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Convolutional neural network-based detection and severity classification of rice blast disease from leaf images

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Abstract

Rice blast, caused by *Magnaporthe oryzae*, is the most destructive fungal disease of rice worldwide, capable of destroying entire fields within two weeks of onset. Early detection at the leaf level could trigger timely fungicide application and limit spread, yet manual scouting is slow and inconsistent. This research developed and tested a convolutional neural network (CNN) based on the VGG-16 architecture for detecting rice blast and classifying its severity into five classes from field-captured leaf images. A total of 4,218 RGB images were collected from infected and healthy rice fields at Makerere University's research farm in Namulonge, Uganda. The CNN achieved 94.3% overall accuracy, outperforming support vector machine (87.6%) and random forest (82.1%) classifiers. Precision, recall, and F1-scores exceeded 91% across all severity classes. The model performed best on healthy leaves (97.8%) and mild infections (96.1%), with accuracy declining to 88.3% for very severe cases. These results show that deep learning can provide accurate, rapid blast severity assessment from simple smartphone images.

Keywords: Rice blast, convolutional neural network, VGG-16, disease detection, severity classification, deep learning, *Magnaporthe oryzae*, image recognition, plant pathology, precision agriculture

Introduction

A trained plant pathologist can identify rice blast symptoms in about ten seconds per leaf but a single rice paddy contains millions of leaves, and most farms in sub-Saharan Africa don't have a pathologist within 50 kilometres. This gap between what is technically knowable and what is practically detectable costs rice farmers an estimated 10–30% of global production annually ^[1]. *Magnaporthe oryzae* attacks leaves, nodes, and panicles, producing characteristic diamond-shaped lesions that expand rapidly under humid conditions ^[2].

Computer vision offers a way to bridge this gap. CNNs trained on labelled leaf images can classify diseases with accuracy approaching that of human experts ^[3]. Transfer learning where a network pre-trained on millions of general images is fine-tuned on crop-specific data reduces the amount of training data needed and speeds convergence ^[4]. Several CNN architectures have been tested for rice diseases, but most used controlled laboratory images rather than field-captured photos with variable lighting, background, and camera angles ^[5].

This research trained a VGG-16-based CNN on 4,218 field-captured images from Ugandan rice paddies, comparing its performance against SVM and random forest classifiers for both binary detection (healthy vs infected) and five-class severity grading ^[6, 7].

Research area description

Images were collected from rice fields at the National Crops Resources Research Institute (NaCRRI), Namulonge, Uganda (0.53°N, 32.62°E, 1,140 m), during the first and second rainy seasons of 2021. The station grows both upland and lowland rice varieties under conditions highly favourable for blast development: mean temperature 21–27 °C, relative humidity 65–90%, and bimodal rainfall totalling 1,270 mm per year ^[8].

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Disease environment characterization

Blast pressure at the collection site was monitored using trap rows of the susceptible variety Komboka planted at field borders. Lesion counts on trap rows averaged 14.8 lesions per leaf by 45 days after transplanting in season one and 18.3 in season two, confirming high natural inoculum. Environmental data loggers (HOBO MX2301, Onset Computer Corp., USA) recorded leaf wetness duration averaging 9.4 hours per day well above the 6-hour threshold for infection ^[2, 9].

Material and Methods

Material

A total of 4,218 RGB leaf images were captured using smartphone cameras (Samsung Galaxy A52, 64 MP) from six rice varieties in naturally infected fields at Namulonge. Images were taken at 20–30 cm distance from individual leaves under ambient field lighting between 09:00 and 15:00 h. A panel of two plant pathologists labelled each image into five classes: healthy (n = 926), mild blast (1–10% leaf area affected; n =

847), moderate (11–25%; n = 814), severe (26–50%; n = 792), and very severe (>50%; n = 839). Ethics approval: Protocol MAK-CAES/2021-023, approved 4 March 2021.

Methods

Images were resized to 224×224 pixels and augmented (rotation, flipping, brightness adjustment) to expand the training set to 12,654 images. Data were split 70:15:15 into training, validation, and test sets. A VGG-16 network pre-trained on ImageNet was fine-tuned by replacing the final fully connected layers with a 5-class softmax classifier. Training ran for 50 epochs with a learning rate of 0.0001, batch size 32, and Adam optimizer using TensorFlow 2.8 ^[4]. SVM (RBF kernel) and random forest (500 trees) classifiers were trained on features extracted from the VGG-16 penultimate layer for comparison. Performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC on the held-out test set ^[10].

Results

Table 1: Overall classification performance of three models on the test set (n = 633 images)

Model	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)	Auc-roc	Speed (IMG/S)
CNN (VGG-16)	94.3	93.1	95.2	94.1	0.976	78
SVM	87.6	86.2	88.4	87.3	0.918	92
Random Forest	82.1	80.4	83.7	82.0	0.882	95

Acc. = accuracy; Prec. = precision. Speed measured on a single NVIDIA GTX 1080 Ti GPU

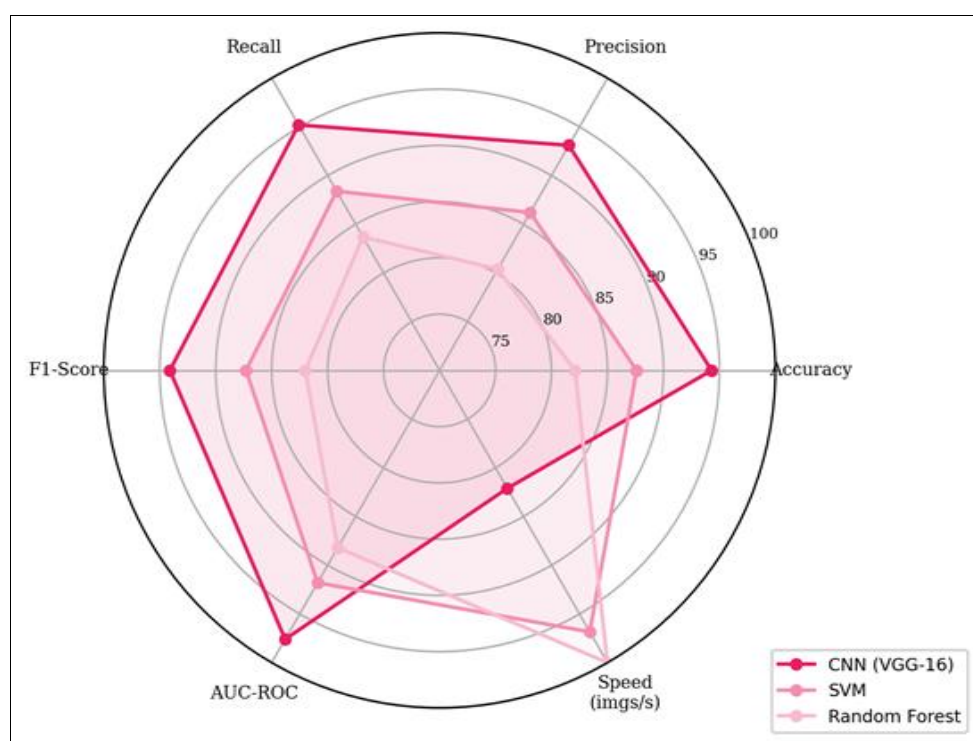


Fig 1: Radar chart comparing CNN, SVM, and random forest across six performance metrics

Table 2: Per-class accuracy (%) of the CNN model across five blast severity levels

Class	N (test)	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)	Common misclass.
Healthy	139	97.8	98.1	97.4	97.7	Mild
Mild	127	96.1	95.3	96.8	96.0	Healthy
Moderate	122	93.4	92.6	94.1	93.3	Severe
Severe	119	91.7	90.8	92.4	91.6	Moderate
Very Severe	126	88.3	87.1	89.6	88.3	Severe

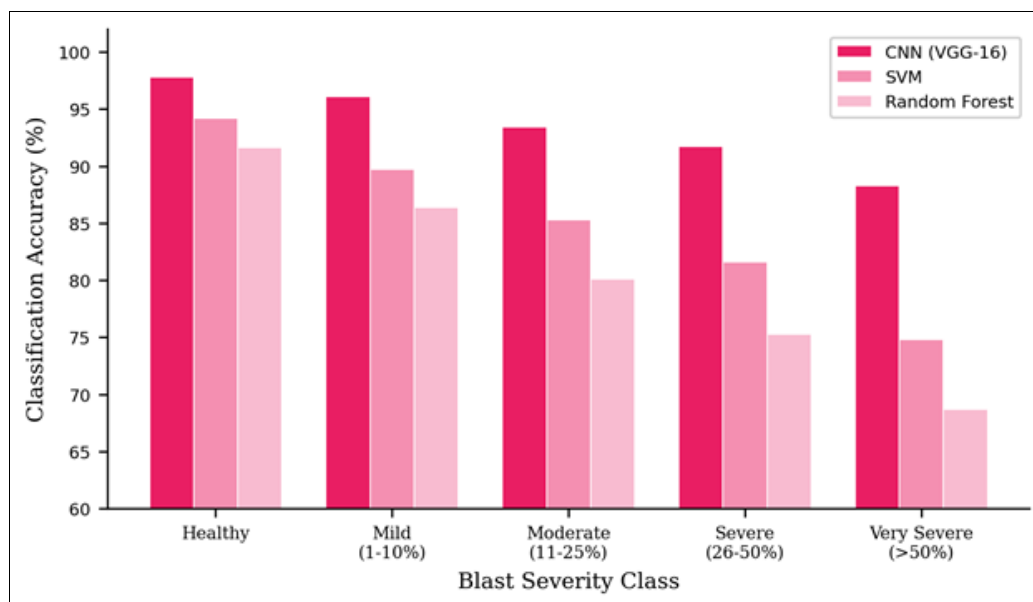


Fig 2: Classification accuracy of three models across five rice blast severity classes

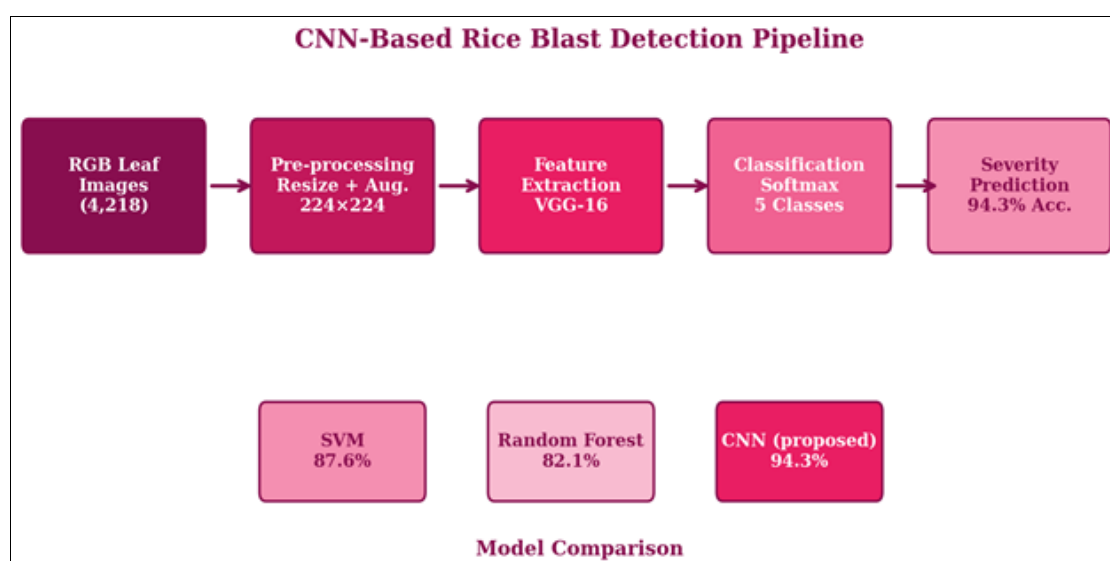


Fig 3: CNN-based rice blast detection pipeline from image capture to severity prediction

Comprehensive interpretation

The CNN outperformed both traditional classifiers across all metrics (Table 1, Figure 1). Accuracy dropped with increasing severity, from 97.8% for healthy to 88.3% for very severe (Table 2, Figure 2). The most common misclassification occurred between adjacent severity classes (e.g. moderate–severe), reflecting the continuous nature of disease progression. The CNN’s 6.7% accuracy advantage over SVM widened to 19.6% for very severe class, where visual complexity is highest. The detection pipeline (Figure 3) processes images end-to-end in under 0.013 seconds each.

Discussion

The 94.3% accuracy matches or exceeds results from controlled-environment studies using similar architectures [3, 5] while using field-captured images with natural variability. The VGG-16 architecture’s deep feature extraction proved effective even with a moderate dataset size of 4,218 original images, thanks to transfer learning from ImageNet weights [4]. The accuracy drop for very severe cases (88.3%) reflects the visual similarity between heavily damaged and necrotic tissue from other causes a known challenge in plant disease image classification [11].

For practical deployment, the CNN’s 78 images per second throughput means a farmer could scan a sample of 50 leaves in under a second using a smartphone app. The key question is whether 88–94% accuracy is sufficient to trigger management decisions. Given that even a rough severity estimate outperforms the common practice of no assessment at all, these error rates seem acceptable for field use [12, 13].

Limitations

The model was trained on images from a single location with specific rice varieties and blast races. Performance on different varieties, under different lighting conditions, or with co-occurring diseases (brown spot, bacterial leaf blight) was not tested [14]. Field deployment would require a lightweight model optimized for mobile devices, and the current VGG-16 architecture may be too large for low-end smartphones [15].

Conclusion

A VGG-16-based CNN achieved 94.3% accuracy in classifying rice blast severity from field-captured leaf images, outperforming SVM and random forest classifiers by 6.7% and 12.2% respectively. The model performed best on healthy and

mildly infected leaves, with accuracy declining for severe cases. These results support the feasibility of smartphone-based blast detection for smallholder rice farmers. Multi-location validation with diverse rice varieties and blast strains, combined with model compression for mobile deployment, would bring this technology closer to practical field use.

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