Research Article ISSN: 2349-2678

Contents lists available at www.ijpba.in

International Journal of Pharmaceutical and Biological Science Archive

NLM (National Library of Medicine ID: 101738825)

Index Copernicus Value 2019: 71.05

Volume 11 Issue 4; July-August; 2023; Page No. 56-63

Global Scenario of Medicinal Plants

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Article Info: Received: 12-05-2023 / Revised: 24-05-2023 / Accepted: 27-07-2023

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Conflict of interest statement: No conflict of interest

Abstract

Agro-industries have been pushed to the brink by the rapid increase in demand for medicinal plants with pharmaceutical importance and the many ayurveda or herbal remedials. However, increased instances of plant diseases have capped aggregate growth, reducing output volume and quality. In this research, we provide the first hybrid deep-spatial temporal textural feature learning model for medicinal plant disease detection (HDST-MPD), which is powered by evolutionary computing. The HDST-MPD model originally used firefly heuristic driven fuzzy C-means clustering to obtain ROI-specific RGB areas, which helped to reduce the likelihood of a class-imbalance issue occurring. Then, it used the AlexNet transferrable network and the gray-level co-occurrence matrix (GLCM) to make the most of the deep spatiotemporal textural data. In this case, high-dimensional features were generated using the AlexNet deep model, and the inclusion of numerous GLCM features aided in leveraging the distribution of textural characteristics. Each sample medical picture was labeled as either "normal" or "diseased" using a composite vector trained on a random forest ensemble using these deep-spatial, temporal, textural feature (deep-STTF) characteristics. In-depth performance evaluation showed that the suggested model is very effective at real-time illness detection and classification in medicinal plants, with an accuracy of 98.97%, precision of 99.42%, recall of 98.89%, F-measure of 99.15%, and an equal error rate of 1.03%.

Keywords: AlexNet , Gray-level co-occurrence matrix ,Heuristic driven segmentation, Hybrid deepTTF feature , Medicinal plant disease detection

Introduction

Plants provide oxygen, which all living creatures on Earth need to survive. Plants come in a wide variety of shapes, sizes, and colors and they all contribute to human survival by keeping the planet's ecosystems healthy. Medicinal plants are plants that are used to cure or prevent human health problems. Herbal treatments come in a wide variety of forms and might show regional variations in terms of "size" and "shapes". From the roots to the foliage, these plants are very therapeutic. Karpooravalli (Coleus ambonicus), Podina (Mentha arvensis), Neem (Adidirachta indica), Thudhuvalai (Solanum trilobatum), Basil (Ocimum sanctum), etc. are just a few of the plants whose leaves find everyday usage. Particular leaf types may be used to treat a variety of medical conditions.

Thus, plants utilized for their specific qualities helpful to human and animal health are considered medicinal plants. Once referred to as "simple" in medieval medicine, now days we would term them the equivalent of traditional or contemporary herbal treatment. In most cases, just a single portion of the plant (leaf, stem, root, etc.) is used for its curative properties. It's possible to get distinct benefits from various plant sections. Plants having therapeutic characteristics may also be utilized as food, condiments, or in the making of hygienic beverages. Before being expanded and debated from the 17th century on and ultimately abandoned by the elite society in the 18th century, the idea of signatures played a vital part in the distinction by analogy of plants important for human healing that dates back to antiquity.

Worldwide, 14-28% of plants are documented as having some kind of medical use, according to research that has been widely disseminated. A large majority of people in the southern Sahara region and 80% of rural populations in developing nations utilize medicinal plants as their primary therapy, according to surveys conducted at the turn of the 21st century.

Literature Review

Margesh Keskar (2023) Agro-industries have been pushed to the brink by the rapid increase in demand for medicinal plants with pharmaceutical importance and the many ayurveda or herbal remedials. However, increased instances of plant diseases have capped aggregate growth, reducing output volume and quality. In this research, we provide the first hybrid deep-spatial temporal textural feature learning model for medicinal plant disease detection (HDST-MPD), which is powered by evolutionary computing. The HDST-MPD model originally used firefly heuristic driven fuzzy C-means clustering to obtain ROI-specific RGB areas, which helped to reduce the likelihood of a class-imbalance issue occurring. Then, it used the AlexNet transferrable network and the gray-level co-occurrence matrix (GLCM) to make the most of the deep spatiotemporal textural data. In this case, high-dimensional features were generated using the AlexNet deep model, and the inclusion of numerous GLCM features aided in leveraging the distribution of textural characteristics. Each sample medical picture was labeled as either "normal" or "diseased" using a composite vector trained on a random forest ensemble using these deep-spatial, temporal, textural feature (deep-STTF) characteristics. In-depth performance evaluation showed that the suggested model is very effective at real-time illness detection and classification in medicinal plants, with an accuracy of 98.97%, precision of 99.42%, recall of 98.89%, F-measure of 99.15%, and an equal error rate of 1.03%.

Sunil C. K (2022) There is no other spice quite like cardamom. It originates in the evergreen woods of the Indian states of Karnataka, Kerala, Tamil Nadu, and the far northeast. Third-largest cardamom producer is India. The devastating effects of plant diseases on agricultural productivity and the security of our food supply cannot be overstated. In the worst-case scenario, plant diseases might wipe out a whole crop. The development and crop yields of cardamom plants are negatively impacted by a wide range of diseases and pests. This research focused on three diseases of grape plants (Black Rot, ESCA, and Isariopsis Leaf Spot) and two diseases of cardamom plants (Colletotrichum Blight and Phyllosticta Leaf Spot of cardamom). Several approaches have been developed for identifying plant diseases, but deep learning's phenomenal success has made it the technique of choice. U2 -Net was used to identify multiscale characteristics from an input picture in order to mask off the undesired background. In this study, we use the EfficientNetV2 model to suggest a method for detecting diseases in cardamom plants. To evaluate the efficacy of the suggested method and to evaluate it against other models, including EfficientNet and Convolutional Neural Network (CNN), a complete series of tests was conducted. The experimental findings demonstrated a 98.26% detection accuracy using the suggested method.

Biswaranjan Acharya (2023) The sheer variety of plant leaves and the mountain of data gathered for research makes it difficult for non-specialists to identify photos of plant leaves. It's challenging to develop an automatic recognition system that can process large datasets and provide a rough assessment. Existing solutions successfully link difficulties including image analysis, sorting, and pattern recognition. In this research, we leverage the Google Maps API and the best available identification algorithm to devise a fully automated plant detection system. India serves as a case study due of the country's extensive biodiversity. The suggested system may provide the precise location of that species, the areas where it is found, and the quickest routes to reach there from the user's present position.

Samreen Naeem (2021) In this research, we suggest using machine learning to categorize the leaves of plants used in alternative medicine. Data about the leaves of medicinal plants from Pakistan's Islamia University at Bahawalpur's Department of Agriculture. The Latin names for these plants are Ocimum sanctum, Mentha balsamea, Aegle marmelos, Melissa officinalis, Nepeta cataria, and Stevia rebaudiana, whereas their common English names are Tulsi, peppermint, bael, lemon balm, catnip, and stevia. A computer vision lab is used to gather the multispectral and digital picture collection. As part of the preliminary processing, we extract only the leaf area and convert it to grayscale. Second, we use the Sobel filter for edge/line recognition based on the seed intensity and produce five observational areas. Sixty-five fused features, including texture, run-length matrix, and multi-spectral features, are recovered from the dataset. We use a chi-squared feature selection strategy to zero down on 14 optimal characteristics for further improvement. After optimizing a dataset consisting of classifications of medicinal plant leaves, five machine learning classifiers are applied to it; these are the multi-layer perceptron, logit-boost, bagging, random forest, and simple logistic. Of these, only the multi-layer perceptron classifier demonstrates a statistically significant improvement in accuracy (99.01%) over the other four. The multi-layer perceptron classifier achieved an accuracy of 99.10% while testing six medicinal plant leaves, including Tulsi (98.10%), Peppermint (99.50%), Bael (98.50%), Lemon Balm (99.50%), Catnip (98.50%), and Stevia (99.50%).

Payal Bose (2021) Plants are the primary factor on Earth. Every part of a plant is essential, both from an ecological and a medical standpoint. However, many different plant species may be found all over the world. Diseases may affect a wide variety of plant types. Therefore, in order to reduce waste, it is necessary to identify the plants and their illnesses. It takes a lot of time to manually determine whether plant diseases exist. This study proposes an autonomous technique for identifying diseases in plants. High-quality photos of leaves are permitted for use in experiments for both training and assessment. Both color-based and region-based thresholding approaches were utilized to identify healthy and sick areas of a leaf's surface. The Histogram Oriented Gradient (HOG) approach and the Local Binary Pattern (LBP) technique were used for feature selection. Finally, Support Vector Machine (SVM) was employed for both binary and multi-class classification. Both feature selection procedures using SVM are found to achieve 99% accuracy. Users now have a graphical user interface to help them navigate the automated system.

Materials and Methods

The sector study of MAPs in many Mediterranean nations was handled through a Delphi poll. This approach is often used to examine market trends and anticipate the development of certain industries. The Delphi survey approach is more reliable than methods that rely on unstructured groups of people since it involves gathering the views of an organized group of experts. Furthermore, the Delphi approach is often regarded as an effective instrument for analyzing market patterns and anticipating sector development.

The first step in the Delphi analysis was to assemble a panel of experts comprised of representatives from the INCREDIBLE partner countries (Spain, France, Italy, Croatia, Tunisia, and Greece), as well as other international organizations active in the MAPs sector. The poll included 23 expert panellists, however the representation across countries was uneven. The number of countries involved varied depending on the maturity of their MAPs supply chain and the significance of the industry to their respective economies. Producers, processors (industries and factories), producers' organizations, end users, commercial middlemen, protected area managers, technicians, and researchers were all questioned throughout the course of the two-round Delphi process.

In addition, the results of workshops and other interactive events linked to the INCREDIBLE project were appraised in order to refine the questionnaire for the preliminary Delphi survey. Over the course of 2018–2020, the first scoping seminar was held in Tunis, and three regional workshops were held in Greece, Spain, and Croatia, attracting a total of more than 150 attendees.

There were five sections to the first questionnaire: The first section was dedicated to gathering background information about the respondent; the second section detailed the MAPs supply chain; the third section analyzed the sector's strengths, weaknesses, opportunities, and threats; the fourth section identified key challenges; and the fifth section made recommendations for the sector's future. In the first Delphi survey phase, each expert responded independently, and participants were instructed to focus only on questions pertaining to their areas of expertise. The names of the experts were kept separate and anonymous throughout the whole Delphi survey procedure.

Expert panelists were asked to rate the importance of remarks made regarding the MAPs industry on a scale from 0 to 10, and the first questionnaire contained both quantitative and qualitative questions. To aid in the ranking process and to prevent redundant SWOT statements, experts were also given two initial lists of obstacles and actions to be performed. Expert feedback was used to refine the questionnaire for a second round, and their views were taken into account when outlining potential next steps and efficient strategies for the industry. In the second round, we had our expert panelists rate each statement independently before averaging their results. To ensure that everyone on the panel had the same information, we asked experts to either reaffirm their initial ratings or revise them based on the average rating from the previous round. After each round, the experts on the panel tallied all of the statements' ratings and produced an aggregated mean and standard deviation. After the two rounds were complete, a worldwide statistical analysis was conducted to investigate the experts' responses. To achieve this, we averaged and sorted the replies to each statement, looking solely at those with mean scores more than 7.5 (see Table 1). The student's t-test was performed to determine whether the difference in scores was statistically significant (H0: the average score is 0, H1: the average score is more than 0).

Table 1: Top prioritised actions to be taken in the MAPs sector identified by expert panel at the end of the second round.

Prioritised Actions to Be Taken	Mark (SD)	*t*-Values
Harmonising wild harvesting regulations in each country	8.26 (1.09)	44.66 ***
Promoting new associationism formulas (cooperatives, development groups, etc.) to share production costs, services and knowledge between all the stakeholders	8.24 (1.50)	33.93 ***
Implementing specific management plans to protect main species collected in public production areas	8.22 (1.40)	35.34 ***
Protecting threatened species through promoting a collaborative forest management plan to raise awareness among private forest owners and MAP collectors	7.92 (1.50)	31.67 ***
Organising a regular course for collectors from all territories in each country to promote sustainable harvesting practices	7.95 (1.31)	36.86 ***
Promoting the traditional use of MAPs among end consumers	7.70 (1.85)	25.27 ***
Implementing the certification of good practices of wild MAPs	7.51 (2.08)	30.69 ***

The primary players in the MAP supply chain were identified and presented to the expert panel through prior INCREDIBLE workshops and events. Along with the stakeholder map detailing the product flow was a brief overview of the supply chain. To ensure the planned supply chain would work for all of the countries in the research region, experts were consulted to verify and enhance it. In the second phase, after receiving feedback on the first, the revised supply chain was submitted for approval.

Results and Discussion

There were 13 distinct types of medicinal plants included in the 862 photos used for this study. The information may be obtained by making a request to the owner of the intellectual property [44]. The first characterisation occurs inside the model itself, while the second occurs between models. Here, we compared the performance of the proposed HDST-MPD model to that of other existing approaches (inter-model evaluation) and analyzed the performance efficiency of various feature extraction models and classifiers (intra-model characterisation).

Intra-model characterization

With the overall suggested HDST-MPD model and related architectural features in mind, this study aims to compare the performance of using GLCM as a single feature against using the composite deep-STTF features. In other words, we tested medicinal plant disease identification and classification using GLCM, AlexNet, and GLCM +AlexNet features (say, deep-STTF hybrid features, independently to see whether combining the two methods improved accuracy. Three feature models, GLCM, AlexNet, and GLCM plus AlexNet (call it deep-STTF or a hybrid feature), are compared for their effectiveness in Table 1. Figure 3 demonstrates an F-measure of 99.15%, recall of 98.89%, precision of 99.42%, and an EER of 1.03% for disease detection and classification in (medicinal) plants using the hybrid feature model (including both GLCM and AlexNet features) described in this study. After establishing that the proposed FFCM segmentation driven deep-STTF feature model outperforms other independent feature modalities, the researchers planned to test the HDST-MPD model's performance using a variety of classifiers. Naive Bayes (NB), Decision Tree (DT), Artificial Neural Network Latent Dirichlet Allocation (ANN-LM), Radial Basis Functions (RBF), Support Vector Machine (SVM), and Random Forest Classifier (RF) were used as machine learning models here. The primary goal here was to extend the solution by determining whether or not a given machine learning model could be successfully combined with the suggested FFCM segmentation driven deep-STTF feature model (i.e., GLCM + AlexNet feature model). The results of the simulations using the various classifiers are listed in Table 2. Notably, the suggested hybrid deep-STTF feature model, which boasts the best performance, was used into this evaluation.

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

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

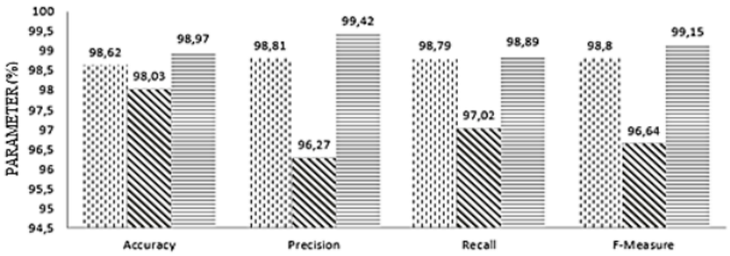

Figure 1: Analysis of feature models

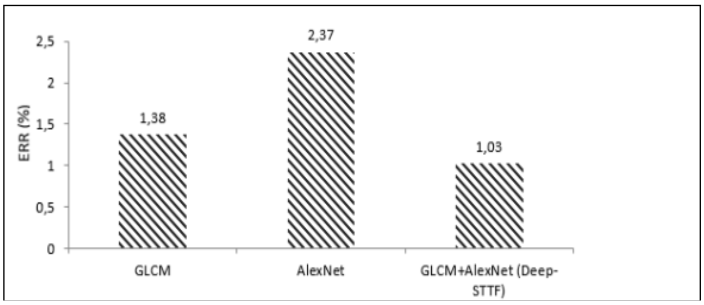

Figure 2: EER performance (%) with the different feature models

Table 3: Intra-model characterization with the different feature environment

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

The results of an internal evaluation using several machine learning techniques are shown in Table 3. In line with RQ3 (discussed in Part 3), the goal here is to determine which machine learning model produces the best results. Table 3 shows that the NB model trained using a Gaussian kernel function had an average accuracy of 89.93% and an error rate of 10.07%. For its part, the DT classifier achieved an accuracy of 93.75 percent at an EER of 6.25 percent when using the suggested deepSTTF feature (i.e., a GLCM +AlexNet feature model). Interestingly, DT outperformed NB in a classification task. Comparatively, the classification accuracy of an SVM using a polynomial kernel function was 94.21%, with an EER of 5.89%. While SVM clearly outperformed the prior-art NB and DT models, the findings showed wide variation in effectiveness.

Two well-known techniques, radial basis functions (RBF) and Levenberg Marquardt (ANN-LM), were used to evaluate the performance of the neuro-computing models by two-class classification. According to the simulation findings, the RBF neural network achieved an accuracy of 92.67 percent with an error rate (EER) of 7.37 percent, while the LM-ANN achieved an accuracy of 94.48% with an EER of 5.52 percent. distinct machine learning models display distinct behaviors over the same input characteristics (i.e.,HybriddeepSTTF), as can be shown by comparing the performance results across the various classifiers. This demonstrates that performance may vary widely, making it challenging to generalize a single classifier. In this research, we use the random forest ensemble classifier to conduct two-class classification, which helps to relieve these problems. In Figure 5, we can see how various classifier models compare to the proposed deep-STTF feature (i.e., GLCM + AlexNet feature) model. Notably, only the top five performing models were kept for display, despite the Naive Bayes classifier's low showing in Table 2.

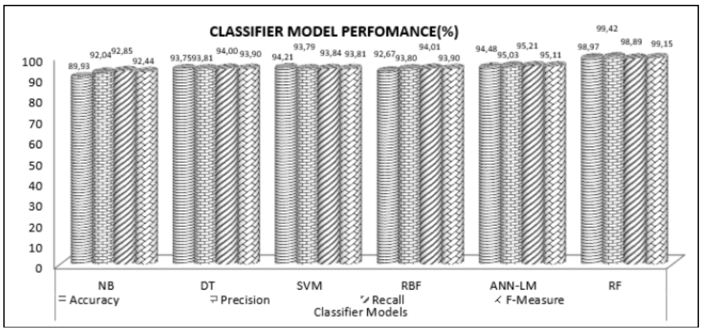

Figure 3: Analysis of the classifier rmodels over $GLCM + AlexNet$ feature

RF uses a classifier that is a combination of numerous separate DTs, a bootstrapped decision tree classifier, rather than a solitary classifier. Consensus-based classification results are more trustworthy than those from competing methods because they take use of the rankings assigned by the several base classifiers. Figure 4 shows that the RF algorithm achieved an accuracy of 98.97% @1.03% EER in classifying plant diseases using the same input feature (i.e., HybriddeepSTTF). Figure 5 demonstrates that, compared to other state-of-the-art machine learning approaches, the RF model may provide better outcomes. As a result, it is argued in this reference that the best results for classifying and detecting illness in medicinal plants may be achieved by the combination of FFCM-driven ROI-segmentation and related ROI-specific deep-STTF characteristics with RF classifier. Accordingly, we find that RQ3 meets the criteria established in 3.

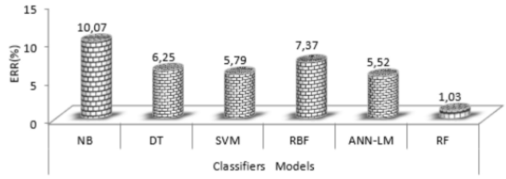

Figure 4: EER (%) analyses of the classifier models over proposed hybrid feature

Inter-model characterization

Here, we evaluate our suggested HDST-MPD model next to existing top-tier methods. Ina recent study used leaf texture data to categorize therapeutic plants. The authors' approach to medicinal plant classification differs from our suggested HDST-MPD model in that it relies largely on edge-based segmentation, followed by the extraction of textural data including entropy, inertia, inverse difference and correlation features, and run-length matrix. The authors used a multi-layer perceptron neural network to accomplish their goals. Even though this is a plant type classification issue, the authors only managed an accuracy of 95.87%, which is much lower than the average accuracy of our suggested HDST-MPD model (98.97%). The authors evaluated the performance of various feature models and discovered that the classification accuracy could be increased to 95.87%, 95.04%, 94.21%, 93.38%, and 92.56%, respectively, when using key features such as the run-length matrix and multi-spectral features with MLP, LogitBoost (LB), Bagging ensemble, RF algorithm, and simple logistic algorithms. It should be noted that also proposes a neural network-based model for disease detection and classification in plants; however, the best accuracy they achieve is only 95.87%, which is much lower than our suggested HDST-MPD model.

Conclusion

This work applied FFCM, a firefly driven FCM clustering model for automated and ROI-specific clustering for disease spot detection and localization, to ensure that only the ROI-specific features are processed for further computation. The final features kept an ideal collection of STTF features and deep features to achieve optimal learning and classification by fusing the retrieved GLCM and AlexNet features using horizontal concatenation. In addition, random forest ensemble learning was employed to classify each test picture as either a healthy or sick sample using the fused composite deep-STTF features. The statistical performance analysis demonstrated that the use of hybrid features (i.e., GLCM and AlexNet features together) yields superior performance (accuracy (98.97%), precision (99.42%), recall (98.89%), and F-measure (99.15%), EER (1.03%)) compared to the GLCM (accuracy (98.62%), precision (98.81%), recall (98.79), F-measure (98.80%), and EER.

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