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Hybrid deep-spatio textural feature model for medicinal plant disease classification

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ABSTRACT

The high-pace rise in the demands of medicinal plants towards pharmaceutical significances as well as the different ayurvedic or herbal remedials have forced agro-industries However, rising plant disease cases have limited the cumulative growth and hence both volumetric production as well as quality of medicine. In this paper a first of its kind evolutionary computing driven ROI-specific hybrid deep-spatio temporal textural feature learning model is developed for medicinal plant disease detection (HDST-MPD). To alleviate any possible class-imbalance problem, HDST-MPD model at first applied firefly heuristic driven fuzzy C-means clustering to retrieve ROI-specific RGB regions. Subsequently, to exploit maximum possible deep spatiotemporal textural features, it applied gray-level co-occurrence matrix (GLCM) and AlexNet transferable network. Here, the use of multiple GLCM features helped in exploiting textural feature distribution, while AlexNet deep model yielded high-dimensional features. These deep-spatio temporal textural feature (deep-STTF) features were fused together to yield a composite vector, which was trained over random forest ensemble to perform two-class classification to classify each sample medicinal image as normal or diseased. Depth performance assessment confirmed that the proposed model yields accuracy of 98.97%, precision 99.42%, recall 98.89%, F-measure 99.15%, and equal error rate of 1.03%, signifying its robustness towards real-time medicinal plant disease detection and classification.

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1. INTRODUCTION

There are a large number of herbs including Karpooravalli (Coleus ambonicus), Podina (Mentha arvensis), Neem (Adidirachta indica), Thudhuvalai (Solanum trilobatum), and Basil (Ocimum sanctum). Naeem *et al.* [1], whose leaves are used for medicine manufacturing or herbal (or ayurvedic) remedial. Noticeably, these plants possess vital anti-bacterial efficiency so as to improve natural immunity [2], [3]. These key facts infer that the medicinal plants are of great significance to support pharmaceutical industry as whole while providing large remedial for ayurvedic and herbal treatments [1]-[4]. Its employees hararchical cluster analysis, fuzzy principle component analysis and linear discriminant analysis [5] like India use aforesaid medicinal plants directly for the different purposes like ayurvedic treatment or herbal remedials [6], [7].

In sync with above discussed significance of medicinal plants in human-life, numerous efforts have been made globally to increase plant's productivity as well as yields efficiency [7]-[10]. In this reference, the different researches have exploited gray-level co-occurrence matrix (GLCM) [1], [7], shape [2] and deep features [4], [10] towards classify and identify the plant disease, the different plants can have the different shape and size of disease patches and hence gives rise to the class-imbalance problem. In addition to the above stated ROI-specific feature learning scope, the exploitation of the depth features can yield superior results [4], [10]. To ensure feature or class-imbalance problem, here executed heuristic driven fuzzy C-means clustering for ROI-specific segmentation. More specifically, it is applied firefly algorithm as heuristic model to provided ROI-specific color feature space. Subsequently, here it is applied hybrid deep-spatio temporal textural feature (deep-STTF) feature extraction model by applying GLCM and AlexNet models. Here, both GLCM as well as AlexNet models were applied distinctly to perform feature extraction that eventually retained optimal set of deep as well as STTF features to yield superior learning and allied performance. The GLCM and AlexNet features were horizontally concatenated to yield single feature vector for further learning and classification. Here, applied random forest ensemble classifier to perform two-class classification, input image is classifies as normal and diseased image. The overall proposed model was developed with MATLAB, where the statistical performance characterization revealed that the proposed Firefly heuristic driven fuzzy c-means (FFCM) driven deep-STTF feature learning model yields superior accuracy of 98.97%, precision 99.42%, recall 98.89%, F-measure 99.15%, and equal error rate of 1.03% than other existing solutions.

The remaining sections of this manuscript encompasses the following. Section 2 discusses the related work, while problem formulation and allied research questions are written in section 3. Section 4 presents the proposed model and its implementation, and the simulation results are discussed in section 5. The conclusion and overall research inferences are discussed in section 6. References used in this manuscript are given at the end.

2. RELATED WORK

Plant diseases can be caused due to both microbial attacks as well as improper social conditions or humidity. Hypothesizing this fact, Kumar *et al.* [11] applied soil-sensor to exploit local condition so as to detect fungal diseases like powdery mildew. On the other hand, leaf's wetness duration feature was applied in [12]. Ashourloo *et al.* [13] exploited hyperspectral images where regression models like partial least square regression (PLSR), v-support vector regression (v-SVR), and Gaussian process regression (GPR) to perform rust plant disease detection. Similarly, Hussein *et al.* [14] used dielectric spectroscopy that exploited the non-linearity of the dielectric contrast behave throughput the image to identify fungal disease in plants. Schor *et al.* [15] authors performed principal component analysis (PCA) over the visual features to detect powdery mildew (PM) and tomato spotted wilt virus (TSWV) in plants.

Recently, author used deep-learning models for plant disease detection, where the key hypotheses were that the use of deep learning suppresses the need of pre-processing over each input image [11]. Yet, generalizing a single solution remained challenge. Nie *et al.* [16] strawberry verticillium wilt detection network (SVWDN) was designed by applying attention-based feature extraction and learning concept. Ahmad *et al.* [17] suggested to use CNN with stepwise transfer learning. Similarly, CNN was applied in [18]. Huang *et al.* [19], asymptotic non-local means (ANLM) image model was developed with parallel CNN (PCNN) and heuristically tuned extreme learning machine (ELM). Here, PCNN acted as feature. Class-imbalance problem in vision-based plant disease detection models was indicated in [20] as well where authors indicated that despite using any deep learning models, learning over complete sample image with small disease region can yield false positive. Sunil *et al.* [21] applied UNet-based segmentation, EfficientNetV2 based feature extraction and learning for disease detection in Cardamom leaf. It resulted the highest accuracy of 98.26%. Multi-layer CNN (MCNN) was applied in [22] for Anthracnose fungal-caused disease detection in Mango tree.

Khan *et al.* [23] performed ROI-segmentation with 3D filtering, and decorrelation. To improve accuracy [24], applied CNN [25], applied convolutional neural network, long short term memory network and water stress prediction. Dwivedi *et al.* [26] applied ELM as feature learning and classifier for plant disease detection. Khattak *et al.* [27] designed CNN-based citrus fruit leave's disease detection. Here, the maximum accuracy obtained was 93.55%. Huang *et al.* [28] designed RELIEF-F for winter Wheat disease detection. Deep learning models like AlexNet, VGGNet, ResNet were applied in [29] for texture feature learning in vision-based plant disease detection. Zhou *et al.* [30] authors applied faster R-CNN was integrated [3l] authors applied deep learning model where the highest accuracy obtained was 96.5%; though this approach was applied to perform disease detection in apple, corn, grapes, potato, sugarcane, and tomato plants [32], [33] driven multi-scale feature fusion for Maize leaf blight detection. Authors examined the efficiency of the different CNN models including Inception, ResNet, Inception Resnet, and DenseNet for plant disease detection [34], where despite using different deep models it showed the highest accuracy of 87%.

Rahman *et al.* [35] stated that despite different claims to have high accuracy deep-learning methods too need ROI segmentation to refine feature space. Sardogan *et al.* [36] CNN with learning vector quantization (LVQ) was used for Septoria leaf disease detection. Devi *et al.* [37] found that the GLCM algorithm can extract sufficiently large textural features to train with random forest algorithm for plant disease detection. Authors applied support vector machine learning over textural features, where it achieved the highest accuracy of 94.1% [38]. Canny edge detection and blurring and flipping was applied to segment the disease spot. Features were processed for EfficientNet and DenseNet that yielded accuracy of 99.8% and 99.75%, respectively author [39] used plant disease in apple is detected. Pardede *et al.* [40] used convolutional auto-encoder for feature extraction in plant disease detection. Sanida *et al.* [41] explored MobileNet-v2 for plant disease detection; yet, it failed in addressing numerous issues including class-imbalance, and ROI-specific learning, reliability over large non-linear inputs. K-means clustering was applied [42] to segment ROI region to improve accuracy towards chilli plant disease detection and classification. Recently, Chen *et al.* [43] detected a rice blast plant diseases and innovative spore generation as new feature extraction model for agriculture is proposed.

3. RESEARCH QUESTIONS

The overall research presented in this manuscript intends to accomplish optimal answers for the following research-questions:

– *RQ1*: Can the use of FFCM clustering model deliver ROI-specific features for optimal class-imbalance resilient feature vectors for learning towards medicinal plant disease classification?
– *RQ2*: Can the use of FFCM driven ROI-specific color-space textural regions with deep-STTF features (using GLCM and AlexNet deep model) yield optimal composite vector for classify and detect disease in medicinal plants?
– *RQ3*: Can the use of random forest ensemble classifier over deep-STTF features (GLCM descriptive statistics with AlexNet deep features) yield high-veracity and reliable medicinal plant disease detection and classification for real-time purposes?

Thus, the overall research intends to achieve the suitable answers for these questions so that a generalizable solution could be designed for medicinal plant disease detection and classification. Overall proposed system is given bellow.

4. SYSTEM MODEL

This research work primarily intends to design a novel and robust evolutionary computing driven ROI-specific hybrid deep-spatio temporal textural feature learning environment for medicinal plant disease detection (here onwards called as HDST-MPD). The implementation schematic of the overall proposed HDST-MPD model is given in Figure 1. The detailed discussion of the proposed HDST-MPD model and allied sequential implementation is discussed in the subsequent sections.

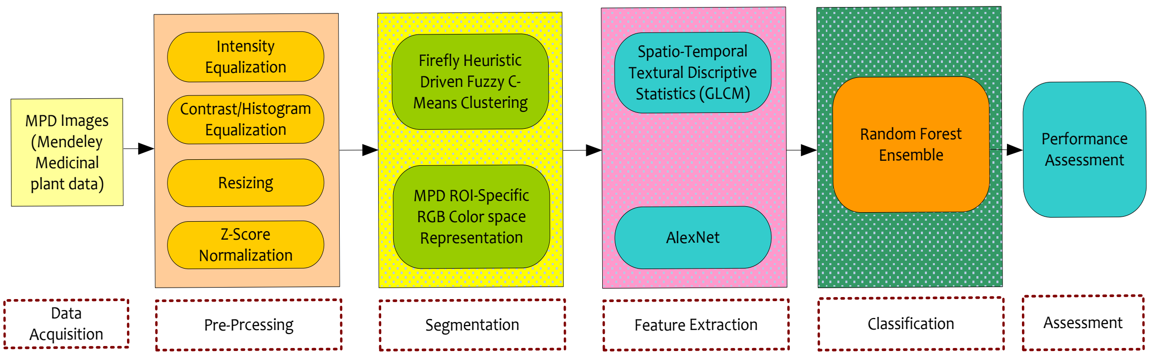

Figure 1. Implementation schematic of the proposed HDST-MPD model

4.1. Data acquisition

As already indicated in the previous sections that the spatio-temporal distribution of medicinal plants often varies from the major cereals plant. For example, the STTF distribution over paddy plant's leaves, vegetable plant's leaves like potato, tomato, and fruits leaves like apple, grapes vary significantly over one to another. Considering this fact, in this paper a specific medicinal plant disease detection model was designed which was trained over a large medicinal plant image. Considered mendeley medicinal plant dataset [44] for our study.

4.2. Preprocessing

At first, it performed image resizing where each input sample was resized to the predefined dimension of 296×400 pixels. Moreover, the input plant leaves images were processed for RGB to gray and thus, gray-level feature representation was obtained. Subsequently, in this work employed contrast adaptive image histogram equalization that minimized the illumination change throughout the region of observation (ROO). It also helped in equalizing resolution and pixel levels to help proper segmentation or target identification. To ensure resilience towards overfitting, local minima and convergence issues, Z-score normalization was performed over each input image.

4.3. FFCM Driven ROI segmentation and color space generation

In this case, merely applying any STTF or deep learning model over complete image can give rise to the class-imbalance problem. This is because the regions covered as disease spot would be significantly lower in comparison to the total size of image (i.e., non-ROI regions). In this case, the ROI (i.e., disease spot) can be the minority class feature, while non-ROI regions and allied features can be the majority class. This as a result can give rise to the class-imbalance problem and hence can impact overall feature learning and classification. To alleviate such problems, it becomes vital to segment merely the ROI-specific regions and learn over the ROI-specific feature space to make classification more accurate and generalizable. Leads inefficient feature extraction and learning (giving rise to the false positive).

4.3.1. Plant disease region or ROI identification

In HDST-MPD in this work applied FFCM to segment the leaf-disease regions while removing non-ROI regions from further computation. Here, FCM algorithm clusters disease region on each input image by exploiting similar spatio-temporal characteristics. It executes ROI-specific segmentation by minimizing intra-cluster distance and thus achieves more accurate ROI localization even under complex spatio-temporal differences. Clustering reduces the need of seed-points (i.e., manual centroid definition). To achieve it and applied a lightweight heuristic concept named firefly algorithm. Here, firefly heuristic model helped in automatizing the overall clustering while ensuring that the relevant pixels are considered in specific regions to cluster different regions including ROI and non-ROIs. FFCM applied FCM as clustering model, while firefly algorithm acted as cluster optimization measure.

4.3.2. FCM clustering

Considering these abilities, in this it considered FCM as the base clustering model to segment ROI-specific regions in each input image. In general, FCM is classified into two distinct types; soft-FCM and hard-FCM. In hard-FCM the input image x is split into multiple clusters ($i.e., G_1, G_2, G_3 \ldots, G_c$), and hypothesizes that the one pattern can belong to merely one cluster. Thus, it forms multiple non-overlapping clusters. In case of soft-FCM method an element x can belong to the multiple clusters. In practice, the at hand medicinal plant leaves can also have the multiple disease spots with gradient variation, color, shape and size differences.

4.3.3. Firefly heuristic based FCM clustering

As already stated, the potential to perform multi-group clustering makes FCM a robust model for automated ROI-segmentation, particularly when the input medicinal plant images carry ambiguous ROI boundaries and non-linear morphologies. Though, FCM yields higher accuracy; however, it relies on membership function and centroid optimality. FFCM being a Firefly heuristic driven model, it requires following certain rules. These are:

Rule-1: firefly represent unisexual living being, which is attracted to another firefly, irrespective of its gender.

Rule-2:on the basis of their brightness intensity one fireflies impacts other firefly. In this mechanism, fireflies impact other fireflies in reverse order. That means, a firefly having higher brightness would attract other fireflies possessing lower brightness. Fireflies with higher inter-entity distance influence lesser to the other nearby.

Rule-3: a firefly possessing the maximum brightness remains unattracted and therefore remains traversing randomly.

Thus, applying above stated function and segmented ROI-regions over each input images. Once segmenting the ROI-specific regions over each input (medicinal plant) image, is multiplied segmented regions with the RGB color space of the original image. Here, our main motive was to retain the ROI-specific textural details for further deep-STFT feature extraction using GLCM and AlexNet. Thus, once obtaining ROI-specific RGB presentation of the segmented disease regions, applied GLCM and AlexNet deep model for respective feature extraction.

4.4. Deep-STTF feature (hybrid-feature) extraction

Once the ROI-specific regions are converted into corresponding R*G*B color space, in this research hybrid feature extraction model was applied. Majority of the classical plant disease detection models where authors have either exploited textural feature or deep feature as standalone features to classify and detect disease in medicinal plants. This paper designed a novel and robust deep-STTF features for classify and detect disease in medicinal plants. More specifically applied GLCM method to exploit multiple orientational, textural and descriptive statics features from the ROI-specific color space. Similarly, employed a transferable deep learning model named AlexNet that provides 4096-dimensional features at the fully connected layer to perform accurate feature learning and classification.

4.4.1. AlexNet deep feature extraction

In HDST-MPDretained the native AlexNet architecture encompassing five convolutional layers (CONV) and three fully connected layers (FC). Interestingly, unlike classical deep models like CNN, RNN, AlexNet provides 4096-dimensional feature vector at FC6 and FC7 layers, which is assumed to have sufficiently large intrinsic deep feature for learning and classification. Since, in HDST-MPD, its intended to exploit hybrid features encompassing GLCM and AlexNet features, the composite features can have the different intrinsic characteristics and therefore the native Softmax layer can’t be applied onto the GLCM feature; though it can be compatible with AlexNet FC6 or FC7 features. An illustration of the overall proposed AlexNet deep architecture is given in Figure 2. As depicted in Figure 2, the proposed AlexNet model retains the native AlexNet architecture with five CONVs and three FC layer; though to retain high-dimensional features here considered FC6 layer as final feature vector for classification. The different layers and corresponding neuron architecture is depicted in Figure 2.

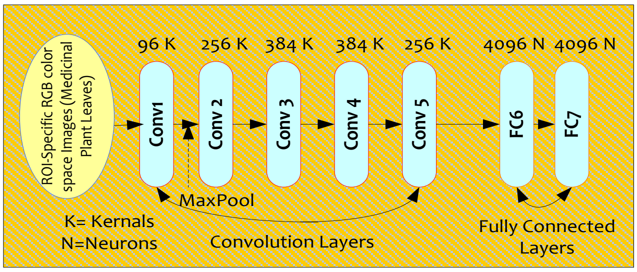

Figure 2. AlexNet transferable deep model

As illustrated in the architecture, the proposed model employs ROI-specific textural input images as input, which is applied in sync with the linear activation function. That means, the input of the CONV 1 is same as that of the original ROI-specific textural representation of the leaves. The CONV1 contains 96 kernels, followed by 256, 284, 384 and 256 kernels at CONV2, CONV3, CONV4 and CONV5, correspondingly.

4.4. Random forest ensemble learning

The, each tree provides vote for the most probable class pertaining to the specific type (i.e., Normal or Diseased). Consider that the total number of training samples be N. In this case, a sample with Ncases are selected arbitrarily from the input feature vector, and the selected samples are applied as training set to constitute a new tree. If there are M inputs, then the best split on these m is employed to split the node. In this work assigned m as constant while performing forest evolution or growth. Thus, applying Random Forest ensemble classifier over the composite feature vector HDST-MPD classified each input image as the normal image or the diseased image. The simulation results and allied inferences are discussed in the subsequent section.

5. RESULTS AND DISCUSSION

In this work, a total of 862 images were taken into consideration containing 13 different medicinal plants. The data can be achieved by requesting the owner with its intellectual rights [44]. First intra-model characterization and second inter-model characterization. Here, in intra-model characterization the performance efficacy with the different feature extraction models and classifiers were examined, while for inter-model assessment we compared the performance of the proposed HDST-MPD model with other existing methods.

5.1. Intra-model characterization

In sync with the overall proposed HDST-MPD model and allied architectural aspects, and intended to assess efficacy with GLCM as standalone feature and with the composite deep-STTF features. In other words, to assess whether the amalgamation of GLCM and AlexNet features yields superior results or not, here performed medicinal plant disease detection and classification with GLCM, AlexNet and $GLCM + AlexNet$ features (say, deep-STTF hybrid features, distinctly. Table 1 shows the efficacy of the different feature models where three different feature models including GLCM, AlexNet and GLCM with AlexNet (say, deep-STTF or hybrid feature).

The hybrid feature model (encompassing both GLCM and AlexNet features), which is proposed in this work shows (medicinal) plant disease detection and classification accuracy of 98.97%, precision 99.42%, recall 98.89%, F-measure of 99.15% is presented in Figure 3 and EER of 1.03% in Figure 4. Once confirming that the proposed FFCM segmentation driven deep-STTF feature model exhibits superior over other standalone feature modalities, and intended to examine the efficacy of the proposed HDST-MPD model with the different classifiers. Here, applied five different machine learning models including Naïve Bayes (NB), decision tree (DT), artificial neural network (ANN-LM), radial basis functions (RBF), support vector machine (SVM) and random forest classifier. Here, the key objective was to assess the suitability of a specific machine learning model with the proposed FFCM segmentation driven deep-STTF feature model (i.e., $GLCM + AlexNet$ feature model) so as to generalize the solution. Table 2 presents the simulated results with the different classifiers. Noticeably, in this assessment, the superiorly performing feature model (i.e., the proposed hybrid deep-STTF feature) was taken into consideration.

Table 1. Intra-model characterization with the different feature environment

Parameters (%)	Feature Models		
	GLCM	AlexNet	$GLCM + AlexNet$ (Deep-STTF)
Accuracy	98.62	98.03	98.97
Precision	98.81	96.27	99.42
Recall	98.79	97.02	98.89
F-Measure	98.80	96.64	99.15
ERR	1.38	2.37	1.03

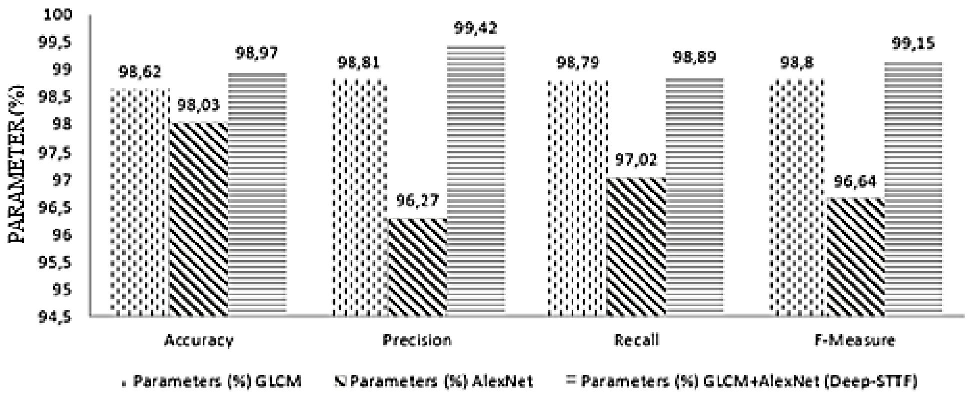

Figure 3. Analysis of feature models

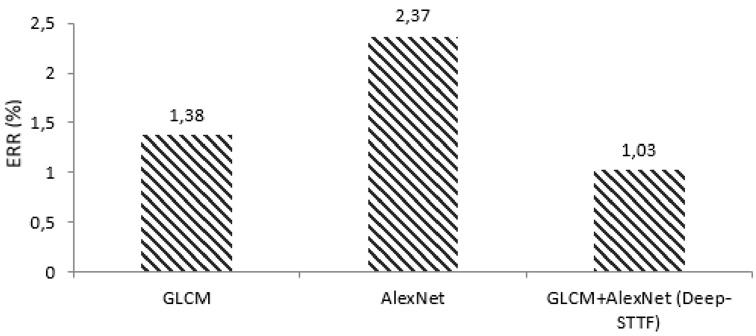

Figure 4. EER performance (%) with the different feature models

Table 2. Intra-model characterization with the different feature environment

Parameters (%)	Classifier Models					
	NB	DT	SVM	RBF	ANN-LM	RF
Accuracy	89.93	93.75	94.21	92.67	94.48	98.97
Precision	92.04	93.81	93.79	93.80	95.03	99.42
Recall	92.85	94.00	93.84	94.01	95.21	98.89
F-Measure	92.44	93.90	93.81	93.90	95.11	99.15
ERR	10.07	6.25	5.79	7.37	5.52	1.03

Table 2 presents the intra-model assessment with the different machine learning methods. In sync with RQ3 (section 3), here intend to assess that which specific machine learning model can deliver the superior performance. Observing the results in Table 2 it can be found that NB model, which was applied with Gaussian kernel function exhibited the average accuracy of 89.93% @EER 10.07%. Similarly, with the proposed deep-STTF feature (i.e., $GLCM + AlexNet$ feature model), DT classifier yielded accuracy of 93.75% @6.25 EER. Interesting, DT performed superior over the NB classifier. Similarly, SVM with polynomial kernel function showed the classification accuracy of 94.21%, at the EER of 5.79%. Undeniably, SVM exhibited superior over the existing NB and DT models; though, the results exhibited diversity in performance. To assess efficacy of the neuro-computing models and applied two well-known algorithms named radial basis functions (RBF) and Levenberg Marquardt (ANN-LM) to perform two-class classification. The simulation results revealed that the neural network (RBF) exhibited the accuracy of 92.67%, while maintaining EER of 7.37%, while LM-ANN exhibited accuracy of 94.48% @5.52% EER. Observing the performance results over the different classifiers it can be easily understood that the different machine learning models exhibit differently over the same input features (i.e.,$Hybrid_{deep-STTF}$). It shows the diversity of performance and hence generalizing a single classifier can be difficult. To alleviate such issues, in this paper it is applied random forest ensemble classifier to perform two-class classification. Figure 5 presents the efficacy of the different classifier models over the proposed deep-STTF feature (i.e., $GLCM + AlexNet$ feature) model. Noticeably, considering poor performance by the Naïve Bayes classifier in Table 2, retained merely five best performing model for presentation.

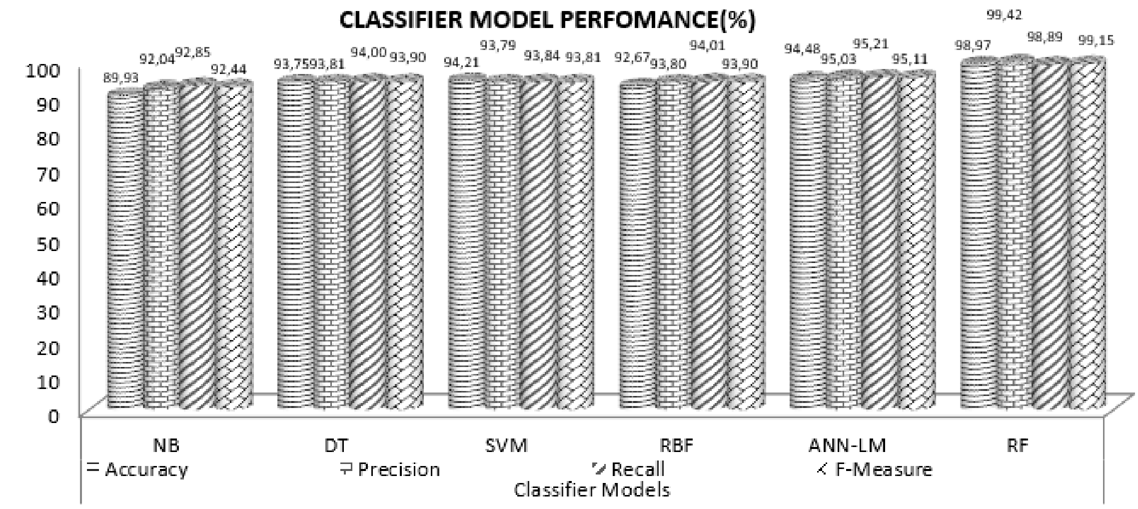

Figure 5. Analysis of the classifier rmodels over $GLCM + AlexNet$ feature

Unlike standalone classifiers as discussed above RF applies bootstrapped decision tree classifier with multiple individual DT as the base classifier. It exploits ranks by the different base classifiers to yield the results and hence being consensus-based classification result, its reliability is superior over the other approaches. Interestingly, over the same input feature (i.e., $Hybrid_{deep-STTF}$), RF algorithm exhibited the plant disease classification accuracy of 98.97% @1.03% EER as shown in Figure 6. The results in Figure 5 show that the use of RF model can yield superior results over other state-of-art machine learning methods. Thus, in this reference, it can be concluded that the FFCM driven ROI-segmentation and allied ROI-specific deep-STTF features with RF classifier can yield the optimal performance towards classify and detect disease in medicinal plants. Therefore, the research question RQ3 as defined in section 3 is found affirmative.

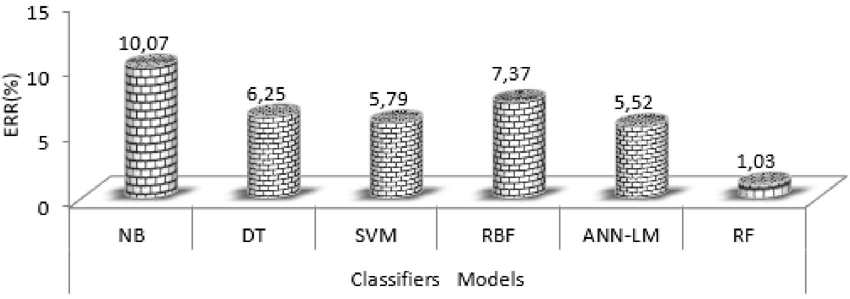

Figure 6. EER (%) analyses of the classifier models over proposed hybrid feature

5.2. Inter-model characterization

In this section it is compared the performance of our proposed HDST-MPD model with other state-of-art techniques. Recently, authors in [1] applied textural features from plant leaves to perform medicinal plant classification. Unlike our proposed HDST-MPD model, authors primarily focused on edge-based segmentation followed by textural features extraction including entropy, inertia and inverse difference and correlation features, run-length matrix to perform medicinal plant classification. In their work, authors applied multi-layer perceptron neural network to perform. Despite being merely plant type classification problem, authors could achieve the accuracy of 95.87%, which is still lower than our proposed HDST-MPD model that exhibited average accuracy of 98.97%. Authors assessed efficacy of the different feature models and found that the key features like run-length matrix, and multi-spectral features could achieve the classification accuracy of 95.87%, 95.04%, 94.21%, 93.38%, and 92.56% using MLP, LogitBoost (LB), Bagging ensemble, RF algorithm and simple logistic algorithms, respectively. Neural network-based plant disease detection and classification model was developed in [35] as well; however, the highest accuracy obtained was 95.87%, which is lower in comparison to our proposed HDST-MPD model.

6. CONCLUSION

This work ensured that only the ROI-specific features are processed for further computation where to guarantee optimal ROI-specific deep-STTF feature learning, this work applied FFCM, a firefly driven FCM clustering model for automated and ROI-specific clustering for disease spot detection and localization. The extracted GLCM and AlexNet features were fused together using horizontal concatenation, and thus the final features retained optimal set of STTF features as well as deep features to make optimal learning and classification. Moreover, the fused composite deep-STTF features were processed for learning and classification using random forest ensemble learning that classified each test image as normal or diseased sample. The statistical performance analysis revealed that the use of hybrid features (i.e., GLCM and AlexNet features together) yields superior performance (accuracy (98.97%), precision (99.42%), recall (98.89%), and F-measure (99.15%), EER (1.03%)), then the GLCM (accuracy (98.62%), precision (98.81%), recall (98.79%), F-measure (98.80%), and EER (1.38%)) and AlexNet (accuracy (98.03%), precision (96.27%), recall (97.02%), F-measure (96.64%), and EER (2.37%)) as standalone feature models.

REFERENCE

[1] S. Naeem *et al.*, "The classification of medicinal plant leaves based on multispectral and texture feature using machine learning approach," *Agronomy*, vol. 11, no. 263, 2021, doi: 10.3390/agronomy11020263.

[2] T. D. Dahigaonkar and R. Kalyane, "Identification of ayurvedic medicinal plants by image processing of leaf samples," *International Research Journal of Engineering and Technology (IRJET)*, vol. 5, pp. 351–355, 2018.

[3] C. Sabarinathan, A. Hota, A. Raj, V. K. Dubey, and V. Ethirajulu, "Medicinal plant leaf recognition and show medicinal uses using convolutional neural network," *International Journal of Global Engineering*. vol. 1, pp. 120–127, 2018.

[4] S. Wallelign, M. Polceanu, and C. Buche, "Soybean plant disease identification using convolutional neural network," *In Proceedings of the Thirty-First International Flairs Conference*, Melbourne, FL, USA, 10 May 2018.

[5] I. M. Simion, D. Casoni, and C. Sârbu, "Classification of Romanian medicinal plant extracts according to the therapeutic effects using thin layer chromatography and robust chemometrics," *Journal of Pharmaceutical and Biomedical Analysis*, vol. 163, pp. 137–143, 2019, doi: 10.1016/j.jpba.2018.09.047.

[6] G. Dhingra, V. Kumar, and H. D. Joshi, "A novel computer vision based neutrosophic approach for leaf disease identification and classification," *Measurement*, vol. 135, pp. 782–794, 2019, doi: 10.1016/j.measurement.2018.12.027.

[7] M. Turkoglu and D. Hanbay, "Leaf-based plant species recognition based on improved local binary pattern and extreme learning machine," *Physica A: Statistical Mechanics and its Applications*, vol. 527, p. 121297, 2019, doi: 10.1016/j.physa.2019.121297.

[8] S. Qadri *et al.*, "Machine vision approach for classification of citrus leaves using fused features," *International Journal of Food Properties*, vol. 22, pp. 2072–2089, 2019, doi: 10.1080/10942912.2019.1703738.

[9] P. Bose, S. Dutta, V. Goyal, and S. K. Bandyopadhyay, "Leaf diseases detection of medicinal plants based on image processing and machine learning processes," *Preprints* (www.preprints.org), pp. 1-7, July 2021, doi: 10.20944/preprints202107. 0638.v1.
[10] B. Bose, J. Priya, S. Welekar, and J. Gao, "HEMP disease detection and classification using machine learning and deep learning," *2020 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom),* 2020, pp. 762-769, doi: 10.1109/ISPA-BDCloud-SocialCom-SustainCom51426.2020.00121.
[11] M. Kumar, A. Kumar, and V. S. Palaparthy, "Soil sensors-based prediction system for plant diseases using exploratory data analysis and machine learning," in *IEEE Sensors Journal,* vol. 21, no. 16, pp. 17455-17468, 2021, doi: 10.1109/JSEN.2020.3046295.
[12] K. S. Patle *et al.*, "IoT enabled, leaf wetness sensor on the flexible substrates for in-situ plant disease management," in *IEEE Sensors Journal*, vol. 21, no. 17, pp. 19481-19491, 2021, doi: 10.1109/JSEN.2021.3089722.
[13] D. Ashourloo, H. Aghighi, A. A. Matkan, M. R. Mobasheri, and A. M. Rad, "An investigation into machine learning regression techniques for the leaf rust disease detection using hyperspectral measurement," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 9, no. 9, pp. 4344-4351, 2016, doi: 10.1109/JSTARS.2016.2575360.
[14] M. I. Hussein, D. Jithin, I. J. Rajmohan, A. Sham, E. E. M. A. Saeed, and S. F. AbuQamar, "Microwave characterization of hydrophilic and hydrophobic plant pathogenic fungi using open-ended coaxial probe," in *IEEE Access*, vol. 7, pp. 45841-45849, 2019, doi: 10.1109/ACCESS.2019.2908061.
[15] N. Schor, A. Bechar, T. Ignat, A. Dombrovsky, Y. Elad, and S. Berman, "Robotic disease detection in greenhouses: combined detection of powdery mildew and tomato spotted wilt virus," in *IEEE Robotics and Automation Letters*, vol. 1, no. 1, pp. 354-360, 2016, doi: 10.1109/LRA.2016.2518214.
[16] X. Nie, L. Wang, H. Ding, and M. Xu, "Strawberry verticillium wilt detection network based on multi-task learning and attention," *in IEEE Access,* vol. 7, pp. 170003-170011, 2019, doi: 10.1109/ACCESS.2019.2954845.
[17] M. Ahmad, M. Abdullah, H. Moon, and D. Han, "Plant disease detection in imbalanced datasets using efficient convolutional neural networks with stepwise transfer learning," in *IEEE Access,* vol. 9, pp. 140565-140580, 2021, doi: 10.1109/ACCESS.2021.3119655.
[18] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks," in *IEEE Access,* vol. 7, pp. 59069-80, 2019, doi: 10.1109/ACCESS.2019.2914929.
[19] S. Huang, G. Zhou, M. He, A. Chen, W. Zhang, and Y. Hu, "Detection of peach disease image based on asymptotic non-local means and PCNN-IPELM," in *IEEE Access,* vol. 8, pp. 136421-136433, 2020, doi: 10.1109/ACCESS.2020.3011685.
[20] Y. Yuan, Z. Xu, and G. Lu, "SPEDCCNN: Spatial pyramid-oriented encoder-decoder cascade convolution neural network for crop disease leaf segmentation," *in IEEE Access*, vol. 9, pp. 14849-14866, 2021, doi: 10.1109/ACCESS.2021.3052769.
[21] C. K. Sunil, C. D. Jaidhar, and N. Patil, "Cardamom plant disease detection approach using EfficientNetV2," in *IEEE Access,* vol. 10, pp. 789-804, 2022, doi: 10.1109/ACCESS.2021.3138920.
[22] U. P. Singh, S. S. Chouhan, and S. Jain, "Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease," *in IEEE Access*, vol. 7, pp. 43721-43729, 2019, doi: 10.1109/ACCESS.2019.2907383.
[23] M. A. Khan *et al.*, "An optimized method for segmentation and classification of apple diseases based on strong correlation and genetic algorithm based feature selection," in *IEEE Access,* vol. 7, pp. 46261-46277, 2019, doi: 10.1109/ACCESS.2019.2908040.
[24] J. Sun, Y. Yang, X. He, and X. Wu, "Northern maize leaf blight detection under complex field environment based on deep learning," in *IEEE Access,* vol. 8, pp. 33679-33688, 2020, doi: 10.1109/ACCESS.2020.2973658.
[25] S. Azimi, R. Wadhawan, and T. K. Gandhi, "Intelligent monitoring of stress induced by water deficiency in plants using deep learning," in *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-13, 2021, no. 5017113, doi: 10.48550/arXiv.2104.07911.
[26] R. Dwivedi, T. Dutta, and Y.-C. Hu, "A leaf disease detection mechanism based on l1-norm minimization extreme learning machine," in *IEEE Geoscience and Remote Sensing Letters,* vol. 19, pp. 1-5, 2022, no. 8019905, doi: 10.1109/LGRS.2021.3110287.
[27] A. Khattak *et al.*, "Automatic detection of citrus fruit and leaves diseases using deep neural network model," in *IEEE Access,* vol. 9, pp. 112942-112954, 2021, doi: 10.1109/ACCESS.2021.3096895.
[28] W. Huang *et al.*, "New optimized spectral indices for identifying and monitoring winter wheat diseases," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 7, no. 6, pp. 2516-2524, 2014, doi: 10.1109/JSTARS.2013.2294961.
[29] S. Barburiceanu, S. Meza, B. Orza, R. Malutan, and R. Terebes, "Convolutional neural networks for texture feature extraction. applications to leaf disease classification in precision agriculture," in *IEEE Access,* vol. 9, pp. 160085-160103, 2021, doi: 10.1109/ACCESS.2021.3131002.
[30] C. Zhou, Z. Zhang, S. Zhou, J. Xing, Q. Wu, and J. Song, "Grape leaf spot identification under limited samples by fine grained-GAN," *in IEEE Access*, vol. 9, pp. 100480-100489, 2021, doi: 10.1109/ACCESS.2021.3097050.
[31] S. V. Militante, B. D. Gerardo, and N. V. Dionisio, "Plant leaf detection and disease recognition using deep learning," 2019 IEEE *Eurasia Conference on IOT, Communication and Engineering (ECICE),* 2019, pp. 579-582, doi: 10.1109/ecice47484.2019.8942686.
[32] F. Marzougui, M. Elleuch, and M. Kherallah, "A deep CNN approach for plant disease detection," 2020 21st *International Arab Conference on Information Technology (ACIT),* 2020, pp. 1-6, doi: 10.1109/ACIT50332.2020.9300072.
[33] P. K. V, E. G. Rao, G. Anitha, and G. K. Kumar, "Plant disease detection using convolutional neural networks," 2021 5th *International Conference on Trends in Electronics and Informatics (ICOEI),* 2021, pp. 1473-1476, doi: 10.1109/ICOEI51242.2021.9453045.
[34] X. Guan, "A novel method of plant leaf disease detection based on deep learning and convolutional neural network," 2021 6th *International Conf. on Intelligent Comp. and Signal Processing (ICSP)*, 2021, pp. 816-819, doi:10.1109/ICSP51882.2021.9408806.
[35] M. A. Rahman, M. M. Islam, G. M. S. Mahdee, and M. W. U. Kabir, "Improved segmentation approach for plant disease detection," 2019 1st *International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT),* 2019, pp. 1-5, doi: 10.1109/ICASERT.2019.8934895.
[36] M. Sardogan, A. Tuncer, and Y. Ozen, "Plant leaf disease detection and classification based on CNN with LVQ algorithm," 2018 *3rd International Conf. Computer Science and Engineering (UBMK),* 2018, pp. 382-385, doi: 10.1109/UBMK.2018.8566635.
[37] R. D. Devi, S. A. Nandhini, R. Hemalatha, and S. Radha, "IoT enabled efficient detection and classification of plant diseases for agricultural applications," 2019 *International Conference on Wireless Communications Signal Processing and Networking (WiSPNET),* 2019, pp. 447-451, doi: 10.1109/WiSPNET45539.2019.9032727.
[38] Kirti and N. Rajpal, "Black rot disease detection in grape plant (vitis vinifera) using colour based segmentation & machine learning," 2020 2nd *International Conference on Advances in Computing, Communication Control and Networking (ICACCCN),* 2020, pp. 976-979, doi: 10.1109/ICACCCN51052.2020.9362812.
[39] V. V. Srinidhi, A. Sahay, and K. Deeba, "Plant pathology disease detection in apple leaves using deep convolutional neural networks: Apple leaves disease detection using EfficientNet and DenseNet," 2021 5th *International Conf. on Comp. Methodologies and Comm. (ICCMC),* 2021, pp. 1119-1127, doi: 10.1109/ICCMC51019.2021.9418268.

[40] H. F. Pardede, E. Suryawati, R. Sustika, and V. Zilvan, "Unsupervised convolutional autoencoder-based feature learning for automatic detection of plant diseases," 2018 *International Conference on Computer, Control, Informatics and its Applications (IC3INA),* 2018, pp. 158-162, doi: 10.1109/IC3INA.2018.8629518.
[41] T. Sanida, D. Tsiktsiris, A. Sideris, and M. Dasygenis, "A heterogeneous lightweight network for plant disease classification," 2021 10th *Intl. Conf. on Modern Circuits and Systems Technologies (MOCAST),* 2021, pp. 1-4, doi: 10.1109/MOCAST52088.2021.9493415.
[42] A. H. B. A. Wahab, R. Zahari, and T. H. Lim, "Detecting diseases in chilli plants using k-means segmented support vector machine," 2019 3rd *International Conference on Imaging, Signal Processing and Communication (ICISPC),* 2019, pp. 57-61, doi: 10.1109/ICISPC.2019.8935722.
[43] W. -L. Chen, Y. -B. Lin, F. -L. Ng, C. -Y. Liu, and Y. -W. Lin, "RiceTalk: Rice blast detection using internet of things and artificial intelligence technologies," in *IEEE Internet of Things Journal,* vol. 7, no. 2, pp. 1001-1010, Feb. 2020, doi: 10.1109/JIOT.2019.2947624.
[44] S. Roopashree and J. Anitha, "Medicinal leaf dataset," Mendeley Data, V1, Oct 2020, doi: 10.17632/nnytj2v3n5.1.

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