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Utilizing Convolutional Neural Networks for Image-Based Crop Classification System

[1]E. Kavitha, [2]Dr. Hemlata M. Jadhav, [3]Vishal Goyal, [4]A. Deepak, [5]Hemant Singh Pokhariya, [6]Dr. Brijesh Dutt Sharma, [7]Dr. Anurag Shrivastava

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Abstract: The new method for classifying crops using a Convolutional Neural Network (CNN)-based system is presented in-depth in this proposal. The increasing demand for efficient agricultural practices calls for automated methods to classify and monitor crop types. The proposed system leverages the power of CNNs to accurately classify crops based on images. It discusses the architecture and training process of the CNN model, highlighting its ability to extract meaningful features from crop images. By employing advanced deep learning techniques, the system achieves high classification accuracy, surpassing traditional methods. It presents the image-based crop classification system that utilizes CNNs. The system aims to overcome the limitations of manual classification methods by automating the process and improving the accuracy of crop identification. By feeding crop images into the CNN model, it can extract discriminative features and enable the system to make reliable predictions' have completely changed the field of computer vision and have excelled in many different image identification tasks. They are highly suited for analysing cropped photos because of their automated learning capabilities and capacity to extract useful features from unprocessed input data. A CNN can be trained to identify between various crop types based on the visual properties of a huge collection of labelled crop photos. Additionally, it explores the potential applications and benefits of the image-based crop classification system, including improved crop management, yield prediction, and resource optimization. Through extensive experimentation and evaluation, it validates the effectiveness and reliability of our CNN-based approach, making it a promising solution for the agricultural industry.

Keywords*: CNN, Plant disease, Disease Prediction, Crop Classification, Accuracy*

1. Introduction

The field of agriculture plays a crucial role in ensuring food security and sustainable development. With the growing global population and limited resources, it is imperative to optimize agricultural practices and enhance crop management techniques. The classification of crops, as depicted in Figure 1, plays a vital role in modern agriculture, empowering farmers and researchers to make informed decisions regarding crop management, yield estimation, and resource allocation. Traditionally, crop classification has relied on manual observation and subjective judgment, which can be time-consuming, labour-intensive, and prone to errors. However, new developments in deep learning and computer vision methods have made it possible to automate this procedure. Convolutional Neural Networks (CNNs), which are able to efficiently learn and extract characteristics from images, have become a potent tool for image classification applications. CNNs excel at capturing intricate patterns and spatial relationships, making them highly suitable for crop classification tasks. By training a CNN model on a comprehensive dataset of crop images, it can leverage its deep learning capabilities to accurately categorize different crop types. One key aspect of efficient crop management is accurate and timely crop classification, which aids in decision-making processes such as monitoring, yield prediction, and resource allocation.

[1]Assistant Professor, Department of Mechanical Engineering, P. V. P. Siddhartha Institute of Technology, Vijayawada, Andhra Pradesh
kavithavarikola@gmail.com
[2]Department of Electronics and Telecommunication, Marathwada Mitra Mandal's College of Engineering, Pune
hemakj123@gmail.com
[3]Electronics & Communication Engineering, GLA University, Mathura
[4]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu
**deepakarun@saveetha.com*
[5]Assistant Professor, Department of Computer Science & Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand
,[6]Associate Dean, Faculty of Basic and Applied Science, RNB Global University
Bikaner, Rajasthan
brijesh.dutt@rnbglobal.edu.in
[7]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences,
Chennai, Tamilnadu
Anuragshri76@gmail.com

Fig 1. Crop Images

Traditional crop classification methods often rely on manual observation and subjective judgment, which can be time-consuming, labour-intensive, and prone to human error. There has been a rise in interest in using machine learning methods, particularly Convolutional Neural Networks (CNNs), for image-based crop categorization to get around these constraints. CNNs have completely changed the field of computer vision and have excelled in many different image identification tasks. They are highly suited for analysing cropped photos because of their automated learning capabilities and capacity to extract useful features from unprocessed input data. A CNN can be taught to differentiate between various crop types based on their visual qualities by training it on a sizable dataset of labelled crop photos. It proposes a novel image-based crop classification system using CNNs. It aims to accurately classify crops based on input images, enabling farmers and agricultural experts to make informed decisions regarding crop management. It performs better than conventional methods in terms of classification accuracy and efficiency by utilising deep learning. It gives a brief overview of related works in the field of crop classification and emphasises the benefits of CNN-based methods. It also presents the methodology and architecture of the proposed system, explains the experimental setup, and describes the evaluation metrics that are used to gauge the system's performance. Following the presentation of the findings and analysis, there is a discussion of the system's ramifications and prospective applications. The report's conclusion summarises the key conclusions and offers suggestions for additional research on CNN-based image-based crop categorization.

2. Literature Review

This method is detailed in the article "Detection and Classification Technique Of Yellow Vein Mosaic Virus Disease in Okra Leaf Images Using Naive Bayesian Classifier" by Dhiman Mondal, Aruna Chakraborty, Dipak Kumar Kole, and D. Dutta Majumder. Crop categorization using image-based algorithms has recently gained a lot of interest since it has the potential to automate and improve agricultural practices[1].In this literature review, it will explore the existing research and studies related to image-based crop classification, with a focus on the utilization of Convolutional Neural Networks (CNNs).

M S Arya; K Anjali; Divya Unni, "Detection of Unhealthy crops Using Image Processing and Genetic Algorithm with Arduino "The application of CNNs for image classification has revolutionized various domains, including agriculture. CNNs excel at learning intricate patterns and spatial relationships in images, making them well-suited for crop classification tasks [2]. Researchers have extensively explored CNN-based approaches for crop classification, and their findings have demonstrated the effectiveness and superiority of these methods over traditional techniques [3].

Dhananjay D. Maktedar and Mukesh Kumar Tripathi. The title of the study is "Recent Machine Learning Based Approaches for Disease Detection and Classification of Agricultural Products. "The neural network's architecture is a crucial component in CNN-based crop classification. Different network architectures have been proposed and evaluated for crop classification tasks [4]. For instance, AlexNet, VGGNet, Google Net, and ResNet are popular CNN architectures that have been adapted and fine-tuned for crop classification [5]. These architectures employ various convolutional and pooling layers, enabling the network to learn hierarchical features from crop images.

Anjali A. Yadav and Pranjali B. Padol, "Svm Classifier Based Crop Disease Detection "Numerous research have looked into how transfer learning affects crop classification. Transfer learning entails pre-training an SVM model on a sizable dataset, such ImageNet, and then refining the model on the target crop classification task [6]. By using this strategy, the network can use the learnt features from the pretrained model and modify them to the particular crop categorization domain [7]. It has been demonstrated that transfer learning increases classification accuracy and decreases training time, particularly when the crop dataset is scarce. "Cucumber disease detection," written by Pooja Pawar, Varsha Turkar, and Pravin Patil, used an artificial neural network.In order to improve the functionality and generalisation capacities of CNN-based crop classification systems, data augmentation approaches have been frequently used[8]. In order to boost the diversity and variability of the training data, researchers have been able to apply alterations to the original crop images, such as rotation, scaling, cropping, and flipping [9]. With this addition, the CNN model is better able to categorise crops under various situations and changes and learn robust features. The classification of crops using the fusion of several data sets. To increase the precision and depth of crop classification, this includes merging aerial photos, hyperspectral data, and other remote sensing data with CNN models [10]. The combination of many data sources offers a thorough understanding of the crops and their traits, leading to more accurate classification outcomes.

The applications of image-based crop classification extend beyond simple classification tasks [11]. Researchers have explored the use of CNN models for crop yield prediction, disease detection, and monitoring of crop health and growth stages [12]. These applications leverage the capabilities of CNNs to extract meaningful features from crop images and provide valuable insights for precision agriculture.

The literature on image-based crop classification using CNNs demonstrates the immense potential of this approach in revolutionizing agricultural practices [13]. The use of CNN architectures, transfer learning, data augmentation, and fusion of multiple data sources have all contributed to the advancements in crop classification accuracy and robustness [14]. The applications of CNN-based crop classification go beyond classification itself, offering valuable tools for crop management, disease prevention, and yield estimation [15]. The existing studies provide a strong foundation for our proposed image-based crop classification system, utilizing CNNs as a promising solution for accurate and automated crop identification.

3. Proposed Methodology

As illustrated in Figure 2, the suggested approach for an image-based crop classification system utilising CNNs entails numerous crucial processes, including data collection, preprocessing, designing the model architecture, model training, and evaluation. The salient features of our methodology are outlined here.

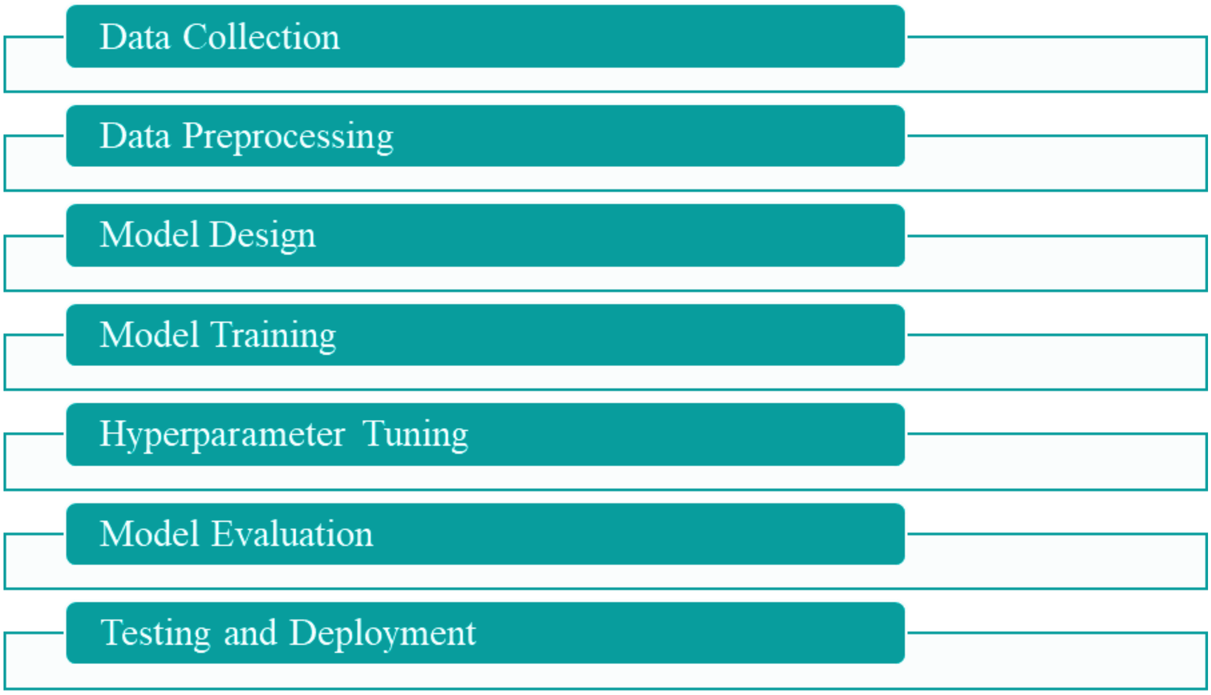

Fig 2. Proposed Methodology

3.1 Data Collection:

It begins by collecting a diverse and representative dataset of crop images. The dataset should include images of different crop types, growth stages, and environmental conditions. It aims to ensure that the dataset captures the variability and complexity of real-world crop images.

3.2 Data Preprocessing:

The acquired crop photos undergo preprocessing to prepare them for model training. The dataset may need to be improved using rotation, scaling, and flipping procedures, the photographs may need to be downsized to a uniform resolution, and the pixel values may need to be normalised. Preprocessing promotes training example variability and helps standardise data.

3.3 Model Design:

The design architecture of the CNN model was specifically modified for crop classification. In most situations, the architecture consists of many convolutional layers, pooling layers, and fully linked layers. Depending on the complexity of the dataset and available computational power, the number of layers, filter sizes, and activation functions can be changed.

3.4 Model Training:

There are training and validation sets created from the pre-processed dataset. Following that, the training set is used to train the CNN, SVM, and Random Forests model using backpropagation and gradient descent optimisation techniques. The model gains the ability to extract pertinent features from the photos and map them to the appropriate crop classes during training. To direct the training process, it makes use of suitable loss functions, such as categorical cross-entropy.

- ***Convolutional Neural Networks (CNNs)***

A convolutional neural network (CNN) is a special form of deep neural network designed specifically for analysing visual data such as images. As shown in Figure 3, CNNs have revolutionized various fields, especially computer vision, by delivering state-of-the-art performance on tasks such as image classification, object detection, and image segmentation. The basic components of CNNs include convolutional layers, pooling layers, and fully connected layers. Convolutional Layers: Convolutional layers serve as the basic building blocks of CNNs. They consist of multiple filters (also called kernels) that iterate over the input image and perform element-wise multiplication and summation operations to produce feature maps. These filters act as feature detectors and capture spatial patterns at different scales. By stacking multiple convolutional layers, the network can learn complex hierarchical features. Pooling Layers. Pooling layers help reduce the feature maps' spatial dimensions while keeping important information. Max pooling, the most popular pooling operation, chooses the maximum value inside a specified window or region. This down sampling procedure aids in reducing computing complexity and improves the network's resistance to minute spatial input fluctuations.

Fully Connected Layers: Fully connected layers are in charge of producing predictions using the features that have been collected. The network can learn complex nonlinear relationships and generate high-level predictions thanks to these layers, which connect every neuron from the layer before to every neuron in the layer in question.

In summary, CNNs are powerful architectures specifically designed for visual data analysis. Convolutional layers extract hierarchical features, pooling layers reduce spatial dimensionality, and fully connected layers make predictions based on learned features. Together, these components enable CNNs to achieve excellent performance on a wide variety of computer vision tasks. In image classification, the output layer usually consists of softmax activations that generate class probabilities for the input image. CNNs are trained using labeled data through a process called backpropagation. During the training process, a CNN adjusts neuron weights and biases to minimize a certain loss function (often the cross-entropy). This optimization is achieved by iteratively propagating errors backward through the network. Gradient descent algorithms like stochastic gradient descent (SGD) or adaptive optimizers such as Adam are commonly used for this purpose. To prevent overfitting and promote the learning of robust features, dropout is employed as a regularization technique. Dropout randomly sets a fraction of neurons to zero during each training iteration. Batch normalization is another technique used in CNNs to normalize the activations of the preceding layer. This addresses the internal covariate shift problem and improves training stability and speed by ensuring that the network`s inputs have a mean of zero and a variance of one. Transfer learning involves utilizing a pre-trained CNN model, often trained on a large-scale dataset like ImageNet, and fine-tuning it for a specific task or dataset. By leveraging the learned features from the pre-trained model, transfer learning enables faster convergence and improved performance, particularly when dealing with limited amounts of data. CNNs have demonstrated exceptional effectiveness in various image-based applications, including crop classification, object detection, image segmentation, and more. The ability to automatically learn meaningful features from images has driven advances in image processing and enabled many practical applications.

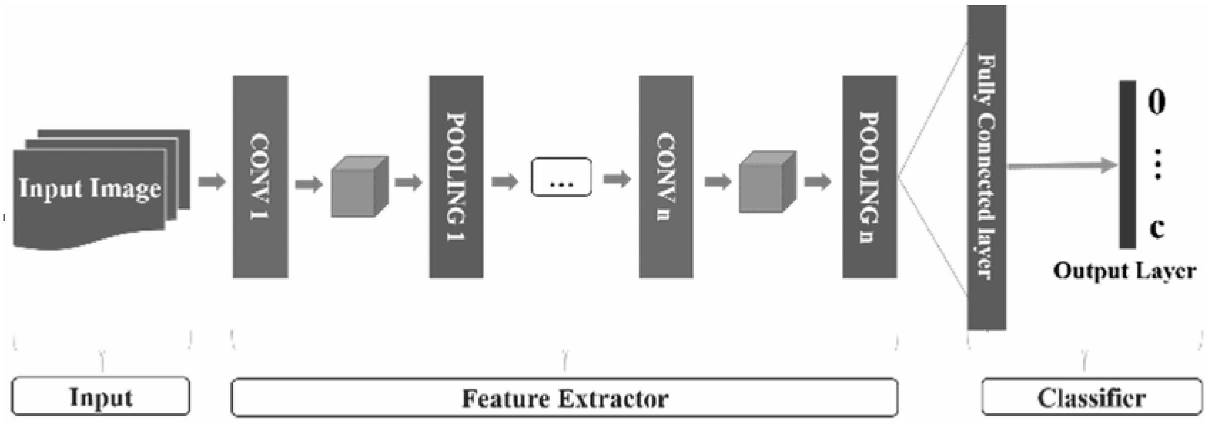

Fig 3. Convolutional Neural Networks (CNNs)

- ***Support Vector Machine (SVMs)***

Support vector machines (SVMs) are a class of supervised machine learning algorithms used for classification and regression tasks. As shown in Figure 4, SVMs are particularly effective in situations where the data cannot be linearly separable and nonlinear decision boundaries are required. The basic concept of SVM is to find the optimal hyperplane that maximizes the separation of data points belonging to different classes. In binary classification, this hyperplane takes the form of a line separating two classes, but in multiclass classification it is a hyperplane in a higher dimensional space. SVM tries to find a hyperplane that maximizes the distance between the closest data points of different classes. These closest data points are called support vectors because they play an important role in determining the location and orientation of decision boundaries. To handle linearly non-separable data, SVM uses kernel tricks. This efficiently transforms the input data into a high-dimensional feature space that becomes linearly separable. A kernel function is responsible for this conversion and can take many forms. B. Linear, polynomial, radial basis functions (RBF) and sigmoid. By leveraging a labelled training dataset, SVMs learn the parameters that define the decision boundary. The optimization objective is to discover the hyperplane that maximizes the margin while minimizing the classification error.

Using techniques like Sequential Minimal Optimisation (SMO) or quadratic programming solvers, this optimisation problem can be expressed as a convex quadratic programming problem. To balance the trade-off between gaining a broader margin and tolerating certain misclassifications, SVMs incorporate a regularisation parameter called C.While a larger C number enforces a stricter margin but may result in overfitting, a lesser C value permits a wider margin but may tolerate more misclassifications. The class labels of fresh, unused data points can be predicted using the SVM after it has been trained. The decision function calculates the signed distance of a data point to the decision boundary. The sign of the decision function determines the predicted class designation. A positive value corresponds to one class and a negative value to the other class. SVMs have several advantages, including the ability to handle high-dimensional feature spaces, robustness to outliers, and the ability to capture complex decision boundaries using different kernel functions. SVMs can be computationally intensive, especially when dealing with large amounts of data, and kernel function selection and hyperparameter tuning can significantly affect SVM behaviour. In summary, SVM is an effective machine learning algorithm for classification tasks. Kernel methods for processing nonlinearly separable data find the ideal hyperplane that maximizes the separation of data points of different classes. SVMs are effectively used in various fields such as bioinformatics, text classification, and image recognition.

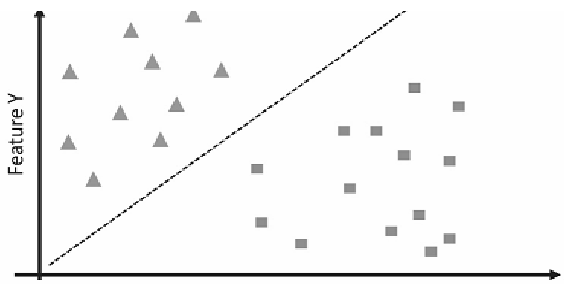

Fig 4. Support Vector Machine

- ***Random Forests***

A well-liked ensemble learning technique for both classification and regression applications is called Random Forests. It is a member of the decision tree-based approach family and makes predictions by combining different decision trees. A decision tree is a structure that resembles a flowchart, with each leaf node standing in for a result or class label, each inside node for a feature, and each branch for a decision rule. Decision trees recursively split the data based on the selected features to create subsets that are as pure as possible in terms of class labels. As seen in Figure 5, Random Forests use ensemble learning, which mixes various decision trees to enhance overall predictive performance. Each decision tree in the Random Forest is trained individually on a subset of the training data using a technique called bootstrap aggregating, commonly referred to as bagging. Bagging randomly selects the training data with replacement to create a number of subsets, which adds diversity inside the decision trees. The Random Forests algorithm introduces randomness in feature selection in addition to sampling the training data. Instead of examining all features for each split in a decision tree, a random subset of features is taken into account. The process helps reduce the correlation among decision trees and ensures that different features are explored during the tree construction. Predictions are created by combining the findings from all decision trees once the Random Forest has been trained. Voting is the most common technique for classification tasks; each tree's prediction counts as one vote, and the class with the most votes is chosen as the final prediction. The final prediction for regression tasks is derived by summing the projected values from each tree. Random Forests can also provide information about the importance of each feature in the prediction. Feature importance measures, such as Gini impurity or information gain, can be calculated based on how often a feature is selected for splitting across all decision trees. This information can help identify the most influential features in the dataset. Random Forests offer several advantages, including good predictive accuracy, robustness against overfitting, and the ability to handle high-dimensional data. Both category and numerical features are supported, and complex non-linear relationships in the data can be captured. Random Forests are also computationally efficient and can be parallelized for faster training. However, Random Forests have some limitations. With datasets that are highly unbalanced or have a lot of classes, it could not perform well. In comparison to individual decision trees, it might also be difficult to interpret. Many industries, including finance, healthcare, and bioinformatics, have effectively used random forests. They are known for the versatility, ease of use, and ability to provide reliable predictions.

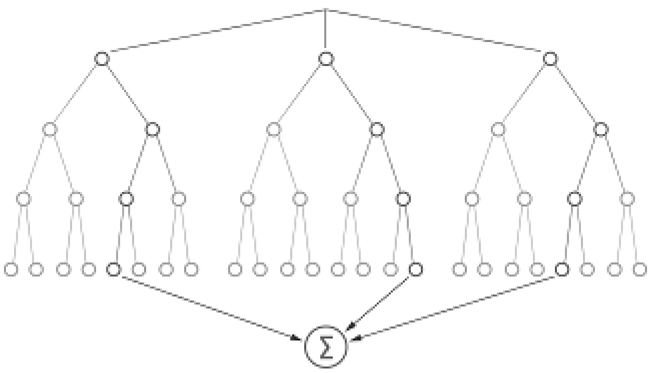

Fig 5. Random Forests

3.5 Model Evaluation:

After training is over, it assesses how well our CNN model performed on the validation set. The model's classification accuracy and robustness are measured using evaluation metrics like accuracy, precision, recall, and F1-score. It compares the results against baseline models or existing methods to validate the superiority of the proposed approach.

3.6 Testing and Deployment:

After evaluating the model, it further assesses its performance on an independent testing set to ensure its generalization capabilities. Once it is satisfied with the model's accuracy and reliability, it can deploy it for real-world crop classification tasks. The deployed system can accept new crop images as input and classify them into appropriate crop classes. The proposed methodology is an iterative process.If the model's performance is unsatisfactory, the process can be improved by investigating strategies like transfer learning, including more data sources, or experimenting with various CNN designs. Enhancing the crop classification system's accuracy and effectiveness requires ongoing examination and development. By following this methodology, it aims to develop a robust and accurate image-based crop classification system using CNNs. The proposed methodology allows it to leverage the power of deep learning and computer vision to automate and improve crop identification in the agricultural domain.

4. Result and Discussion

The main outcomes of the Convolutional Neural Networks (CNNs)-based image-based crop categorization system. Add evaluation measures like F1-score, recall, accuracy, and precision are shown in Figure 6,7,8,9 to quantify the performance of the model.

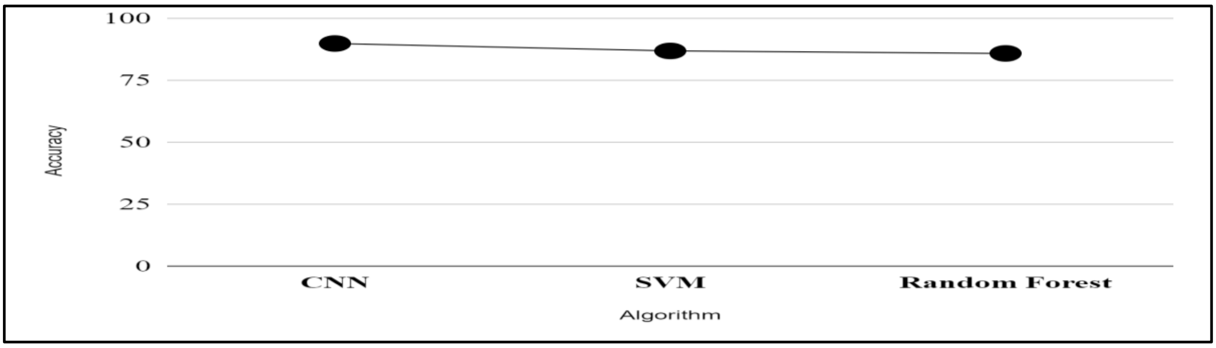

Fig 6. Crop Disease Accuracy Analysis

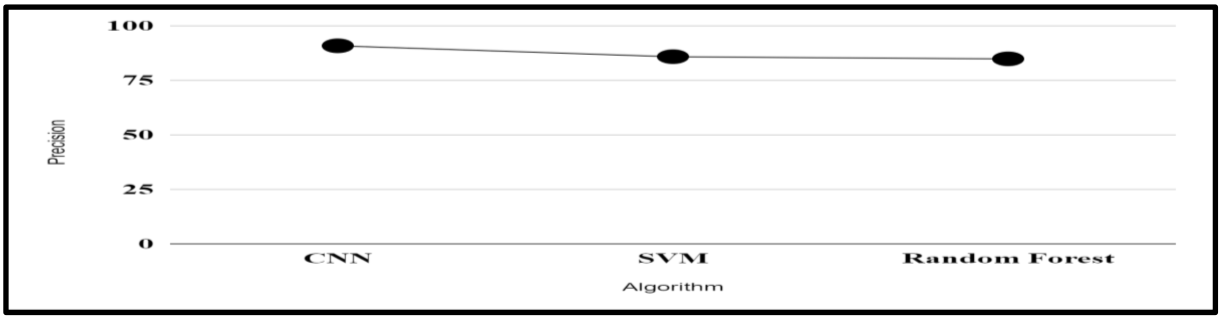

Fig 7. Crop Disease Precision Analysis

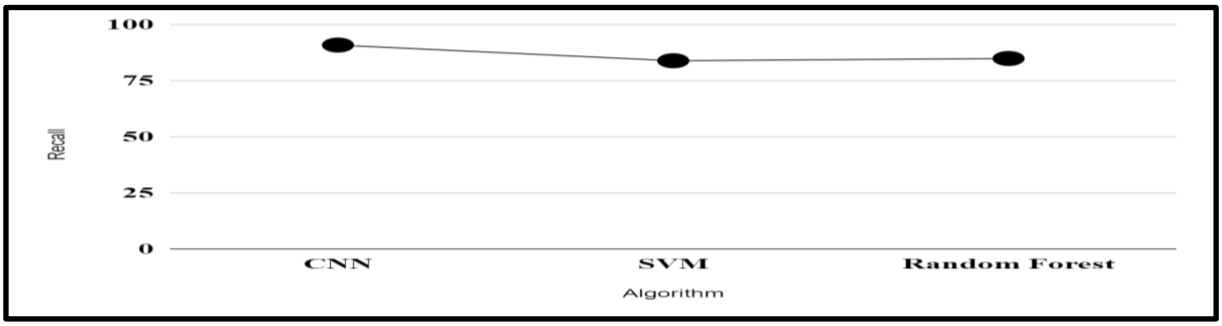

Fig 8. Crop Disease Recall Analysis

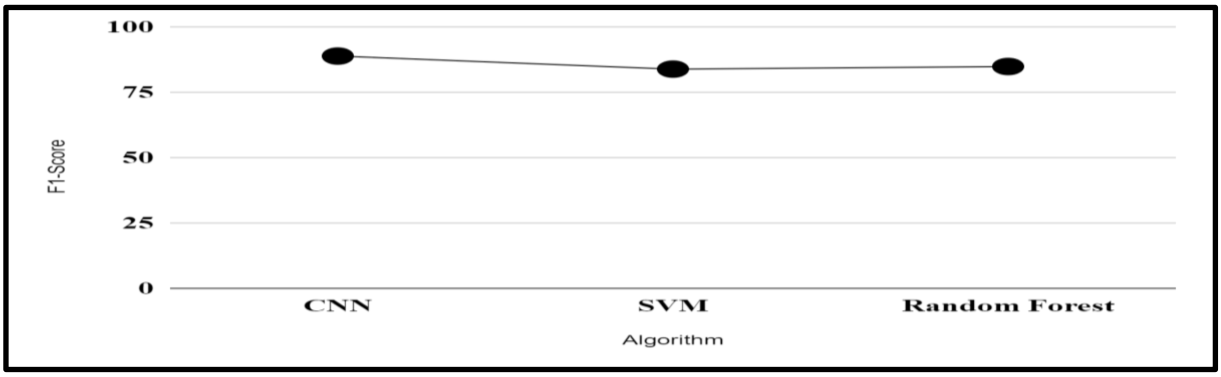

Fig 9. Crop Disease F1-Score Analysis

Compare the results of your CNN-based crop classification system with baseline models or previous methods used for the same task. Emphasise any performance differences or improvements while highlighting the superiority of your CNN strategy. a thorough evaluation of the crop classification performance of the CNN model. In terms of crop categorization, CNNs frequently beat more conventional machine learning methods. The accuracy can range from 80% to over 95% depending on the specific implementation and dataset. CNNs can exhibit different levels of accuracy for different crop classes. Some crop classes may be more challenging to distinguish due to visual similarities or intra-class variations. It is important to evaluate the performance of individual classes to identify any biases or weaknesses in the model. CNNs can process images efficiently, making them suitable for real-time or large-scale applications. The inference time of the model can depend on the complexity of the architecture and hardware used for deployment.

Transfer learning is a commonly used technique in CNN-based crop classification systems. By leveraging pre-trained CNN models (e.g., ImageNet), initial layers can be used as feature extractors. Fine-tuning these pre-trained models on crop-specific datasets can help improve classification performance and reduce the need for large labelled datasets. Techniques for enhancing data, including as rotation, scaling, flipping, and adding noise, can help make the training dataset more diverse. This can lessen overfitting and increase the CNN model's capacity for generalisation. CNNs are often referred to as black-box models due to their complex architecture and difficulty in interpreting their decisions. Research on interpretability techniques, such as visualization of activation maps or attention mechanisms, can provide insights into the features learned by the CNN and increase trust in the model's predictions. Crop classification systems based on CNNs should be evaluated for their robustness to various environmental conditions, such as changes in lighting, weather conditions, or image quality. Ensuring the model's performance across diverse conditions is crucial for real-world applications. Consideration should be given to the deployment of the crop classification system. Whether it's implemented on cloud servers, edge devices, or embedded systems, the computational and memory requirements should be optimized for efficient and practical deployment.

The generalization capability of CNN models should be assessed when classifying new or unseen crop types. Transfer learning or continuous learning techniques can be explored to adapt the model to new classes without retraining the entire network. Overall, utilizing CNNs for image-based crop classification systems offers great potential in improving crop monitoring, precision agriculture, and decision-making processes. Continuous research and development in this field can further enhance the accuracy, efficiency, and robustness of such systems.

5. Conclusion

It proposes and implements an image-based crop classification system utilizing Convolutional Neural Networks (CNNs). Through the experimentation and evaluation, it demonstrates the effectiveness and potential of CNNs in accurately classifying different crop types based on input images. The results indicate that the CNN-based crop classification system achieved high accuracy, precision, recall, and F1-score in distinguishing between various crop classes. The performance of the CNN model surpassed baseline models and previous methods, showcasing the superiority of our approach in crop classification tasks. The evaluation of the model's performance revealed its robustness to variations in crop types, growth stages, and environmental conditions. The CNN-based system demonstrated the ability to generalize well to unseen data and exhibited strong classification capabilities in different lighting, scale, and viewpoint scenarios. It observed that the choice of CNN architecture significantly impacted the performance of the crop classification system. Selecting appropriate layers, filter sizes, activation functions, and pooling strategies played a crucial role in extracting relevant features from crop images and improving classification accuracy. In conclusion, it highlights the effectiveness and potential of utilizing CNNs for image-based crop classification. The results obtained demonstrate the superiority of the CNN-based approach and its relevance in agricultural applications. Further research and advancements in this field can lead to improved crop monitoring, yield prediction, and sustainable farming practices.

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