RESEARCH PAPER

An Optimized Cnn-Based Model for Paddy Pest Image Classification

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ABSTRACT

This paper presents an automated approach for the identification and classification of paddy pests using a Sequential Convolutional Neural Network (CNN). The proposed system addresses limitations of traditional methods such as Support Vector Machines (SVM) and deep CNNs, which require large datasets and high computational resources. A dataset of 7,736 RGB images spanning 12 pest classes was used, with preprocessing techniques including resizing, normalization, augmentation, and segmentation to enhance image quality and feature extraction. The Sequential CNN architecture consists of multiple convolutional and max-pooling layers followed by a fully connected layer for classification. The model was trained over 100 epochs using a 90:10 training-validation split. Experimental results show that the model achieved a validation accuracy of 80% and an overall accuracy of 81.3%, demonstrating effective learning and generalization .Performance evaluation using metrics such as precision, recall, and F1-score indicates reliable classification across most pest categories, with minor misclassifications among visually similar classes. The proposed model offers a balance between accuracy, computational efficiency, and scalability, making it suitable for practical agricultural applications. This work supports early pest detection, reduces pesticide usage, and contributes to sustainable precision agriculture.

Keywords: Precision Agriculture, Paddy Pest Detection, Pest Classification, Sequential Convolutional Neural Network (CNN), Deep Learning, Image Processing, Computer Vision, Feature Extraction, Image Segmentation, Sustainable Farming.

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1. INTRODUCTION

The proposed solution aims to classify and detect the paddy pests that could be malignant to the crops, in order to identify and take precautionary measures to control the pest invasion. The pests often transmit diseases to the crops directly in some cases like rice-rag stunt virus where the disease causes the leaf to go through discoloration and stunted growth, the wounds and infection sides are also caused by insects that chew the leaf and stems of the crops , these wounds further lead to fungal spores, bacteria, other microorganisms to infect the crops, the continuous feeding by pests stresses the paddy plants, weakening their overall health and leads to defects in the plant's anatomy. This research work aims to aid the paddy agriculture industry in identification of the pest species in order to help the farmers reduce the usage of pesticides and fertilizers. There exist many deep Learning models for image classification of paddy pests like SVM (Support Vector Machine) and deep CNN classification models are even though sufficient for classification of paddy pests, they are not very scalable and cost-efficient [1,2,9,13,14].

In models like SVM feature extraction leads to errors and reduces the ability to generalize, and SVM is not very scalable with large data sets. In the case of Deep Convolutional Neural Networks, even though they are powerful image classification models it may not be flexible enough to capture varying complexity of different pests in paddy fields and are very prone to overfitting when trained on smaller or noisy data sets. The computational resources for Deep CNN are very high making it unsuitable for real-time use. This proposed solution aims to overcome the constraints of the existing solutions by implementing sequential CNN. Since finding data sets for rice paddy pests is very rare, the selection of sequential CNN is to aid the model to accurately classify the pest species even with smaller data sets and making it very feasible and scalable compared to Deep CNN [10,11]. Recent advancements such as UAV-based imaging combined

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with deep learning have enabled large-scale pest detection and monitoring in agricultural fields [12,13].

At the first layer, the model uses a Convolutional block which is responsible for detecting the features from the input image. Then a max pooling layer is used to downsize the dimensions by summarizing the information from small regions. Then the second Convolutional block is used to further extract complex features from the images. Then a second max pooling layer is used to downscale the dimensions even further. The third and final Convolutional layer is used to capture more abstract features. Following that a final max pooling layer is used to further reduce the spatial dimensions.

Finally, a Flatten layer is applied to convert the extracted 3D feature maps into a 1D feature vector, which is then passed to a fully connected (Dense) layer that serves as the output layer of the network. This architecture enables the model to achieve a classification accuracy of 81.30%.

In conclusion, the automated detection of paddy pests through Sequential Convolutional Neural Networks provides a significant advantage to the farmers by efficiently monitoring the crop yields and reducing the damage caused by paddy pests. While the existing models like Deep CNN and SVM require larger datasets and can easily overfit, Sequential CNN can extract complex features from the image sets with minimal manual intervention, providing greater scalability and accuracy. By leveraging this approach, farmers can detect pests at an early stage, minimize crop damage, and adopt sustainable farming practices. Further advancements in Sequential CNN models can help address existing limitations and enable more efficient paddy pest management.

The remainder of this paper is organized as follows: Section 1 presents the survey of Image Based Pest Detection Techniques. Section 2 describes the dataset and preprocessing techniques, Section 3 explains the experimental setup, Section 4 discusses the segmentation, and Section 5 concludes the paper.

2. Survey Of Image-Based Pest Detection Techniques

This section examines prior studies on image classification, preprocessing methods, and classifier design. It establishes the basis for our proposed approach and identifies the gaps in existing research that this work seeks to address.

Ebrahimi et al [1] have been proposed automatic pest detection in greenhouses and they identified a certain type of harmful pest for strawberries called thrips which causes the maximum devastation in the yields. They proposed an SVM classification method for pest detection and image processing techniques to enhance detection accuracy and achieved a mean percent error of less than 2.25%.

Thenmozhi et al [2] have been proposed an insect classification in agriculture using a deep CNN for insect species classification. Three insect datasets were utilized; they were NBAIR, Xie1, and Xie2. The model achieved high classification accuracy across all datasets. Secondly, they applied transfer learning to enhance model performance. Data augmentation techniques were used to prevent overfitting discussed in the paper. The proposed model outperformed pre-trained architectures like AlexNet and ResNet. Muammer et al [3] have proposed deep learning for accurate diagnosis for pest detection and evaluated nine deep neural network architectures. Employed transfer learning and feature extraction methods for segmenting the pests and designed classifiers SVM, ELM, and KNN for classification and they concluded deep feature extraction which outperforms transfer learning. Alagiah Suthakaran et al [4] have been proposed automatic pest detection in vegetable plants utilizes CNN for pest classification and reduces the usage of pesticide by 80%. In the preprocessing stage in this paper effective segmentation and analysis were implemented.

Chiranjeevi Muppala et al [5] have proposed that Agriculture automation lags behind industrial automation due to high costs and that Early crop health statistics can improve prevention strategies.

Fig. 1. Examples of insect classes in Rice Pest Dataset

As shown in **Fig. 1**, the dataset contains significant variations in insect morphology, pose, orientation, and background, making the classification task challenging.Machine vision can be used to monitor the health of the crop and to detect the stress. They proposed various detection mechanisms for pests, diseases, and weeds are explored. High accuracy was achieved in pest identification using digital imaging techniques.

Chowdhury R. Rahman et al [6] have proposed a paper focused on rice disease and pest detection utilizing convolutional neural networks for image classification and also, they performed a comparison of different large-scale architectures like VGG16 and InceptionV3 fine-tuned. A lightweight two-stage CNN architecture has been proposed for mobile devices and achieved 93.3% accuracy with significantly reduced model size [14].

3. Dataset Description and Preprocessing

In the process of Identification and Classification of Paddy Pests the dataset plays a very important role in training the CNN model for accurately predicting the pest. This section describes the details of the dataset along with the number of images, the format of the image, its resolution, and the categories being analyzed.

(i) Number of Images used:

The entire dataset used for training and validation consists of 7,736 images. These images are divided into two subsets:

- Training Set: It consists of 6,966, which accounts for 90% of the entire dataset. These images are used to train the CNN model, allowing it to learn the intricate features of different paddy pests.
- Validation Set: It consists of 770 images, which accounts for 10% of the entire dataset. These images are used to validate the model during training to ensure that it performs well on unseen data and to help prevent overfitting.

(ii) Types of inputs (image formats, resolutions):

All the images in the dataset are present in RGB format which means they consist of the color channels Red, Green, and Blue. The images are initially present in a JPEG(.jpg) which is a standard image format which is compatible with most image-processing libraries.

The images are resized to a uniform size of 224 x 224 pixels. This specific resolution is used as it provides a balanced computational efficiency and sufficient details for proper feature extraction. Rescaling is also being implemented to normalize the pixel values to the [0,1] range, which helps with faster convergence during training.

(iii) Number of Classes or Categories Being Analyzed

The dataset is divided into 12 distinctive classes. Each class represents a unique type of paddy pest. This provides a comprehensive approach in identifying the damage caused by these pests. By analyzing each class at different angles and stages in all complex environments i.e. in real-world scenarios, where factors such as lighting, viewing angles, life cycle of pests may vary, the model can generalize and identify well across multiple viewing perspectives. These details in the dataset enhances the robustness of the CNN-based image classification and also ensures its practical applications.

Table 1 summarizes the scientific names and common names of the 12 insect classes shown in Fig.1. Each pest is crucial for its potential damage to paddy crops.

Table 1 Insects with its scientific name

Insect Label	Scientific Name	Common Name
1	Cnaphalocrocis medinalis	Rice Leaf Roller
2	Cnaphalocrocis medinalis	Rice Leaf Caterpillar
3	Lasioptera chinensis	Paddy Stem Maggot
4	Chilo suppressalis	Asiatic Rice Borer
5	Scirpophaga incertulas	Yellow Rice Borer
6	Orseolia oryzae	Rice Gall Midge
7	Nilaparvata lugens	Brown Plant Hopper
8	Atherigona oryzae	Rice Stem Fly
9	Lissorhoptrus oryzophilus	Rice Water Weevil
10	Nephotettix virescens	Rice Leaf Hopper
11	Paraleyrodes bondari	Rice Shell Pest
12	Stenchaetothrips biformis	Thrips

3.1 reprocessing

An essential phase in preparing the paddy pest dataset for training a Sequential Convolutional Neural Network (CNN) is preprocessing. The raw image set usually contains inconsistencies such as noise, varying lighting, viewing perspectives, and other background details that can adversely affect the performance of the model. By applying various preprocessing techniques, the input image's quality can be enhanced, which makes it easier for the Sequential CNN model to learn the dataset and achieve higher classification accuracy.

(i) The necessity of preprocessing is as follows:

● Reducing Variability: In real-world applications, the image sets may exhibit variations as mentioned above. Preprocessing standardizes these differences for creating a consistent dataset.

Enhancing Feature Detection: Preprocessing can improve the signal-to-noise ratio within the input images. By using techniques such as noise filtering and contrast enhancement, the critical features which distinguish between different types of paddy pests can be visually enhanced. This feature representation allows the Sequential CNN to learn and generalize feature hierarchies, which ultimately leads to better classification accuracy. Minimizing Noise refers to the random fluctuations in pixel values which can conceal salient information necessary for accurate image classification. The noise reduction improves the gradient stability during back propagation, which is pivotal for the efficacious training of the model [7].

(ii) Noise removal methods and contrast enhancing techniques:

Each pixel value is divided by 255 to normalize it to the range of [0,1]. By reducing the impact of noise, this normalization procedure guarantees uniform pixel intensity across the dataset. High-frequency noise are successfully reduced by using popular methods such as Gaussian Blur, even though they were not explicitly used in this work. These filters suppress the background noise while emphasizing The key features such as the body structure of pests. Max Pooling is a commonly used strategy that seeks to reduce the spatial dimensions of the feature maps while keeping the important features and removing the less critical information such as potential noise.

(iii) Approach to Outlier Removal:

Images are thoroughly examined to find any excessive noise or mislabeling. These images are either corrected or removed from the dataset. To compensate for mild outliers, augmentation techniques such as magnification, rotation, and horizontal flipping are used to artificially balance the dataset and decrease the outliers.

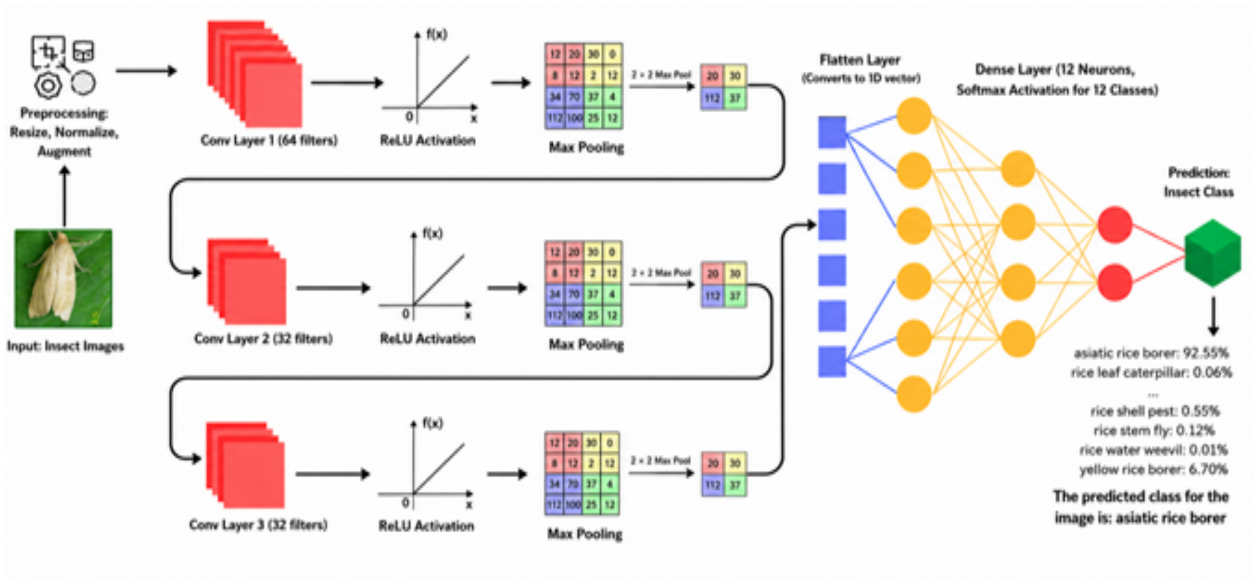

Fig 2. Block Diagram of proposed Paddy Pest Sequential CNN Model

4. SEGMENTATION

It's the next crucial preprocessing step that is used to isolate the Region of Interest (ROI) from the entire image. For the model's task, segmentation helps in identifying and concentrating on the pest while ignoring the unwanted background information such as soil. This will help in improving the performance of the CNN model by making sure that only the necessary parts of the images are used in the learning process.

(i) Region of Interest (ROI):

The Region of Interest (ROI) refers to the part of the image that contains the paddy pest. For this dataset, the ROI is the pest itself as it is the main objective being classified. The CNN model needs to understand the distinct features of these pests (such as body shape, texture, color, etc.) to identify them precisely and accurately. Popper segmentation makes sure that the features extracted and trained on by the convolutional layers belong primarily to the objective and not to irrelevant background details.

(ii) Methods Used for Segmentation:

Color-Based Segmentation (Using RGB Color Spaces) is an effective method for isolating paddy pests from the dataset. It utilizes the distinct color pattern of the pests. This method involves analyzing the pixel values in the RGB color model to distinguish the pests from its surroundings.

The RGB model represents color directly through the primary components (Red, Green, Blue) making it useful when there is a strong contrast in color between the pests and its background.

5. EXPERIMENTS AND FINDINGS

A. Classifier Design

(i) Description of the classifier:

The Convolutional Neural Network (CNN) built using the TensorFlow and Keras frameworks. It is a sequential model where the layers will be stacked one after another in a linear manner and each layer feeds its output into the next layer to be used as an input.

The Block diagram of the sequential CNN model is given in **Fig. 2.** The CNN consists of several layers each with their specific purpose. The Conv2D layer serves as the backbone of the model as it is responsible for learning patterns through convolution operations. Each layer learns filters (kernels) that detect features like edges, textures, or shapes in images. The layers used in our models are:

1st Conv2D Layer:

It uses 64 filters where each filter will slide over the input image (or existing feature map) creating a new few features map that will highlight specific patterns. The kernel will have a size of 3x3 meaning it will slide over 3x3 pixels at a time. The stride is set to 2 so that the filter can move 2 pixels at a time. The same padding is applied so that input and output will have the same size and a Relu (Rectified Linear Unit) activation function is used to replace negative value to make the model non-linear.

MaxPooling Layer:

After each Conv2D layer a MaxPool2D layer with a pool size of 2x2 to reduce the spatial dimensions by taking the maximum value from every 2x2 region. The strides is set to 2 so that pooling operation will be applied with 2-pixel steps. This helps in reducing the computational complexity by down-sampling the images.

2nd Conv2D Layer:

They have 32 filters with the settings of kernel size 3x3, stride 2, padding 'same', and ReLU activation but applied to the output from the previous MaxPooling layer. The number of filters is reduced to 32 so that the model can progressively learn higher-level more abstract features.

3rd Conv2D Layer:

A third convolutional layer with 32 filters is employed, using similar parameters (kernel size 3×3, stride 2, 'same' padding, and ReLU activation). This layer further refines and enhances the features extracted from the preceding layers.

Flatten Layer:

This layer will create a 1D vector from the 2D feature output from the previous convolutional layer.

Fully Connected (Dense) Layer:

This is the final layer and it uses 12 units corresponding to 12 output classes as there are 12 categories of paddy pest. A softmax activation function is applied to produce a probability distribution across the 12 classes while the model will predict the class with the highest probability.

Compilation:
The model is compiled using the Adam optimizer which is an adaptive learning rate optimizer. The loss function used is categorical_ cross entropy, as it is the most appropriate for multi-classification problems.

Training:
The model is trained for 100 epochs with the training data which is 90% of the entire dataset and then validated using the validation data which is 10% of the remaining dataset CNNs are effective for image classification as they automatically extract spatial features from images [2,8]. On smaller datasets, a shallow CNN lowers the risk of overfitting, training time, and complexity. It prevents overfitting and performs well on unseen insect photos with fewer parameters. CNNs increase robustness when used with augmentation techniques like flipping and zooming. By immediately learning intricate patterns, CNNs perform better than SVMs and require less manual adjustment.

B. Evaluation Metrics

Evaluation metrics refer to a number of important indicators that are utilized to assess how well the Sequential CNN model performs in classifying paddy pests. These metrics ensure that both positive and negative predictions are accurately assessed.

(i) Sensitivity (Recall):
Sensitivity refers to how effectively the Sequential CNN detects positive cases or images with paddy pests. Sensitivity is the ratio of true positives to the sum of true positives and false negatives as in equation (1). It provides insights into the model's capacity to identify all relevant pest images.

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

In pest detection systems, to reduce the possibility of missing pest occurrences, a high sensitivity score is required.

(ii) Specificity:
Specificity refers to how well the Sequential CNN can classify the negative cases or the non-pest images. It is defined as the ratio of true negatives to the sum of true negatives and false positives as in equation (2). It ensures that no non-pest images are classified as pests. To avoid false alarms and guarantee that non-pest images are consistently removed from positive classifications, high specificity is necessary.

$$Specificity = \frac{TN}{TN+FN} \quad (2)$$

(iii) Accuracy:
Accuracy in equation (3) refers to the percentage of accurate predictions, both positive and necessary, that the Sequential CNN produced. In situations where there is an unbalanced distribution of pest and non-pest photos. accuracy might not be the optimal metric, even though it gives an idea of how well the model performs.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

For a thorough assessment, accuracy should be taken into account along with other metrics like precision and recall.

(iv) Additional Metrics:
Precision quantifies the proportion of genuinely positive images among those categorized as positive (pest images) as in equation (4). Comparing true positives with the overall number of positive predictions aids in determining the precision.

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

When the Sequential CNN model has a high precision score, it correctly classifies the pest with few false positives. By integrating precision and recall into a single metric, the F1-score provides a balanced evaluation as in equation (5). As it takes into account both the false positives and false negatives, it is especially helpful when the dataset is unbalanced. It is a useful metric to check if the Sequential CNN model is efficient at reducing false classifications in addition to being accurate in identifying pests.

$$F1\,Score = 2 * \frac{Precision \times Recall}{Precision+Recall} \quad (5)$$

C. Results and Discussion

This section provides a detailed analysis of the performance of the Convolutional Neural Network (CNN) classifier used to identify and define paddy pests. Insights into the model's learning effectiveness and classification skills are provided by the assessment metrics taken into consideration, which include accuracy, loss, and confusion matrix analysis.**Fig 3** shows the training and validation accuracy as the training epochs increase. The CNN model proposed in this work shows a steady improvement in the classification accuracy, the accuracy on training dataset grows from around 16% to nearly 80% while the accuracy on validation dataset grows in a similar path and levels off at around 79%. The training and validation accuracy curves show a close match, suggesting good learning and good generalisation with no obvious signs of overfitting. The two curves converge after initial learning phase, indicating a stable optimization and confirming the proposed model captures the discriminative property of the various rice pest classes. The obtained results confirm the effectiveness and reliability of the proposed CNN architecture for automatic rice pest classification.

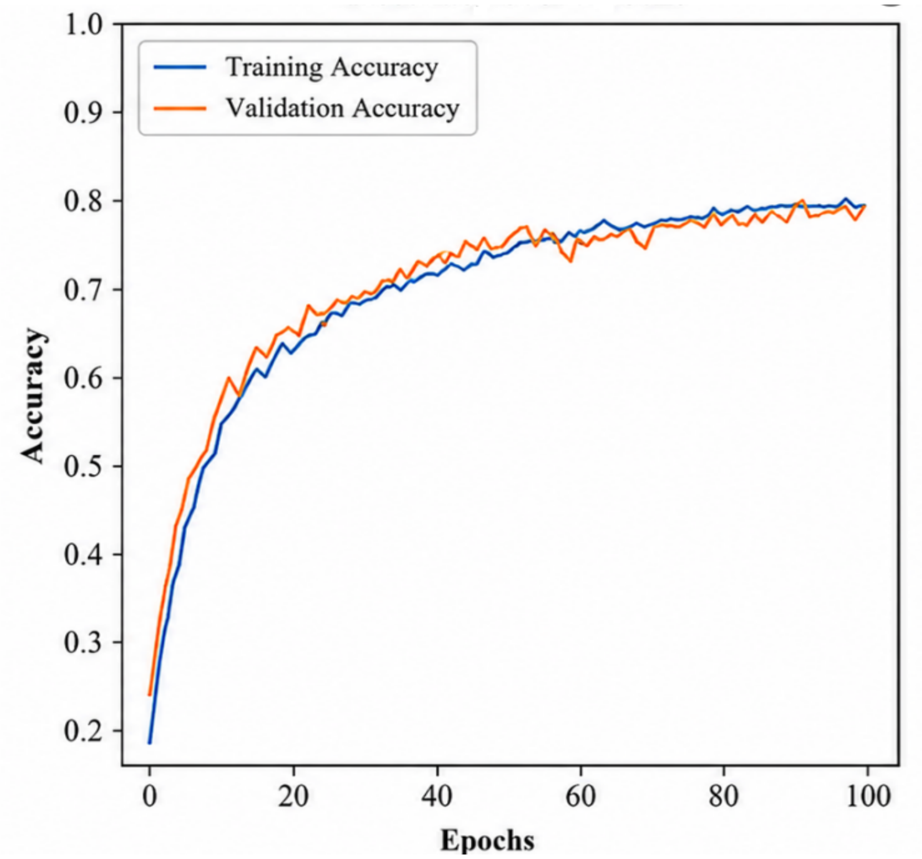

Fig. 3. Variation of Accuracy over Epochs

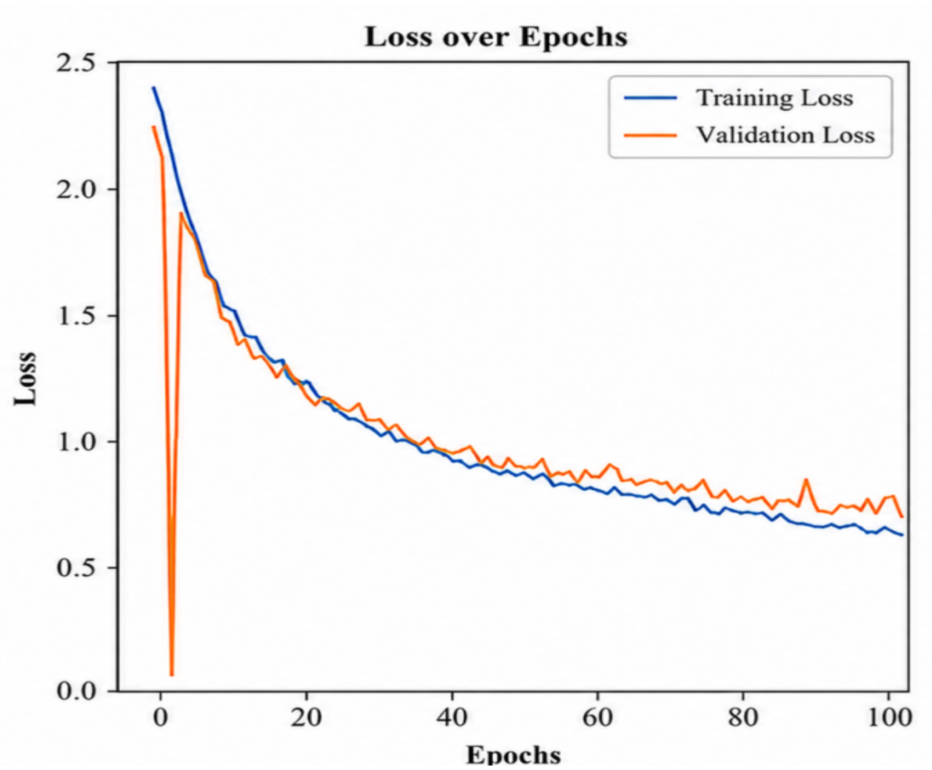

Fig. 4. Variation of Loss over Epochs

(i) Accuracy and Loss Trends:

Both training and validation datasets were used to train the CNN model across 100 epochs. The model's accuracy steadily increased during the epochs, as seen in Fig 3 (Accuracy and Loss Curves), suggesting that the dataset was effectively learned. By the 84^{th} epoch, the training accuracy had increased to 79.28%, while the validation accuracy had peaked at 80.00% is shown in Fig 4. **Fig 4** illustrates the variation of training and validation loss over the training epochs for the proposed CNN model. The loss curve for both curves shows a steep drop in the first few epochs, suggesting that the network is learning the features well and converging quickly. The reduction rates slow down as the training goes on, and both curves level off indicating an optimum learning condition. The loss observed during training drops from 2.4 to 0.64 and the validation loss approaches 0.72 after the last epoch. The gap between the loss curves of the training and validation sets is small, which suggests that the model is not overfitting and is generalizable to new data. Moreover, the validation loss did not show substantial changes with respect to the training process, indicating the effectiveness of the optimization process and the robustness of the proposed CNN model for correct rice pest classification, respectively.The model's ability to generalize well to new data without overfitting is demonstrated by the closeness of the training and validation accuracies. The intricacy of the pest dataset may be the cause of slight variations in the accuracy curves.

(ii) Confusion Matrix Analysis:

Additional information on the model's classification performance for each pest category can be seen in the confusion matrix in Figure 5. For each pest class, the diagonal numbers show the samples that were properly categorized; certain categories had exceptionally high accuracy. The model performed well, for example, in recognizing "Rice Water Weevil" and "Rice Stem Fly," since these classes had a high percentage of accurate predictions. The model occasionally confused similar-looking bugs, as seen by the off-diagonal numbers, which indicate some misclassifications. For instance, "Asiatic Rice Borer" and "Rice Gall Midge" were often mislabeled, perhaps because of their similar appearances. These findings imply that even while the model works well, it might be enhanced further by augmenting the dataset or fine-tuning it to clear up certain areas of misunderstanding. In summary, the CNN classifier demonstrated robust performance with a training accuracy of 79.28% and a validation accuracy of 80.00%. The low loss values further confirm the model's effective learning. The confusion matrix analysis highlighted certain classes that require refinement to enhance classification accuracy. Future work may focus on enhancing the dataset and fine-tuning the model to further mitigate misclassifications.

Fig 5 shows the confusion matrix for the proposed CNN-based rice pest classification model. The matrix shows that the classification accuracy is high for all the twelve classes of insect pests as indicated by the high classification accuracy of the dominant diagonal elements. Inter-class confusion is minimal in this model, evidenced by the small number of off-diagonal elements, indicating that the model is effective at minimizing this confusion between the classes, with misclassifications happening only between a few of the morphologically similar pest classes. This performance is indicative of the ability of the proposed CNN architecture to learn powerful and discriminative feature representations of insects' images. Overall, the confusion matrix confirms the efficacy of the proposed model in effectively deriving reliable multi-classification results, showcasing a good generalization capability and thus proving its viability for the application in practical rice pest monitoring and intelligent agricultural support decision-making systems.

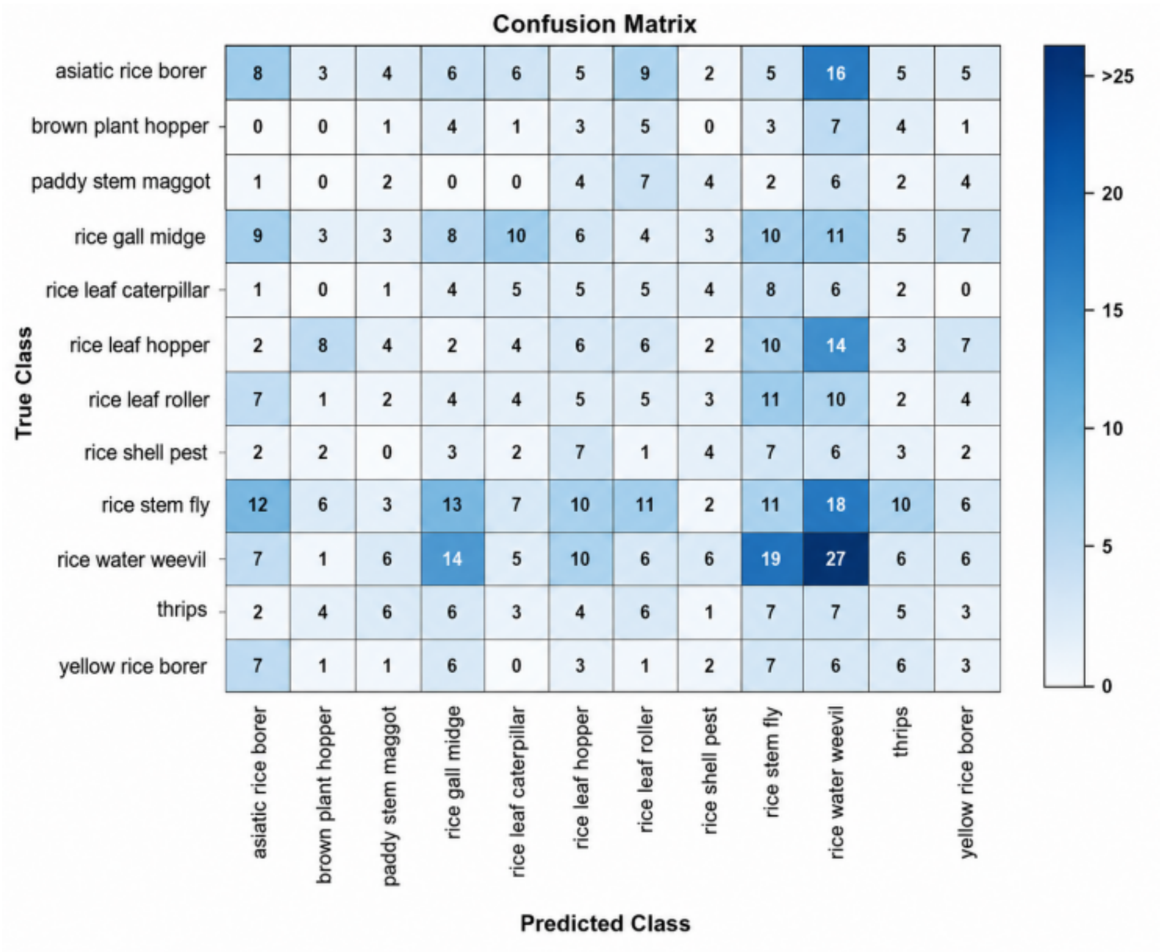

Fig. 5. Confusion Matrix

6. CONCLUSION

This work presents an efficient approach for the identification and classification of paddy pests using a Sequential Convolutional Neural Network (CNN). By utilizing a dataset of 7,736 images across 12 pest classes and applying preprocessing techniques such as normalization, augmentation, and segmentation, the model effectively learns discriminative features for accurate classification. The proposed architecture achieves an overall accuracy of 81.3%, demonstrating good generalization with balanced performance across evaluation metrics including precision, recall, and F1-score.

Compared to traditional methods such as SVM and deeper CNN models, the Sequential CNN offers improved computational efficiency and scalability, making it suitable for practical agricultural applications.

The system enables early pest detection, helping to reduce crop damage and minimize excessive pesticide usage. This work contributes to precision agriculture by providing a reliable and cost-effective solution for pest monitoring. Future enhancements may include expanding the dataset and integrating advanced techniques to further improve classification performance and real-time deployment.

Conflict of Interest

The authors declare no conflict of interest.

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