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Nutrient Deficiency of Paddy Leaf Classification using Hybrid Convolutional Neural Network

Sherline Jesie R[1*] and Godwin Premi M S[2]

[1]*Department of Electronics and Communication Engineering, Sathyabama Institute of Science & Technology, Chennai, Tamil Nadu, India; sherlinejesie88@gmail.com*
[2]*Department of Electronics and Communication Engineering, Sathyabama Institute of Science & Technology, Chennai, Tamil Nadu, India; msgodwinpremi@gmail.com*

***Correspondence:** Sherline Jesie R, Email: sherlinejesie88@gmail.com

ABSTRACT- For billions of people worldwide, enhancing the quantity and quality of paddy production stands as an essential goal. Rice, being a primary grain consumed in Asia, demands efficient farming techniques to ensure both sufficient yields and high-quality crops. Detecting diseases in rice crops is crucial to prevent financial losses and maintain food quality. Traditional methods in the agricultural industry often fall short in accurately identifying and addressing these issues. However, leveraging artificial intelligence (AI) offers a promising avenue due to its superior accuracy and speed in evaluation. Nutrient deficiencies significantly impact paddy growth, causing issues like insufficient potassium, phosphorus, and nitrogen. Identifying these deficiencies in paddy leaves, especially during the mid-growth stage, poses a considerable challenge. In response to these obstacles, a novel approach is proposed in this study—a deep learning model. The methodology involves gathering input images from a Kaggle dataset, followed by image augmentation. Pre-processing the images involves using the Contrast Limited Adaptive Histogram Equalization (CLAHE) model, while the extraction of features utilizes the GLCM model. Subsequently, a hybrid convolutional neural network (HCNN) is employed to classify nutrient-deficient paddy leaves. The simulation is conducted on the MATLAB platform, and various statistical metrics are employed to assess overall performance. The results demonstrate the superiority of the proposed HCNN model, achieving an accuracy of 97.5%, sensitivity of 96%, and specificity of 98.2%. These outcomes surpass the efficacy of existing methods, showcasing the potential of this AI-driven approach in revolutionizing disease detection and nutrient deficiency identification in paddy farming.

Keywords: Paddy leaves, Nutrients deficiency, Nitrogen, Phosphorous, Potassium and Hybrid CNN.

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1. INTRODUCTION

Paddy is an indispensable food for billions around the world and many farmers mainly rely on rice as their main source of income [1]. It also serves as a livelihood for a fifth of the world's population, and the increase in the population also demands more production. China ranks first in paddy cultivation and India holds second place. Paddy is mainly a rice crop that has a hull to protect the inner edible kernel. The hull is removed from the paddy after processing for consumption. African (Oryza glaberrima) and Asian rice (Oryza sativa) are the two types of rice cultivated worldwide. Paddy is highly prone to different diseases such as nutrient deficiency and toxicity, and pests that hinder their growth and yield.

Paddy crops usually need an optimal nutritional balance with higher macro elements. Carbon, hydrogen, oxygen, magnesium, and sulfur come under the essential macro elements list [2]. The paddy crop requires only a minimal amount of microelements such as manganese, copper, zinc, molybdenum, and chlorine. The paddy yield is significantly impacted if the macro- and micronutrients are either less than or more than the amount of nutrients needed. The nutritional deficiency that affects paddy crops is boron, calcium, phosphorous, potassium, copper, iron, manganese, and nitrogen.

Lower potassium (K), Nitrogen (N), calcium (Ca), and phosphorous (P) levels in the plant lead to stunted growth which needs to be investigated more [3]. Low NPK levels can potentially impair photosynthesis and cause a variety of diseases. Nitrogen deficiency affects the protein and chlorophyll contents in plants and hinders its growth. The details regarding the NPK deficiency are provided in Table 1.
The infected plant leaf disease images are the first choice of farmers since most people today in this world have access to smartphones. The main challenge faced here is to differentiate nutrient deficiency in plants from other diseases caused by pests and toxicity. However, plant pathologists are needed to interpret the diseased leaf images which require significant time and manual processing and are sometimes prone to error [4]. This paves the way for automatic nutrient deficiency detection in plants. The machine learning techniques designed have shown

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great progress in different tasks such as disease recognition [5], machine fault analysis, and food adulteration detection. These technologies have reduced manual errors and offer improved decision-making to consumers.

The major contributions of this paper are specified by the points shown below:

- This work mainly aims to classify the potassium, nitrogen, and phosphorous deficiency in paddy crops.
- To present a hybrid Convolutional Neural Network (CNN) architecture to achieve optimal performance in identifying nutrient deficiency in rice leaves.
- To overcome the under-fitting problem, the images in the dataset are subjected to data augmentation and CLAHE is applied to minimize the presence of unusual noise, aging, and illumination conditions.
- Use GLCM to customize the texture features to enhance the classification accuracy.

The balance sections of this paper are arranged in view of that. *Section 2* offerings the literature evaluation and *section 3* explain the proposed hybrid CNN model in depth and the experimental investigation deliberated in *section 4*. At end, the entire paper is concluded at *section 5*.

2. LITERATURE SURVEY

Liao et al. [6] presented a hybrid architecture to identify the nutrient deficiency in rice plans by integrating the architectures of LSTM and CNN. They tested the model using the images obtained from the rice fields captured using an unmanned aerial vehicle (UAV). This hybrid model yielded an accuracy of 83.81% when tested using the Huanghuazhan dataset. Rani et al. [7] utilized the Deep Belief Network (DBN) to identify the pest-infected and nutrient-deficient leaves in the paddy crops. The k-means clustering model employs for partition the input image into different clusters and the mayfly optimization algorithm is used to eliminate the redundant features. When evaluated using the Kaggle dataset, this model yields an accuracy of 98%.

Lamba et al. [8] integrated Generative Adversarial Network (GAN) and CNN to form a neural network-based hybrid model termed GCL. For feature extraction, the images in the dataset are augmented using GAN and CNN is employed. The LSTM is set as a classifier to classify different rice leaf diseases. This model yields an accuracy of 97% when tested using different datasets. Jeong et al. [9] utilized the DNN architecture to plant leaf disease classification. They investigated the tomato leaf miner disease using two models of DNN for both segmentation and classification. The two DNN variations were obtained using Mask RCNN and ResNet.

Alshammari et al. [10] utilized the RNN architecture to classify olive leaf disease. The Gaussian filter and min-max normalization are used for noise removal and image normalization. Wavelet transform is applied for segmentation and ant colony optimization algorithm is used for feature selection. Sharma et al. [11] presented a transfer learning-based ensemble architecture named DeepBatch to analyze nutrient deficiency in rice plants. The segmentation process is done using a bitwise logical AND operation and the classification is done using various pre-trained structures like UNet, XNet, and SegNet. The proposed hybrid CNN demonstrates the application of a low-cost GLCM model for feature extraction and other standard image processing techniques to effectively train the hybrid CNN. In the existing literature, very few authors have focused on the issues associated with unknown noise, illumination effects and *etc.*, which need to be addressed during nutrient deficiency detection. This issue is rectified in the proposed work using the Contrast Limited Adaptive Histogram Equalization.

3. PROPOSED METHODOLOGY

An essential role in agriculture and crop production is nutrients. The agricultural yields mainly decreased due to the shortage of nutrient. *Figure 1* depicts the overall workflow diagram for proposed methodology. Various steps involved in shortage of nutrient in paddy leaf classification is explained as follows;

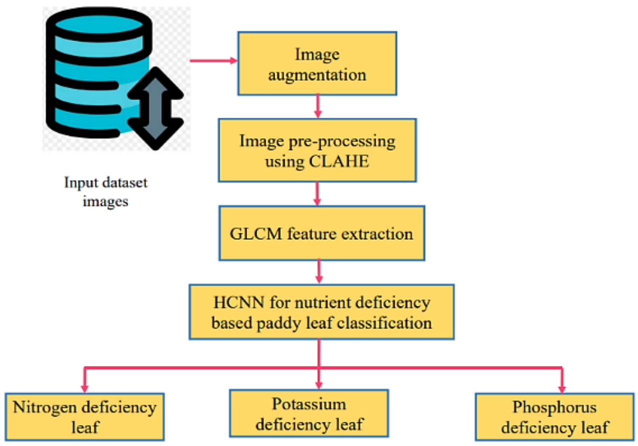

Figure 1: Proposed model diagram

3.1 Image data collection and augmentation

Based on exact and the availability of reliable data, obtain the results of classification accuracy in research activities of data science. Collect the input dataset images from Kaggle dataset and it involves 1156 paddy leave images. From this, 440 Nitrogen, 333 Phosphorous and 383 Potassium deficiency-based leaf images. The pale yellow or light green leaves are nitrogen deficiency with dark brown older leaves are phosphorous deficiency and the potassium deficiency is based on irregular necrotic spots or rusty brown [12]. The input images are augmented into 8072. Among this, the nutrient deficiency based 3080 nitrogen, 2331 phosphorous and 2681 potassium deficiency images.

3.2 Pre-processing

The augmented images pre-processed by using CLAHE. The entire image histogram with density dynamic range is expanded to improve the leaf image quality [13]. Perform improvement process also uniform intensity distribution with result image are obtained by normalizing image intensity distribution in histogram equalization (HE). An entire image density distribution utilized using histogram equalization and to set

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medium average intensity, some images cause a faded effect. The local data optimization performed in which the histogram equalization operation modifies based on Adaptive HE. Form of a grid, divide the images into the regions of rectangles and apply standard HE towards every region.

Again, split the images into small regions then apply AHE to every section but the noises are not removed effectively. CLAHE model is developed to remove the noise from an image and increase the contrast enhancement [14]. CLAHE model pre-process the images to tested or trained images. From its background, the leaf regions are highlighted via enhancing contrast. The abnormality spots and textures of leaf appearances improved via contrast boost up and the below formula computes the contrast improved images that represented as

$$IM\ .IM(a,b) = \left[\frac{255}{max_u - min_u}(IM(a,b) - min_u)\right] \quad (1)$$

The function of round off is $[\ ]$. Depending upon the paddy image, the minimum and maximum intensity is $\min_u$ and $\max_u$. An enhanced leaf image contrast is obtained with the RGB channels separately that perform the enhancement of contrast.

3.3 Feature extraction

According to certain angle orientation and certain distance intensity in the image, the relationship among the pixel's probability value results is calculated using GLCM matrix. To analyze leaf image texture, the common extraction model of GLCM is used and also it extracts the shape and color features. The process of feature extraction is to reduce the number of redundant data [15]. The window adaptive approach of GLCM extracts the internal gradient information characteristics also the statistical features are extracted. At certain angle and distance, the number of pixel values pair occurrences are represented via mapping GLCM input leaf image into a table. Over the range of one to eight pixels and 0-360 degree, vary the values of distance and angles.

In the leaf image, number of greyscale levels and each array dimension are equal because the two-dimensional array is GLCM. The 256 columns and 256 rows for 8-bit image. The angle value and distance combination are 256x256 matrix.

Large values of GLCM diagonal elements, represent the image texture homogeneity ($Homo$). When the homogeneity is maximum, there is similar image pixel values [16].

$$Homo = \sum_{j=0}^{M-1}\sum_{k=0}^{M-1}\frac{R(a,b)}{1+(a-b)^2} \quad (2)$$

The image texture heterogeneity is represented in terms of dissimilarity (*Dis*). The linear weights with GLCM cell values are multiplied by obtaining dissimilarity features.

$$Dis = \sum_{j=0}^{M-1}\sum_{k=0}^{M-1}|a-b|R(a,b) \quad (3)$$

An angular second moment feature based on the square root represent the energy feature (Ene). Normalized matrix is the unity of energy maximal value.

$$Ene = \sqrt{\sum_{j=0}^{M-1}\sum_{k=0}^{M-1}\{R(a,b)\}^2} \quad (4)$$

According to the group of pixels, the difference among large and smaller pixel values are measured by using contrast (Con) features.

$$Con = \sum_{j=0}^{M-1}\sum_{k=0}^{M-1}(R(a,b)(a-b))^2 \quad (5)$$

For various angles and offset values, these features are extracted by obtaining feature vector.

3.4 Classification

This section utilizing hybrid CNN model to classify the nutrient deficiency in paddy leaf. The three major layers like pooling, convolution and fully connected layers are the particular neural network type present in CNN. In previous approaches, learn the network adopts criteria. Compared to other image classification model, less pre-processing utilized via CNN. This study combines three CNN architectures [17]. Due to greater number of features, reduce the smaller size based on input tuple each of it has typical funnel arrangement. To achieve the resultant classification, apply dense and flattened layer. In the layer of classification, the effects are analyzed by varying the features per layer and the number of convolution layers. Test and define four architectures namely CNN1, CNN2 and CNN 3 that involves 2 convolutional layers, 2 ReLu functions and 2 pooling layers. The ReLu act as an activation function in all convolutional layers.

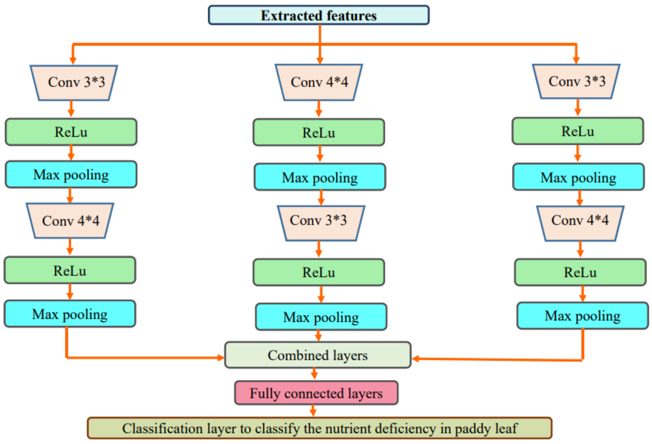

Figure 2: HCNN for paddy leaf classification based on nutrient deficiency

From the previous sections, GLCM extracts the features of leaf for classification. *Figure 2* depicts the HCNN for paddy leaf classification based on nutrient deficiency. The HCNN is the combination of CNN1. CNN2 and CNN3. The convolutional layers related to the number of filters in which 4×4 and 3×3 are the filter sizes of convolutional layers. The filter layers of every convolution following the operation of batch normalization and ReLu. Where, 2 is the factor for max poling and 0.5 is for dropout rate [18]. The layer size of 4×4 and 3×3 that extract the input data features connected to the layer of convolutional. The filters based on narrow, wide and short assign the convolutional layers by considering the vertical and horizontal features.

4. EXPERIMENTAL INVESTIGATION

This section presents the experiments conducted on nutrient deficiency in paddy leaves using the hybrid CNN architecture.

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Table 1. Experimental Configuration

Parameters	Values
Input image size	224×224
Learning rate	2e-4
Number of epochs	50
Optimizer	Root mean square propagation
Activation function	Rectified Linear Unit (ReLU)
Softmax layer size	4×1
Batch size	32

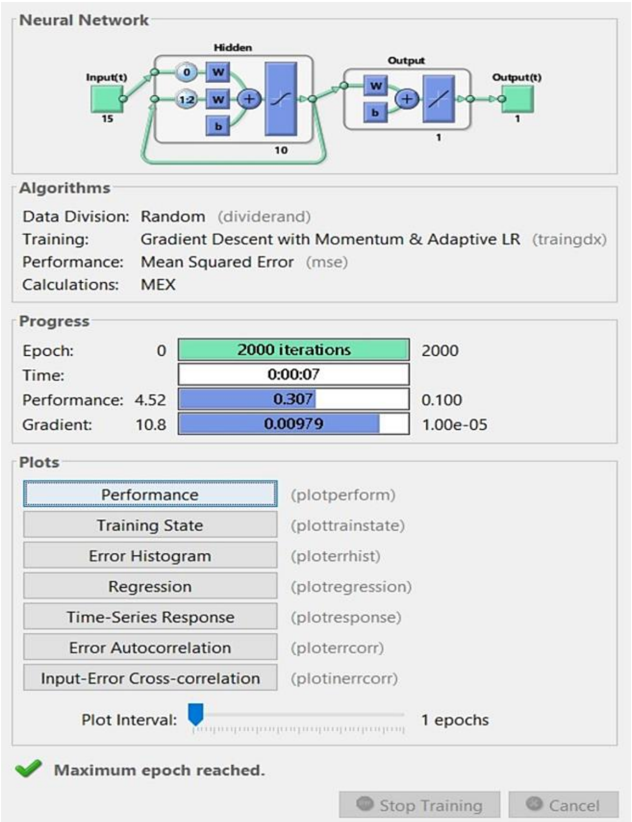

Figure 3: Snapshot of the neural network training obtained from the NNtraintool

The experiments are conducted on the working platform of MATLAB. The dataset utilized in this study is the Nutrient-Deficiency-Symptoms-in-Rice obtained from the Kaggle website. We analysed the proposed model evaluation to associate it with other techniques such as DNN, DBN, LSTM, and RNN using different performance metrics such as error rate, confusion matrix, sensitivity, specificity, accuracy, F-measure, and kappa score. The neural network snapshot along with different parameters are present in *figure 3*. The experimental settings are presented in *table 1*.

4.1 Dataset description

The Nutrient-Deficiency-Symptoms-in-Rice dataset [19] is used in this study. The images in this dataset are in the JPG format and the samples in the dataset are shown in *figure 4*. The dataset was updated by Weeraphat Raksarikon in the year 2020. It consists of three classes of nutrient deficiency in paddy such as phosphorous, potassium, and nitrogen. Since the images in the dataset are initially imbalanced and very small in size, it is augmented using the data augmentation technique to create a feature-rich model for training. The steps used for data augmentation are random flipping, crop, resize, zoom, and rotate. Data dissemination before and after augmentation is shown in *table 2*.

Table 2. Data dissemination before and after augmentation

Class	Number of images before augmentation	Number of images after augmentation
Nitrogen	440	3080
Phosphorous	333	2331
Potassium	383	2681

4.2 Performance evaluation metrics

The sensitivity and specificity can be computed from the confusion matrix as follows

$$Sensitivity = \frac{\alpha}{Numberofpositivepredictions} \tag{6}$$

$$Specificity = \frac{\gamma}{Numberofpositivepredictions} \tag{7}$$

Sensitivity and specificity measure the number of positive and negative labeled class predictions. Recall is also known as sensitivity.

$$Accuracy = \frac{\alpha+\gamma}{\alpha+\beta+\gamma+\delta} \tag{8}$$

Precision mainly measures the number of accurate positive predictions of the overall number of positives and it is computed as shown below:

$$Pr\,e\,cision = \frac{\alpha}{\alpha+\beta} \tag{9}$$

The recall and precision with its harmonic mean is F-measure and expressed as;

$$F - measure = 2 \times \left[\frac{Pr\,ecision \times sensitivity}{Pr\,ecision + sensitivity}\right] \tag{10}$$

Kappa coefficient (KC) mainly measures the consistency of the classifier and it is evaluated using the confusion matrix values. A higher value shows that the classifier is very effective and it is computed as follows:

$$KC = \frac{2\times(\alpha\times\gamma-\beta\times\delta)}{(\alpha+\delta)\times(\delta+\gamma)\times(\alpha+\beta)\times(\beta+\gamma)} \tag{11}$$

Error rate mainly measures the prediction error of the model in hand with the actual model and it is computed as follows:

$$error\_rate = 1.0 - accuracy \tag{12}$$

The dataset is partitioned into two where 80% of image is used to train whereas the balance 20% to test image. The distribution of each class image in the dataset is presented in *table 2*. A total of 6104 images is used for training whereas the rest 1526 images are employed to test image.

4.3 Experimental outcomes

Figure 5 depicts the performance of graphical representations with respect to F-measure, recall, precision and error rate is as

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shown in Figure 5 (a) to (c). The work performance of proposed is associated to state-of-art approaches namely DNN, DBN, LSTM and RNN. The results demonstrate in *figure 5 (a) to (c)*, the F-measure, recall and precision comparison with other approaches that the proposed method offers superior results.

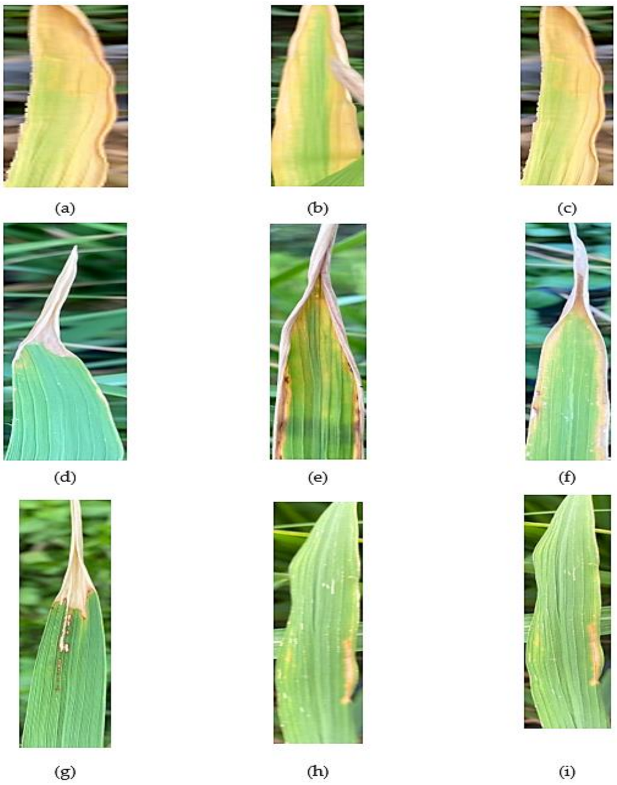

Figure 4: Image samples in the kaggle dataset; (a)-(c) Samples of nitrogen deficiency; (d)-(f) Samples of phosphorous deficiency; and (g)-(i) Samples of potassium deficiency

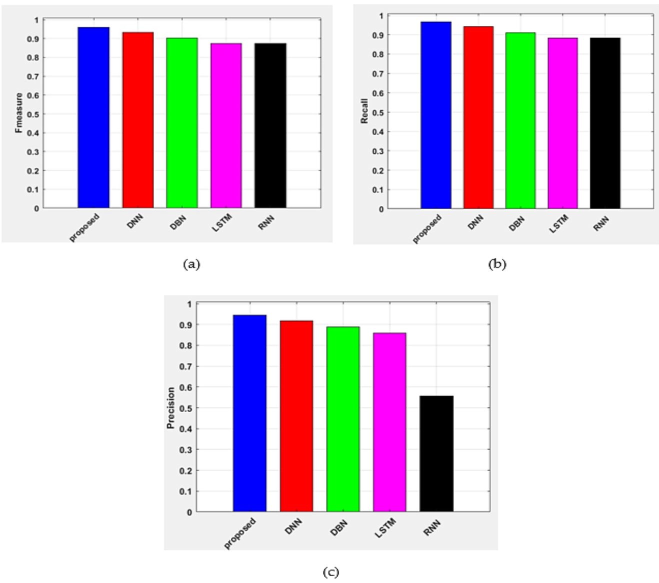

Figure 5: Analysing the performance based on (a) F-measure, (b) Recall and (c) Precision

The proposed model offers a minimal error rate that contrasted to other methods. The misclassification rate of the hybrid CNN is 0.02 which is relatively less contrasted to the DNN (0.04), DBN (0.07), LSTM (0.11), and RNN (0.11).

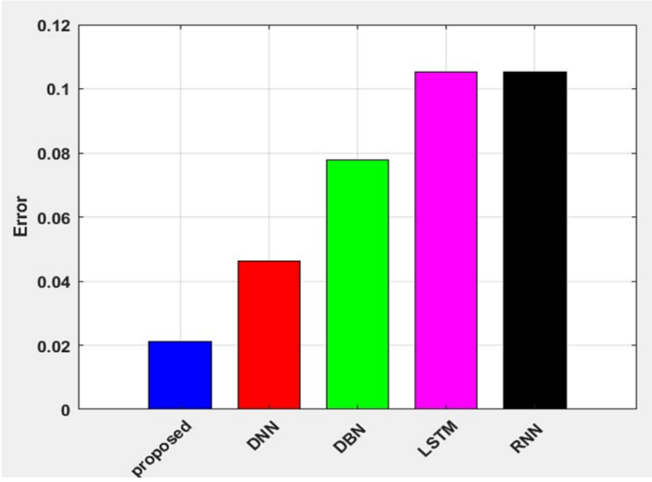

Figure 6: Analysing the performance

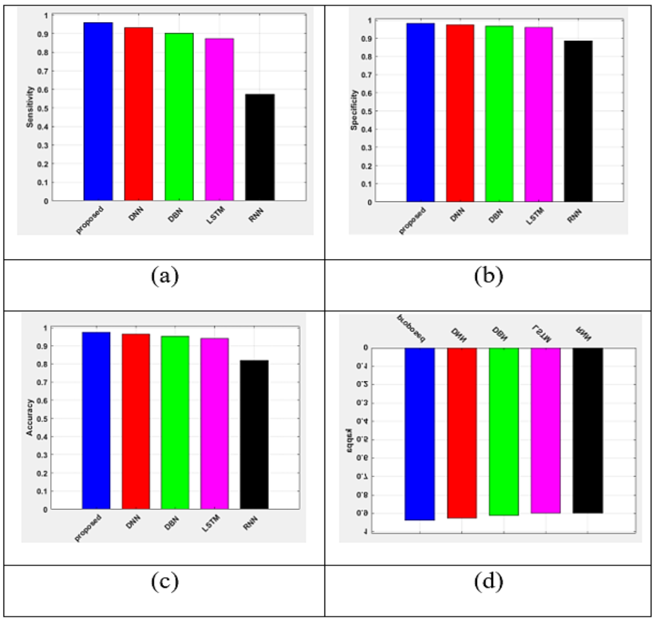

Figure 7: Analysing the performance based on (a) Sensitivity, (b) Specificity, (c) Accuracy and (d) Kappa

Figure 7 depicts the graphical representation to evaluate the performances of sensitivity, specificity, accuracy and kappa as shown in *figure 7 (a) to 7 (d)*. The proposed work performance contrasted to previous methods namely DNN, DBN, LSTM and RNN. The results of sensitivity for DNN, DBN, LSTM, RNN and proposed is 93.6%, 90.2%, 87.3%, 57.2% and 96%. Similarly, the results of specificity for DNN, DBN, LSTM, RNN and proposed is 97.6%, 96.7%, 96%, 88.5% and 98.2%. The accuracy results of various techniques like DNN, DBN, LSTM, RNN and proposed is 96.5%, 95.5%, 94.03%, 82% and 97.5%. The results demonstrate in *figure 7 (a) to (c)*, the sensitivity, specificity and accuracy comparison with other approaches that the proposed method offers superior results. *Figure 7 (d)* plot the state of art results of kappa. The performance evaluation in terms of kappa is compared to different approaches such as DNN, DBN, LSTM, and RNN. The proposed model offers a higher kappa value when contrasted to other techniques. The misclassification rate of the hybrid CNN is 93.7 which is relatively higher when compared to the DNN (92.7), DBN (91.1), LSTM (89.8), and RNN (74.5).

5. CONCLUSIONS

In agriculture, nutrient deficiency in plants serves as a crucial threat to global economic development and growth since it affects agricultural outcomes. If the disease is diagnosed in the initial stage, then it will be effective in preventing the further progression of the disease. This highlights the need for an efficient automated method for classifying and identifying different nutrient deficiencies in paddy such as phosphorous, nitrogen, and potassium. Even though different approaches address this issue in the literature, they are mainly focused on leaf disease prediction rather than nutrient deficiency analysis. Therefore, this paper presents a novel hybrid CNN approach for nutrient deficiency in paddy plants. To improve the disease prediction accuracy, we have incorporated a GLCM technique. This step helps to enhance the image representation capability and transform the spatial dependency between different feature maps. The nutrient-deficient paddy leaf images used in this work are obtained from the Kaggle dataset. Compare the proposed model by different techniques such as DBN, DNN, LSTM, and RNN in terms of confusion matrix, specificity, sensitivity, F-measure, accuracy, precision, recall, kappa score, and error rate. The proposed graphical values demonstrate 96% F-measure, 96.8% recall, 94.5% precision, 96% sensitivity, 98.2% specificity, 97.5% accuracy, 93.7% kappa and 0.02% error rate. When compared to existing methodologies, the empirical findings produced utilizing the proposed framework produce competitive outcomes.

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