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Corn Disease Detection based on Deep Neural Network for Substantiating the Crop Yield

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Abstract: This work provides an extensive review of corn leaves disease prediction. Plant diseases are considered a significant threat to economic loss and production in worldwide agriculture. The monitoring and prediction of conditions play a substantial role in agricultural-based disease prediction. The disease over the plants shows a significant negative impact on crop cultivation. Thus, an automated system is essential for predicting crop diseases, aiming to help the farmers predict disease over the corn leaves. The target of the automated system is to predict the spread of the disease and damages in the plants. The advancements in Artificial Intelligence (AI) pave the way for modern technological improvements for analyzing these conditions in a productive manner where the results show prominence over technological growth. The sub-group of AI is Machine Learning (ML) and Deep Learning (DL) approaches. Both these models work efficiently in disease prediction; however, DL works efficiently with the samples of the vast dataset and gives superior prediction accuracy compared to other approaches. This comprehensive analysis shows a technological path for predicting corn leaves disease more broadly to improve the prediction accuracy and reduce computational complexities. These approaches are well-suited for various real-time studies when resource-constraint devices are used for analysis.

Keywords: Disease prediction, corn leaves, Artificial Intelligence, Machine Learning and Deep Learning

1 Introduction

In the Indian agricultural disease, maize is considered the third-most essential food after wheat and rice. The rust and blight over the leaves are determined as the joint disease, leading to a substantial loss in the Indian economy [1]. When the infections are identified in the preliminary stage with the remedial measures, the cultivation of crops is improved substantially. Thereby, the quality of the disease is preserved. The disease symptoms of the corn leaves can be predicted in the earlier stage with the manifestation of infected regions over the various part of the leaves, i.e., symptoms like variations in the spots, color, and blight [2]. From the researchers' point of view, Machine Learning and Deep Learning approaches successfully classify and predict a wider variety of corn diseases from the images captured from the field. Recently, the advancement in DL has laid a more robust path and shows its manifestation towards various prevailing approaches in computer vision for classifying images [3]. Some conventional computer vision approaches for plant disease prediction need a manual assortment of features for a better decision-making process [4]. On the contrary, DL approaches' Convolutional Neural Network (CNN) learns automatically the vital features with the visual mapping of multi-layers during image processing. The stages of the network model concentrate on the higher-level layers and visual elements towards the complex visual concepts.

Speaking about corn seeds, it is of two types known as hybrid and open-pollinated. The formerly mentioned seeds are unique, where the production needs more experience, time, and cost than the production of other cereal-based crops [5]. It includes the cross-mutation of two inbred concepts that merge to produce a wider variety of hybridization. These inbred lines have both the male and the female plants for pollen production, generate hybrid seeds, and create a newer quality of crops. Some essential metrics are considered throughout the process to fulfil the corn seed's purity and quality [6]. At the same time, the later model produces the plant where the seed gives more plant-like parent corn. The seeds of these plants are produced manually with normal pollination. The significant concepts behind the plantation of these sorts of plants are open-pollinated, non-hybrid corn seeds

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with excellent taste. Some non-hybrid forms of corns are used as animal feed [7]. The classification and the analysis of these seeds are accomplished to attain information regarding variety, quality, and production. Insect- and disease-free crops are considered the best quality crop. The quality assurance and type rely on the preliminary concept for the verification purpose. Moreover, it is depicted as the initial stage of performing some functionality for separating the corn seeds. The higher corn seed utilization shows corn seed's significance, quality, and yield. Generally, classification process is done by experts who consider some visual corn seed attributes for providing certification. The standard visualization process requires tedious, long-time, expensive, and personal knowledge. The separation of corn seeds using machine functionality includes predicting corn seed varieties and properties, indicating preliminary operations via image processing and pattern recognition. Image processing is considered a faster and accurate prediction model connected with multiple agricultural products in various existing research. In [8], the classification and analysis are performed using image processing approaches where the study provides essential information regarding the seed quality, outliers, and impurities.

Similarly, it is essential to validate the corn variety before planting to attain a superior combination of crop cultivation. However, the traditional prediction approaches are adopted in various countries with certain drawbacks with adopting human resources. It is considered as a complex task for predicting corn varieties. Corn seed classification is essential for diminishing cost and enhancing the cultivation. Some technological advancement helps to compute the combinations of the seed images. The learning methods can be adapted to predicting both corn variety and disease. However, the variation relies on only the features related to corn variety and disease. Initially, the images of corn leaves are essential for the prediction process, where the images are captured from the cameras. ML approaches to motivate investigators to overcome some conventional drawbacks connected with human visual perception for the past few decades. Based on extensive analysis, these learning approaches are used for crop classification, grading the corn quality, land for cultivation, and solutions for various medical issues. Some investigators have adopted ML approaches for categorizing the seed varieties and propose content-based recovery for prediction purposes. The prediction accuracy with these approaches is discussed below: Artificial Neural Network (ANN) gives 95% prediction accuracy, Support Vector Machine (SVM) gives 84% accuracy. Guevara et al. [9] adopts Linear Discrimination Analysis (LDA) for wheat prediction and attains 96% accuracy where the author considers 50 different varieties of features to feed the classifier. Daskalov et al. [10] adopt the ANN model to classify the rice varieties and attains 93% prediction accuracy. The author classified five different types of rice using multi-layer perceptron and reaches 99% accuracy and neuro-fuzzy model to achieve 95% accuracy without any feature selection and attains 94% and 96% after feature selection. Li et al. [11] considers the prediction of wheat with morphological features using ANN and achieves 85% accuracy. The author merges three diverse feature selection approaches for predicting the crop using ANN and attains 95% accuracy over the morphological features, i.e., 26 optimized features. Qiu et al. [12] partition three diverse types of wheat using five morphological features and attain prediction accuracy ranging from 85% to 95%. Zhang et al. [13] discriminate corn using Mahalanobis Distance Discrimination and Back Propagation NN to achieve 90% prediction accuracy. The author models an automated framework for corn seed prediction and its disease. The images are acquired from the digital cameras, and a classifier model like SVM is used to achieve 93% accuracy. Ali et al. [14] use Discriminant Analysis to classify the corn seed and consider wavelength features to attain 98% accuracy. In some cases, a remote sensing dataset is used to classify the corn seeds using a computer vision model. It uses color and shape features to distinguish abnormal and normal corn seeds. The hyperspectral image model is used to classify the damaged corn seed and attain 90% accuracy using the mean spectrum classifier.

This comprehensive analysis discusses the various feature selection techniques, classification, and optimization approaches for predicting corn disease. This automated framework includes 1) pre-processing, 2) feature selection, 3) feature extraction, and 4) classification approaches. The statistical information is captured, and features are extracted and selected to enhance the classification accuracy. This study extensively analyses both the ML and DL approaches with specific performance measures like accuracy, precision, recall, F-measure, and so on. The motivation is to predict the corn disease from the corn leaves.

2 DISEASE PREDICTION STRATEGIES IN MACHINE LEARNING APPROACHES

Predicting leaf disease is to analyze the location and presence of changes over the leaf images. The detection process includes pre-processing, segmentation, image location, and enhancement. The pre-processing step is crucial to diminishing the noise and computational time over a substantial period and pretends to give higher prediction accuracy. Qadri et al. [15] attain 99% prediction accuracy using the Otsu method that evaluates adjacent edge points with optimal segmentation. This method adopts maximal in-between class variance and identifies the most suitable optimal segmentation process. Qadri et al. [16] adopt two diverse datasets composed of 88 various species. The successive dataset comprises 77 species where these images are captured from the complex background data. Fig 1a - Fig 1d depicts four different types of Makkai known as Desi, Kashmiri, Syngenta, and Pioneer.

While analyzing the functionality of Machine Learning approaches, feature extraction plays an essential role in reducing input data dimensionality and efficiently performs classification. While investigating the factors related to disease prediction, considers plant features like leaves color, shape, texture, barks, flowers, and fruits. Some common factors are utilized to extract feature dimensionality and perform the dimensionality reduction process. The feature extraction process helps the investigators to distinguish the stages of plant disease and indicates the plant species appropriately. From all these features mentioned above, leaves are essential as they can be collected easily compared to the other parts plant. It is owing to the competency of the leaves availability and maintenance compared to other regions. Vardhan et al. [17] anticipate a visual consistency-based feature extraction model for extracting features like shape complexity, convexity, horizontal symmetry, vertical eccentricity, rectangularity, and aspect ratio. The provided images are rotated to some orientation level to observe the object characteristics. The observation shows that the plant features show higher consistency over lamina dissimilarity. Vo et al. [18] extract geometric features like aspect ratio, width, length, diameter, and other factors from the leaf images. Some other morphological features are also extracted and used for analysis. These features include regularity, smooth factor, perimeter ratio of diameter, narrow factor, physiological width and length, vein features, and perimeter ratio. From those mentioned above, the author states that the perimeter ratio of diameter, vein feature, rectangularity, physiological size, and aspect ratio are considered the most suitable features. It is analyzed based on the potential to emphasize the variation among the leaves. Walden et al. [19] claim that the contours of leaves are extracted with simple approaches like the Sobel operator and thresholding for preserving the image structure. Some other system makes use of edge information-based features before performing classification process. The recognition rate is higher with the hauling out of edge information adopting centroid contour distance measure. It shows higher results when compared to the angle code model as it gives only a 58% prediction rate. Wang et al. [20] adopt the statistical model for extracting essential features for disease prediction in corn leaves. The author considers the histogram-based features and statistical moments to eliminate information loss w.r.t pixel, texture information, and pixel position. El et al. [21] believe curvature-based scaling space for extracting the root cause information, i.e., it includes the order of teeth, spacing, shape, etc., for predicting the disease over the plant specifies. Here, 88% accuracy is attained during the prediction of plant disease. Fig 2 depicts the generic view of prediction flow.

3 REVIEWS ON VARIOUS FEATURES

Texture features are known as second-order statistical features captured devoid of pixel distance and angles. These features are measured with GLCM and include five various texture features known as energy, inverse difference, inertia, entropy, and correlation. These features are mathematically expressed as in Eq. (1) - Eq. (5):

$$Energy = \sum_m \sum_n (C_{mn})^2 \tag{1}$$

$$Inversedifference = \sum_m \sum_n \frac{C_{mn}}{|m-n|} \tag{2}$$

$$Inertia = \sum_m \sum_n (m-n)^2 C_{mn} \tag{3}$$

$$Entropy = \sum_m \sum_n C_{mn} log_2 C_{mn} \tag{4}$$

$$Correlation = \frac{1}{\sigma_a \sigma_b} \sum_x \sum_y (x-\mu_a)(y-\mu_b) C_{xy} \tag{5}$$

Here, 'm' is mass, 'n' is velocity, 'x' and 'y' are variables, σ_a and σ_b specify the standard deviation of data 'a' and 'b', μ_a and μ_b are mean of data 'a' and 'b'. El et al. [22] discuss histogram features by choosing appropriate objects based on rows and columns. The binary objects are utilized as a mask for feature extraction and compute the individual pixel intensity based on object parts. It is termed as statistical features or first-order histogram and includes skewness, mean, SD, entropy, and energy. It is mathematically expressed as in Eq. (6) - Eq. (11):

$$P(h) = \frac{K(h)}{N} \tag{6}$$

$$\bar{i}(mean) = \sum_m \sum_n \frac{k(m,n)}{k} \tag{7}$$

$$\sigma_h(standard\ deviation) = \sqrt{\sum_{h=0}^{p-1} (h-\bar{h})^2 P(h)} \tag{8}$$

$$Skew = \frac{1}{\sigma_h^3} \sum_{h=0}^{p-1} (h-\bar{h})^3 P(h) \tag{9}$$

Fig. 1: (a) Desi Makkai, (b) Kashmiri Makkai, (c) SygentaMakkai and (d) Pioneer Makkai

$$Entropy = -\sum_{1=0}^{q-1} q_i log_2[q_i] \quad (10)$$

$$Energy = \sum_{h=0}^{p-1} [P(h)]^2 \quad (11)$$

Here, 'h' specifies total image pixels, 'q' represents greyscale value ranges from 0-255, i.e. the successive values of 'm' rows and 'n' columns, $K(h)$ is grayscale values of instances, $P(h)$ is first-order histogram probability. Gao et al. [23] discusses spectral features and essential for image classification and is evaluated in different forms, and these are mathematically expressed as in Eq. (12):

$$spectral\ region\ power = \sum_{u,v \in Region} \sum \left| T(u,v)^2 \right| \quad (12)$$

Here, 'T' specifies the dimension of amplitude-time of 'u' and 'v' regions. These feature extraction approaches are hybridized to overcome the drawbacks of pixel noise. The images hold geometrical, spectral, and statistical features, and it is executed during corn leaf classification [24]. The hybrid feature dataset comprises spectral, histogram, and texture features, where these features are extracted for corn seed images. Region of Interest (ROI) is determined for the extracted features [25].

4 REVIEWS ON CLASSIFICATION APPROACHES

Kho et al. [26] discuss plant disease classification relies on shape and view of leaves. The author adopts hyperspheres classification for categorizing 20 diverse plant species like geometrical and morphological features. It reduces the storage requirements and classification time

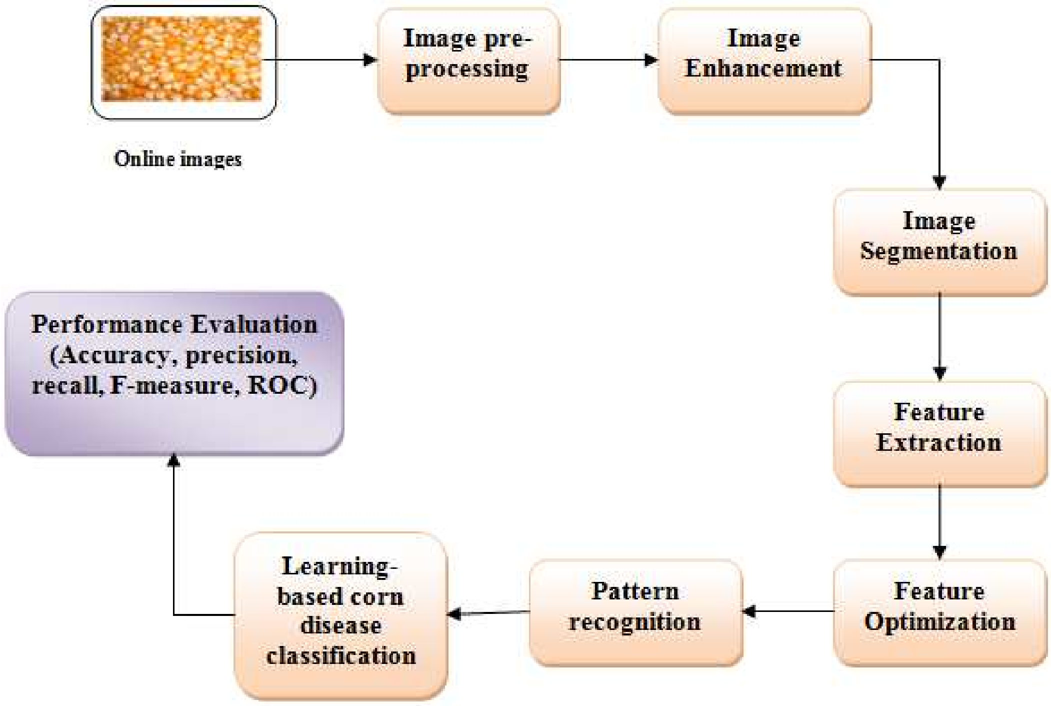

Fig. 2: Generic view of prediction flow

substantially evaluated to classifier model. Kukreja et al. [27] discuss the image retrieval process, consists of HoG, wavelet, pyramid, HSV, and top-hat techniques for automatically predicting the leaves. The model can offer better accuracy of 90% and captures the image with appropriate background, noiseless, and suitable lighting. Brown et al. [28] attain superior outcomes with an accuracy of 96% using BPNN as it is relatively better than the PNN model and sensitive than SVM. The model considers the prediction of medical plants with 90% accuracy using the RF classifier model, and it comprises several individual DT based on the ensemble-based forecast. This classifier model predicts the potential of non-linear features and high dimensional data with features like contours and shapes. The classification process is performed with the extracted feature input fed to the classifier, including RGB values, number of vertical and horizontal distance maps, bounding box, width, length, perimeter, area, etc. The author considers exceptional classifiers like ANN and HoG, which attain 98% accuracy over 950 samples. Snoek et al. [29] use GoogleNet to predict plant species using shape transformation and brightness using SIFT and HoG. Some extracted features are linear or light oval, elongated, longleaf, lanceolate, etc. The descriptor is invariant of rotation and scale, where key points are identified and allocated with specific values. Thus, a promising outcome is achieved with 90% accuracy. Fig 3a depicts the rust-infected corn leaf, Fig 3b illustrates the leaf blight infection, and fig 3c shows the typical corn leaves.

5 REVIEWS ON HYPER-PARAMETER TUNING

Optimizations of hyper-parameters are essential for enhancing the generalizability and prediction accuracy. Generally, k-fold CV is adopted to predict most acceptable hyper-parameter values using the training data. Moreover, the data is independently distributed, does not possess time-series data, and the validation strategy does not produce test distribution. Here, a validation set is defined with dataset acquired from the time point. The training set is generated using time points from the validation observation. Thus, further observations are not utilized for prediction. Therefore, optimizing the hyper-parameter values and choosing the most acceptable model using the training set is needed and performed with a walk-forward CV. Bayesian optimization pretends to offer unknown function approximation like the Gaussian process. The optimization approach is significantly diverse from other searching models over the underlying function, and the new observations are updated. This difference provides hyperparameter tuning is superior to grid while determining superior solutions evaluated to random search. The optimization model gathers the samples with definitive information in alliteration by

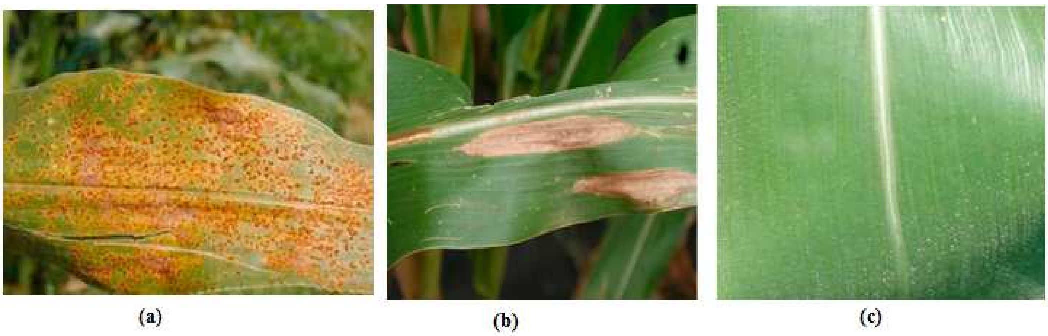

Fig. 3: (a) Rust infected corn leaf (b) Leaf blight infected (c) Healthy corn leaves

balancing exploitation and exploration. Therefore, the Bayesian search is chosen as hyperparameter tuning search over the CV process. It is performed to reduce MSE comprising of hyperparameter values with Bayes rule to generate asubstitute model.

In Linear Regression (LR), the relationship among the response variable and predictors, absence of correlation, normal residual distribution, and error variance across predictors are established. The multiple LR is mathematically expressed as in Eq. (13):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon \tag{13}$$

Here, 'Y'specifies response variable, X_j specifies independent variables, β_j specifies coefficients, and 'ε' represents error team. It is evaluated by diminishing loss function as depicted in Eq. (14):

$$L = \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2 \tag{14}$$

$$L = \sum_{i=1}^{n} \left(Y_i - \widehat{\beta_0} - \widehat{\beta_1} X_{i1} - \widehat{\beta_2} X_{i2} - \cdots - \widehat{\beta_p} X_{ip} \right)^2 \tag{15}$$

Here, $\widehat{y_i}$ specifies the prediction of y_i. James et al. [30] discuss Least Absolute Shrinkage and Selection Operator is determined as the regularization technique competent to certain variables which is set as zero coefficient. Here, LR is added to the penalty term ($|\beta_i|$) to shrink coefficients towards zero. It is mathematically expressed as in Eq. (15):

$$L = \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{16}$$

Here, λ represents the shrinkage parameter is specified before performing learning tasks. Ke et al. [31] discuss bootstrap aggregation, also known as the tree-based ensemble approach to diminish prediction variance and increase generalizability by DT from training data with sample replacement. RF is depicted as a bagging ensemble where the values are random. The number of predictors selects the split candidates over alliteration. It makes the process superior to bagging as RF de-correlates the tree. It uses various observations, bootstrapping samples for evaluating the error rates. Author et al. [32] discuss stacked generalization for reducing the generalization error by performing learning tasks using ML models and actual response values of the dataset. It performs k-fold CV for out-of-bag validation. The prediction model produces newer training set for successive levels of task learning with the original training set size. It is composed of the following steps:
1) Consider training and validation set.
2) Training of base learner and prediction is performed for validation set.
3) Record the data measure and leads training set to move forward.
4) Repeat steps 1-4 until it reaches the original training set.

Oliveira et al. [33] discuss optimized weighted ensembles for the generation of optimization models. It provides a better trade-off between the variance and the bias of the prediction process [34]-[35]. It has the competency to identify the least bias-variance and bias. It is mathematically expressed as in Eq. (16):

$$E\left[\left(f(x) - \widehat{f}(x) \right)^2 \right] = \left(Bias\left[\widehat{f}(x) \right] \right)^2 + var\left[\widehat{f}(x) \right] + var(\varepsilon) \tag{17}$$

Here, $var\left[\widehat{f}(x)\right]$ specifies variance of $\widehat{f}$ of squared sampling deviation, ε specifies sample variance. The bias and the variance show a better trade-off where the objective function can be measured with mean squared error.

6 REVIEWS ON DEEP LEARNING

There are various deep learning approaches like CNN, DBN, AE, and RNN. This section discusses these approaches as they work efficiently for prediction process.

a. Convolutional Neural Networks

CNN resembles human visual system and adopted over various computer vision tasks. It consists of three layers like convolutional, pooling and fully-connected layers. The initial layer utilizes convolutional function for spatial data encoding while the FC encodes global information. Other CNN includes AlexNet, ResNet, VGGNet, and GoogLeNet. The features are learned automatically and outcomes in better performance. Generally, the model represents input and output values. The CNN learning process requires huge amount of data to overcome over-fitting issues and need faster convergence rate [36].

Guo et al. [37] depicts CNN for non-vessel and vessel segmentation and it has three-convolutional and two FC layers. Sevas et al. [38] depicts pixel-wise supervised segmentation process for image training. Similarly, pre-processing is performed with whitening, normalization, gamma correction with transformation. It is force against sensitive vessels and reflex. Zilly et al. [39] depict retinal blood vessel segmentation for disease prediction. Convolutional layers are samples to same image sizes, trained and concatenated during image. Zhang et al. [40] accomplish CNN discriminative features and k-NN to done PCA for evaluating local structure distribution. It is a probabilistic model for blood vessel segmentation. Fu et al. [41] adopts FCN with structural prediction for blood vessel segmentation with diverse label inference. The layered CNN is adopted for segmentation and normalization. Here, some segmentation issues are provided to handle classification issues and sometimes time consuming with independent number of pixels during pixel classification.

b. Auto-encoder

Maji et al. [42] illustrates auto-encoder with input, output and hidden layers. It is provided for the training of stacked auto-encoder. The model training is of two types: pre-training and fine-tuning. It is tuned with gradient descent and back-propagation. There are two types and they are de-noising and sparse network. It is provided for feature extraction. The sparsity is achieved with hidden unit penalization or activations of unit biases. Author et al. [43] demonstrates de-noising auto-encoders and works effectually for prediction purposes to eradicate input and deals with appropriate version. Table 1 depicts the comparison of various DL approaches.

c. Recurrent neural networks

Author et al. [44] provided NN type for context learning from the provided input and composed of diverse parameters related to input, output and hidden output weights. The output needs to be provided with superior iterations and integrated with provided input for attaining output.

d. Deep belief networks

Author et al. [45] discusses the network model with restrictive and cascading Boltzmann machine. It provides diverse algorithm for handling the similarity between the projections and input. The probability depicts the similarity between the probabilistic and degeneration solutions. It is pre-trained unsupervised using greedy learning. Later, it is fine-tuned with gradient descent and back-propagation algorithms.

7 REVIEWS ON STATISTICAL PERFORMANCE METRICS

1) Root Mean squared Error

It is depicted as the square root of average prediction-based deviation from the appropriate values as in Eq. (17):

$$RMSE = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}} \tag{18}$$

Here, y_i specifies the actual values, $\hat{y}_i$ specifies the prediction value, and 'n' specifies the number of data points.

2) Relative Root Mean Squared Error

It is the normalized mean to the actual mean values expressed in percentage. It is mathematically expressed as in Eq. (18):

$$RRMSE = \frac{RMSE}{\hat{y}} \tag{19}$$

3) Mean Bias Error (MBE)

It is depicted as the model for demonstrating the average bias during prediction. It is mathematically expressed as in Eq. (19):

$$MBE = \frac{\sum_i (y_i - \hat{y}_i)^2}{n} \tag{20}$$

4) Mean Directional Accuracy (MDA)

It provides metrics for predicting the probability of identifying the correct time series direction. While other

Table 1: Comparison of various DL approaches

Approaches	Explanation	Advantages	Disadvantages
Deep Neural Networks	It is effortless for learning because of hidden layers. It is helpful for diverse applications to perform classification and regression.	It is utilized for better performance and the most acceptable accuracy.	Huge time is needed for the training process
Convolutional Neural Networks	It is efficient for image-processing	It is entirely faster with better performance	Training labels are needed during classification process
Recurrent Neural Networks	It is beneficial for dealing with the sequence format. Weights are shared among the network.	It is operated sequentially and provides better accuracy	It needs a vast sized dataset for superior performance
Deep Belief Network	It is entirely used for supervised learning.	Greedy isadopted in every layer to prediction	It needs outstanding superior computational complexity during training process
Deep auto-encoder	It is used for dimensional reduction.The size is same for both input and output	Not labelled input data and diverse applications such as de-noising, andsparse auto-encoder. It offers superior sturdiness to input data.	Requires pre-trained process
Deep Boltzmann machine	It works inuni-directional using Boltzmann	With suitable interference and discrete function for predicted value	It needs a vast dataset for analysis, utilization, optimization of parameters

metrics like MBE, RRMSE, and RMSE are crucial for evaluating time series direction. It is mathematically expressed as in Eq. (20):

$$MDA = \frac{\sum_t lsign(y_t - |y_{t-1}) \ == \ sign(\hat{y}_t - y_{t-1})}{n} \quad (21)$$

Here, 'y_t' and '$\hat{y}_t$' are specified as the actual values, 't' is the prediction time, '1' sets the indicator function, and sign (.) defines the sign function.

8 Reviews on performance metrics

Some performance metrics are performed for disease prediction and they are:

1) Accuracy: It is ratio of classified samples over total instances as in Eq. (21):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (22)$$

Here, $TP \longrightarrow$ true positive; TN $\longrightarrow$ true negative; $FP \longrightarrow$ false positive and FN $\longrightarrow$ false negative.

2) Sensitivity: It is depicted as the TPR or recall. It is the fraction of appropriately classified positive samples;

3) Specificity: It is termed as TNR. It is the ratio of appropriately classified negative samples;

4) Precision: It is termed as positive predictive value and it is expressed as in Eq. (22), Eq. (23), Eq. (24), and Eq. (25):

$$Sensitivity\ (recall) = \frac{TP}{TP+TN} \quad (23)$$

$$Specificity = \frac{TN}{TN+FP} \quad (24)$$

$$Precision = \frac{TP}{TP+FP} \quad (25)$$

$$F = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (26)$$

5) Logarithmic loss: It represents accuracy by false classification penalization and expressed as in Eq. (26):

$$Logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} Y_{ij} log P_{ij} \quad (27)$$

Here, 'N' is several samples; 'M' is several labels; Y_{ij} the binary value of label 'j' is proper classification. P_{ij} is the probability of labels (allocated). It is expressed as in Eq. (27) and Eq. (28):

$$IOU = \frac{Area(A \cap G)}{Area(A \cup G)} \quad (28)$$

$$E = 1 - IOU \quad (29)$$

Here, 'A' is the segmentation output, and 'G'represents manual ground truth value segmentation. It is for measuring distance between closed boundary curves and expressed in Eq. (29):

$$B = \frac{1}{n}\sum_{\theta=1}^{\theta_n}\sqrt{(d_g^{\theta})^2 - (d_a^{\theta})^2} \quad (30)$$

Here, d_g^{θ} and d_a^{θ} are the distance among the curve centroid to points; 'n' specifies total amount of angular samples. It is expressed as in Eq. (30):

$$DSC = \frac{2TP}{2TP + FP + FN} \quad (31)$$

It ranges from 0 and 1 and it is used to measure boundary over the overlapped region. It gives quality segmentation.

9 RESEARCH LIMITATIONS

Following are some of the research limitations based on the extensive analysis of learning approaches for corn disease prediction:

1) There are only very few datasets available over the online resources to predict corn diseases.

2) The construction of the benchmark dataset is essential.

3) When the images are captured from the same resource, it limits the generalization ability as the symptoms of the disease may occur in the same plant.

4) The adoption of a meta-heuristic optimization approach is required to attain the global solution during the disease prediction process.

5) The hybridization of the learning classifier model is needed to overcome the drawbacks of successive models.

10 CONCLUSION

This work provides an extensive review of corn leaves disease prediction. The occurrence of the disease shows a negative impact and needs an automated system for predicting crop diseases. The automated systems are used to indicate the stages of the disease, and it is achieved with the adoption of advanced techniques like Machine Learning (ML). Deep Learning (DL) approaches where both models work efficiently in disease prediction. Here, a comprehensive analysis is performed. The reviews are done on the various online available datasets, feature selection, feature extraction, and classification processes using both DL and ML approach to improve prediction accuracy and reduce computational complexities. These approaches are well-suited for various real-time analyses when resource-constraint devices are used for analysis. The research constraints are also discussed, and it helps the young researchers to make further research extensions.

Conflicts of Interests
The authors declare that they have no conflicts of interests

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