International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I6P220

Volume 70 Issue 6, 165-184, June 2022

Original Article

Evolutionary Computing Driven ROI-Specific Spatio-Temporal Statistical Feature Learning Model for Medicinal Plant Disease Detection and Classification

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Received: 21 March 2022 Revised: 17 May 2022 Accepted: 29 May 2022 Published: 27 June 2022

Abstract *- Plants can be hypothesized to be the inevitable need of living beings on earth. Amongst the gigantically large plant species and varieties, the medicinal plants have a distinct and significant role in herbal remedies, ayurvedic medicine, the pharmaceutical industry, and the major modern medicine world. Various medicinal plants like roots, stems, and leaves are used for the abovementioned purposes; however, their efficacy depends on their intrinsic health condition. In other words, a medicinal plant with healthy and non-contentious characteristics can positively impact medicinal uses. On the contrary, plants with the disease can have a negative or insignificant impact on medicinal purposes. In sync with this fact, detecting plant disease over the different medicinal plants can be vital for healthy plant selection and identifying diseases for preventive measures or decisions. Despite the robustness of the vision-based automatic plant disease detection and classification systems, the non-uniform disease patterns, non-ROI feature learning, and inferior feature space confine the efficacy of the major at-hand solutions. To alleviate such limitations, in this paper, a highly robust evolutionary computing-driven ROI-specific Spatio-temporal statistical feature learning model is developed for medicinal plant disease detection and classification. To ensure solution optimality, the proposed model first performed pre-processing employing image histogram equalization, intensity equalization, and Z-score normalization, followed by annotations. Subsequently, a first-of-its-kind Firefly algorithm-driven Fuzzy C-Means clustering (FFCM) was developed for ROI segmentation. Subsequently, the proposed model performed an ROI-specific color space overlay to reconstruct ROI in RGB color space to extract significant Spatio-temporal statistical or textural features. In the proposed model, eight Gray-level co-occurrence metrics named correlation, heterogeneity, entropy, energy, contrast, mean, standard deviation, and variance were extracted as STTF features, which were subsequently applied to perform two-class classification for healthy and diseased medicinal plant classification. The simulated results revealed that the proposed model yields superior medicinal plant disease detection and classification performance in terms of accuracy (98.62%), precision (98.81%), recall (98.79%), and F-Measure (0.988).*

Keywords *- GLCM Features Heuristic-based ROI Segmentation, Medicinal Plant Disease Detection, Neuro-computing.*

1. Introduction

The life of a living being can be hypothesized to be centered on plants and their product called oxygen. In other words, living beings rely primarily on oxygen from different plants and herbs. The gigantic types of plants on earth have different significance toward living beings. However, based on reachability and scientific understanding, plants are categorized into certain categories, including cereals, medicinal plants, wood plants, etc. The different plants play significant roles in maintaining the earth's biodiversity while providing air and water to living beings, including humans. In addition to the air mentioned above and water support, a significantly large number of plants provide grains for food, medicine, wood, etc., thus helping human beings for sustainable living on earth. Amongst the known bio-diversity centered on the term plant, medicinal plants have distinct and undeniably a specific role where it provides ingredients for medicine, ayurvedic treatment resources, herbal remedies, etc. Several medicinal plants are employed for disease treatment and prevention.

Interestingly, these medicinal plants have been employed for generations, and still, the scientifically enriched and advanced pharmaceutical industry depends on these medicinal plants to produce high-efficacy medicines. Medicinal plants possess unique and highly significant properties ranging from its root to leaves and are serving a savior role for humanity on earth. There are many herbs, including Karpooravalli (Coleus ambonicus), Podina (Mentha arvensis), Neem (Adidirachta indica), Thudhuvalai (Solanum trilobatum), Basil (Ocimum sanctum), etc. [1], whose leaves are used for either making enriched medicines or are employed in natural form to perform ayurvedic or herbal remedies. Several (medicinal) plant leaves are effective in treatments like skin disease, blood purification, ingestion, etc. In addition, several medicinal plants like Turmeric and Giloy, whose roots are employed as medicinal components to improve anti-bacterial efficiency and increase natural immunity [2][3]. In this manner, the different medicinal plants are used differently to provide expected remedials for both human beings and animal health and hygiene. Contemporarily, medicinal plants have emerged as the inevitable ingredient for traditional and modern medicines to safeguard human and animal life. Few medicinal plants are employed as a whole; only one of its parts, like leaf, stem, or root, is applied for remedies. The different parts of the medicinal plants can be of different significance and are applied for different remedial purposes or medicine manufacturing [1-4]. In addition to the medicinal significance, such plant extracts can also be employed for food or condiment purposes. Numerous sanitary drinks use medicinal plant extract [1]. Different pieces of literature reveal that across the world, almost 14-28% of plants fall under the medicinal category [1]. Research conducted at the start of the 21st century reveals that 3-5% of the patients in western countries, whereas in developing countries, 80% of the rural population, medicinal plants are used for health hygiene [6][7].

The above discussions reveal the significance of medicinal plants for human beings; however, the success of medicinal plant-driven remedies primarily depends on the originality of the plants, ingredients, and plant health. Unfortunately, in the current-day scenario, the herbal medicine market is flooded with low-standard products, despite claiming to be herbal or organically produced. Despite being prepared with medicinal extracts, the failure or low significance of large medicines or medicinal plant-driven herbal remedies can’t be ruled out. A key reason behind such inferior cases can be the ineffective, manipulated, or corrupted plant or its part. In other words, the presence of a disease in a plant can erode the sanity of its natural ingredient and hence can make a medicinal plant insignificant.

On the other hand, applying such a plant or its parts for medicine manufacturing or any allied herbal remedies can be of no significance [1-10]. To alleviate such problems guaranteeing optimality of the plant health is a must. There are several plant diseases whose impact is often reflected over the leaves. In other words, analyzing a plant’s leaf can help identify a normal or healthy plant or a diseased plant. Different kinds of plant diseases like rust, bacterial or fungus-driven diseases, etc., impacts plant leaves.

Consequently, the attacked or diseased plant leaves often become pale, dried, white surfaced, or sometimes black corroded. Discoloration and changes in leaf shape and sizes often characterize plant disease. Despite above stated vision-based assessment, guaranteeing optimality of plant disease detection often remains a challenge for industries due to differences in shape, size, huge volume, and different kinds of (similar) leave in the same place.

Moreover, manual plant disease detection and classification is a highly tedious task and therefore requires a certain automated approach to detect and classify the normal and diseased plants. To achieve such goals, automatic vision-based computer recognition systems have gained widespread attention [9][10]. Vision-based plant disease detection and classification systems apply different Spatio-temporal and textural features of the plant leaf to learn and classify images as normal or diseased. In other words, computer-based plant disease detection methods use many plant images as input to learning the features that enable them to classify images as the normal plant or the diseased plant.

A few years ago, I struggled greatly in sync with the vital signs of plant disease detection demands. Most at-hand systems use plant leaves’ textural information, Spatio-temporal feature distribution, and shape and size to train machine learning algorithms for further classification. Most of the existing systems have applied (GLCM) features [1][7], shape information [2], and deep features [4][10]to perform plant disease detection and classification. However, those approaches applying shape, size, and textural information often employ segmentation to detect the region of interest. This approach has always been criticized due to its high reliance on the efficacy of segmentation and allied computations. Considering such limitations, many efforts have been made to apply deep learning methods. Unlike segmentation-based approaches, deep learning methods directly inputs complete image as input and extracts cumulative feature from the sample to perform further learning. Undeniably, deep learning methods avoid the need for typical pre-processing and segmentation; however, the impact on non-ROI feature learning can impact overall classification results. To alleviate non-ROI-specific feature extraction and learning segmentation as a pre-feature extraction method seems more justifiable. However, in sync with medicinal plants, which have the non-linear ROI patterns (i.e., the shape, size, non-uniform disease (fungal attack, bacterial attacks, etc.) gradient, the classical standard thresholding-based segmentation can be ineffective. In other words, to cope with non-linear disease pattern detection (say, segmentation) over medicinal plants of different sizes, colors, etc., an improved segmentation method is required. To meet this demand, clustering-based segmentation or region growing concepts can be the viable solution; however, being a complex approach, later (i.e., region growing) can’t be appropriate for the medicinal plant disease detection task. Though clustering methods like Fuzzy C-Means (FCM) can yield fast ROI-segmentation over non-linear surfaces or feature gradient (or distribution); however, guaranteeing cluster optimality remains a challenge. To improve FCM-based clustering for ROI segmentation, using heuristic methods can be of great significance, where heuristic models like genetic algorithms, swarm techniques, ant colony, etc., can help optimize the centroid and enable fast and accurate ROI segmentation.

Moreover, most existing methods have applied segmented ROI regions as input to directly extract binary features and entropy to perform feature extraction and further classification. However, there can be severe textural and gradient differences in real-world problems over the plant's surface; therefore, existing methods can't be justifiable. To alleviate this problem, the segmented ROI regions can be converted into equivalent RGB textural ROI, which can subsequently be processed for feature extraction. This approach of improved segmentation and corresponding RGB space reconstruction can help perform ROI-specific feature extraction, guaranteeing more improved features for medicinal plant disease detection and classification. Notably, unlike typical plant disease detection systems, very few pieces of literature are available on medicinal plant disease detection and classification. Most of the existing plant disease detection methods are found to be low in accuracy; hence, improving features and classification methods can yield superior performance.

Considering above stated problems and allied scopes, the proposed model emphasizes the multiple innovative dimensions, including heuristic-driven disease region (say, ROI) segmentation, ROI-specific RGB color feature space construction, and multiple Spatio-temporal feature extraction, and improved classification. In this research, many medicinal plants, including Amaranthus Viridis, Basella Alba, Brassica Juncea, Citrus Limon, etc., were considered for plant disease detection and classification. The different medicinal plants obtained the plant leaf samples containing both normal and diseased leaves. Once performing the basic pre-processing tasks like histogram equalization, intensity equalization, Z-normalization, and resizing, unlike classical segmentation methods, the proposed model applied FFCM to perform ROI-specific segmentation over input images. Once the disease-specific ROI regions were segmented in each plant leaf, the GLCM feature extraction method was applied to extract different Spatio-temporal statistical features. In this work, a total of eight GLCM features, including contrast, homogeneity, energy, entropy, correlation, standard deviation, variance, mean, Kurtosis, and Skewness, were extracted from each input sample (i.e., ROI-specific color image). Once extracting these STTF features, horizontal concatenation was applied to retrieve a cumulative feature vector for further classification. The obtained feature vector was processed for classification using LM-ANN, which possesses superior learning ability to the other neuro-computing models. It classified each input sample image as the normal plant and the diseased plant. The statistical performance characterization in accuracy, precision, recall, and F-measure reveals that the proposed model achieves superior performance to the other existing medicinal plant disease detection and classification systems.

The other sections of this manuscript are divided as follows. Section 2 presents related work on detecting plant disease, whereas Section 3. Section 4 presents Problem formulation, how research methodology is used, and its implementation. Section 5 presents the results .in section 6 presents the conclusion and future work.

2. Related Work

In the past, researchers have made an effort by exploiting different factors, including local soil conditions [11][25], leaf image analysis, etc., to perform plant disease detection. Interestingly, most of these methods have applied machine learning methods to learn the local patterns of Spatio-temporal features to detect diseased plants and their type(s). Kumar et al. [11] applied soil-sensor data to perform fungal diseases like powdery mildew, anthracnose, rust, and root rot/leaf blight prediction in the plant. They employed a multi-layer perceptron classifier over the micro-meteorological data to perform plant disease prediction, where the highest accuracy could be achieved at 98%. Patle et al. [12] exploited the leaf wetness duration (LWD) information obtained by the polyimide flexible substrate-driven leaf wetness sensors to perform fungal disease prediction. However, it was costly, weather dependent, and even complex in execution. Hyperspectral images were applied by Ashourloo et al. [13], where the regression method was applied to perform leaf rust disease detection. The authors assessed the efficacy of the three different regression models, including partial least square regression (PLSR), v-support vector regression (v-SVR), and Gaussian process regression (GPR), to perform rust-disease detection, where GPR was found superior over the other state-of-art methods. These proposed learning models were employed over the non-imaging spectrometer in the electromagnetic region of 350-2500 nm. A similar effort was made by Hussein et al. [14]. They employed dielectric spectroscopy to exploit the variations of the dielectric contrast behaviour over the images to perform pathogenic fungal disease detection in plants. Undeniably, these approaches [13][14] were highly complex and hence less scalable toward real-time problems. Schor et al. [15] applied the PCA method to perform powdery mildew (PM), and tomato spotted wilt virus (TSWV) disease detection. Here, the PCA-based method yielded superior performance with the pixel-level classification (accuracy 95.2%) than the leaf-condition-based classification result (accuracy 64.3%). Exploring in-depth, it can easily be found that exploiting pixel-level Spatio-temporal textural features (STTF) can yield superior performance over the image as whole input-based models.

Considering the ease of implementation, many efforts have been made by applying deep learning methods to perform plant disease detection. For instance, Nie et al. [16] developed a strawberry verticillium wilt detection network (SVWDN) by applying an attention-based method for feature extraction and learning. Noticeably, the authors applied the Faster R-CNN model to perform feature extraction, followed by SVWDN for classification. Despite the claim for 99% accuracy, the researcher could not address non-ROI feature learning and its impact on overall accuracy. Moreover, the authors [16] designed their model as an annotated supervised learning concept; hence, its efficacy over the unknown non-linear disease pattern remains suspicious. Recalling a very significant problem of class imbalance in machine learning-based plant disease prediction models, Ahmad et al. [17] developed CNN with a stepwise transfer learning method. Similarly, Jiang et al. [18] applied CNN for apple leaf disease detection. To improve efficacy over a large input image, the authors developed INAR-SSD (SSD with Inception module and Rainbow concatenation) model to perform apple leaf disease detection. Interestingly, despite training over a large input dataset, authors could achieve the mAP of 78.80%. In sync with the real-time operating environment, Huang et al. [19] developed an asymptotic non-local means (ANLM) image algorithm along with a hybrid concept encompassing parallel CNN (PCNN) and heuristically tuned extreme learning machine (ELM) to perform peach disease detection. The highest accuracy of this model could be achieved at 90.5%. Recalling the at-hand challenges in non-linear disease region segmentation for vision-based methods, Yuan et al. [20] stated that despite the theoretical superiority, most of the existing deep learning methods undergo limited performance and false-positive due to higher class imbalance and non-ROI feature learning. In this reference, the authors [20] developed Spatial Pyramid-Oriented Encoder-Decoder Cascade CNN (SPEDCCNN) model for plant disease detection. Noticeably, to improve efficacy, authors [20] applied two distinct neuro-computing models encompassing a region disease detection network and a region disease segmentation network. Here, the first model combined cascade-CNN with a spatial pyramid to detect the ROI region. To further improve feature efficiency, a three-level CNN was designed to perform feature extraction and classification. Despite high accuracy (90%), this approach underwent exceedingly high computational complexity. Patil et al. [21] focused on applying UNet-based segmentation followed by EfficientNetV2-based feature extraction and learning to perform Cardamom plant disease detection and classification. The highest accuracy reported by them was 98.26%. Singh et al. [22] developed a multi-layer CNN (MCNN) model for Anthracnose, well-known fungal disease detection in Mango tree (leaf). Similar to [21], realizing the need for an ROI-specific segmentation model, Khan et al. [23] focused on disease spots. Correlation-driven expectation-maximization was applied to improve segmentation accuracy over the plant leaf surface. Subsequently, the local binary patterns (LBP) feature was extracted from the segmented ROI regions and later processed for SVM-based classification. Sun et al. [24] developed CNN driven multi-scale feature fusion instance detection concept for Maize leaf blight detection. Functionally this approach was highly complex due to multi-level complexities, including retinex-based image enhancement, RPN-driven anchor box adjustment (acts as segmentation), transmission-module-based network learning, etc. Moreover, the authors found convincing results at the cost of 60000 iterations that can be too exhaustive for a real-time solution. Dwivedi et al. [26] designed the L1-Norm minimization extreme learning model (ELM) to improve plant disease detection's accuracy, reliability, and run-time efficiency. Additionally, the authors applied the different pre-processing and feature learning methods to perform one-class classification. They found that neuro-computing can be a suitable alternative for time-efficient plant disease detection and classification. Khattak et al. [27] applied CNN-based automatic citrus fruit and lave disease detection system. More specifically, the authors detected and classified plant diseases. The highest accuracy reported was 94.55%. Huang et al. [28] developed a RELIEF-F model for winter Wheat disease detection. The highest accuracy for powdery mildew, yellow rust, and aphids were 86.5%, 85.2%, 91.6%, and 93.5%, respectively. Barburiceanu et al. [29] applied the different deep-learning methods, AlexNet, VGGNet, and ResNet, for texture feature extraction and plant leaf disease detection and classification. Zhou et al. [30] developed fine-grained-GAN for grape leaf spot identification. The authors improved R-CNN faster with the fine-grained-GAN as a local spot area detector, which acted as a segmentation model. Subsequently, it applied ResNet50 to perform feature extraction and classification, which achieved the highest accuracy of 96.27%. Militante et al. [31] applied the deep learning method for plant leaf detection and allied disease recognition. The highest accuracy reported was 96.5% towards the leaf classification of the apple, corn, grapes, potato, sugarcane, and tomato plants. Marzougui et al. [32] and Kumar et al. [33] applied CNN for plant disease detection. Guan et al. [34] assessed the efficacy of the different CNN models like Inception, ResNet, Inception Resnet, and DenseNet towards plant leaf disease detection and classification. Interestingly, the authors found that stacking these deep learning models can yield the maximum accuracy of 87%, which was higher than the CNN as a standalone deep model. Recent research by Rahman et al. [35] stated that despite using a deep neural network, a vision-based model requires superior ROI segmentation for accurate disease detection. Executing their improved segmentation model followed by deep learning-based feature extraction over the Plant-Village database, the author could achieve the highest accuracy of 99.25%. CNN with learning vector quantization (LVQ) was applied by Sardogan et al. [36] for Septoria leaf disease spot detection. Devi et al. [37] revealed that using GLCM features, specially trained over random forest classifier, can yield (plant disease detection) accuracy of 99%. Kirti et al. [28] also discussed the significance of improved segmentation, who performed black rot disease detection in Grape Plant (Vitis vinifera) leaves. SVM-based classification in [38] yields the highest accuracy of 94.1%. Despite the claim to have higher accuracy with EfficientNet (99.8%) and DenseNet (99.75%), Srinidhi et al. [39] could not address non-ROI feature learning for Apple plant leaf disease detection. Though, to improve segmentation, the authors suggested using Canny edge detection and blurring and flipping; yet, it could not resolve major at-hand problems in the real world. A similar limitation was observed in the MobileNet-v2-based plant disease detection system [41]. Pardede et al. [40] developed an unsupervised convolutional auto-encoder to perform feature learning and classification for plant disease detection. However, the authors found it challenging to retain ROI-specific features and suitability. Wahab et al. [42] developed K-Means segmented SVM for Chilli plant disease detection and classification. Bose et al. [43] developed a deep learning ensemble model for Hemp disease detection and classification. They claimed their model to have an accuracy of 98%, yet, their approach to using the whole image as input for feature extraction questions its generalizability.

3. Problem Formulation

Vision-based medicinal plant disease detection systems can be vital for non-invasive prohibitory solutions. Yet, the complex and non-linear Spatio-temporal features make accurate disease spot (say, ROI) detection challenging. The presence of disease spots and diversity of leaf-related diseases on the different non-linear surfaces makes disease type assessment difficult. Moreover, the diversity of disease types and corresponding Spatio-temporal textural diversity over non-linear (say, varying color, shape, size and gradient, etc.) surfaces make plant disease detection a mammoth task. Unlike other plant disease detection such as apple plant disease detection, cardamom plant disease detection, grapes plant, paddy, etc., where the leaf sizes and shapes are broad, flat, and linear, almost the majority of the medicinal plants possess small and densely distributed leaves with aforesaid Spatio-temporal textural and local feature differences. It makes ROI segmentation and corresponding feature extraction difficult.

On the other hand, observing samples of the medicinal plants and their allied disease diversity, it can be found that the location, severity, and Spatio-temporal presence of disease elements are relatively small compared to the background image components neighboring non-ROI spaces, etc. In this case, extracting ROI and non-ROI features for training a complete input space can impact learning efficacy and classification results. It can severely give rise to the false-positive performance problem and hence inappropriate for real-time purposes. Such issues can severely impact the performance of the deep -learning-based methods until the images are processed for pre-processing and ROI-specific resizing. Doing so even violates the expectation or motive of deep learning methods that advocate removing pre-processing tasks and learning over the overall image to make the classification. These inferences reveal that a vision-based medicinal plant disease detection and classification system can be effective when it possesses ROI-specific Spatio-temporal features for learning and classification. Learning ROI-specific Spatio-temporal features can yield more accurate classification results; however, the success of this approach's roots in the fact that how effective medicinal plant disease (here onwards called MPD) specific ROI-region(s) segmentation has been done and how significant Spatio-temporal features have been extracted to perform machine learning-driven accurate MPD classification. Most existing plants that detect the disease and classification methods have applied wavelet analysis, local binary patterns, and varied types of deep learning models like CNN, GAN, ImageNet, DenseNet, ResNet, etc. However, these methods use a complete plant leaf's image to perform feature extraction and hence can impose irrelevant feature space or attributes, which can hinder the classification efficacy. Despite deep feature presence learning over the non-ROI feature space can force the model to undergo skewed learning and hence can result in false-positive performance. Training to extract feature(s) over ROI-specific textures is necessary to alleviate such issues. As a result, it can improve the feature's intrinsic information to achieve higher prediction accuracy and reliability.

In sync with above stated key issues and allied scopes, in this work, the emphasis is made on improving almost all steps, including pre-processing, ROI-specific MPD detection and segmentation, ROI-specific Spatio-temporal (textural) statistical feature (STTF) extraction, followed by Levenberg Marquardt ANN (LM-ANN) learning for plant disease detection and classification. In this work, different medicinal plant leaf samples representing the normal as well as diseased (leaf) samples were obtained from the different plants, including Amaranthus Viridis (Arive-Dantu), Basella Alba (Basale), Brassica Juncea (Indian Mustard), Citrus Limon (Lemon), Hibiscus Rosa-Sinensis, Mentha (Mint), Moringa Oleifera (Drumstick), Murraya Koenigii (Curry), Ocimum Tenuiflorum (Tulsi), Piper Betle (Betel), Santalum Album (Sandalwood), Syzygium Cumini (Jamun), and Tabernaemontana Divaricata (Crape Jasmine). Recalling that the feature diversity (say, morphological as well as Spatio-temporal diversity) of disease regions limits most of the classical systems, a large set of medicinal plant images can be considered. Moreover, to include Spatio-temporal diversity, many leaves' images with different colors, shapes, sizes, and ROI-gradient or distribution (say, disease or affected textural region on leaves) can be employed. To further improve input images and Spatio-temporal (say, local quality), pre-processing techniques like histogram equalization, contrast equalization, medium filtering, Z-score normalization, etc., can be employed. It can help retrieve the uniform local conditions for each image for ROI segmentation. Towards ROI-specific feature extraction, heuristic methods like the Firefly algorithm can be applied with FCM clustering, which can perform accurate ROI-specific segmentation even over the non-linear surface. Noticeably, in the FFCM model, the

Firefly algorithm can be applied to improve iterative FCM centroid estimation that eventually can improve clustering performance to get accurate ROI even by reducing the cost of connected component analysis tasks. Unlike classical segmented binary image learning-based methods, ROI-specific textural images can yield superior performance. Considering this, the segmented ROI regions can be transformed into RGB space images by performing image overlapping or RGB-channel multiplication with the segmented ROI image and the original RGB image. Once the ROI-specific textural image is obtained in color space, different STTF features can be extracted, including GLCM features. This research focuses on assessing the efficacy of the hybrid GLCM feature encompassing contrast, homogeneity, energy, entropy, correlation, standard deviation, variance, mean, Kurtosis, and Skewness to perform medicinal plant disease detection and classification. About the combined features (from GLCM), using a non-linear pattern learning model such as adaptive neuro-computing methods can be superior for image classification. In this reference, this work proposes to use LM-ANN, a non-linear neuro-computing model with the ability to act as the steepest gradient, as well as gradient descent learning can be applied to perform medicinal image classification. In this manner, the proposed model can classify each input sample as a normal or diseased image, which can be vital for real-time plant health monitoring tasks. The proposed model can also be effective for industrial purposes where it can help identify or separate healthy and diseased plants to make optimal manufacturing decisions. Thus, a few research questions have been defined in sync with the above-stated research problem and allied scopes. These questions are:

RQ1: Can the use of the Heuristically driven clustering model be effective in segmenting non-linear disease components segmentation in medicinal plants?

RQ2: Can using ROI-Specific textural information with GLCM features be effective toward an accurate and reliable medicinal plant disease detection system?

RQ3: Can the amalgamation of ROI-specific GLCM features encompassing contrast, homogeneity, energy, entropy, correlation, standard deviation, variance, and the mean be effective towards accurate medicinal plant disease detection and classification?

RQ4: Can multiple GLCM features with LM-ANN yield an accurate and reliable vision-based solution for medicinal plant disease detection and classification?

4. System Model

The key steps employed in the proposed work are given as follows:

Step-1 Data Acquisition,
Step-2 Pre-processing,
Step-3 Heuristic-driven ROI specific Segmentation,
Step-4 ROI-specific color space GLCM Feature Extraction,
and Step-5 Classification and Performance assessment.

The overall proposed method and allied algorithmic innovations are depicted in Fig. 1

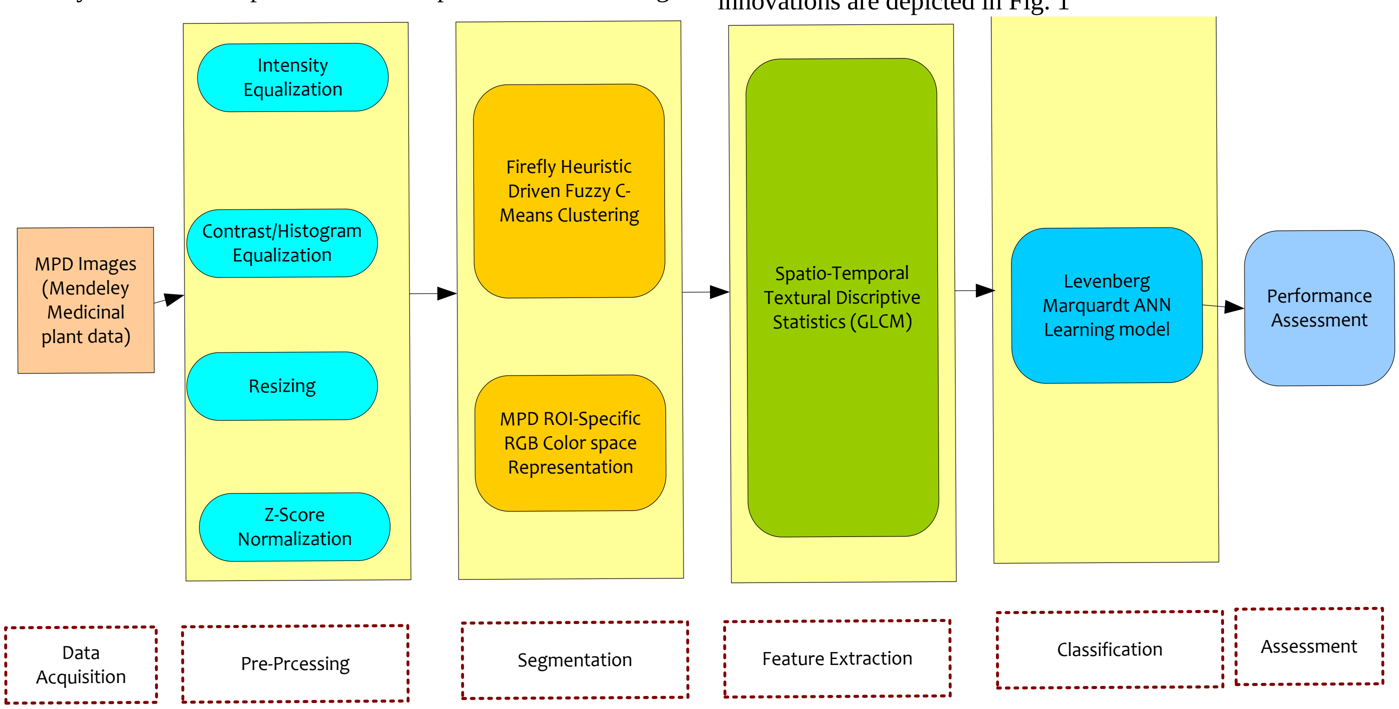


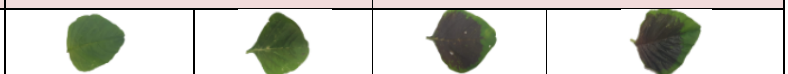
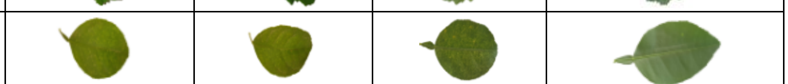
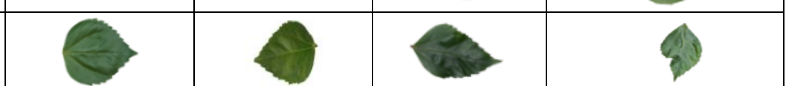
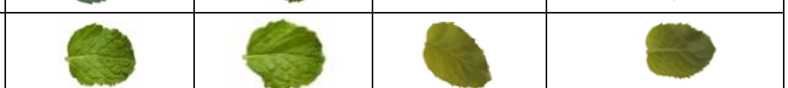
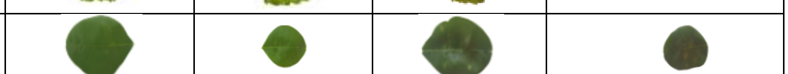
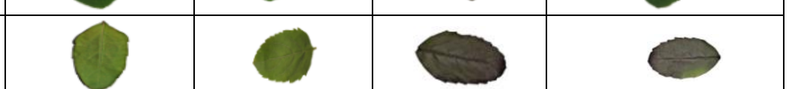
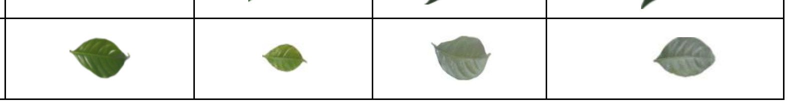
Fig. 1 Evolutionary computing driven ROI-Specific STTFF feature learning model for medicinal plant disease detection and classification

A detailed discussion of the overall proposed model is given in the subsequent sections.

4.1. Data Acquisition

Unlike classical plant disease detection problems, this research mainly considered the medicinal plant's disease detection and classification. Undeniably, the leaf's color remains almost the same in major medicinal or non-medicinal plants; however, local textural and allied Spatio-temporal features often vary. For instance, the Spatio-temporal features of paddy leaves, tomato leaves, etc., are quite different than Syzygium Cumini (Jamun). It is because the leaves of paddy or rice plants often used to be linear with long structure and unidirectional textural flow. Medicinal plants like Hemp, Amaranthus Viridis, Moringa Oleifera, Hibiscus Rosa-Sinensis, Santalum Album, etc. are non-linearly distributed in different directions. Numerous medicinal plants have filamentous and non-linear bone lines spread across the plant. It differentiates medicinal plants from non-medicinal plants. Though medicinal plants are merely 18-24% of the plant species on earth, the inter-textural similarity can't be avoided. However, exploring more significant and frequently used medicinal plants, a total of 13- medicinal plants data were obtained for the study; in this work, considered normal leaves as well as disease leaves (say, diseased plants samples) for the key medicinal plant named Amaranthus Viridis (Arive-Dantu), Basella Alba (Basale), Brassica Juncea (Indian Mustard), Citrus Limon (Lemon), Hibiscus Rosa-Sinensis, Mentha (Mint), Moringa Oleifera (Drumstick), Murraya Koenigii (Curry), Ocimum Tenuiflorum (Tulsi), Piper Betle (Betel), Santalum Album (Sandalwood), Syzygium Cumini (Jamun), and Tabernaemontana Divaricata (Crape Jasmine). 862 leaf images from 13-different plant types were collected from [44][https://data.mendeley.com/datasets/nntj2v3n5]. A snippet of the data considered is given in Table I.

Table 1. Examples of the different medicinal normal and diseased plant leaves

Medicinal Plant Types	Normal Plant leaves		Diseased plant leaves	
Amaranthus Viridis (Arive-Dantu)				
Basella Alba (Basale)				
Brassica Juncea (Indian Mustard)				
Citrus Limon (Lemon)				
Hibiscus Rosa-Sinensis				
Mentha (Mint)				
Moringa Oleifera (Drumstick)				
Murraya Koenigii (Curry)				
Ocimum Tenuiflorum (Tulsi)				
Piper Betle (Betel)				
Santalum Album (Sandalwood)				
Syzygium Cumini (Jamun)				
Tabernaemontana Divaricata (Crape Jasmine)				

The images above clearly show the variation in Spatio-temporal textural features between the normal medicinal plant leaves and the diseased leaves. Though in this work, the plant leaves are already processed in such a manner that the non-ROI spaces are less; however, there are several samples, including the one in Amaranthus Viridis (Arive-Dantu), where the difference between the ROI and non-ROI feature space can easily be visualized, segmentation seems to be significant. Thus, once obtaining the set of 862 images representing the normal and diseased plant leaves from the different medicinal plants, pre-processing was performed. A snippet of the pre-processing methods employed in this work is given in the subsequent section.

4.2. Preprocessing

Observing the sample images (Table I), it can easily be found that there exists severe change in resolution, shape, and sizes, and other Spatio-temporal differences between the normal and the diseased plant leaves. In sync with this fact, to improve feature learning efficiency, the input images were first processed for image resizing, where each input image was resized to 296×400 pixel dimensions. Subsequently, each image was converted into gray-level feature space using the RGB2Gray function, followed by image histogram equalization that intends to reduce the impact of change in illumination over the region of observation (ROO). Moreover, it equalizes overall pixel level and allied resolution to improve further feature extraction. To further alleviate any possible overfitting, local minima, and convergence-related issues, by applying Z-Score normalization over each input image. This work achieved normalization by applying mean and standard deviation values. Noticeably, Z-score signifies the variation of scaling that represents the number of standard deviations away from the mean value. In this manner, the Z-score method helps in guaranteeing that the feature distributions possess mean=0 and a standard deviation of 1. Mathematically, Z-score for a point x is obtained as per (1).

$$x^i = \frac{(x-\mu)}{\sigma} \tag{1}$$

In (1), x represents the mean, while the standard deviation value is given by σ. Now, once performing preprocessing tasks over each input image, it was processed for heuristic-driven ROI-specific segmentation. A detailed discussion of the proposed segmentation model is given in the subsequent section.

4.3. Heuristic FFCM driven ROI segmentation

Though the images depicted in Table I represent uniform color and textural differences between the healthy plant leaf and the diseased leaves; however, there are numerous samples where the disease regions are specifically different than the normal images, and even a single image possesses both normal textural cues as well as diseased Spatio-temporal spaces. On the other hand, to ensure a cost-efficient vision-based automated solution, to cope with the real-world condition where the vision-based method requires segmenting plant region and dropping the non-ROI spaces (say, background). This work develops a highly robust heuristic-driven ROI segmentation model to cope with such demands. Observing key pieces of literature in Section II, it can easily be found that improving segmentation to retain ROI-specific textural regions can enable a more (intrinsically improved) efficient feature vector for learning. Unlike classical static threshold-based or morphology-based segmentation methods to cope with ROI non-linearity and change in patterns, the proposed model has applied a clustering-based method. The Fuzzy C-Means method has been applied to perform ROI segmentation. However, recalling the key limitation of clustering methods, i.e., centroid optimality, the proposed model applies a heuristic method that primarily functions for cluster optimization and segmentation. In sync with a lightweight and computationally efficient heuristic-based FCM, this research applied the Firefly algorithm that tunes centroid value for FCM and even assists in optimizing clusters. The Firefly algorithm not only intends to enable swift and accurate ROI segmentation; but also alleviates the need for a manual seed-point definition that eventually makes the overall process automated and efficient. A detailed discussion of the overall proposed FFCM-driven segmentation toward medicinal plant disease detection is given in the subsequent sections.

4.3.1. Plant Disease Spot Localization

As discussed in previous sections, the proposed method applied cluster-based segmentation to cope with ROI-specific segmentation over non-linear plant leaf morphology and disease spot non-linearity. This work applied the FCM clustering algorithm over input image(s) that clusters distributed pixels over ROO to retain ROI-specific regions while dropping background or insignificant image components. The proposed FCM method intends to cluster spot regions possessing similar Spatio-temporal characteristics or similarities to achieve it. Moreover, it performs ROI segmentation by reducing the intra-cluster distance, achieving superior and more accurate ROI detection. Additionally, the clustering approach alleviates the need for seed-point definition, which is further improved by applying a heuristic model named Firefly algorithm. In the proposed method, the Firefly algorithm helped optimize or tun the centroid information, making clustering over non-linear feature space faster, more accurate, and even automatic. Before discussing the proposed FFCM-driven ROI (i.e., disease spot) segmentation, a brief of the FCM algorithm is given as follows.

4.3.2. Fuzzy C-Means Clustering Method

Consider x_i Be the pixels of the input medicinal plant leave's image. Now, the key motive of FCM is to group n the number of pixels distributed across the input leaf image, representing (2).

$$x = \{x_1, x_2, x_3, \dots, x_n\} \tag{2}$$

In (2), $x_{i \in d}$ refers to the feature vector encompassing d real-valued estimations signifying x_i The feature element of the input image's pattern. Functionally, the Fuzzy concept enables FCM to apply certain membership functions that eventually enhances clustering decision over unannotated non-linear feature space$x_{i \in d}$. In addition, the ability of FCM to enable feature elements or instances participating in multiple clusters and label them accordingly makes FCM more efficient in achieving higher accuracy, even over non-linear feature space or varying Spatio-temporal feature conditions. It makes the proposed model more efficient in coping with ROI segmentation over medicinal plant disease data, where the edges and ROI-specific textural gradients are varying and highly complex. Typically, FCM methods are broadly classified into two types; soft-FCM and hard-FCM, where the latter variant divides input image x into multiple groups$(say, G_1, G_2, G_3 \ldots, G_c)$. Here, one pattern can belong to only one cluster; thus, each pattern is labelled as a specific non-overlapping cluster. Unlike hard-FCM, in the soft-FCM method, a feature element or pixel-instance x can belong to multiple clusters; however, for an ROI-specific learning case, there is a highly complex feature non-linearity and textural gradient. In medicinal plant disease cases, a single plant leaf can have multiple ROI patches or spots even with gradient variation, color, shape and size differences, etc. About the at-hand problem, soft-FCM can be more appropriate. In this case, the clustering results are obtained as the membership matrix, also known as the Fuzzy Partition Matrix, given as (3).

$$U = \left[u_{ij}\right]_{(c,n)} \tag{3}$$

In this work, the function mentioned above (3) for (2) is estimated using equation (4).

$$M_{FCN} = \left\{ u \in R^{c,n} \middle| \sum_{j=1}^{c} U_{ij}, 0 < \sum_{j=1}^{n} U_{tj<n} \right\} \tag{4}$$

In (1), $u_{ij} \in [0,1]$ refers to the Fuzzy membership function for $i-th$pattern in $j-$th cluster, where it follows the pre-condition $U_{ij} \in [0,1]$in sync with conditions like $1 \leq j \leq c$ and $1 \leq i \leq n$. Here, FCM has been applied over complete pixel instances across an image that minimizes an objective function to form an accurate cluster(s) iteratively. Mathematically, it is derived as (5).

$$J_m = \sum_{j=1}^{c} \sum_{i=1}^{n} u_{ij}^{m} \left\| x_i - v_j \right\| \tag{5}$$

In (5), $\left\{v_j\right\}_{j=1}^{c} \|.\|$ Refers to the centroid of the cluster. Typically, in the FCM algorithm, the centroid is obtained as the inner-product norm from x_i To the $j-th$ cluster centers. In this work, the fuzzy membership function represents the level of the pattern's fuzziness –the classification results by employing a weight parameter $m \in [1, \infty]$. Moreover, it applies the following sequential steps to perform clustering.

- Initiate input pixel's clustering by introducing an initial (say, random) cluster centroid c.
- Estimate the membership metrics for each pixel instance available in each cluster.
- Update the centroid by performing objective function minimization iteratively.
- Estimate membership function repeatedly (6) and update the centroid until there are stable or repeating centroid values over iterations. In the proposed work, the fuzzy membership value for each pixel is estimated as per (6).

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|} \right)^{\frac{2}{m-1}}} \tag{6}$$

The classical FCM models applied (7) to perform centroid estimation and update.

$$v_j = \frac{\sum_{i=1}^{n} u_{ij}^{m} . x_i}{\sum_{i=1}^{n} u_{ij}^{m}} \tag{7}$$

Despite numerous acknowledged uses of FCM methods, its efficacy over the non-linear feature specie remains suspicious [15]. In this paper, it is found that the proposed heuristic model optimizes clustering efficacy to achieve ROI-segmentation even over non-linear or complex feature space to alleviate this problem. Considering computationally lightweight and efficient heuristic towards FCM optimization, the Firefly algorithm was applied in this work. A detailed discussion of the proposed Firefly model and its implementation with FCM is given in the subsequent section.

4.3.3. Firefly Algorithm-Based FCM

The ability to perform adaptive multi-group clustering makes FCM a potential candidate for at hand ROI-segmentation task, especially when the input is images with unclear ROI boundaries and varying morphology. Despite such robustness, the high reliance on membership function, and centroid value, it often remains suspicious. Applying the Firefly algorithm improves centroid assignment while minimizing the cost function iteratively to address such limitations. The efficacy of the Firefly algorithm to yield expected clustering result even with lower iterations make it efficient towards hand ROI-segmentation. In this proposed model, the Firefly algorithm reduces the inter-cluster distance to help clustering optimization. Here, the proposed clustering optimization measure was developed in sync with the Firefly's behavior, especially light flashing and brightness-based mobility behavior. Thus, it employs light-generation behavior as a stimulating signal that helps attract other Fireflies existing in nearby locations. In this reference, assuming each input image pixel as an individual Firefly member, it intends to attract other pixels or the Fireflies based on corresponding brightness behavior and allied sensitivity. In this manner, the proposed Firefly-based FCM model, here onwards, called FFCM, helps cluster the input feature instances as ROI and non-ROI space without involving human seed-point definition like in other region growing based segmentation methods. It makes the proposed model automated. Here, cluster optimization using FFCM enables multiple cluster generation and can provide a broader feature space about the different plant disease spots on a single leave. It can help in improving the feature extraction and hence learning. In sync with the proposed FFCM-driven ROI segmentation task, a proposed heuristic model follows the following three conditions to perform clustering and its optimization.

Rule-1: Fireflies are the unisexual living being and, therefore, can be attracted to the other Firefly, irrespective of gender.

Rule-2: Fireflies influence other Firefly based on their illumination intensity. In this process, the Fireflies influence other Fireflies in reverse order. In other words, a Firefly with higher brightness attracts other Fireflies with lower brightness. On the contrary, Fireflies possessing higher inter-entity distance influence lesser than the other nearby Firefly. Mathematically, the attraction model functions in sync with the following condition.

$$I \propto \frac{1}{r^2} \tag{8}$$

In (8), r^2refers to the square of the inter-Firefly (or inter-instance) distance. In this manner, a higher value of r^2 signifies inferior attractiveness β . In case a Firefly (representing a single entity or pixel) with no nearby Firefly possessing higher brightness moves towards the one possessing higher intensity.

Rule-3: A Firefly with the highest brightness would not be attracted and remains moving randomly.

In the FFCM model, the Firefly algorithm calculates the suitable counts of centroids in each input medicinal plant image to segment Roi-specific region(s). The proposed model intends to calculate and update the centroid in $N-$dimensional search space. Here, it is performed by applying a correlation between the inter-instance distance and a defined objective function. To implement the Firefly algorithm, the proposed model initially distributes the population of Fireflies arbitrarily throughout the search space. Noticeably, each instance or pixel value is hypothesized to be the random population in this method. The proposed model employs two steps: estimating the intensity differences, also called the objective function. Here, Fireflies possessing either lower or higher illumination influence or attracts other Firefly possessing lower or higher illumination or brightness. This functional paradigm enables gathering the pixel elements possessing the same pattern to a centroid, which eventually helps cluster formation. Consider that the at-hand search space possesses n Fireflies while x_i Be the solution for an $i-th$ Firefly. Thus, the fitness function $f(x_i)$ Signifying the fitness value for x and allied brightness be I, defines the real location of $i-$th Firefly. The proposed model estimates Firefly's intensity as per (9).

$$I_i = f(x_i) 1 \leq i \leq n \tag{9}$$

Now, estimating the value of each Firefly's intensity (9), the proposed model starts swarm movement in which the Fireflies get attracted to the other Firefly based on the brightness. In other words, Fireflies attract other Fireflies, where the attractiveness of one member or element is directly proportional to the neighboring Firefly's intensity. Noticeably, each Firefly has a certain fixed attractiveness βthat primarily relies on the inter-element distance r_{ij} Exists in between the i and $j-th$ Firefly.

$$r_{ij} = \|x_i - x_j\| \tag{10}$$

$$\beta(r) = \beta_0 exp^{\{-\gamma d(i,j)^2\}} \tag{11}$$

In (11), $\beta_0$refers to the attractiveness, hypothesizing that the Fireflies are present at the same position signifying zero inter-instance distance (i.e., $r = 0$). The other parameter γ signifies the light absorption coefficient, hypothesizing that the $j-th$ Firefly has higher brightness than the $i-th$ Firefly. In sync with this condition, the $i-th$ Firefly moves toward $j-th$ Firefly. Here, the distance moved by Firefly is obtained as per (12). Here, $rand$ states a random number existing between 0 and 1.

$$x_i(t+1) = x_i(x_j - x_i) + \alpha(rand - 0.5) \tag{12}$$

Thus, the Firefly algorithm first calculates the suitable position of the Firefly, proving the optimal centroid value about the ROI region. The following equation (13) signifies the set of possible position vectors A, and a_i refers to the centroid where $a_i \in A$. In (13), the parameter s_i signifies the centroid over feature space $d\{a_1, a_2, \dots, a_d\}$. Here, the value of the centroid is updated iteratively to improve FCM for better clustering. The process of centroid update continues till all solutions have unchanging values.

$$A = (s_1 \{a_1, a_2, \dots, a_d\}, s_2\{a_1, a_2, \dots, a_d\}, s_3 \{a_1, a_2, \dots, a_d\} \tag{13}$$

The proposed model applied 60 Fireflies (say, the initial population) for simulation. Moreover, the total number of generations was fixed at 100. In the proposed work, to achieve optimal clustering Firefly algorithm applies the Rosenbrock function. Here, the Rosenbrock function helps estimate the fitness value signifying the likelihood of a pixel becoming the centroid. Regarding the Firefly algorithm, an element with higher brightness is assumed to have a low fitness value, enabling other Fireflies to get attracted and thus control the movement. At the same time, assessing two distinct Fireflies a and b, with b having higher brightness compared to the $a'th$ Firefly. Subsequently, a moves in the direction of b. Firefly model being an iterative method, continues over a fixed iteration and therefore updates the solution with an updated population $a' = a'_1, a'_2, a'_{31}, \dots, a'_N$, by applying the objective function $f(a')$ (here, Rosenbrock function). As stated, the proposed model applied the Rosenbrock function, a well-known non-convex function that is employed to solve convexity problem optimization. The proposed model applies the Rosenbrock valley function where the global minima exist within a narrow, long, and parabolic-shaped flat valley. Practically, estimating the valley, as the mentioned earlier region is a difficult task, and this is because not all solutions possess the unit value (i.e., 1). (14).

$$f(x,y) = (a-x)^2 + b(y-x^2)^2 \qquad (14)$$

To achieve global minima values at $(x,y) = (a,a^2)$The proposed objective function model needs to satisfy the condition defined as $f(x,y) = 0$. In function, the Rosenbrock function is defined in such a manner that it fulfills the condition given as $a = 1$ and $b = 100$. On the other hand, with $a = 0$ the proposed Rosenbrock function results in a symmetric function and minimum at the origin. It found that applying a multidimensional generalization approach with the Rosenbrock function achieves global minima. Mathematically, it is defined as (15).

$$f(x) = \sum_{i=1}^{N-1} 100(x_{i+1} - x_i^2)^2 (1-x_i)^2 \qquad (15)$$

In the above-derived function (15), the array $X = [x_1, x_2, \dots, x_N] \in \mathbb{R}^N$ possesses unit minima at $N = 3\ (at(1,1,1))$. Moreover, it retains two minima following the condition as $4 \leq N \leq 7$. This approach accomplishes targeted global minima possessing all ones, particularly when the local minima exist near $(x_1, x_2, \dots, x_N) = (-1,1,\dots,1)$. In the proposed model, the condition mentioned above was achieved by assigning the function's gradient as zero. It becomes possible only when the function derived (15) remains a rational function of x. The proposed model applied FFCM to segment the ROI-specific regions over each input medicinal plant leaf image. Now, once performing segmentation of the ROI-specific region, it was processed for feature extraction. In this work, different GLCM features characterizing the different Spatio-temporal textural features were obtained from each input image and allied segmented ROI regions.

4.4. ROI-specific color space GLCM Feature Extraction

In most of the existing segmentation-based feature extraction models, segmented binary images are processed for feature extraction. However, recalling that the textural features of each medicinal input image (Table I) used to be non-linear and complex, unlike existing approaches in the proposed model, converted the binary image into equivalent ROI-specific color feature space. This method converts the segmented ROI-specific region into R*G*B color space image. In this manner, the ROI-specific segmented region is converted into an equivalent color-space region, which is subsequently processed for the textural feature extraction using GLCM methods. GLCM is a statistical feature model that measures the likelihood of the pixel's grayscale values over an input medicinal plant image. In sync with the statistical characteristics, the grayscale values exist between the disease spot regions or the ROI pixels and corresponding neighboring pixels. The GLCM method extracts the high-dimensional statistical features, including entropy, energy, contrast, variance, mean, etc. This work shows that the different STTF features can be distributed over the ROI-specific regions (in images). Therefore different STTF features were obtained over the ROI regions, which were later amalgamated to generate a composite feature vector for learning and classification. Here, the extracted STTF features were represented as a matrix signifying the matrix of pixel intensities $I(x,y)$. Thus, the estimation of the probability matrix $P_{i,j}$For each input, a medicinal image was obtained. Noticeably, the probability matrix, as stated above, represented the intensity disparity between the image pixel i and j, which was later employed to detect motion pattern(s). Here, gray-scale signifies the pair relation in one direction, and thus estimating the gray-scale information, a matrix signifying the relationship matrix was obtained. In this work, a symmetric matrix S was obtained by adding the gray-scale information with the corresponding transpose value. It, as a result, estimated the combined association in one direction. In the proposed work, at first, the relationship matrix, often called association matrix S was normalized as per (16) and finally estimated the probability matrix P.

$$P_{i,j} = \frac{S_{i,j}}{\sum_{i,j=0}^{N-1} S_{i,j}} \qquad (16)$$

Once obtaining the probability matrix values $P_{i,j}$ Its examined different Spatio-temporal textural features, representing the low-level textural signature. In the proposed model, a total of 10 different GLCM features were extracted. These features are from (a) to (g)

Here, the key motive behind applying GLCM mentioned above features was to ensure maximum possible STTF feature retention in different dimensions to enable superior learning towards plant disease detection and classification. A brief of the features extracted is given in the subsequent sections.

4.4.1. Contrast

About the STTF feature definition, contrast is defined as the change in the value of the grayscale parameter over an input medicinal plant image (here, ROI-specific RGB image component). About the above-derived probability matrix (16), the pixel pairs exist as diagonal elements in $P_{i,j}$(16) signifies significant disparity in contrast or its allied grayscale values. For at hand medicinal plant disease detection problem, the texture contrast signifies the overall changes in the local pixel intensities throughout the ROI-segmented areas (in RGB feature space). Typically, the irregularity present over the

ROI-specific regions in the Spatio-temporal texture can be assessed by exhibiting statistical measurement and allied (textural) continuity analysis. This work found that estimated contrast value over the ROI-specific color space region by applying equation (21).

4.4.2. Energy

To assess energy distribution throughout the ROI-specific RGB space regions, calculated estimated angular second moment (ASM) value that estimates the rotational acceleration over the Spatio-temporal input space. Mathematically, estimated ASM is observed using (17). Typically, the value of angular second moment increases uniformly across the gray-scale values throughout the ROI-specific RGB color space.

$$ASM = \sum_{i,j=0}^{N-1} {P_{i,j}}^2 \tag{17}$$

Once the ASM values (17) were estimated, the energy value was measured as per (18).

$$ENR = \sqrt{ASM_{i,j}} \tag{18}$$

4.4.3. Entropy

Entropy, also called pixel-disturbances, shows how non-linearly the gray-scale values are distributed across the ROI-specific RGB color space. In general, the value of STTF entropy increases with an increase in non-linear pixel distribution. This work obtained estimated entropy for ROI-specific regions using (19).

$$ENT = \sum_{i,j=0}^{N-1} P_{i,j}\left(-lnP_{i,j}\right) \tag{19}$$

4.4.4. Homogeneity

Homogeneity, also defined as the Inverse Different Moment (IDM), entails that higher homogeneity is in sync with lower contrast. In other words, the higher the contrast, the lower the homogeneity. Mathematically, applying equation (20) to estimate the homogeneity distribution across the ROI-specific RGB textural space.

$$HOM = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{20}$$

Low contrast results in higher homogeneity in sync with the linear magnitude distribution across ROI-specific regions. Therefore, mathematically using (21) to estimate the contrast over the input ROI-specific region pr image.

$$CONT = \sum_{i,j=0}^{N-1} P_{i,j}\,(i-j)^2 \tag{21}$$

4.4.5. Correlation

Correlation represents a feature signifying descriptive statistics across an image region or grid. In addition to the correlation information, we estimated three other descriptive statistics parameters: mean, standard deviation, and variance. To estimate the mean value, it examined the symmetric features of the probability matrix (16) and thus obtained two distinct mean values which are the same. Mathematically,

$$\mu_i = \sum_{i,j}^{N-1} i\left(P_{i,j}\right) \tag{22}$$

$$\mu_j = \sum_{i,j}^{N-1} j\left(P_{i,j}\right) \tag{23}$$

The above-derived statistical mean values (22) and (23) were later used to estimate variance and standard deviation as per (24) and (25), respectively.

$$\sigma_i^2 = \sum_{i,j}^{N-1} P_{i,j}(i-\mu_i)^2 \tag{24}$$

$$\sigma_i = \sqrt{\sigma_i^2} \tag{25}$$

$$\sigma_j = \sqrt{\sigma_j^2}$$

Once estimating mean and variance values, derives correlation information using (26).

$$CORR = \sum_{i,j}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \tag{26}$$

4.4.6. Skewness

The above-stated STTF features discussed the disruptive statistical statistics along with the gray-level values probability statistics. In addition to the above-stated feature sets, directional or orientational features were extracted in this research to train the model. In this reference, skewness and Kurtosis values which are the symmetrical features, were obtained. The skewness of the probability matrix (16) signifies the lack of symmetry. Skewness is characterized by shade feature, in which a high cluster shade indicates asymmetrical nature. Mathematically, skewness is estimated as per (27).

$$SKEW = \sum_{i,j}^{N-1} P_{i,j}\left(i-\mu_i+j-\mu_j\right)^4 \tag{27}$$

4.4.7. Kurtosis

In addition to the Skewness feature, Kurtosis (KURT) was obtained in this work, signifying ‘peakedness’ of the Gray-scale value distribution across the ROI-specific color space. The higher value of Kurtosis signifies that the magnitude of the feature distribution is primarily strenuous towards the tail(s) in comparison to (towards) the mean value.

On the other hand, the lower kurtosis signifies that the magnitude of feature distribution remains strenuous towards the spike, which is nearer to the mean value. In this manner, its found Kurtosis distribution across the ROI-specific color textural region. Once estimating the overall features as discussed above, it was found that the performed horizontal concatenation yields a cumulative STTF feature vector, which is obtained as per (28).

$$STTF\_GLCM_{Feat} = Conc(CONT, ENE, ENT, HOM, CORR, Mean, Var, STD, Kur, Skw \quad (28)$$

Now, once estimating the composite feature vector (i.e., $STTF\_GLCM_{Feat}$), we projected it for feature learning and classification.

4.5. LM-ANN Based Classification

Several machine learning models have been developed for classification in the last few years. However, learning over non-linear feature space, especially in frequency domain analysis and image processing problems, remains challenging. However, neuro-computing or neural network methods have distinct efficacy among the major machine learning methods. Undenibaly, ANN is one of the most used neuro-computing models in different classification problems, including image processing and allied classification tasks. However, learning over non-linear unsupervised feature instances often remained challenging for ANNs. In sync with enhancement motives, different innovations were made in the past that gave rise to the different ANN variants, including ANN-Steepest Descent (ANN-SD), ANN-Gradient Descent (AN-GD), ANN-with adaptive learning (ANN-GDX), ANN-RBF and ANN-Levenberg Marquardt (ANN-LM). However, the adaptive learning capability of ANN-LM makes it superior to other variants. Functionally, LM-ANN can adapt to both ANN-SD and ANN-GD, making weight tuning fast, more accurate, and hence more efficient for non-linear feature learning. Considering this fact, in this paper, ANN-LM was applied as a classifier to perform learning over the composite STTF feature vector (28) for medicinal plant disease detection and classification. This work examined two-class classification to classify each input image as a normal or a diseased medicinal plant. To perform two-class classification by designing ANN-LM with one input layer, one hidden layer, and one output layer. The extracted feature vectors were given as input to each neuron (at the input layer). To be noted, each of the feature elements (i.e., 10 features as discussed above; ($CONT, ENE, ENT, HOM, CORR, Mean, Var, STD, Kur, Skw$)) were given as distinct input to perform two-class classification. The ANN-LM model considered in this study is given in Fig. 2.

As depicted in Fig. 2, the proposed ANN-LM model applies multiple neurons encompassing each STTF GLCM feature. Here, the linear activation function is applied at the input layer. To retain lower computational overheads and weight estimation costs, consider ANN-LM with merely $N + 1$ hidden nodes, where N is the number of input nodes. To learn STTF GLCM features, the proposed ANN-LM method performs the error-minimization concept, which estimates error as the difference between the expected value and the observed output. The process of error-minimization continues iteratively until it yields a minimum or near zero error condition (Fig. 2). Once reaching the zero-error condition, it classifies each input image as the normal image or the medicinal diseased image sample. In function, with linear activation function, the proposed ANN-LM model generates output same as the input, signifying, $\mathrm{O_o} = \mathrm{I_i}$ (Fig. 2). The hidden layer's output is inputted to the output layer that applies the Sigmoid function (29) to get the expected result $\mathrm{O_h}$. In (26), the variable I_h states the hidden layer's input. Functionally, it is defined as $Y' = f(W, X)$ where Y' states the output vector, while X and W indicate the input and the weight values, correspondingly. by applying mean square error as the error model (27). In (30), y represents the observed value, while $\mathrm{y_i'}$ States the expected value.

$$O_h = \frac{1}{1 + e^{-I_h}} \quad (29)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i' - y_i\right)^2 \quad (30)$$

Though the above-stated method is often used in all ANN variants; however, unlike ANN-SD or ANN-GD, ANN-LM exhibits localization of the minimum value of the multivariate function, called Sum of Squares (SoS) of the non-linear real-valued functions. It, as a result, makes the computation faster and apt for adaptive weight updates to learn over non-linear patterns. Unlike classical neuro-computing models, it also helps avoid convergence problem, which is quite often in major machine learning algorithms. It makes it suitable for large and non-linear features. Moreover, its ability to perform ANN-SD and ANN-GD enables swift error minimization. ANN-LM applies (31) to perform weight updates.

$$W_{j+1} = W_j - \left(J_j^T J_j + \mu I\right)^{-1} J_{j^{e}j} \quad (31)$$

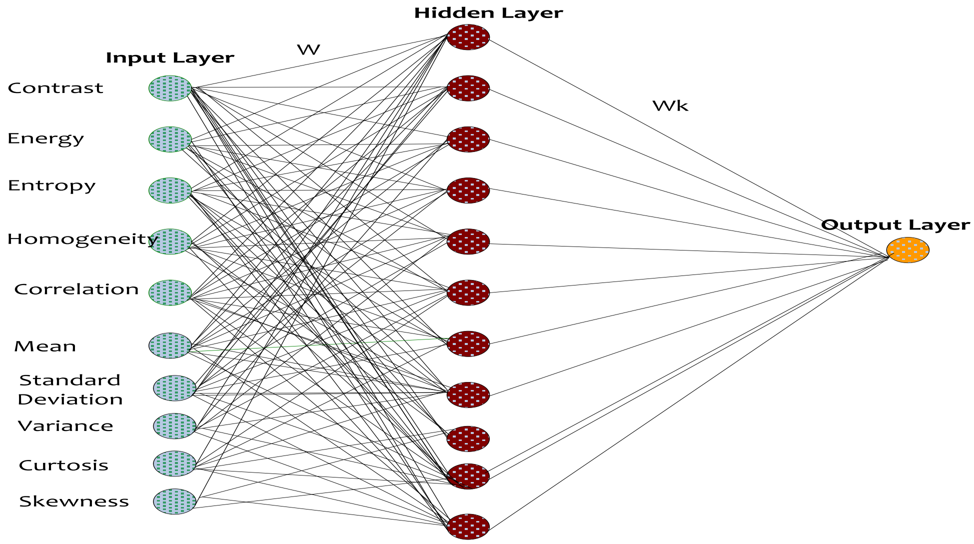


Fig. 2 ANN-LM architecture for STTF composite feature learning

In weight update (29), W_j represents the current weight while W_{j+1} signifies the updated weight. The variable I states the identity matrix. The Jacobian matrix J involved in (31) is given in (32). In (31), the parameter μ represents the combination coefficient, while the lower value of μ makes ANN-LM behave like ANN-GD. Similarly, the higher value of μ makes it function as ANN-SD. In (32), the parameter N refers to the total weight counts, while the total input feature is given by P. The output is given by M.

$$J = \begin{bmatrix} \frac{d}{dW_1}(E_{1,1}) & \frac{d}{dW_2}(E_{1,1}) & \cdots & \frac{d}{dW_N}(E_{1,1}) \\ \frac{d}{dW_1}(E_{1,2}) & \frac{d}{dW_2}(E_{1,2}) & \cdots & \frac{d}{dW_N}(E_{1,2}) \\ \vdots & \vdots & & \vdots \;\; \vdots \\ \frac{d}{dW_1}(E_{P,M}) & \frac{d}{dW_2}(E_{P,M}) & \cdots & \frac{d}{dW_N}(E_{P,M}) \end{bmatrix} \quad (32)$$

Thus, applying the above-stated ANN-LM model, it classifies each SQL query as the normal and diseased medicinal images and labels them as 0 and 1, respectively. Finally, the confusion metrics are obtained based on the classification results, which helps assess statistical performance efficacy in terms of accuracy, precision, recall, and F-Measure. A detailed discussion of the results obtained is given in the subsequent section.

5. Results and Discussion

Plant disease often results in reduced yield or productivity and loss of resources and time that can eventually impact the socio-economic endeavors of farmers and allied industries. Unlike typical non-medicinal plants, the scarcity of medicinal plants and their emerging significance in the pharmaceutical sector, herbal remedies, and numerous hygiene-oriented remedials have alarmed academia-industries to detect medicinal plant disease in the early stage to reduce detrimental impact. Though, in the past, many efforts have been made toward plant disease detection; however, most of the data available and even used in the research are broad in size with clearly edge-defined disease spots. In such a case, detecting ROI and learning ROI-specific features is easier than the one with unclear boundaries, non-linear textural distribution, and varying morphological traits. Moreover, very fewer research is conducted on medicinal plant disease detection where the plant's leaves can have diverse patterns with exceedingly high non-linear STTF characteristics. In addition, most existing approaches have applied complete plant images as input to perform feature extraction and learning, where learning over non-ROI regions or allied Spatio-temporal features can impact the system's overall efficacy. To alleviate this problem and train a machine learning model over ROI-specific textural STTF feature cues, this research work developed a robust Evolutionary Computing Driven ROI-Specific Spatio-Temporal Statistical Feature Learning Model for Medicinal Plant Disease Detection and Classification. More specifically, in this work, a total of 13-different kinds of medicinal plant leave samples encompassing both normal and diseased were considered. These medicinal plants were Amaranthus Viridis (Arive-Dantu), Basella Alba (Basale), Brassica Juncea (Indian Mustard), Citrus Limon (Lemon), Hibiscus Rosa-Sinensis, Mentha (Mint), Moringa Oleifera (Drumstick), Murraya Koenigii (Curry), Ocimum Tenuiflorum (Tulsi), Piper Betle (Betel), Santalum Album (Sandalwood), Syzygium Cumini (Jamun), and Tabernaemontana Divaricata (Crape Jasmine). Here, a total of 862 medicinal leaf samples obtained from [44] were considered as pre-processing is performed adaptive intensity equalization, histogram equalization, and Z-score normalization, which enabled more efficient segmentation and further feature extraction. It designed the proposed model as a segmentation and ROI-specific feature learning concept, and therefore a novel Firefly algorithm-based FCM (FFCM) was designed to perform disease spot segmentation. To implement Firefly-based FCM, the Rosenbrock function was applied as an objective function, where the initial number of populations was 60, while the initial β -value was assigned as 1. Now, once segmenting the ROI-specific regions, to regain the original textural distribution, segmented ROI was multiplied with R*G*B channels that eventually resulted from ROI-Specific textural input in R*G*B domain data. The RGB-specific textural input was processed for GLCM-based feature extraction, where 10 different GL-occurrence features were obtained from each input image. Its extracted features are Contrast, Energy, Entropy, Homogeneity, Correlation, Mean, Standard deviation, Variance, Kurtosis, and Skewness. Once extracting these 10-different features, it performed horizontal concatenation to generate a composite STTF feature vector, $STTF\_GLCM_{Feat}$. This feature vector was further processed for classification using ANN-LM, an adaptive neuro-computing model that classifies each input image as the normal or diseased medicinal image leaf. The proposed ANN-LM model found one input layer with 10 neurons, one hidden layer with 11 neurons (to retain low computational overheads and avoid local minima and convergence issues), and one output layer with binary output. The number of epochs was maintained at 500, where the learning rate was fixed at 0.01. Additionally, it was executed with a momentum value of 0.5 while the validation threshold was fixed at 10. The overall proposed model was developed using MATLAB 2019b development and simulation platform. The simulation was performed over a central processing unit armored with Microsoft Window operating system with i5 Intel processing unit, 8 GB RAM operating at 3.6 GHz processor.

To assess performance by applying statistical performance analysis in terms of accuracy, precision, recall, and F-measure. Noticeably, to achieve it, confusion metrics were obtained in terms of true positive (TP), true negative (TN), false positive (FP), and false-negative (FN). A snippet of the mathematical formulation employed towards the performance parameter derivation is given in Table 2.

Table 2. Performance Parameters

Parameter	Mathematical Expression
Accuracy	$\frac{(TN+TP)}{(TN+FN+FP+TP)}$
Precision	$\frac{TP}{(TP+FP)}$
Recall	$\frac{TP}{(TP+FN)}$
F-measure	$2.\frac{Recall.Precision}{Recall+Precision}$

The overall assessment of the proposed medicinal plant disease detection system was done in the form of two broad approaches: intra-model assessment and inter-model assessment. Here, an intra-model assessment was performed to examine the performance of the proposed medicinal plant disease detection model with three different machine learning approaches. In contrast, the inter-model assessment was performed to examine relative performance analysis with other existing state-of-the-art methods, such as [1-10]. The detailed discussion of the results obtained and allied inferences are given as follows:

5.1. Intra-Model assessment

This research mainly focused on improving ROI-specific feature learning to avoid any likelihood of non-ROI features in the training feature vector. In other words, it is intended to train the model only with the ROI-specific STTF features and hence applied FFCM to segment the ROI regions or the diseased spot region, which was later processed with R*G*B color space generation. In this reference, a question arises whether using FFCM (i.e., ROI-specific STTF feature learning) gives better results than the complete (or the whole) image learning. To achieve a justifiable answer for it, the simulated proposed model with and without FFCM. However, applying three different ANN variants, including ANN-GD, ANN-SD, ANN-RBF, and ANN-LM, performs feature training and classification. Here, the key motive was to assess whether the proposed ROI-specific STTF features can yield superior performance or not. In addition, it is wanted to identify the best performing neuro-computing model for at hand medicinal plant disease detection task. The simulation environment for intra-model assessment can be understood in Table 3.

Table 3. Simulation Test Case

Dataset	Features	Classification Model
[44]	Without FFCM (i.e., complete Image as input for STTF feature extraction)	ANN-GD
		ANN-SD
		ANN-RBF
		ANN-LM
	FFCM driven ROI-specific features (i.e., $STTF\_GLCM_{Feat}$. (28)	ANN-GD
		ANN-SD
		ANN-RBF
		ANN-LM

To examine the performance efficacy of the proposed model, it is found to be executed the algorithms with the different input samples (say, test samples), and the average performance over six random input test cases was obtained.

The average statistical performance outputs are given in Table 4.

Table 4. Intra-Model Performance characterization

Features	Classification	Accuracy (%)	Precision (%)	Recall (%)	F-Measure
Without FFCM (i.e., complete Image as input for STTF feature extraction)	ANN-GD	92.76	92.28	93.31	93.31
	ANN-SD	91.10	92.86	93.39	93.39
	ANN-RBF	92.17	94.47	95.25	94.85
	ANN-LM	**94.71**	**94.83**	**96.68**	**95.74**
FFCM driven ROI-specific features (i.e., $STTF\_GLCM_{Feat}$. (28)	ANN-GD	94.65	94.48	95.51	94.99
	ANN-SD	93.12	93.71	94.49	94.09
	ANN-RBF	95.40	96.66	95.57	96.11
	ANN-LM	**98.62**	**98.81**	**98.79**	**98.80**

Observing the simulation results, it can easily be found that in comparison to the original image-driven feature model, the proposed FFCM-driven ROI-specific STTF features have yielded higher accuracy (98.62%) and precision (98.81%), recall (98.79%) and F-Measure (0.988). Compared to the proposed ROI-specific STTF feature-based model, the existing approach (i.e., without ROI segmentation) could achieve the highest accuracy of 94.71%, precision, recall, and F-measure of 94.83%, 96.68%, and 0.9574, respectively. A similar performance pattern can be found in the different neuro-computing models (i.e., ANN-GD, ANN-SD, ANN-RBF, and ANN-LM). About the classifier-based performance analysis, these performance outcomes reveal that the proposed ANN-LM algorithm outperforms other neuro-computing variants. The graphical depiction of the relative performance between the proposed FFCM-driven ROI-segmentation-based plant disease detection model and without a segmentation-based model (i.e., the original input data [44] were processed for GLCM feature extraction). Noticeably, in sync with the relative neuro-computing model's performance for further analysis, the results obtained from ANN-LM were considered. In other words, the performance outputs mentioned in Fig. 3 have been obtained with ANN-LM-based classification. Now, observing the results (Fig. 3), it can be found that the proposed FFCM-driven ROI-specific STTF features yield almost 4% higher accuracy, precision, recall, and F-Measure. It confirms the superiority of the proposed FFCM-driven ROI-specific feature learning model for medicinal plant disease detection systems.

The result (Fig. 3) confirms that the proposed FFCM-driven ROI-specific texture feature with the ANN-LM learning model can achieve superior performance in medicinal plant disease detection and classification. Moreover, it confirms that using FFCM segmentation-driven ROI-specific features can yield superior performance in medicinal plant disease detection and classification.

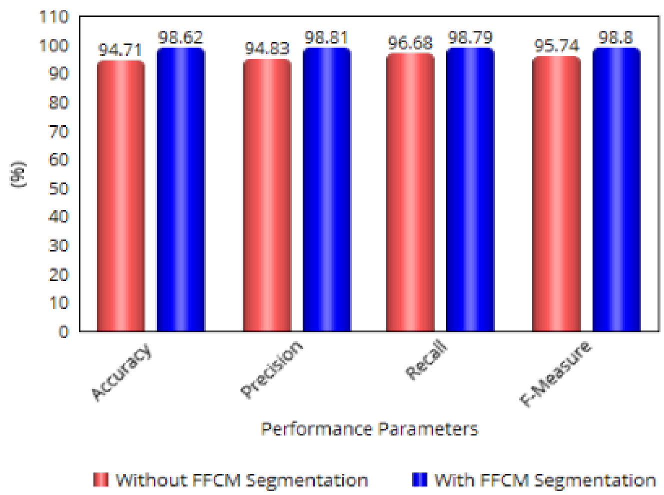


Fig. 3 Relative performance assessment (Intra-model characterization)

Thus, the research questionnaire defined as RQ1, RQ2, and RQ4 is found in affirmation. Considering it as the final results, it investigated to be performed inter-model performance assessment.

5.2. Inter-Model Assessment

In this section, the performance comparison of the proposed model is done with the other state-of-art methods. Considering that few efforts were made toward medicinal plant disease detection systems, a depth literature analysis was done. Exploring in-depth, it is identified three recent efforts where authors have considered medicinal plant leaves dataset to perform either plant classification or plant disease detection. Naeem et al. [1] focused on exploiting textural features to perform medicinal plant classification. The authors first performed seed intensity-based edge/line detection utilizing the Sobel filter. Subsequently, the authors extracted textural features, including textural features (they applied entropy, inertia, and inverse difference and correlation features), run-length matrix, and multi-spectral features to perform medicinal image classification. Noticeably, the authors merely applied their proposed texture-driven learning model (they applied multi-layer perceptron (MLP)) for plant leaf (say, medicinal plant type) classification that classifies input images into multiple types of medicinal plant (species). Authors [1] claimed that the highest accuracy obtained with MLP was 99.01%; however, plant-specific classification accuracy was near 98.40%. Though, the average accuracy of their proposed model was 95.87%. The depth performance analysis for [1] revealed that their proposed feature model (i.e., fused feature set encompassing textural features (they applied entropy, inertia, and inverse difference and correlation features), run-length matrix, and multi-spectral features) could achieve the highest accuracy of 95.87%, 95.04%, 94.21%, 93.38%, and 92.56% using MLP, LogitBoost (LB), Bagging ensemble, Random Forest algorithm and Simple logistic algorithms, correspondingly. Their research revealed that the neuro-computing model MLP performs superior over the other machine learning methods. However, comparing the performance of the proposed model, it can be found that the proposed FFCM-driven STTF textural features (including Contrast, Energy, Entropy, Homogeneity, Correlation, Mean, Standard deviation, Variance, Kurtosis, and Skewness) perform superior accuracy (98.62%), precision (98.81%), recall (98.79%) and F-Measure (0.988) than the existing MLP based method [35], which could achieve the highest average accuracy of 95.87, precision of 96.1%, recall of 95.9% and F-measure of 0.958. This result confirms the robustness of the proposed model over the existing approach. Though, authors [1] found that, unlike standalone classifier-based learning models, its ensemble (combining the different base classifiers) can yield superior performance. Despite their innovation with ensemble learning, they could achieve the highest accuracy of 99%, almost the same as found in the proposed model. Noticeably, this proposed ANN-LM-based model's computational cost is significantly lower than their proposed [1] ensemble learning environment. To further examine the relative performance of the plant disease detection and classification systems and calculate compared efficacy of the existing methods like [2-10].

Table 5. Inter-Model performance assessment

Reference	Features	Classifiers	Accuracy (%)
[1]	Texture Features + multi-spectral features	MLP	99.01
[2]	Shape and Color Features	SVM	96.66
[3]	Texture Features	CNN	97.80
[4]	Morphological Features	CNN, LeNet	98.32
[5]	Texture Features	PCA, LDA	92.90
[6]	Fused Features	RF	98.40
[7]	Texture Features	LBP	93.50
[8]	Multi-Features	MLP	98.14
[9]	HOG and LBP	SVM	98.14 (LBP) 99.00 (HOG)
[10]	Color + Shape + Texture	SVM, AlexNet feature with random forest, VGG16 Inception	75.00 (SVM), 90.67 (AlexNet+RF), 98.50 (VGG with transfer learning) 95.2 (Inception with SVM)
Proposed Model	**Texture Feature**	**ANN-LM**	**98.62%**

Observing the results in Table III, where the different approaches employing different feature models and allied learning algorithms or machine learning algorithms have been applied, it can be found that the proposed FFCM-driven ROI-specific STTF feature yields superior performance to the existing methods. For instance, authors in [3] applied a textural feature learned over the CNN Softmax classifier, resulting in an accuracy of 97.80%. Compared to this method, the proposed model yields 98.62%, which is higher than the existing method [3]. Similarly, authors in [5][7] too applied textural features as input to train over PCA and LDA driven systems and LBP (local binary patterns), respectively. Authors could get the highest accuracy of 92.90% [5] and 93.50% [7], which is significantly lower than this proposed FFCM-driven ROI-specific STTF feature learning model for medicinal plant disease detection and classification system. A few approaches employing shape [2] and morphological cues [4] could achieve the highest accuracy of 98.32% and 96.66%, which still falls below this proposed model. These results confirm that using FFCM-driven segmentation and ROI-specific feature learning model strengthened the proposed model to yield superior over the existing approaches. Though, the work in [1] applied textural as well as multi-spectral features (authors used a total of 60 different features) which were later trained over a heterogeneous ensemble learning model encompassing five different base classifiers named MLP, LogitBoost (LB), Bagging ensemble, Random Forest algorithm and Simple logistic algorithms for plant type classification. Undeniably, this approach (i.e., 4]) can be highly computational complex and exhaustive and makes no sense to be applied for real-time applications. In this reference, the proposed model that merely applies a certain basis pre-processing concept followed by FFCM-driven ROI-segmentation and ROI-specific GLCM feature extraction (which are learned over ANN-LM) yields superior performance to meet real-time purposes. Bose et al. [9] focused on applying different feature extraction and selection methods like Histogram Oriented Gradient (HOG) and Local Binary Pattern (LBP) to perform medicinal plant disease detection and classification. In this work, the authors applied a support vector machine (SVM) as a classifier to perform a two-class classification. The highest accuracy claimed by the authors was 99%. Noticeably, the authors applied the morphological segmentation concept with a static threshold, which can't be generalized to be effective over non-linear input images with unclear edges and varying light intensity, which is common in a real-time application environment. An interesting inference with the work in [9] is that the accuracy with the LBP feature was 98.14%, while HOG features yielded 99% accuracy. Unlike this model, the reliability of the proposed model can be more generalizable. Authors in [10] developed a HEMP leaf disease detection and classification system, where color histogram information, shape, and texture features were obtained for learning. Authors [10] applied SVM to perform multi-class classification for different plant disease detection and prediction. However, the SVM classifier could achieve the highest accuracy of 75%, while the modified AlexNet with Random Forest algorithm could achieve the average accuracy of 90.67%.

On the contrary, VGG16 with transfer learning could achieve the average classification accuracy of 98.50%, while Inception with SVM classifier could achieve the average accuracy of 95.2%. Thus, observing all these results, it can be confirmed that the proposed FFCM-driven STTF textural features with ANN-LM show superior efficacy over the other existing methods. The overall research conclusion and allied inferences are given in the subsequent section.

6. Conclusion

In this paper, a highly robust Evolutionary Computing Driven ROI-Specific Spatio-Temporal Statistical Feature Learning Model for Medicinal Plant Disease Detection and Classification. As the name indicates, this research emphasized improving the feature model to enable more efficient learning and hence classification for medicinal plant disease detection and classification. In sync with the unclear leave's boundaries, unclear disease spot morphological, and varying textural distribution across input image, this research at first performed pre-processing using adaptive histogram equalization, intensity equalization, and Z-normalization. This feature-sensitive pre-processing enabled uniform textural or Spatio-temporal features across the image to further segment and feature extraction. Unlike classical approaches where the whole image is processed for feature extraction, this research applied a heuristic-driven clustering-based ROI segmentation concept. It employed the Firefly Algorithm-based Fuzzy C-Means clustering method, enabling automated and accurate ROI segmentation across the image. Once segmenting the ROI-specific regions, unlike classical shape and morphology-driven methods, the ROI regions were converted into R*G*B space color images that guaranteed that only ROI-specific color images were retained. At the same time, the background components were dropped from further computation or feature extraction (and learning). This approach helped reduce computational costs and retained significant features to perform more efficient learning. In this work, 10 STTF textural features, especially the GLCM features encompassing Contrast, Energy, Entropy, Homogeneity, Correlation, Mean, Standard deviation, Variance, Kurtosis, and Skewness, were extracted to perform further feature learning and classification. Unlike standalone feature learning methods, this research work amalgamated all STTF features by applying horizontal concatenation. The fused feature vector was applied for further classification using different ANN learning models. The depth assessment revealed that using the proposed FFCM-driven ROI-specific STTF feature with the ANN-LM algorithm exhibits superior performance to other state-of-art methods. The proposed FFCM-driven ROI-specific STTF feature with the ANN-LM model exhibited an average accuracy of 98.62%, a precision of 98.81%, recall of 98.79%, and F-Measure of 0.988, which was superior to other existing methods like texture driven SVM based approaches (75%), shape and color feature-driven SVM based methods (96.6%), AlexNet (90.67%), VGG (98.50%), PCA/LDA (92.90%), LBP methods (93.50%), etc. The depth assessment also revealed that the proposed FFCM-driven ROI-specific STTF feature with the ANN-LM model achieves superior performance over the classical textural feature-driven methods, even applying common pre-processing and ANN-LM as a classifier. It confirms that using FFCM-driven ROI-specific STTF features can yield superior performance in medicinal plant disease detection and classification. The future focus can be on applying cost-efficient and lightweight ROI segmentation concepts with hybrid deep-STTF feature learning. As a result, this can improve intrinsic feature information and reduce the computational cost. This approach can reduce the computational cost of FFCM heuristic-driven ROI segmentation.

Acknowledgment

Authors thanks to Management and Principal of Gurunanak Dev Engineering College Bidar, Karnataka, India, for providing the necessary support to carry out this research work.

Reference

[1] S. Naeem, A. Ali, C. Chesneau, M. H. Tahir, F. Jamal, R. A. K. Sherwani, and M. U. Hassan, The Classification of Medicinal Plant Leaves Based on Multispectral and Texture Feature Using Machine Learning Approach, Agronomy. 11 (2021) 263.

[2] Dahigaonkar T.D, Kalyane R, Identification of Ayurvedic Medicinal Plants by Image Processing of Leaf Samples, Int. Res. J. Eng. Technol IRJEF. 5 (2018) 351–355.

[3] Sabarinathan C, Hota A, Raj A, Dubey V.K, Ethirajulu V, Medicinal Plant Leaf Recognition and Show Medicinal Uses Using Convolutional Neural Network, Int. J. Glob. Eng. 1 (2018) 120–127.

[4] Wallelign S, Polceanu M, Buche C, Soybean Plant Disease Identification Using Convolutional Neural Network, In Proceedings of the Thirty-First International Flairs Conference, Melbourne, FL, USA. (2018).

[5] Simion I.M, Casoni D, Sârbu C, Classification of Romanian Medicinal Plant Extracts According to the Therapeutic Effects Using Thin Layer Chromatography and Robust Chemometrics, J. Pharm. Biomed. Anal. 163 (2019) 137–143.

[6] Dhingra G, Kumar V, Joshi H.D, A Novel Computer Vision Based Neutrosophic Approach for Leaf Disease Identification and Classification, Measurement. 135 (2019) 782–794.

[7] Turkoglu M, Hanbay D, Leaf-Based Plant Species Recognition Based on Improved Local Binary Pattern and Extreme Learning Machine. Phys. A Stat. Mech. Appl. 527 (2019) 121297.

[8] Qadri S, Furqan Qadri S, Husnain M, Saad Missen M.M, Khan D.M, Muzammil-Ul-Rehman Razzaq A, Ullah S, Machine Vision Approach for Classification of Citrus Leaves Using Fused Features, Int. J. Food Prop. 22 (2019) 2072–2089.

[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. (2021) 1-7. Doi:10.20944/preprints202107. 0638.v1.

[10] B. Bose, J. Priya, S. Welekar, and Z. Gao, HEMP Disease Detection and Classification Using Machine Learning and Deep Learning, IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking ISPA/BDCloud/SocialCom/SustainCom. (2020) 762-769.

[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. 21(16) (2021) 17455-17468.

[12] K. S. Patle, R. Saini, A. Kumar, S. G. Surya, V. S. Palaparthy and K. N. Salama, IoT Enabled, Leaf Wetness Sensor on the Flexible Substrates for In-Situ Plant Disease Management, in IEEE Sensors Journal. 21(17) (2021) 19481-19491.

[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. 9(9) (2016) 4344-4351.

[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. 7 (2019) 45841-45849.

[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. 1(1) (2016) 354-360.

[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. 7 (2019) 170003-170011.

[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. 9 (2021) 140565-140580.

[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. 7 (2019) 59069-59080.

[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. 8 (2020) 136421-136433.

[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. 9 (2021) 14849-14866.

[21] S. C. K, J. C. D and N. Patil, Cardamom Plant Disease Detection Approach Using EfficientNetV2, in IEEE Access. 10 (2022) 789-804.

[22] U. P. Singh, S. S. Chouhan, S. Jain, and S. Jain, Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease, in IEEE Access. 7 (2019) 43721-43729.

[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. 7 (2019) 46261-46277.

[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. 8 (2020) 33679-33688.

[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, Art no. 5017113. 70 (2021) 1-13.

[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, Art no. 8019905. 19 (2022) 1-5.

[27] A. Khattak et al., Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model, in IEEE Access. 9 (2021) 112942-112954,.

[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. 7(6) (2014) 2516-2524.

[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. 9 (2021) 160085-160103.

[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. 9 (2021) 100480-100489.
[31] S. V. Militante, B. D. Gerardo and N. V. Dionisio, Plant Leaf Detection and Disease Recognition using Deep Learning, IEEE Eurasia Conference on IOT, Communication and Engineering ECICE. (2019) 579-582.
[32] F. Marzougui, M. Elleuch, and M. Kherallah, A Deep CNN Approach for Plant Disease Detection, 21st International Arab Conference on Information Technology (ACIT). (2020) 1-6.
[33] P. K. V, E. G. Rao, G. Anitha, and G. K. Kumar, Plant Disease Detection using Convolutional Neural Networks, 5th International Conference on Trends in Electronics and Informatics ICOEI. (2021) 1473-1476.
[34] X. Guan, A Novel Method of Plant Leaf Disease Detection Based on Deep Learning and Convolutional Neural Network, 6th International Conference on Intelligent Computing and Signal Processing ICSP. (2021) 816-819.
[35] M. A. Rahman, M. M. Islam, G. M. Shahir Mahdee and M. W. Ul Kabir, Improved Segmentation Approach for Plant Disease Detection, 1st International Conference on Advances in Science, Engineering and Robotics Technology ICASERT. (2019) 1-5.
[36] SM. Sardogan, A. Tuncer and Y. Ozen, Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm, 3rd International Conference on Computer Science and Engineering UBMK. (2018) 382-385.
[37] R. D. Devi, S. A. Nandhini, R. Hemalatha and S. Radha, IoT Enabled Efficient Detection and Classification of Plant Diseases for Agricultural Applications, International Conference on Wireless Communications Signal Processing and Networking WiSPNET. (2019) 447-451.
[38] Kirti and N. Rajpal, Black Rot Disease Detection in Grape Plant Vitis Vinifera Using Colour Based Segmentation & Machine Learning, 2nd International Conference on Advances in Computing, Communication Control and Networking ICACCCN. (2020) 976-979.
[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, 5th International Conference on Computing Methodologies and Communication ICCMC. (2021) 1119-1127.
[40] H. F. Pardede, E. Suryawati, R. Sustika and V. Zilvan, Unsupervised Convolutional Autoencoder-Based Feature Learning for Automatic Detection of Plant Diseases, International Conference on Computer, Control, Informatics and its Applications IC3INA. (2018) 158-162.
[41] T. Sanida, D. Tsiktsiris, A. Sideris and M. Dasygenis, A Heterogeneous Lightweight Network for Plant Disease Classification, 10th International Conference on Modern Circuits and Systems Technologies MOCAST. (2021) 1-4.
[42] A. H. Bin Abdul Wahab, R. Zahari and T. H. Lim, Detecting Diseases in Chilli Plants Using K-Means Segmented Support Vector Machine, 3rd International Conference on Imaging, Signal Processing and Communication ICISPC. (2019) 57-61.
[43] B. Bose, J. Priya, S. Welekar and Z. Gao, Hemp Disease Detection and Classification Using Machine Learning and Deep Learning, IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking ISPA/BDCloud/SocialCom/SustainCom. (2020) 762-769.
[44] [Online]. Available: https://data.mendeley.com/datasets/nntj2v3n5