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Multi-Class CNN-Based Detection of Rice Leaf Diseases Using Cross-Entropy Loss Optimization

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ABSTRACT
Rice is a primary food source for over 50% of the global population, and crop diseases can cause yield losses of up to 70% annually in affected regions. Early and accurate detection of leaf diseases is crucial to prevent significant agricultural and economic setbacks. However, traditional manual diagnosis methods are time-consuming, labor-intensive, and often inaccurate due to visual similarities between diseases like Brown Spot, Leaf Blast, and Neck Blast. Existing machine learning techniques such as Artificial Neural Network (ANN) models using Stochastic Gradient Descent (SGD) and Adam optimizers offer basic classification capabilities but often lack precision due to limited generalization on complex features. To overcome these limitations, this work introduces a novel approach that combines advanced image preprocessing, effective data augmentation, and a Categorical Cross-Entropy Loss Optimized Convolutional Neural Network (CCEL-OCNN). The preprocessing stage involves noise reduction, contrast enhancement, and resizing to a consistent dimension, ensuring uniformity across samples. Image augmentation techniques such as rotation, flipping, and zooming are employed to artificially expand the dataset and improve model robustness against overfitting. Unlike traditional ANN-SGD or ANN-Adam frameworks, the proposed CCEL-OCNN model is explicitly optimized using categorical cross-entropy loss to enhance multi-class classification performance across four key rice leaf categories: Brown Spot, Healthy, Leaf Blast, and Neck Blast. This model not only improves detection accuracy but also accelerates convergence during training. Experimental results demonstrate that CCEL-OCNN outperforms existing models in terms of classification accuracy, sensitivity, and generalization, offering a scalable and efficient solution for smart agriculture systems.

Keywords: Multi-Class Classification, Cross-Entropy Loss Optimization, Plant Disease Detection, Precision Agriculture, Crop Health Monitoring

1. INTRODUCTION

Rice blast disease, caused by the fungus Magnaporthe oryzae, stands as one of the most destructive afflictions in global rice cultivation. It is present in 85 countries and annually destroys enough rice to feed more than 60 million people. In India, during severe outbreaks, neck and panicle blast infections can inflict yield reductions of over 50%, with national-scale yield losses during wet-season epidemics ranging from 27–35%. These staggering losses underscore the disease's capacity to destabilize food security, particularly in regions heavily reliant on rice as a staple. Bacterial leaf blight, another major threat caused by Xanthomonas oryzae, is remarkably devastating under certain conditions. In severe cases, early-stage epidemics can decimate up to 80% of the crop, especially when susceptible rice varieties are affected. Even in more moderate contexts—such as in the Philippines—losses vary seasonally from 7.2% in dry seasons to as high as 22.5% during wet seasons, while resistant cultivars see greatly reduced losses around 1.8–9.5. This underscores the influence of environmental conditions and varietal resistance in mitigating yield damage.

Beyond these, sheath blight—triggered by Rhizoctonia solani—can further erode yield, sometimes by up to 50%, particularly in intensive rice-growing areas of Asia. More broadly, plant diseases across all crops contribute to a global average yield reduction of roughly 10% in developed regions, and over 20% in developing areas annually. The Food and Agriculture Organization estimates that plant diseases and pests are responsible for about 25% of total crop loss worldwide. Together, these figures underscore the urgent need for early detection and effective disease management systems to safeguard global food production.

The broader trend toward data-centric agriculture—often called digital agriculture—is fueling demand for advanced decision support tools that process and interpret rich datasets in real time. As Dr. Ashish Agarwal notes, analytics-driven platforms transform raw sensor feeds into actionable insights on disease risk, soil health, irrigation timing, and yield forecasting. Similarly, Cropin's large-scale deployment in India demonstrated how data analytics can raise yields by 30% and revenues by nearly 37% across thousands of small farms. In this context, accurate automated disease detection within crop imagery isn't just technically compelling—it's essential for ensuring resilient, sustainable, and profitable agriculture at scale.

2. LITERATURE SURVEY

Subbarayudu et al. [6] proposed an automated hybrid deep learning framework for paddy leaf disease identification and classification. They created an end-to-end system that performed image acquisition, preprocessing, feature extraction, feature selection, and classification. Their method employed MobileNetV3 as the feature extractor, augmented by a hybrid optimization strategy combining Genghis Khan Shark Optimization with Simulated Annealing for effective feature selection. The combination intended to improve classification accuracy by focusing on the most informative attributes. This model delivered strong performance, yet its drawback involved potential computational complexity due to the dual-stage feature selection framework. Naresh Kumar and Sakthivel [7] introduced a fusion vision boosted classifier that integrated VGG19 for deep feature extraction and LightGBM as the classifier. They utilized a curated dataset of 2,627 rice leaf images divided into training, validation, and test sets, achieving accuracies above 97 % across all sets. Their fusion approach aimed to leverage deep convolutional features with gradient-boosted decision trees for efficiency and performance. However, the drawback lay in limited robustness to feature interactions, as fixed feature extraction via VGG19 may overlook subtle discriminative nuances between similar diseases. Padhi et al. [8] enhanced paddy leaf disease diagnosis by developing a hybrid CNN model that incorporated simulated thermal imaging alongside regular RGB images. They augmented a dataset of 5,932 rice leaf images with thermal data to capture early stress responses not visible in standard imagery. By combining thermal and visual features, the model improved early detection accuracy. Yet the drawback pertained to feature fusion complexity; integrating thermal and visual data introduced challenges in aligning feature representations effectively. Bhola and Kumar [9] proposed a hybrid model combining deep transfer learning with a Support Vector Machine (SVM) to identify leaf diseases across corn, rice, and wheat. They used DenseNet201 as a feature extractor and employed SVM for classification, achieving high accuracy—99.82% for corn, 98.75% for wheat, and 84.15% for rice—while keeping the model lightweight with only 20.2 million parameters. The model excelled in cross-crop flexibility and computational efficiency. However, the method suffered from limited rice-specific feature extraction, leading to comparatively lower rice classification accuracy. Aguirre-Rodríguez et al. [10] applied a unique image processing technique called the Stretched Neighborhood Effect Color to Grayscale (SNECG), along with thresholding and gamma correction, to boost machine learning (ML) models like logistic regression, multilayer perceptron, SVM, decision tree, and random forest (RF). The RF model achieved a precision of 88.31% across five rice disease categories, validating the method's effectiveness and usability via an interface for decision support. Despite that, converting to grayscale lost crucial color-based lesion features which reduced disease discrimination finesse.

Firdaus et al. [11] enhanced rice leaf disease classification by modifying convolutional neural network (CNN) architectures using ResNet50 combined with data augmentation techniques like random zoom and multilayer perceptron (MLP) tuning. Through grid search, they identified a three-layer MLP without additional compression as the most effective, delivering test accuracy of 0.92 (and precision, recall, F1-score of 0.94, 0.92, 0.92 respectively). Nonetheless, the architectural adjustments introduced higher computational complexity, potentially limiting model deployment on resource-constrained devices. Rahman et al. [12] proposed a real-time monitoring system that detected leaf diseases across multiple plant types, including rice, using a comprehensive dataset of over 30,900 images from eight crops. They developed and evaluated several CNN architectures, such as custom CNN, VGG16, VGG19, InceptionV3, MobileNet, DenseNet121, and Xception. The custom CNN achieved 95.62% accuracy for leaf-level classification, while DenseNet121 delivered 98% accuracy on rice. A web and mobile application enabled real-time deployment of the best models. The drawback lay in potential overfitting to specific CNNs, which may fail to generalize across new varietal patterns. Martins et al. [13] developed RiceLeafClassifier-v1.0, a lightweight, quantized convolutional neural network built from scratch (rather than via transfer learning). It classified five rice leaf conditions—blast, bacterial blight, brown spot, healthy, and red stripe—using a training set of 2,807 images and achieving 94% accuracy. Quantization reduced model size from 78 MB to 6.5 MB, enabling efficient deployment on edge devices like Raspberry Pi. The drawback concerned limited feature richness; the small model size may have constrained learning of fine-grained lesions. Raman, et al. [14] introduced a hybrid neural architecture combining convolutional and graph attention mechanisms in a dual-branch convolutional graph attention network (DB-CGANNet). They preprocessed images using upgraded weighted median filtering (Up-WMF) and gamma-based CLAHE for noise and contrast enhancement, then extracted features via DWT, GLRLM, and VGG19, optimized by a Bio-Inspired Artificial Hummingbird (BI-AHB) algorithm. The model achieved over 98.9% accuracy. The drawback involved high feature extraction complexity, as combining statistical, wavelet-based, and deep features increased architectural intricacy.

Lipsa et al. [16] presented an interpretable and explainable CNN for rice leaf disease detection that incorporated three explainability techniques: layer-wise relevance propagation (LRP), SHapley Additive exPlanations (SHAP), and Local Interpretable Model-agnostic Explanations (LIME). They used a modified LRP to trace layer contributions, SHAP to analyze model outcomes, and LIME to highlight image regions influencing classification. The system achieved 96.5% accuracy while ensuring transparency in model decisions. It delivered clarity to end users by visualizing which leaf regions drove disease predictions. However, the method suffered from computational overhead and latency due to embedding multiple explainability modules within the classification pipeline. Shafik et al. [17] introduced a hybrid CNN combining Inception and Xception architectures for efficient plant disease classification. They fused the parallel architectures to enhance feature diversity and computed multi-scale representations while maintaining model efficiency. The hybrid network offered improved recognition performance across diverse plant disease images with reduced parameter count compared to standalone deep CNNs. It balanced accuracy with speed better than conventional architectures. The drawback lay in the architectural intricacy that complicated gradient flow and made model tuning substantially more difficult. Chithrakkannan and Krishnamoorthy [18] proposed a hybrid deep learning system that employed a multipath refinement network with region-attention segmentation for automatic rice leaf disease diagnosis. They refined disease-affected regions via segmentation, applied region-wise attention to emphasize infection zones, and merged the outputs through a multipath architecture for classification. Their system elevated detection precision by isolating disease-relevant features from leaf images. It operated effectively under mixed or occluded background conditions. Yet the attention-based segmentation introduced substantial architectural complexity, increasing training time and model maintenance burden. Kumar et al. [19] enhanced rice leaf disease classification by embedding image data into vector representations, then applying Support Vector Machine (SVM) classifiers with diverse kernel functions. Their embedding approach captured texture and shape through handcrafted and neural embeddings before SVM-based classification. They offered a detailed comparison across linear, polynomial, and RBF SVM kernels, revealing optimal combinations for distinct disease types. This approach yielded robust classification while maintaining generalization across varied symptom appearances. Nevertheless, the reliance on fixed embeddings led to limited adaptability to novel image variances and missed capturing latent, discriminative visual features. Vijayan and Chowdhary [20] proposed a hybrid feature-optimized convolutional neural network (CNN) for rice crop disease prediction. They fused handcrafted texture features with CNN-derived deep representations to enhance diagnostic accuracy. The framework combined both approaches to improve disease detection within rice leaf images. However, feature fusion complexity increased, leading to higher computational cost during inference.

Das et al. [21] introduced an ensemble model that combined genetic algorithm (GA) with deep learning for rice disease prediction. The GA optimized model hyperparameters and ensemble weights to boost classification robustness. The system generated corrective alerts before disease onset using symptom-based training data. The hyperparameter optimization via GA added significant algorithmic complexity and slow tuning. Akkamahadevi and Adaickalam [22] developed a deep learning framework combining convolutional neural networks and deep neural networks for early paddy disease prediction. They applied image enhancement and filtering techniques to improve diagnostic sensitivity. The system aimed to enrich paddy production through accurate early detection. The blending CNN and DNN architectures introduced redundancy and increased parameter count, impairing feature differentiation efficiency. Roni et al. [23] performed a comparative analysis of deep learning techniques such as object detection and YOLO models for rice leaf disease detection. They evaluated various architectures on detection speed and classification accuracy within field conditions. The evaluation outlined strengths of YOLO in real-time application. The object detection models struggled with precise lesion localization due to coarse feature granularity. Alfred et al. [24] optimized dataset diversity to improve deep learning model performance for rice blast disease identification. They curated variable training data capturing field, weather, and imaging variance to enhance generalization. The strategy improved model robustness across diverse conditions. The increased data diversity induced noisy feature variations, complicating consistent feature extraction. Sahasranamam et al. [25] employed a DenseNet-121 based architecture for paddy leaf disease classification and prediction. The architecture extracted dense feature maps and leveraged skip connections to improve gradient flow and classification accuracy. The system achieved high accuracy relative to ResNet-50. The DenseNet-121 incurred higher computation due to dense connectivity, increasing runtime cost.

3. PROPOSED SYSTEM

The proposed methodology as shown in Figure 4.1 presents a novel, hybrid approach that combines structured image preprocessing, extensive data augmentation, and a CCEL-OCNN, going beyond the capabilities of existing approaches such as Artificial Neural Networks trained with Stochastic Gradient Descent (ANN-SGD) and Adam Optimizer (ANN-Adam). While existing models struggle with limited feature learning, poor convergence on multiclass labels, and overfitting in smaller datasets, the proposed approach strategically overcomes these drawbacks. This combination—specifically the integration of categorical cross-entropy optimization with preprocessing and augmentation—is not explored in current surveys and enables highly accurate detection across four rice leaf conditions: Brown Spot, Healthy, Leaf Blast, and Neck Blast. The proposed model significantly improves classification performance by better capturing subtle disease-specific patterns and enhancing model generalization. The process begins with the acquisition of a high-quality rice leaf image dataset. The images are collected under various environmental conditions to simulate real-world agricultural settings, including variations in lighting, background, and camera angles. Each image is carefully labeled into one of four categories: Brown Spot, Healthy, Leaf Blast, and Neck Blast. After collection, the dataset is divided into training, validation, and test sets to enable effective supervised learning and unbiased evaluation of the models. To ensure consistency and improve learning efficiency, all images undergo a preprocessing phase. This includes resizing each image to a fixed dimension (such as 128×128 or 224×224 pixels) for compatibility with deep learning models. Finally, all pixel values are normalized to a [0, 1] scale, which helps stabilize and speed up the training process by ensuring uniform input distribution. Since deep learning models require large and diverse datasets to generalize well, image augmentation is applied to artificially expand the dataset. This involves performing random rotations, horizontal and vertical flips, zooming, and brightness adjustments. Shear transformations are also introduced to make the model robust against geometric distortions. These transformations simulate real-world variations and significantly reduce the risk of overfitting. The result is a more diverse and comprehensive training set, enabling the model to learn better from limited data. As part of the baseline comparison, two traditional Artificial Neural Network (ANN) models are trained using different optimizers. The first uses Stochastic Gradient Descent (SGD), a classical optimization technique that updates weights incrementally and requires fine-tuning of the learning rate. However, ANN-SGD typically suffers from slower convergence and poor handling of local minima. The second baseline uses the Adam optimizer, which combines momentum and adaptive learning rates to accelerate training and better handle sparse gradients. While ANN-Adam generally performs better than SGD, both models lack the ability to extract spatial features crucial for distinguishing between visually similar leaf diseases.

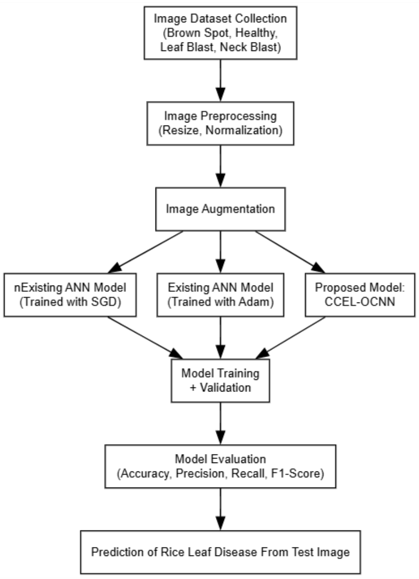

Figure 1. Proposed System Architecture.

The core innovation of this work lies in the development of a Categorical Cross Entropy Loss Optimized Convolutional Neural Network (CCEL-OCNN). This architecture begins with multiple convolutional layers designed to automatically extract spatial and texture-based features from the input images. Batch normalization is applied to stabilize and accelerate training, while ReLU activation functions introduce non-linearity. Max pooling layers reduce spatial dimensions, and dropout layers prevent overfitting by randomly deactivating neurons during training. The final fully connected layer uses Softmax activation for multi-class classification, and the entire model is trained using categorical cross-entropy loss. This loss function ensures the network distinctly separates each class, which is especially valuable in cases where symptoms overlap visually, such as between *Leaf Blast* and *Neck Blast*. All three models—ANN-SGD, ANN-Adam, and the proposed CCEL-OCNN—are trained on the same augmented and preprocessed dataset using their respective configurations. During training, performance is monitored using validation data to detect overfitting or underfitting. Once training is complete, the models are tested on the unseen test set. Evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix are used to measure classification effectiveness. These metrics help assess not only how well each model performs overall but also how accurately it distinguishes between individual disease classes. The final step involves comparing the performance of all models. The ANN-SGD model achieves moderate accuracy, but its learning is slow and unstable due to fixed learning rates. The ANN-Adam model shows improved results but still struggles with distinguishing fine-grained disease features. In contrast, the proposed CCEL-OCNN model significantly outperforms both traditional methods, achieving higher classification accuracy and stronger generalization across all disease categories. The model's ability to learn spatial patterns, combined with effective preprocessing and augmentation, makes it more reliable for real-time agricultural applications.

The CCEL-OCNN as shown in Figure 2 model leverages convolutional operations alongside enhanced feature normalization and deep regularization to perform highly accurate classification tasks. This architecture is particularly advantageous in image-based or spatially structured datasets where extracting and refining local features is crucial. The model utilizes Adam optimizer for its adaptive learning capabilities, ensuring faster and more stable convergence. With layers like multiple Conv2D blocks, batch normalization, dropout, and dense fully connected classifiers, CCEL-OCNN balances learning complexity, spatial awareness, and generalization effectively.

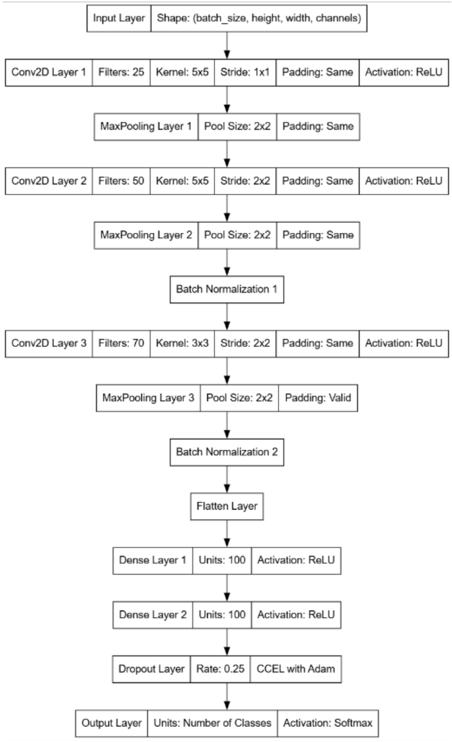

Figure 2. Proposed CCEL-OCNN.

The model accepts a 4D input tensor of shape (batch_size, height, width, channels), typically processed image data. The InputLayer captures this format, preparing the input data stream for convolutional feature extraction in subsequent layers. The first Conv2D layer applies 25 filters of size (5,5), using ReLU activation and same padding to preserve spatial dimensions. This stage captures basic edge-level and texture patterns, essential for early visual recognition cues. A MaxPooling2D layer follows with a pool size of (2,2), reducing spatial dimensions by half while keeping the most dominant features. The padding is kept same to preserve feature alignment across borders. The second Conv2D layer increases the filter depth to 50 and uses a larger stride (2,2) while maintaining the 5x5 kernel. This doubles the receptive field size, capturing more abstract features and spatially broader context. Another MaxPooling2D layer reduces the feature map dimensions again, compacting spatial information to avoid overfitting while preserving critical details. A BatchNormalization layer follows, stabilizing the activations and reducing internal covariate shift. This accelerates training and allows higher learning rates, benefiting convergence. A third Conv2D layer with 70 filters and a smaller kernel size (3x3) captures intricate spatial relationships. With a stride of (2,2) and same padding, it refines features learned in earlier layers. A third MaxPooling2D with valid padding aggressively shrinks the feature maps, finalizing the most compressed and information-rich representation before flattening. A Flatten operation transforms the pooled feature map into a 1D vector, which is passed through two Dense layers, each with 100 ReLU-activated units. These layers learn high-level feature interactions and decision boundaries for the classification task. A Dropout layer with a rate of 0.25 is applied to reduce overfitting. Finally, a Dense output layer with softmax activation predicts class probabilities across y_train.shape[1] categories, giving the final classification result Y_pred.

3.2 CCEL Training and Testing Strategy

CCEL is a widely used loss function for multi-class classification problems, especially when the output layer uses a softmax activation. Its major advantage lies in its capability to penalize the incorrect class predictions proportionally to their confidence, making it highly sensitive and accurate in probabilistic predictions. It effectively enhances convergence speed and accuracy, ensuring that the model learns distinct decision boundaries among classes. CCEL is especially beneficial in deep learning models where class probabilities are crucial, such as image recognition, NLP, and medical diagnostics. By optimizing the model to minimize the divergence between predicted and actual class distributions, CCEL leads to robust and reliable classification performance.

The first critical step in CCEL is to transform the categorical labels (Y_train and Y_test) into one-hot encoded vectors. This transformation ensures that each class is represented by a vector with a 1 in the position of the class index and 0 elsewhere. It aligns the format of true labels with the probabilistic output of the softmax layer, enabling accurate calculation of the categorical cross-entropy. During the forward pass, the CNN model computes the raw output logits from the last dense layer. These logits are passed through the softmax activation function, which normalizes them into a probability distribution over the classes. Each output node represents the predicted probability for a particular class, summing to 1 across all nodes. For each training example, the CCEL function evaluates the negative log of the predicted probability assigned to the true class. This operation penalizes confident but incorrect predictions heavily while rewarding confident and correct predictions. The calculated negative log likelihood for each sample is aggregated over the entire batch (typically using a mean operation) to compute the final loss value for that batch. This value is then used to guide the model's learning by indicating how far off its predictions are from the true values. The next key step involves computing the gradients of the CCEL with respect to the weights and biases of the network. Because of the softmax-CCEL combination's mathematical properties, this gradient computation simplifies. This simplification reduces computational complexity and accelerates learning in multi-class models. Once the loss gradient with respect to the output is obtained, it is backpropagated through each preceding layer. At each layer, the chain rule is applied to compute gradients with respect to that layer's weights, biases, and inputs, ensuring that the entire network is tuned towards minimizing the total loss. After computing the gradients, an optimizer updates the weights and biases of each layer in the direction that reduces the loss. While CCEL itself does not define how updates happen, it provides the precise loss landscape which the optimizer uses to navigate during training. During training, the average CCEL loss across all batches in an epoch is recorded and monitored. A decreasing loss trend across epochs indicates that the model is learning effectively. Spikes or plateaus may indicate learning issues such as overfitting, underfitting, or poor learning rates. Post training on each epoch, the model evaluates the CCEL on a separate validation set to measure generalization. If training loss decreases but validation loss increases, it signals overfitting. In such cases, regularization or dropout may be employed to control complexity. During testing, the model produces class probabilities using the trained parameters. The class with the highest predicted probability (argmax of the softmax output) is selected as the final prediction. Though CCEL is not directly used during inference, its optimized model ensures that these final predictions are as accurate as possible.

Advantages of CCEL-OCNN

- **Optimized Convolution Layers**: Combines multiple Conv2D stages to extract shallow to deep hierarchical features, improving classification robustness.
- **Fast and Stable Learning with Adam**: The Adam optimizer adapts learning rates during training, achieving faster convergence with minimal tuning.

- **Effective Normalization**: BatchNormalization layers mitigate internal covariate shift, improving stability and generalization.
- **Built-in Regularization**: Dropout and MaxPooling reduce overfitting, allowing the model to handle diverse input scenarios more reliably.
- **Deep Abstraction Capability**: Multiple dense layers after CNN encoding enable learning of complex decision functions with greater classification precision.

4. RESULTS DESCRIPTION

Figure 3 shows the Distribution of Classes before Augmentation, depicted as a bar graph with class labels "BrownSpot," "Healthy," "LeafBlast," and "NeckBlast" on the x-axis and their respective counts on the y-axis, ranging from 0 to 1750. The counts are approximately 1200 for BrownSpot, 1450 for Healthy, 1750 for LeafBlast, and 1000 for NeckBlast, highlighting an imbalanced dataset with LeafBlast having the highest number of images and BrownSpot the lowest. This visualization, generated by the SampleDisplay function, provides insight into the initial class distribution after loading 5380 total images from the dataset, as indicated by the accompanying text: "Rice leaf Class Labels found in dataset are ['BrownSpot', 'Healthy', 'LeafBlast', 'NeckBlast'], Rice Leaf Dataset Loading is Completed, Total Images Found in Dataset = 5380." The imbalance suggests the need for augmentation to improve model performance.

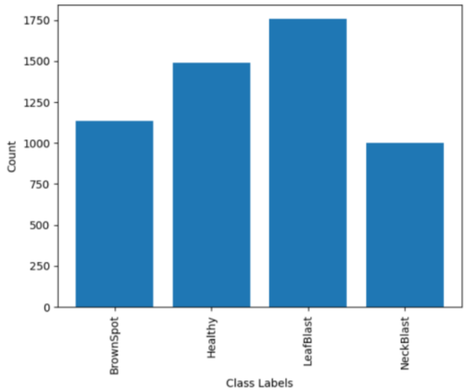

Figure 3. Distribution of Classes before Augmentation.

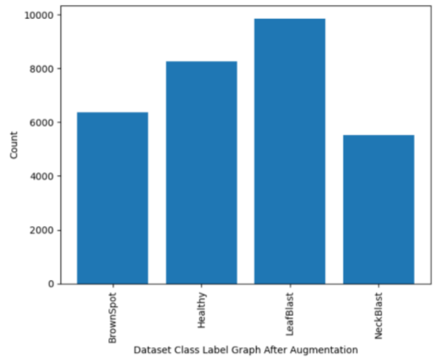

Figure 4. Distribution of Classes after Augmentation.

Figure 4 shows the Distribution of Classes after Augmentation, presented as a bar graph with the same class labels on the x-axis and counts on the y-axis, now ranging from 0 to 10000. The augmented counts are approximately 6000 for BrownSpot, 8000 for Healthy, 10000 for LeafBlast, and 5000 for NeckBlast, reflecting a significant increase to a total of 30001 images, as noted in the text: "Image Augmentation Completed, Total images found in dataset After Augmentation : 30001." This graph, produced by the AugImage function, demonstrates the effect of the ImageDataGenerator with parameters like rotation, shear, and horizontal flip, which aimed to balance the dataset and enhance robustness, though LeafBlast still retains the highest count, indicating a slight residual imbalance.

Figure 5 shows the Proposed CCEL-OCNN Confusion Matrix, a 4x4 heatmap with true and predicted classes, using a viridis color map. The diagonal elements are significantly higher: 1244 for Brown Spot, 1615 for Healthy, 1940 for Leaf Blast, and 1141 for NeckBlast, with minimal off-diagonal errors (e.g., 4 for Healthy misclassified as Brown Spot and 17 for LeafBlast misclassified as NeckBlast). This matrix, produced by calculateMetrics after applying the CCEL_Loss_Optimization function, reflects an impressive accuracy of 98.98%, precision of 99.01%, recall of 99.11%, and F1-score of 99.06%, showcasing the effectiveness of the custom optimization in achieving near-perfect classification.

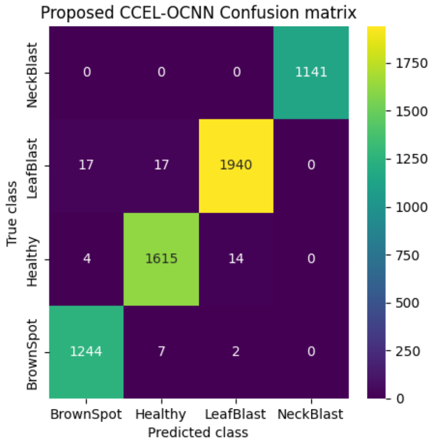

Figure 5. Proposed CCEL-OCNN Confusion Matrix.

Figure 6 shows the Prediction Results from a Test Image, displaying four sub-images of resized rice leaf images (400x300 pixels) with predicted labels overlaid in red text using OpenCV. The labels are "Predicted As: Neck Blast," "Predicted As: Healthy," "Predicted As: Leaf Blast," and "Predicted As: Brown Spot," each shown with the corresponding leaf image, indicating the predict function's ability to classify new images using the trained extension_model. The images vary in appearance (e.g., brown spots, healthy green, blasted areas), and the accurate labeling suggests the model's generalization capability, though the specific accuracy for these predictions is not quantified in the figure.

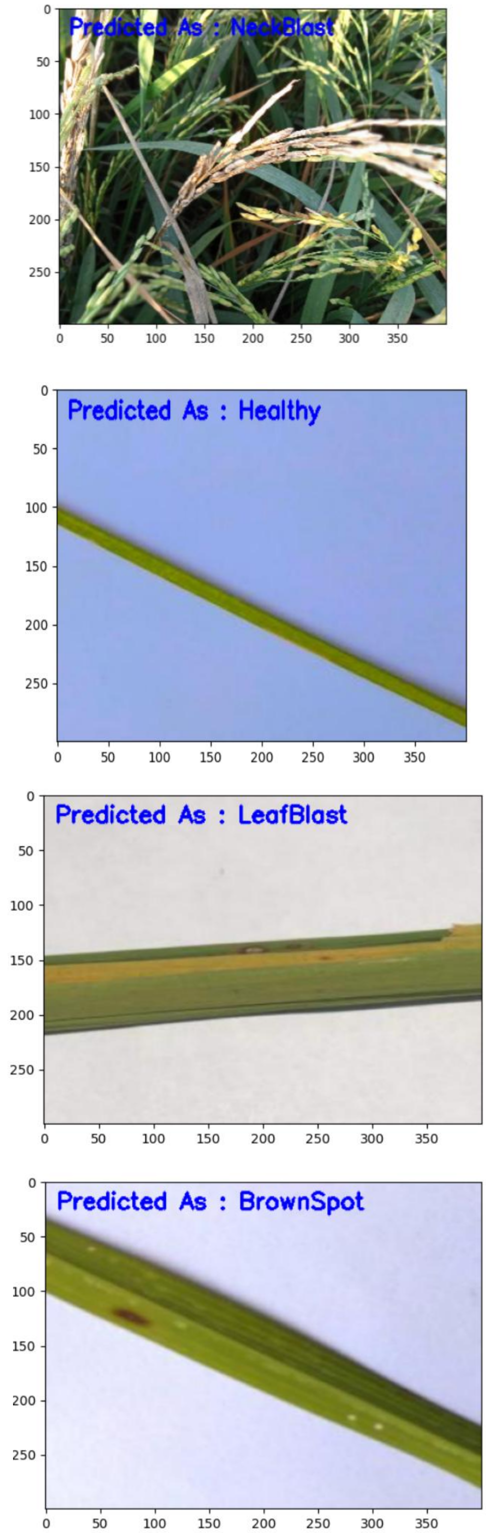

Figure 6. Prediction Results from Test Image.

Figure 7 and Table 1 shows the Performance Comparison Graph, a bar chart comparing the performance metrics of the three algorithms (ANN with SGD, ANN with Adam, Proposed CCEL-OCNN) across parameters Accuracy, FSCORE, Precision, and Recall. The x-axis lists the algorithms, while the y-axis ranges from 0 to 100. For ANN with SGD, values are approximately 73% (Accuracy), 75% (FSCORE), 76% (Precision), and 74% (Recall); for ANN with Adam, around 77%, 79%, 80%, and 79% respectively; and for Proposed CCEL-OCNN, nearly 99% across all metrics. This graph, generated by PerformanceGraph, visually confirms the superior performance of the proposed model, as also detailed in the table.

Table 1. Performance Comparison.

Algorithm Name	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Existing ANN SGD	72.67	76.08	74.49	75.13
Existing ANN Adam	77.37	79.92	78.98	79.19
Proposed CCEL-OCNN	98.98	99.01	99.11	99.06

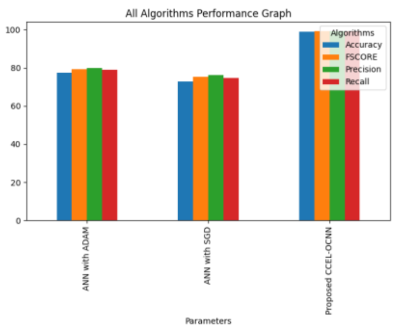

Figure 7. Performance Comparison Graph.

5. CONCLUSION

The experimental results reveal a significant performance gap between the existing ANN models and the proposed CCEL-OCNN algorithm. The ANN using SGD optimizer achieved an accuracy of 72.67%, with a precision of 76.08%, recall of 74.49%, and an F1-score of 75.13%. These metrics show moderate classification capability but indicate potential issues with consistency and generalization. The ANN model using the Adam optimizer demonstrated improved performance, reaching 77.37% accuracy, 79.92% precision, 78.98% recall, and 79.19% F1-score. This indicates that optimization plays a crucial role in enhancing the ANN's ability to learn discriminative patterns in plant disease classification. In contrast, the proposed CCEL-OCNN achieved a remarkable performance leap, with 98.98% accuracy, 99.01% precision, 99.11% recall, and 99.06% F1-score. These results signify near-perfect classification, showcasing the robustness of the proposed architecture in capturing intricate patterns and subtle disease symptoms from plant images. The high F1-score reflects the model's balanced performance between precision and recall, minimizing both false positives and false negatives. This performance makes CCEL-OCNN a highly reliable solution for real-time and automated plant disease diagnosis systems. The CCEL-OCNN model can be extended to classify a wider range of plant diseases across multiple crops. Real-time mobile or drone-based disease detection systems can be built using this architecture. Integration with IoT and remote sensing technologies can enhance precision agriculture. Future research may explore lightweight CCEL-OCNN variants for deployment on edge devices.

REFERENCES

[1] Mukherjee, Rashmi, Anushri Ghosh, Chandan Chakraborty, Jayanta Narayan De, and Debi Prasad Mishra. "Rice leaf disease identification and classification using machine learning techniques: A comprehensive review." *Engineering Applications of Artificial Intelligence* 139 (2025): 109639.

[2] Bakhtiar, Raffael Hizqya, Yasi Dani, and Dani Suandi. "Machine learning based classification of rice leaf diseases: A comparative

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study." *Commun. Math. Biol. Neurosci.* 2025 (2025).

[3] Ismail, Usman Idris, Hui Na Chua, Rosdiadee Nordin, and Muhammed Kabir Ahmed. "A comprehensive review of deep learning approaches for rice disease detection: Datasets, methodologies, and future directions." *Smart Agricultural Technology* 11 (2025): 100976.

[4] Santhosh, C. S., et al. "Deep Learning-Based Automated Diagnosis and Classification of Rice Leaf Diseases Using CNN Architectures for Sustainable Agriculture." *2025 12th International Conference on Information Technology (ICIT)*. IEEE, 2025.

[5] Raigonda, Megha Rani. "Identification And Classification of Rice Leaf Disease Using Hybrid Deep Learning." *Journal of Scientific Research and Technology* (2025): 93-101.

[6] Subbarayudu, Chatla, and Mohan Kubendiran. "An automated hybrid deep learning framework for paddy leaf disease identification and classification." *Scientific Reports* 15, no. 1 (2025): 26873.

[7] Naresh Kumar, B., and S. Sakthivel. "Rice leaf disease classification using a fusion vision approach." *Scientific Reports* 15, no. 1 (2025): 8692.

[8] Padhi, Jagamohan, Kunal Mishra, Ashoka Kumar Ratha, Santi Kumari Behera, Prabira Kumar Sethy, and Aziz Nanthaamornphong. "Enhancing paddy leaf disease diagnosis-a hybrid CNN model using simulated thermal imaging." *Smart Agricultural Technology* 10 (2025): 100814.

[9] Bhola, Amit, and Prabhat Kumar. "Deep feature-support vector machine based hybrid model for multi-crop leaf disease identification in Corn, Rice, and Wheat." *Multimedia Tools and Applications* 84, no. 8 (2025): 4751-4771.

[10] Aguirre-Rodríguez, Elen Yanina, Alexander Alberto Rodriguez Gamboa, Elias Carlos Aguirre Rodríguez, Juan Pedro Santos-Fernández, Luiz Fernando Costa Nascimento, Aneirson Francisco da Silva, and Fernando Augusto Silva Marins. "Rice leaf disease detection using the Stretched Neighborhood Effect Color to Grayscale method and Machine Learning." *Scientia Agropecuaria* 16, no. 1 (2025): 123-136.

[11] Firdaus, Mohamad, et al. "Optimizing rice leaf disease classification through convolutional neural network architectural modification and augmentation techniques." *International Journal of Electrical & Computer Engineering (2088-8708)* 15.3 (2025).

[12] Rahman, Kazi Naimur, et al. "A real time monitoring system for accurate plant leaves disease detection using deep learning." *Crop Design* 4.1 (2025): 100092.

[13] Martins, Oluwaseun O., Christiaan C. Oosthuizen, and Dawood A. Desai. "RiceLeafClassifier-v1. 0: A Quantized Deep Learning Model for Automated Rice Leaf Disease Detection and Edge Deployment." *Engineering Reports* 7, no. 6 (2025): e70231.

[14] Raman, Ramesh, and Sangeetha Jayaraman. "Artificial intelligence for sustainable farming with dual branch convolutional graph attention networks in rice leaf disease detection." *Scientific Reports* 15, no. 1 (2025): 10595.

[15] Mustofa, Sumaya, Shahrin Khan, Shahriar Ahmed Shovo, Yousuf Rayhan Emon, and Md Sadekur Rahman. "Optimizing Soursop Leaf Disease Classification with a Lightweight Ensemble Model and

Explainable AI." *Current Plant Biology* (2025): 100526.

[16] Lipsa, Swati, Ranjan Kumar Dash, and Debasis Gountia. "Interpretable and Explainable Convolutional Neural Network for Rice Leaf Disease Detection." *SN Computer Science* 6, no. 6 (2025): 700.

[17] Shafik, Wasswa, Ali Tufail, Chandratilak Liyanage De Silva, and Rosyzie Anna Awg Haji Mohd Apong. "A novel hybrid inception-xception convolutional neural network for efficient plant disease classification and detection." *Scientific Reports* 15, no. 1 (2025): 3936.

[18] Chithrakkannan, R., and N. R. Krishnamoorthy. "Hybrid Deep Learning Network for Automatic Diagnosis of Rice Leaf Diseases Using Multipath Refinement Network with Region Attention Mechanism-Based Segmentation Model." *International Journal of Image and Graphics* (2025): 2750052.

[19] Kumar, S. Ratan, M. Appala Srinuvasu, A. Vamsidhar, and B. Dinesh Reddy. "Enhancing rice leaf disease classification accuracy with svm kernels using image embedding techniques for feature extraction: a comprehensive analysis." *Multimedia Tools and Applications* (2025): 1-32.

[20] Vijayan, S., and Chiranji Lal Chowdhary. "Hybrid feature optimized CNN for rice crop disease prediction." *Scientific Reports* 15, no. 1 (2025): 7904.

[21] Das, Sunanda, Tanvir H. Sardar, and D. S. Sahana. "An ensemble technique using genetic algorithm and deep learning for the prediction of rice diseases." In *Machine Learning Hybridization and Optimization for Intelligent Applications*, pp. 289-303. CRC Press, 2025.

[22] Akkamahadevi, C., and Vijayakumar Adaickalam. "An effective deep learning framework for diseases prediction to enrich paddy production." *International Journal of System Assurance Engineering and Management* (2025): 1-10.

[23] Roni, Md Hafizur Rahman, Md Ibrahim Adham Aomy, Shamsun Nahar, Noshin Un Noor, and Mohammad Anwar Hossain. "Comparative Analysis of Deep Learning Techniques for Rice Leaf Disease Detection: Object Detection and YOLO Model Evaluation." In *2025 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, pp. 1-6. IEEE, 2025.

[24] Alfred, Reuben, Judith Leo, and Shubi Felix Kaijage. "Optimizing dataset diversity for a robust deep-learning model in rice blast disease identification to enhance crop health assessment across diverse conditions." *Smart Agricultural Technology* 10 (2025): 100726.

[25] Sahasranamam, V., T. Ramesh, R. Rajeswari, A. Karthikkumar, and D. Muthumanickam. "AI-Driven Paddy Leaf Disease Classification and Prediction using DenseNet-121." In *6th International Conference on Deep Learning, Artificial Intelligence and Robotics (ICDLAIR 2024)*, pp. 272-292. Atlantis Press, 2025.