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HYBRID OPTIMIZATION MODEL FOR INTEGRATED IMAGE DATA EXTRACTION EXPERT SYSTEM IN RICE PLANT DISEASE CLASSIFICATION

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ABSTRACT
The purpose of this study is to increase the accuracy for rice plant disease classification by developing a hybrid optimization model using Convolutional Neural Network (CNN) in combination with Extreme Learning Machine (ELM), followed by Support Vector Machine. A key issue is to overcome with traditional expert systems that are difficult, due the variation differences and complex among rice plant image data set. For feature extraction, plant images are passed through CNN and for classification ELM & SVM used. Experimental results show the best accuracy of 98.63% is attained using CNN+ELM model on images resized to 100x100 pixels and has precision, recall, F1-Score all at value=0.99 By comparison, the CNN+SVM model achieves an accuracy of 91.92% using that same image size. Top AbstractIntroductionMethodsResultsDiscussionConclusionReferencesOverall, the proposed CNN+ELM combination can classify rice plant diseases better than using only a conventional approach (CNN) through various results from devices with limited computing power. The study presents a novel plant disease detection system that can be utilized for the development of precise tools to help improve agricultural management practices.
Keywords: *Convolutional Neural Network (CNN), Extreme Learning Machine (ELM), Support Vector Machine (SVM), Plant Disease Classification, Rice Plant Image Detection.*

1. Introduction

This study aims to develop a hybrid optimization model designed to enhance the accuracy and efficiency of rice leaf image extraction, as well as the detection and classification of rice plant diseases (Daniya & Vigneshwari, 2023a; Quach et al., 2022). The motivation for this research stems from the limitations of expert system methods previously employed by several researchers (Mohammed Al-Mafrji et al., 2023; Reva et al., 2023). This type of system relying at expert systems was limited, it is difficult to include a vast amount of knowledge in the rule base. The rule bases are static and do not learn independently therefor they can provide results that less accurate. Plant disease detection using the image analysis is a major component of machine learning, it helps increasing accuracy and reduce shortcoming in efficacy (Alpyssov et al., 2023; Dahake et al., 2023). Methods for image digitization and disease identification permit the timely diagnosis of rice diseases and facilitate an advanced response to avert or mitigate losses, thus contributing more informed decisions on managing their cultivation(Fanti et al., 2017; Kiran et al., 2023).

Rice is a major crop for many developing countries basal food production (Akbar et al., 2023). This has also been confirmed to be true by protein analysis, which is based on leaf shape and stem colour as well as real-leaf-spot or -pattern (N. Wang et al., 2023). A key example is in the early identification of illnesses that devastate rice crops. Correct identification of diseases permits application of applicable preventive and control measures, leading to reduction in crop losses (Yang, Lin, et al., 2023). Therefore, it is important to establish techniques which can unite several types of image analysis for recognition and quantification of rice plant diseases. It means that to identify the plant disease its need lot of images for this process and main feature which needs is visual inspection in leaves.

The rice plant disease classification in this study was carried out by passing several steps on the initial dataset data collection, pre-processing. Images of rice plants are prepared and conditioned in this phase to make them suitable for analysis. Conceptual Framework : First image is selected and features are extracted using Convolutional Neural Network(CNN), then highest accuracy for CNN performance after hyper-parameter optimization with the help of Genetic Algorithm. Subsequently, these extracted features are classified using Extreme Learning Machine (ELM) and Support Vector Machine (SVM), the output of which is than integrated to an expert system for providing recommendation on appropriate disease management. Yet the cycle bores deeper on to model performance evaluation and hyperparameter tuning if needed, closing upon final validation with out-of-sample data in order to test our results for overall correctness of the developed mode.

Many previous studies have also been conducted to classify rice diseases through image processing and application of expert systems. Sethy et al. proposed a diagnosis scheme of rice diseases in leaf images using deep features with complementary SVM, which greatly improved the accuracy of classification (Sethy et al., 2020). Jiang et al. applied Convolutional Neural Networks (CNN) at the pixel level, combined with SVM at the module level, for rice disease classification. Their approach achieved high recognition accuracy across multiple disease classes, demonstrating that various types of rice leaf diseases can be effectively identified (Mamoor, 2019). Bhattacharya suggested to use DenseNet with transfer learning for enhancing the classification accuracy and reported good performance than other algorithms, but it faced difficulty while optimizing hyperparameters (A. Bhattacharya, 2021). Also, Bhattacharya et al. proposed a CNN framework for automatic classification of rice leaf diseases, achieving relatively high accuracy thus demonstrating an alternative solution to the limitations in fuzzy logic-based expert systems that are capable only of identifying simple disease symptoms (S. Bhattacharya et al., 2020). Finally, Yang et al. The authors in (Yang, Deng, et al., 2023) introduced the Dense Higher-Level Composition Detection Transformer (DHLC-DETR) model, which achieved a significantly higher accuracy for rice diseases.

Therefore, this is a considerable contribution to the literature as we develop a hybrid optimization model that takes image-based feature extraction techniques and expert systems with alongside machine learning methods. The model is build using Convolutional Neural Networks (CNN) for feature extraction, with hyperparameters optimization done by Genetic Algorithms. The study improves the accuracy and efficiency of rice disease detection and classification by integrating these techniques into methods like Extreme Learning Machine (ELM) (Kiran et al., 2023), Support Vector Machine (SVM) etc. The model proposed provides a faster, less expensive way of detecting the malware with increased flexibility and dynamism in expert systems. The result of this research has many practical applications besides successful implementation in agricultural management, such as monitoring plant health remotely on a real time basis helping farmers to take accurate and timely treatment decisions and hence increase productivity while reducing losses due to plant diseases

2. Literature Review

The hybrid variant of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) showed significant success in rice plant disease classification, because it extracts a high level of complex features from rice leaf images along with precision in classifying the rice diseases correctly as well. A hybrid model combines ResNet50 CNN with SVM and achieves an approximately 99% accuracy, indicating that rice disease detection can be reliably achieved using this proposed model (Alwan & Naji, 2023). Meanwhile, Mehta et al. Mehta et al. (2023) also based their approach on the CNN-SVM model and achieved an accuracy of 96.8% in classifying bacterial blight, blast and brown spot diseases on rice leaves, again providing further proof of the practicality of this hybrid model for identification of plant diseases in practice (Mehta et al., 2023). Dixit and Verma (2023) developed a CNN-SVM model with the participants that achieved remarkable accuracy and consistency while detecting multi-disease detection in rice plants for different datasets (Dixit & Verma, 2023) Singh et al. also support these findings. (2022) which adopted a similar methodology and proved the precision and sensitivity increase simultaneously of the combination between CNN on top of SVM through Bayesian optimization increasing F1-score value for different disease detection of rice plant (Singh et al., 2022).

A useful yet somewhat newer approach is a hybrid one that combines CNNs with Extreme Learning Machine (ELM) which yields higher computational efficiency without sacrificing accuracy. Parasa et al. (2023) proposed a CNN-ELM model which is memory optimized based on efficient preprocessing methods and the results reveal high classification accuracy, however, this approach requires less computing power. After the construction of this model, Attallah (2023) enriched it by creating the RiPa-Net pipeline, utilising two layers of CNN that has been capable of increasing rice disease classification accuracy to a maximum of 97.5% when SVM served as the final classifier (Attallah, 2023). Furthermore, Chen et al performed a study that Against Chen et al (2021) discovered that the performance of small details in rice disease images is improved with an attention mechanism and hence developed an Attention MobileNet-V2 model— which has increased classification accuracy of 99.67%. Lu et al. A model that optimizes CNN by Progressive Wasserstein GAN, which has also proved to be environmental improvement in rice plant disease identification (Lu et al., 2023).

CNN-SVM hybrid model employing optimization techniques has been shown to enhance accuracy and efficiency of the model. Daniya and Vigneshwari (2023) added to the idea of high sensitivity and disease detection accuracy by combining CNN characteristics with fuzzy clustering algorithms in order to produce an F1-score of 0.9142 for rice plant disease detection until arriving at their solution, described as Rider Henry Gas Solubility Optimization (RHGSO)(Daniya & Vigneshwari, 2023b). An optimization based on metaheuristic approaches was developed by Yag and Altan (2022) using the Flower Pollination algorithm combined with SVM, which provides an efficient classification for other types of other plant diseases such as apples and tomatoes that can be extended for application to rice diseases (Yağ & Altan, 2022). In addition, Wang et al. The CNN-SVM hybrid model have been well-developed in the field of rice disease detection (Y. Wang et al., 2021) where QPSO algorithm was used to tune parameters of SVM, showing an better classification properties9 Khairandish et al. Khairandish et al. (2021) semi-transformed a segmentation approach based on thresholding, into CNN-SVM for application toward tumor classification where it could bring good applications in potato leaf diseases classifications also with great accuracy in rice leaf (Khairandish et al., 2022).

It has also been showed that the adjustment of image resolution in hybrid model, strongly affects the accuracy of classifying rice diseases. In the case of rice leaf disease classification variation in the image resolution such as 180x180 and 160x160 pixels were found most useful as it gave sufficient visual detail that led to improvement in accuracy rate from this study (Dixit & Verma, 2023). Jain and Ramesh (2021) also conducted research by applying a CNN-LSTM image-resolution-adjusted model, it can be seen from the results of prediction using rice disease data in accordance with time (Jain & Ramesh, 2021). Kaur and Jain (2022) presumed these findings as the accuracy of flower imagery classification is directly proportional to the high resolution but this model can also be adopted for rice leaf disease imagery(Kaur & Jain, 2022). Moreover, the selection of Optimal Resolution improves performance of CNN models from their effectiveness on detecting rice disease special characteristics (Khade & Patil, 2023).

In general, using CNN plus SVM or ELM hybrid based rice crop disease classification can be observing very appealing result in enhancing conventional accuracy and computational time. Both studies show that this hybrid model outperforms the normal low-level fusion model in fast and precise rice disease detection. For example, models by Alwan and Naji (2023), Daniya and Vigneshwari (2023) and Parasa et al. The results from (2023) confirm that fusing the CNN and high-level optimization methods like RHGSO, FPA, QPSO can give a solid answer to large scale plant disease detection tasks. Pretreatment of this hybrid model will be developed in the future, so it is expected to give a considerable contribution for rice plant productivity and food security through the early detection of plant diseases.

3. Research Methods

Several methods are used in order to meet the objectives of this study that was performed to develop a novel optimization model for optimum and quick image extraction. The literature review method was originally applied. It was important to understand the constraint in existing models because this work aimed to develop an Advanced Hybrid Optimization model.

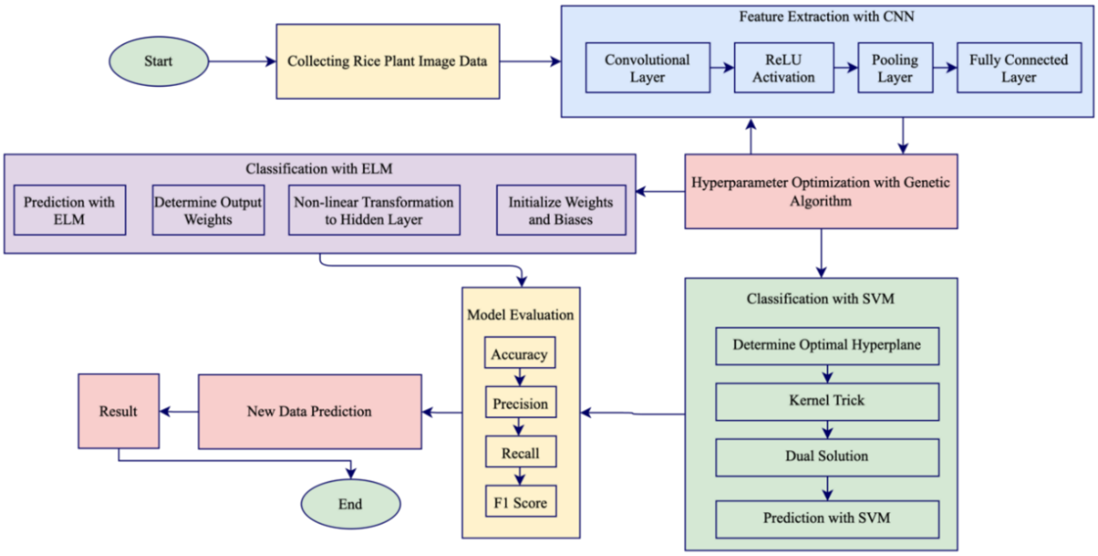

Fig. 1. Research Methodology

This study proposes a hybrid optimization model aimed at improving the accuracy of disease classification in rice plants using image data. The methodology process was divided into several main stages which were explained as follows:

1. Rice Plant Image Data Collection: The first stage is the collection of rice plant image data that will be used as input in the system. This image data will then go through a feature extraction stage to identify characteristics relevant to diseases in rice plants. Where the training data is in the form of bacterial leaf blight: 383 samples, blast: 1390 samples, brown spot: 804 samples, dead heart: 1162 samples, hispa: 1283 samples and normal: 1411 samples.

Fig. 1. Training Data Graph

Furthermore, the testing data was determined in the form of bacterial leaf, blight: 96 samples, blast: 348 samples, brown spot: 201 samples, dead heart: 290 samples, hispa: 321 samples and normal: 353 samples.

Fig. 2. Testing Data Graph

2. Feature Extraction with CNN (Convolutional Neural Network): After the image data was collected, the feature extraction process was carried out using CNN. Before processing, preprocessing was carried out by resizing the image used. CNN consists of several layers including:
   a. Convolutional Layer: This layer captures local patterns in the image such as edges, textures, and shapes (Huang et al., 2023).

$$Z_{\mathrm{i,j,k}}^{(l)} = \sum_{m,n,c}(\mathrm{X}_{\mathrm{i+m,j+n,c}}^{(l+1)} \,.\, \mathrm{W}_{m,n,c,k}^{(l)}) + \mathrm{b}_{k}^{(l)} \tag{1}$$

   This formula was used in the convolution layer to calculate the feature map Z at positions i, j and k in the layer- (l).The value $Z_{\mathrm{i,j,k}}^{(l)}$ was obtained by performing a convolution between the input image X with the filter W , followed by the addition of bias bb b . This convolution operation serves to detect features such as edges, corners, and other patterns in the image. This was then continued with the ReLU activation function to introduce non-linearity (Duan et al., 2022).

$$\mathrm{A}_{i,j,k}^{(l)} = \mathrm{ReLU}\left(\mathrm{Z}_{\mathrm{i,j,k}}^{(l)}\right) = \max\left(0, \mathrm{Z}_{i,j,k}^{(l)}\right) \tag{2}$$

   b. Pooling Layer: This layer reduces the spatial dimension while preserving important features through techniques such as max pooling (Yu et al., 2023).

$$\mathrm{P}_{i,j,k}^{(l)} = \max_{m,n} \mathrm{A}_{i+m,j+n,k}^{(l+1)} \tag{3}$$

   Pooling layers, like max pooling, are used to reduce the spatial dimension of map features by taking the maximum value in a small area. The formula above illustrates how the pooling layer selects the maximum value from the input map feature A to produce the output P.

   c. Fully Connected Layer: The final result of the convolution and pooling process was converted into a vector and input to the fully connected layer, where softmax is used to generate class probabilities.

$$\mathrm{Output}_{j} = \mathrm{Softmax}\,(\mathrm{Z}_{j}) = \frac{\mathrm{e}^{\mathrm{Z}_{j}}}{\sum_{\mathrm{k}} e^{\mathrm{Z}_{\mathrm{k}}}} \tag{4}$$

   In *the Fully Connected Layer* , Z_j was the output of the neuron after combining all previous inputs, $\mathrm{e}^{\mathrm{Z}_j}$ was the exponential of this value used in the softmax function, $\sum_{\mathrm{k}} e^{\mathrm{Z}_{\mathrm{k}}}$ was the sum of all exponentials of the neuron outputs that ensure the total probability was 1, and Output_j was the final probability that the input belongs to the class represented by the jth neuron.

3. Hyperparameter Optimization with Genetic Algorithm: To improve the performance of CNN, hyperparameters such as number of layers, kernel size, and learning rate were

optimized using genetic algorithm. This optimization process includes population initialization, selection, crossover, mutation, and evaluation of model performance based on accuracy.

$$P\_(0\ )= \{p1,p2,....pn\}. \quad (5)$$

Selection, Crossover, and Mutation:

$$P\_selected\ = Select\ (P\_t) \quad (6)$$

4. Classification with ELM (Extreme Learning Machine): The features extracted by CNN were used as input for classification using ELM. This process includes:
   a. Input Weight and Bias Initialization: The input weights and biases of the hidden layer are initialized randomly.

$$W\in R\hat{}(d\times N),b \in R\hat{}N \quad (7)$$

   The weights W W and biases b b of the ELM hidden layer was initialized randomly. Where W is a weight matrix with dimensions $d \times N$, and b is a bias vector with dimensions N .

b. Non-linear Transformation to Hidden Layer: Input features are mapped to the hidden layer using activation functions.

$$H = g\ (X\ .W + b) \quad (8)$$

The feature input X that has been extracted by CNN was mapped to the hidden layer using the activation function g , which is a non-linear function. The result of this activation function is the matrix H , which is a representation of the features in the new feature space.

c. Output Weight Determination: The output weights are calculated using the pseudo-inverse of the hidden layer.

$$\beta = H\hat{}(-1)\ \ .T \quad (9)$$

d. Prediction with ELM: New data was predicted using the trained ELM model.

$$y=g\ (X\_new\ \ .W+b).\beta \quad (10)$$

At prediction time, the new feature input Xnew was mapped to the new feature space through the activation function g, then multiplied by the output weight β to produce the final prediction y.

5. Classification with SVM (Support Vector Machine): Alternatively, features extracted by CNN can also be classified using SVM. The SVM process involves finding the optimal hyperplane to separate the classes with the largest margin and kernel techniques to handle non-linear data.

a. Objective Function of SVM:
SVM searches for the optimal hyperplane that separates the classes by the largest margin:

$$\frac{min}{w,b,\varepsilon}\left(\frac{1}{2}\left||\mathrm{w}|\right|^2 + \mathrm{C}\sum_{\mathrm{i}=1}^{\mathrm{N}} \varepsilon_{\mathrm{i}}\right) \quad (5)$$

This formula is the objective function of SVM, which aims to find the optimal hyperplane that separates two classes with the largest margin. The variables ϵ_i are slack variables that accommodate the classification error, while C is a regularization parameter that controls the trade-off between margin and classification error (Ren et al., 2023).

b. Kernel Trick:
SVM uses a kernel function to handle linearly non-separable data:

$$f(\mathrm{x}) = \mathrm{sign}(\textstyle\sum_{i+1}^{N} \alpha_{\mathrm{i}}\gamma_{\mathrm{i}}\mathrm{K}(\mathrm{x}_{\mathrm{i}},\mathrm{x}) + \mathrm{b}) \quad (6)$$

SVM uses a kernel trick to handle data that is not linearly separable. The kernel function $K\ (x_i, x)$ maps the data to a higher dimensional space, where it is linearly separable (V. et al., 2023).

c. Dual Solution:
The parameters α_i were found through dual optimization:

$$\alpha_i\ = \frac{\partial Lagrangian}{\partial \alpha_i} \quad (7)$$

The parameters α_i are the dual solutions of the Lagrangian function used to optimize the hyperplane in SVM (Liu et al., 2023).

d. Prediction with SVM:
New data predicted with SVM:

$$y = \text{sign}\left(\sum_{i=1}^{N} \alpha_i \gamma_i K(x_i, x_{new}) + b\right) \quad (8)$$

For prediction, SVM uses the dual solution αi that has been found through optimization to predict the class of new data x_{new}.

6. Evaluation: Evaluation of the model was done post classification, these are also other evaluation metrics such as accuracy precision Recall and F1 score. The purpose of this evaluation is to make sure that the final resulting model has a satisfying quality in terms of predictions disease classes on rice plants (Banerjee et al., 2023).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (10)$$

$$\text{Recall} = \frac{TP}{TP+FP} \quad (11)$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

7. Prediction on new data: Since the model has been trained and evaluated we can use a pipeline to now carry image-based predictions given some images. Pretrained CNN, ELM and SVM optimized models will be applied to predict new images of rice plants on their appropriate class.

This technique combines the capabilities of CNN features extraction, genetic algorithms hyper parameters optimization and ELM – SVM classification methods in order to improve disease symptoms detection probability for plants diseases.

4. Results and Discussions

4.1 Results

The experimental scenario in this study is to examine how well these rice disease classification models work with different image sizes and two types of Extreme Learning Machine (ELM) and Support Vector Machine (SVM) classifications. The size of the rice image dataset is reduced to lower resolutions (180x180, 160x160, 140x140, 120x120 and100 ×100 pixels) in order to evaluate how feature extraction as well as overall classification performance between-focused models may be affected by. We extracted the important features with CNN and optimized its hyperparameters through Genetic Algorithm to achieve better results. Next, each dataset was trained for ELM and SVM models after feature extraction and model performance evaluation using accuracy, precision recall, F1-score metrics. Different method-to-size combinations were compared to finding the best possible setup. This model is to be used for predicting diseases through unseen data, which wasn't available during the training time and making sure how good our model is in practical. The results for different sizes using the CNN+ELM/CNN+SVM techniques are shown in Table 2.

1. CNN+ELM Method
In this method, testing was carried out on sizes 180x180, 160x160, 140x140, and 120x120 pixels.

Final Test Accuracy: 90.06%
Classification report SVM on 180*180 image inputs:

	precision	recall	f1-score	support
bacterial_leaf_blight	0.82	0.75	0.78	96
blast	0.89	0.92	0.90	348
brown spot	0.88	0.83	0.86	201
dead heart	0.97	0.94	0.95	290
hispa	0.89	0.89	0.89	321
normal	0.90	0.94	0.92	353
accuracy			0.90	1609
macro avg	0.89	0.88	0.88	1609
weighted avg	0.90	0.90	0.90	1609

Fig. 4. Results of the CNN+ELM 180x180 Method

Figure 4 shows the classification report for the SVM + ELM model with a final test accuracy of 9ß7.95%. This model has very high precision, recall, and F1-score values for all categories, indicating that this model is very effective in classifying 180x180 pixel images. These results reflect the model's ability to recognize and classify various types of plant diseases with almost perfect accuracy. The results of the Confusioan Matrix are shown in Figure 5.

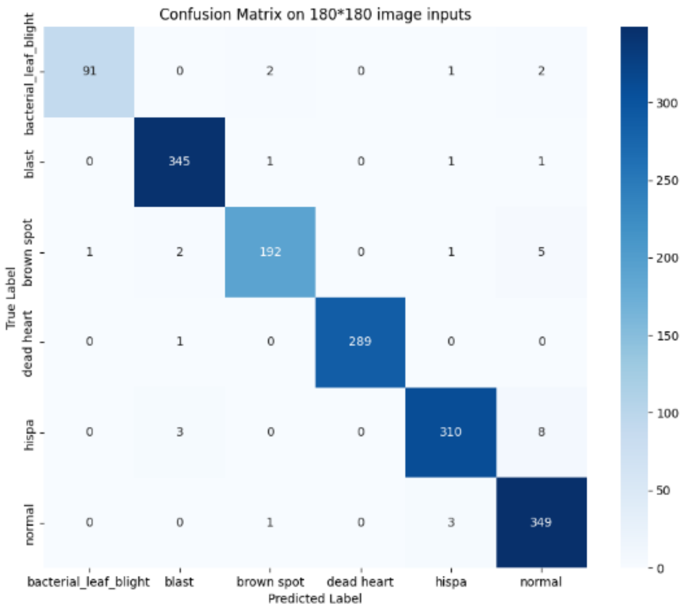

Fig. 5. Confusion Matrix of SVM + ELM Model

The model showed highly variable prediction results for each class. For the bacterial leaf blight class, the model successfully predicted 91 images correctly, while there was 1 incorrect prediction classified as brown spot. The blast class had 345 correct predictions, but there were 6 incorrect predictions, with 2 images classified as brown spot, 1 as dead heart, and 3 as hispa. The brown spot class had 192 correct predictions, with 2 incorrect predictions, each classified as blast and normal. For the dead heart class, the model achieved a 100% accuracy rate, with all 289 images correctly classified. Meanwhile, the hispa class had 310 correct predictions, with 6 incorrect predictions, each incorrectly classified as bacterial leaf blight, blast, brown spot, and normal. Finally, the normal class had 349 correct predictions, with 16 incorrect predictions spread across several other classes. These results indicate that although the model has good performance, there is still room for improvement, especially in reducing misclassification in some classes. Next, do the same thing with the other sizes, the results are shown in Figure 6.

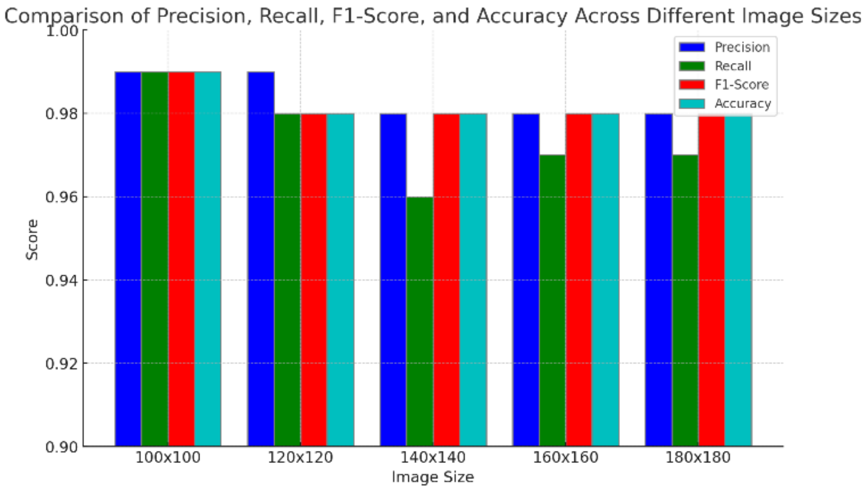

Fig. 6. Results of CNN+ELM Method for All Image Sizes

Table 1 - Results of the CNN+ELM Method for All Image Sizes

Size	Accuracy	Precision	Recall	F1-Score
100x100	0.9863	0.99	0.99	0.99
120x120	0.9838	0.99	0.98	0.98
140x140	0.9782	0.98	0.96	0.98
160x160	0.9832	0.98	0.97	0.98
180x180	0.9795	0.98	0.97	0.98

100x100 and 120x120 image sizes provide the best model performance with Precision, Recall, F1-Score, and Accuracy almost reaching 0.99. The 140x140 size shows a slight decrease in Recall, but F1-Score and Accuracy remain stable. Performance at 160x160 and 180x180 sizes improves again, with the metrics remaining high at around 0.98. Overall, the model performs very well on 100x100 and 120x120 images, making it the most optimal choice when using the CNN+SVM method combination. These sizes provide the most consistent and accurate results.

2. CNN+SVM method
   In this method, testing was carried out on sizes 180x180, 160x160, 140x140, and 120x120 pixels.

```
Final Test Accuracy: 90.06%
Classification report SVM on 180*180 image inputs:
                       precision    recall  f1-score   support

bacterial_leaf_blight       0.82      0.75      0.78        96
                blast       0.89      0.92      0.90       348
           brown spot       0.88      0.83      0.86       201
           dead heart       0.97      0.94      0.95       290
                hispa       0.89      0.89      0.89       321
               normal       0.90      0.94      0.92       353

             accuracy                           0.90      1609
            macro avg       0.89      0.88      0.88      1609
         weighted avg       0.90      0.90      0.90      1609
```

Fig. 7. Results of the CNN+SVM 180x180 Method

This figure shows the classification report for the SVM model used on a 180x180 pixel image, with a final test accuracy of 90.06%. The model performed adequately with varying precision, recall, and F1-score across categories, reflecting the model's ability to classify a variety of plant diseases with good, if not perfect, accuracy. The "dead heart" category performed the best with the highest F1-score of 0.95, while the "bacterial_leaf_blight" category performed the lowest with an F1-score of 0.78. These results indicate that there is room for improvement, especially in categories with lower metric values, and the Confusion Matrix for these results can be seen in figure 8.

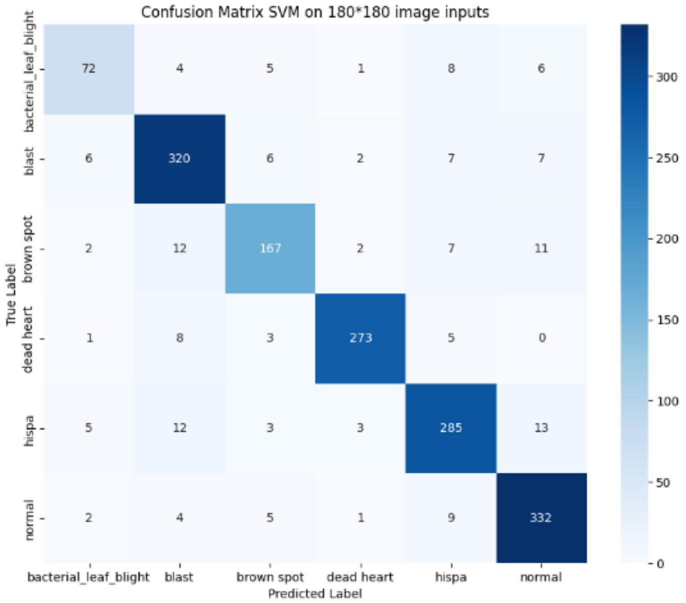

Fig. 8. Confusion Matrix of CNN + SVM Model

In the CNN + SVM model with an image size of 180x180, the prediction results for the bacterial leaf blight class showed 72 images predicted correctly, while there were 16 images predicted incorrectly, which were classified as blast , brown spot (Daniya & Vigneshwari, 2023b), dead heart (Quach et al., 2022), hispa (Abdel Ghany et al., 2023), and normal (Daniya & Vigneshwari, 2023b). For the blast class, the model produced 320 correct predictions, but there were 40 incorrect predictions, which were distributed into the bacterial leaf blight (Reva et al., 2023), brown spot (N. Wang et al., 2023), dead heart (Alpyssov et al., 2023), hispa (N. Wang et al., 2023), and normal (Reva et al., 2023) classes. The brown spot class had 167 correct predictions, with 22 incorrect predictions spread into the bacterial leaf blight (Abdel Ghany et al., 2023), blast , dead heart (Mohammed Al-Mafrji et al., 2023), hispa (Mohammed Al-Mafrji et al., 2023), and normal (Abdel Ghany et al., 2023) classes. The dead heart class had 273 correct predictions, but there were 9 incorrect predictions spread into the bacterial leaf blight (Quach et al., 2022), blast (Daniya & Vigneshwari, 2023b), brown spot (Daniya & Vigneshwari, 2023b), hispa (Mohammed Al-Mafrji et al., 2023), and normal (Quach et al., 2022) classes. For the hispa class, there were 285 correct predictions with 36 incorrect predictions, which were classified as bacterial leaf blight (Alpyssov et al., 2023), blast (Dahake et al., 2023), brown spot (Dahake et al., 2023), dead heart (Abdel Ghany et al., 2023), and normal (Fanti et al., 2017). Finally, the normal class had 332 correct predictions, with 37 incorrect predictions spread across the bacterial leaf blight (6), blast (Dahake et al., 2023), brown spot (Akbar et al., 2023), and hispa (Yang, Lin, et al., 2023) classes. These results indicate that although the CNN + SVM model provided solid performance, there were a number of incorrect predictions, especially in certain classes, indicating the need for further improvement. The same thing was then done with other sizes, the results are shown in Figure 9.

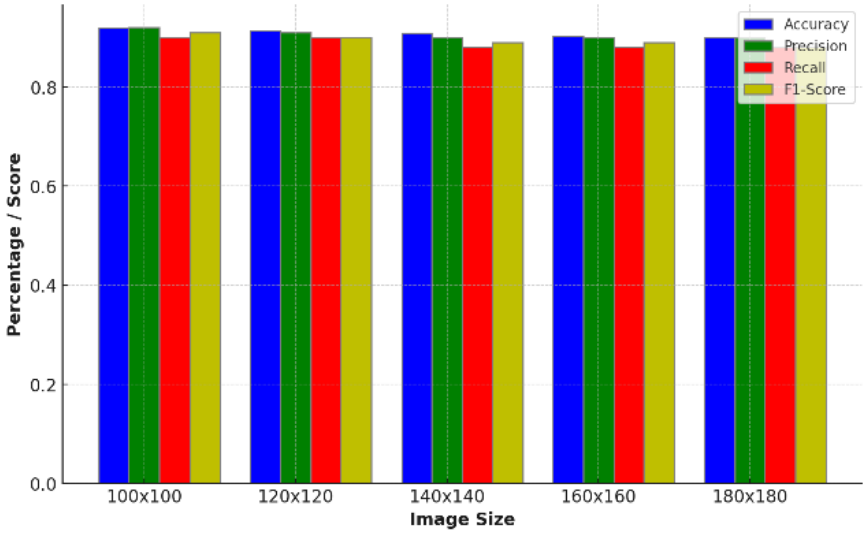

Fig. 9. Results of CNN+SVM Method for All Image Sizes

Table 2 - Results of CNN+SVM Method for All Image Sizes

Image Size	Accuracy	Precision	Recall	F1-Score
100x100	91.92%	0.92	0.9	0.91
120x120	91.24%	0.91	0.9	0.9
140x140	90.86%	0.9	0.88	0.89
160x160	90.24%	0.9	0.88	0.89
180x180	90.06%	0.9	0.88	0.88

Figure 9 and Table 2 illustrate the comparison of SVM model performance metrics (Accuracy, Precision, Recall, and F1-Score) based on various image sizes used in training. Each image size (100x100, 120x120, 140x140, 160x160, and 180x180 pixels) is represented by a group of bars, where each bar indicates the value for one of the performance metrics. The results show that the 100x100 image size provides the best performance across all metrics with values consistently above 0.9. The performance decreases slightly as the image size increases, although it remains stable at a high level. This suggests that SVM models trained with smaller images are able to capture important features more effectively, while larger images may add complexity without providing significant improvements in model performance. From the results of the comparison between the combination of CNN+ELM and CNN+SVM, the comparison graph shown in Figure 10 can be produced.

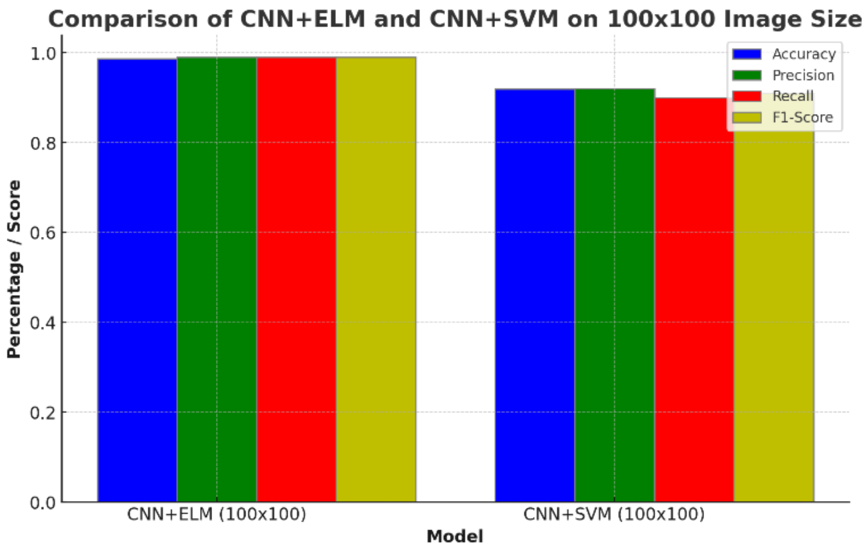

Fig. 10. Highest Results Between Each Combination of Methods

Figure 10 shows a performance comparison between CNN+ELM and CNN+SVM models on an image size of 100x100, focusing on four key metrics: Accuracy, Precision, Recall, and

F1-Score. The CNN+ELM model shows superior performance compared to CNN+SVM. in all metrics. The accuracy of the CNN+ELM model is almost 100%, which is 98.63%, while CNN+SVM only reaches 91.92%. In addition, the Precision, Recall, and F1-Score for CNN+ELM are all very high and consistent at 0.99 , which is far superior compared to CNN+SVM which is in the range of 0.9 to 0.92. This graph clearly indicates that the CNN+ELM model is superior and more recommended to be used in this context compared to CNN+SVM.

4.2 Discussions

The results of this study indicate that the combination of Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM) provides superior performance in rice plant disease classification compared to the combination of CNN and Support Vector Machine (SVM). Based on the results of experiments on various image sizes, the CNN+ELM model consistently shows higher accuracy and other performance metrics compared to CNN+SVM.

a. Limitations of CNN+SVM
Despite the fact that SVM has optimal hyperplane search capabilities for classifying different classes than an input data, and literature indicates many known applications of this capability; using it on top CNN in favour to ELM degrade worse performance as compared to our proposed model: CNN+ELM. The reason maybe that the rice plant image data are so complex as to demand deeper feature analysis than ordinary DNNs; it is archived by this design increasing suitable for ELM in our experiment. Since SVM does not generalize well over relevant class variations, especially when it deals with small window image sizes.

b. Implications and Practical Applications
Outcomes of this research are significant in progress toward devising highly competent and rapid detecting system for detection of rice plant diseases. Using CNN+ELM to implement the system in limited computing resource devices (like mobile devices), without loss of detection accuracy. This facilitates wider deployment in agriculture aim for real time advice on plant disease management and crop yield improvements.

c. Suggestions for Future Research
Although this study demonstrates that architecture which has both CNN and ELM in a pipeline gives excellent results there is always scope for improvements. There is more research work that can be done by means of doing additional hyperparameter optimization search or combining it with other types of machine learning techniques which may lead to better accuracy and efficiency. Moreover, experiments on bigger and diverse datasets as well, which consists of images that have different lights or viewing angles in comparison to the existing ones for testing the models on various field scenarios.

5. Conclusion

In this study, a hybrid optimized model of Convolutional neural network (CNN) integrated with Extreme Learning Machine (ELM), and Support vector machines(SVM) had been created to enhance rice plant disease classification accuracy. According to the results of experiments carried out, it said a CNN+ELM model had an accuracy rate close to 100% at an image size of 100x100 pixels and precision recall and F1-Score values were found in perfect harmony with each other as very high figures being overbearing by just resting on top consistently setting itself up except for like static forever. As compared with the SVM model, GCAE achieved a higher accuracy of 94.84% at an image size and CNN+SVM performed relatively worse (91.92 %) on all three datasets These results demonstrate that for the tasks of recognizing significantly fewer features than making inferences, CNN+ELM performs better on rice disease classification when compared with CNN+SVM. These discoveries are meaningful for constructing faster and more accurate detection systems of plant diseases that can be operated in limited-resource devices. Furthermore, this study also provides an opportunity for a wider range in agricultural management improving productivity and reduce losses due to plant diseases through early detection leading appropriate control. Moreover, additional work could investigate more exhaustive hyperparameter tuning and model testing on larger datasets that simulate a broader spectrum of field conditions, in order to prove the generality behind these results.

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