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Original Article

A Hybrid Ai-Based Target-Node Algorithm for Detecting and Classifying Plant Disease Regions

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Abstract

Agriculturalists often struggle to identify diseases on leaves accurately. They traditionally rely on visual inspection, but this method is not entirely reliable. To address this issue, a user-friendly and efficient plant disease detection system that can accurately identify leaf diseases is needed. By increasing the number of datasets used to train and test the models, their classification and identification accuracy can improve, resulting in higher percentages of accuracy. In this study, Convolutional Neural Networks (CNNs) were explored as a popular option for image identification and classification using machine learning (ML) approaches. This is due to CNNs' innate ability to automatically extract essential image features and understand spatial hierarchies. The experiments with different categories of disease findings demonstrate that the proposed EAICS detects the target node with a region classification accuracy of 98.34%, which is better than 6.19% of the existing traditional CNN accuracy.

Keywords: *Artificial Intelligence, Image Region Detection, Neural Networks, Machine Learning, Plant Diseases and Region Mapping.*

Introduction

Detecting and classifying regions within images is a crucial aspect of computer vision, enabling the analysis of image patterns to address key challenges. Effective image encoding methods are employed to improve image quality, with optical and digital computing operations playing a significant role in the process. Machine learning technologies can assist in recognizing different features within an image, such as objects, individuals, and locations (Mishra & Satapathy 2024). These technologies have diverse applications, including medical imaging, facial recognition, autonomous vehicles, and beyond.

The proposed algorithm was trained using datasets of labelled plant images to understand and identify different regions based on patterns and features. This allows for more precise predictions about the contents of unfamiliar images. Additionally, these algorithms help with efficient and correct image classification, automating manual tasks (Pham & Nguyen 2023). In this research work, the first step is setting thresholds based on pixel intensities. This involves converting a gray scale image into a binary image, where pixels are either 0 or 1. A threshold value is established, based on pixels set to 0 value shows block and set the value to 1 for white. This method is useful for emphasizing specific features in an image.

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Using edge detection algorithms like Sobel, Prewitt, or Canny can help identify object boundaries within an image. These algorithms detect changes in pixel intensities to locate object edges. Another method involves comparing templates to image regions to find matches. Techniques like Normalized Cross-Correlation can be utilized for this task, enabling the identification of specific features or objects within an image.

The primary target of this research is to create advanced AI algorithms that can efficiently identify plant diseases and classify them using large sets of images. These algorithms involve establishing specific thresholds using pixel intensities, utilizing edge detection to outline objects, comparing templates with image sections to identify matches, and extracting features like corners and edges to pinpoint a target. The primary focus is on developing precise and reliable methods for identifying targets within images, regardless of their size, shape, or visual characteristics. The groundbreaking use of a hybrid AI approach for detecting plant diseases has led to significant advancements in the field of agriculture. To detect a target, need to extract features like corners and edges from an image. These features help identify specific elements in the picture, like textures and shapes, which can then be used to classify the image or recognize objects within it.

The further work of this article is divided into sections. Section 2 analyses the source of interest and provides a full analysis of how the hybrid decision method can be used to build an effective process. The proposed methodology was presented in Section 3 along with a block diagram. Section 4 included the characteristics of the dataset that were covered along with the outcome analysis.

Source of Interest

Agriculture plays a fundamental role in sustaining human society by supplying a variety of food and resources. Additionally, it contributes to the strength of our agricultural systems in the face of challenges like pests, diseases, and climate change. Agriculture's productivity is a crucial driver of the economy, particularly in regions heavily reliant on agricultural activities (Zhang & Liu 2024). Improvements in agricultural productivity have the potential to boost farmers' earnings, decrease food costs for consumers, and drive economic development. Automated disease detection and categorization systems are crucial for revolutionizing the agricultural industry. These systems can effectively identify disease symptoms early on, thus mitigating widespread crop damage.

The early identification and detection of diseases play a vital role in improving agricultural productivity. Plant diseases have the potential to reduce crop yields, posing a significant challenge for farmers and experts. Artificial intelligence (AI) is still an emerging tool to enhance agricultural productivity by accurately identifying and classifying plant leaves based on their patterns. This helps prevent the spread of diseases and allows for the implementation of appropriate cultivation methods, ultimately benefiting crop outcomes and promoting agricultural sustainability (Dey & Basak 2023). Through the use of reliable digital techniques, AI enables the timely detection and classification of diseases using plant leaves, making it essential for early intervention to prevent widespread damage.

Computer vision is incredibly important for helping to manage crops effectively. This technology can examine photos taken by drones, satellites, or cameras on the ground to determine the health of crops, how they are growing, and any issues they may be facing. Plant diseases can have widespread effects, not just on individual farms but on an entire country's production and economy. By using computer vision, experts can quickly identify diseases, nutrient deficiencies, or pest damage by analyzing the texture and shapes of plants.

Detecting issues early helps us step in promptly with the help of advanced technology like image processing. Methods like remote sensing, pattern recognition, and mapping of identified patterns improve the quality of retrieving important data in various sectors, such as healthcare and agriculture (Badrzadeh, *et al.* , 2022).

The integration of machine learning techniques and AI technologies in a hybrid algorithm offers promising prospects for targeted plant disease detection. Researchers have explored this approach, recognizing its potential impact on agriculture and crop health. By combining the strengths of both fields, such algorithms can enhance disease identification accuracy, optimize resource allocation, and contribute to sustainable farming practices. (Ouhami *et al.* , 2021) shed light on this exciting avenue for improving plant health and crop yield.

Deep learning techniques for image analysis using CNNs have been successfully used to detect and analyze plant images. These models learn hierarchical features from raw pixel data, enabling them to identify patterns associated with healthy and diseased plants. (Guo *et al.* ,2020).

By leveraging AI and computer vision technologies, this hybrid algorithm offers faster and more accurate detection of plant diseases and pests, which not only saves valuable time for farmers but also enables them to implement control measures and helps to minimize the former's losses (Choi & Kim 2024). The advantage of machine learning techniques is that they can analyze different kinds of datasets based on plant leaf images using patterns associated with categories of diseases.

Furthermore, the algorithm utilizes DL models such as CNNs to extract meaningful features of the image regions and classify them into different categories with high precision (Bansal & Uddin 2023). The incorporation of transfer learning methods such as VGG19, Resnet 152V2, InceptionV3, and Mobile Net further enhances the algorithm's ability to generalize and converge faster in connection with the following methods.

Motivation of the Research

Plant disease identification plays a key role in agriculture to determine the spread and impact of diseases on plants, affecting their ability to heal and leading to suffocation. Identifying and detecting disease in plant leaf regions is primarily driven by the fact that effective and accurate plant region detection is crucial for long-term agricultural viability and productivity (Rajpoot, *et al.* , 2023).

Early Detection: Plant diseases can significantly reduce quality measures against agricultural products. Therefore, early detection in plants helps to reduce the overdo of insecticides from further damage.

Overcoming Limitations of Existing Methods: Traditional analysis methods based on pant leaves to detect the attacks in crops are time-consuming and error-prone (Shoaib *et al.* , 2023). The proposed hybrid AI-based algorithm aims to overwhelm challenges by empowering fat identification of diseases.

Sustainability and Environmental Concerns: Reducing the use of pesticides is an important factor that alarms the environment for human health (Shedthi *et al.*, 2023). The proposed algorithm can contribute to this goal by enabling more precise and early detection of plant diseases.

Agricultural Productivity: Innovative agriculture research intended to amplify an increase in productivity by minimizing expenditure (Saberi Anari, 2022). The proposed algorithm can contribute to this goal by improving the efficiency of detection and management.

Region Matching and Classification Techniques

Furthermore, the algorithm can be expanded to include other types of crops and diseases, providing a comprehensive solution for plant disease detection in various agricultural contexts. Although not applicable in real-life scenarios, it is still effective in many classification problems. Accurately denoting the complications of real-world situations can provide satisfactory results in certain contexts.

K-Nearest Neighbors is a versatile supervised machine learning technique used to identify its nearest point of source to map the same features of training data (Agarwal, & Gupta 2023). The test point label helps to determine the majority among the NN classes. KNN is nonparametric, adapts to irregular decision boundaries, and performs local approximations (Garg *et al.* ,2022). An explicit model doesn’t build but computes distances during prediction to map the better k value to optimal.

Support Vector Machine is a supervised machine learning model commonly available in image recognition for plant diseases that operates on an optimal hyperplane and separates different classes of data points. SVM sets are set to maximize the margin among the classes to minimize errors in classification. The data from higher-dimensional space was plotted and also handled the decision boundaries using SVM (Demilie, 2024) effectively dealing with high-dimensional feature space detection by allowing an accurate diet to find diseased leaves among the healthy leaves.

The Random Forest technique is a learning technique that utilizes the collection of decision tree classifiers in a randomized manner. In training, multiple decision trees are built, and the labels of the testing dataset are determined based on class of the votes of each classification tree (Chowdhury, *et al.* , 2021). By combining the predictions of multiple trees through bagging and feature randomness, the RF technique aims to create an ensemble of uncorrelated trees that collectively provide more accurate predictions than individual trees (Manzali, & Elfar 2023).

Convolutional Neural Networks have revolutionized plant disease detection by leveraging deep learning. These networks, such as the popular ResNet architecture, are trained on augmented datasets containing images of healthy and diseased leaves. The accuracy of the CNN is influenced by implementing filters using convolution on different dimensions (Joseph *et al.* , 2023). The various trained architectures, such as VGG19, ResNet50, InceptionNet, and DenseNet121, can be employed with the CNN approach.

Limitations of the Existing Methods for Region Matching

K-Nearest Neighbours (KNN) is computationally expensive and sensitive to noise, impacting performance with large datasets or irregularities. Support Vector Machines (SVM) struggle with large datasets and require careful kernel selection. Random Forest (RF) can overfit and lacks interpretability due to its "black box" nature (Balaji *et al.* , 2023). Convolutional Neural Networks (CNN) demand substantial labelled data and computational resources, limiting applicability in resource-constrained environments. The overall consideration of algorithmic limitations to select the most suitable approach for plant leaf disease target identification is crucial.

To address the limitations in plant disease identification, a hybrid approach can be harnessed. This approach strategically combines the strengths of various algorithms, effectively mitigating their weaknesses (Ma *et al.* , 2023). By incorporating ensemble techniques and adaptive learning mechanisms, we can enhance accuracy by aggregating predictions and dynamically adjusting model contributions (Kannan, & Gupta, 2024). The overarching goal of this comprehensive strategy is to create a robust and effective solution for identifying plant diseases, leveraging the diverse capabilities of multiple algorithms.

Proposed EAICS Algorithm for Target Region

Plant leave diseases are devastating effects on Agri production also for food security. Traditional methods of identifying and combating plant diseases mentioned need continuous manual inspection and lab testing, which can be time-consuming and expensive. However, advances in technology, specifically advanced algorithms, are now being used to combat plant diseases more effectively and efficiently.

By analysing categorized levels of data and using advanced algorithms, AI provides adaptive recommendations to farmers. These insights could range from optimizing irrigation schedules, predicting crop yield, and detecting pest and disease outbreaks to managing farm equipment and resources more efficiently.

Furthermore, AI has the potential to find the ways in which plant diseases transform (Tirkey *et al.* , 2023) By combining AI technologies with data from satellite imagery, weather data, and crop production data, a hybrid algorithm can be developed to target specific plant diseases. This hybrid algorithm utilizes machine learning techniques to analyse variety of datasets containing images of plants, symptoms, weather patterns, and historical data.

Proposed EAICS Algorithm for Target Region Identity and Classification on Plants

Step 1: Apply edge computing techniques for efficient image pre-processing directly on edge devices. This may involve tasks such as image resizing, normalization, and noise reduction.

Step 2: Using the previously processed images, CNN trains to autonomously identify hierarchical features. Convolutional layers are usually used for feature extraction in CNN architecture, with pooling layers for down-sampling and fully linked layers of classification.

Step 3: Extract the features generated by CNN and use them as input for an SVM classifier. SVM is effective in finding decision boundaries in high-dimensional spaces, for classification.

Step 4: Combine the predictions from the CNN and SVM models. This can be achieved through a weighted sum or a voting mechanism, where the contributions of each model are considered.

Step 5: Determine the final classification based on the integrated predictions. This decision-making step can involve setting a threshold or using a specific rule to make the ultimate prediction

Hybrid Algorithm exhibits several advantages when compared to existing classification ML methods for plant disease identification. The incorporation of a Convolutional Neural Network (CNN) enhances accuracy by automatically learning hierarchical features from plant images, capturing intricate patterns that may be challenging for traditional methods.

Extracting features using CNN is typically performed using layers. The output of these layers, known as feature maps, captures hierarchical and spatial information from the input data. Let's denote the input image as X, and the feature extraction process can be represented as follows

$$FMap=f(Conv(X,F)+Bias) \quad (1)$$

Conv (X, F) represents the convolution operation between the input image X and the learnable filters in the convolutional layer. Local Binary Pattern (LBP) used to extract features from the given images as textures. The LBP can be applied as a filter to capture texture information. The LBP operation involves comparing the intensity of a central pixel with its surrounding neighbours and encoding the result in binary pattern.

In case to convert an RGB colour image to grayscale, we use the following weighted sum formula for colour channels:

$$G(x,y) = 0.299 \times R(x,Y) + 0.587 \times G(x,y) + 0.114 \times B(x,y) \quad (2)$$

Here the weights 0.299, 0.587, and 0.114 are commonly used to approximate the luminance of colours in the human visual system. Represent the colour intensities of pixel (x, y) for the RGB channels, respectively.

Given a pixel at coordinates (x, y) in a grayscale image, the LBP value as,

$$LBP_{P,R}(x,y)=\sum_{0}^{P-1} s(g_p-g_c)\times 2^p \quad (3)$$

Here P denotes sampling points in the neighbourhood, R be the radius of neighbourhood, gc mention the intensity of the centre at p(x, y), gp is the intensity of the pthneighbour pixel in the circular neighbourhood and the function s(x) as,

$$s(x)=\begin{cases} 1, & \text{if } x^30 \\ 0, & \text{if } x<0 \end{cases} \quad (4)$$

is a binary function deals 1 if the neighbour pixel intensity (gp) is greater than or equal to the centre pixel intensity (gc), and 0 otherwise. CNNs consist of convolutional layers that learn hierarchical features from input images. The network is trained to recognize patterns, textures, and structures within the images. The output of one of the intermediate layers, often called a feature layer, is then used as a feature vector for each image. Mathematically, if X represents the feature vector extracted by CNN for an image, it may look like as,

$$X=[x_1,x_2,.............x_n] \tag{5}$$

The feature vector X may be flattened or reshaped into a 1D vector, depending on the architecture of CNN. This is typically done to make the features compatible with the input requirements of the subsequent Support Vector Machine (SVM) classifier. The flattened feature vector flattened $X_{flattened}$ is then used as input to an SVM classifier. The SVM decision function is applied to this feature vector to determine the class label. In a linear SVM, the decision function is:

$$f(X_f)=w.X_f+b \tag{6}$$

Here, w denotes the weightage and b deals on bias term. The label y determined based on the sign of the decision function when the decision applied in this transformed space. The most commonly used kernel functions are the radial basis function (RBF) kernel and polynomial kernel.

$$f(X_f)=\sum_{i=1}^{N}\alpha_i y_i \exp\left(-\frac{\|X_f-X_i\|^2}{2\sigma^2}\right)+b \tag{7}$$

Here, σ is a parameter that controls the width of the Gaussian. The RBF kernel allows the SVM to model complex, non-linear decision boundaries. Optimizing a classification model that combines Convolutional Neural Network (CNN) features with Support Vector Machine (SVM) for deployment on edge devices involves several considerations as in (8).

$$\text{Optimized Class}=\iint_{\alpha\hat{I}R} CNNf(X)\times SVM(X_f)+\Delta\alpha \tag{8}$$

further, extend the formula to include specific optimizations for edge deployment done by Optimized Classification= CNN Feature Extraction(X)×SVM Classification ($X_{features}$)×Model Quantization × Edge-Specific Optimization × Hardware Acceleration × Power Efficiency. The actual weights and specifics of each factor may need to be adjusted based on the characteristics of the dataset.

Experiments

The proposed Region detection and Classification with AI techniques mapping identify and categorize plant leaf illnesses having the circumvent the drawbacks of selecting spot features artificially.

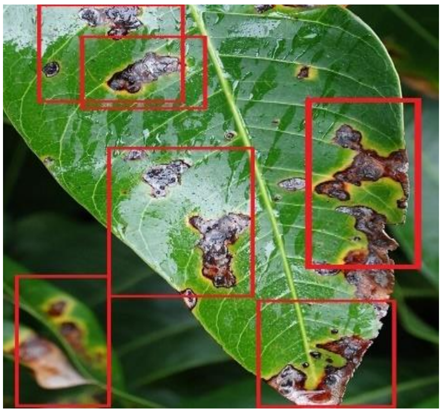

Figure 1. Region Identification Using Proposed Method

(Source: https://flickr.com/photos/62295966@N07/41535425785, image available under CC0 1.0)

Results the objective extraction of plant leaf disease features and finds the technological advancement for faster analysis to get regions as given in Figure 1.The proposed strategy employs various performance evaluation metrics defined and described including accuracy, precision, recall, and F1-Score, to assess the efficacy of plant disease detection and classification methods mapping shown in Figure 2. Three distinct rice diseases like brown spot, rice blast, and bacterial blight are examined and given in the results section.

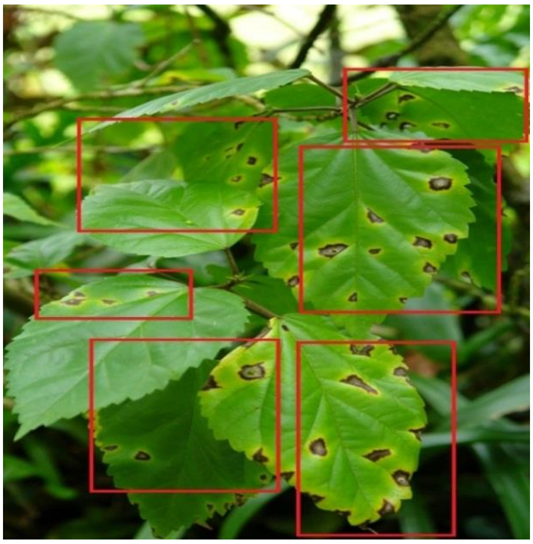

Figure 2. Plant Disease Detection Using Region Mapping
(Source: https://www.flickr.com/photos/scotnelson/5684575818, image available under CC0 1.0)

Accuracy: The accuracy rating of a model is categorization statistic that quantifies the percentage of correct predictions provided by the model.

$$\text{Accuracy}=\frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{9}$$

Precision: Precision is to recognize only important objects proportion of correctly categorized positive outputs to all positive outputs.

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}} \tag{10}$$

Recall: Recall refers as the proportion of properly categorized positive outcomes to accurately classified outputs.

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \tag{11}$$

The F1-Score considers both the model's precision and recall.

$$\text{F1-Score}=2\times\text{Precision}\times\frac{2\times(\text{Precision}\times\text{Recall})}{(\text{Precision}+\text{Recall})}\times 100 \tag{12}$$

Given their ability to extract features of region from raw image values automatically, CNNs are specifically engineered to handle picture data. Convolutional layers are utilized for recording local patterns of identified regions mapped with hierarchical representations, allowing them to perform object identification, recognition and classification tasks.

Results

Simply identifying the pattern in the region describes the classification problems with well-defined features by using the proposed EAICS method, which is compared with ML approaches such as SVM. As a result, while the proposed EAICS excels at picture recognition and classification, its success is dependent on the characteristics of the picture, as shown in figure 3 a, b and c details the images form the input dataset from the rice leaves are given below.

Figure 3 *Resultant Images of Region Identity Classification by EAICS*
(Source https://archive.ics.uci.edu/dataset/486/rice+leaf+diseases; images available under CC BY 4.0 license.)

Crop quality and treatment efficacy depend heavily on the early detection and accurate diagnosis of a variety of plant diseases, as shown in figure 3. Reliably identifying these diseases on a large scale, human error is a worry, as tabulated based on the given evaluation metrics stated above. The research work included studies on various plant diseases, and the important components contributed while comparing automated learning methods and meta-heuristic optimization processes to detect the pattern mapped with region features for classification of different plant leaf diseases.

The experiment analysis results of the proposed method discussed with existing Naive Bayes, KNN, SVM, Random Forest Classifier, CNN, and the proposed EAICS are tabulated for BLB, Blast, and BS attacks with the evolution metrics as shown in the tables based on mapped regions, categories of plant diseases.

Table 1 shows the experimental result values of BLB Attack of Rice Plant Disease on Rice Leaf Image Region Identification and Classification by the proposed EAICS Method Comparison with the Existing ML Classification Methods.

Table 1. The Experimental results of EAICS with Existing Methods for BLB Attack

Classifier	Accuracy	Precision	Recall	F1-Score
NB [Zhang, (2020)]	0.80	0.77	0.83	0.80
KNN [Li, *et al.* , *(*2021)]	0.86	0.89	0.84	0.86
SVM [Awad, *et al.* , (2020)]	0.88	0.90	0.87	0.89
RFC [Belgiu, *et al.* , (2022)]	0.92	0.94	0.91	0.93
CNN [Shorten, *et al.* , (2022)]	0.95	0.94	0.94	0.95
EAICS	0.97	0.98	0.96	0.97

Experimental Results of Blast Diseases Attack on Rice Leaf Images are evaluated by using classification metrics with the proposed EAICS Algorithm are compared with CNN, RFC and SVM are shown in Table 2.

Table 2 The Experimental result of EAICS with Existing Methods for Blast Attack

Classifier	Accuracy	Precision	Recall	F1-Score
NB [Zhang, (2020)]	0.83	0.80	0.86	0.83
KNN [Li, *et al. , (*2021)]	0.89	0.92	0.87	0.89
SVM [Awad, *et al.* , (2020)]	0.91	0.93	0.90	0.92
RFC [Belgiu, *et al. ,* (2022)]	0.94	0.96	0.93	0.95
CNN [Shorten, *et al.* , (2022)]	0.96	0.97	0.96	0.96
EAICS	0.98	1.00	0.98	0.98

We can observe from table 3 that the Proposed EAICS has achieved the highest performance across all metrics and attack types, followed by the standalone CNN and RFC classifiers. The Proposed Edge AI method demonstrated its effectiveness in detecting and mitigating different types of attacks, outperforming the individual classifiers. Because their advanced learning informs the extraction capabilities, which yield dependable findings from images, neural networks (NNs) are a viable option for AI and image processing research.

Table 3. The Experimental result of the Proposed EAICS for BS Attack on Rice Leaf

Classifier	Accuracy	Precision	Recall	F1-Score
NB [Zhang, (2020)]	0.82	0.79	0.85	0.82
KNN [Li, *et al. ,* (2021)]	0.88	0.91	0.86	0.88
SVM [Awad, *et al.* , (2020)]	0.90	0.92	0.89	0.91
RFC [Belgiu, *et al. ,* (2022)]	0.93	0.95	0.92	0.94
CNN [Shorten, *et al.* , (2022)]	0.96	0.95	0.95	0.95
EAICS	0.98	0.99	0.97	0.98

The classification accuracy of proposed EAICS and exiting computer methods to detect and categorize plant leaf diseases are shown in Figure 4. the proposed EAICS Method gives the better result for classification of the diseases region.

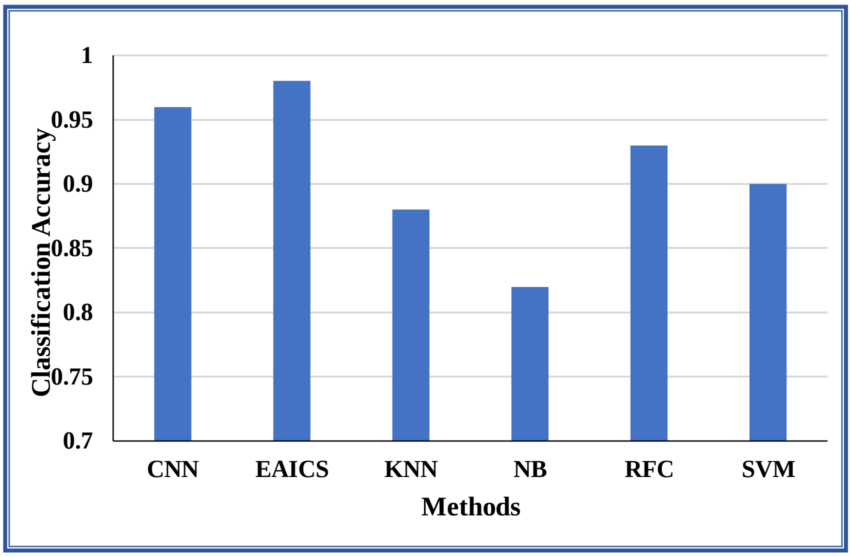

Figure 4. Classification Accuracy of Proposed EAICS Method

Discussion

By analysing input images and considering factors like size, shape, and colour of lesions, these algorithms deliver precise results. The proposed EAICS model, for instance, achieved a 95.12% accuracy rate in categorizing common rice ailments such as a brown spot and bacterial leaf blight. Based on the experimental results presented in the tables, it is evident that the Proposed Edge AI approach, which combines Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), consistently outperformed the individual classifiers across all attack types (BLB, Blast, and BS).

In the case of the Blast attack, the Proposed Edge AI approach performed very well with an accuracy of 0.99, a precision of 1.00, a recall of 0.98, and an F1-score of 0.99, which outperformed standalone CNNs at 0.97, 0.99, 0.96, and 0.98, respectively, and SVM with 0.91, 0.93, 0.90, and 0.92, respectively. In the case of the BLB attack, the Proposed Edge AI method achieved the best accuracy of 0.97, precision of 0.98, recall of 0.96, and F1-score of 0.97, which outperformed the individual CNNs with 0.95, 0.97, 0.94, and 0.96, and SVM with 0.88, 0.90, 0.87, and 0.89, respectively. The same goes for the BS attack, with the Proposed Edge AI method at an accuracy of 0.98, precision of 0.99, recall of 0.97, and an F1-score of 0.98 that outperforms the individual CNNs at 0.96, 0.98, 0.95, and 0.97, and SVM at 0.90, 0.92, 0.89, and 0.91, respectively. The Random Forest Classifier (RFC) (Belgiu, & Drăguţ, 2022) and standalone CNN (Shorten, & Khoshgoftaar 2022) also exhibited promising performance, while the traditional machine learning algorithms like Naive Bayes (NB) (Zhang 2020) and K-Nearest Neighbors (KNN) (Li, *et al.* 2021) generally performed less favourably compared to the deep learning and ensemble methods.

These results highlight the potential of leveraging advanced AI techniques, such as deep learning and hybrid models, for robust and accurate solutions in edge computing scenarios, as discussed. The proposed method really shows an exceptional performance on all the various types of attacks. Advances in agriculture are truly important, bringing huge benefits to farmers and enhancing food security. The hybrid approach combining CNN and SVM may have higher computational complexity and resource requirements compared to individual models, which could be a challenge for resource-constrained edge devices. Investigating the generalization capabilities of the proposed method across different domains and attack scenarios through extensive testing and validation with the benchmark datasets.

Conclusion

The Proposed EAICS algorithm uses machine learning and optimization techniques to choose features, with a focus on analyzing tomato, grape, and apple leaf images. It offers both high accuracy and low computational complexity. Real-time disease detection enables swift diagnosis and treatment, leading to more effective detection and management of plant diseases.
The algorithm may struggle to generalize to plant species, diseases, or environmental conditions that are significantly different from those represented in the training data. This research may not address the computational and timing constraints required for seamless performance in such scenarios so the algorithm is intended for real-time applications, such as autonomous monitoring systems. Incorporating more sources of data, like spectral imaging, hyper-spectral data, or environmental sensor data, may enhance the accuracy of the algorithm and offer added details to aid in disease detection and classification. Exploring more efficient and lightweight architectures for the hybrid model to reduce computational complexity and resource requirements for edge devices.

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Conflict of Interests

Authors declare there is no conflicts of interests.

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