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An Enhanced CNN-based ELM Classification for Disease Prediction in the Rice Crop

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Abstract – To meet the demands of a constantly expanding population, intensive farming is becoming more popular in the modern day. This strategy, meanwhile, increases the possibility of a wider range of plant illnesses. By reducing crop productivity in terms of both quantity and quality, these infections represent a threat to food production and ultimately result in a fall in the economy. Fortunately, new opportunities for early diagnosis of such epidemics have emerged because of technological improvements, which are advantageous for society as a whole. The difficulties created by technology and bio-mutations create a potential for additional breakthroughs, notwithstanding the significant contributions made by researchers in the field of agricultural disease diagnosis. The suggested framework comprises three key phases: preprocessing, feature extraction, and the classification of leaf diseases. To optimize computational resources and memory utilization, the input image undergoes pre-processing as a preliminary step. Afterward, a Convolutional Neural Network (CNN) is utilized on an extensive dataset of labeled images to capture pertinent features for the diagnosis of rice leaf diseases. The suggested model utilizes an Efficient Selective Pruning of Hidden Nodes (ELM) classifier based on the RBF kernel to classify the input data.

Keywords – Pruning, a leaf disease, CNN, and the Extreme Learning Machine.

I. INTRODUCTION

Particularly in the framework of Indian civilisation, rice plays an important role as the principal food supply for a significant portion of the world's population. This frequently consumed staple food is nutrient-rich, particularly in carbs, which give the body its necessary energy [1]. In many nations, rice farming not only sustains livelihoods but also helps to maintain economic stability. However, some bacterial and fungal diseases that affect crop quality and productivity might affect rice crops.

Early detection of these illnesses can considerably increase rice crop output and growth, improving farmer livelihoods. Farmers can save treatment costs by foreseeing infections early on and by using the right fungicides and farming techniques. Researchers now favour this proactive approach because of its potential to have a favourable economic impact. Using cutting-edge tools like remote sensing and image processing, researchers are actively involved in analysing and categorising disease signs.

To improve the quality of digital photos or extract useful information from them, a field known as digital image processing (DIP) uses mathematical techniques to edit the images. DIP has become more significant as a result of the expanding accessibility of digital images, including pictures, medical imaging, and satellite images [2]. Given the critical significance of rice as a staple crop, it is imperative to treat the many diseases that may seriously impair the development and productivity of rice plants. The ability to predict diseases early can completely alter farmers' livelihoods. Here is a quick rundown of several prevalent ailments affecting rice plants:

Brown spot: When small, oval in shape sores appear on the leaves, a fungus disease known as brown spot is present (see Figure 1). These lesions have brown centres with golden haloes. If the infection is serious enough, it may cause early leaf

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senescence and a loss in photosynthetic capacity, which would ultimately lower agricultural production.

Figure 1: Brown Spot

Bacterial Leaf Blight: If not appropriately controlled, the bacterial pathogen that causes bacterial leaf blight (Figure 2) can have major detrimental effects on crop productivity. The formation of water-soaked lesions on the leaves, which subsequently turn yellowish-brown, is one of the disease's symptoms [3]. Affected leaves on infected plants may also wilt and dry out. To lessen the harm that this disease does to rice crops, efficient control techniques are required.

Figure 2: Bacterial Leaf Blight

Leaf Smut: As shown in Figure 3, a fungal infection that largely affects the grains is the main source of rice leaf smut. The grains of infected rice panicles undergo a metamorphosis, becoming huge, greenish-brown spore masses. Not only does this issue reduce the quality of the grain, but it also costs farmers money. To reduce the negative effects of rice leaf smut on crop productivity and overall profitability, effective management techniques are crucial.

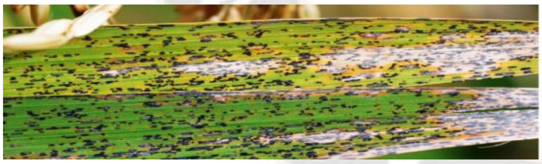

Figure 3: Smut Leaf

This study focuses on addressing the challenges of underfitting and overfitting in pattern categorization through the implementation of the ELM classifier network's architectural design. The objective is to overcome these challenges by carefully selecting the optimal number of hidden nodes in the network. This approach offers a logical framework for enhancing the network's functionality and its capacity for pattern categorization.

Three primary stages make up the suggested methodology: pre-processing, feature extraction, and classification. Pre-processing is a crucial stage in the processing of images that tries to improve key aspects of the image data while reducing unwanted distortions. To make sure that the dataset is correctly ready for upcoming processing tasks, it is essential to complete this preliminary stage.

The second phase involves training a CNN to extract pertinent features using a sizable dataset of labelled photos. CNNs are well-suited for image processing applications due to their capability to extract features.

Following the extraction of the features is used to predict illness. With the help of a sizable number of hidden nodes that were chosen at random and their corresponding weight values, this method starts the classifier design process. The classifier's prediction accuracy is evaluated by assessing the responses of the input vector to determine the significance of each hidden node. A streamlined network topology is created by repeatedly deleting unimportant nodes while keeping the crucial ones. When new and untested examples are applied to this simplified structure, competitive prediction accuracy results.

To achieve precise prediction of rice leaf diseases, the suggested methodology entails some phases, using SABP-ELM. This all-encompassing strategy guarantees improved accuracy and successfully addresses problems caused by underfitting or overfitting in pattern classification. The model tackles these issues and provides better performance by carefully building the classifier network and utilising pruning methods.

II. LITERATURE SURVEY

An extensive study into computational techniques for precisely identifying grain leaf diseases was carried out by Manavalan et al. [4]. To accurately diagnose these disorders, their study used a variety of techniques. To detect illnesses in rice leaves The author of [5] used transfer learning and a deep CNN architecture. Their strategy used cutting-edge methods to increase the precision of disease identification in rice leaf analyses. Brown patches, bacterial leaf blight, and leaf blasts are common diseases that damage rice plants. To discriminate between disease-free plants and those that are infected, the suggested method combined the weights of the feature extraction.

The MyGreen solution, an Internet of Things (IoT)-based smart greenhouse system for sustainable agriculture, was presented in another study by Tripathy et al. [6]. Data collecting, resource allocation, optimisation, and time management were all included in the system's data analytics, which boosted accuracy, productivity, and learning speed while lowering computation costs.

In addition, the author from [7] proposed an improved version of the deep learning framework EfficientDet-D2 for the detection of plant diseases. A collection of 3038 photos was used in the study to identify and categorise minute sick regions,

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showing improved performance with faster processing times. This method successfully assessed the efficiency of cutting-edge models for diagnosing diseases.

A model was suggested for the diagnosis of plant leaf diseases in an article by [8]. The model's classification step incorporates pre-processing and data collecting. It was done using a collection of 38 pictures of both healthy and ill plant leaves. The method greatly improves disease identification's accuracy, consistency, and dependability.

To diagnose plant diseases, Cap et al. presented LeafGAN, a unique image-to-image translation method [9]. To distinguish the leaf region and restore healthy photos, LeafGAN uses the label-free leaf segmentation model. To prevent overfitting and ensure the model performs at its best, the classification of training images is an essential step during the training process. This improves the model's dependability, effectiveness, precision, and robustness. Gaining better results requires improving picture quality.

Data augmentation methods were created by Abayomi-Alli et al. [10] to identify illnesses in cassava leaves. ImageNet is the dataset used to discriminate between various leaf picture kinds. The model successfully recognises plant illnesses by classifying the mid-level picture features. These methods can be used to increase classification accuracy. Specifically, the classification accuracy is 95% when using high-quality images. A multi-class detection strategy is also investigated for recognising different plant diseases. While SoftMax is used for classification, many deep CNN architectures, like AlexNet and GoogleNet, are used for feature extraction [11]. The suggested method successfully detects several plant diseases with a 95% accuracy rate when testing the classification of each image.

III. METHODOLOGY PROPOSED

The proposed methodology's process is depicted in Figure 4. Following input of the dataset photographs, preprocessing is applied as the first step. The essential traits that were extracted using CNN are then used to identify diseases. We use an improved ELM classifier that includes pruning of hidden nodes and selective processing. Based on the most important parameters collected using CNN, this procedure guarantees the precise detection of leaf illnesses [12].

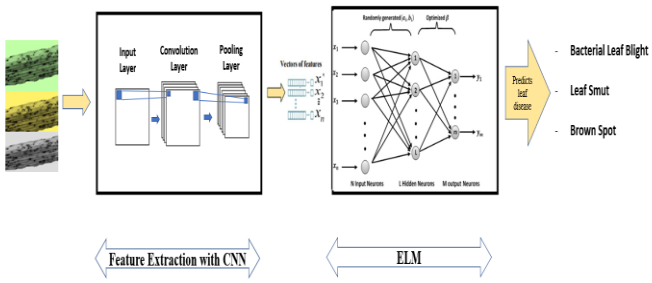

Figure 4: Proposed flow diagram

The recommended method uses CNN and SABP-ELM in combination to predict rice crop illnesses with high accuracy. The methodology uses extraction of characteristics, preliminary processing, and categorization as its three main techniques. In the initial step, pre-processing techniques are utilized to improve the quality of visual input by preserving critical information and minimizing unwanted distortions [13]. CNN is a good choice for disease diagnosis in rice leaves since it has demonstrated success in extracting features from images and carrying out image processing tasks.

The CNN extract latent information from the input data to forecast diseases. The SABP-ELM technique, which involves giving weight values to multiple hidden nodes, is used in the classifier design. When these nodes respond to the input vectors, the SABP-ELM approach assesses their performance and determines their significance in terms of prediction accuracy. Pertinent nodes are kept, while those that are not are trimmed [14]. This procedure produces a compact network structure that, when applied to untested scenarios, shows competitive prediction accuracy.

ELM uses a cutting-edge method for picture classification that involves selective analysis and pruning of hidden nodes, further improving its performance [15].

- Dataset

Disease management is essential for ensuring rice output and productivity, especially in Asian nations. Given that illnesses can have a major impact on production rates, we used a Kaggle dataset of 5000 JPEG photos of rice leaves to assess the efficacy of our suggested technique. We increased the data collection to 10,000 photos utilising a variety of data augmentation methods to further improve the dataset and address overfitting.

Data augmentation techniques like rotation, flipping, and cropping, we introduce various variations to the input dataset, thereby improving the model's performance and its capacity to generalize [16].

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The dataset consists of four leaf classification classes: Healthy, Leaf Smut, Bacterial Leaf Blight, and Brown Spot. It comprises a total of 1000 examples of healthy leaves, 2553 instances of Brown Spots, 3632 samples of Leaf Smut, and 2815 photographs corresponding to Bacterial Leaf Blight. This comprehensive collection encompasses a wide range of instances for effective training and evaluation.

- Pre-processing

Pre-processing an image tries to improve image quality, decrease noise, and prepare image data for further processing. The main goals of picture pre-processing are to increase the data's quality and usefulness for analysis or modelling. A rescaling technique is used to improve the quality of the input data, which comprises photographs of various sizes. The photos are downsized to 256x256 pixels, which is the industry standard. The total image quality is increased, the computational and memory needs for pre-processing are decreased, and constant dimensions are guaranteed [17].

In picture pre-processing, the normalisation of pixel values is a widely used method. It entails adjusting an image's pixel intensities to fit between 0 and 1. To ensure consistency and compliance with algorithms or analysis techniques that demand input values within a standardised range, normalising the data is an essential step. The data are adjusted to a similar scale as a result of the normalisation process, enabling fair comparisons and the efficient application of different algorithms or analysis approaches. The image data can be processed more efficiently and is made more suited for a variety of jobs by normalising the pixel intensities.

- Feature extraction using CNN

Deep learning neural networks called CNNs, or convolutional neural networks, are created specifically for processing and analysing data in a grid-like pattern. They are made up of many layers, including flattening, pooling, and convolutional layers. Through convolution operations, in which a collection of kernels is convolved across the input, convolutional layers extract local features from the input data. A 3x3 kernel size is typically employed to extract local features and spot patterns in the input.

One or more pooling layers are then applied to the output, which reduces the size of the image while increasing processing effectiveness. A one-dimensional vector is created from the output after it has gone through the pooling layers. The CNN architecture then receives this vector and applies it to one or more fully connected layers [18]. Depending on the task at hand, these completely connected layers divide the input into various types.

Depending on the task and dataset, optimisation strategies are used to enhance the performance of CNNs. CNNs are widely used in industries including security, entertainment, and healthcare and have proven to perform exceptionally well in a variety of image and video processing applications. Due to their interconnected layers of nodes that function on incoming data, notably photos and videos, they are regarded as excellent tools for tasks like image processing, categorization, and recognition.

- SABP-ELM classification

The SABP-ELM classifier is used to categorise the leaf disease-affected patches after extracting the pertinent information. The classification process for leaf diseases involves applying the SABP-ELM technique, which selectively analyzes and prunes hidden nodes to achieve accurate categorization of the affected areas. This process ensures the effective classification of leaf diseases based on the extracted features:

Modern ML techniques like the ELM have been shown to perform exceptionally well in tasks including classification, clustering, and regression [19]. ELM performs noticeably better than equivalent traditional forecasting models. In comparison to conventional neural learning approaches, this model efficiently prunes hidden nodes using either an RBF kernel or a sigmoid kernel.

Our SABP-ELM approach not only facilitates quick learning but also performs exceptionally well in terms of generalisation. The advantage of ELM over traditional neural networks is that it is less prone to overfitting [20]. This property results from ELM's random weight generation, which lessens the propensity to memorise training data and overfit. These weights connect the input and hidden layers. ELM is a great option for applications where training time is important because it also has faster training capabilities than traditional neural networks.

The SABP-ELM strategy provides an ELM classifier that makes it easier to build the network architecture methodically. This method uses an analysis of the hidden nodes' behaviour in response to input vectors to create the classifier [21]. In the beginning, many hidden nodes with weight parameters chosen at random are used. Then, superfluous hidden nodes are pruned, leaving just the pertinent ones that help the classifier make accurate future predictions. To learn the non-linear activation function using M different observations, the ELM needs a minimum of M hidden nodes.

The hidden layer of ELM does not require tuning, in contrast to conventional training techniques and ELM. In the ELM feed-forward network, the hidden layer's parameters are chosen at random. By dispersing the inputs, hidden neuron biases, and weights of the hidden layer outputs at random, training error is

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minimised. Analytical calculations are performed to determine the output weights [22].

The weight vectors in the ELM represent the threshold or bias of the hidden neurons. When there is zero error and M instances, the hidden neuron's ELM can be written as,

$$\sum_{k=1}^{M} \alpha_k h\left(w_k * y_j + a_k\right) = \chi_k, k = 1,2, \dots, M \qquad (2)$$

$$\alpha = \begin{bmatrix} \alpha_1^T \\ \vdots \\ \alpha_K^T \end{bmatrix} \qquad (3)$$

$$\lambda = \begin{bmatrix} \chi_1^T \\ \vdots \\ \chi_M^T \end{bmatrix} \qquad (4)$$

In this context, the pseudo-inverse is represented by a special matrix called the alpha matrix. A hidden neuron's threshold or bias is represented by the symbol. 'h' stands for the activation function. The hidden neuron output's jth column is calculated as. The linear system's least-squares solution is discovered via the ELM learning process. The Gaussian radial basis function (RBF) is a popular and often utilised kernel function.

- PERFORMANCE METRICS

Using a gathered dataset, the suggested SABP-ELM model, which is based on CNN, is trained and assessed. The definitions of several performance metrics are provided below:

1.1. Matrix of confusion

It provides helpful insights on the accuracy and effectiveness of classification algorithms by contrasting the anticipated and actual values for a particular dataset. By analysing the confusion matrix, we gain a better understanding of how well our proposed algorithm anticipates leaf diseases and detects instances of misdiagnosis. The confusion matrix, which considers all classes in Table 1.

	H	BLB	BS	LS
H	TH	FBLB	FBS	FLS
BLB	FH	TBLB	FBS	FLS
BS	FH	FBLB	TBS	FLS
LS	FH	FBLB	FBS	TLS

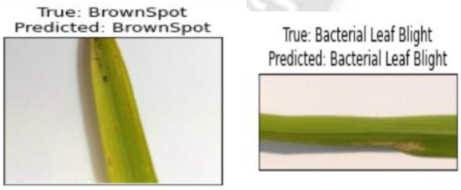
Table 1: The complex matrix that results from using our suggested approach

Validation loss/accuracy graphs, which offer useful insights into a model's performance throughout both the training and validation stages, are frequently used to illustrate a model's efficiency. During the training phase, a model's learning progress is assessed using training loss/accuracy graphs. Throughout the training process, these graphs help to influence decisions and provide insightful information about the model's effectiveness.

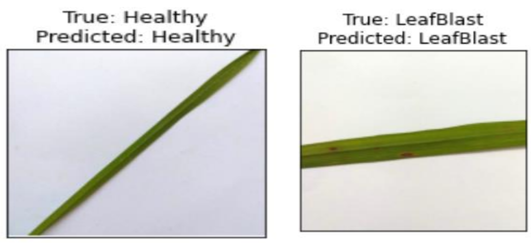
IV. DISCUSSION AND RESULTS

In this section, we provide an overview of the results obtained from our suggested methodology and discuss their implications. We conducted a comprehensive evaluation of our approach, comparing it with other existing methods in use. By employing various data augmentation techniques, we enhanced the dataset, improving its diversity and quality. We split the dataset into a training set and a testing set in order to evaluate the performance of our proposed model. The model was trained using the training set, which made up 80% of the dataset (8000 photographs), and the test set, which made up the remaining 20% (2000 photographs), which was used to assess the model's performance.

In this situation, there are 3 different types of rice leaf infections, and the datasets are processed through multiple layers of image processing using the designated architecture for training, testing, and classification. The outcomes of the deployment are shown in Figure 6. The results of analysing every image in the testing dataset are shown below, along with the actual labels and expected labels. Our model successfully predicts the Brown Spot condition shown in Figure 5a on a leaf.



5a) Brown Mark 5b) Infectious Blight Leaf



5c) Leaf Healthy 5d) Leaf Smut/Blast

Figure 5: Analysis of results

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Table 2 displays the confusion matrix, which is an essential tool for assessing the classification model's effectiveness.

	H	BLB	BS	LB
H	664	0	10	0
BLB	0	580	0	2
BS	15	0	453	0
LS	0	4	0	272

Table 2: Confusion matrix

Figure 6 illustrates the training and validation accuracy of the proposed technique for the entire dataset.

Similar to images 8 and 6 show a blue line for the validation loss and a red line for the training loss. This graph enables us to evaluate the model's generalizability to fresh data and monitor the convergence of the model as it is trained. It helps inform judgements about the model's optimisation and generalizability and offers insightful information about how well the model performs.

By showing how accuracy and loss measurements have improved over time, these graphs shed important light on the effectiveness of our suggested strategy. These visualisations aid in our evaluations of model generalisation and optimisation by showing how well our model is learning. They assist us in making defensible decisions on the effectiveness and development of our approach.

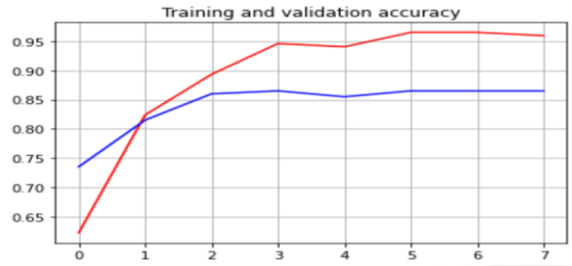

Figure 6: When assessing the model's performance, both the training and validation accuracy were taken into consideration

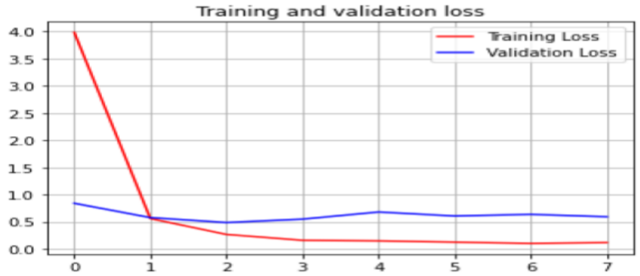

Figure 7 Performance gained by predicting the loss of validation and training

The recall, f-measure, accuracy, and precision of the proposed model were assessed for disease prediction, as shown in Table 3. The model was validated using the validation set, which made up 20% of the data and was trained using the remaining 80%. The proposed model's total accuracy rate was found to be 96%.

Disease name	Accuracy	F1-measure	Recall	Precision
Bacterial Leaf Blight	0.96	0.94	1.00	0.96
Average	0.96	0.97		
Healthy	1.00	1.00	1.00	0.96
Leaf Smut	0.96	1.00	1.00	1.00
Brown Spot	0.94	0.96	9	6

Table 3 Results gained after prediction

V. CONCLUSION

This study introduces a novel technique for classifying paddy leaf diseases, including Healthy, Brown spot, Bacterial Leaf Blight, and Leaf Smut. The supplied images are initially cropped and scaled to optimize computational efficiency and memory usage. The classification task is performed using the SABP-ELM, a CNN-based classifier. The experimental implementation is conducted on Google Colab. Through thorough evaluation of the loss function and close examination of the probability value, it becomes evident that our approach yields lower loss compared to other methods. Our suggested strategy also significantly enhances sensitivity, reaching approximately 96.99%.

REFERENCES

[1] Hai-Jun Rong, Yew-Soon Ong, Ah-Hwee Tan, Zexuan Zhu, A fast pruned-extreme learning machine for classification problem. www.elsevier.com, H.-J. Rong et al. / Neurocomputing 72 (2008) 359–366.

[2] Xiong, Y. and Lu, Y., 2020. Deep feature extraction from the vocal vectors using sparse autoencoders for Parkinson's classification. IEEE Access, 8, pp.27821-27830.

[3] Zhihong Man a,n, Kevin Lee a , Dianhui Wang, A new robust training algorithm for a class of single-hiddenlayer feedforward neural networks, Z. Man et al. / Neurocomputing 74 (2011) 2491–2501

[4] Sen, P.C., Hajra, M. and Ghosh, M., 2020. Supervised classification algorithms in machine learning: A survey and review. In Emerging technology in modelling and graphics (pp. 99-111). Springer, Singapore.

[5] Krishnamoorthy, N., Prasad, L.N., Kumar, C.P., Subedi, B., Abraha, H.B. and Sathishkumar, V.E., 2021. Rice leaf diseases prediction using deep neural networks with transfer learning. Environmental Research, 198, p.111275

[6] Tripathy, P.K., Tripathy, A.K., Agarwal, A. and Mohanty, S.P., 2021. MyGreen: An IoT-Enabled Smart Greenhouse for

Sustainable Agriculture. IEEE Consumer Electronics Magazine, 10(4), pp.57-62.
[7] Savarimuthu, N., 2021. PLDD-A Deep Learning Based Plant Leaf Disease Detection. IEEE Consumer Electronics Magazine.
[8] Geetharamani, G. and Pandian, A., 2019. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computers & Electrical Engineering, 76, pp.323-338.
[9] Cap, Q.H., Uga, H., Kagiwada, S. and Iyatomi, H., 2020. Leafgan: An effective data augmentation method for practical plant disease diagnosis. IEEE Transactions on Automation Science and Engineering.
[10] Abayomi-Alli, O.O., Damaševičius, R., Misra, S. and Maskeliūnas, R., 2021. Cassava disease recognition from low-quality images using enhanced data augmentation model and deep learning. Expert Systems, 38(7), p.e12746.
[11] Dhanachandra, N., Manglem, K. and Chanu, Y.J., 2015. Image segmentation using K-means clustering algorithm and subtractive clustering algorithm. Procedia Computer Science, 54, pp.764-771.
[12] Ray, S. and Turi, R.H., 1999, December. Determination of number of clusters in k-means clustering and application in colour image segmentation. In Proceedings of the 4th international conference on advances in pattern recognition and digital techniques (pp. 137-143).
[13] Ponti, M., Nazaré, T.S. and Thumé, G.S., 2016. Image quantization as a dimensionality reduction procedure in color and texture feature extraction. Neurocomputing, 173, pp.385-396.
[14] Lee, Y.J. and Mangasarian, O.L., 2001. SSVM: A smooth support vector machine for classification. Computational optimization and Applications, 20(1), pp.5-22.
[15] Tan, Ping, Weiping Sa, and Lingli Yu. "Applying extreme learning machine to classification of EEG BCI." In 2016 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), pp. 228-232. IEEE, 2016.
[16] Peng, X., Lin, P., Zhang, T. and Wang, J., 2013. Extreme learning machine-based classification of ADHD using brain structural MRI data. PloS one, 8(11), p.e79476.
[17] Al-Yaseen, W.L., Othman, Z.A. and Nazri, M.Z.A., 2017. Multi-level hybrid support vector machine and extreme learning machine based on modified K-means for intrusion detection system. Expert Systems with Applications, 67, pp.296-303.
[18] Olatunji, S.O., 2011. Comparison of Extreme Learning Machines and Support Vector Machines on Premium and Regular Gasoline Classification for Arson and Oil Spill Investigation. Asian Journal Of Engineering, Sciences & Technology, 1(1).
[19] Dange, B. J. ., Mishra, P. K. ., Metre, K. V. ., Gore, S. ., Kurkute, S. L. ., Khodke, H. E. . and Gore, S. . (2023) “Grape Vision: A CNN-Based System for Yield Component Analysis of Grape Clusters ”, International Journal of Intelligent Systems and Applications in Engineering, 11(9s), pp. 239–244. Available at: https://ijisae.org/index.php/IJISAE/article/view/3113.
[20] Gore, S. ., Dutt, I. ., Dahake, R. P. ., Khodke, H. E. ., Kurkute, S. L. ., Dange, B. J. . and Gore, S. . (2023) “Innovations in Smart City Water Supply Systems ”, International Journal of Intelligent Systems and Applications in Engineering, 11(9s), pp. 277–281. Available at: https://ijisae.org/index.php/IJISAE/article/view/3118.
[21] Tholkapiyan, M. ., Ramadass, S. ., Seetha, J. ., Ravuri, A. ., Vidyullatha, P. ., Shankar S., , S. . and Gore, S. . (2023) “Examining the Impacts of Climate Variability on Agricultural Phenology: A Comprehensive Approach Integrating Geoinformatics, Satellite Agrometeorology, and Artificial Intelligence”, International Journal of Intelligent Systems and Applications in Engineering, 11(6s), pp. 592–598. Available at: https://ijisae.org/index.php/IJISAE/article/view/2891.
[22] Upadhyay, S.K. and Kumar, A., 2022. A novel approach for rice plant diseases classification with deep convolutional neural network. International Journal of Information Technology, 14(1), pp.185-199.
[23] Bari, B.S., Islam, M.N., Rashid, M., Hasan, M.J., Razman, M.A.M., Musa, R.M., Ab Nasir, A.F. and Majeed, A.P.A., 2021. A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. PeerJ Computer Science, 7, p.e432.
[24] Wang, Y., Wang, H. and Peng, Z., 2021. Rice diseases detection and classification using attention based neural network and bayesian optimization. Expert Systems with Applications, 178, p.114770.
[25] Tiwari, V., Joshi, R.C. and Dutta, M.K., 2021. Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images. Ecological Informatics, 63, p.101289

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