Identification of Paddy Blast Disease Field Images Using Multi-layer CNN Models

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Abstract

Farmers and agricultural experts can take action on many areas of paddy crop handling and management practices with the use of actionable information from the in-field diagnosis of paddy blast disease. To successfully diagnose the blast disease affecting fifteen different paddy crop varieties, three transfer learning multi-layer convolutional neural network (CNN) models, such as, CapsNet, EfficientNet-B7, and ResNet-50 are presented in this paper. The field images of blast disease are captured and classified based on disease severity levels, such as low, medium, high, and severe. The study employing the CapsNet model with dataset consisting a total of 20,000 labeled images demonstrate the significant results with the testing efficiency of 90.79% and validation efficiency of 93.29%. The ResNet-50 and EfficientNet-B7 models have yielded the average testing efficiencies of 85.10% and 88.72%, respectively. On the held out blast disease affected paddy field image dataset, the CapsNet model outperformed the EfficientNet-B7 and ResNet-50 CNN models related to both classification efficiency and computational efficiency.

1. Introduction

More than half of the world's population relies on paddy (Oryza sativa L.) as a staple diet. Paddy farming is very common in India, and farmers are easily implementing the technique and getting a good result. In an irrigated ecosystem, paddy is mainly affected by the prevalence of diseases, and high fertility levels have a significant impact on crop yield. Paddy crop suffers from many biotic and abiotic stresses [Anami et al., 2020]. Paddy crop is subjected to attack of many diseases including fungal, bacterial, nematodes, and viral diseases. Fungal diseases like, brownspot(Helminthos porium oryzae), sheathblight(Rhizoctoniasolani), blast (Pyriculariaoryzae), narrow leaf spot(Cercospora oryzae), leaf scald (Microdochium oryzae), sheath rot(Sarocladium oryzae), bakanae disease or foot rot(Gibberella fujikuroi), udabatta disease(Balansia oryzae) and leaf smut(Entyloma oryzae) bacterial diseases, such as bacterial leaf streak(Xanthomonas oryzae pv. oryzicola) and bacterial leaf blight(Xanthomonas oryzae pv. oryzae) are of economic importance. Viral disease, such as paddy tungro disease(Paddy tungro spherical virus and Paddy tungro bacilliform virus) is more common and destructive under Indian condition. There is an urgent need to address the early detection of paddy diseases considering the expansion of the paddy field in India, where the farming community almost entirely depends on this essential food crop [Yakkundimath et al., 2022]. Information on paddy disease incidence, resistance cultivars, and field-based disease management is very scarce.

Artificial intelligence in the form of deep neural networks has flourished in the past few years and applications based have become a part of our day-to-day life. AI-based deep learning is currently been extensively accomplished research area and successfully applied in numerous applications including image processing, natural language processing, speech processing, computer vision, etc. Deep learning models achieved comparable results and outperformed human experts in agricultural, industrial, automobile sectors in image analysis and object recognition. Deep learning, also referred to as deep structured learning is a class of machine learning algorithms that uses multiple layers to extract highlevel features from the network for pattern recognition and classification, which is primarily responsible for the development of effective methodologies and the need for powerful computing facilities.

Numerous contemporary agricultural applications are the result of significant advancements in machine learning. The early stages of disease symptoms are used to detect plant pathogens using machine learning techniques. Designing a machine vision system that can identify and discriminate real-time images from the outside world is always a challenge. One of the applications taken into account in the current work is the processing of images of diseases affecting paddy crops. Blast is one of the rice diseases that spreads most in the field and has the most impact on global paddy productivity and quality. Under favorable conditions, the blast disease can results in total crop failure. Hence, the authors of this work conceived an idea of identification of blast disease affected paddy field more specifically. In this direction, literature survey has been done to learn about cutting-edge technological applications in the core research topic.

Using field images, techniques are suggested by [Anami et al., 2020] for the automated biotic and abiotic paddy crop stress classification. The approach uses deep convolutional neural network (DCNN) framework. An average efficiency of 92.89% is achieved by the framework, which is tested on 30,000 images of five distinct paddy crop varieties taken in the field under 12 different stress categories (including healthy/normal). Many image processing algorithms are presented in [Barbedo, 2013] for automatically classifying, identifying, and quantifying plant disease severity. These techniques are expected to be helpful for researchers by giving a comprehensive review of vegetable pathology and automatically detecting plant diseases using pattern recognition algorithms. CNN method is employed for classification of milled rice grains [Bhupendra et al., 2022] using high-magnification images of damaged rice refractions. To enable damage classification of milled rice grains obtained through on-field collection, five different cutting-edge memory-efficient DCNN models are adopted and fine-tuned. It is reported that in case of EffcientNet-B0, the classification score of 98.37% is achieved in small prediction time of 0.122s. CNN models designed for automatic sound detection and recognition using simple leaves images of normal and diseased plants [Ferentinos, 2018]. An open database of 87,848 images, consisting of 25 different plants in a set of 58 different classes, is used to train deep learning models, namely, GoogLeNet, Overfeat, AlexNet, VGG, and AlexNetOWTBn. It is shown that a best recognition rate of 99.53% is achieved. The classification of diseases in rice leaf images is demonstrated in [Krishnamoorthy, 2021]. The proposed approach optimizes parameters with transfer learning approach for the classification task. The InceptionResNetV2 achieved 95.67%% classification accuracy. In [Malvade et.al., 2022], presented an automated detection method for categorizing biotic stresses on paddy crops from the field images using CNN models. The proposed work provides an empirical evaluation of the top CNN models using transfer learning from ImageNet weights, namely, VGG-16, DenseNet-121, Inception-V3, ResNet-50, and MobileNet-28. The best classification accuracy of 92.61% is reported using ResNet-50. A multi-scale feature extraction method is applied in [Meng et al., 2021] to improve the identification efficiency of rice diseases. The technique uses the features based on multi-scale stacked autoencoder (MSSAE). An overall classification accuracy of 95% resulted for proposed MSSAE model. Deep-CNN transfer learning-based model developed for classification of rice leaf disease can be found in [Latif et al., 2022]. A modified VGG19-based transfer learning algorithm can accurately classify six distinct rice diseases. A classification efficiency of 96.08% is achieved using the non-normalized augmented dataset. Several machine learning tools methods are discussed in [Singh et al., 2016], for vehicular classification based on plant stress phenotyping and plant breeding activities, such as identification, classification, quantification and prediction. Automated disease symptoms categorization using rice plant images has been proposed in [Yakkundimath et. al., 2022]. The method uses pre-trained GoogleNet and VGG-16 CNN models with 12,000 labelled images of three different rice diseases and 24 different symptoms. The results obtained are 91.28% and 92.24% for GoogleNet and VGG-16, respectively using a 3-fold cross-validation method. The problem of rice disease detection based on Fuzzy C-Means, K-Means and Faster Region based-CNN fusion is discussed by [Zhou et al., 2019]. Several issues with the rice disease images have been resolved, including blurred image edges, significant background interference, noise, and low detection accuracy. The best classification efficiency of 97.2% is reported using Faster Region based-CNN algorithm.

The literature survey has revealed that deep learning algorithms and architectures are powerful and widely used in the identification of paddy diseases. And much of their success comes from a change in the design of neural network architecture with a progressive increase in the number of layers. To the best of our knowledge, it is observed that no considerable work has been reported in the literature on the development of deep learning models for identification of blast disease affecting paddy using in-field images. It has been also observed that identification of blast disease severity of an affected paddy crop using field images is not attempted to the best of knowledge. Hence, authors have worked in this direction and proposed certain methodologies. The paper is divided in four sections. Section 2 discusses the method proposed, image dataset preparation, and introduces the considered deep learning techniques. Section 3 provides experimental findings as well as a discussion of the efficiency of the deep learning techniques under consideration. Finally, the conclusion with further research aims is presented in Section 4.

2. Proposed Methodology

The proposed work is an extension of work originally presented [Malvade et al., 2022]. The aim of the present work is to implement blast disease severity of an affected paddy crop using field images with deep learning techniques, namely, convolutional neural network. Early identification of blast disease signs and symptoms is done to classify the levels of disease severity. The proposed method comprises of two stages. In the first stage, image dataset preparation is done and in the second stage DCNN is used for the classification of blast disease severity levels. An overview of the proposed work adopted is shown in Fig. 1.

2.1 Image dataset preparation

The dataset of in-field images of blast disease affected is created by capturing the images from paddy crop varieties, namely, Abhilasha, Bhagyajyothi, Budda, Intan, Jaya, Jayashree, Mugad Dodiga, Mugad

Suganda, MGD-101, SIRI-1253, PSB-68, Rajkaima, Redjyothi, MTU-1001, and MTU-1010. Using a Nikon D3300 digital SLR camera with 24 megapixel resolution, a total of 3,987 blast affected images with a resolution of 4624×3472 are obtained by maintaining the focal distance of 1.0 m from each of the rice crop varieties. The camera is set on a tripod stand facing down towards the ground to provide a rigid and secure base as well as ease of movement. The object's axis is held at a 45^0 degree angle with the camera lens. Near solar noon, the images are captured in the paddy fields with natural light [Malvade et al., 2022].

The blast disease identities are confirmed by the experts. Each image in the created image dataset is associated with an expert marked label indicating blast disease. The blast disease present is categorized into various disease severity levels such as low, medium, high, and severe [Chung et al., 2022]. A general view of the studied blast affected paddy field crops based on disease severity levels is shown in Fig. 2.

Using various image augmentation techniques, such as shear transform, random rescaling horizontal flip, and vertical flip, the initial field image dataset of 3,987 images is increased to 20,000 labelled images considering 5,000 images into account per blast disease severity levels, such as low, medium, high, and severe. All of the augmented images differ significantly from the originals.

2.2 Architecture and configuration of DCNN models

The present work has selected three different popular DCNN architectures that are widely used for computer vision applications, namely, ResNet-50, EfficientNet-B7, and CapsNet. DCNN receives the augmented raw images as input, and from the images, features are extracted that are used to train the classifier. The input layer, convolution layer, rectified linear unit (ReLU) layer, max-pooling layer, and fully connected layer or output layer constitute the convolutional neural network architecture. The network is tuned using stochastic gradient descent (SGD) algorithm to minimize the loss function. The efficacy of the test dataset and cross-entropy loss is used to evaluate the CNN models. [Yakkundimath et.al., 2022]. All the model implementations are based on the open source deep learning framework Keras. All the experiments are conducted on an Ubuntu Linux server with a 3.40 GHz i7-3770 CPU (16 GB memory) and a GTX 1070 GPU (8 GB memory). To assess the prediction efficiency of the individual DCNN model, the enhanced image dataset is divided into 80% training set (4,000 images per blast disease severity) and 20% testing set (1,000 images per blast disease severity). The validation set is made up of 10% of the training dataset. The classification efficiency of pre-trained ResNet-50, EfficientNet-B7, and CapsNet CNN models is computed using Expression. (1) & (2). The DCCN classification methodology based on transfer learning adopted is given in Algorithm 1.

$$\text{Classification efficiency (\%)} = \frac{\text{Correctly classified sample images}}{\text{Total sample images for testing}} \times 100 \qquad (1)$$

$$\text{Average classification efficiency (\%)} = \frac{\text{Classified correctly sum of sample images}}{\text{Total sample images}} \times 100 \qquad (2)$$

Algorithm 1 DCNN classification of blast disease severity

Description: Features are extracted from the augmented raw images that are given as input to the algorithm. The significant features are computed using base layers and upper layers to classify the images. Finally, the algorithm returns the consolidated confusion matrix of classification. The consolidated confusion matrix includes the performance of classification for test image data set.

Parameters : ε: epochs, ξ: Iteration step, β: batch size; η: CNN learning rate; w: ImageNet weights, n: number of training examples for every iteration, $P\left(x_i = k\right)$: probability of input x_i associated to the predicted k^{th} class, k: classes index.

// Input: X_{train}: Paddy blast disease training dataset, X_{test}: Paddy blast disease testing dataset.

// Output: Consolidated assessment metrics corresponding to the classification performance.

Step 1. Prepare the labeled datasets sets for training, validation and testing, by randomly selecting the samples.

Step 2. Set CNN models (ResNet-50, EfficientNet-B7, CapsNet) base layers i.e., input layer, hidden layer, and output layer.

Step 3. Set CNN models (ResNet-50, EfficientNet-B7, CapsNet) upper layers i.e., convolution, pooling, flatten, and dropout layers.

Step 4. Set parameters: ε, β, η.

Step 5: Assign network weights (w_1, w2,….w_n) & upload the pre-trained CNN.

Step 6: Set the network parameters and determine weights.

Step 7: Train the CNN and compute the initial weights

for ξ = 1 to ε do

Select randomly mini-batch from (size: β) from X_{train}

Forward propagation and compute loss (E) using Expression. (3).

$$\mathrm{E}\left(\mathrm{W}\right) = -\frac{1}{\mathrm{n}}\sum_{\mathrm{xi}=1}^{\mathrm{n}}\sum_{\mathrm{k}=1}^{\mathrm{k}}\left[\mathrm{y_{ik}}\mathrm{logP}\left(\mathrm{x_i} = \mathrm{k}\right) + \left(1 - \mathrm{y_{ik}}\right)\log\left(1 - \mathrm{P}\left(\mathrm{x_i} = \mathrm{k}\right)\right)\right]$$

3

Back-propagation and adjust weights with SGD using Expression. (4).

$$W = W_{k-1} - (\partial E(W)/\partial W)$$

4

Update weights with adam optimizer

end

Step 8: Store calculated weights in the database.

Step 9: Using the test dataset, estimate the accuracy of the CNN models X_{test}.

Step 10: With test dataset compute model assessment metrics.

Stop.

2.2.1 ResNet-50

The transfer learned ResNet-50 model which was pre-trained on the ImageNet dataset [Kaiming et al., 2016] is adapted to classify blast affected paddy field images based on disease severity levels. The augmented images are resized to the input size 224 x 224 pixels and using 7x7 and 3x3 kernel sizes, initial convolution and max-pooling are carried out, respectively [Malvade et al., 2022]. The learning rate and the maximum number of epochs are set to 0.0001 and 40, respectively, in the network tuning parameters. The batch size for the network is set to 32. The network is trained using Adam optimizer.

2.2.2 EfficientNet-B7

EfficientNet is a highly potential and light weight CNN model which has shown an overwhelming performance in classifying images on ImageNet, CIFAR-100, and other

image datasets [Tan and Le, 2019]. The model is also considered as a good model for transfer

learning. Considering the image resolution, the present work has adapted EfficientNet-B7

variant which is built for ImageNet dataset classification. The model is initialized with pre-

trained ImageNet weights and it is fine-tuned on the dataset prepared [Malvade et al., 2022]. To train the model, the parameters, such as batch size, epochs, and learning rate are set to 32, 40, and 0.0001, respectively. The dropout rate is set to its default value i.e., 0.2. The augmented images are resized to the input size 224×224 pixels. The network is trained using Adam optimizer.

2.2.3 CapsNet

CapsNet is a new type of ANN architecture based on the concept of capsules [Sabour et al., 2017]. A capsule is a small group of neurons and the activity of each neuron in a group is to determine the features of a component in an image, such as position, size, and hue. Each capsule has a single component to classify. There two categories of capsules, such as primary and parent capsules. The primary capsules are present in input layer and the parent capsules are present in higher layers of CNN. The information from primary capsules is supplied to the parent capsules that agree with its prediction based on the routing-by-agreement concept. The CapsNet retains within an image the position and orientation of each component in contrast to conventional CNNs [Malvade et al., 2022]. The implementation of CapsNet architecture is based on [Sabour et al., 2017] research paper and deployed it in the same way for all the experiments. The images are scaled down to 224x224 pixels. The network is trained using Adam optimizer with initial learning rate of 0.0001, maximum epochs of 40, and batch size of 32.

3. Results And Discussion Of Classification

The experiments are carried out with three deep-learning network models including ResNet-50, EfficientNet-B7, and CapsNet. The models are optimized to make them compatible with the constructed image dataset and improve their performance. Separate training and testing have been conducted on each model. The plot of training and validation efficiency curves of ResNet-50 model is shown in Fig. 3.

The plot of training and validation loss curves of ResNet-50 is shown in Fig. 4.

The training score statistics of ResNet-50 derived from Figs. 3 & 4 are depicted in Table 1. From Table 1, it is observed that the ResNet-50 model has reached highest training efficiency and highest validation efficiency of 91.63% and 83.56%, respectively for 40 epochs.

Table 1
Training and validation efficiency/loss for ResNet-50 Model

Epoch	Time Elapsed (hh:mm:ss)	Training Efficiency	Training Loss	Validation Efficiency	Validation Loss	Base Learning Rate
1	00:45:35	0.7197862971	2.76	0.52693929	1.28	1.00E-04
10	00:48:46	0.8434515118	1.23	0.73456452	1.12	1.00E-04
20	00:53:12	0.8115117624	1.12	0.74233584	1.12	1.00E-04
30	00:58:34	0.9100000000	1.17	0.81546456	0.78	1.00E-04
40	00:58:27	0.9163385262	1.01	0.83560516	0.79	1.00E-04

The plot of training and validation efficiency curves of EfficientNet-B7 model is shown in Fig. 5.

The plot of training and validation loss curves of EfficientNet-B7 model is shown in Fig. 6.

The training score statistics of EfficientNet-B7 derived from Figs. 5 & 6 are depicted in Table 2. From Table 2, it is observed that the EfficientNet-B7 model has reached highest training efficiency and highest validation efficiency of 92.66% and 89.62%, respectively for 40 epochs.

Table 2
Training and validation efficiency/loss for EfficientNet –B7 Model

Epoch	**Time Elapsed (hh:mm:ss)**	**Training Efficiency**	**Training Loss**	**Validation Efficiency**	**Validation Loss**	**Base Learning Rate**
1	01:05:34	0.48132949854	0.4825	0.39542162133	0.312086	1.00E-04
10	01:08:06	0.51688109030	0.179242	0.40731177587	0.212441	1.00E-04
20	01:02:27	0.61187772239	0.80507	0.52187772239	0.46368	1.00E-04
30	01:08:56	0.83906733576	0.23358	0.65906733576	0.258509	1.00E-04
40	01:06:29	0.92666237412	0.151176	0.89625694912	0.230446	1.00E-04

The plot of training and validation efficiency curve of CapsNet model is shown in Fig. 7.

The plot of training and validation loss curve of CapsNet model is shown in Fig. 8.

The training score statistics of CapsNet derived from Figs. 7 & 8 are depicted in Table 3. From Table 3, it is observed that the CapsNet-B7 model has reached highest training efficiency and highest validation efficiency of 95.62% and 93.29%, respectively for 40 epochs.

Table 3
Training and validation accuracy/loss for CapsNet Model

Epoch	**Time Elapsed (hh:mm:ss)**	**Training Efficiency**	**Training Loss**	**Validation Efficiency**	**Validation Loss**	**Base Learning Rate**
1	01:33:11	0.6754216213295	0.405578	0.46542162132	0.290146	1.00E-04
10	01:30:26	0.7646881090300	0.889135	0.77731177586	1.874039	1.00E-04
20	01:30:43	0.8218777223945	0.80507	0.81385639202	0.46368	1.00E-04
30	01:28:35	0.9190673357589	0.23358	0.90040100817	0.258509	1.00E-04
40	01:30:49	0.9562569491233	0.151176	0.93294562432	0.230446	1.00E-04

The training and validation performances of all the models are compared and the results are listed in Table 4. From Table 4, the highest training efficiencies of 91.63%, 92.66%, and 95.62% are obtained from the ResNet-50, EfficientNet-B7, and CapsNet models, respectively and the highest validation efficiencies of 83.56%, 89.62%, and 93.29% are obtained from the ResNet-50, EfficientNet-B7, and CapsNet models For the all the training methods, the CapsNet model has shown very high efficiency on the training and validation dataset.

Table 4
Comparison of training and validation performance results from the different DCNN models

Sl. No.	DCNN Model	Image Size	Training Time (hh:mm:ss)	Training (%)	Validation Efficiency(%)
1	ResNet-50	224 × 224 pixels	00:58:27	91.63	83.56
2	Efficient-B7	224 × 224 pixels	01:06:29	92.66	89.62
3	CapsNet	224 × 224 pixels	01:30:49	95.62	93.29

Further, the performance of the ResNet-50, Efficient-B7, and CapsNet models are evaluated using the test image dataset and the confusion matrices are plotted for the test results as shown in Figs. 9, 10, and 11.

From the confusion matrices, the performance metrics, such as precision, recall, and F1-score are computed for ResNet-50, Efficient-B7, and CapsNet models and listed in Table 5, 6, and 7.

Table 5
Performance metrics for blast disease severity identification using the ResNet-50 CNN model

Sl. No.	Blast disease severity	Evaluation Parameters		
		Precision (%)	Recall (%)	F1 Score (%)
1	Low	82.94	83.60	83.27
2	Medium	78.52	84.80	81.54
3	High	85.60	83.20	84.38
4	Severe	94.47	88.80	91.55
Average (%)		**85.38**	**85.10**	**85.18**

Table 6
Performance metrics for blast disease severity identification using the EfficientNet-B7 CNN model

Sl. No.	Blast disease severity	Evaluation Parameters		
		Precision (%)	Recall (%)	F1 Score (%)
1	Low	84.25	85.60	84.92
2	Medium	82.54	83.20	82.87
3	High	90.51	90.87	90.69
4	Severe	96.71	94.00	95.33
Average (%)		**88.50**	**88.41**	**88.45**

Table 7
Performance metrics for blast disease severity identification using the CapsNet CNN model

Sl. No.	Blast disease severity	Evaluation Parameters		
		Precision (%)	Recall (%)	F1 Score (%)
1	Low	86.15	89.60	87.84
2	Medium	90.42	86.80	88.57
3	High	91.60	91.60	91.60
4	Severe	95.20	95.20	95.20
Average (%)		**90.84**	**90.80**	**90.80**

The graphical representation of paddy blast disease identification results based on severity levels using the ResNet-50, Efficient-B7, and CapsNet models is shown in Fig. 12. From Fig. 12, the highest and lowest classification efficiencies of 95.30% and 83.20% are obtained for severe blast affected paddy field using CapsNet model and medium blast affected paddy field using Efficient-B7, respectively.

In Table 8, the summary of the test results derived from Fig. 12 and Table 5, 6, & 7 are depicted and compared. From Table 8, it is observed that the CapsNet model has higher potential than the ResNet-50 and EfficientNet-B7 models in predicting the paddy blast disease severity from the field images with the highest average blast disease severity identification efficiency of 90.79%. The test findings show that the ResNet-50 and EfficientNet-B7 models have given almost comparable performances with the average blast disease severity identification efficiencies of 85.10% and 88.72%, respectively.

Table 8
Comparison of testing performance results from the different DCNN models

Sl. No.	DCNN Model	Image Size	Classification Accuracy (%)
1	ResNet-50	224 × 224 pixels	85.10
2	Efficient-B7	224 × 224 pixels	88.72
3	CapsNet	224 × 224 pixels	90.79

4. Conclusion

Leading pre-trained deep learning convolutional neural network models have been used to identify the severity of blast disease affecting rice crops using field images. The performance of the CapsNet model is estimated and compared with the EfficientNet-B7 and ResNet-50 models. The CapsNet model outperformed the EfficientNet-B7 and ResNet-50 models on the augmented paddy blast disease image dataset in terms of both efficiency and computational efficiency. However, the work was not extended due to the limitations of the computational resources. The proper tuning of hyperparameters in the models and increasing the input image dimensions will probably improve the performance of CapsNet model. There is a scope for deploying other popular models, such as GoogleNet, NasNet-Large, Inception-V3, etc. Further, the scope exists for extending the current paddy blast disease image dataset identification using drone images.

Declarations

Credit authorship contribution statement

Dr. Rajesh Yakkundimath: Data collection, Methodology, Conceptualization, Writing, Reviewing & Editing.
Mr. Girish Saunshi: Data Creation, Visualization, Software, Validation

Ethical responsibilities of authors

All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of authors” as found in the Instructions for Authors.

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Conflict of interest

The corresponding author certifies that none of the other authors have any competing interests.

Data availability

Dataset associated with this article are available at https://www.kaggle.com/datasets/girishkleit/paddy-infield-images

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Figures

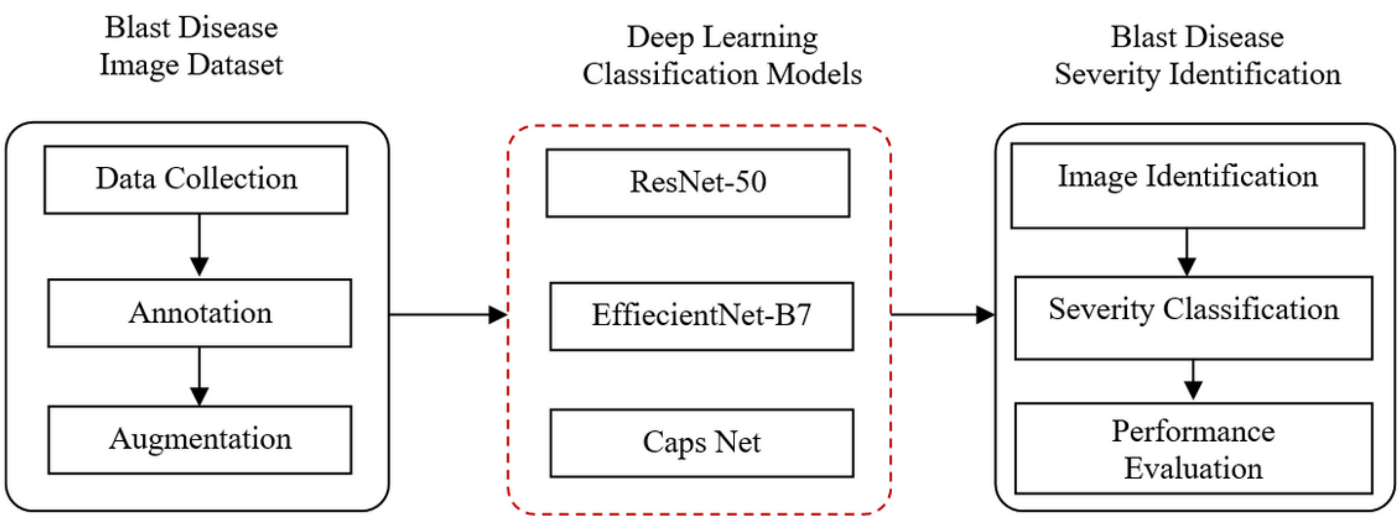

Figure 1

Schematic overview of the proposed method

Figure 2

Field crop images of blast affecting paddy crop

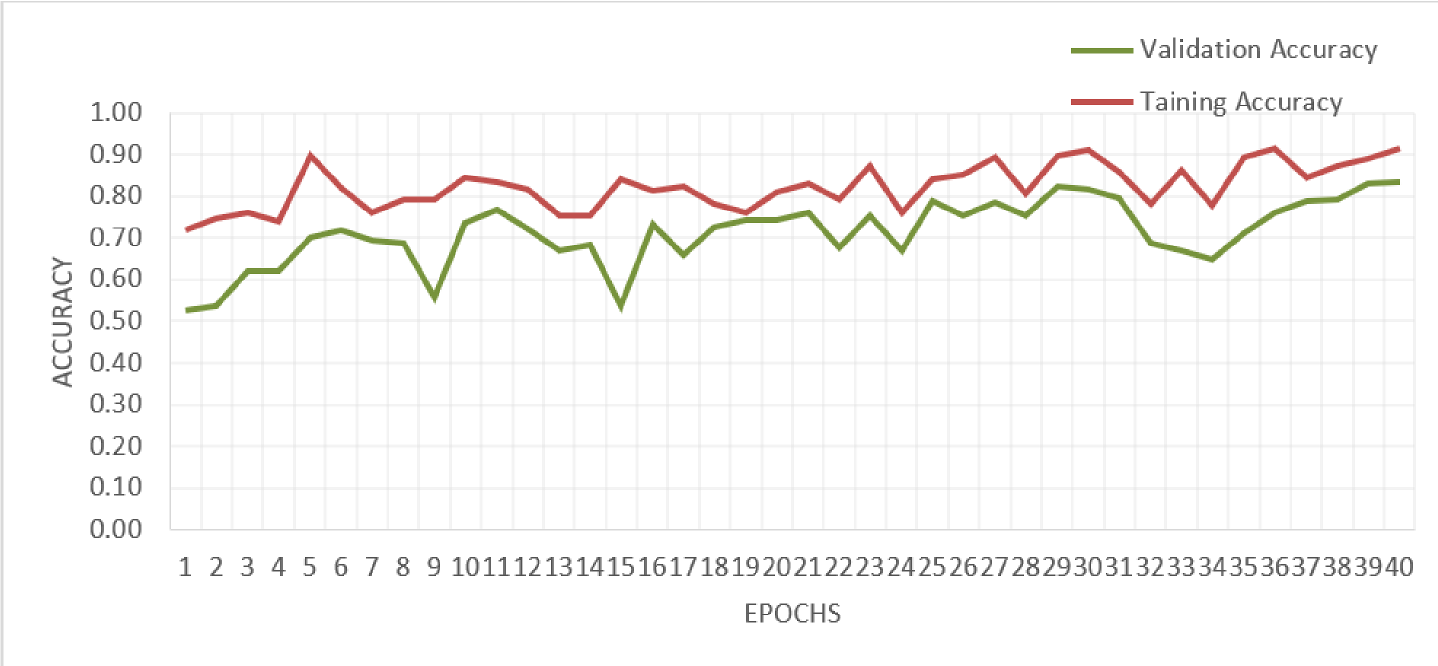

Figure 3

Training and validation efficiency curve for ResNet-50 CNN model

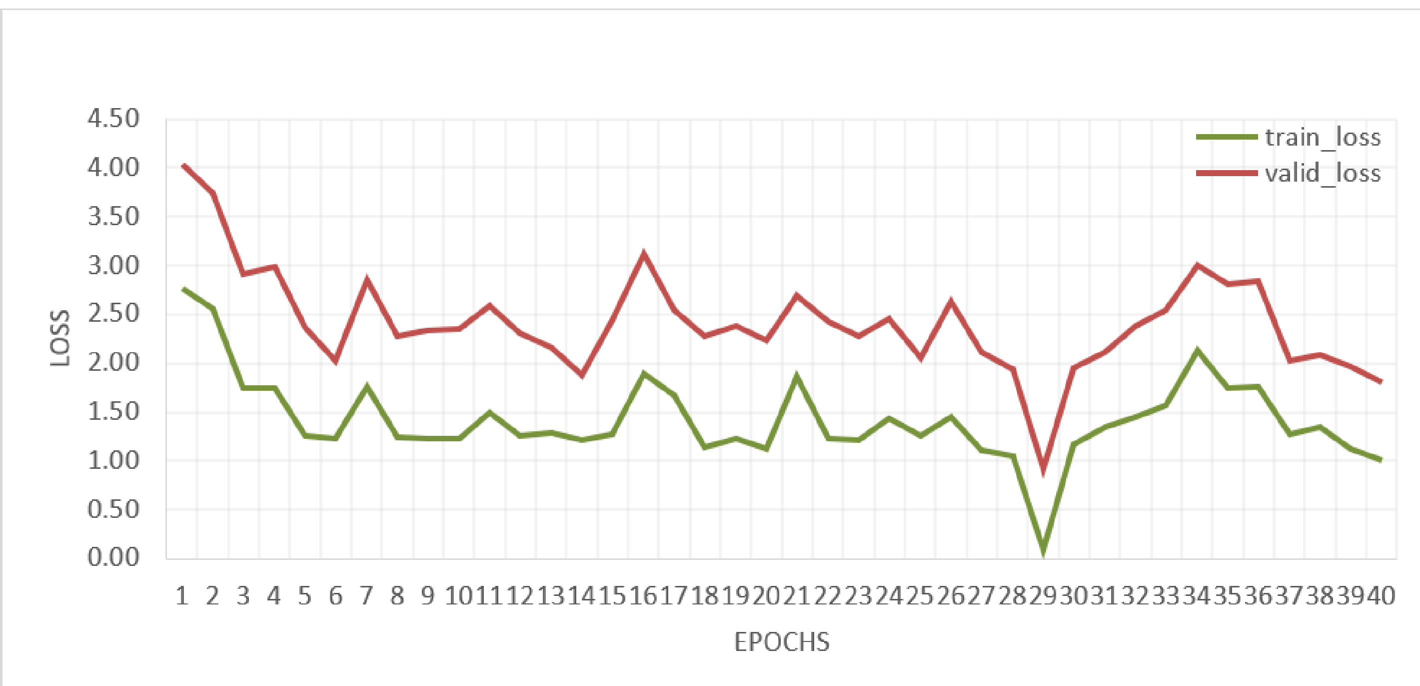

Figure 4

Training and validation loss curve for ResNet-50 CNN model

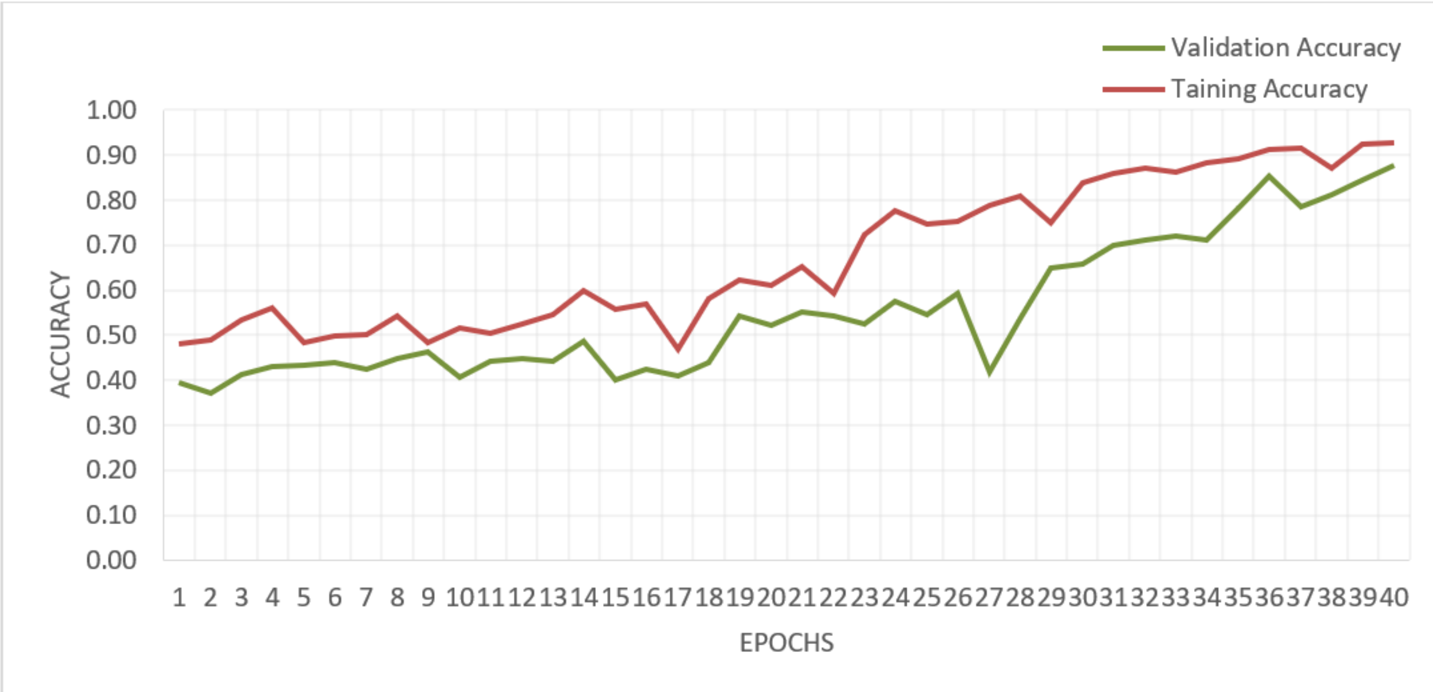

Figure 5

Training and validation efficiency curve for EfficientNet-B7 CNN model

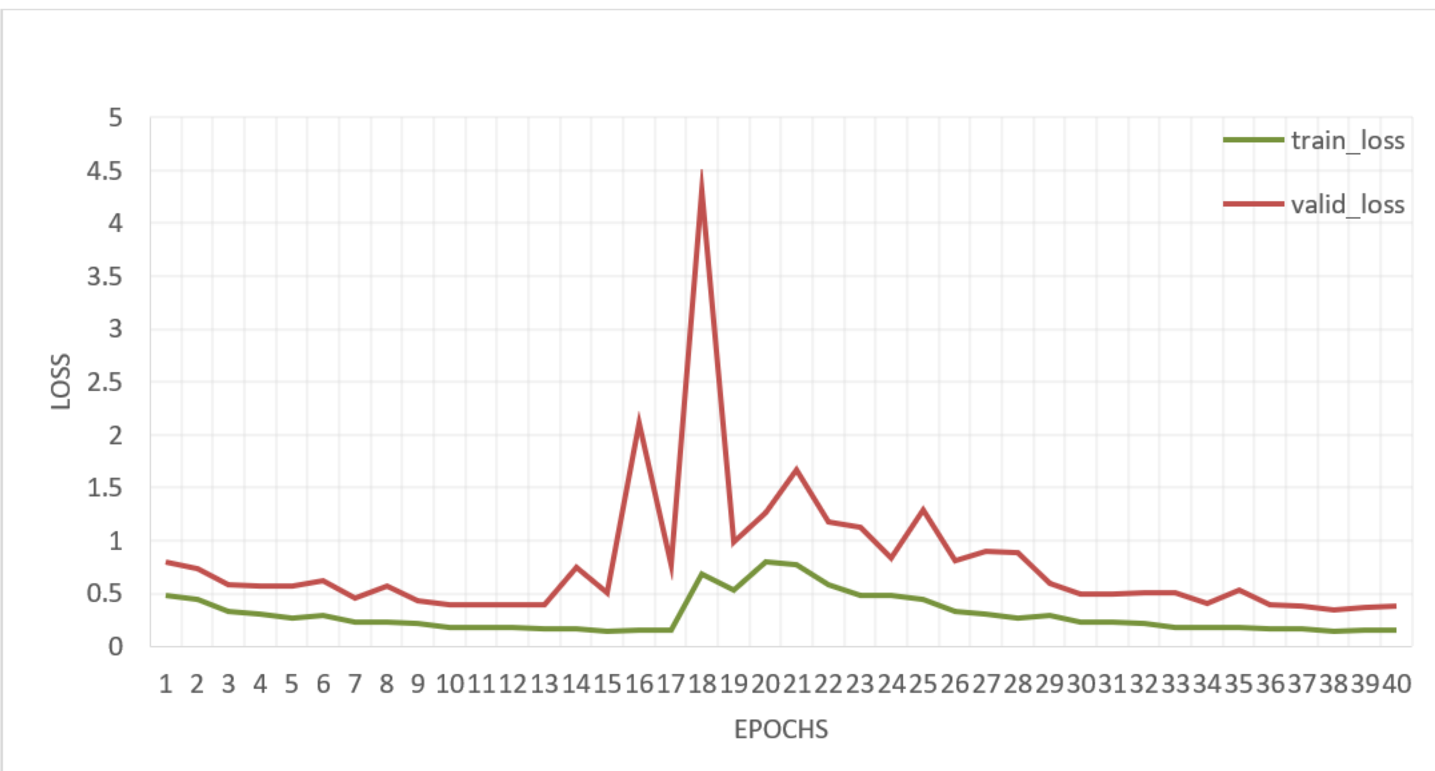

Figure 6

Training and validation loss curve for EfficientNet-B7 CNN model

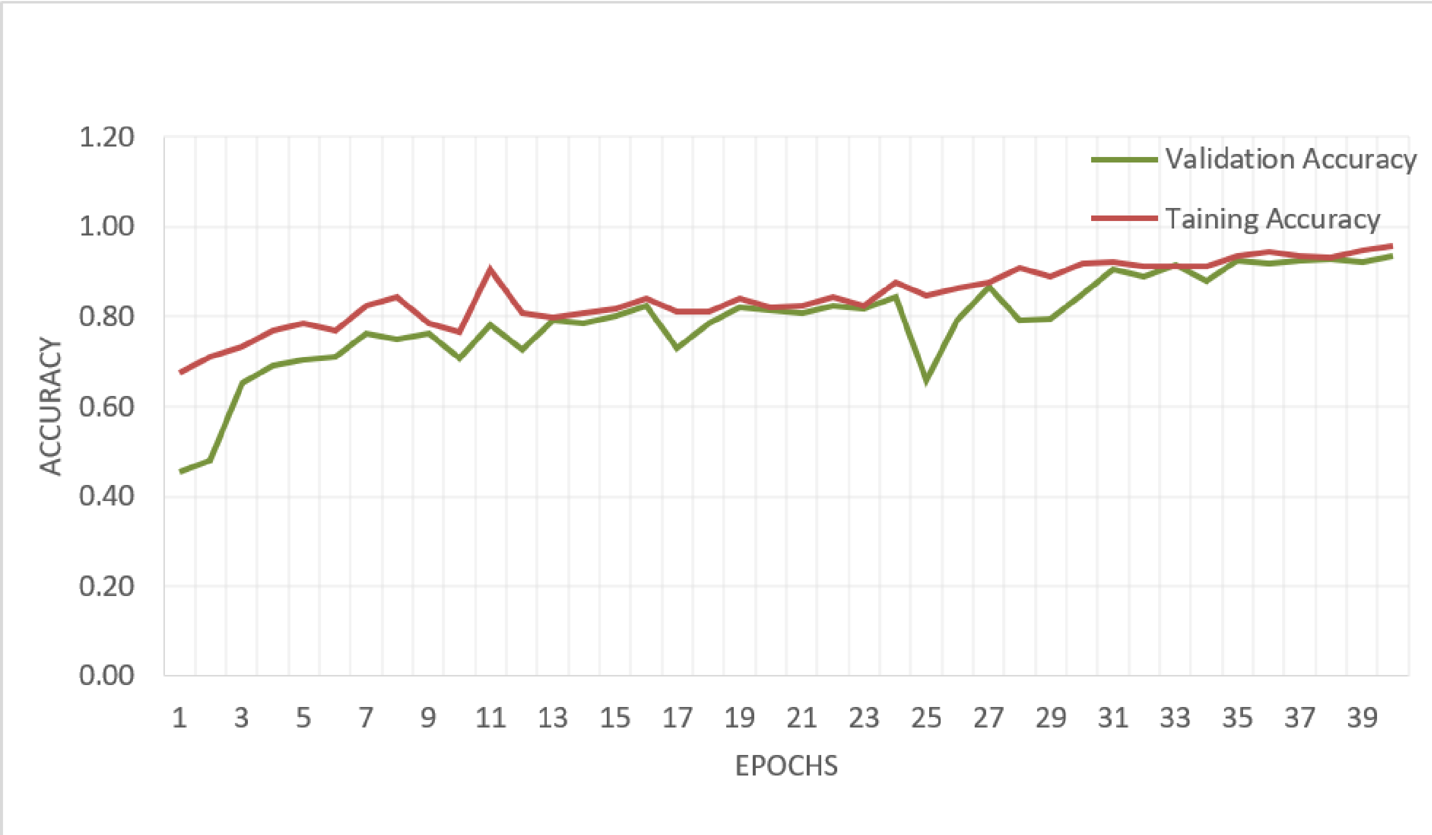

Figure 7

Training and validation efficiency curve for CapsNet CNN model

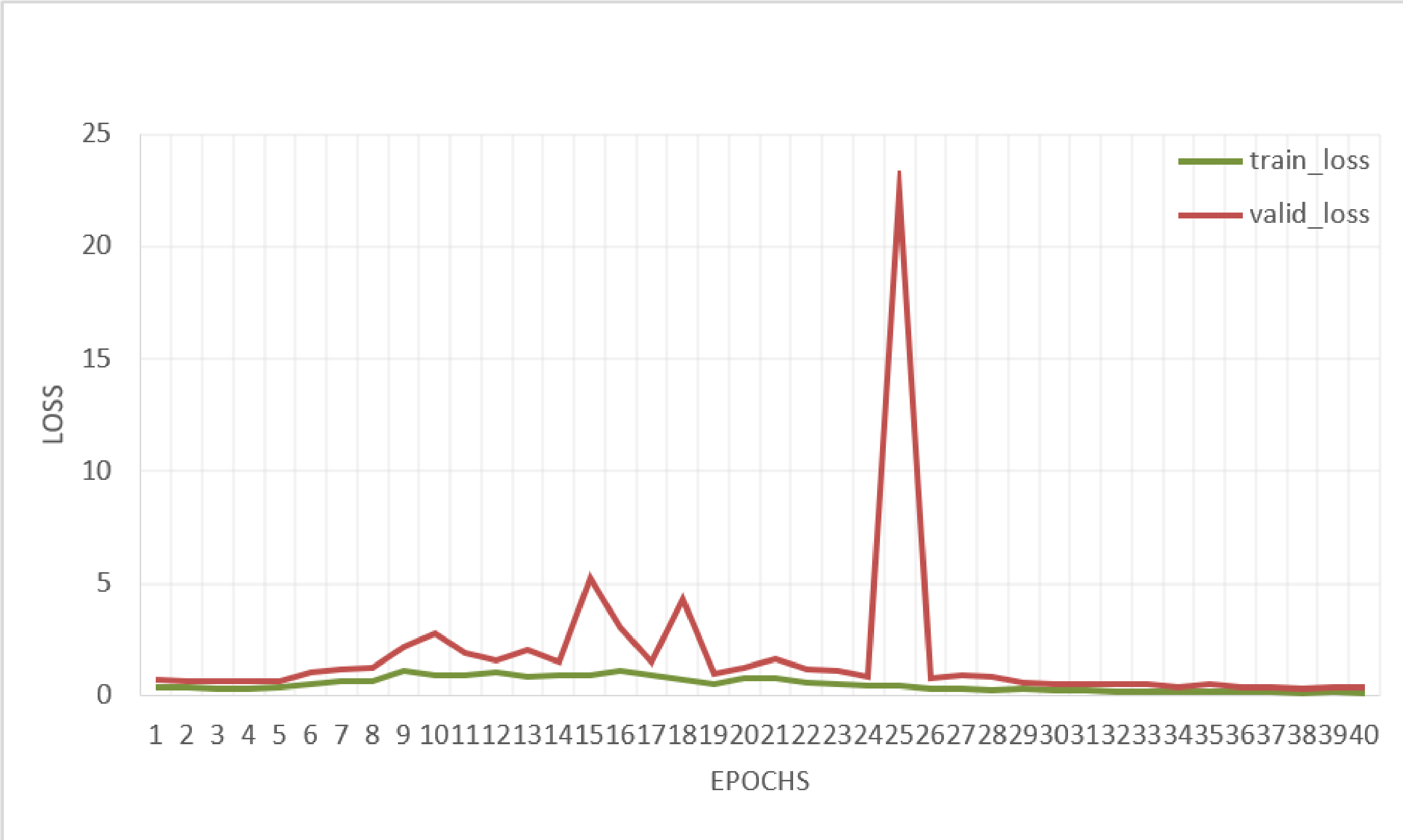

Figure 8

Training and validation loss curve for CapsNet CNN model

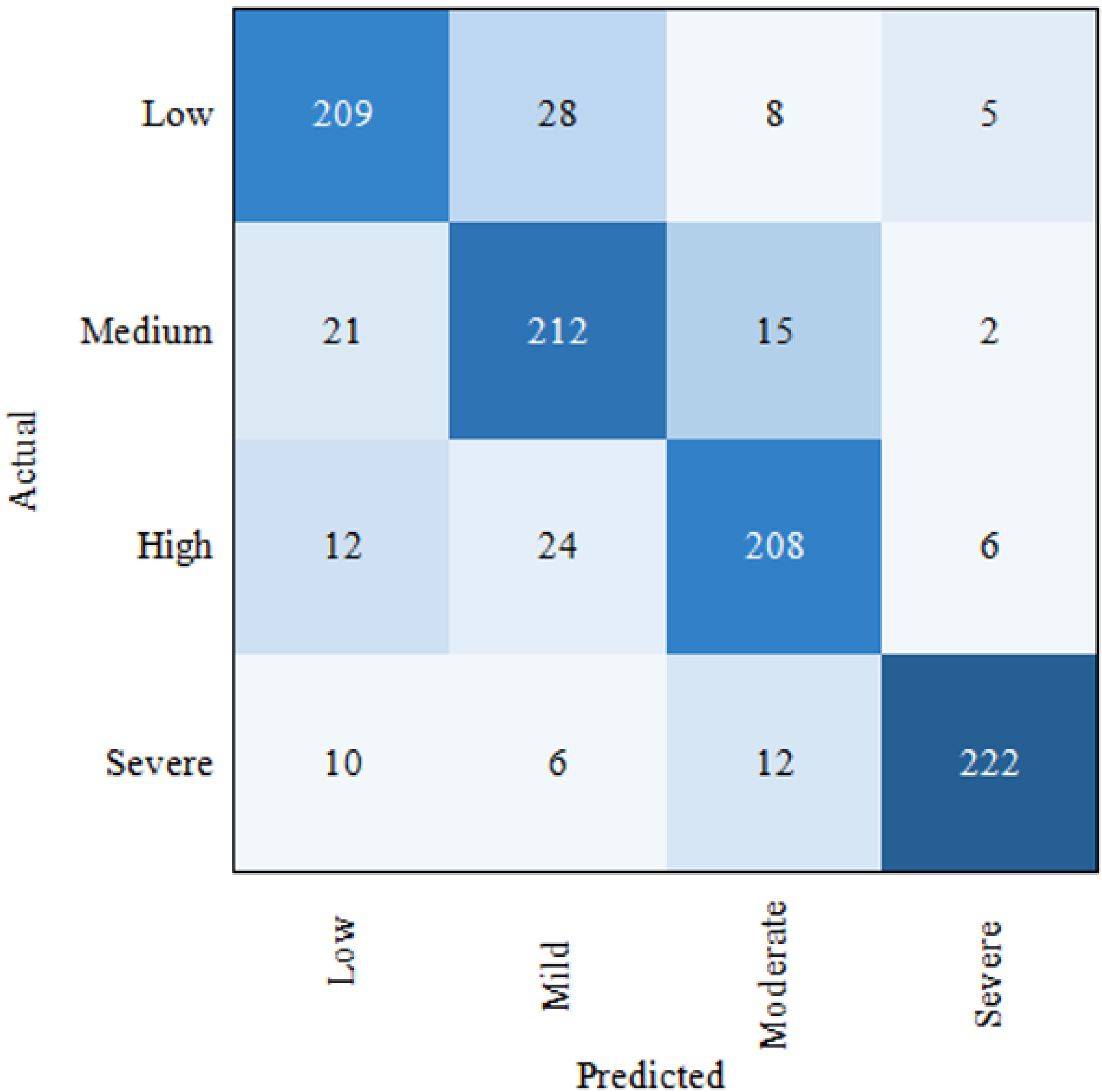

Figure 9

Confusion matrix for blast disease severity identification using the ResNet-50 CNN model

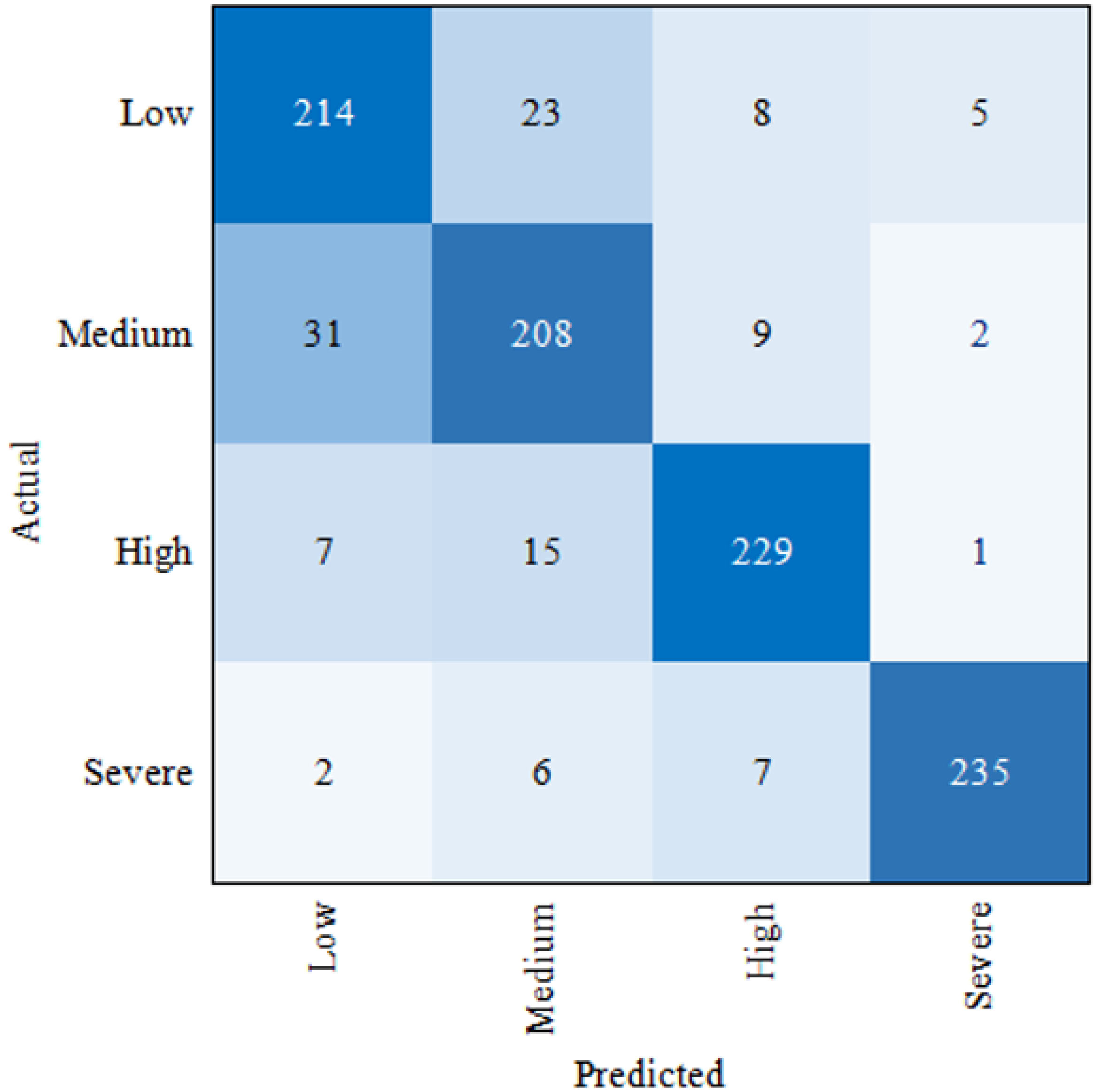

Figure 10

Confusion matrix for blast disease severity identification using the EfficientNet-B7 CNN model

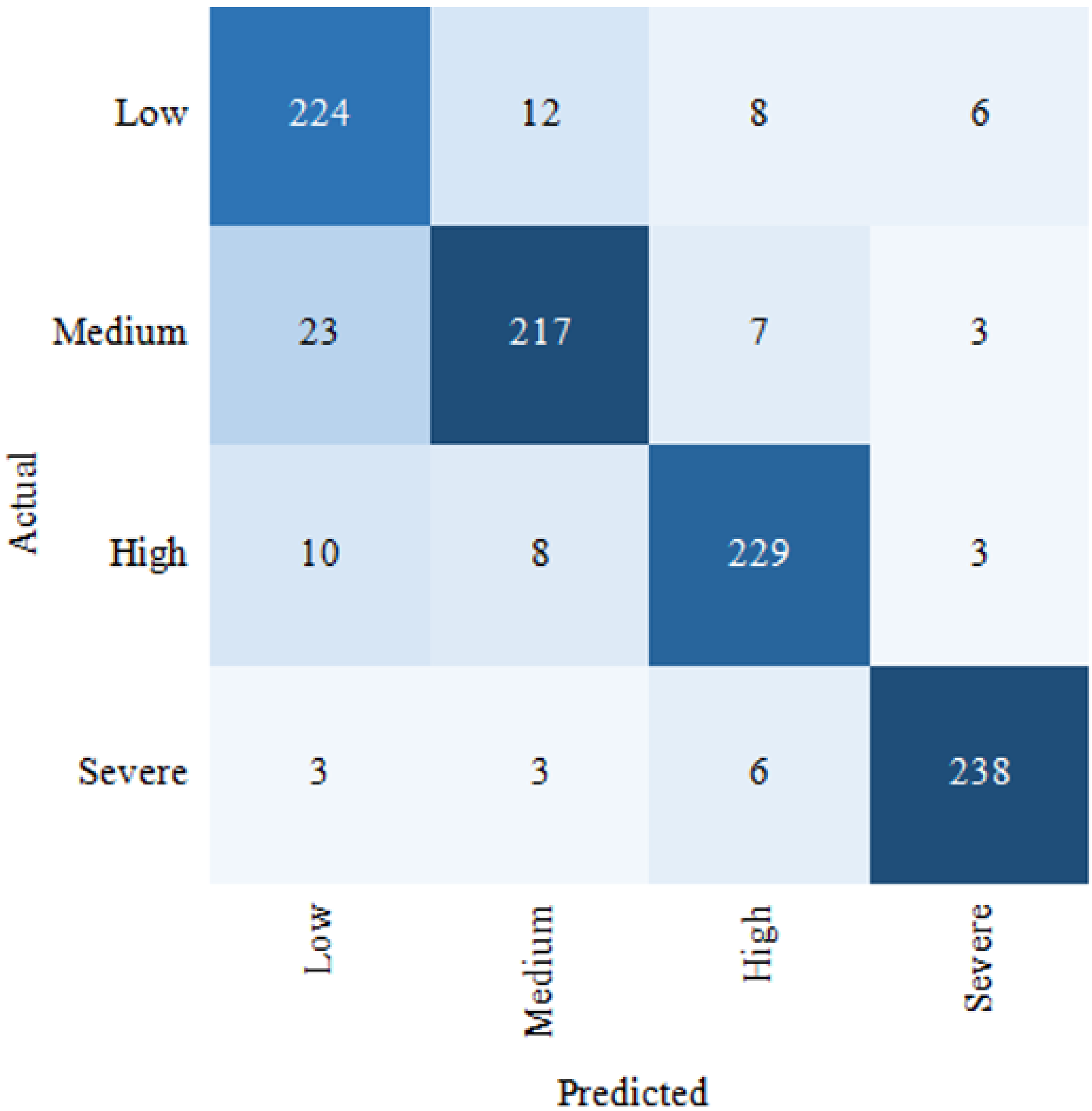

Figure 11

Confusion matrix for blast disease severity identification using the CNN CapsNet model

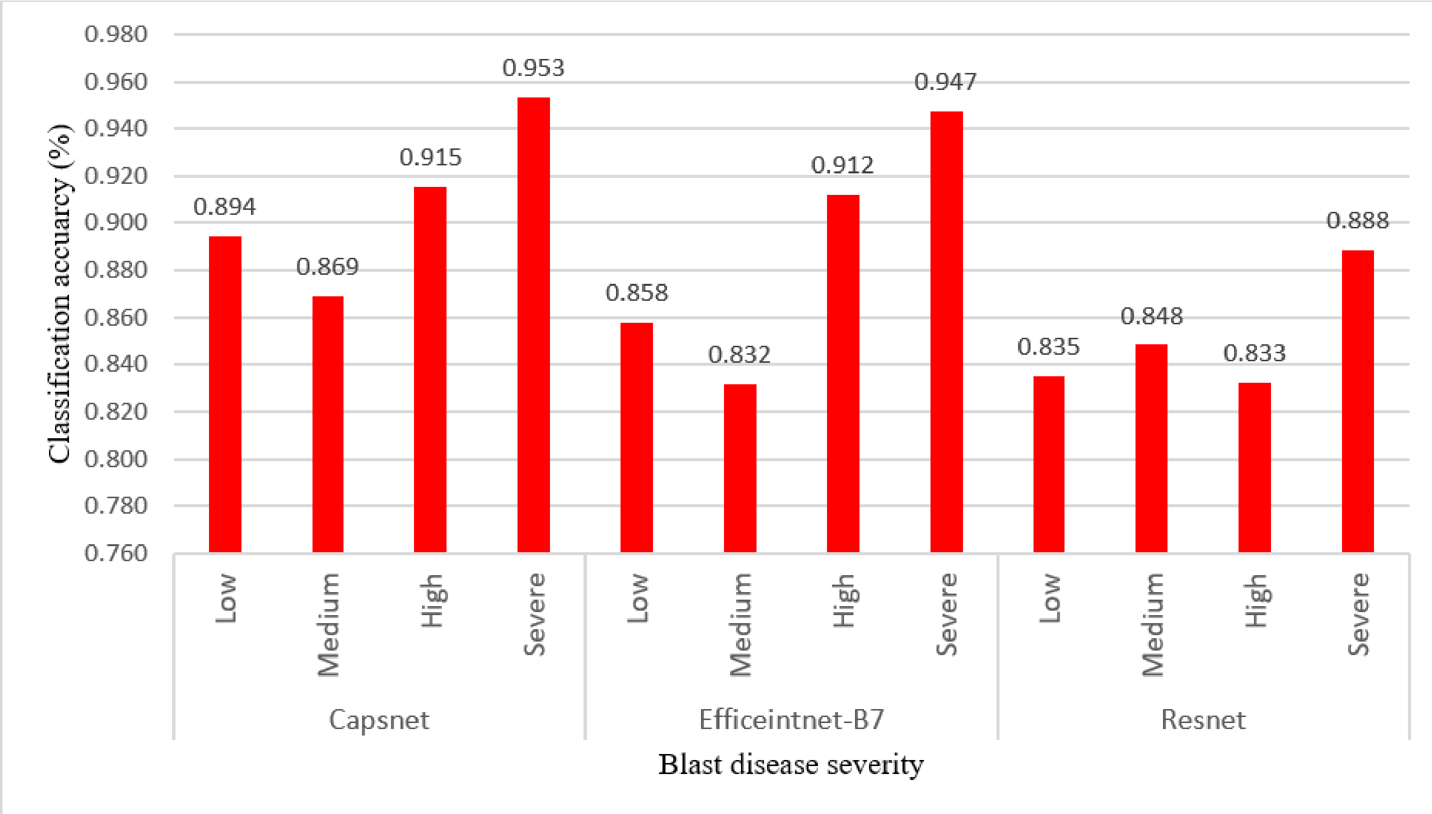

Figure 12

Blast disease severity identification efficiencies using the CNN models.