Proposed Convolution Recurrent Neural Network (CRNN) Model for Identifying Bacterial and Viral Attacks on Plantain Leaves

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Abstract

Machine learning plays a major role in finding out the different types of disease attacks on plantain leaves. Deep learning is a subset of machine learning which works very similar to that of machine learning algorithms in extracting the infected parts of the plantain leaves with implementing various automated systems. The deep learning algorithms incorporating machine learning algorithms are commonly known to be artificial neural networking algorithms. Recurrent networking is one of the concepts used for prediction infections accurately with minimum time concern. Image process techniques are mostly considered for accurate and effective ways of detecting the infected parts of plantain leaves. The techniques followed in recurrent networking and steps followed in images processing can combinedly give a best solution in predicting type of infections in plantain leaves. This research paper focuses on various steps involved in image processing in extracting the infected parts from plantain leaves and shows significant accuracy in implementing the proposed CRNN algorithm in identifying the infected parts of the plantain leaves.

Keywords: *Machine Learning, Deep Learning, CRNN, Image Process Techniques, ANN, Plantain Leaves.*

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1. Introduction

India is considered to be an agricultural country for using most of the land in the agriculture field for exporting and internal usage of many agricultural products. The subsequential products developed in India are also mostly exported worldwide and have many demands in other foreign countries, where production of such crops is mostly not available. The quality and quantity are the main factors needed for earning better revenue and may help agricultural farmer's betterment. The growth of the crops can be affected with many factors depending upon many circumstances. Most of the production of crops is affected by unknown disease attacks at the crop early stage, which is a nightmare for many farmers and agricultural officers to identify the type of infections that occur on plant surfaces. Thus, it is very important to stop the spread of such unidentified and identified infections on agricultural crops.

There are many scientific and clinical techniques available for detecting such infections on crop surfaces. Even though there are many methods, it has many practical difficulties in analyzing the infections with accurate results. The early detection of infections can be very useful in solving problems related to crop growth and problems related to yielding. The methodology implemented using image processing and analyzing techniques using deep learning subset of machine learning plays a major role in identifying the infected parts of the plantain leaves with accurate and time saving strategy.

Farmers and agricultural officers are finding it very difficult to identify the type of disease caused in the plantain crop. The common attacks found on the plantain crops are due to bacteria and fungus effects. Few of the bacterial and virus attacks are found as Panama disease, Moko disease, Sigatoka disease, Blackspot disease, Bunchy top virus, and infectious chlorosis and Streak virus. Most of the attacks listed above have common symptoms and make many complications in differentiating the type of disease. The early disease identification process is also very difficult due to the lack of differentiating types of infections. The early detection and giving a proper solution to the found problem will make farmers happy in satisfying many ecumenical barriers. The process can be useful in increasing the yielding of plantain crops.

The image processing techniques such as image resizing, feature extraction and analysing the infected part of the plantain leaves are carried out in this research work. The collected plantain images from various agricultural farms are scrutinized using pre-processing techniques. The irrelevant objects found on the collected plantain images are to be removed before resizing the images. The resizing process is carried out for better image processing simulations during testing and training.

The pre-processing stage is followed by a feature extraction process, where necessary features are collected from bacterial infected parts found on the surface of the plantain leaves. The convocation method and Rectified Linear Unit strategy are also implemented in segmenting the features extracted from the pre-processed plantain leaf. The feature extraction process uses Convolution Neural network (CNN) and Rectified Linear Unit for classification process. This procedure followed in the feature extraction process is very useful in categorizing best features from overall features. The images of plantain leaves are collected from the plant village database, which consist of 50,000 images of various plants affected from various diseases.

The proposed Convolution Recurrent Neural Network (CRNN) is a hybrid machine learning algorithm, which is used for identifying the disease infected parts of the plantain leaves. This proposed CRNN basically follows a deep neural networking algorithm for user InterVision in simulating the results.

2. Proposed model for plantain disease identification

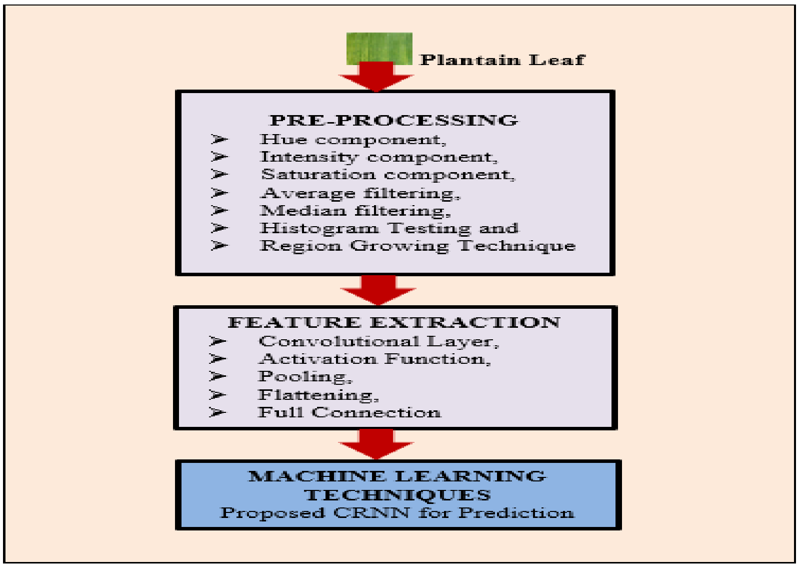

Figure 1. Proposed CRNN model for infection identification

The proposed model explains the full working of identifying the disease infected parts found on the collected plantain leaves. The first stage of the research work starts with the data collection stage, where images of plantain leaves are collected from the plant village database, which consist of 50,000 images of various plants affected from various diseases. The full focus of the research work is to identify the disease infected part of the plantain leaves, so the collected data is scrutinized specifically to classify the plantain leaves. Various methodologies and techniques followed in this research work are explained clearly in below sections.

2.1. Pre-processing collected plantain leaves

The image processing stage starts with collecting the disease affected plantain crop images from farmers and agricultural officers for understanding the type of disease and remedial actions given for the disease attacks. The images collected from the farmers may contain only disease affected parts or full images of the plantain leafs. The initial stage of image formatting and pre-processing starts with converting the RGB images into grayscale for better image processing. The collected RGB images can also give the best solution for the identification process, there are other models such as HSV, CMYK, RGB, HIS and L*a*b are also used for analyzing processes. The acquired images are standardized for with the usage of HSV and HIS color models, which significantly used similar to human prediction strategy. In early-stage Hue of HIS color saturation along with color intensity are gathered in HSV model.

The pre-processing step is one of the important stages for removing the irrelevant parts from the affected parts of the plantain crop. The removal of irrelevant or uninfected parts from the infected parts are the most important section of the research work. The images are resized into 512 X 512 for a convenient identification process in the analyzing stage. Resized images undergo a filtering process, where few important filtering techniques of image processing are applied. Low pass Gaussian-filtering technique and high pass Gaussian filtering techniques are applied after applying Median filtering and Wiener Filtering techniques.

2.2. Feature Extraction

Feature extraction process followed after the pre-processing stage is the most important process followed in the disease identification process. The features identification or selection process are mostly carried out with classification algorithms. The important factors such as types of layers have to be given more attention during selecting features. The increase in the number of parameter usage may have the highest probability of increasing the complicity in using the proposed disease identification process. The problem may also lead to increase the time duration in execution and even creates problems in analysis results. The characterization for each network varies from each other may not remain a factor that affects the ultimate goal of the proposed model and can help in increasing the accuracy as well as to reduce the implementation complicity. The identified object from the image has to be merged with other extracted features using the model, which is more useful in extracting the exact features for the identification process.

Convolution Neural Network is used for classifying the healthy and unhealthy plantain leaves. There are many stages in convolution neural network models for fine tuning infected parts. The collected output functions undergo many operations in the convolution layer repeatedly to produce better results. The operations of convolution implement the output functions as feature mapping from the plantain leaf images. The basic strategy followed in convolution layering is to collect the features from input plantain leaf images. This layering technique is useful in transforming the plantain images into spatial information on the data. The weightage given in the layering is very useful in specifically selecting the convolution kernels and training them with considering the input on CNN.

This special activation function is used for non-linearity in training deep learning neural networks and works effectively with unsupervised pre-processed data. Sigmoid function is mostly used as activation function in much of research work, which is different from using rectified linear units. The process of using Rectified linear units in mapped layers of convolution makes very accurate simulation with less computation time. The rectified linear unit used for mapping infected parts of plantain leaf can be further used in many complex datasets for easy computation and for reducing time.

There are two types of pooling strategies followed for CNN processing such as average pooling and Global pooling. The filtering techniques in averages pooling finds the average element's presence in the region mapped after the convolution layering. The average pooling process is usually carried out after the max-pooling for finding the average of elements in identified regions. Single value conversion is carried out in global pooling, where every channel is reduced into a single channel. The three dimensions of channels such as nh x nw x nc are reduced into 1 x 1 x nc feature mapping for a convenient simulation process. The process is considered as an alternative of using nh x new dimensions of feature mapping.

The previous steps of convolution layer and pooling process are very useful in extracting the necessary features by the means of mapping with high accuracy. The feature mapping collected from the pooling process has to be arranged column vise as in the figure 7 for easy evaluation in the final neural network implementation process. This process is also used in flattening the obtained result from the pooling process. Fully Connected layer is considered as a feed forward neural networking process of making meaning for obtained mapped layers. The activated neurons by using rectifier linear units are to be connected together to form neurons in the next layer. The dimensions of all layers are to be made into single dimension data before using it into a fully connected layering process. Figure 8 shows a significant difference between output layer connectivity and fully connected layers. The process of obtaining the region obtained after the convolution layering and pooling process are taken for one dimensional data conversion before producing the necessary result by the means of neural networking in predicting infection in plantain leafs.

3. Machine Learning algorithm in identification process.

Implementing machine learning algorithms in analyzing the classified infected parts are the final step followed in this research work. The process of implementation uses deep learning algorithms, which is the most similar technique to machine learning algorithms. The only difference in using the deep learning neural network algorithm instead of machine learning algorithm is that it is evaluated and tested with human InterVision.

The important factor of using deep learning techniques in prediction and analysing process, because of its feature engineering process for reducing practical difficulties. The traditional approaches followed in image classification techniques are based upon the hand engineering rather than the feature engineering process, which may affect the performance of the overall result analysis. This feature engineering task is helpful in reducing the time spent on extraction process and identification process as well as it is helpful in solving many complex problems with multitasking. The process followed in deep learning depends upon the trained variables rather than relying on using the located features in the previous stage.

3.1. Proposed Convolution Recurrent Neural Network (CRNN)

The proposed CRNN is the model which is a hybrid model adapted from convolution neural network of deep learning and Recurrent neural network. The process of conventional layer, activation function, pooling, flattening, and fully connected layers are the basic layers followed by combining the recurrent neural network technique. The processing of the collected images is carried out with various stages of convolution layers such as convolution layer, activation functional layer, pooling layer, flattening layer and full connection layer. The obtained regions after the final fully connected layers in the convolution layer are taken for the Recurrent Neural Networking process.

The basic concept of the Recurrent Neural network is to work with the output collected from the previous stage and to give as input in the current stage. In the traditional Neural networking process, the inputs and outputs were worked independently and created issues in predicting the next subsequence information. The problems are solved with the usage of hidden layers and RNN attains a new view for predicting the necessary information. Hidden layer is considered to be the most important layer in the RNN algorithm.

Recurrent neural network algorithms have the capacity to store the information and calculations made previously and it is able to use the same parameters for each and every input for performing the same task without any margin. The task can be carried out with the usage of a hidden layer, mostly used for storing those temporary variables. The process can be useful in reducing the complexity in parameter setting unlike in traditional neural network algorithms.

The equation used for the calculating the current state in CRNN model is given as follows

$h_t = f(h_{t-1}, X_t)$

where: h_t - current state, h_{t-1} - previous state and x_t - input state.

The equation used for activation function for CRNN model is given bellow

Formula for applying Activation function (tanh)

$H_t=\tanh(W_{hh}h_{t-1}+W_{xh}X_t)$

where: w_{hh} - weight at recurrent neuron, w_{xh} - weight at input neuron.

The output obtained from the CRNN can be calculated with the equation

$Y_t=W_{hy}h_t$

where: Y_t – output, W_{hy} -> weight at output layer

The training stage of CRNN model follows two parts such as Forward propagation and Back Propagation. The first part of the CRNN forward propagation is responsible for collecting and calculating the output values obtained from convolutional layers. Back propagation plays a major role in sending the balance that were accrued for updating the weights, which follows the traditional neural network training process.

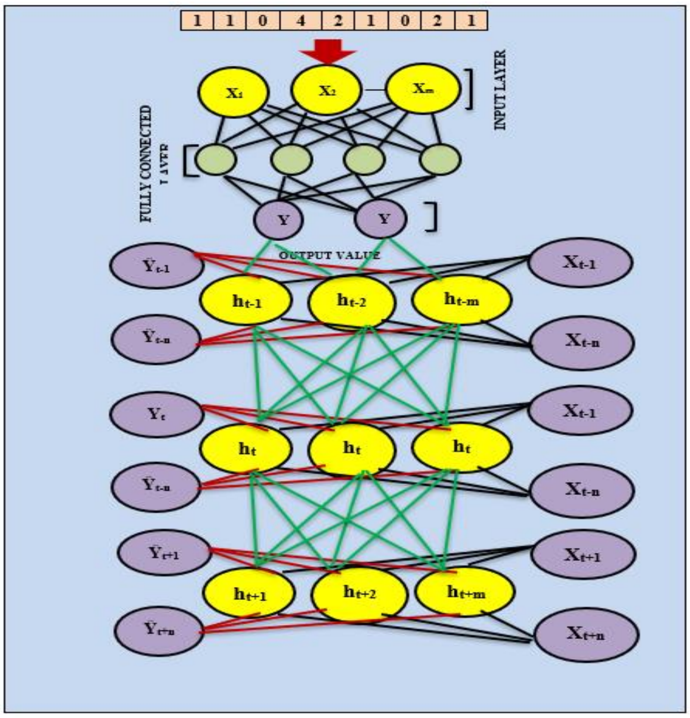

FIGURE 3. The Unfolded Convolutional and Recurrent Neural Network.

According to Fig. 3, an unfolded recurrent neural network is presented in Fig. 3. The standard RNN is formalized as follows:

Given training samples xi(i = 1, 2, . . ., m), a sequence of hidden states hi (i = 1, 2, . . ., m), and a sequence of predictions yˆi(i = 1, 2, . . ., m). Whx is the input-to-hidden weight matrix, Whh is the hidden-to-hidden weight matrix, Wyh is the hidden-to-output weight matrix, and the vectors bh and by are the biases [26]. The activation function e is a sigmoid, and the classification function g engages the SoftMax function. Forward Propagation Algorithm and Weights Update Algorithm are described as Algorithms 1 and 2 respectively. The objective function associated with RNNs for a single training pair (xi, yi) is defined as f(θ) =L(yi : ˆyi) [26], where L is a distance function which measures the deviation of the predictions yˆi from the actual labels yi . Let η be the learning rate and k be the number of current iterations. Given a sequence of labels yi(i = 1, 2, . . ., m).

Algorithm 1 Forward Propagation Algorithm

Input xi(i = 1, 2, . . ., m)
Output yˆi
1: for i from 1 to m do
2: tɩ = Whxxi + Whhhi−1+bh
3: hi = sigmoid (ti)
4: si = Wyhhi+by
5: yˆi = SoftMax (si)
6: end for

Algorithm 2 Weights Update Algorithm

Input hyi, yˆii(i = 1, 2, . . ., m) Initialization θ = {Whx , Whh, Wyh, bh, by}
Output θ = {Whx , Whh, Wyh, bh, by}
1: for i from k downto 1 do
2: Calculate the cross entropy between the output value and the label value:
L(yi : ˆyi P) ← - i P j yij log (yˆij) + (1 − yij) log(1 − ˆyij)
3: Compute the partial derivative with respect to θi : δi ← dL/dθi
4: Weight update: θi ← θiη + δi
5: end for D. EVALUATION METRICS

Stages followed in the CRNN model are as follows

Stage 1.

4. RESULTS AND DISCUSSION

The training and testing process carried out in this research work uses the output values collected from the convolutional neural network and used as input for the recurrent neural network technique. The healthy and infected parts are converted into the values through the convolutional technique and taken for the recurrent process. The type of infections found on the plantain leaves are Black Sigatoka, Sigatoka disease, Panama disease, Moko disease, Bunchy top virus, Infectious chlorosis and Streak virus which can be rectified by applying convolution neural network model and makes the model automated in early convolution stage, later it is systematically solved with recurrent neural networking algorithms. The process is evaluated with various neural networking algorithms with various measurements. Plantain leaf infections numbered 3,689 are found among collected 50,000 images of various disease affected parts of the plant.

The important performance evaluate is based on the accuracy of the proposed neural network model. The proposed CRNN model is tested with accuracy in concerning true positive and true negative error rate. The True Positive (TP) is equivalent to those correctly rejected, and it denotes the number of anomaly records that are identified as anomaly. The False Positive (FP) is the equivalent of incorrectly rejected, and it denotes the number of normal records that are identified as anomaly. The True Negative (TN) is equivalent to those correctly admitted, and it denotes the number of normal records that are identified as normal. The False Negative (FN) is equivalent to those incorrectly admitted, and it denotes the number of anomaly records that are identified as normal.

Accuracy: the percentage of the number of records classified correctly versus total the records shown in (2).

$$\mathrm{AC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad \text{------} \quad (2)$$

True Positive Rate (TPR): as the equivalent of the Detection Rate (DR), it shows the percentage of the number of records identified correctly over the total number of anomaly records, as shown in (3).

$$\mathrm{TPR} = \frac{TP}{TP+FN} \quad \text{-----------------}(3)$$

False Positive Rate (FPR): the percentage of the number of records rejected incorrectly is divided by the total number of

Table 1. The percentage of accuracy confusion matrix

Predicted Class/ Actual Class	Anomaly	Normal
Anomaly	TP	FP

Normal	FP	TN

normal records, as shown in (4).

$$FPR = \frac{FP}{FP+TN} \quad (4)$$

Hence the proposed CRNN is to obtain the accuracy and detecting the infected part of the plantain leaves with lower false positive rate.

The accuracy of the proposed CRNN is tested with the other classifiers such as Deep neural network (DNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Back Propagation Neural Network (BPNN) and Feed Forward Neural Network (FFNN). The proposed CRNN model tested with the plantain leaves are taken into evaluation process using MATLAB tool. Table 2 shows complete picture of the accuracy with sensitivity, specificity and F-Measures.

Table 2. Comparison analysis for different classifier with proposed CRNN

Classifiers	Sensitivity	Specificity	F-measures
DNN	71.110	93.005	68.250
CNN	83.200	93.706	73.100
RNN	73.736	93.746	68.500
BPNN	68.370	92.970	67.925
FFNN	66.775	92.926	64.940
CRNN	84.826	94.165	78.865

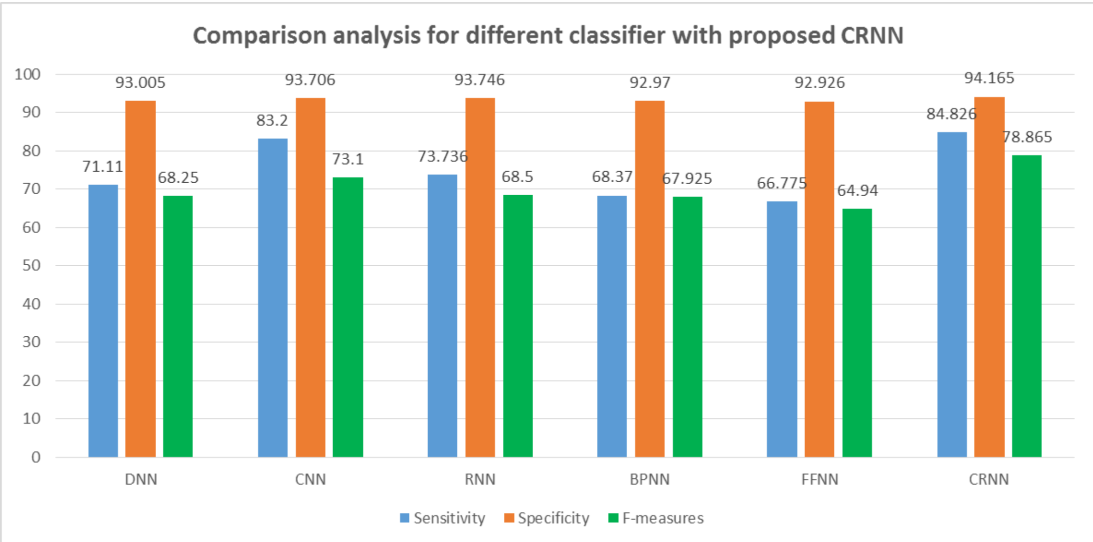

Figure 4 Comparison analysis for various classifiers with CRNN

The comparison for finding the sensitivity, specificity and F-measures is carried out for checking the perfect prediction process. The infected parts of the plantain leaves are tested with various classifiers as shown in table 2. The identification process is tested with each and every classifier with different types of bacterial attacks found on the plantain leaves. The lowest sensitivity was found on the Feed Forward Neural Network and highest sensitivity results are noted in proposed CRNN model. Same testing and implementation for Specificity also tested and received highest specificity on CRNN 94.165% and lowest specificity rage is found on Feed Forward Neural Network (FFNN) 92.926%. The lowest specificity point is very close to the range of Back Propagation Neural Network (BPNN) with 92.970%. The F-Measure calculation also done with different classifiers, where high rage of results was observed on proposed CRNN as 78.865% and lowest F-measure range was found on Feed Forward Neural Network (FFNN).

Table 4. Accuracy of the proposed CRNN model

Classifiers	Accuracy
DNN	92.486
CNN	93.717

RNN	93.505
BPNN	93.486
FFNN	93.256
CRNN	97.956

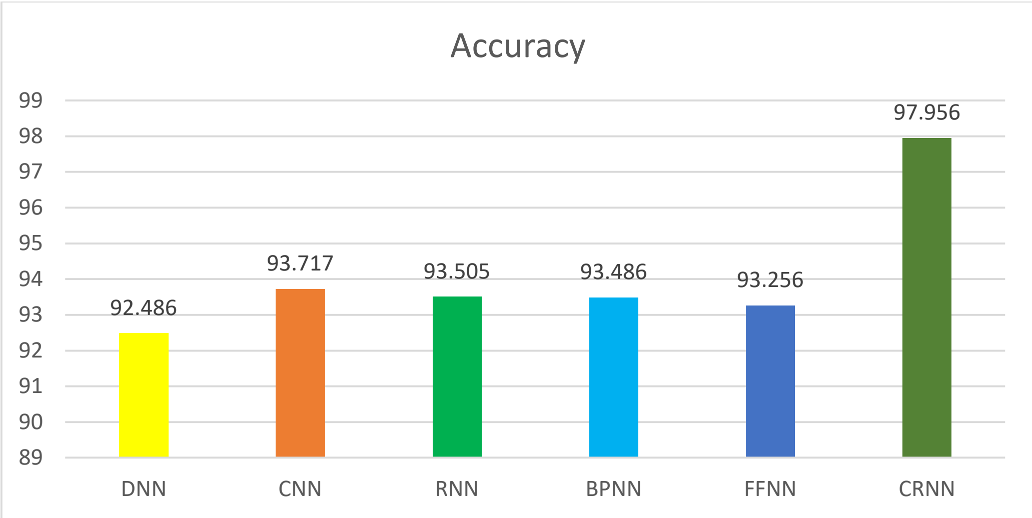

Figure 5 Accuracy of the proposed CRNN model

The accuracy of the proposed CRNN was tested with the same different set of classifiers. The prediction and identification of infected parts of the plantain crop is analysed individually. The set of testing variables collected from convolution methods are applied to different classifiers with different iterations and results are calculated. Table 3 shows that the proposed CRNN model performance is best 97.956% compared with other classifiers. The least accuracy if observed in Deep neural network (DNN) with 92.486%, which is almost known to be a traditional neural networking strategy in finding the infected part of the plantain leaves.

5. Conclusion

The image processing technique implemented in finding the disease infected parts of the plantain leaves is considered to be a finniest research area in finding the affected parts of plantain leaves. The classification algorithms used in traditional way of identification has many practical difficulties such as time concussion and accuracy in identifying the infected parts. The process followed before are lack in using the activation function perfectly in analysing of image processing. The proposed CRNN suggest that the identification process can also be possible without automatic activation function. This research paper also gives significant justification for using the combinations of automatic and systematic activation function. Convolution and recurrent neural network combinations are useful in increasing the accuracy of identification process.

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