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Pest and Disease Identification in Paddy by Symptomatic Assessment of The Leaf using Hybrid CNN-LSTM Algorithm

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Abstract: The crop damage is caused by various types of pests that feed on the leaf, stem, roots or entire part of the plants and also by fungal, bacterial and viral infections. In most cases, the diseases are transmitted from one plant to another by vectors. The pests act as vectors in spreading most of the viral infections. It is necessary to identify the disease incidence or pest infestation in the early stages itself and contains its spread before it causes any damage to plants. Several machine and deep learning approaches are involved in rice disease and pest identification. In the preceding works Long Short-Term Memory (LSTM) and CNN algorithms respectively were used in identification and classification of the disease and pest that affects paddy. Here, a Hybrid CNN-LSTM method is applied for rice disease and pest identification using the various symptoms exhibited in paddy leaves. The accuracy of 97.8% in pest and disease identification proves the superiority of this method over the existing methods.

Keywords: Disease Classification, Hybrid CNN-LSTM, Leaf Disease Detection, Pest Identification

I. INTRODUCTION

Paddy is one among the field crops that provides a staple food for 2.7 billion people in the world. In India paddy is cultivated in over an area of 44.6 million hectares with an average production of 1855 kg/ ha. The total production in India is estimated to be 80 million tones (TNAU paddy expert system). The production of rice is limited by different factors viz., pest infestation, disease incidence, nutrient deficiency and environmental factors. Great economic loss occurs due to the above said factors. The pests are the insects, pathogens, weeds, arthropods, vertebrates, nematodes and mites which limits the productivity and profitability of crops world-wide by damaging the valuable crops either directly or indirectly. Leaf folder, stem borer, gundhi bug, thrips, leaf hopper and army worm are the major insect pests that cause major damage in paddy. 22 percent yield loss in paddy can be attributed to insect pests.

Hence in the present scenario, control or eliminate the pests through appropriate techniques is important. Bacteria, fungi and virus inflict diseases in paddy. Losses are very heavy due to diseases and even famines are reported due to severe disease incidence. Brown leaf spots, Rice tungro disease, Blast, Bacterial leaf blight, Sheath blight, Sheath rot and false smut are few of the diseases that severely affect the paddy production. Blast is one of the severe most diseases which results in 10 -30% loss of rice harvest which may be enough to feed 60 million people [1]. The famous Bengal famine during 1943 was caused by the severe outbreak of brown leaf spot. Similarly, the blast was a severe epidemic in Thanjavur the rice bowl of Tamilnadu in 1919. Tamilnadu Agriculture University (TNAU), reported an expected grain loss of 70 to 80% due to the blast disease in terms of paddy [2]. In most cases the diseases are transmitted from one plant to another by vectors. The pests act as vectors in spreading most of the viral infections. Identification of pest infestation or disease incidence at the appropriate time becomes pivotal to eliminating crop damage. Generally, diseases play spoilsport to crop production while infrastructure lacuna in early detection of diseases rubs salt to it [3]. Visual identification of the symptoms, microscopic evaluation of morphological characters of the casual organism, microbiological techniques and molecular analysis are the most common methods of disease identification [4]. In general, it takes more time and little amount of drudgery is involved for the farmers of interior areas to redress and identify diseases for non-availability of experts and even then, if experts are available there are chances of mis identification since it's done by naked eye [5]. To overcome this, an appropriate automated system is required for the diagnosis of paddy diseases. The sample pictures of rice leaves exhibiting those typical disease symptoms are given in the Fig.1 (a), Fig.1 (b) and Fig.1 (c) and those images of pest incidence are given in Fig. 2 (a), Fig.2 (b) and Fig.2 (c) Proper usage of digital image processing in the field of paddy cultivation to identify diseases is boosted in such a way that, diseases can be visually identified by considering the variations in leaf appearance and its general visual features. Hence, the imagination of the visual patterns is not a harder task to form a multivariate identity based on each leaf disease type [6]. IRRI knowledge bank data shows that almost 37% of the rice production is lost through various infections and infestations annually. If an infection or infestation is detected early it can be contained

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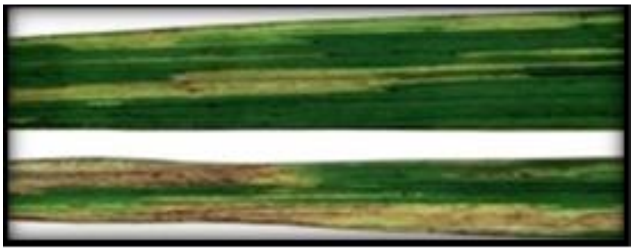

Fig.1 (a) Bacterial leaf Blight

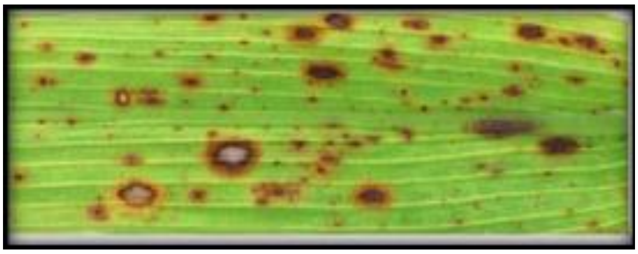

Fig.1(b)Brown Spot

Fig.1(c) Leaf Blast

Fig.2 (a) Thrips

Fig.2 (b) Army worm

Fig.2(c) Rice leaf folder

by applying proper control measures. Not only good management practices but also timely detection of pest and disease is also significant in controlling production loss [7]. Nowadays neural network almost mimics human intelligence and has become the most powerful computational tool. Researchers around the globe started using this tool in almost every problem domain. Many numbers of ideas are put forth on the application of image processing in pest and disease identification.

The present study is focused on Rice disease detection and pest identification using a Hybrid CNN-LSTM algorithm. In section II, the related work based on the disease detection and pest identification is provided. Section III deals with description of proposed methodology. While, research result and its discussion is being done in the section IV and conclusion of the study is presented in section V.

II. RELATED WORKS

A. D. Nidhis et al [8] used K means clustering to segment the input image, point feature matching techniques for disease identification and disease severity is calculated in terms of the percentage of the affected area. There is scope for developing algorithms that can increase the detection rate. Archana et al [9] apply colour transformation and K mean clustering techniques for image segmentation. The proposed method fails in clear differentiation among the diseases and can be augmented by using pigment extraction through feature analysis. K.

Ahmed et al [10] discussed the application of decision tree as it produced 97.9167% accuracy in disease detection but a small alteration in the data affects the algorithm structure resulting unstable results. S. Arivazhagan et al [11] used classification of the images by implementing minimum distance criterion and SVM algorithms, which has an overall accuracy percent of 87.66%. Although the disease can be detected early the low accuracy percentage give scope for further improvement. Piyush Chaudhary et al [12] used CIELAB colour model and OTSU algorithms for diseased spot detection and classification of the diseases is done by calculating dimensions of disease spots. The vein colours can sometime influences the result which needs to be further probed. Harshad Kumar B. Prajapathi et al [13] in their study applied K-means clustering alongside feeding intersection values for segmentation, SVN algorithm for classification of diseases and achieved 93.33 % accurate in terms of training and 73.33% accurate in testing, which provides opportunity for further enhancement of results using other algorithms. Divya Verma et al [14] used CNN technique for classifying different plant diseases. It showed an accuracy of 97% during classification but the disadvantage is, it needs a larger data set for training. K. Mythili et al [15] proposed RDA-Bi-LSTM-EERNN algorithm by alteration of Bi-LSTM-EERNN with RDA based optimizations to predict crop yield. The accuracy thus obtained is 97.6004%. The accuracy over a larger data set is yet to be proved. Norhalina Senan et al [16] in their study tried detecting and classifying the diseases of paddy using five layered CNN algorithm and got an accuracy of 93%. The images were augmented with a C++ application developed based on OpenCV before classification. Minu Eliz Pothen et al [17] accomplished 94.6 % accuracy in their proposed work SVM+HOG with polynomial kernel function in early detection of diseases using paddy leaf images and its classification. S.

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Ramesh et al [18] proposed identification and classification of Paddy diseases using ODNN alongside Jaya Algorithm. The proposed DNN_JOA is 98.9% accurate for the blast, 95.7% for bacterial blight, 92% for sheath rot, 94% for brown spot and 90.57% for normal leaf image.

The results provide ample opportunity for improvement using advanced methods. Ranjana Agarwal et al [19] the pest attack and disease spreads widely, which leads to great risk in damaging the valuable crops. Hence it is important to monitor the crops continuously and also there is a need for forecasting the pest attack accurately based on the weather condition which can be done by using the techniques like regression analysis, complex polynomials through GMDH technique, yet it is challenging. Muhammad Hammad Saleem et al [20] in their review of existing ML and DL methods for detection and classification of plant diseases states that CNN model is superior in identifying diseases in plants. Similarly, the state-of-the-art CNN model named VGG-inception architecture outclassed the performance of existing DL architectures.

Further established a fact that, although there are some DL models/architectures developed for hyperspectral image classification for plant disease detection, there lies an ample scope for improvements in the sector for better detection of plant diseases. K. Thenmozhi et al [21] in their research used an effective deep CNN model to classify insect pest, which contain 6 convolutional layers, 5 max pooling with one fully connected layer and an output layer with softmax. An accuracy of 96.75, 97.47 and 95.97% was attained for classification in the study.

The computational time is more comparing to the other algorithms which has to be improved. Vijay Singh et al [22] segmentation of plant leaves based on Genetic algorithm was implemented for detecting and classifying plant diseases automatically. A brief survey of various classification techniques was also dealt in. Zhengming Wan et al [23] proposed a method called generalized split-window is used for the retrieval of Land-Surface Temperature (LST) from AVHRR and MODIS data. The factors of LST-split window algorithm are shown as varying with respective to viewing angle, which was demonstrated using the simulation of accurate radiative transfer.

Disease and pests which causes extensive damage to paddy crop can be identified with the use of various ML and DL techniques. The methods like ANN, CNN and RNN were used to detect the plant disease and pests. It consumes more time as these algorithms can perform a single operation at a time. So, several methods were developed to speed up the processing time, but faced difficulties either in any of its identification processes.

A hybrid CNN-LSTM is proposed in the present study, which can identify the pest and disease simultaneously in a limited time. Paddy leaf images exhibiting the symptoms of pest infestation and disease infection is used as dataset and these images are processed using image processing techniques.

III. METHODOLOGY

In the proposed method, the detection of disease and pests that causes damage to the paddy crop is identified by using a Hybrid CNN-LSTM algorithm. The Fig.3 below shows the steps involved in classification of rice disease and pest identification using leaf images.

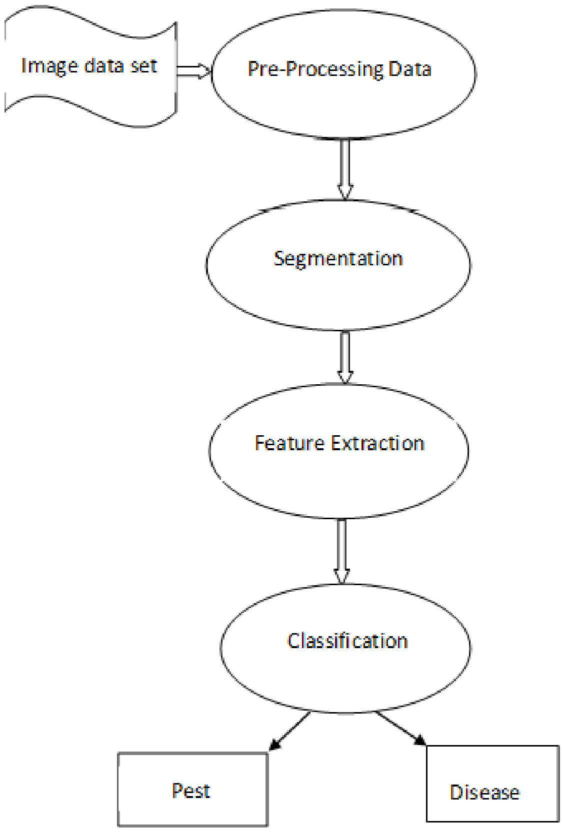

Fig.3: Block Diagram Showing the Modules of The Present Research Work

3.1 Image Acquisition:

Leaf images were captured from paddy fields by using a high-resolution digital camera. The collected images were transferred from the camera to computer for implementing the procedures for disease detection and pest identification.

3.2 Pre-Processing:

Removal of unwanted noise from the background as a preliminary step is known as pre-processing. The median filter, a nonlinear statistical filter which replaces the value of current pixel with that of median value of pixels in the neighbouring region is used for noise reduction. Median filter is widely used considering its effectiveness in removing noise while preserving the edges. The given dataset is resized and cropped into the required dimensions. By applying hue value, background of the image can be neglected. The image is then converted into HSV model from RGB model. At first, the whites of the image are reduced, which is the S value. To create the mask, the binary image is converted from the entry value and original image is fused with the binary image. After several trials the entry value is selected. By transferring the pixel value to 0's, background of the image is annihilated and finally, the image contains only the portion of disease and pest.

3.3 Segmentation:

Segmentation is being done by K-means clustering. Grouping of images based on specific attributes is known as clustering. By using clustering method, the leaf and the pest images are grouped. Both the diseased and non-diseased part is expected to be clustered using this method. The clustering process is applied to the background removed HSV image.
The parameter like brightness and darkness is also removed and the input image contains only the pure color components. The problem in randomness has been overcome during the histogram basic analysis. To design a perfect segment the centroid value is fed to the histogram. The unwanted portion is removed in this process. Histogram is created for the background removed image. The hue value and count in the bin are extracted from the designed histogram. The threshold value differentiates between normal and diseased portion of the leaf images.

3.4 Feature Extraction:

The color attributes were extricated using feature extraction. The mean and standard deviation values are included in the extraction of color attributes. Logistic regression is implicated to extract features in the image. When a target class contains a categorized value, logistic regression can be applied.
The aim is to predict, identify and classify the disease and pest that affects the rice, the dataset is trained with logistic regression in such a way to fulfill this aim. In this paper, three rice diseases and the pests that infect rice are identified. The probability of target class is determined using different binary classifier in multi-class logistic regression.

3.5 Classification

A Hybrid Convolution Neural Network-Long Short-Term Memory (Hybrid CNN-LSTM) technique is used to detect diseases and identify pests of paddy based on the deep learning feature.
Various fully connected layers are formed by adapting the deep feature method with transfer learning. To construct a potent amalgam for identifying rice disease and pest, a deep feature is extracted and fed into the LSTM layer. An individual model layer and a LSTM layer are formed as a fully connected layer. The input image is detected by SoftMax layer and classification layer. Thus, the Hybrid CNN-LSTM detects a plant disease or identifies a pest.

Algorithm of hybrid CNN-LSTM model

```
function cnn_model(x)
weights ← define weights
biases ← define biases
x ← reshape (x, shape ~ [pixel_x, pixel y, slice count])
convl ← relu_activation_func (conv3d (x, weights [0]) +
biases[0])
convl ← dropout (0. 5)
convl ← max_pool3d (convl)
conv2 ← relu_activation_func (conv3d (convl, weights [1]) +
biases [1])
conv2 ← dropout (0. 5)
conv2 ← max_pool3d (conv2)
fully_connect ← reshape (conv2, inverse (weights [2]))
fully_connect ←relu_activation_func (fully_connect *
weights [2] + biases [2])
fully_connect ← dropout (0.8)
output ← fully_connect * weights [3]) + biases [3]
return output
end function
training the cnn model
    pixel_x ← 50, pixel y ← 50
    slice count ← 91
    classes ← 2
    epochs ← 500
    for e ← (0, epochs)
    train_data, valid_data ~ test_train_split (final_dataset, 0.
8)
    for data ← train data
    x ← data [0], y ← data [1]
    prediction_results ← cnn_model (x)
    cost ← calculate_cross_entropy_mean (prediction results,
y)
    optimizer ← adam (learning_rate = le-3). min (cost)
    end for
end for
training the lstm model
    features ← ["features"]
    classes ← [ 'group']
    x ← dataset [features]. values
    y ← dataset [classes]. values
    train_data, test_data, valid_data ← test_train_split (x, y,
0.30, 0.20)
    batch size ← 4
    lstm_ model ← sequential_ model ([embedding_layer
    (train_data.length,
    output_length, train_data.columns), lstm_layer
    (output_length)), dense_layer (output_length,
    activation='sigmoid'))])
    loss ← 'binary_crossentropy', optimizer ← 'adam',
    epochs ← 100
    lstm_model.compile (loss, optimizer)
    lstm_model.train (train_data, epochs, batch_size,
valid_data)
```

The above algorithm is described as follows:

The CNN Model consists of 4 layers viz., a convolution layer, a pooling layer, another fully connected layer and an output layer. The input image, taken as x which is preprocessed and is fed into the first layer of the network. Here x is convolved against 3D filter and max pooled to get the output, $f(x)$.
The dropout is used to prevent overfitting of the model. The dropout value is set as 0.5. The LSTM model is trained using the same dataset which was used for CNN model training. LSTM model consists of 3 layers viz., an Embedding layer, a LSTM layer and a dense layer with activation function, sigmoid which can also be considered as the output layer. At first the input, x is given into the embedding layer to get the output $f(x)$ with dimensions the same as the dimension used in CNN model training.

$$f(x) = \mathrm{embedding}\,(\mathrm{length}(x), \mathrm{output} - \mathrm{dimension}, \mathrm{input} - \mathrm{length}(x)$$

The $f(x)$ is then given as input to the LSTM layer, which trains the hidden layers once. The number of hidden units in the layer is taken as the argument to get then output, $g(x)$. After the model training got completed, it is then tested with the test dataset for model evaluation.

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IV. PERFORMANCE EVALUATION

Using the Hybrid CNN-LSTM algorithm, detection of disease incidence and pest infestation was done. The simulation outcome shows the results obtained by the proposed Hybrid CNN-LSTM model.

Dataset:

The dataset of pest is taken from NBAIR and dataset of rice disease is taken from Kaggle. Around 120 rice leaf images are taken as the dataset for disease identification out of which 70% was used for training and 30% was used in testing. The dataset of pest contains 500 images in which 70% were used for training and 30% of the images were used in testing. The hybrid CNN-LSTM classifier algorithm is utilized to classify the rice leaves based on the disease incidence or pest infestations. The following terms determines the estimation of specificity, sensitivity and accuracy.

(i). Specificity

Specificity is the process of estimating the true classification of non-diseased plants to that of total of non-diseased plants.

$$\text{Specificity} = \frac{\text{True non} - \text{diseased plants}}{\text{Total non} - \text{diseased plants}} \times 100$$

(ii). Sensitivity

Sensitivity is the process of estimating the total number of diseased to the true classification of diseased plants.

$$Sensitivity = \frac{\text{True diseased plants}}{\text{Total diseased plants}} \times 100$$

(iii). Accuracy

The estimation of accuracy is defined as the product of sensitivity and prevalence added with the product of specificity with (1- prevalence).

$$Accuracy = (\text{sensitivity})(\text{prevalence}) + (\text{Specificity})(1 - \text{prevalence})$$

Table.1 represents the PSNR, Specificity, Sensitivity and Accuracy of the detection of diseased and identification pest affected. PSNR value gives the difference between the quality of input and the reconstructed output image, i.e., the input image after preprocessing and feature extraction, would be fed into the classifier and the ratio of error found in output image when compared to the input image has been calculated. If the value of PSNR greater than 25dB, then the reconstructed output image would be considered to have better quality.

Table.1: Representation of PSNR, Specificity, Sensitivity and Accuracy

Method	PSNR	Specificity	Sensitivity	Accuracy
Hybrid CNN-LSTM	29.9523dB	90.9%	66.6%	97.8%

Fig. 4 represents the validation accuracy in rice disease detection. The training progress for detection of pests is done over a long term. The graph represents the loss and accuracy during training. Based on the start time and elapsed time, the accuracy for the identification of insects or pest can be identified. The graph is plotted for Accuracy vs Iteration and Loss vs. Iteration. At the starting stage, the accuracy in detection of rice disease is low and finally, the detection accuracy increased to 79.1%. The loss rate is also high during the starting stage and got reduced at the final stage. Fig. 5 shows the validation accuracy of pest identification. The accuracy of the detection of pest identification is about 86.6%. Table 2 shows the accuracy, specificity and sensitivity against increased periods. Here when the period is increased slowly from 0.001 seconds the percentage of accuracy, specificity and sensitivity were found to increase and attained the maximum level at 0.01 seconds.

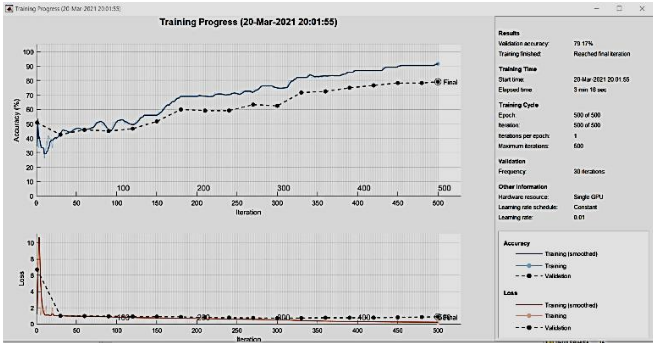

Fig. 4: Validation Accuracy of Rice Disease During Training

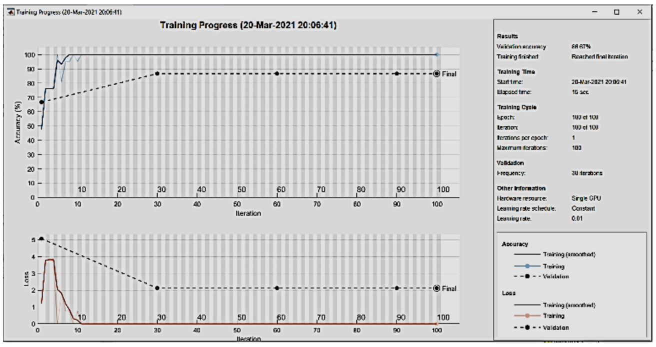

Fig. 5: Validation Accuracy of Pest Identification During Training

Table. 2: Representation of time vs. Accuracy, Sensitivity and Specificity

Time	Accuracy	Sensitivity	Specificity
0.001	9.8	7.3	9.9
0.002	19.6	13.5	19.8
0.003	28.5	21.4	30.1
0.004	38.4	31.2	37.2
0.005	49.6	35.7	42.3
0.006	57.4	39.8	49.8
0.007	69.5	42.5	63.4
0.008	79.8	50.2	71.4
0.009	88.5	54.3	77.8
0.01	97.8	66.6	90.9

Fig. 6 represents the graph plotted for Accuracy vs. Time. As the time increases the accuracy rate also increases. Without any dropping in accuracy, it reached the highest point. The time is taken from 0 to 0.01. At time 0, the accuracy was 0 and when the time has gradually increased, the accuracy is also increased. At time 0.01, the accuracy is 97.8%. Thus, the accuracy is 97.8% during final stage. Fig. 7 represents the graph plotted for Sensitivity vs. Time. As time increases, the sensitivity rate also increases. Without any dropping in sensitivity, it reached the highest point.

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The time is taken from 0 to 0.01. At time 0, the sensitivity was 0 and when the time has gradually increased, the sensitivity gets increased. At time 0.01, the sensitivity is about 66%. Thus, the sensitivity is 66.6% during the final stage. Fig. 8 represents the graph plotted for Specificity vs. Time. As time increases, the specificity rate also increases. Without any dropping in the specificity, it reached the highest point.
The time is taken from 0 to 0.01. At time 0, the specificity was 0 and when the time has gradually increased, the specificity is also increased. At time of 0.01, the specificity is 90.9%. Thus, the specificity is 90.9% during the final stage.

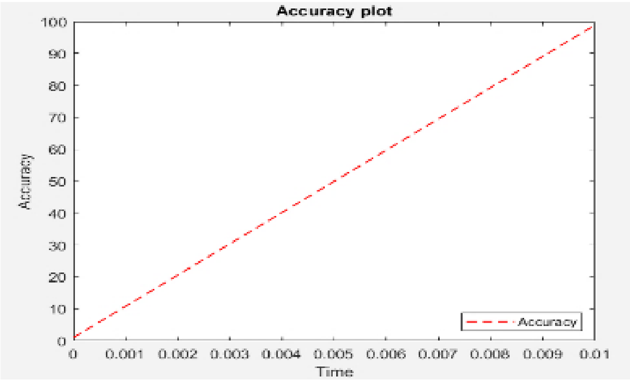

Fig. 6: Accuracy Vs. Time

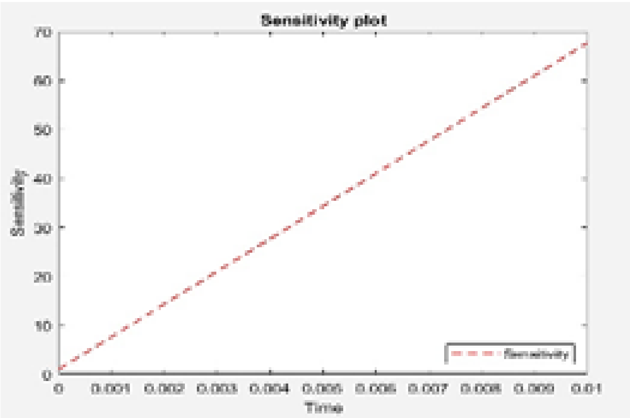

Fig.7: Sensitivity and Time

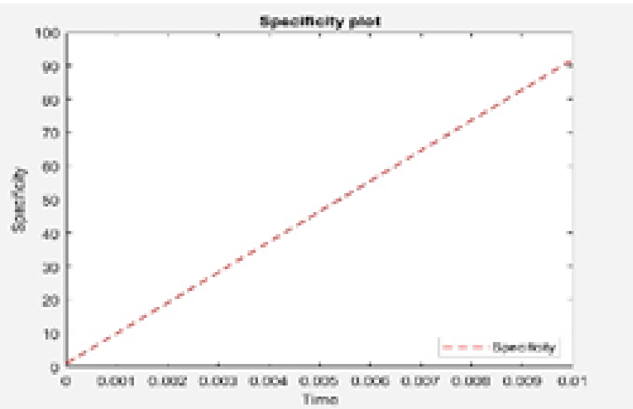

Fig. 8: Specificity Vs. Time

V. RESULTS AND DISCUSSION

5.1 Pest Identification

The following figures (Fig.9, Fig.10 and Fig.11) shows the various steps involved in the pest identification process. The collected images of the paddy leaves were moved to a computer and the noise removal process was done by the median filtering technique. Then, the images were segmented using K means clustering. Grouping the images based on specific attributes was done at this stage wherein, unwanted background colors were also neglected. Logistic regression algorithm was used for feature extraction process to extract the color and texture of the segmented image. Finally, the hybrid CNN-LSTM algorithm was applied to identify whether the leaf image shows symptoms of disease infection or that it contains pest or it has both pest and disease symptoms. Here in this case the pest identified was plant hopper and disease identified was brown spot.

Fig. 9: Color Image of Pest

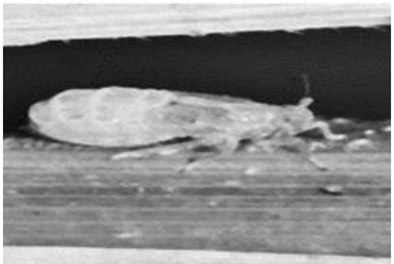

Fig. 10: Median Filtered Image of Pest

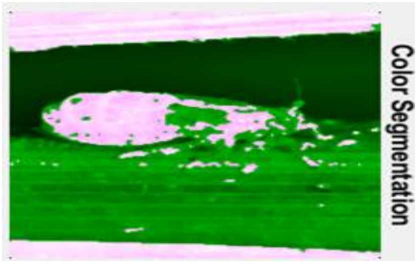

Fig.11: Color Segmented Image

Fig.12: Color Image of a Leaf

Fig.13: Median Filtered Image

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Fig.14: Color Segmented Image

5.2 Disease detection

The following figures (Fig. 12, Fig.13 and Fig. 14) below shows the various steps involved in the disease detection process. The collected images of the paddy leaves were moved to a computer and the noise removal process was done by the median filtering technique. Then, the images were subjected to segmentation using K means clustering, in which clustering was carried out to group the images based on specific attributes and the unwanted background color was also removed. Logistic regression algorithm was used for feature extraction process to extract the color and texture of the segmented image. Finally, the hybrid CNN-LSTM algorithm was applied which can identify whether the leaf image shows symptoms of disease infection or that it contains pest or it has both pest and disease symptoms. Here in this case the disease is identified as the brown spot. In the present study, the disease and pest were identified using a deep learning network and image processing techniques. The accuracy ranges from 70% to 90% during the first training progress and later it was found to increase to 97.8%, hence an accurate estimation of detection can be done using this method. In this single GPU the software is used and the iteration carried out is 100%. Maximum iteration rate of each epoch is 100. The result shows the accuracy obtained from the validation period to the final iteration. The accuracy and the loss during training are mentioned in the graph. Thus, by using the hybrid model CNN-LSTM model, the disease detection and pest identification is done effectively. Table 3 shows the different levels of accuracy between existing and proposed methods.

Table. 3 Comparison between existing and proposed methods

Techniques	Accuracy
Machine learning Techniques	97.0%
LBP and Histogram	94.6%
DNN with Jaya Algorithm	90.5%
Proposed method: Hybrid CNN-LSTM	97.8%

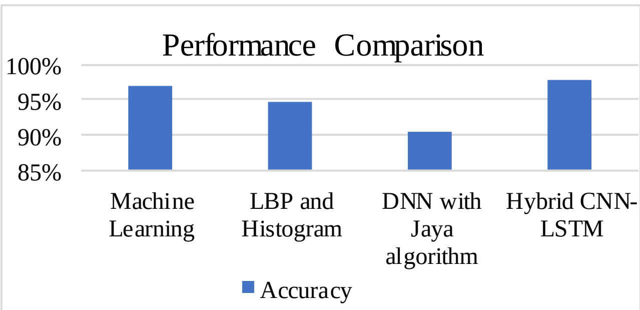

Fig.15: Detected Rice Leaf disease and Pest

While using the machine learning method 97.0% accuracy can be obtained, but only the disease can be detected but not the pest is identified the leaf has got both the symptoms. The fact is that, the existing methods can only predict any one of the criteria i.e., either pest or disease. In contrast to this, the proposed hybrid model of CNN-LSTM can detect both the disease also, identifies the pest simultaneously. Fig.15 shows the graphical representation of performance comparison among some of the existing methods with Hybrid CNN-LSTM the proposed model.

VI. CONCLUSION

This research aims at developing and integrated ML technique for rice disease detection and pest identification by analyzing the symptoms exhibited in the leaf. A Hybrid CNN-LSTM algorithm is used. This study uses Median filter for preprocessing ie., noise removal. K means clustering for segmentation and Logistic Regression for feature extraction were also used in the study. The CNN method can estimate and produce the result for the large number of data set and the LSTM algorithm can test the recurrent layer or the hidden layer to produce the output. So, when these two methods are combined and formed as a hybrid model, it provides a better result. The accuracy of the hybrid CNN-LSTM algorithm for rice disease and pest identification is about 97.8%. Conflict of Interest: There were no conflicts of interests.

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