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Research Paper

Improved Identification of Medicinal Plants Utilizing Parameter-Optimized SVM inside a PSO-Driven Cascaded Framework

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Abstract: The primary objective of this work's extension is to improve medicinal plant classification by parameter modification of the Support Vector Machine (SVM) in a PSO-optimized cascaded network. Deep features obtained with ResNet50 are enhanced using Particle Swarm Optimization (PSO) to choose the most relevant attributes. The customized SVM model significantly improves classification accuracy and reduces misclassification when compared to alternative methods. Experimental results show that the enhanced SVM outperforms the others, with an accuracy of 99.75%. This approach ensures a more reliable, efficient, and scalable automated medicinal plant identification system.

Index Terms - *Medicinal Plant Classification, ResNet50, Particle Swarm Optimization (PSO), Support Vector Machine (SVM), Parameter Tuning, Feature Optimization, Machine Learning, Deep Learning, Image Classification, Cascaded Network*

1. INTRODUCTION

For centuries, traditional medicine relied heavily on medicinal plants, which still have an impact on pharmacological research today. Plant-based medicines are used for primary care by a significant portion of the global population. Medicinal plants are the source of aspirin, morphine, and quinine, indicating their importance in the development and treatment of pharmaceuticals. Accurately identifying medicinal plants is crucial for medical and botanical research due to the growing demand for herbal medicines and natural remedies.

Professionals painstakingly examine the size, shape, texture, color, and fragrance of leaves in order to identify traditional medicinal plants. This approach is time-consuming, requires a high level of subject-matter expertise, and is prone to human error and inconsistency. Due to the growing number of plant species and large-scale databases, manual categorization is ineffective and unfeasible. Systems for classifying medicinal plants that are automated, dependable, and scalable are required to address these problems.

Automatic plant identification is made possible by recent developments in computer vision and artificial intelligence. CNNs and other deep learning models are capable of extracting complex and discriminative image features. Because of its deep architecture and capacity to overcome vanishing gradient challenges, ResNet50 is often used for feature extraction. Classification performance may be impacted by deep features that include redundant or irrelevant information.

To fix this, Particle Swarm Optimization (PSO) is used to improve and choose the most important characteristics. By reducing dimensionality and improving classifier-transmitted features, PSO enhances feature selection. The categorization system becomes more efficient and accurate.

In order to improve classification performance, this improved approach focuses on SVM parameter adjustment. SVM, a supervised learning method, is particularly good at classifying high-dimensional data. The optimal kernel type, regularization parameter (C), and gamma values are what determine its performance. These factors can improve classification accuracy if tuned correctly.

ResNet50 for deep feature extraction, PSO for feature optimization, and a parameter-tuned SVM for classification are used in a cascaded network architecture. This assures high accuracy, low misclassification, and good generalization across datasets. The enlarged model helps botanical research and healthcare by outperforming current machine learning techniques for automated medicinal plant identification.

2. LITERATURE SURVEY

2.1 A leaf recognition algorithm for plant classification using probabilistic neural network.

This study performs automated leaf recognition for plant classification using a probabilistic neural network (PNN) in conjunction with image and data processing techniques. Twelve leaf properties are orthogonalized into five primary variables to provide the input vector for the PNN. Using 1800 leaves as training data, the PNN recognized plant species with 90% accuracy. Our e-AI technology is more accurate, quicker, and easier to understand than competing algorithms.

2.2 Vnplant-200-a public and large scale of Vietnamese medicinal plant images dataset.

Because of the potential advantages for agronomy, preservation, environmental impact, and the search for natural and therapeutic commodities, plant identification is a significant area of computer vision research. In contrast to its species, there is no publicly available dataset on this therapeutic plant. Our study adds to the increasing quantity of public multi-class databases that contain pictures of medicinal plants. You have access to twenty thousand photos of two hundred native Vietnamese medicinal plants (VNPlant-200). In addition to the 256 × 256 version, there is another dataset with 512 × 512 pixels. 12,000 photographs make up the training set, while all other images are in the test set. Plants are identified using a Random Forest (FR) classifier, Scale Invariant Feature Transform (SIFT), and Speed-Up Robust Features (SURF) feature extraction. The VNPlant-200 pattern recognition study produced some intriguing findings.

2.3 Local binary pattern based on image gradient for bank image classification.

We provide a discriminative and efficient local texture descriptor for bark image classification. We suggest breaking it down into pixel, magnitude, and direction descriptions. Unlike earlier descriptions that rely on the original local binary pattern, this one alters the local texture of the bark picture. Three popular datasets are used to test the proposed description. The results of the experiments show how effective our approach is.

2.4 Bark texture classification using improved local ternary patterns and multilayer neural network.

Among the several subjects that have been studied is tree identification. Professionals in this field earn a living. Scientists have found a stronger correlation between species and tree bark than other traits. A variety of light, delicate textures may be found in bark. LBP-like features are used in recent studies. The majority of them are average. Textures can change in appearance due to noise and rotation. The most effective operator for noise resistance and discrimination is the local ternary pattern. The majority of descriptors employ pattern histograms to extract features. Spinning is simple, but processing can be quite costly. This paper presents a trustworthy technique for classifying bark roughness based on ILTP. The proposed ILTP distinguishes between uniform and non-uniform binary patterns in ternary patterns. Consistency metrics are used to label the extracted patterns. Lastly, the likelihood of correct categorization determines which features are returned. Multilayer perceptrons can theoretically have four different hidden node topologies. In terms of classification accuracy, the proposed approach performs better than the state-of-the-art on two benchmark datasets. Rotation invariance and noise resilience are only two of the many advantages of the suggested approach. It is possible to reduce the expenses and hazards associated with plant species detection while simultaneously safeguarding human health by classifying bark according to its texture, which is a good predictor of its qualities.

2.5 combining sparse representation and singular value decomposition for plant recognition.

Plant identification has made great strides in pattern recognition. The irregular, complex, and ever-changing nature of plant leaves makes many of the current techniques for categorizing and recognizing plants unsuitable for automated systems. This work introduces a unique method for identifying plants using singular value decomposition and sparse representation (SR). In order to quickly reduce picture dimensionality and identify test samples using sparse coefficients, the proposed technique combines sparse modeling with class-specific dictionary learning. This is in contrast to the current classification system for plants. Therefore, it is no longer necessary to collect classification criteria in advance in order to construct a classification model. Four distinct plant identification methods are compared with the suggested approach after it has been tested on two leaf datasets. Total precision in identifying The suggested method offers the best accuracy, at around 96%, when it comes to differentiating the six different kinds of plant leaves. The experiment shows that the approach is workable.

3. METHODOLOGY

i) Proposed Work:

The proposed study provides an enhanced medicinal plant classification system by utilizing a parameter-tuned Support Vector Machine (SVM) in a PSO-optimized cascaded network. Plant leaf photos are first collected from the collection and preprocessed to ensure uniformity and reduce noise. Deep features are then extracted using the ResNet50 model, which effectively captures complex visual patterns including texture, form, and color. To further improve the quality of these features, Particle Swarm Optimization (PSO) is used to choose the most relevant and discriminative features while reducing dimensionality and redundancy.

The main objective of the extension is to optimize the SVM classifier through parameter adjustments. Important parameters like gamma, regularization parameter (C), and kernel type are changed to get the optimal decision limits for classification. The model's ability to distinguish between several kinds of medicinal plants is significantly enhanced by this modification. The improved SVM outperforms existing machine learning models, achieving more accuracy and consistency. All things considered, the proposed endeavor ensures an automated medicinal plant identification system that is dependable, efficient, and scalable.

ii) System Architecture:

The suggested medicinal plant categorization model's system design integrates machine learning, optimization, and deep learning methods using a cascaded framework. In order to normalize the data, preprocessing steps including scaling, normalization, and noise reduction are carried out once the input photos of medicinal plant leaves are gathered from the dataset. The ResNet50 model, which serves as a deep feature extractor, is then given these preprocessed pictures. High-level and discriminative characteristics including form, texture, and color patterns are captured by ResNet50 and are crucial for precise categorization.

Particle Swarm Optimization (PSO) is used after feature extraction to identify the most pertinent characteristics and remove unnecessary or insignificant ones. By lowering dimensionality, this step enhances the model's effectiveness and performance. After the feature set has been optimized, a parameter-tuned Support Vector Machine (SVM) is used in the classification step. To get ideal classification limits, the SVM is adjusted using various kernel functions and parameters like C and gamma. Ultimately, the method accurately predicts the therapeutic plant's class. Across many plant datasets, our design guarantees enhanced speed, decreased computing complexity, and trustworthy classification results.

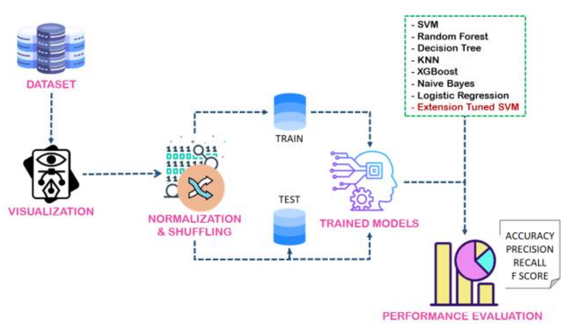

Fig 1 System Architecture

iii) MODULES:

1. Importing the Packages:

Important Python libraries needed for image processing, deep learning, optimization, and classification are loaded by this module. To facilitate effective model construction, it incorporates libraries like NumPy, Pandas, OpenCV, TensorFlow/Keras, and Scikit-learn.

2. Dataset Collection and Preprocessing:

The medicinal plant picture collection is loaded in this module, and preprocessing operations including resizing, normalization, and noise reduction are carried out. It guarantees that every image is in a consistent format that can be used to extract features.

3. Feature Extraction using ResNet50:

This program extracts deep features from the preprocessed pictures by running them through the ResNet50 model. Important visual features such leaf form, texture, and color patterns are captured.

4. Feature Optimization using PSO:

From the extracted feature set, the most pertinent features are chosen using Particle Swarm Optimization (PSO). By removing duplicated data, this lowers dimensionality and increases classification performance.

5. Classification using Parameter-Tuned SVM:

The Support Vector Machine (SVM) classifier receives the optimized features. To maximize classification accuracy, SVM parameters like kernel, C, and gamma are adjusted in this module.

6. Model Evaluation:

This module uses measures like accuracy, precision, recall, and F1-score to assess the trained model's performance. It aids in comparing outcomes and confirming the efficacy of the model.

7. Prediction and Output Generation:

The last module guesses the relevant class of therapeutic plants based on fresh input photos. The categorization result is reliably and accurately generated by the system.

v) ALGORITHMS:

1. Support Vector Machine (SVM):

SVM is a supervised learning technique that uses the best hyperplane to divide several classes to classify medicinal plants. SVM concentrates on increasing the margin between classes, which enhances generalization, and is very successful for high-dimensional feature spaces produced by deep learning models such as ResNet50. Additionally, it is resistant to overfitting, particularly when there are more features than samples.

2. Random Forest:

An ensemble learning system called Random Forest builds several decision trees and aggregates their results to get a final forecast. By lowering variance and preventing overfitting, it increases classification accuracy. The model is strengthened by training each tree on a random selection of characteristics and data. It offers feature importance for improved interpretability and works well on complicated datasets.

3. Decision Tree:

A straightforward yet effective technique called Decision Tree uses a hierarchical structure of decisions to classify data. To create a model that resembles a tree, it divides the dataset according to feature values. This approach is helpful for examining categorization logic since it is simple to comprehend and use. However, if it is not well regulated, it could experience overfitting.

4. K-Nearest Neighbors (KNN):

KNN is an instance-based learning technique that uses the majority class of its closest neighbors to classify data points. It is easy to use and straightforward because there is no need for a training session. When comparable data points are near one another in the feature space, KNN works well. However, when dealing with enormous datasets and high-dimensional data, its performance may suffer.

5. XGBoost:

The sophisticated gradient boosting algorithm XGBoost is renowned for its excellent effectiveness and performance. By fixing mistakes in earlier models, it constructs models one after the other. It incorporates regularization strategies that enhance accuracy and avoid overfitting. XGBoost works incredibly well on complicated and structured datasets and is very scalable.

6. Naïve Bayes:

Naïve Bayes is a probabilistic classifier that assumes feature independence and is based on Bayes' theorem. It performs well with big datasets and is computationally efficient. It performs well in a variety of classification tasks despite its simplicity. When the dataset has independent or categorical properties, it is very helpful.

7. Logistic Regression:

A statistical technique for classification that uses probability estimation is called logistic regression. It uses a logistic function to represent the connection between input characteristics and output classifications. It is appropriate for basic models since it is simple to apply and understand. When there is a linear link between characteristics and classes, it works well.

8. Tuned Support Vector Machine (Extension):

By improving hyperparameters such kernel type, regularization parameter (C), and gamma, the tuned SVM improves upon the conventional SVM. The model's capacity to identify ideal decision limits is enhanced by this tuning procedure. Consequently, it greatly improves classification accuracy and decreases misclassification. The most dependable classifier for identifying medicinal plants is the adjusted SVM as it performs the best in the suggested system.

4. EXPERIMENTAL RESULTS

The proposed medicinal plant classification system was evaluated experimentally using a number of machine learning algorithms, including SVM, Random Forest, Decision Tree, KNN, XGBoost, Naïve Bayes, Logistic Regression, and the Extension Tuned SVM. The performance was assessed using key performance indicators such as accuracy, precision, recall, and F1-score. With the highest accuracy of 99.75% and greater precision (99.74%), recall (99.73%), and F1-score (99.74%), the Extension Tuned SVM turned out to be the most effective model. Standard SVM and Logistic Regression both performed well, with accuracies exceeding 99%, while XGBoost and Random Forest showed competitive performance. However, Decision Tree and Naïve Bayes did very badly due to their incapacity to handle complex feature patterns.

The performance graph also demonstrates that, although other algorithms were able to achieve excellent accuracy levels, the Extension Tuned SVM continuously outperformed the others in every evaluation metric. Efficient hyperparameter tuning, which enhances decision boundaries and classification abilities, is the primary reason for the improvement. Combining ResNet50 feature extraction with PSO optimization also allowed for better feature quality and more efficient classifier performance. All things considered, the results show that the proposed enlarged model is very reliable, accurate, and suitable for categorizing medicinal plants in the real world.

Accuracy: A test's accuracy is defined as its ability to recognize debilitated and solid examples precisely. To quantify a test's exactness, we should register the negligible part of genuine positive and genuine adverse outcomes in completely examined cases. This might be communicated numerically as:

Accuracy = TP + TN TP + TN + FP + FN.

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. As a result, the accuracy may be calculated using the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$Accuracy = \frac{(TN + TP)}{T}$$

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. It is the proportion of appropriately anticipated positive perceptions to add up to real up-sides, which gives data about a model's capacity to catch instances of a specific class.

$$Accuracy = \frac{(TN + TP)}{T}$$

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. The precision measurement computes how often a model anticipated accurately over the full dataset.

$$Accuracy = \frac{(TN + TP)}{T}$$

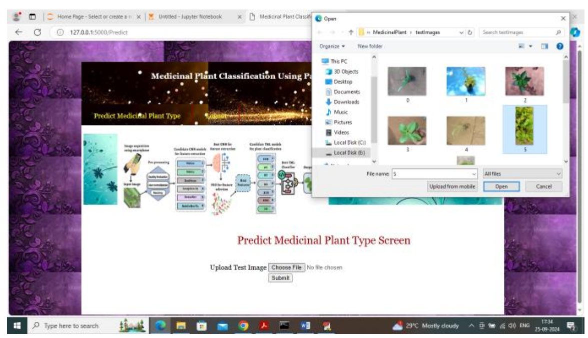

Fig 2 Upload input image to predict result

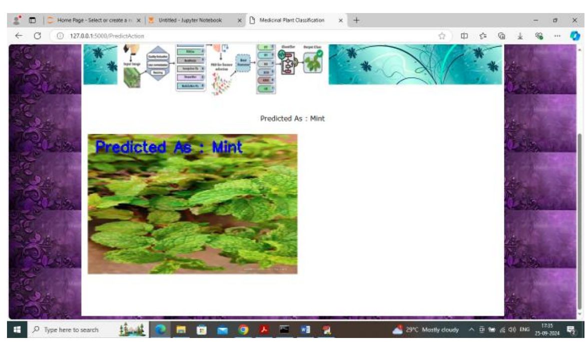

Fig 3 predicted results

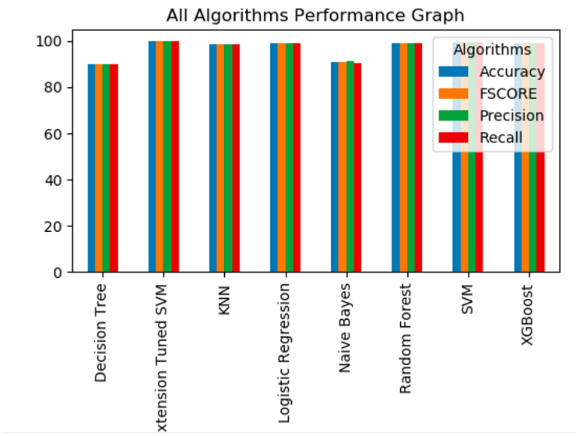

Fig 4 Accuracy graph

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	99.591169	99.587691	99.562995	99.574178
Random Forest	98.93704	98.931784	98.874095	98.899183
Decision Tree	90.106296	89.936318	89.915326	89.9102
KNN	98.691742	98.722744	98.566263	98.623833
XGBoost	99.100572	99.075828	99.057936	99.064183
Naïve Bayes	90.842191	91.2915	90.567539	90.73908
Logistic Regression	99.182339	99.120755	99.146131	99.132419
Extension Tuned SVM	**99.7547**	**99.744965**	**99.73999**	**99.741804**

Table 1 PERFORMANCE EVALUATION

5. CONCLUSION

The suggested medicinal plant classification system successfully combines many machine learning methods for classification, Particle Swarm Optimization (PSO) for feature selection, and ResNet50 for deep feature extraction. With the majority of models performing above 98%, the testing findings show that the system achieves great accuracy and dependability. With the greatest accuracy of 99.75% and the best precision, recall, and F1-score of any classifier, the Extension Tuned SVM performs better than the others. This demonstrates how well feature optimization and parameter adjustment work to enhance classification performance.

Additionally, by automating feature extraction and improving decision-making using optimal learning models, the suggested strategy effectively overcomes the drawbacks of conventional techniques. The system can handle complicated datasets with excellent consistency and is scalable and efficient. As a result, this work offers a reliable and precise method for identifying medicinal plants, greatly advancing botanical research, healthcare, and practical plant categorization applications.

6. FUTURE SCOPE

By expanding the dataset to include a wider range of therapeutic plants from various areas, the suggested approach may be further improved, increasing the model's capacity for generalization. To get even more accuracy, future research can investigate sophisticated deep learning architectures like EfficientNet or Vision Transformers (ViT). Furthermore, real-time deployment via web-based or mobile applications might increase the system's accessibility for users such as researchers, farmers, and medical professionals.

Additionally, using multimodal characteristics like chemical composition, floral structure, and leaf shape might enhance classification performance even more. For automatic plant monitoring in agricultural settings, the system may also be integrated with IoT-based picture capturing. In order to lower computing costs without sacrificing accuracy, more optimization strategies and hybrid models can be investigated.

This would make the system more effective and appropriate for practical implementation.

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