deep DenseNet Network for the identification of paddy diseases, resulting in an accuracy of 99.94%. This underscores the promise of advancements in deep learning technologies, such as convolutional neural networks, for enhancing disease detection and rectifying shortcomings in conventional manual approaches [14].

This paper examines the application of the ConvNeXt-L method for feature extraction within the DLCPO-DCPLD technique, which automates the classification of paddy leaf diseases, thereby improving accuracy and efficiency relative to conventional methods, while not specifically addressing pre-trained CNN models [15].

AI-based systems have been extensively applied to plant disease diagnosis in the past few years. Seyam and Pathak (2024) introduced AgriScan, a deep learning-based cross-platform app to enhance disease detection speed and accuracy in crops. The system employs CNNs trained on massive image databases of plants for identifying various plant diseases with high accuracy (S et al., 2024; Upganlawar et al., 2024). Such CNN-based models use transfer learning and data augmentation to become more adaptable among different species of plants and different environmental conditions [17].

3. Methodology

This section outlines the methodology employed for training a Convolutional Neural Network (CNN) model using the EfficientNetB3 architecture for image classification. The implementation was carried out using Python and the TensorFlow library with Keras API.

3.1. Workflow Chart

Figure 1 illustrates the entire process through a clear and easy-to-understand flowchart, making the steps straightforward to grasp

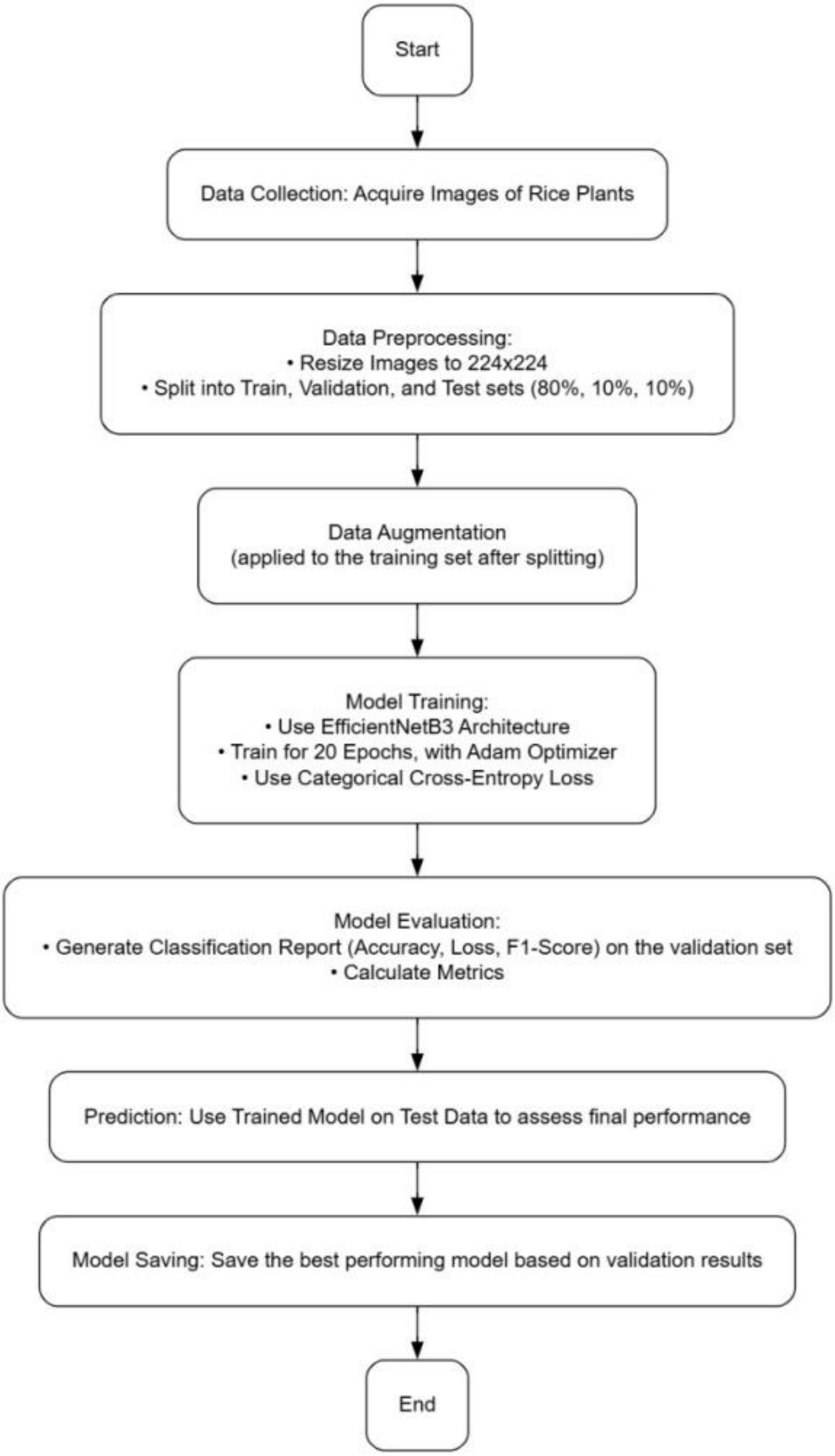

Figure 1. *Workflow chart.*

3.2. Data Preparation

Figure 2. *Sample image data from paddy doctor dataset.*

1. Data Collection: The dataset comprised images of rice plants, categorised into different disease classes. Data were collected from the Paddy Doctor: Paddy Disease Classification dataset available on Kaggle. Figure 2 shows a sample of the utilized image data.

2. Image Resizing: All images were resized to 224×224 pixels2. This standardization ensured consistent input dimensions for the CNN model, improved computational efficiency, and facilitated model training.

3. Data Augmentation: To enhance the robustness and generalisation ability of the model, data augmentation techniques were applied to the training dataset after the initial data splitting and resizing. These techniques were implemented to increase the diversity of the training data and reduce overfitting. The specific augmentations employed included:

4. Random Horizontal Flips: Creating mirrored versions of the images along the vertical axis.

5. Random Vertical Flips: Creating mirrored versions of the images along the horizontal axis.

6. Random Rotations: Rotating the images by random angles within a defined range (e.g., +/- 15 degrees) to introduce variations in image orientation.

7. Random Zoom: Applying random zoom levels (e.g., up to 10%) to simulate variations in the distance and scale of the subject in the images.

These augmentations were performed online during the training process. By applying these transformations, the model was exposed to a wider range of variations in the paddy leaf disease images, making it more resilient to unseen data and improving its ability to accurately classify diseases1. The application of these data augmentation techniques was crucial in achieving the reported accuracy of 96% with the EfficientNetB3 model.

3.3. Data Splitting and Distribution

The dataset was split into training, validation, and test sets using a stratified approach to maintain class distribution across each subset. Figure 3 shows the data distribution among the training, test, and validation datasets.

1. *Training set:* 80% of the total dataset (8325 images) was allocated for model training.
2. *Validation set:* 10% of the total dataset (1041 images) was reserved for hyperparameter tuning and model evaluation during training.
3. *Test set:* The remaining 10% (1041 images) was kept separate for final model evaluation and performance assessment.

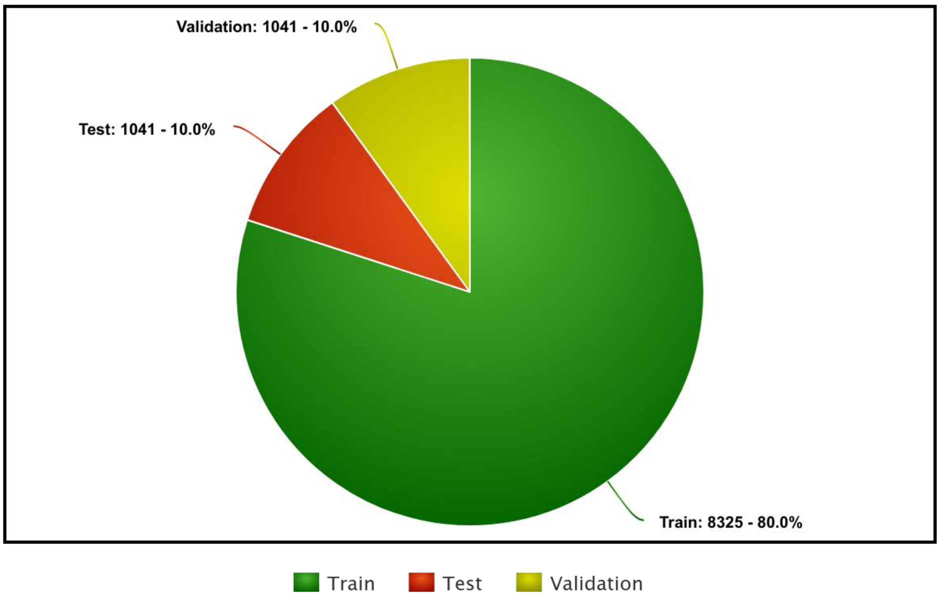

Figure 3. *Data distribution proportionality between the three sets.*

3.4. Model Training

1) *Model Architecture:* The EfficientNetB3 architecture was chosen due to its efficiency and performance on image classification tasks4. EfficientNetB3 is part of the EfficientNet family and employs a compound scaling method to optimise both the depth and width of the network. The base EfficientNet architecture utilizes Mobile Inverted Bottleneck Convolution (MBConv) blocks, incorporating depthwise separable convolutions and squeeze-and-excitation modules. EfficientNetB3 consists of multiple MBConv blocks arranged in layers, followed by a convolutional layer, batch normalisation, a Swish activation function, global average pooling, and finally, a fully connected layer with a softmax activation function for classification. The specific configuration of EfficientNetB3 includes approximately 7 convolutional layers (referring to the main convolutional building blocks) and has 3.1 million trainable parameters. The model was implemented using the EfficientNetB3 class available within the tensorflow.keras.applications module.
2) *Training Parameter:* The model was trained for 20 epochs using the Adam optimizer with a learning rate of 0.0018. The batch size used during training was. The learning rate was kept constant throughout the training process. The Adam optimizer was chosen for its efficiency in training deep neural networks.
3) *Loss Function:* Categorical Cross-Entropy served as the loss function to quantify the disparity between anticipated and actual class labels. The loss for a certain sample is computed as follows:

$$L = -\Sigma(i=1 \text{ to } C)\ [y_i * \log(\hat{y}_i)]$$

C is the total number of classes, y_i signifies the true label (one-hot encoded) for class i, and $\hat{y}_i$ represents the projected probability for class i produced by the model. This loss function imposes more penalties on the model when the projected probability for the correct class is low, so motivating it to give higher confidence to the accurate label. Categorical Cross-Entropy is especially appropriate for multi-class classification tasks, such as the identification of paddy leaf diseases, where each input picture is assigned to one of several potential disease categories. During training, the model parameters are adjusted to minimize loss, hence enhancing the model's capacity to properly categorize novel, unseen data [18].

3.5. Model Evaluation and Metrics

Upon concluding the training procedure, a detailed classification report was systematically produced to assess the performance of the trained model for each individual class. This report included essential parameters, such as accuracy, recall, F1-score, and support, offering significant insights into the model's prediction performance and its effectiveness across different categories in the dataset.

Alongside the classification results, essential performance measures, including accuracy, loss, and F1-score, was rigorously computed for both the training and validation datasets. These measures were essential for tracking the convergence of the model throughout the training and were pivotal in detecting possible overfitting problems.

The loss measure offers insight into the model's prediction inaccuracies, directing the optimization process during training. The F1-score, assessed independently for the training and validation sets, facilitates a comparison study essential for verifying the model's resilience. A consistent evaluation of these critical measures is vital for confirming that the model not only conforms to the training data but also generalizes effectively to novel data, thereby validating its relevance in practical situations.

3.6. Prediction and Model Saving

1) *Test Predictions:* The trained model was employed to forecast the class labels for the unseen test set, thereby assessing its performance in a practical context. This technique is essential for evaluating the model's generalization capacity and resilience as it offers insight into the model's adaptability to data outside the training set. To guarantee a thorough assessment, many metrics were utilized to examine the accuracy, precision, recall, and F1-score of the model's predictions.
2) *Model Preservation:* The resulting model, demonstrating optimal performance on the validation set, was retained for future applications and deployment. This stage is essential for repeatability and future research progress as it enables further investigation and use of the model in similar activities or fields. By storing the model in a meticulously organized framework, researchers can guarantee the preservation of the precise parameters and configurations utilized during training, thereby upholding the integrity of subsequent studies and practical applications.

4. Results and Discussion

4.1. Training and Validation Performance

To evaluate the performance of the CNN model trained on EfficientNetB3, we monitored both the training and validation losses and accuracy over 20 epochs. The results are shown in Figure 4.

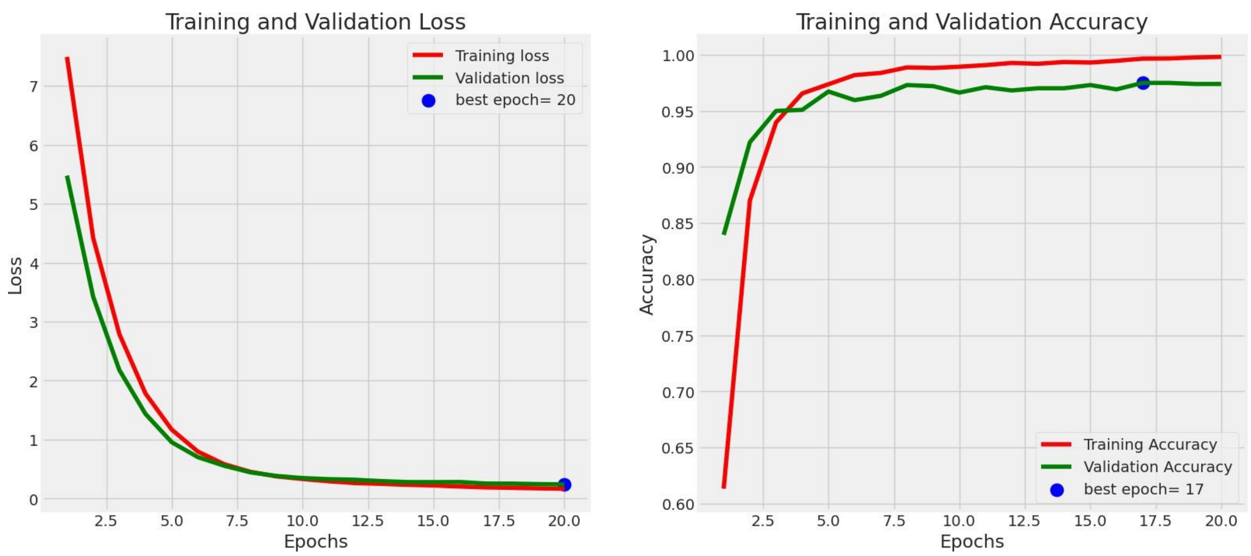

Figure 4. *Training and Validation Loss and Accuracy.*

The training loss and validation loss curves exhibited a steady decline over the epochs, with both converging to low values. The training loss starts at approximately 7.5 and drops to below 0.5 by the 20th epoch, whereas the validation loss starts higher than the training loss but follows a similar decreasing trend, stabilizing at approximately 0.5. This indicates that the model effectively learned and generalized well to the validation set. The training accuracy begins at approximately 60% and quickly improves, reaching nearly 100% by the 20th epoch. The validation accuracy closely follows, starting at approximately 65% and stabilizing at approximately 97%. The best validation accuracy was observed at the 17th epoch, indicating minimal overfitting and good generalization.

4.2. Loss and Accuracy Calculations

4.2.1. Training and Validation Loss

The loss for each sample is calculated using the categorical cross-entropy loss function, which is given by

$$\text{Loss} = -\sum_{i=1}^{N} y_i \log(y_i)$$

where y_i is the true label, $\hat{y}_i$ is the predicted probability for class i, and N is the number of classes. The average loss over all samples in a batch was used to update the model weights during the training. The training loss was calculated over the training dataset and the validation loss was calculated using the validation dataset.

4.2.2. Training and Validation Accuracy

Accuracy is calculated as the ratio of correctly predicted samples to the total number of samples and is defined as

$$\text{Accuracy} = \frac{Number\ \ of\ \ Correct\ \ Predictions}{Total\ \ Number\ \ of\ \ Predictions}$$

The accuracy of the model was computed for both training and validation datasets. High training accuracy combined with high validation accuracy indicates that the model generalizes well to unseen data.

4.3. Confusion Matrix Analysis

The confusion matrix in Figure 5 provides a detailed breakdown of the model performance across different classes.

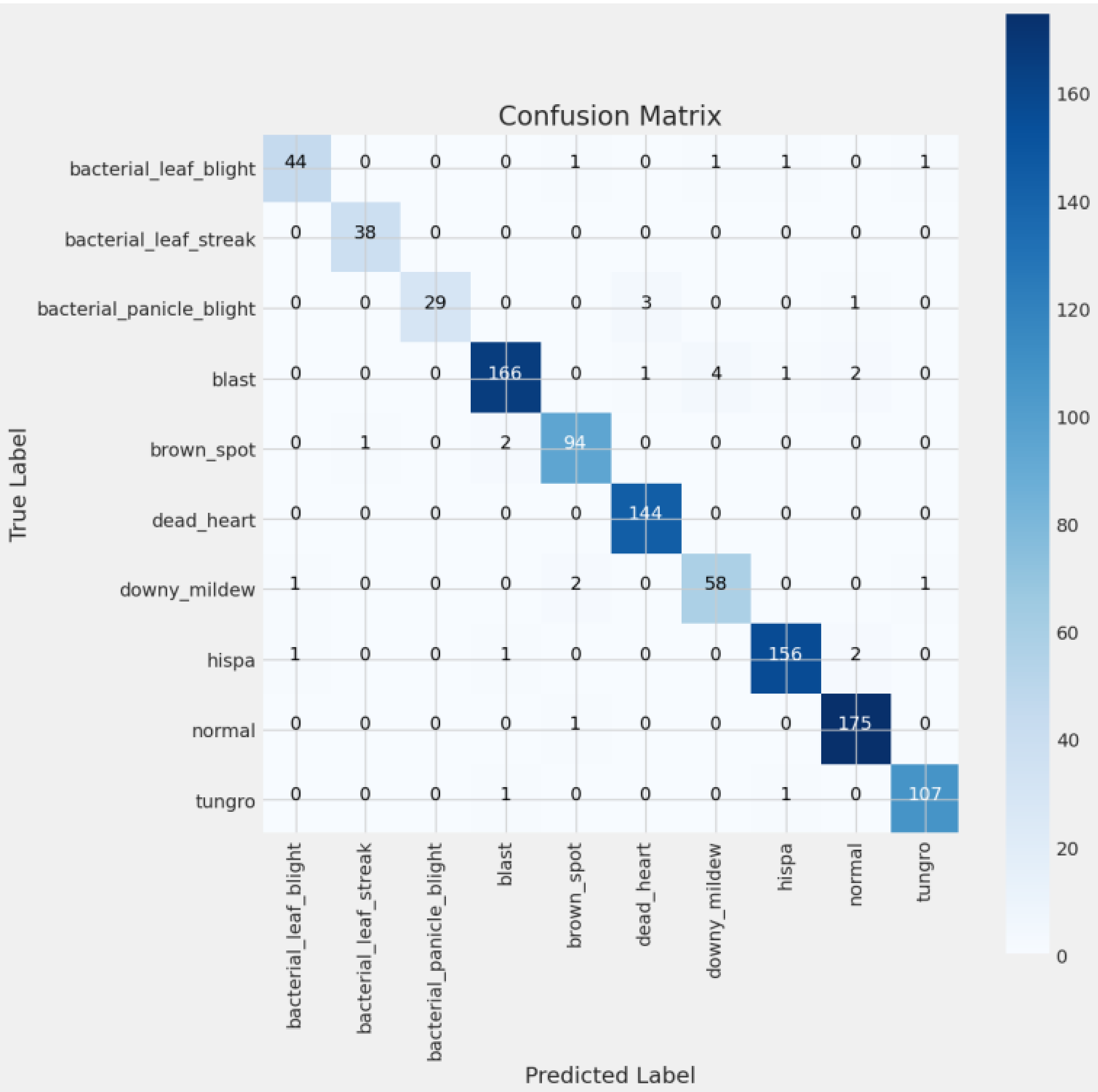

Figure 5. Confusion Matrix.

The confusion matrix shows the numbers of correct and incorrect predictions for each class. The diagonal elements represent the true positives (correct predictions), whereas the off-diagonal elements represent false positives and false negatives. The confusion matrix shows that the model performed exceptionally well for most classes, with high true-positive rates and low misclassification rates. For example, a class blast has 166 correct predictions and only a few misclassifications. Similarly, the normal class yielded 175 correct predictions, indicating a high degree of accuracy. However, some classes exhibit slight confusion, such as bacterial panicle blight being misclassified as blast (3 instances). This suggests that although the model is highly accurate, there is still room for improvement in distinguishing between certain classes.

4.4. Classification Report

The classification report (Table 1), derived from the confusion matrix, and provides additional metrics such as precision, recall, and F1-score for each class. A summary of the classification reports is as follows.

Table 1. *Classification Report.*

Class	Precision	Recall	F1-score	Support
bacterial_leaf_blight	0.94	0.88	0.91	50
bacterial_leaf_streak	0.95	1.00	0.97	38
bacterial_panicle_blight	0.91	0.83	0.87	35
blast	0.97	0.95	0.96	174
brown_spot	0.92	0.96	0.94	98
dead_heart	1.00	1.00	1.00	144
downy_mildew	0.90	0.91	0.91	64
hispa	0.97	0.97	0.97	161
normal	0.98	0.99	0.98	177
tungro	0.97	0.99	0.98	108
Accuracy			0.96	1049
Macro avg	0.95	0.95	0.95	1049
Weighted avg	0.96	0.96	0.96	1049

1) Precision measures the accuracy of positive predictions, defined as

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

2) Recall measures the ability to identify all positive instances, defined as

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

3) F1-score is the harmonic mean of precision and recall, defined as

$$\text{F1-score} = 2\frac{Precision \cdot Recall}{Precision+Recall}$$

The high precision and recall across most classes indicated that the model's predictions were accurate and reliable.

4.5. In-Depth Analysis

The results indicate that the Convolutional Neural Network (CNN) model, which was trained using EfficientNetB3, demonstrates a high degree of accuracy coupled with strong generalization capabilities. The convergence of the training and validation loss curves, along with a minimal disparity between the training and validation accuracies, suggests that the model does not exhibit underfitting or overfitting.

4.5.1. Analysis of Overfitting and Underfitting

1) *Overfitting:* This phenomenon occurs when a model excels on training data but falters on validation data. However, this was not observed in this case, as evidenced by the closely aligned training and validation

curves.

2) *Underfitting:* Conversely, underfitting transpires when a model performs inadequately on both training and validation datasets. This scenario was also absent given that both training and validation accuracies were commendably high.

4.5.2. Insights from the Confusion Matrix

1) *High True Positives:* A majority of classes exhibit a significantly high number of true positives, signifying that the model accurately identifies a large proportion of samples.
2) *False Positives and False Negatives:* Despite the competent performance, there are instances of misclassification (i.e., false positives and false negatives), particularly among classes sharing similar visual characteristics, such as bacterial panicle blight and blast. This observation underscores the necessity of enhanced feature differentiation during the learning process.

4.5.3. Metrics of Precision, Recall, and F1-Score

1) *High Precision and Recall:* Elevated precision and recall values indicate that the model is proficient in both identifying true positives and minimizing false positives.
2) *Balanced F1-Scores:* The consistently high F1-scores across various classes reflect an optimal equilibrium between precision and recall.

4.6. Discussion

The results demonstrate that the CNN model trained on EfficientNetB3 achieves a high accuracy and generalization capability. The convergence of the training and validation loss curves and the minimal gap between the training and validation accuracy suggest that the model is neither underfitting nor overfitting.

The confusion matrix and classification report further confirmed the model's robust performance with high precision, recall, and F1-scores across all classes. Some minor misclassifications indicate potential areas for improvement, possibly through more extensive data augmentation or the tuning of hyperparameters.

Overall, the model's performance was highly satisfactory, making it a reliable tool for the classification of rice diseases. Future work could focus on addressing slight misclassifications and further optimizing the model for even higher accuracy and robustness. This might include:

1) *Data Augmentation:* Enhance the dataset with more diverse samples to improve model robustness.
2) *Hyperparameter Tuning:* Fine-tune learning rates, batch sizes, and other parameters to achieve better performance.
3) *Model Architecture Improvements:* Experiment with different CNN architectures or ensemble methods to further enhance accuracy.

5. Conclusion

In conclusion, this study investigated the use of various pre- trained Convolutional Neural Network (CNN) models to detect dis-eases in paddy leaves. The authors collected images of paddy leaves with different diseases, applied standard image-processing techniques, and trained the EfficientNetB3 model on these images. They evaluated the model based on accuracy, precision, recall, and the F1-score. The results show that the EfficientNetB3 model achieved a remarkable accuracy of 96%. This study found high precision and recall for most disease classes, indicating that the model was generally accurate in its pre-dictions. Specifically, for bacterial leaf blight, the model achieved a precision of 0.94, recall of 0.88, and F1-score of 0.91. For bacterial leaf streaks, it achieved a precision of 0.95, recall of 1.00, and F1-score of 0.97. The precision, recall, and F1-scores for other diseases, such as blasts, brown spots, dead hearts, downy mildew, hispa, normal, and tungro, were similarly high, with most exceeding 0.90. The overall accuracy was 96%, with macro-and weighted averages of precision, recall, and F1-scores of around 0.95 and 0.96, respectively. The authors demonstrated that the EfficientNetB3 model is highly effective in detecting paddy leaf diseases. This can help farmers diagnose diseases quickly and accurately, potentially leading to better crop yields and improved food security. The success of the EfficientNetB3 model underscores the critical role of deep learning in advancing agricultural practices and enhancing the productivity and stability of paddy fields.

Abbreviations

AI	Artificial Intelligence
CNN	Convolutional Neural Network
GAN	Generative Adversarial Network
MBConv	Mobile Inverted Bottleneck Convolution
SVM	Support Vector Machine
ViT	Vision Transformer

Author Contributions

Sazzad Hossain: Data Curation, Methodology, Software, Visualization

Touhidul Alam Seyam: Methodology, Conceptualization, Resources, Project Administration, Writing – Review & Editing

Avijit Chowdhury: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft

Rajib Ghose: Formal Analysis, Investigation, Validation

Arifur Rahaman: Methodology, Investigation, Supervision

Zarin Hadika: Validation, Writing – Original Draft, Visualization

Abhijit Pathak: Supervision, Conceptualization, Writing – Review & Editing

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Data Availability Statement

The data supporting the outcome of this research work has been reported in this manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Deep Learning Approach for Paddy Field Detection Using Labeled Aerial Images: The Case of Detecting and Staging Paddy Fields in Central and Southern Taiwan. Remote sensing, https://doi.org/10.3390/rs15143575

[2] Salman, Qadri., Hadia, Bibi., Muhammad, Imran, Sharif., Francesco, Marinello. (2023). Comparing Inception V3, VGG 16, VGG 19, CNN, and ResNet 50: A Case Study on Early Detection of a Rice Disease. Agronomy, https://doi.org/10.3390/agronomy13061633

[3] Dingju, Zhu., Jianbin, Tan., Kai, Leung, Yung., Andrew, W., H., Ip. (2023). Crop Disease Identification by Fusing Multiscale Convolution and Vision Transformer. Sensors, https://doi.org/10.3390/s23136015

[4] V., Senthil, Kumar., M. K., Jaganathan., Abhishek, Viswanathan., M., Umamaheswari., J., C., Vignesh. (2023). Rice leaf disease detection based on bidirectional feature attention pyramid network with YOLO v5 model. Environmental research communications, https://doi.org/10.1088/2515-7620/acdece

[5] Leong, Qi, Yang., Xiaoyun, Yu., Shaoping, Zhang., Huanhuan, Zhang., Shuang, Xu., Hu, Long., Yingwen, Zhu. (2023). Stacking-based and improved convolutional neural network: a new approach in rice leaf disease identification. Frontiers in Plant Science, https://doi.org/10.3389/fpls.2023.1165940

[6] A High-Quality Rice Leaf Disease Image Data Augmentation Method Based on a Dual GAN. IEEE Access, https://doi.org/10.1109/access.2023.3251098

[7] Alam, T.S., Jowthi, C. B. & Pathak, A. Comparing pre- trained models for efficient leaf disease detection: a study on custom CNN. Journal of Electrical Systems and Inf Technol 11, 12 (2024). https://doi.org/10.1186/s43067-024-00137-1

[8] Soo, Jun, Wei., Dimas, Firmanda, Al, Riza., Hermawan, Eko, Nugroho. (2022). Comparative study on the performance of deep learning implementation in the edge computing: Case study on the plant leaf disease identification. Journal of agriculture and food research, https://doi.org/10.1016/j.jafr.2022.100389

[9] Chakraborty, A., Chakraborty, A., Sobhan, A., & Pathak, A. Deep Learning for Precision Agriculture: Detecting Tomato Leaf Diseases with VGG-16 Model. International Journal of Computer Applications, 975, 8887.

[10] Ghazanfar, Latif., Sherif, Elmeligy, Abdelhamid., Roxane, Elias, Mallouhy., Jaafar, Alghazo., Z., A., Kazimi. (2022). Deep Learning Utilization in Agriculture: Detection of Rice Plant Diseases Using an Improved CNN Model. Plants, https://doi.org/10.3390/plants11172230

[11] A. Chowdhury, “Advancing Multi-Class Arc Welding Defect Classification: DEEPTLWELD Intelligent System Utilizing Computer Vision, Deep Learning, and Transfer Learning on Radiographic X-ray Images for Bangladesh’s Manufacturing Sector,” 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS), Cox’s Bazar, Bangladesh, 2024, pp. 1-6, https://doi.org/10.1109/COMPAS60761.2024.10796006

[12] Monoronjon, Dutta., Md, Rashedul, Islam, Sujan., Mayen, Uddin, Mojumdar., Narayan, Ranjan, Chakraborty., Ahmed, Al, Marouf., Jon, Rokne., Reda, Alhajj. (2024). 1. Rice Leaf Disease Classificationaˆ A Comparative Approach Using Convolutional Neural Network (CNN), Cascading Autoencoder with Attention Residual U-Net (CAAR-U-Net), and MobileNet- V2 Architectures. Technologies (Basel), https://doi.org/10.3390/technologies12110214

[13] Salma, Akter., Rashedul, Islam, Sumon., Haider, Ali., Heeaˆ Cheol, Kim. (2024). 2. Utilizing Convolutional Neural Networks for the Effective Classification of Rice Leaf Diseases Through a Deep Learning Approach. Electronics, https://doi.org/10.3390/electronics13204095

[14] J. K. V, D. Tauro, P. M. R, C. DSouza and B. Correia, ”Paddy Care: Paddy Disease Identification and Classification Using Deep DenseNet Network,” 2024 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), Mangalore, India, 2024, pp. 377-382, https://doi.org/10.1109/DISCOVER62353.2024.10750707

[15] Athar, Hussain., Balaji, Srikaanth., P. “4. Deep Learning with Crested Porcupine Optimizer for Detection and Classification of Paddy Leaf Diseases for Sustainable Agriculture.” Journal of machine and computing, undefined (2024). https://doi.org/10.53759/7669/jmc202404095

[16] Hossain, S., Seyam, T. A., Chowdhury, A., Xamidov, M., Ghose, R., Pathak, A. (2025). Fine-tuning LLaMA 2 interference: a comparative study of language implementations for optimal efficiency. arXiv preprint arXiv: 2502.01651.

[17] Seyam, T. A., Pathak, A. AgriScan: Next.js powered cross-platform solution for automated plant disease diagnosis and crop health management. *Journal of Electrical Systems and Inf Technol* 11, 45 (2024). https://doi.org/10.1186/s43067-024-00169-7

[18] Chowdhury, A., Seyam, T. A., Babar, M. U. A., Khan, C., & Akter, S. (2025). Efficient Malware Classification Using Multiprocessing and Bag-of-Words Vectorization. Advances in Networks, 12(1), 19–28. https://doi.org/10.11648/j.net.20251201.12

Biography

Sazzad Hossain is a distinguished professor, researcher, academic teaching advisor with extensive experience in ICT sector and a writer. Currently he is working as a visiting Professor at Samarkand State University in the faculty of Artificial Intelligence and Computer Technologies, Samarkand, Uzbekistan. He is also the Head of the Department of International Education Development at Synergy University, Moscow, Russia. He received his PhD. in Electrical and Computer Engineering from Portland State University, Oregon, USA. His doctoral dissertation in Quantum Computing takes background and ideas from several fields of physics, mathematics, computer science, computer engineering, and biology. He completed his Master in Electrical and Computer Engineering from the same university in the USA. He received his Bachelor of Science in Electrical System Network Engineering from Moscow Technical University (Popularly known as Moscow Power Institute), Moscow, Russia.

Touhidul Alam Seyam is a dedicated Software Engineer and Research Assistant with expertise in full-stack development, machine learning, and academic research. Currently, he is a Research Assistant at BGC Trust University Bangladesh and a Software Engineer at Hello World Communications Limited. His research primarily focuses on AI-driven healthcare solutions, agricultural technology, and disease prediction models. Seyam has published multiple SCOPUS and Springer-indexed papers, contributing significantly to leaf disease detection, tuberculosis risk assessment, and cardiovascular risk prediction using machine learning. Beyond research, he has successfully developed and deployed Next. js and Django-based web applications, showcasing his proficiency in React, Golang, PostgreSQL, and cloud-based solutions. Passionate about innovation, Seyam actively participates in competitive programming and holds multiple industry certifications from platforms like IBM, Google Skillshop, and HackerRank. His work reflects a commitment to leveraging AI and software engineering to address real-world challenges in healthcare and agriculture.

Avijit Chowdhury is an emerging researcher in the field of Artificial Intelligence, hailing from Chittagong, Bangladesh. He is currently pursuing a Bachelor’s degree in Mechanical Engineering at Chittagong University of Engineering and Technology (CUET), where he also serves as a research assistant. Driven by a deep interest in computer science, Avijit has been passionate about coding and software development since his school years. His academic and research interests lie primarily in artificial intelligence, machine learning, and software engineering. Over the past three years, he has actively engaged in research and development projects in these areas, which has inspired him to pursue a Master's degree in Computer Science. His long-term goal is to harness the power of intelligent systems to automate complex tasks, improving efficiency and reducing the need for manual intervention. Avijit has contributed to the scientific community through publications in several SCOPUS- and Springer-indexed journals, particularly in the domain of machine learning. In addition to his academic achievements, he has practical experience in full-stack development, having built multiple end-to-end applications using the MERN (MongoDB, Express.js, React, Node.js) stack. Furthermore, he has completed professional certifications from leading institutions such as Google, IBM, and Meta, demonstrating his commitment to continuous learning and technical excellence.

Rajib Ghose is a distinguished researcher in the field of computational intelligence, specializing in formal verification, cryptography, and cloud security. His research interests encompass optimization algorithms, AI ethics. With an extensive academic background, he has contributed to advancing secure computing methodologies, distributed systems, and bioinformatics. He has published numerous articles in reputed scientific journals. His work in knowledge representation and formal analysis has significantly influenced the development of secure and efficient computational frameworks. In addition to his research, Rajib Ghose is actively engaged in academia, mentoring students and researchers in the areas of AI-driven cybersecurity and computational complexity. His interdisciplinary expertise continues to shape modern approaches to secure computing and intelligent data analysis.

Arifur Rahaman is a committed researcher and Assistant Professor in the department of Computer Science and Engineering at Sonargaon University, having over 7 years of experience in academia and research. His areas of expertise encompass the NLP, Machine Learning, Deep Learning, and Image Processing, Computer Vision and IoT. He has authored 4 research papers published in leading journals and presented at international conferences. He has a passion for exploring emerging technologies and is currently delving into Deep Learning and Computer Vision. Outside of academics, he enjoys reading, conducting research, and engaging in insightful discussions. Dedicated to both learning and teaching, he aims to inspire his students and make meaningful contributions to the rapidly advancing field of technology.

Zarin Hadika is a university lecturer in Computer Science and Engineering (CSE) with a passion for teaching and research. Her work focuses on image processing and computer vision, and she has presented research on cross-modal person re-identification using HOG, tackling challenges in pattern recognition and visual data analysis. She loves exploring new technologies and is currently diving into Cloud Computing and AI. Beyond academics, she enjoys reading, researching, and having thoughtful discussions. Committed to both learning and teaching, she strives to inspire her students and contribute to the ever-evolving tech world.

Abhijit Pathak is a dedicated researcher and Assistant Professor in Computer Science and Engineering at Sonargaon University with over 16 years of experience in academia and research. His expertise includes Internet of Things (IoT), Machine Learning, Artificial Intelligence, and Software Development. He has made significant contributions to interdisciplinary research, focusing on automation, AI-driven solutions, and data analytics. Pathak has published over 30+ research papers in top-tier journals and international conferences. His research impact is reflected in a Google Scholar h-index of 9 and citations exceeding 628. He has been recognized among the top 7 scientists globally from BGC Trust University Bangladesh by the AD Scientific Index 2024. He actively mentors students, leads AI and IoT-driven projects, and supervises undergraduate and postgraduate research. As a Commonwealth Scholarship recipient, he has received multiple awards for academic excellence and leadership in technological innovation.

Research Field

Sazzad Hossain: Quantum computing, Data science, Computational intelligence, Internet of Things, Pattern recognition, Deep learning, Computer vision, Reinforcement learning, Edge computing, Secure computing, Privacy-preserving AI, Neural networks.

Touhidul Alam Seyam: Artificial intelligence, Machine learning, Cybersecurity, Smart cities, Big data analytics,, Fault-tolerant computing, AI-driven surveillance, Human-robot interaction.

Avijit Chowdhury: Computer vision, Natural language processing, Speech recognition, Computational linguistics, Text mining, AI-powered translation, Sentiment analysis, Explainable AI, Knowledge graphs, Conversational AI, Information retrieval.

Rajib Ghose: Formal verification, Computational complexity, Cryptography, Artificial intelligence, Machine learning, AI ethics, Knowledge representation, Bioinformatics, Distributed computing, Algorithmic game theory.

Arifur Rahaman: NLP, Machine Learning, Deep Learning, and Image Processing, Computer Vision and IoT.

Zarin Hadika: Computational neuroscience, AI-assisted healthcare, Biomedical data analysis, Artificial intelligence, Machine learning, Digital signal processing, AI-driven diagnostics, Emotion recognition, Computational psychology, Assistive technologies.

Abhijit Pathak: Artificial intelligence, Machine learning, Parallel computing, Neuromorphic computing, Complex systems modeling, Adaptive algorithms, Evolutionary computation, AI-driven simulations, Computational fluid dynamics, AI for space research.