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Article

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Abstract
The major aim of the study is to determine some of the diseases affecting rice plants which lead to crop loss. The suggested model is designed into four primary phases, i.e., pre-processing, feature extraction, feature selection, and classification. The proposed models have been applied to two sets of data that include Rice Disease and the Rice Leaf Disease Image that constitute a total of four types of classes of the paddy leaves: healthy, blast, bacterial blight, and tungro. The dataset images are initially upgraded in the first stage of pre-processing in order to enhance the quality of the images. A Gaussian filter is used to eliminate noise on the green spectral band and to convert the input images to RGB color space. The step second involves deriving color and texture information out of each of the pre-processed images. The third step Features selection SVM-RFE has been used to select features with the help of the intersection with the ARFA technique. The fourth step involves a final step where the features chosen are applied to classify the kind of disease existing in each picture. ABi-LSTM model is used in the classification process and the accuracy is 97.05.
Keywords: paddy leaf plant, SV-RFE, ABi-LSTM, deep learning and median filter.

1. Introduction

The main method used in the contemporary world to produce enough food to feed the expanding population is agriculture. The forestry, fishing, and agriculture industries account for the majority of the GDP. However, the proportion of India's GDP that comes from agricultural products is steadily decreasing [1]. The paddy plant is one of the most significant plants in the world. Given that rice is a staple food for massive populations around the world. It is essential to boost the volume and the quality of rice [2, 21, 22, and 23].

Plant diseases are the main reason for this major reduction in agricultural output. Only by thorough examination and research, individual will be able to observe and assess the severity of the illness.

More time is needed for this procedure, and more experts in plant disease diagnosis are needed. Plant growth and development are influenced by several environmental factors, including temperature, rainfall, sunshine, and climate change [3,24]. Plant growth requires the right conditions of the soil, including pH, nutrients, and moisture [4,25]. The amount and quality of the ultimate crop might be greatly decreased by the presence of plant diseases. Pests and diseases account for 25% of crop losses as per the Food and Agriculture Organization's (FAO) estimations [5, 26]. It is crucial to regulate this parameter as a result. If not, it may negatively impact agricultural output by negatively affecting plant growth.

Plant diseases cost farmers all around the world a substantial amount of money each year. It is reasonable to anticipate these losses in between planting and harvesting agricultural products [6, 27]. In addition to these issues, plant diseases pose a serious risk to human health since they can cause liver illness, skin allergies, stomach difficulties, and strokes. Among the Leaf spots, bacterial wilt, ergot, rust, powdery mildew, and nematodes are among the frequent crop plant diseases [7, 28]. Strong measures must be used to identify, prevent, and manage plant diseases. Requirements for timely and appropriate technology creation include the ability to rapidly and reliably diagnose a variety of plant diseases. The most important part of a plant is thought to be its leafs. The deterioration and eventual loss of leafs is caused by a number of variables, including illnesses, pests, inadequate nutrition, lack of sunshine, and floods. One of the main factors influencing a plant's ability to develop is disease-related damage to its leafs. Plant functions such as transpiration, photosynthesis, germination, pollination, and others are significantly reduced by diseases. Consequently, it is thought that detecting leaf (foliar) diseases early on is essential to increasing agricultural productivity. The three main pathogens responsible for illness are fungi, viruses, and bacteria. Crop output has decreased, and these infections are to blame [8]. Fungi have been shown to be the pathogen that most

Significantly affects crop development out of all of them. Common foliar diseases that affect plants include Downy mildew, Anthracnose, Early and late blight, bacterial spots, apple scab, rust on leafs and common rust [9, 10].

To face the difficulties of growing output and to keep up with future agricultural trends, innovative solutions are required. Therefore, effective identification and management of plant leaf diseases depend on accurate diagnosis. A farmer may expend money, effort, and time trying to identify a problem with an unidentified cause until a disease is identified. Thus, in order to replace the visual evaluation method with an efficient automated system for diagnosing plant diseases, both new method development and enhancements to current techniques are needed. With more precision and less expense, image processing algorithms [11], [12] identify every factor connected to plant leaf diseases. These (image processing) methods can access the more precise characteristics of visual complaints.

2. Related Work

There has also been research done by authors on related work to classify the paddy diseases based on their characteristics. The CNN model has been employed by Senan et al. [13]. In this method, 3355 photos were collected in total and divided into 4 groups, namely, leaf blast, Hispa, Tungro and healthy rice pictures. Then the photos were classified using the five-layer CNN approach which was recommended. The suggested CNN solution provides a maximum accuracy of 93% compared to state-of-the-art comparison models. Using information gain or entropy factors, higher-order information characteristics could not be extracted using rice photos.

In an attempt to identify and categorize paddy leaf diseases, Ramesh and Vydeki [14] developed a better DNN with the Jaya strategy. The five types of images to be used in analysis are blast infections, bacterial blight, tungro, sheath rot, and normal. In order to eliminate the background, the RGB pictures were first transformed to HSV images. Binary pictures generated using the hue and saturation components were used to define which areas were hit and which ones were not hit. A clustering technique was used to separate the sick part and the background part as well as the normal part. Diseases were classified with DNN JOA, or optimized DNN with JOA. To perform the stability test of this approach in the right way, a feedback loop must be formed in the course of post-processing. The results of the experiments obtained were compared to those of DAE, DNN and ANN.

Patil and Kannan [15] provided the evolutionary and machine learning-based methods of diagnosing the diseases of plants. The first step was to prepare the featureset, which was due to the picture pre-processing method. Then, the relevant features were removed using the feature extraction methods in the processed photos. The genetic algorithm and the closest neighbor strategy were applied to detect diseases in the leaf of rice.

Sakhamuri and Kumar [16] developed a more effective system to classify and detect rice leaf disease with the help of deep learning and metaheuristic approach. The main objectives of the technique were to increase the training performance, precision, and universality. Using the pre-processing technique, noises and artifacts were removed out of the input image.

Dubey and Choubey [23] have suggested that Plant disease prediction is still a problem facing the farmers. Therefore, an effective solution is required. Thus, an effective paddy leaf disease identification has been suggested using the OSVM. The performance of the SVM classifier is optimally chosen with the help of ASFOA to change the classifier parameters. The SVM and ASFO algorithm mathematical formulations are well explained. The performance of the proposed method and its effectiveness in comparison with another method have also been analyzed by a variety of metrics.

Dubey and Choubey [24] have utilized the ANN and ASFO calculations have been clearly clarified. The execution of the prescribed strategy has been analyzed based on diverse measurements and adequacy compared with a distinctive strategy.

Based on a successful azim et al. [17] developed a system for rice leaf disease classification using feature extraction method. A model to differentiate between the three rice leaf diseases, bacterial leaf blight, tungro spot and leaf smut, was developed through this approach. The areas influenced by the disease were separated by the using hue threshold and the background of the photos was removed by the saturation threshold. Color, form, and texture were restored to their distinctive qualities from the destroyed portions. Integrated within this model is the extreme gradient boosting decision tree ensemble, which performed better than a few tested classification methods. Using the same dataset, previous research on rice leaf diseases on the UCI dataset have lower accuracy (86.58%) than our model.

3. Proposed Hybrid Classification Method

The general purpose of this study is to detect multiple rice diseases which may lead to failure of crops. The model architecture is arranged on the basis of four clear phases: pre-processing, feature extraction, feature selection and classification provided with help of the training dataset. From the beginning at hand, the pre-processing step strives to improve the input images from the dataset, with better clarity over glamour in mind. In order to reduce noise in the green channel, Gaussian filter is implemented, converting the input images to the RGB color space.

In turn, we extract color and texture features from all the improved images. Two methods will be applied during the feature selection process: Features are firstly chosen by implementing the SVM-RFE technique, and then refined using the ARFA procedure. After the relevant features are extracted they are applied to the classification phase in which every image goes through an analysis in order to determine which disease they represent. The identification of the disease is realized through the ABi-LSTM (Attention-based Bidirectional Long Short-Term Memory) classifier. A summary of the framework of the proposed methodology can be seen in Figure 1.

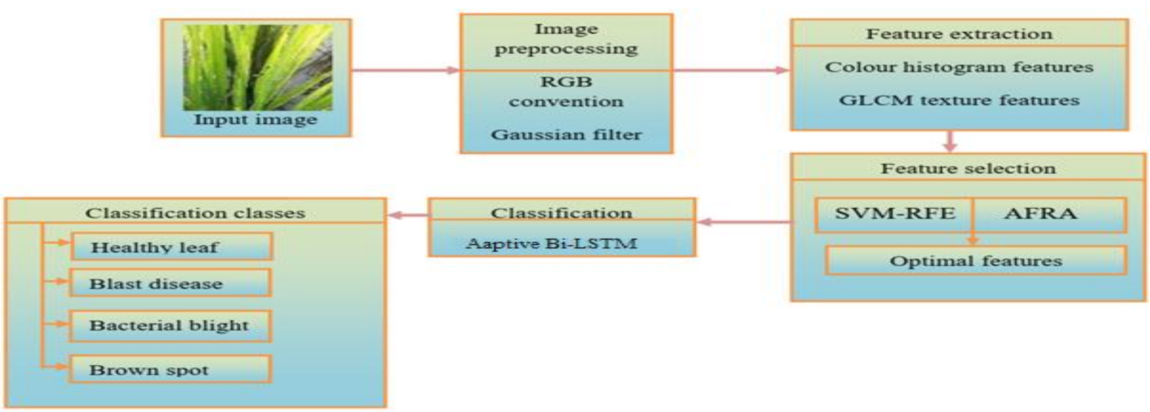

Figure 1: Process for classifying leaf diseases that is being proposed

3.1 Pre-processing

In pre-processing the first approach uses a median filter for noise removal while on the second approach a Gaussian filter is used which is shown here.

$$M(p,q) = \underset{(a,b)\in S_{ij}}{Median}\{X(a,b)\} \quad \text{.........(1)}$$

3.2 Extraction of features

From the picture, after pre-processing, we pull out the key entities from each of the green bands. In this study, two feature sets are retrieved: texture features and features of color histogram.

3.2.1 Features of a color histogram

The colour histogram is a widely recognised colour characteristic that may be utilised for extracting picture data. Our suggested method uses the mean and standard deviation to derive colour visual elements from the rice plant's leaf picture.

- **Mean** The mean, which characterizes an image's brightness, is its average value. The mean of a bright picture is usually higher than the mean of a boring one. We use equation (2) to calculate the mean.

$$M_j = \frac{1}{A}\sum_{i=1}^{A} P_{ji} \qquad \text{.....(2)}$$

Here, P_{ji} indicated as j^{th} A channel of color at the i^{th} picture pixel.

$$\sigma_j = \sqrt{\left(\frac{1}{T}\sum_{i=1}^{n}\left(X_{ji} - Y_j\right)^2\right)} \qquad \text{.....(3)}$$

3.2.2 Texture feature

The textures are taken out of every image using the GLCM features. Twenty-two GLCM characteristics are taken out of every picture in this research.

3.3 Feature selection

In this work, we show a novel feature selection strategy based on optimization, and machine learning. Firstly, we select the features through the SVM-RFE method. Then the ARF method is used to once again select the feature. After the selection procedure, we merge the two features and choose the common features. The process of classifying makes use of these attributes. Below is a description of the feature selection procedure;

3.3.1 Feature selection using SVM-RFE

This is followed by feature extraction after which the SVM-RFE technique is used to select the key features. In the case of integration between SVM and RFE, a SVM-RFE is created. In the selection of features, SVM-RFE eliminates the insignificant features that SVM captures and employs the rest as the new feature in re-training the classifier [14]. Decision function, also known as the hyper plane, is built in the proposed SVM.

$$H\left(\vec{q}\right) = \left(\vec{r}\,.\,\vec{p}\right) + a \qquad \text{.....(4)}$$

3.3.2 ARFA-based feature selection

Stimulated by the hunting style of red foxes and the methods used to survive, Adaptive Red Fox Algorithm (ARFA) is a nature-inspired meta heuristic optimization approach. Attraction to their adaptability, catlike senses, and exact pattern of movement, red foxes are very effective for finding food and survival in changes of their habitats. The use of these special abilities in mathematical models allows the development of the approaches to optimization that can be used in solving complex problems, including feature selection in such an area as machine learning.

1. Population Initialization:

The process is started with arbitrary selection of population of candidate solutions (foxes). Each fox relates to a potential combination of the features of the dataset.

2. Fitness Evaluation:

Each fox is evaluated using a prescribed objective function (might be the accuracy of classification, the number of features, or the trade off between them).

3. Fox Movement Strategy:

Foxes search the search space by imitating the following behaviours among others system

Approaching optimal solution localization with fine-tuning of local regions of the solution space. Steering away from danger to increase diversity in search and get out from local optima.

4. Adaptivity Mechanism:

The search strategy varies by changing the extent that algorithm explores as opposed to exploits, in pursuit of a smoothly balances exploration of new ideas and betterment of existing ones. This feature allows ARFA to adjust its search program.

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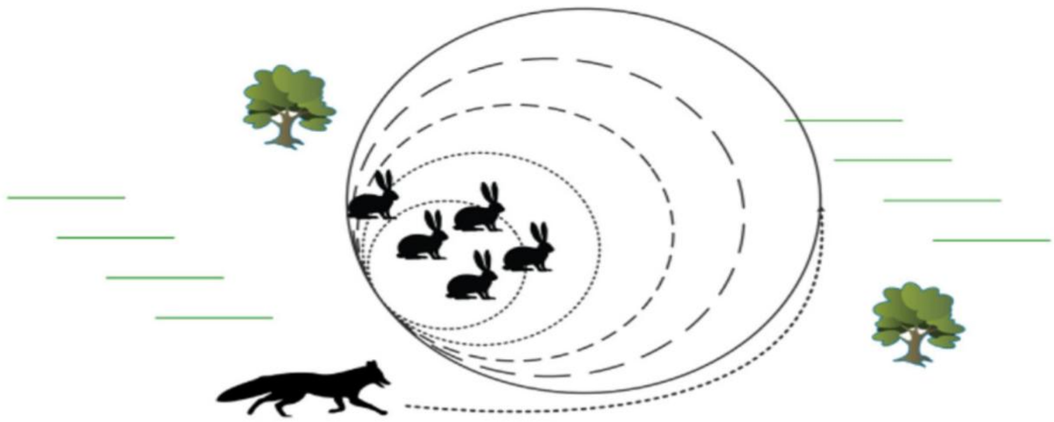

Figure 2: The way the red fox hunts

Table 1: Adaptive Fox Optimization Algorithm (AFOA)

Adaptive Fox Optimization Algorithm (AFOA)

Initialize the red fox population $Y_i \ = \{y_1, y_2, ..., y_n)$

While $It < MaxT_{It}$

Initialize $ds_{It}, S_{env}, tst_{It}, dp_{It}, j_{It}, MinT_{It}, a, and\ Fit_n$

Determine each search agent's fitness level.

Choose the best position and fitness amongst the fox population (Y) in every iteration.

If $fit_i > fit_{i|+1}$

$Fit_n = fit_{i+1}$;

Best position= $Y(i,:)$;

End if

If2 $r \geq 0.5$

If3 $d > 0.18$

Set the time at random;

Determine ds_{It} by using Equation (4)

Determine S_{env}

Determine dp_{It} by using Equation (5)

T_t = average time;

$T = T_t / 2$;

Determine j_{It} by using Equation (6)

Calculate $Y_{(It+1)}$ by using Equation (7)

Else if $d \leq 0.18$

Set the time at random;

Determine ds_{It} by using Equation (8)

Determine S_{env}

Determine dp_{It} by using Equation (9)

T_t = average time;

$T = T_t / 2$;

Determine j_{It} by using Equation (10)

Calculate $Y_{(It+1)}$ by using Equation (11)

EndIf3

Else

Find $MinT_{It}$ by using Equation (4)

Explore $Y_{(It+1)}$ by using Equation (7, 11)

Change the exploration agent's search position using Levy Flight,

End If 2

Check the position and make changes if it exceeds the limitations.

Assess the fitness of search agents.

Update Best position

$It = It + 1$;

End while

return Best position & Best Fitness

3.3.3 Hybrid features selection

The SVM RFE method, which only chooses attributes linked to categories, is first used in this research to choose the attribute. Next, we use the ARF algorithm to choose the features. Next, we merge the two characteristics that were chosen. We choose the traits that they all have in common. These standard characteristics are used to further processing. Figure 3 depicts the feature selection procedure.

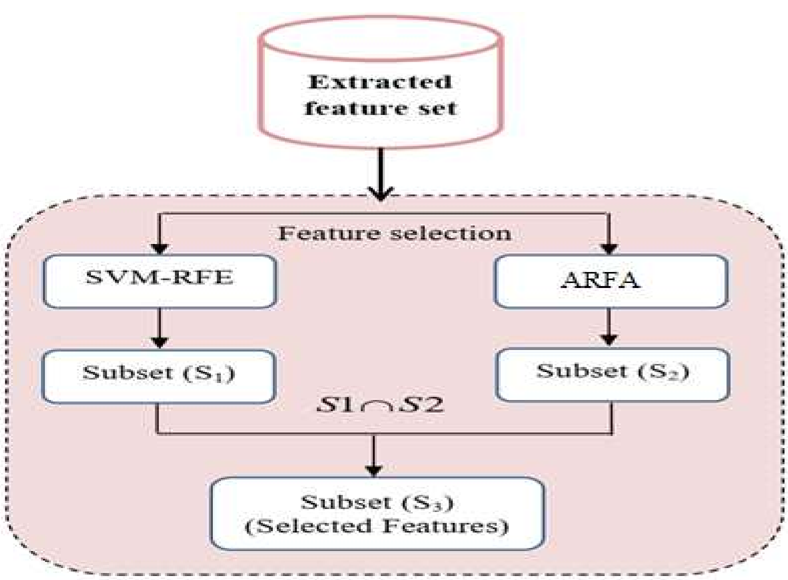

Figure 3: Feature selection process

4. Adaptive bi-long short-term memory for classification (ABi-LSTM)

The ABi-LSTM model is a new model of deep learning which builds upon the network of the traditional Bi-LSTM.

By mobilizing adaptive strategies, one improves the model's ability to manipulate successive data in an efficient manner and develop superior classification results which is especially relevant to such disciplines that make use of subtle feature interactions, as evidenced in image-based medical diagnosis.

Classification Workflow Using ABi-LSTM

1. Input Layer: After pre-processing and feature selection the disease-affected rice plant images are formed as sequence data.

2. Bi-LSTM Layers: The implications of the processing in both directions through the Bi-LSTM layers allow achieving extraction of contextual features from the input sequence.

3. Adaptive Processing Layer: The poorest systems use attention mechanisms or adaptive modules to calculate weights of the best outputs generated by the Bi-LSTM layer.

4. Output Layer: The processed representation is subject to a dense layer before being transformed by either a softmax or sigmoid activation to be classified to multiple or two classes, as demanded.

5. Results

In this section, the leaf disease categorization model that was previously provided. The following is a list of the many methods for creating screenshots and confusion maps. Figure 4 depict the Classification screen picture for bacterial blight illness.

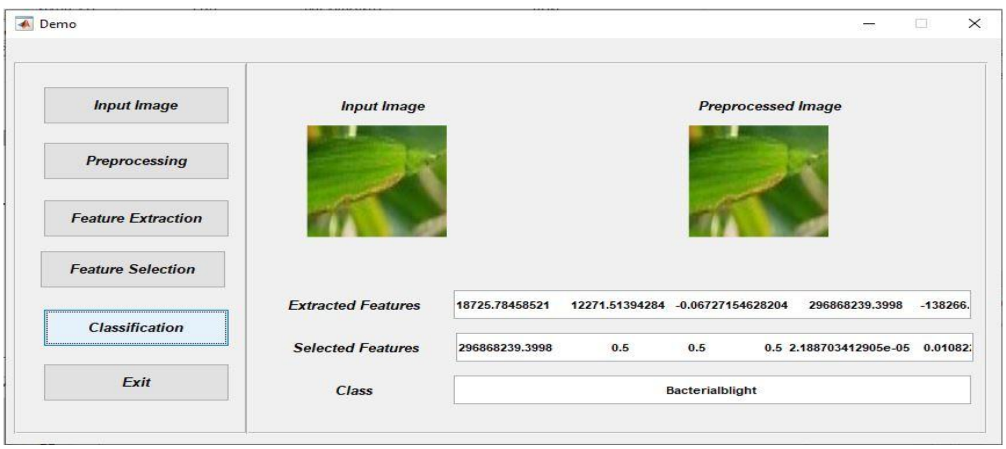

Figure 4: Classification screen picture for bacterial blight illness

Figure 5 depict an image showing the categorization of blast illness.

Figure 5: An image showing the categorization of blast illness

Figure 6 depict an image showing the categorization of Tungro illness

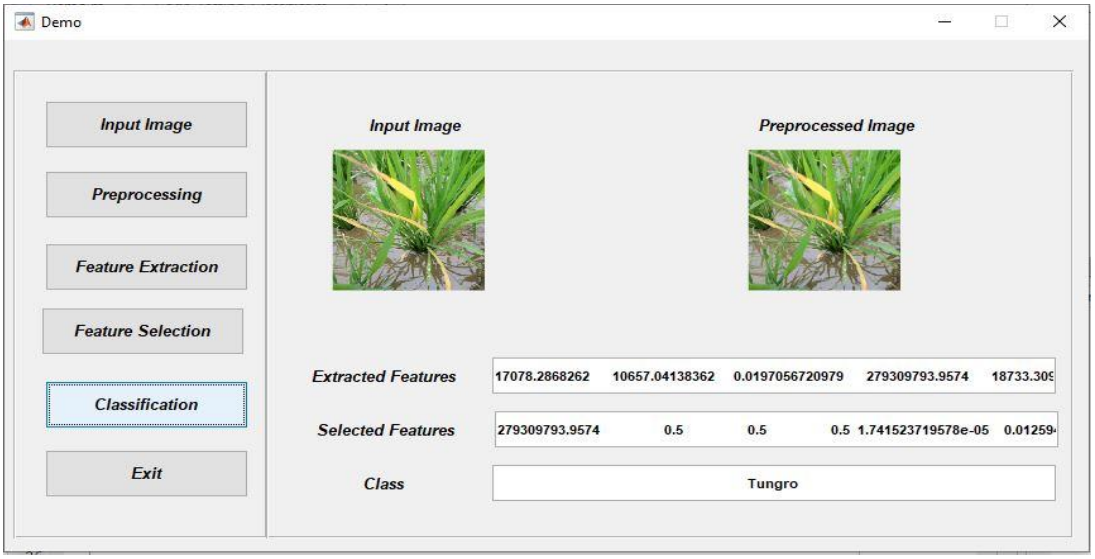

Figure 6: An image showing the categorization of Tungro illness

Classes	Blast Leaf	Bacterial Leaf	Tungro	Healthy leaf
Blast Leaf	310	0	0	5
Bacterial Leaf	2	284	0	0
Tungro	0	7	253	0
Healthy leaf	0	0	8	97

Figure 7: Confusion Matrix

Comparison with Existing Work in Terms of Accuracy

The proposed SVM-RFE and ARFA → ABi-LSTM model demonstrates a significant improvement in accuracy compared to existing methods such as ANN, DNN, GRU, LSTM, and Bi-LSTM.

This improvement highlights the effectiveness of integrating optimized feature selection with advanced bidirectional learning. Hence, the proposed approach establishes superior reliability and precision for paddy plant leaf disease classification.

Table 2: Comparison with Existing Work in Terms of Accuracy

Source	Plant name	Techniques	Accuracy (%)
Rajendran et al.[18]	Paddy plant	ANN	89.50
Nalini et al.[19]	Paddy plant	DNN	92.30
Pant et al.[20]	Paddy plant	GRU	91.20
Venkatakrishnan et al.[21]	Paddy plant	LSTM	94.50
Chinna et al. [22]	Paddy plant	Bi-LSTM	93.00
Our Study	Paddy plant	SVM-RFE and ARFA ->ABi-LSTM	97.05

The performance of each of the classifiers is measured in terms of accuracy to check its efficiency in leaf disease detection of paddy plants. The Artificial Neural Network (ANN) model of all the methods had the lowest accuracy of 89.50, which is low in terms of multidimensional nonlinear interaction of the features. GRU model made slight improvements and came up with an accuracy of 91.20, and Deep Neural Network at 92.30.
The Bi-LSTM model was further improved and attained 93.00 percentage whereas the LSTM model attained a greater percentage of 94.50 indicating its higher capacity to obtain long term dependencies of any sequential data. The suggested SVM-RFE and ARFA ABi-LSTM algorithm achieved the best result of 97.05, which is better than all the other algorithms since it adopts a hybrid approach of feature selection and high-level bidirectional learning.

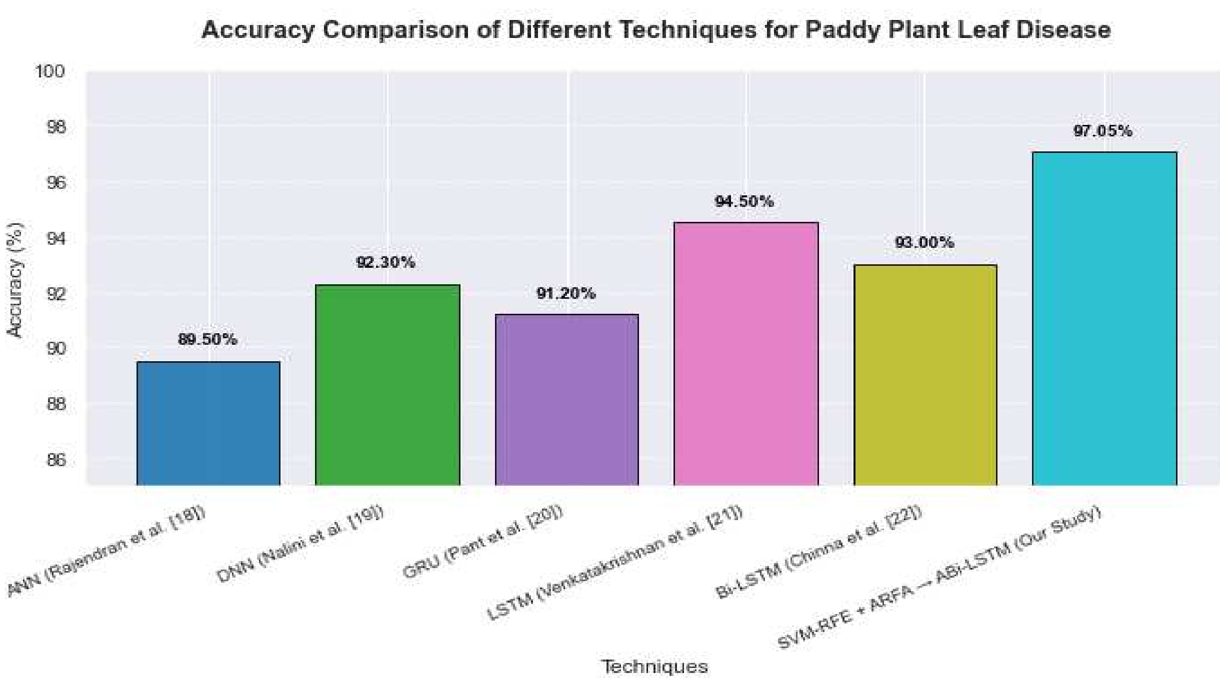

Fig. 8: Comparison with Existing Work in Terms of Accuracy

6. Conclusion

The study presented in this paper managed to design a powerful model of identifying and classifying plant diseases that seriously affect rice crop yield. The four-step model that has been suggested including pre-processing, feature extraction, feature selection, and classification was very accurate and robust. SVMRFE and ARFA algorithms showed good results in terms of maximizing features, which minimized redundancy and enhanced the efficiency of the model. The ABiLSTM classifier attained excellent accuracy of 97.05 which confirms that the model is effective in identifying and differentiating the four types of paddy leaf conditions namely healthy, blast, bacterial blight and tungro. The results demonstrate the importance of combining high-order feature optimization and deep learning to detect disease in rice in early and accurate stages. Such a strategy can help farmers and researchers exercise timely disease management strategies, which have an effect on increasing agricultural production and sustainability.

Data Availability:

https://www.kaggle.com/datasets/nirmalsankalana/rice-leaf-disease-image

Conflict of Interest

The authors declare no conflict of interest, financial or otherwise.

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