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# Multi Techniques for Agricultural Image Disease Classification and Detection: A Review

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## ABSTRACT

The agriculture sector has a significant impact on the market in every country. Identifying crop disease with conventional methods is a hard operation and it needs more time, effort, and experts with continuous farm monitoring. Blight and other crop diseases have severe consequences on crop yields and cause enormous economic losses worldwide. Plant health monitoring and disease detection are critical components of sustainable agriculture. Machine learning and deep learning techniques are used to identify plant diseases and associated with severity detection in plant leaves. The adoption of these techniques still faces several important challenges. In recent years, improvements in technology and researchers' interest in this area have made it possible to obtain an optimal solution. In addition to providing a detailed explanation of the proposed technique, which is deep learning architecture that uses the deep convolutional extreme learning machine (DC-ELM) for faster training, this study focuses on how machine learning and deep learning techniques detect plant diseases and infections that affect different crops. The proposed model is capable of providing good computational performance and allowing the learning process to be completed with less processing time. Finally, several challenges and problems with the existing system, as well as future research objectives, are enumerated and discussed.

## INTRODUCTION

Agriculture is an aspect of everybody›s lives, either directly or indirectly. Natural disasters such as disease and pests impair plant growth and may even cause it to die during the entire growing cycle (Conrad et al. 2020). Plant disease is a disorder caused by a change in a plant's morphology, metabolism, or activity. Plant diseases are caused by infectious organisms (fungi, bacteria, or viruses) that are specified in Fig. 1, which are known as biotic diseases (Vishnoi et al. 2021). The most prevalent plant diseases are blight, spot, rust, and canker. Plant disease outbreaks harm agricultural production. Food insecurity will worsen if plant diseases are not detected in time (Chen et al. 2020a). Plant diseases represent a huge hazard to small-scale farmers since they can destroy their whole food supply (Li et al. 2021). Farmers used to follow expert recommendations by inspecting specimens of infected plants with their own eyes, or an expert could visit the field and provide appropriate solutions. To treat plant diseases, farmers were taking prophylactic steps. Finding reliable specialists is challenging, the practice of ongoing expert supervision is costly and time-consuming, and it is ineffective in large fields (Hang et al. 2019). It is important to identify agricultural products and diseases accurately and promptly. So, we need a certain automatic, fast, accurate, and less expensive system to detect plant diseases.

This review article focuses on artificial intelligence approaches for plant disease identification and recognition, comparing them based on the datasets used, prototypes used, and performance metrics compared with other techniques (Liu et al. 2020). This study also looks at how classic machine learning algorithms have evolved since deep learning (Khan et al. 2021). Image processing techniques are also applied to identify and classify plant diseases in a quick, automatic, and accurate manner. Thermal, hyperspectral (Gu et al. 2019, Lin et al. 2020), multispectral, and fluorescent image processing approaches can help detect plant illnesses early. The systematic phases of image processing are image acquisition, image preprocessing, image segmentation, feature extraction, feature selection, and classification. The issue with this technique is its limited accuracy, which necessitates several major operations to achieve higher levels of accuracy. Large amounts of pre-existing data are difficult to implement due to the limited number of manually generated feature parameters. These

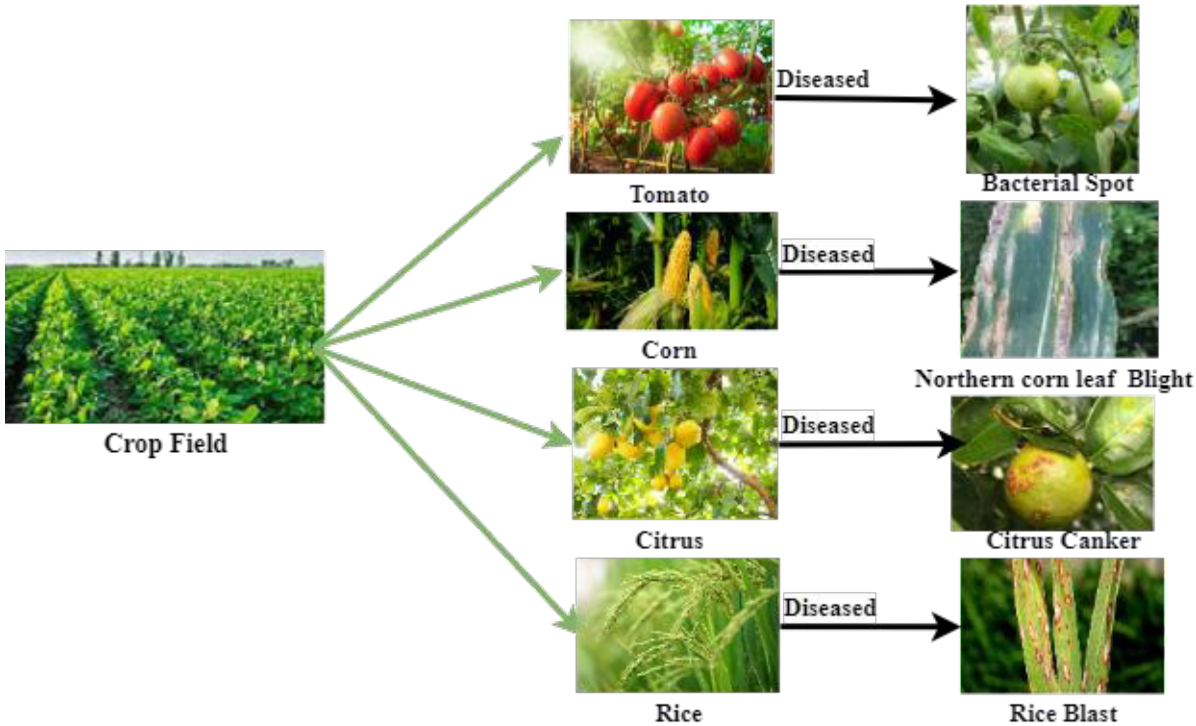


Fig. 1: Sample healthy and diseased crop images.

issues can be solved using artificial intelligence techniques (Yuan et al. 2021).

Traditional machine learning algorithms were initially used to detect plant diseases using plant images, resulting in limited accuracy and dataset range. Due to advancements in artificial intelligence and computer vision technology, deep learning has recently become popular in image identification (Turkoglu et al. 2022). Convolutional Neural Network (CNN) is the most commonly used neural network model in deep learning. CNN has great auto-learning, flexibility, and generalization capabilities (Xiong et al. 2021). CNN is based on biological nervous and visual systems. It is an unsupervised deep-learning classification model which provides more detection and classification accuracy. Deep learning improves accuracy while also broadening the scope of identifying and classifying plant diseases (Sladojevic et al. 2016). There are numerous CNN models obtainable, such as AlexNet, VGG, GoogLeNet, ResNet, and others. Different methods are available based on depth, configuration, nonlinearity, and several units. The dropout rate and learning rate are two variables that can be adjusted in complicated processes for solving Identification and pattern recognition problems.

Section 2. Provides related work Section 3. Proposed DC-ELM model. Section 4. Comparative analysis based on existing technologies. Section 5. The research findings and future work are concluded.

## RELATED WORK

There are several methods for examining plant diseases and pests in agriculture. Conventional machine-learning approaches have been widely adopted in agriculture. According to the study, there are different deep learning models with transfer learning that can detect plant diseases more accurately, and transfer learning has been widely applied to speed up training and enhance the performance of deep learning models. Transfer learning is an optimization that allows rapid progress, and is also associated with the issue of multitasking.

### Traditional Crop Diseases Detection and Classification Techniques

Image processing techniques are extremely crucial in the automatic detection and early identification of plant diseases to rise plant production and quality. Image processing approaches such as noise removal, image segmentation, feature extraction, classification, and so on (Al-Windi et al. 2021). Techniques for segmentation include with K-Means clustering, fuzzy C-Means clustering, and color segmentation algorithms, among others. The technique of extracting features from different instances of the same class is known as feature extraction (Ali et al .2019). The wheat leaf disease infected severities with powdery mildew were recognized based on the machine learning algorithm and hyperspectral imaging dataset. The finest model was selected by comparing the accuracy of various dimensionality reduction algorithms, which are principal component analysis (PCA), random forest (RF), and successive projection algorithms, and three different identification models were created by support vector machine (SVM) ( Jiang et al. 2020), random forest, and probabilistic neural network. The final result showed that the SVM model with PCA dimensionality reduction ensured the finest result, with a classification accuracy of 93.33% (Zhao et al. 2020).

In this section, the performance of several classification algorithms, such as Random Forest (RF), Support vector machine (SVM), Decision tree(DT), K-nearest neighbors(KNN), and Naive Bayes(NB) on a tomato disease dataset is evaluated, and it is discovered that RF classification techniques beat other algorithms. When compared to other algorithms for classifying plant diseases, the RF algorithm achieves 89% accuracy (Neelakantan 2021). Machine learning-based system for leaf disease classification and detection model utilizes SVM, NB, and convolution neural network (CNN), and Histogram equalization remains used for pre-processing, and the PCA technique is used to extract image features (Pallathadka et al. 2021). The deep features of thirteen CNN models (11 most often used + 2 tiny architectures) were extracted from a specific layer, and the characteristics were then given to an SVM classifier to identify rice leaf disease. The efficiency of the classification models for recognizing rice leaf diseases is evaluated using transfer learning with SVM techniques. Finally, a comparison was made between deep feature plus SVM, transfer learning, bag of features, and classic image classification methods. The comparison of plant disease detection and classification techniques is précised in Table 1.

Table 1: Comparison of various techniques in plant disease detection.

| Reference | Plant Name | Technique Used | Metrics | Research Gap |
|---|---|---|---|---|
| (Rahman et al. 2020) | Rice | Stacked CNN | This architecture reduces the model size by 98% compared to the VGG16 or other similar models. | To use memory-efficient CNN models to get high accuracy. |
| (Sethy et.al. 2020) | Rice | Deep feature plus SVM | This technique has improved the performance of classification models for identifying rice leaf diseases. | To add more varieties of rice disease data by using a suitable CNN model. |
| (Wang et al. 2021 | Rice | CNN with Bayesian optimization | The model has better test accuracy. | Using different optimization algorithms and hyperparameter tuning will improve the performance. |
| (Archana & Sahayadhas 2018) | Rice | K-mean clustering | Automatic rice disease identification was achieved. | Some pigments in the leaves are not extracted properly which leads to less accurate results. |
| (Ramesh & Vydeki 2020) | Rice | Deep neural network, Jaya optimization algorithm(DNN-JOA) | This proposed system archives better Classification and test accuracy. | Improved methods can enhance the best performance. |
| (Li et al. 2020) | Rice | Custom backbone DCNN network | This approach is capable of detecting diseases using Video images | Real-time crop diseases and pest video detection system is needed |
| (Shrivastava & Pradhan 2021) | Rice | Support vector machine (SVM) classifier, | SVM achieves the highest classification accuracy compared to the other 7 classifiers. | Results are reported for a small dataset. Training speed was slow. |
| (Jiang et al. 2021) | Rice | CNN(Improved VGG16) | The proposed model can recognize multiple crop diseases at the same time. The fine-tuning method gives more accuracy than the reuse model method. | Fine-tuning with more parameters will give more accuracy. |
| (Abbas et al. 2021) | Tomato | Conditional Generative Adversarial Network(C-GAN) DenseNet 121 | The proposed system improves network generalizability and C-GAN prevents Overfitting. | The disease identification system is not developed. |
| (Fuentes et al. 2017) | Tomato | Deep meta-architecture and feature extractor. | The proposed system deals with different illumination conditions, different sizes of images, and different backgrounds of images. This system not only Recognizes the disease but also identifies the location. | This model applies to a single crop. |

Table cont....

| Reference | Plant Name | Technique Used | Metrics | Research Gap |
|---|---|---|---|---|
| (Trivedi et al. 2021 | Tomato | Deep Convolutional Neural Network (DCNN) | It achieves 98.6%classification accuracy. | Results are reported for biotic diseases in the crop leaf. |
| (Thangaraj et al. 2021) | Tomato | DCNN model, Adaptive moment estimation (Adam), stochastic gradient descent (SGD) | This proposed model achieves better recognition accuracy on a small dataset. | Results are reported for a single crop. |
| (Yang et al. 2020) | Tomato | LFC-Net(Location, Feedback and Classification networks) | This model achieves high performance with an accuracy of up to 99.7% | Results are reported for a Limited number of diseases only. |
| (Gadekallu et al. 2021) | Tomato | PCA, Whale optimization algorithm, DNN | This proposed model achieves better training and testing accuracy. Loss percentage and time is taken for training have reduced. | Results are reported for a single crop. |
| (Liu & Wang 2020) | Tomato | MobileNetv2-YOLOv3 | Limited memory consumption, and higher recognition accuracy. | The results are represented for a single disease. |
| (Chakraborty et al. 2021) | Tomato | VGG 16 | This model achieves high-performance accuracy. | The results are represented for a single disease. |
| (Yu et al. 2022) | Maize | Multi-stage Grey wolf optimizer (MGWO) | The proposed system can obtain a more accurate solution. | Higher Time complexity |
| (Singh et al. 2022) | Maize | AlexNet | It gives efficient results in the case of smaller datasets. | It requires more epoch size for attaining high accuracy. |
| (Subramanian et al. 2022) | Maize | VGG16, , Bayesian optimization | This system efficiently works with the dataset which is not extremely large. Requires low computational power and less training time to retrain some of the top layers | Fewer hyperparameters have been taken for optimization. |
| (Waheed et al. 2020) | Maize | Optimized DenseNet model | This model achieves better accuracy in identifying three types of diseases | Results are reported for three types of diseases only. |
| (Khalili et al. 2020) | Soybean | Gradient Tree Boosting (GBT) | The proposed model was the best-performing classifier, giving better accuracy in terms of sensitivity is 96.25% and specificity is 97.33%. | Limited classification accuracy was achieved. |
| (Yan et al. 2020) | Bean | U-Net-based ResNet model, Robotic perception framework | The proposed system detects the bean leaves accurately from uncontrolled environmental conditions. | For large datasets, efficiency and reliability didn't prove. |
| (Annrose et al. 2022) | Soybean | Hybrid deep learning model with an optimization algorithm | The proposed method gives better training and testing accuracy. | Data overfitting issues. |
| (Nihar et al. 2021) | Bean and tomato | Modified convolutional neural network architecture (ModCNN) | Time-effective and cost-effective approaches. | Limited accuracy was achieved. Takes too many epochs to get better accuracy. |
| (Zeng et al. 2020) | Citrus | Deep Convolutional Generative Adversarial Networks Inception_v3 model | A deep learning model with Augmentation will give better disease severity detection accuracy. Which is 20% more than the model trained on the original dataset. | Real environment image datasets are needed to test in real-time scenarios. Traditional augmented methods are not applied. |
| (Sharif et al. 2018) | Citrus | Optimized weighted segmentation method, Multi-Class Support Vector Machine (M-SVM) | This system achieves better segmentation accuracy, best features are selected for disease classification. | Results are reported for a small dataset. Overfitting |
| (Elaraby et al. 2022) | Citrus | AlexNet Stochastic Gradient Descent with momentum | The AlexNet classifier is more accurate than the VGG19 classifier. | This model applies to standard-sized image datasets. It requires more epochs |
| (Syed-Ab-Rahman et al. 2022) | Citrus | Feature extractor and region proposal network | The region-based classification gives more accurate results. | It is applied to small datasets. Overfitting. |
| (Zou et al. 2020) | Tea | Decision Tree & Random Forest | Feature selection with random forest made the classification result more accurate. | Lack of datasets. |

Table cont....

| Reference | Plant Name | Technique Used | Metrics | Research Gap |
|---|---|---|---|---|
| (Patil & Burkpalli 2021) | Cotton | Multilayer Perceptron, Support Vector | Artificial neural networks (MLP) give 96.69% accuracy, better accuracy compared to other classifiers. Classifier performance was better while using color feature extraction. | It takes a long time to train a large dataset. Texture features are not taken for classification. |
| (Azadbakht et al. 2019) | Wheat | v-Support Vector Regression | The severity of wheat leaf rust diseases varied under high, medium, and low LAI levels. | It is not possible to extract all wavelengths at each level of the LAI. |
| (Yebasse et al. 2021) | Coffee | Deep neural network | Achieves better classification accuracy compared to other naive approaches. | Localization is not done on the diseases. Only black box testing does not effectively detect the defective region. |
| (Singh et al. 2019) | Mango | AlexNet architecture, Multilayer convolutional neural network | This model automatically extracts the image without segmentation. | Training times are high. |
| (Khan et al. 2022) | Cucumber | Entropy-ELM technique with deep learning | Fine-tuned pre-trained model with augmentation improves accuracy. Feature selection techniques reduce the Computational time. | The augmentation process increases the time. Few features are ignored during the feature selection process. |
| (Jiang et al. 2019) | Apple | Deep CNNs, GoogLeNet Inception | High accuracy and faster detection speed. | Uniform background images were taken. |
| (Singh 2019) | Sunflower | Segmentation –particle swarm optimization | The proposed system achieves good segmentation accuracy. | The main limitation of the image segmentation technique is the need for a faster search speed to lower search time. |

Originating from Artificial Neural Networks (ANNs) (Ferentinos 2018) are the most prominent algorithms in machine learning. Machine learning algorithms are the best choice for identifying homogeneous plant images captured in a lab environment. Machine learning problems have recently been addressed with deep learning and convolutional neural networks. (Li et al. 2018). Northern maize leaf blight is a deadly disease that affects maize health. The field's varied background and varying light intensities make illness detection more challenging. To identify maize leaf blight, a multi-scale feature fusion instance recognition approach based on a CNN is presented. The NLB dataset is used here. The suggested technique consists of three primary steps: data set preparation, network fine-tuning, and the detection module (Sun et al. 2020). This research investigates the use of discrete lesions and spots for plant disease detection instead of considering the entire leaf (Barbedo 2019). In this study, the CNN technique requires a large and wide variety of datasets, which is an important limitation in deep learning (Barbedo 2018).

## MULTI CROP'S DISEASE DETECTION USING DEEP CONVOLUTIONAL EXTREME LEARNING MACHINE

The proposed method for detecting plant diseases based on images employs deep transfer learning with deep convolutional neural networks. Extreme learning machine architecture will be able to maximize the benefits of deep learning

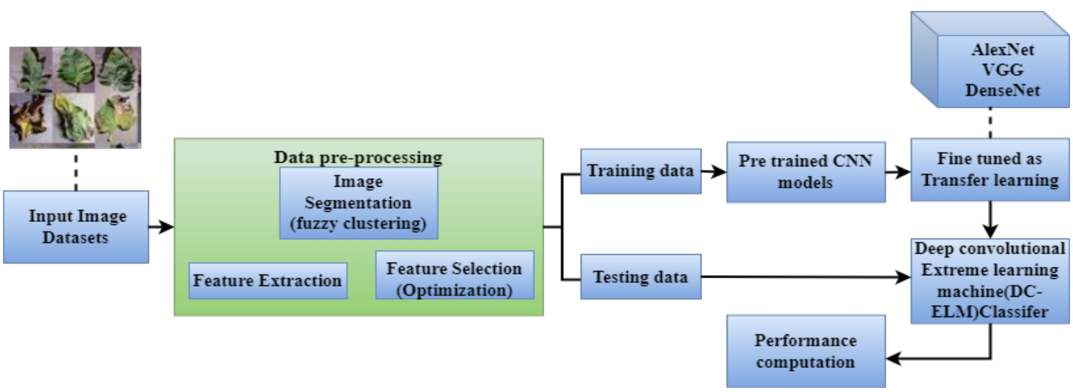


Fig. 2: Block diagram of the proposed DC-ELM System Model.

when used to detect plant diseases using leaf images. Previous research has shown that CNN can effectively recognize plant leaf disease and also suffer from some challenges that as lengthy training time, Iterative methods based on gradient methods can take longer to adjust weights and have a higher computational cost. As a result, it is necessary to investigate alternative approaches; it appears that DC-ELM outperforms other conventional learning algorithms.

The general architecture of the proposed DC-ELM system is illustrated in Fig. 2, which involves input image datasets, pre-processing, the deep learning architecture module, the transfer learning module, the deep convolutional Extreme learning machine, and the performance metrics.

## Image Dataset

Deep learning architectures were examined and trained on the input plant leaf image dataset to categorize and recognize diseases in the plant image dataset. The dataset is first divided into two sections. The training data, followed by the test data, with a ratio of 80% and 20%, respectively. The datasets contain images of healthy and diseased leaves (Albattah et al. 2022). An enormous volume of training data is required to effectively train a deep-learning classification model. As a result, augmentation operations have been performed on the training dataset to increase the size of the image dataset used in training and avoid overfitting, which can occur when limited training data is used during training.

## Data Pre-Processing

The images are collected in real-time conditions and contain noise. Preprocessing is the process of removing noise, which improves the quality of images (Cristin et al. 2020). Therefore, images are preprocessed before extracting features for the disease detection system to increase its computational accuracy. The time taken to process an image is also reduced when resizing and cropping an image. The simplest way to prevent over-fitting is to train the model on a significant amount of data. Augmentation is the process of creating additional training data from existing data. Throughout the training, the images were exposed to augment such as brightness, and contrast in color augmentation techniques, and image flipping left-right, flipping up-down, scaling, and rotating are position augmentation techniques were randomly used to make the model more effective (Gajjar et al. 2021), To augment the data, several techniques such as Generative adversarial networks (GANs) (Nerkar & Talbar 2021), neural style transfer, and adversarial training are used. Segmentation is used to divide an image into interesting regions (Sai Reddy & Neeraja 2022).

Features are relevant and discriminating attributes/information associated with objects that differentiate one object from others. Features are useful for identifying objects and classifying them. Feature extraction is key to building the classification/recognition model and determining the relevant attribute characteristics of each class (Kurmi et al. 2022). Generally, features such as shape, color, size, corners, edges, and so on are taken into account for object recognition. Feature selection techniques are employed to find the most applicable features from the characteristic vector. Analysis (PCA) score, entropy, and covariance of extracted points are measured for extracted features are measured

## Pre-Trained Deep Learning Models

Artificial neural networks are mathematical models which reflect common principles of brain function through their neurons and synapses. CNNs (Zekiwos & Bruck 2021) are a subset of traditional artificial neural networks that are mainly concentrated on applications with repeated patterns in various areas of the modeling of an image-based recognition system. Pre-trained models, which were trained previously on different datasets, perform tasks like classification, and feature extraction. The core CNN architectures are AlexNet, DenseNet, and the VGG16 metrics phase. The pre-trained model architecture requires less training and effort to build.

### *AlexNet Model*

AlexNet (Wang 2022) is a 60-million-parameter eight-layer deep network with five convolutional layers and three completely connected layers. It is a conventional convolutional neural network model that employs dropout to avoid overfitting by randomly disregarding some neurons and employs a rectified linear unit (RELU) as an activation function. The model uses two GPUs at the same time to accelerate neural network training. As a result, when compared to other models, AlexNet (Dhaka et al. 2021) excels at image categorization and object recognition.

### *DenseNet Model*

DenseNet (Vallabhajosyula et al. 2021) is used in CNN networks to optimize the connecting patterns between layers. To overcome the drawback of maximum data flow, each layer in this network is directly connected to the other layers. DenseNet has fewer feature maps than regular CNN. DenseNet solves gradient-related issues. The DenseNet model's layers have direct access to the results from the input images as well as a gradient loss function. The DenseNet uses a typical feed-forward network, with each layer's output being linked to the previous layer via a composite operation. These operations include layer pooling, batch normalization, and an activation function. The DenseNet concept can be broken down into small dense blocks. The transition layers in the dense blocks are responsible for down-sampling while batch normalization is applied.

### *VGG16 Model*

The VGG16 (Abed et al. 2021) model is a deep convolution model with 13 convolutional layers, five pooling layers, and three fully connected layers. Six block structures are present in all VGG configurations. The feature extraction layer is made up of these six blocks, with the remaining three completely connected layers serving as the classification layer.

## Transfer Learning

Transfer learning is the process of re-applying a formerly trained deep learning model to a new problem. We describe a unique approach for fusing data at multiple levels of abstraction to improve transfer learning efficiency (Cruz et al. 2017). Transfer learning (Johnson et al. 2021) is a common deep learning strategy that involves transferring pre-trained model weights to a new classification problem, as shown in Fig. 3. As a concern, training is more efficient than it improves the performance of the model also improves computational efficiency. TL is particularly important in deep convolutional neural networks (Chen et al. 2020b). Transfer learning involves the concept of fine-tuning. Fine-tuning improves accuracy on lesser datasets and is quicker than starting from scratch. To improve accuracy, hyperparameters are fine-tuned using a transfer learning approach.

## Deep Convolutional Extreme Learning Machine (DC-ELM)

An Extreme Learning Machine (ELM) (Aqel et al. 2021, Zhang et al. 2017) is a classification technique for Single Hidden Layer Feed Forward Neural Networks (SLFNs) or Multiple Hidden Layer Feed-Forward Neural Networks (MLFNs). It improves the speed of convergence training and eliminates the need for multiple iterations to change the hidden layer weights (Imran & Raman 2020). ELM is a one-of-a-kind training method because it does not use gradient calculations to update network weights (Alagumariappan et al. 2020). The ELMs are believed to have the ability to learn thousands of times faster than networks trained using the backpropagation technique (Bhatia et al. 2020). The DC-ELM (Santos et al. 2019) is a deep convolutional extreme learning machine that integrates the speed of ELM training with the capability of CNN. In the final hidden layer, DC-ELM employs stochastic pooling to drastically reduce feature dimensionality. This saves both training time and computational resources (Pang & Yang 2016). The DC-ELM combines the convolutional neural network's feature abstraction performance with the extreme learning machine for fast training (Rodrigues et al. 2021). The example architecture of DC-ELM is shown in Fig. 4.

## The Optimizer Used in DL and TL

Image processing requires bio-inspired optimization strategies. By reducing noise and blurring, it improves image

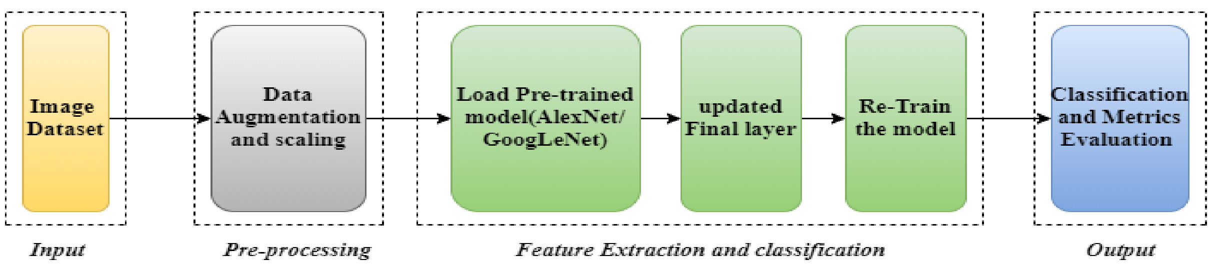


Fig. 3: Classification based on transfer learning.

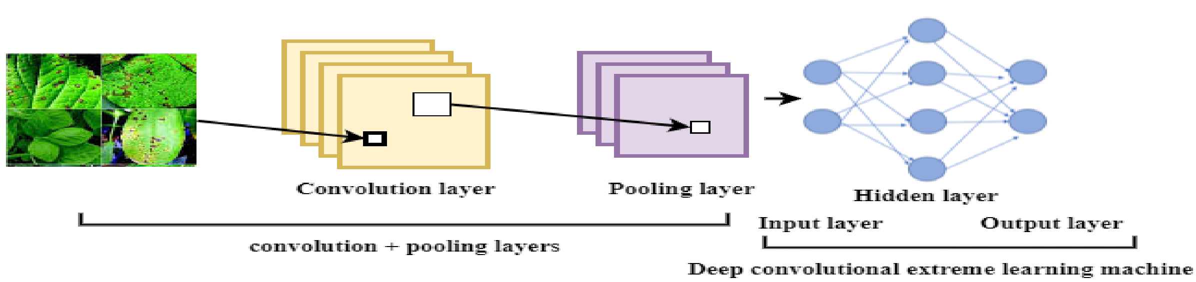


Fig. 4: Example of a CNN-based DC-ELM architecture.

enhancement, restoration, segmentation, edge detection, and pattern recognition. So far, various optimization strategies for various image-processing applications have been proposed (Jino Ramson et al. 2019). The accuracy of the deep learning model is greatly influenced by optimization algorithms. To train a neural network architecture, create a loss function that measures the difference between model predictions and the label that wish to predict. Various optimizers can be used to adjust your weights and learning rate. On the other hand, choosing the best optimizer is dependent on the application. DL optimization approaches include (SGD) Stochastic Gradient Descent (Saleem et al. 2020, Gong et al. 2020) and (Adam) Adaptive Moment Estimation (Alzubaidi et al. 2021).

An optimization method is used in the plant disease detection system for feature selection and feature extraction. This optimization technique aids in the selection of the best features, which improves the performance of the classifier.

### Performance Computation

The confusion matrix elements are used to calculate the performance measures, used to evaluate the models' performance (Hariri & Avsar 2022). A relative study using the accuracy, sensitivity, and specificity metrics demonstrate the method's efficacy. Accuracy, Sensitivity, Specificity, Precision, Recall, and F1 Score are some of the performance metrics that are evaluated (Djimeli-Tsajio et al. 2022).

The accuracy rate at which a plant disease is detected, and is calculated as the ratio of correctly identified positive and negative samples to total samples, as shown below. The sample count is evenly distributed across the different classes of diseases.

$$\text{Accuracy} = \frac{\text{number of samples correctly identified}}{\text{total number of sample}} \times 100\%$$

The loss function should be calculated using training loss with accuracy, training result, and validation loss with accuracy, validation loss. This F1 score assists us in determining both recall and precision of the total number of classes specified in the diseases.

$$\text{F1 Score} = 2 * \frac{\text{Precision} - \text{Recall}}{\text{Precision} + \text{Recall}}$$

The proposed DC-ELM models perform the metrics in terms of classification accuracy, loss function, and F1-Score.

## COMPARATIVE ANALYSIS BASED ON THE EXISTING TECHNIQUE

To evaluate the performance, a comparison was made with existing approaches presented in the survey. The survey found TL with optimization outperforms the vast majority of associated tasks. While analyzing the performance of TL-based approaches to other state-of-art techniques, specific, accurate, and appropriate comparisons were made between

Table 2: Comparison of deep learning model used in plant disease classification with accuracy.

| Type of plant | Type of diseases | Method used | Classification Accuracy | References |
|---|---|---|---|---|
| Rice | Bacterial Leaf Blight, Rice Blast, Sheath Blight, Healthy Leave | Support vector machine (SVM) classifier | 94.65 | (Shrivastava & Pradhan 2021) |
| Wheat | wheat leaf rust | v-Support Vector Regression | 95 | (Azadbakht et al. 2019) |
| Tea | Anthracnose, Brown leaf spot, tea white star | Decision Tree & Random Forest | 80 | (Zou et al. 2020) |
| Rice<br>Wheat | Bacterial blight, brown spot, leaf blast<br>Leaf rust, powdery mildew | CNN (improved VGG16) | 97.22<br>98.75 | (Jiang et al. 2021) |
| Tomato | Early blight, bacterial leaf spot, curl virus, fruit canker, and powdery Mildew. | DCNN | 99.55 | (Thangaraj et al. 2021) |
| Corn | corn common rust, gray leaf spot, northern corn leaf blight | CNN (DenseNet) | 98.06 | (Waheed et al. 2020) |
| Bean<br>Tomato | Mosaic Virus<br>Tomato curl leaf | ModCNN | 97.69 | (Nihar et al. 2021) |
| Citrus | Anthracnose, Black spot, Citrus Canker | Multi-Class Support Vector Machine (M-SVM) | 97 | (Sharif et al. 2018) |
| Cotton | bacterial blight | Multilayer Perceptron, Support Vector (ANN) | 96.69 | (Patil & Burkpalli 2021) |
| Coffee | Coffee leaf rust | Deep neural network (DNN) | 98 | (Yebasse et al. 2021) |

the Deep learning and ML-based strategies used to solve the specific problem addressed in each study. Deep learning is currently struggling to model numerous complicated data modalities at the same time. Another important area of modern deep learning research is multi-tasking with extreme learning machines.

The accuracy of the classification of machine learning and deep learning methods is compared in Table 2. The classification accuracy of different CNN models and machine learning models for plant disease identification was discovered. The comparison result shows that deep learning models outperform machine learning models in terms of accuracy.

## CONCLUSION

Deep learning with DC-ELM concepts is used in the proposed model to accurately identify plant diseases that can automatically identify signs of plant disease and is performed with high accuracy. In comparison to traditional image processing methods, which handle plant disease and pest recognition tasks in multiple steps. We conducted a survey on the detection and classification of diseases in various agricultural products using image processing, machine learning, and deep learning techniques. We identified 60 relevant studies by evaluating the specific region and issue they concentrate on, practical aspects of the models used, datasets used, data preprocessing and data augmentation techniques used, and overall performance according to the achievement criteria listed by each paper. Then, in terms of performance, we compared transfer learning to other existing approaches. As per the comparison transfer learning with optimization and DC-ELM beats other common imaging approaches. In the future, we intend to extend the broad concepts and best-practices ensemble learning technique, as detailed to additional sectors of agriculture where this modern method has not yet been fully implemented, to improve the performance of the model the research is extended based on multi-task learning with extreme learning machine.

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