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EFFICIENT COFFEE PLANT DISEASE PREDICTION WITH ADAPTIVE FEATURE SELECTION AND DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

The problem of predicting disease in coffee plant is briefly analyzed and there exist numerous techniques around the issue. However, the approaches struggle to achieve maximum accuracy in predicting possible disease which affects the growth of plant. Towards this, an efficient Adaptive Invariant Feature Selection and Approximation based Disease Prediction with DCNN (AIFSADP-DCNN) is sketched. The method applies Intensity Deviation Normalization technique to normalize the leaf image and enhance the image quality Further, Color Quantization Segmentation algorithm is enforced towards segmenting the coffee plant features. Next, color, texture, and distribution features are extracted from the segmented image. Concern features extracted are trained with deep convolution neural network with three layers of convolution and pooling layers. The output layer neurons are designed to measure Color Constraint Support (CCS), Texture Constraint support (TCS) and Distribution Constraint Support (DCS) towards various classes of features. Finally, the method estimates plant disease support (PDS) towards various classes based on which the method identifies the disease class. The proposed model improves the performance of disease prediction in coffee plants with higher accuracy up to 96.5%.

Keywords: D*isease Prediction, Plant Management, Deep Learning, CNN, AIFSADP-DCNN, PCS, DCS, TCS, CCS*

1. INTRODUCTION

Indian agriculture sector has the responsibility in maintaining the cultivation rate and achieving required yield from any kind of plants and fruits. As the population increases day by day they have the responsibility to improve the yield being achieved from various agriculture sectors. However, the yield of any plant is greatly depending on how the plant being monitored and maintained. Any plant has different stages from cultivation, crop and yield. In each stage, the plant would be monitored and would suffer from various diseases and pests. The problem is very much simple when the agriculture area is least but when the plant being cultivated in huge area then it would be different. So, there must be a monitoring and management system for the maintenance of the plants. The disease appear in the plant must be identified and based on that required fertilizer should be supplied to the plant towards improving the crop and yield.

Disease prediction in plant management is a routine to detect the disease appears in the plant. In manual examination, it would be done with least accuracy as the most diseases would be similar in appearance. So, this encourages the design of automated system which involve in identifying and predicting the disease appear in the plant. Image processing plays vital role in predicting the disease which would involve in the preprocessing to normalize the image of the plant and segmentimage features to extract the concern feature towards predicting the disease. There exist number of approaches available to handle the image classification problem from Support vector machine (SVM), Genetic Algorithm, Particle swarm optimization, naïve bayes classifier and neural network. However,

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the machine learning algorithms are suitable to handle least volume of data only. But in order to achieve higher accuracy in disease prediction it is necessary to handle huge volume of data which has great impact on the prediction accuracy. Among the deep learning algorithms, the CNN has great performance as it convolve the features to least dimension and produces higher accuracy.

Further, efficacy of any classification model is depends on the kind of features, number of features considered and the kind of similarity measure being used towards classification. The generic methods would use color; shape and texture features towards classification but including deviation features would support the maximization of prediction accuracy. With all these consideration, this article populates an Adaptive Invariant Feature Selection and Approximation based Disease Prediction with DCNN (AIFSADP-DCNN) which applies Intensity Deviation Normalization technique to normalize the leaf image and enhance the quality of the image. The method applies the technique in the top layer of the color feature which hikes the feature appearance and support the selection of pixel in the segmentation. Further, the method applies Color Quantization Segmentation algorithm towards segmenting the features of the coffee plant. The segmentation algorithm groups the features according to the quantization achieved by any pixel. Next, the color, texture, and distribution features are extracted from the segmented image. Extracted features are trained with deep convolution neural network designed with three layers of convolution and pooling layers. The output layer neurons are designed to measure Color Constraint Support (CCS) which represent the support of color feature towards predicting the disease, Texture Constraint support (TCS) represent the support of texture feature to get into the disease class and Distribution Constraint Support (DCS) which represent the distribution of feature in the leaf supporting the image to get into the disease class towards various classes of features. Finally, the method estimates plant disease support (PCS) towards various classes based on which the method identifies the disease class.

The article is organized to present a detailed introduction on section 1 and deep analysis of related works in section 2. The section 3 presents the brief working of the proposed model and section 4 discusses the evaluation results with the conclusion in section 5.

2. RELATED WORKS:

A patch based classification model is presented in [1], which applies semanticorient segmentation and performs classification with VCG-Beet CNN. The model is depending on VGG16 (visual graphics group) CNN model to perform classification.

In [2], an transfer learning model is presented towards crop and weed identification. The method combines the result of pre-trained models of Xception, Inception-Resnet, VGNet, MobileNet and Densenet in feature extraction and uses several classifiers like SVM, XGBoost and logistic regression. A combined model of deep learning and image processing is presented in [3], which initially identifies the vegetables using Center-Net model and applies color index segmentation in extracting the features to perform classification with genetic algorithm.

In [4], presents a transfer learning model to classify the sugar beet and volunteer potato under field conditions. The model uses the pretrainedAlexnet with image net data set and based on that analyze the performance of various classification models like AlexNet, VGG-19, GoogLeNet, ResNet-50, ResNet-101 and Inception-v3 for their accuracy.

An RGB and depth feature based recognition model is presented in [5], to find the weed in wheat fields. The spatial RGB features are extracted and distribution measures are computed to perform classification with AdaBoost algorithm.

A CNN based rice pest and disease detection model is presented in [6], which collects rice pest images and processed to generate the model. The method introduces higher performance in classification with the support of pre-trained models.

The method applies multiple classifiers in the detection of weed. An FPGA based DNN is presented in [7], which performs weed control with the IoT devices and sensors. The method uses CNN in the detection of weeds where the communication is performed with IoT devices.

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In [8], an deep learning model is presented which uses CNN towards feature extraction. Further, the method uses deep CNN model in classifying insect species onthree publicly available insect datasets. The model efficacy is compared with pre-trained models like AlexNet, ResNet, GoogLeNet and VGGNet forinsect classification.

An unsupervised learning model is presented in [9], to support the detection of weed with its density and distribution. The method applies CNN model in weed detection and support the growth of agriculture.

In [10], the author evaluates the performance of various deep CNN models towards classification of weed in bell pepper field. A fully convolved network model is presented in [11], to classify the weed as well as crop of the plant. The method uses the spatial information with the encoder and decoder structure towards classifying the crop and weed using semantic information.

In [12], analyze the performance of different classifiers in classifying the paddy crops and weeds with digital images. The method extracts texture, color and shape features in classifying the image. The performance of random forest and SVM are investigated.

A hybrid CNN model is presented in [13], to classify Rumexobtusifolius. The model uses CNN in extracting the features as well as classifying them.

A k-means feature learning based weed identification model is presented in [14], which classify soybean seedlingsand its associated weeds by constructing weed identification model according to K-means clubbed with CNN.

A semantic based weed classification model is presented in [15], which perform weed classification with the use of spectral images collected. The method uses SegNet, CNN with encoder decoder models to support the growth of sugar plants. A detailed analysis of various classifiers is presented in [16], which evaluates the efficacy of different classifiers like random forest, SVM, MLP and KNN using different image sets. A partial transferable CNN based model is presented in [17], which uses spatial resolution in classification. A deep learning segmentation model (DeepVeg) is presented in [18], which is designed to classify smallest damage class and segment them effectively. A feature selection technique is sketched in [19], which combines SVM with backward support (SVM-b) and random forest towards effective classification. An efficient weed and crop segmentation model is sketched in [20], to support the fertilizer regulation. The method uses Maximum Likelihood Classification (MLC) to label the image and according fertilizer regulation is carried out. A deep neural network model is presented towards super-high purity seed sorting in [21], which uses deep neural network in the recognition of weeds and performs localization and classification. A pixel based crop and weed classification model is presented in [22], which generates the local binary patterns and histograms in classifying the weeds. Also, the method uses morphological segmentation with max tree structure towards efficient classification.

A real-time machine learning approach for carrot plants classification in organic farming is presented in [23], which usesCNN in preprocessing and extracting the features of plants and perform classification accordingly.

A semantic segmentation based crop and weed classification is presented in [24], which uses water and topography maps of the field to perform segmentation using semantic features. Accordingly, the method performs fertilizer regulation.

A remote sensing and machine learning based invasive plant detection model is presented in [25], which uses various classification algorithms in performance analysis. A machine learning based crop and weed detection model is presented in [26], which performs spray on specific sites of the tobacco crop fields. A deep learning based strawberry fruit class identification model is presented in [27], which uses encoder-decoder network to identify the disease class of strawberries.

A visual analysis based weed classification and SVM based feature selection model is presented in [28], which extract the weed features using Gabor Wavelet and Fast Fourier Transform (FFT). The method analyzes the features using Support Vector Machines (SVM) to perform classification.

A late fusion multi-model deep neural network (DNN) is presented in [29], towards weed classification. The method uses Bayesian conditional probability-based method to calculate the voting and priority weights, based on which classification is performed.

A patch based deep learning model (SesameWeedNet) is presented in [30], which generates ensembles of aerial image with CNN. The method uses VGG towards feature extraction and segmentation. The depth wise convolution model mobileNet is used to perform classification. A remote sensing and neural network based approach is presented in [31], which classifies the weeds and analyze the growth of weed towards productivity. Also the method analyze the growth and spread behavior to support crop and weed classification. The classification is performed with LSTM network. A patch image based weed detection in sugar beet crop is presented in [32], which performs semantic segmentation to find the weed. A texture and shape feature based grass weed classification is presented in [33], which extracts gabor features, histogram of oriented gradients (HoG) and local binary patterns to perform classification. An OTSU and PCA based weed classification model is presented in [34], which performs segmentation, and applies double thresholding based 3D-Otsu method in extracting the features to perform classification. PCA has been used to perform classification.

A naïve bayes classification scheme is sketched in [35], towards weed classification which extracts weed and crops features to perform classification. In [36], they analyze the performance of Joint Unsupervised Learning of Deep Representations and Image Clusters (JULE) and DeepClustering for Unsupervised Learning of Visual Features (DeepCluster), using two public weed datasets. Further, ansemi-automatic data labeling is sketched to minimize labeling cost. A K mean clustering based approach is sketched in [37], which clusters the features of various crops and weeds to perform efficient classification. A region based CNN with SVM based weed detection model [38], extracts the features of weed and crop using region based CNN where SVM is used as classifier. A decision tree based weed classification model [39], generates the tree according to the weed features extracted using FFT algorithm and performs classification accordingly. Single-shot object-detection algorithm [40], has designed to detect diseases and pests on coffee leaves using YOLO models. A rapid disease prediction scheme is sketched in [41], which deep learning models. A Hybrid Vision Graph Neural Networks (HV-GNN) based model is sketched in [42], to support early disease prediction in coffee plants. An enhanced deep learning framework is sketched in [43], which integrates CNN, GoogLeNet and ResNet18 for extracting features where PCA and SVD are adapted for reduction of dimension. The ANOVA and Chi-square are used for feature selection to perform disease prediction.

The methods analyzed are struggling to meet the performance requirement in predicting plant disease.

Adaptive Invariant Feature Selection and Approximation Technique for Efficient Coffee Plant Disease Prediction Using Deep CNN

3. PROPOSED METHODOLOGY

The proposed Adaptive Invariant Feature Selection and Approximation based Disease Prediction with DCNN (AIFSADP-DCNN) method applies Intensity Deviation Normalization technique to normalize the leaf image and enhance image quality. Further, the method applies Color Quantization Segmentation algorithm towards segmenting the features of the coffee plant. Next, the method extracts color, texture, and distribution features from the segmented image. The deep CNN designed with three layers of convolution and pooling layers is trained with concern features. The neurons in output layer measures Color Constraint Support (CCS), Texture Constraint support (TCS) and Distribution Constraint Support (DCS) towards various classes of features. Finally, plant disease support (PCS) is measured towards various classes to identify the disease class.

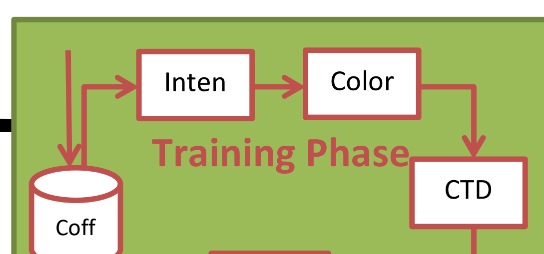

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Figure 1: Architecture of AIFSADP-DCNNModel

The work flow of the AIFSADP-DCNNscheme is sketched in Figure 1, and the stages of the flow are presented in detail.

3.1 Intensity Deviation Normalization:

The coffee plant image given contains several features and contains certain noise pixels introduced by the capturing device. To eliminate the noise particles from the image, intensity deviation normalization is applied. The method collects the features of red layer and constructs a window size of k with the value 5. The window has been traversed through each region of the image. In each window, the intensity features are extracted and Intensity Average value (IAV) is measured. Accordingly, Intensity Deviation Value (IDV) for each pixel is measured. According to IDV value, the method adjusts the pixel with IAV to maximize the intensity of the pixel to enhance image quality.

Algorithm:

Given: Coffee Plant Image CPimg

Obtain: Enhanced Image Eimg

Step1: FetchCPimg

Step 2: Construct window size k=5

Step 3: [R,G,B]= Extract RGB Features from CPimg

Step 4: for each window w

Compute Intensity Average Value

$$IAV = \frac{\sum_{i=1}^{Size(R(W))} Sum(R(W).Intensity)}{k\times k}$$

For each pixel p from w

Compute IDV = Dist(IAV,p.Intensity)

If IDV $> \frac{IAV}{3}$ then

p.intensity = p.intensity+IAV

End

End

End

Step 5: stop

The intensity deviation normalization algorithm estimates IAV for various window features and estimates IDV to find the noisy pixels to adjust the pixel values to normalize the image.

3.2 Color Quantization Segmentation:

The color quantization segmentation algorithm use N-neighbor circular features towards segmentation in all three layers of the image. The value of N is about 3 and the features of such circular features are cropped and the features in all three layers are extracted. Further, the method estimates the quantization and mean value in each layer. Using the quantization value and mean value, the method computes the quantization distance value and means distance value. Now, the mean distance value is within the mean value, and then the specific group is selected. Second, the method estimates cluster selection score (CSS) which is measured against the pixels of specific group and finds the cluster to index the pixel.

Algorithm:

Input: Enhanced Image Eimg

Output: Segmented Image Simg

Step 1: FetchEimg

Step 2: initialize k=5

Step 3: Initialize Coffee, field, disease groups.

Step 4: for each pixel p

for each N neighbor color window cow

EstimateNmeanNm = $\frac{\sum_{i=1}^{Size(cow)} cow(i).pixelvalue}{size(cow)}$

Compute Quantization value Qv = $\frac{\sum_{i=1}^{size(Cow)1} Dist(cow(i),,Nm)}{size(Cow)}$

Compute Quantization Distance Value QDV = Dist(p.value, Nm)

If QDV<Qv then

Select the window cow.

end

End

Identify N neighbor values Nns = $\overset{N}{\underset{i=1}{Choose}}(neighbor\ pixel\ value\ from\ the\ window)$

For each group g

For each pixel value q from the set

Compute Texture similarityTsm = $\frac{\sum_{i=1}^{size(g)} Dist(q,g(i))}{size(g)}$

End

Compute Cluster Selection ScoreCSS = $\frac{\sum Tsm}{N\times N}$

End

Group G = Select cluster with higher CSS value.

Simg(p) = Index the pixel to the selected group.

End

Step 5: Stop

The color quantization segmentation algorithm use pixel color values in different windows of circular region. According to CSS value, the pixel group is identified and segmented.

3.3 CTD Feature Extraction

The proposed model concern about the green, red, distribution and texture features. As the coffee field image contains the green and red layers on to represent the plant features, the method extracts the green and red layer features. Also, the method considers the texture features as it represent various shapes of the diseased region of the plant and consider the distribution feature which represent diseased feature. From the segmented image, the method extracts the texture region from the color image and split the region into four different sub regions. From each sub region, the method extracts the green and red features initially. Extracted features are converted into feature vector to train the network. Also, the method extracts the gray feature from the texture and converts into feature vector. Further, the method computes the distribution feature according to the gray feature obtained from the texture. All features are converted in to feature vector to support CNN Training.

3.4 CTD-DCNN Training:

The proposed model has been designed with three convolution and pooling layers with one input and output layers. To perform training, the method reads the data set and applies preprocessing on each image and performs segmentation to extract the features like color, texture and distribution features. Extracted features are converted into feature vector and generate number of neurons to initialize them with the features extracted. The convolution layer neurons convolve the feature vectors into similar size in first level and convolve the feature into one dimension in the second level. The output layer neuron estimates Color Constraint Support (CCS), Texture Constraint support (TCS) and Distribution Constraint Support

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(DCS) to compute Plant Disease Support (PDS) towards classification.

3.5 Disease Prediction:

The proposed CTD-DCNN model performs disease prediction on coffee plants according to color, texture and distribution features. To start with, the method read the input coffee plant image and applies Intensity deviation normalization to remove the noise from the image. Second, the method applies color quantization segmentation algorithm which groups the features into different groups. From the segmented image, the method identifies the ROI and extracts the feature of color, distribution and texture features. All the feature vectors generated are passed to the network trained, and the convolution layer convolves various features. At the output layer, the neuron estimates Color Constraint Support (CCS), Texture Constraint support (TCS) and Distribution Constraint Support (DCS) to compute Plant Disease Support (PDS) towards classification.

Algorithm:

Input: DCNN trained CTD-DCNN, Test image Timg

Output: Class C

Step 1: Read CTD-DCNN and Timg.

Step 2: Pimg = Intensity Deviation Normalization (Timg)

Step 3: Simg = Color quantization segmentation (Pimg)

Step 4: [C,T,D]= Perform Feature Extraction

Step 5: pass feature vectors into CTD-DCNN network.

At convolution layer 1

Convolve green layer, red layer feature by computing mean values. This yields two mean values as feature vector.

Apply pooling

At convolution Layer 2

Convolve distribution feature into single value.

Apply pooling

At convolution layer 3

Convolve texture feature into one dimension value.

Apply pooling

At output layer

For each disease classDc

Compute Color Constraint Support (CCS).

$$CCS = \frac{\sum_{i=1}^{size(Dc)} \sum_{j=1}^{4} Dist(Dc(i).G(j),G(i)) / 4}{size(Dc)} \times \frac{\sum_{i=1}^{size(Dc)} \sum_{j=1}^{4} Dist(Dc(i).R(j),R(i)) / 4}{size(Dc)}$$

Compute Texture constraint support (TCS)= $\frac{\sum_{i=1}^{size(Dc)} \sum_{j=1}^{4} Dist(Dc(i).T(j),T(i)) / 4}{size(Dc)}$

Compute distribution constraint Support (DCS) = $\frac{\sum_{i=1}^{size(T)} Count(T(i).value > Mea\ (T))}{size(T)}$

Compute Plant Disease support (PDS).

$$PDS = \frac{CCS}{TCS} \times DCS$$

End

Step 6: Class Dc = Choose the disease class with maximum PDS.

Step 7: Stop

The above algorithm represents how disease prediction on coffee plant is performed. The method computes CCS, TCS and DCS values to measure PDS value against various disease classes to perform disease prediction.

4. RESULTS AND DISCUSSION:

The performance of proposed Adaptive Invariant Feature Selection and Approximation Technique based DCNN model for efficient disease prediction on coffee plant has been implemented. The method has been evaluated for its performance at various key factors with different size of samples. In each test suite, the efficacy has been measured under different factors and mapped with other approaches.

Performance on Sensitivity %			
	5000 Samples	10000 Samples	20000 Samples
DeepVeg	82	85	88.6
SVM-B	85	88	90.7
CNN-SVM	87	90	93.6
AIFSADP-DCNN	89	91	94.2

Table 1: Performance Analysis of AIFSADP-DCNNon Sensitivity

The efficacy of AIFSADP-DCNNapproach is gauged on its sensitivity according to various numbers of samples at the training class. In any class, the efficacy of the approach has been gauged and mapped with others. The AIFSADP-DCNNalgorithm achieves higher sensitivity in all the test suites used.

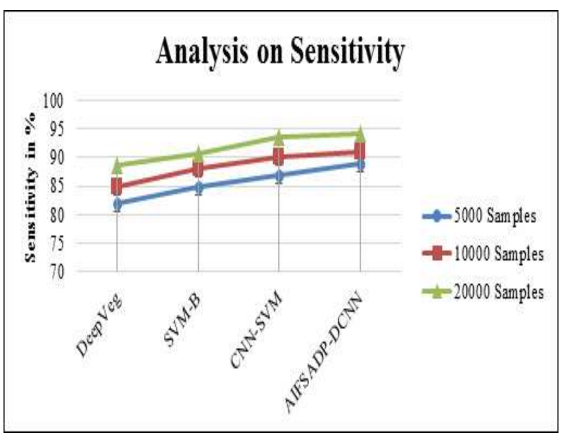

Figure 2: Analysis on sensitivity

The efficacy of methods in terms of sensitivity is measured and compared in Figure 2. The AIFSADP-DCNNmethod improves the sensitivity performance up to 94.2 % compare to other approaches. .

Analysis on specificity				
	DeepVeg	SVM-B	CNN-SVM	AIFSADP-DCNN
5000 Samples	78.3	84.6	87.2	89.4
10000 Samples	82.4	87.3	89.9	91.7
20000 Samples	87.2	91.2	94.2	95.6

Table 2 Analysis on Specificity

The specificity in classification is gauged by considering different number of records in training. In each test case, the efficacy of the methods are gauged and mapped in Table 2. The AIFSADP-DCNN model stimulates higher specificity than others.

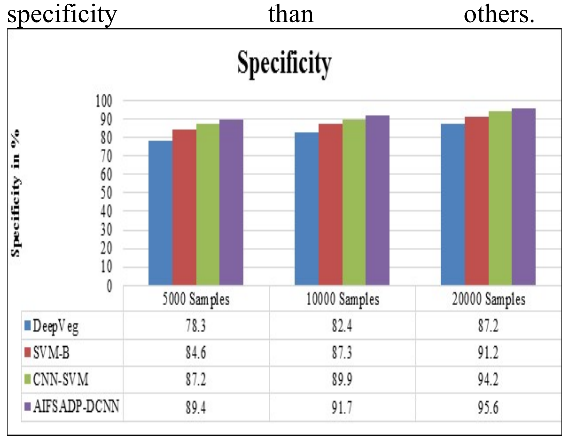

Figure 3: Analysis on Specificity

The specificity in classification is gauged by considering different number of records in training. In each test case, the efficacy of the methods are gauged and mapped in Figure 3. The AIFSADP-DCNNmodel stimulates higher specificity than others.

Performance on Accuracy %			
	5000 samples	10000 Samples	20000 Samples

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DeepVeg	82.4	85.9	90.06
SVM-B	84.8	87.7	91.66
CNN-SVM	86.6	89.7	94.6
AIFSADP-DCNN	88.3	91.8	96.5

Table 3: Performance analysis on Prediction Accuracy

The accuracy of different methods in disease prediction on coffee plant is gauged at varying size of samples in the training set and plotted in Table 3. The AIFSADP-DCNN model introduces higher accuracy in all size of samples.

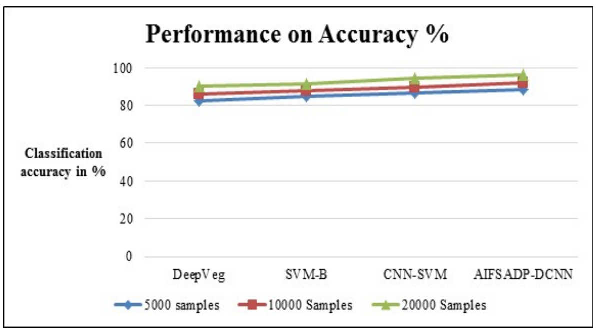

Figure 4: Analysis on classification accuracy

The accuracy of different methods in disease prediction on coffee plant is gauged at varying size of samples in the training set and pictured in Figure 4. The AIFSADP-DCNN model improves prediction accuracy up to 96.5%.

Table 4: False Classification Ratio

The poorness in classification introduced by different approaches are gauged and plotted in Table 4. The proposed AIFSADP-DCNN algorithm down line the ratio than others.

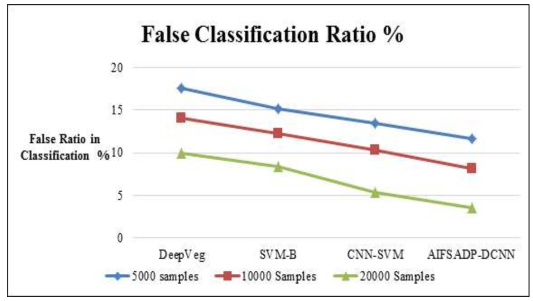

Figure 5: Analysis on False Classification Ratio

The poorness in classification introduced by different approaches are gauged and plotted in Figure 5. The proposed AIFSADP-DCNN algorithm down line the ratio than others.

Table 5: Time complexity

Analysis on time complexity				
No of samples	DeepVeg	SVM-B	CNN-SVM	AIFSADP-DCNN
5000 Samples	5.4	3.2	2.8	2.4
10000 Samples	11.2	5.4	3.7	2.9
20000 Samples	18.1	10.5	8.6	6.3

The performance of various approaches are gauged for their time complexity and plotted in Table 5. In each test case, the AIFSADP-DCNNapproach introduces least value than others.

False Classification Ratio %			
	5000 samples	10000 Samples	20000 Samples
DeepVeg	17.6	14.1	9.94
SVM-B	15.2	12.3	8.34
CNN-SVM	13.4	10.3	5.4
AIFSADP-DCNN	11.7	8.2	3.5

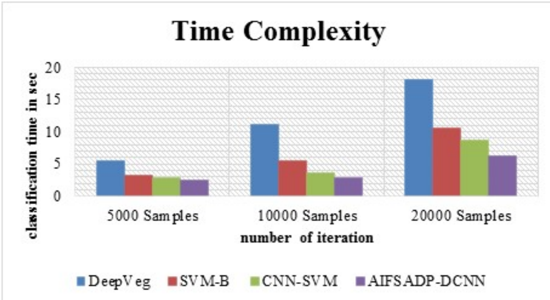

Figure 6: Time Complexity

The performance of various approaches are gauged for their time complexity and pictured in Figure 6. In each test case, the AIFSADP-DCNN approach introduces least value than others.

5.CONCLUSION

This article presented an efficient Adaptive Invariant Feature Selection and Approximation based Disease Prediction with DCNN (AIFSADP-DCNN) is presented in this article. The method applies Intensity Deviation Normalization technique to normalize the leaf image and enhance the quality of the image. Further, the method applies Color Quantization Segmentation algorithm towards segmenting the features of the coffee plant. Next, the method extracts color, texture, and distribution features from the segmented image. Extracted features are trained with deep convolution neural network designed with three layers of convolution and pooling layers. The output layer neurons are designed to measure Color Constraint Support (CCS), Texture Constraint support (TCS) and Distribution Constraint Support (DCS) towards various classes of features. Finally, the method estimates plant disease support (PDS) towards various classes based on which the method identifies the disease class. The proposed model improves the performance of disease prediction up to 96%.

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