

A CNN-LSTM-Based Approach for the Early Detection of Rice Seed Diseases

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ABSTRACT

A novel approach is presented in this study, utilizing a Convolutional-Neural-Network Long Short Term-Memory (CNN-LSTM) model for detecting diseases in rice seeds. The CNN component was used for extracting features from seed images, while LSTM addressed the gradient descent problem. The model was evaluated using two open-access datasets containing both healthy and unhealthy samples. The analysis revealed that the proposed model achieved 98.4% accuracy, 98.01% precision, 98.7% recall, and 98.4% F1-score on the first dataset and 98.5% accuracy on the second dataset. These results were compared with previous works, and the highest performance was achieved in the CNN-LSTM model. The findings demonstrated the significant potential of the current model for practical applications in agricultural quality control and disease management, contributing to improved crop health and food security.

Keywords-rice seed disease; CNN-LSTM; feature extraction; crop health; deep learning

I. INTRODUCTION

Rice is one of the major cereal crops, providing the main source of calories for over half of the world's population [1]. Specifically, rice seeds are of great importance as they directly determine crop yield, grain quality, and resilience against biotic and abiotic stresses. High-quality seeds ensure not only uniform crop stands but also improved resistance to pests and diseases, as well as better adaptability to changing climates [2]. For many Asian countries, particularly India, Indonesia, China, and Bangladesh, rice is a basis of food security and rural incomes [3-6]. Except in Asia, rice consumption remains substantial in Africa, Latin America, and parts of the Middle East, reflecting its global importance [7].

However, rice cultivation faces several challenges, including water shortages, soil degradation, pest invasions, and disease [8]. These issues are further affected by climate change, which increases rainfall variability and the occurrence of extreme weather events [9]. At the same time, the high input costs and labor shortages complicate seed production [10]. In response, technologies such as precision agriculture, which utilize satellite imagery, drones, and IoT sensors, have been proposed for optimizing water use and fertilizer application, as well as for enabling early pest detection [11, 12]. Similarly, modern breeding methods, like Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) and marker-assisted selection, have contributed to the development of rice

varieties with enhanced drought tolerance and disease resistance [13].

Seed-borne diseases have the highest impact among all the threats to rice productivity by reducing germination rates, seedling vigor, and the total yield [14, 15]. Pathogens, such as *Magnaporthe oryzae* (rice blast) and *Xanthomonas oryzae* (bacterial leaf blight), can persist in seeds and spread rapidly under favorable conditions [16]. The conventional methods for seed inspection are usually slow and inaccurate, prompting scientists into Artificial Intelligence (AI) systems for disease detection [17]. Convolutional Neural Networks (CNNs) have demonstrated strong performance in image-based disease identification [18, 19].

Several studies have investigated rice disease detection using Deep Learning (DL) and Transfer Learning (TL) approaches. For instance, authors in [20] evaluated DL models including ResNetSt-50, SE-ResNet-50, and DenseNet-121, reporting 91% accuracy using an ensemble strategy. In [21], ML classifiers were applied, achieving 99.2% accuracy. In [22], an optimized VGG-19 TL approach was utilized, reaching an accuracy of 96.08%. Authors in [23] employed image preprocessing and ensemble-based classification with improved prediction results. Similarly, authors in [24] introduced the Rice-Leag Plaque-Net (RLPNet), integrating YOLOv3 for feature extraction, obtaining 91.84% accuracy across five rice leaf disease classes. In [25], TL was combined with multimodal data sources, such as images, weather, and soil parameters, to

enhance detection accuracy and interpretability. In [26], image detection was enhanced through YOLOv8, achieving 89.9% accuracy, while authors in [27] proposed YOLOX, an optimized YOLOv7-tiny variant with higher performance.

Despite these advances, most research focuses on the detection of rice leaf diseases, with limited work emphasizing seed-borne diseases. This gap is critical since seed infections can affect the entire crop cycle. For this reason, the current work proposes a CNN Long Short-Term Memory (CNN-LSTM) model for rice seed disease detection. This combination extracts discriminative features from seed images (CNN module), while mitigating gradient descent issues and enhancing classification performance (LSTM module). Hence, this work presents a model specifically designed for detecting diseases in rice seeds.

II. METHODOLOGY

For the detection of the rice seed condition, this work presented a CNN-LSTM approach. The CNN helped in extracting features from the rice seed, whereas the LSTM approach solved the issue of gradient-descent in CNN.

A. Convolutional Neural Networks

The CNN model used for extracting features from disease rice seed is depicted in Figure 1, with the following process: Convolutional Layer, Pooling Layer, and finally Fully Connected Layer (FCL). From each convolutional layer and pooling layer, the features were extracted from the disease rice seed image.

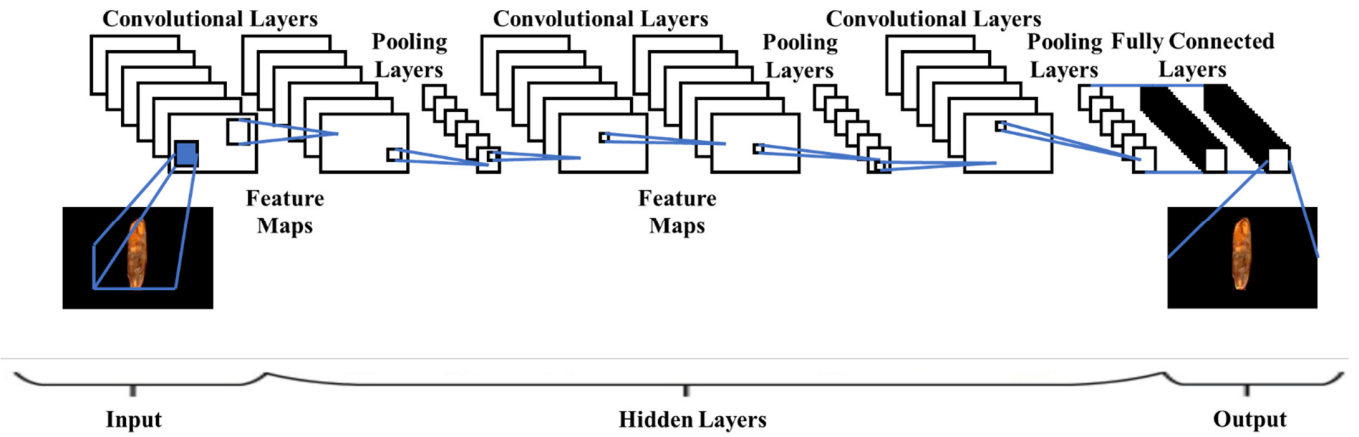


Fig. 1. Feature extraction process using CNN.

1) Convolutional Layer

In CNN-LSTM model, the input mappings of features were initially computed for convolution layers:

$$F_j^{(n)} = \sum_{k=0}^K F_k^{(n-1)} * \omega_{kj}^{(n)} + b_j^{(n)} \quad (1)$$

where $*$ denotes 2D convolutions functioning, $F_k^{(n-1)}$ is the k^{th} feature-mapping produced within $(n-1)^{th}$ level, $\omega_{kj}^{(n)}$ is the k channel of j^{th} convolutions-kernel within n^{th} level, $b_j^{(n)}$ is the j^{th} bias within n^{th} level, and $F_j^{(n)}$ denotes j^{th} feature-mapping produced within n^{th} level.

The CNN approach utilized three convolution kernels of sizes 1×1 , 3×3 , and 5×5 . The convolution-layers "H/V 1~5" in the horizontal/vertical series contained 64, 64, 64, 128 filters each, with kernel sizes $5 \times 5 \times 1$, $3 \times 3 \times 64$, $5 \times 5 \times 64$, $3 \times 3 \times 64$, and $3 \times 3 \times 128$, correspondingly. These layers produced output sizes of $256 \times 256 \times 64$, $127 \times 127 \times 64$, $63 \times 63 \times 64$, $31 \times 31 \times 64$, and $15 \times 15 \times 64$. Similarly, layers "I1~4" in the interleaved sequence included 64 filters with sizes of $1 \times 1 \times 128$, $5 \times 5 \times 64$, $5 \times 5 \times 64$, and $3 \times 3 \times 64$, resulting in $127 \times 127 \times 64$, $63 \times 63 \times 64$, $31 \times 31 \times 64$, and $127 \times 127 \times 64$,

respectively. In every single convolution layer, the stride was initialized to 1.

2) Batch Normalization Layer

Batch normalization is necessary to address the issue of the changing distribution of internal node inputs during training. The activated and convolution layers work together in a batch normalizing layer to achieve this. The process of batch normalization starts with calculating the batch's variance and mean:

$$\mu = \frac{1}{m} \sum_{i=0}^m x_i \quad (2)$$

$$\sigma^2 = \frac{1}{m} \sum_{i=0}^m (x_i - \mu)^2 \quad (3)$$

where σ^2 is the variance, μ represents the mean, m is defined as the data in a given batch, and x_i represents the i^{th} information of a given batch.

Each input is then normalized:

$$\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (4)$$

where ϵ represents a tiny floating-point value that is bigger than 0 in order to avoid the errors caused by division by zero.

Finally, the normalized output is adjusted and moved accordingly:

$$y_i = \gamma \hat{x}_i + \beta \quad (5)$$

where y_i represents the i^{th} batch-normalization level outcome and γ and β are learnable parameters.

Hence, using this, the activation performance's non-linear functionality is capable of being used by newly created information. The layer of batch-normalization prevents dramatic changes to back-end parameters, brought about by tiny changes to front-end parameters.

3) Activation Layer

In most cases, a non-linear-function known as activation-function is added after the convolution layer to make up for their lack of flexibility. The activation process takes information produced by the convolution layer and maps it to a new space, allowing for more accurate data classification. Activating functions, like ReLU, TanH, and Sigmoid, are commonly utilized. In this work, the TanH function was employed, reducing information to the interval [-1, 1]. TanH performs well with features that have significant variations, as it can amplify their influence. The fact that TanH's average value is 0 makes it a better choice over Sigmoid in real-world applications. Although ReLU function training is quicker, it is sensitive during the process and is unable to accommodate a higher level of learning. Thus, the CNN activating levels are therefore configured according to the TanH function.

4) Pooling Layer

The feature-mapping is intended to be down-sampled by the layer used for pooling. This method integrates a hierarchical framework by expanding observable windows with ongoing layers of convolution and decreasing the number of elements in feature-mapping. Due to this, the CNN approach makes advantage of max-pooling in addition to global mean-pooling. With the exception of the fifth layer that pools feature in horizontal/vertical sequences, every one of the additional layers of pooling in this work used maximal pooling, resulting in the highest possible value in every feature within the input-mapping window. To accurately represent the concepts of right/left, down/up, and center, maximum pooling layers employed 3×3 kernels with a stride of 2. When used as part of the whole connection layer, the global average pooling reduced the parameters of the CNN by sampling features below 1, as achieved through the use of average pooling. Before the final layer of pooling of both vertical and horizontal sequences was applied and average global pooling was only considered.

B. LSTM

To solve the problem of gradient descent in CNN, this work incorporated LSTM. In the LSTM network, the process of gates is crucial for encoding the long-range dependency of the input, as illustrated in Figure 2. It usually consists of three gates: the input, forget, and output gates.

The input-gate (i_x^t) was utilized to determine which value holds significance for the updating of the present stage, while the forget-gate (f_x^t) aimed to determine whether important information has to be dropped or stored. Finally, the output-

gate (o_x^t) was used for controlling which information has to be transmitted for the subsequent hidden-state. The complete evaluation of the gates was obtained through:

$$f_x^t = \sigma(W_f X_t + U_f h_{t-1} + b_f) \quad (6)$$

$$i_x^t = \sigma(W_i X_t + U_i h_{t-1} + b_i) \quad (7)$$

$$o_x^t = \sigma(W_o X_t + U_o h_{t-1} + b_o) \quad (8)$$

$$c_x^t = f_t * c_{t-1} + i_t * \tilde{c}_t \quad (9)$$

$$\tilde{c}_x^t = \tanh(W_c X_t + U_c h_{t-1} + b_c) \quad (10)$$

$$h_x^t = o_x^t * \tanh(c_x^t) \quad (11)$$

where h_x^t and c_x^t represent the hidden and cell-states for a given time-step t , with input data as X_t , σ symbolizes the sigmoid-function which controls the input data in gates. When σ equals to 0, it blocks the data for a given gate (data will not be fed into the subsequent stage), while when σ is 1, it does not block the data for a given gate (data will be allowed to be fed into the subsequent stage). Moreover, (b_f, b_i, b_o, b_c) denotes bias values and $(W_f, W_i, W_o, W_c, U_f, U_i, U_o, U_c)$ are the weight matrices for the respective gates.

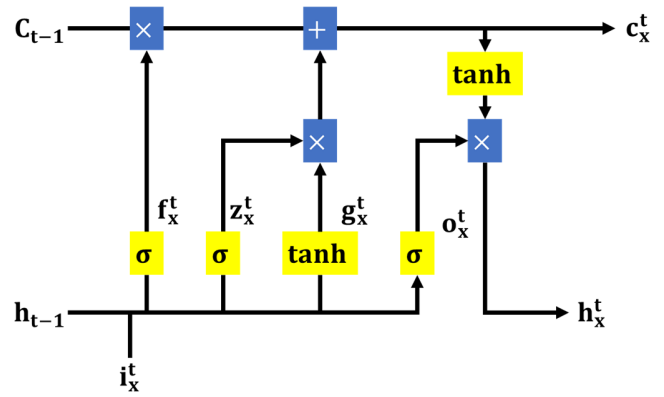


Fig. 2. LSTM network.

A total of 256 units were considered for LSTM. For better optimization, this work utilized Adam Optimizer with an enhanced threshold-aware (Accuracy-Error tradeoff) weight optimizer learner. After the optimization, the LSTM went to the dense layer to achieve better accuracy for classification.

III. RESULTS AND DISCUSSION

To evaluate the CNN-LSTM model, two datasets containing healthy and diseased rice seed images were utilized [28, 29]. High-resolution images were captured from various cities across Pakistan, including Kandhkot, Shikarpur, Sukkur, Moro, and Kashmore, using a DSLR camera to ensure sufficient quality. Some examples of these images are displayed in Figure 3.

All experiments were conducted on Windows 11 with 16GB RAM, executed on Python. The datasets were preprocessed and enhanced to facilitate their use in ML applications. Preprocessing steps included rescaling, cropping, image enhancement, contrast adjustment, flipping, and saturation adjustments. The dataset from [29] has been successfully

utilized in prior research [30], with the results being effective for detecting fungal blast disease in rice seeds and serving as a valuable resource for similar research efforts.

The dataset from [28] contains a total of 1,007 samples, categorized into two classes: healthy (501 samples) and unhealthy (506 samples). This dataset was divided using a 70:30 split, resulting in 706 samples for the training set (351 healthy, 355 unhealthy) and 301 samples for the testing set (150 healthy, 151 unhealthy). The dataset [29] includes six distinct classes, with one being healthy and five representing specific rice leaf diseases, which were predefined in training and validation partitions. The class distributions are: Bacterial Leaf Blight (BLB) (350 train and 88 validation), Brown Spot (373 train and 93 validation), Healthy (371 train and 93 validation), Leaf Blast (363 train and 91 validation), Leaf Scald (358 train and 90 validation), and Narrow Brown Spot (NBS) (352 train and 88 validation), leading to a grand total of 2,710 samples (2,167 for training and 543 for validation).



Fig. 3. Examples of rice seed images from the datasets.

The performance metrics employed for the evaluation of CNN-LSTM included: accuracy, precision, recall, and F1-score:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (15)$$

In these expressions, True-Positive (TP) represents correctly the classified healthy samples (actual class is healthy and model is healthy). True-Negative (TN) represents correctly the unhealthy samples (actual class is unhealthy and model is unhealthy). False-Positive (FP) refers to unhealthy samples that are incorrectly classified as healthy, and False-Negative (FN) is the classification of healthy samples as unhealthy.

The performance of the CNN-LSTM model was evaluated and compared with several existing state-of-the-art models using rice seed and leaf disease datasets. For standard evaluation, all models were implemented and assessed using Kaggle rice seed datasets. Table I compares the performance

metrics of different datasets, with the proposed model achieving the highest metrics, outperforming DCNN [22], RLPNet [24], CNN [25], YOLOv8 [26], and YOLOv7 [27]. Specifically, the CNN-LSTM accomplished an accuracy of 98.4%, a precision of 98.01%, a recall of 98.7%, and an F1-score of 98.4%, indicating its robustness in correctly identifying both healthy and diseased rice seeds. Among the comparative models, DCNN [22] performed reasonably well with 96.08% accuracy, while YOLO-based methods, YOLOv8 [26] and YOLOv7 [27], showed lower performance, achieving 89.9% and 88.5% accuracy, respectively. These results highlighted the effectiveness of the CNN-LSTM architecture in capturing discriminative features from seed images and improving classification over conventional DL and object detection-based models.

TABLE I. PERFORMANCE EVALUATION ON DATASET [28]

Reference	Model	Accuracy	Precision	Recall	F1-Score
[23]	DCNN	96.08	95.5	95	95.2
[25]	RlpNet	91.84	91	90.5	90.7
[26]	CNN	92.5	92	91.8	91.9
[27]	YOLOv8	89.9	89.5	89	89.2
[28]	YOLOv7	88.5	88	87.5	87.7
Proposed	CNN-LSTM	98.4	98.01	98.7	98.4

Table II presents the performance of the CNN-LSTM model for both datasets and a comparison with related works on rice leaf disease datasets. The confusion matrices for datasets [28, 29] achieved by CNN-LSTM are presented in Figures 4 and 5, respectively. The CNN-LSTM achieved 98.4% accuracy on dataset [28] and 98.5% on dataset [29], demonstrating strong generalizability across different datasets and tasks. Other models showed lower performance on their respective datasets: DCNN [22] achieved 96.08% on dataset [29], RLPNet [24] obtained 91.84% on collected leaf dataset, CNN [25] achieved 93% on a mixed collected and web-scraped dataset, YOLOv8 [26] reached 89.9% on collected leaf images, and YOLOv7 [27] achieved 92.2% on collected leaf data.

TABLE II. PERFORMANCE EVALUATION WITH OTHER SIMILAR STATE-OF-THE-ART WORKS ON RICE LEAF DISEASE

Ref	Model	Dataset	Classes	Accuracy (%)
[22]	DCNN	[29]	5	96.08
[24]	RlpNet	Collected	5	91.84
[25]	CNN	Collected + Web Scrapping	7	93
[26]	YOLOv8	Collected	3	89.9
[27]	YOLOv7	Collected	5	92.2
Proposed	CNN-LSTM	[28]	2	98.4
		[29]	6	98.5

Overall, the comparative analysis demonstrated that the CNN-LSTM model not only surpassed the existing DL and object detection methods in rice seed disease detection but also maintained high performance across rice leaf datasets. This indicates the model's ability to generalize well to different data distributions and its potential applicability for large-scale agricultural disease monitoring. The integration of CNN for feature extraction and LSTM for handling sequential

dependencies likely contributed to the superior accuracy, precision, and robustness of the model.

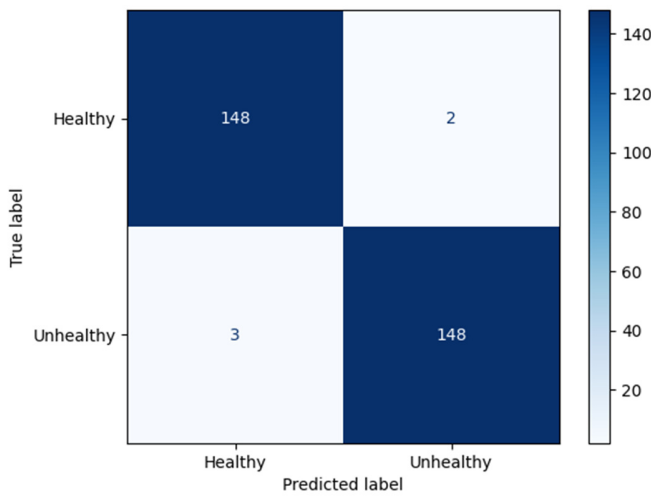


Fig. 4. Confusion matrix for dataset [28].

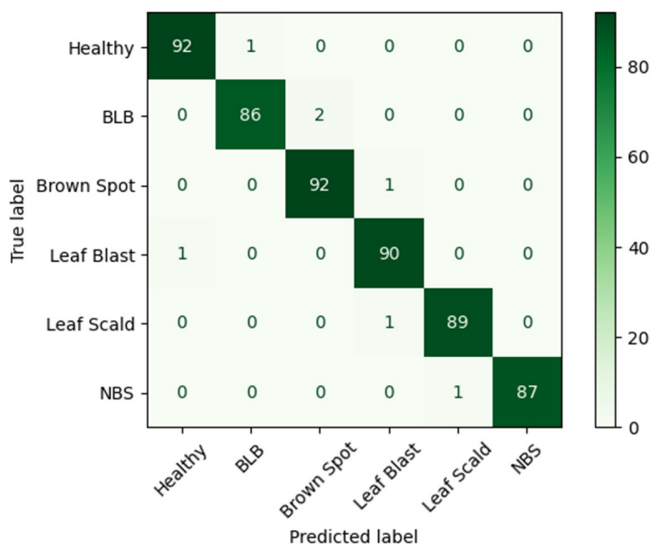


Fig. 5. Confusion matrix for dataset [29].

IV. CONCLUSION

This work presented a Machine Learning (ML) model integrating a Convolutional Neural Network (CNN) with Long Short Term Memory (LSTM) for the detection of rice seed diseases. The model was evaluated using two datasets and its performance was compared with models in previous studies. The proposed CNN-LSTM model outperformed significantly, achieving an impressive accuracy of 98.4%, a precision of 98.01%, a recall of 98.7%, and an F1-score of 98.4% for the dataset [28], while the accuracy of dataset [29] was 98.5%. These results demonstrate the model's robustness and effectiveness in distinguishing between healthy and diseased rice seeds. The integration of CNN and LSTM ensured high accuracy and reliability in rice seed disease detection, highlighting its potential for practical applications in

agricultural quality control and disease management. Future work could focus on further optimizations and adaptations of this model to other crops and agricultural contexts, aiming to enhance food security and crop health management on a broader scale, as well as extending the research on the classification of rice quality.

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