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Analysis of Recognition Performance of Plant Leaf Diseases Based on Machine Vision Techniques

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Abstract

Agriculture is the primary source of income for the majority of the population in Bangladesh. Agriculture is also a big part of the economy of the country. Therefore, it's more necessary to grow our crops and fruits and boost their harvests. Fruits are adored by the people of this country, and farmers love growing fruits. Owing to numerous diseases, both the quality and quantity of fruits are not meeting expectations. Native fruits are contracting many types of new diseases, and the magnitude of the problem is increasing alarmingly. To deal with this issue, quick detection of the disease and correct treatment or recuperation is required. In many cases, locals fail to even detect rare diseases. Thanks to the huge advancement in technology, rare diseases can now be detected with the use of the right technologies. A good plant's growth is dependent on its leaves. Early leaf disease detection can help in keeping the leaves disease-free, as well as the plants and fruits. Our research focuses on identifying litchi leaf diseases by employing sophisticated image processing technologies to ensure the freshness of the leaves. A machine-vision-based technique, i.e., the *Convolutional Neural Network* (CNN), has been used in this research work.

Keywords: Agriculture; Litchi; Leaf Disease; Deep Learning; Convolutional Neural Network; Plants; Disease Recognition.

1. Introduction

Bangladesh is a predominantly agricultural country. Agriculture is the largest employment sector, making up a large percentage of Bangladesh's GDP and employing almost 50% of the total workforce. A plurality of the people of Bangladesh earn their living from agriculture. Also, the agriculture sector has a huge potential to grow to not only meet the local demands but also export crops and fruits globally and earn foreign revenue. In agriculture, the detection of disease in plants is a significant task. Agriculture is extremely important to the country's economy. Early and accurate detection and diagnosis of plant diseases during plant production are critical for reducing both qualitative and quantitative losses in crops.

Fruit is one of the major crops cultivated in Bangladesh. Many seasonal fruits are grown in Bangladesh, including mango, jackfruit, litchi, and papaya, which account for about 79% of the harvested area. With its sweet white scented flesh, litchi is one of the most popular fruits in our country and is planted in most of the courtyards. Litchi is picked between May and July. These months are known as "Modhu Mash" in Bangladeshi tradition. During the "Modhu

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Mash," 46% of the fruits are collected. Litchi production is currently over 12800 MT per year, with approximately 4,800 hectares under cultivation. Because of the high death rate of young lychee plants caused by numerous leaf diseases of litchi leaves, the expansion of litchi is generally slow in government horticultural centers. It is possible to increase the production of litchis and export them as well, so that farmers could benefit more. We're trying to figure out how to recognize litchi leaf illness so that the litchi tree can stay healthy and disease-free. We use image processing with the CNN Algorithm, a cutting-edge machine learning technology that can anticipate the outcome and show us which leaves are disease-free and which are not. We collect some images with a camera or other form of camera equipment in our system, then submit them to the system for analysis. Using image processing techniques, the system's fervor is ejected, and this ejected characteristic allows us to provide a model for forecasting which disease the captured life photos are suffering from. Our proposed model is based on CNN and can provide us with a high level of accuracy in recognizing leaf illness.

2. Literature Review

A plethora of work has been done on various plant leaf disease detection. We discuss the related works under two broad categories. The first category presents the works done for leaf or plant disease detection and the second category presents the works done for litchi leaf disease detection. First, we discuss the works done for plant or leaf disease detection. Rastogi et al. [1] suggested a method that, in the first phase, uses artificial neural network based training and classification to recognize leaf illness. They rate the disease in the second phase based on the amount of disease present in the leaf. Sardogan et al. [2] reported a tomato leaf disease detection and classification technique based on a convolutional neural network model and the *Learning Vector Quantization* (LVQ) algorithm.

Padol et al. [3] identified and classified grape leaf disease by SVM classifier using segmentation by *K*-means clustering. To detect and diagnose illnesses in tomato leaves, Tm et al. [4] used a modest version of the LeNet convolutional neural network model. Panigrahi et al. [5] used supervised machine learning techniques to build multiple models for maize plant disease prediction and discovered that the random forest approach has the best accuracy. Image processing techniques based on image segmentation, clustering, and open-source algorithms were proposed by Ashok et al. [6] to identify tomato plant Leaf disease. Agarwal et al. [7] used a CNN-based technique to identify the illness of tomato plant leaves. Three convolutional and three max-pooling layers are followed by two fully connected layers in their model. Ahmed et al. [8] introduced a machine learning-based rice leaf disease detection system. The three most frequent rice plant diseases were discovered. Using *K*-means clustering and a support vector machine, Habib et al. [9] suggested an online machine vision-based expert system for papaya disease identification. Using *K*-means clustering and a Random Forest classifier, Habib et al. [10] suggested another online expert system for jackfruit illness detection and classification. Using *K*-means clustering and a multiclass support vector machine, Majumder et al. [11] developed an automated method for detecting carrot flaws. Pre-trained CNN models and the ensemble approach of these models were also used in several studies for recognizing diseases of leaves and pests [12, 13].

Second, we discuss the works done for litchi plant and leaf disease detection. Rani et al. [14] detected the infected area in litchi fruit and leaf using fuzzy set operation for otsu-based color image segmentation. They only detected the presence of diseases in litchi fruit and leaf but didn’t identify what the disease is. Though there have been numerous studies on various plant and leaf disease detection, this is the first effort that we are aware of that uses a CNN to spot litchi leaf disease.

3. Research Methodology

To recognize the litchi diseases in 2D images layer by layer, we have utilized CNN. At first, the captured image is preprocessed, i.e. image scaling and augmentation take place. Since we have dealt with three litchi leaf diseases such as leaf blight, leaf mite, and red rust, a CNN model can easily be made to classify photos by addressing diseases in the photographs of the leaves and then determine the specific disease. All these methods comprise our research methodology which is shown in Figure 1.

4. Dataset Preparation

We have created a fresh dataset for this work. Most of the images are collected locally, i.e. visiting several locations in rural areas of Bangladesh, and the rest from the Internet. We have gathered all of the leaf photographs in JPG format, and the resolutions are obviously not the same. An image of each litchi leaf disease is provided in Figure 2. Thus, three thousand three hundred and ten (3,310) images have been collected in total under three disease categories, e.g. leaf blight, leaf mite, and red rust. After the image augmentation, this size becomes nine thousand nine hundred and thirty (9,930). The disease-wise frequency distribution of these images is tabulated and shown in Table 1.

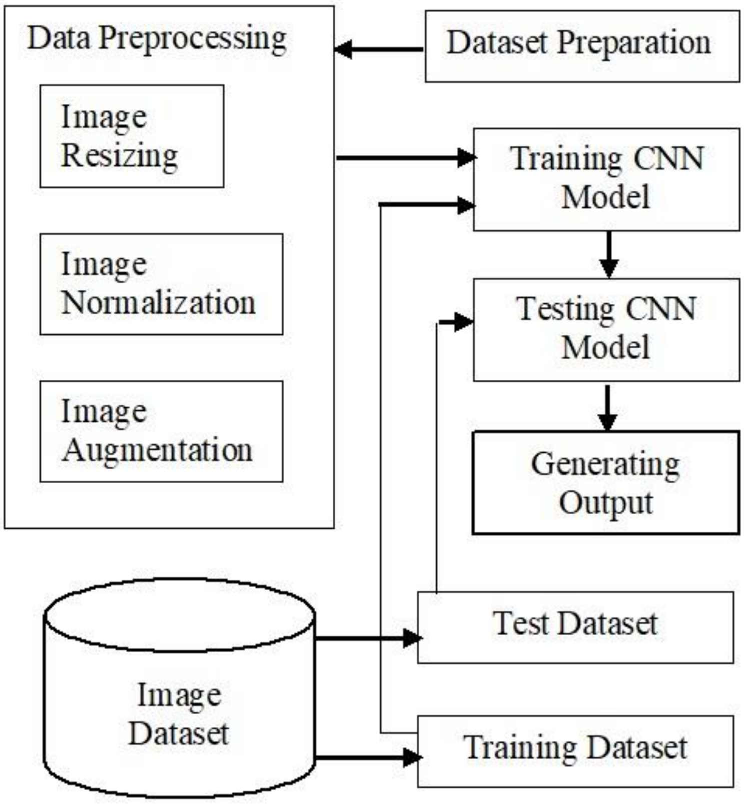

Figure 1. Research methodology deployed

(a) Disease	(b) Image
Leaf Mite:	
Leaf Blight:	
Red Rust:	

Figure 2. Sample of the image dataset prepared. (a) Disease name. (b) Image.

Table 1. Distribution of image data

Class	Initial Frequency	Augmented Frequency
Leaf Mite	930	2790
Leaf Blight	1110	3330
Red Rust	1240	3720

5. Data Pre-processing

This is the challenge of processing photos as data for feeding them to a CNN. This is a crucial consideration when rearranging data for training and improving accuracy. Before data pre-processing, our data was disorganized in terms of size. We have performed image scaling, normalization, and augmentation to have the image data ready to be fed to a CNN.

- ***Image Resizing:*** We adjusted all of the pictures in the collection to a fixed height and width because they were all of the various sizes. This is necessary since the neural network cannot function with pictures of varied sizes.
- ***Image Normalization:*** Our dataset contains colorful images, with each pixel having a value ranging from 0 to 255, depending on the RGB value. For a CNN model, calculating such values is extremely difficult and time-consuming. This is why we subtracted 255 from all pixel values between 0 and 1.
- ***Image Augmentation:*** Since we don't have enough data for a CNN model, image augmentation is a fantastic concept. The training of CNN models usually necessitates an enormous amount of data. In general, the more data there is, the better the model performs. Obtaining huge amounts of data, on the other hand, has its own set of issues. The issue with a paucity of data is that our CNN model may not be able to learn the pattern or function from the data, and so may not perform well on unlabeled data. So, we have used image augmentation techniques instead of manually collecting data for days.

6. Convolutional Neural Network (CNN)

A CNN belongs to the class of deep artificial neural networks (ANN's). This is especially crucial to deep learning, which learned to break down various forms of input using perceptron, a grinding AI unit calculation. CNN operations rely on contributions to separate design acknowledgment for the most part, and it works effectively with spatially linked data. CNN has a learnable limit, just like ANN. There are several levels in the CNN, including an input layer, an output layer, and other layers [15]. We can apply it to our disease recognition issue. A picture can be broken into numerous layers; CNN's first layer, for example, is the information layer. This layer will pixel-by-pixel read the pictures. There are also other types of strata, which are covered here.

- ***Pooling layer:*** The pooling layer, which is a non-straight layer, separates data components and reduces the number of boundaries, preventing overfitting and preserving the most important data. We can determine the size of the Pooling Layer that will allow us to remove unnecessary highlights while keeping the essential ones. MaxPooling, Average Pooling, and Min Pooling are three different types of pooling layers.
- ***Flatten layer:*** Flatten layer center of the convolutional layer and entirely associated layer. Smoothing is the technique of transforming all of the 2-dimensional clusters into a single-dimensional element vector. A solo smoothing structure is created by this smoothing structure. The thick layer will use a lengthy, consistent direct vector for the final layout layer.
- ***Fully connected layer:*** This layer is the final step of a CNN organization, and it corresponds to the information component vector. Loads, predispositions, and neurons are all part of the FC layer. It connects neurons in one layer to neurons in a different layer. Every neuron in the FC layer is recombined to efficiently and precisely organize each piece of data. It's used to organize photographs into different categories by preparing them. FC layers differ from multilayer perceptron layers in that each neuron has complete connections to all previous layer initiations.

7. Training Methodology

After training the CNN model with the training data set, its performance with the test data set. Because accuracy isn't well-adapted for evaluating classification models generated from unbalanced data sets, where the number of observations in various classes varies significantly, accuracy isn't a reliable indicator of a classifier's true performance in performance analysis. As a result, in addition to accuracy, several more measures are needed to evaluate a classifier's performance, as explained in [16-18].

For a binary, or two-class problem (*TN*'s), the number of false positives (*FP*'s), false negatives (*FN*'s), true positives (*TP*'s), and true negatives (*TN*'s) is presented in a confusion matrix. In the event of multiclass concerns, i.e.

problems with more than two classes, the resulting confusion matrix will be of dimension $n \times n$ ($n > 2$). There are n rows, n columns, and $n \times n$ entries in total in the matrix. This matrix cannot be used to calculate the number of *FP*'s, *FN*'s, *TP*'s, or *TN*'s. The values of *FP*'s, *FN*'s, *TP*'s and *TN*'s for class ***i*** are computed using the following equations [9]:

$$TP_i = a_{ii}. \tag{1}$$

$$FP_i = \sum_{j=1, j\neq i}^{n} a_{ji}. \tag{2}$$

$$FN_i = \sum_{j=1, j\neq i}^{n} a_{ij}. \tag{3}$$

$$TN_i = \sum_{j=1, j\neq i}^{n} \sum_{k=1, k\neq i}^{n} a_{jk}. \tag{4}$$

The final confusion matrix is 2×2 in size and possesses, for all classes, the average values of the n confusion matrices when using this method. This confusion matrix is used to calculate the recognition system's accuracy, sensitivity, specificity, and precision. Once trained, the performance of our CNN is evaluated in the index of these criteria using a test data set. As a consequence, CNN will be able to identify litchi leaf diseases based on photos. The following percentages of accuracy, sensitivity, specificity and precision are estimated depending on the confusion matrix:

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \times 100\%. \tag{5}$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100\%. \tag{6}$$

$$Precision = \frac{TP}{TP+FP} \times 100\%. \tag{7}$$

$$Specificity = \frac{TN}{FP+TN} \times 100\%. \tag{8}$$

The holdout approach is used to evaluate the performance of the deployed CNN classifier using the evaluation criteria described in Equations 5 to 8 [16].

8. Result and Discussion

We use our approach to machine-vision-based litchi leaf disease recognition to undertake an inquiry, as illustrated in Figure 1. The training and testing components of the enlarged dataset were separated. The holdout technique is used to determine the fraction of data kept for training and testing [16]. Eighty percent (80%) of the augmented dataset was used for training, while the rest (20%) of the dataset was used for the test. We do not choose this split whimsically but rather a lot of experimentation which is shown in Figure 3.

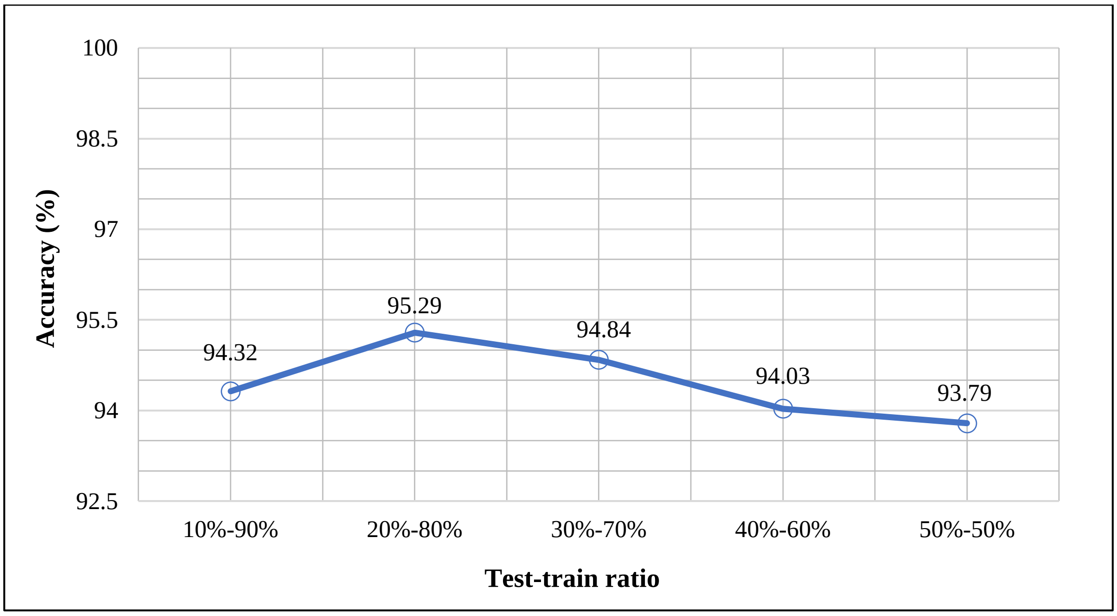

Figure 3. Training and validation accuracy in the course of epochs

We employ a validation set to avoid model overfitting. The detailed specifications of the CNN model are provided in Table 2. The ReLU function, which stands for the rectified linear unit function, was used to activate the convolution and dense layers.

Table 2. The detailed specifications of the CNN model used

Layer	Output	Number of Parameters
conv2d (Conv2D)	(None, 633, 615, 16)	448
batch_normalization(BatchNormalization)	(None, 633, 615, 16)	64
max_pooling2d (MaxPooling2D)	(None, 316, 307, 16)	0
dropout (Dropout)	(None, 316, 307, 16)	0
conv2d_1 (Conv2D)	(None, 314, 305, 32)	4,640
batch_normalization_1(BatchNormalization)	(None, 314, 305, 32)	128
max_pooling2d_1(MaxPooling2D)	(None, 157, 152, 32)	0
dropout_1 (Dropout)	(None, 157, 152, 32)	0
conv2d_2 (Conv2D)	(None, 155, 150, 64)	18,496
batch_normalization_2(BatchNormalization)	(None, 155, 150, 64)	256
max_pooling2d_2(MaxPooling2D)	(None, 77, 75, 64)	0
dropout_2 (Dropout)	(None, 77, 75, 64)	0
conv2d_3 (Conv2D)	(None, 75, 73, 128)	73,856
batch_normalization_3(BatchNormalization)	(None, 75, 73, 128)	512
max_pooling2d_3(MaxPooling2D)	(None, 37, 36, 128)	0
dropout_3 (Dropout)	(None, 37, 36, 128)	0
flatten (Flatten)	(None, 170496)	0
dense (Dense)	(None, 128)	21,823,616
batch_normalization_4(BatchNormalization)	(None, 128)	512
dropout_4 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 3)	387

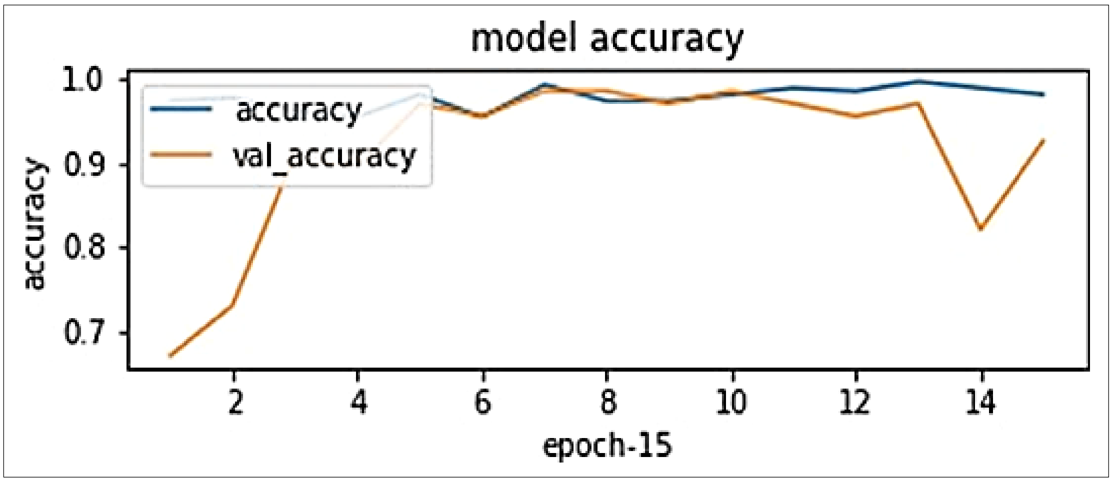

Figure 4. Training and validation accuracy in the course of epochs

The softmax function was also utilized to activate the last dense layer, which predicted the target variables, namely the three litchi leaf diseases. For the perfection of the results, we trained the CNN for some epochs. We have achieved our destination after 15 epochs, which is shown in Figure 4. As seen in Figure 4, there isn't much of a difference between training and validation accuracy, so this model is currently acceptable. Figure 4 shows the normalized 3×3 confusion matrix. Table 3 shows the complete results of the recognition of all three leaf diseases, as calculated using the confusion matrix. We can observe from this table that 95.29% accuracy was attained. Moreover, we observe that red rust and leaf mite have the highest and lowest recognition rates of 97.05% and 94.21%, respectively. Red rust has not only the highest accuracy but also the highest precision and sensitivity, whereas leaf mite has the highest specificity.

Table 3. The entire results of the recognition of all three leaf diseases

Class	Accuracy	Precision	Sensitivity	Specificity
Leaf mite	94.21%	91.94%	88.14%	96.75%
Leaf blight	94.61%	93.09%	91.18%	96.43%
Red rust	97.05%	93.55%	98.58%	96.20%
Overall	95.29%	92.94%	92.94%	96.47%

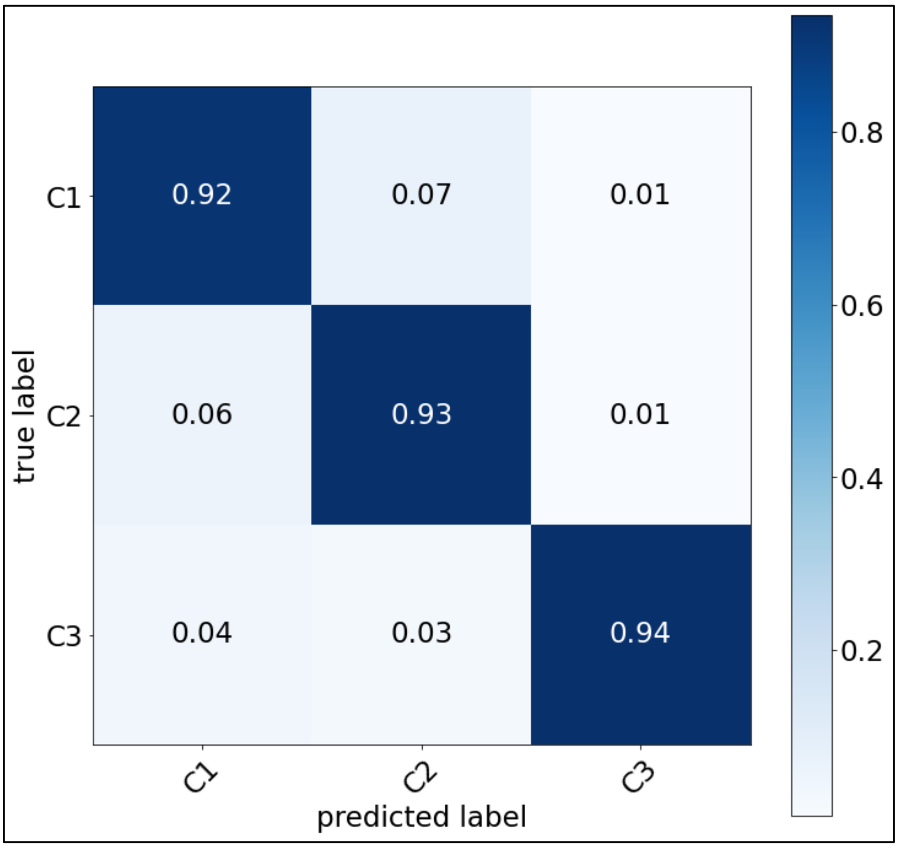

Figure 5. The normalized 3 × 3 confusion matrix, C1, C2, and C3 represent leaf mite, leaf blight, and red rust, respectively

9. Conclusion

We have reviewed data preparation, data processing, the train and test technique, and CNN and its layers in this study. Our model is more accurate, despite its simplicity. Finally, we feel that CNN can be advantageous and efficient in any image processing system. We can secure our fruits from disease and export them abroad using this technology, which will benefit farmers and the Bangladeshi economy. We may solve our unemployment problem by gradually increasing fruit cultivation. Since we are developing a CSV test dataset, i.e., a processed dataset, anyone can work with our dataset in the future. This will help us to make further progress on that report. In this study, the proposed CNN has obtained an overall 95.29% accuracy, whereas it has acquired a 97.05% accuracy in the red rust class, which is higher than all other classes. In the future study, we will expand our dataset by increasing the number of images and classes. We will also conduct some experimental studies where the performance of some state-of-the-art pre-trained CNN's will also be examined for this task.

10. Declarations

10.1. Author Contributions

Conceptualization, I.H. and M.T.H.; methodology, I.H. and M.T.H.; software, M.A. and M.A.; validation, S.N., M.A. and M.A.; formal analysis, M.A. and M.A.; investigation, M.A. and M.A.; resources, I.H.; data curation, I.H.; writing—original draft preparation, I.H.; writing—review and editing, S.N. and M.T.H.; visualization, S.N. and M.T.H.; supervision, S.R.H.N. and M.T.H.; project administration, S.R.H.N. and M.T.H..; funding acquisition, I.H. All authors have read and agreed to the published version of the manuscript.

10.2. Data Availability Statement

The data presented in this study are available in the article.

10.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

10.4. Institutional Review Board Statement

Not applicable.

10.5. Informed Consent Statement

Not applicable.

10.6. Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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