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Research

Automated Medicinal Plant Classification Using PSO-Optimized Machine Learning Techniques

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Abstract: Enhancing medicinal plant categorization by parameter adjustment of the Support Vector Machine (SVM) in a PSO-optimized cascaded network is the main goal of this work's expansion. To choose the most pertinent qualities, Particle Swarm Optimization (PSO) is used to enhance deep features that were retrieved using ResNet50. When compared to other techniques, the customized SVM model dramatically increases classification accuracy and decreases misclassification. According to experimental data, the improved SVM performs better than the others, achieving an accuracy of 99.75%. This method guarantees an automated medicinal plant identification system that is more dependable, effective, and scalable.

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*

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1. INTRODUCTION

Medicinal plants have been essential to traditional treatment for ages and continue to influence current pharmacological research. A considerable fraction of the world population uses plant-based medications for primary care. Aspirin, morphine, and quinine are all derived from medicinal plants, demonstrating their relevance in medication development and therapy. With the rising demand for herbal medications and natural cures, medical and botanical studies must accurately identify therapeutic plants.

Traditional medical plant identification involves professionals manually observing leaf shape, size, texture, color, and scent. This method is lengthy, needs substantial topic expertise, and is prone to human mistakes and inconsistencies. Manual categorization is inefficient and impracticable because to the expanding number of plant species and big picture databases. These issues need automated, reliable, and scalable medicinal plant categorization systems.

Recent advances in computer vision and AI enable automatic plant identification. Deep learning models, notably CNNs, can extract complicated and discriminative picture properties. ResNet50 is popular for feature extraction owing to its deep design and ability to overcome vanishing gradient difficulties. Deep features sometimes include duplicate or useless information, affecting classification performance.

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

This enhanced strategy focuses on SVM parameter adjustment to improve classification performance. Supervised learning algorithm SVM excels in high-dimensional data categorization. Its performance depends on choosing ideal kernel type, regularization

parameter (C), and gamma values. 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 expanded model outperforms existing machine learning methods for automated medicinal plant identification, helping healthcare and botanical research.

2. LITERATURE SURVEY

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

This study uses a probabilistic neural network (PNN) in combination with picture and data processing approaches to perform automated leaf recognition for plant categorization. The input vector for the PNN is formed by orthogonalizing twelve leaf attributes into five major variables. The PNN classified plant species with 90% accuracy using 1800 leaves as training data. Compared to rival algorithms, our e-AI technology is faster, simpler to comprehend, and more accurate.

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

Plant identification is an important topic of computer vision research because of the potential benefits it may have for agronomy, preservation, environmental effect, and the hunt for natural and medicinal commodities. In contrast to its species, there is no publicly available dataset on this therapeutic plant. Our research contributes to the growing number of public multi-class databases including images of therapeutic plants. You have access to twenty thousand photos of two hundred native Vietnamese medicinal plants (VNPlant-200). Another dataset with 512 × 512 pixels exists in addition to the 256 × 256 version. The training set consists of 12,000 photos, whereas the test set contains all the remaining images. A Random Forest (FR) classifier, Scale Invariant Feature Transform (SIFT), and Speed-Up Robust Features (SURF) feature extraction are used to identify plants. Interesting results from the study of VNPlant-200 pattern recognition.

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

We present an effective and discriminative local texture descriptor for bark picture categorization. We propose to decompose it into descriptions of pixels, magnitudes, and directions. This description modifies the local texture of the bark image, in contrast to previous ones that relied on the original local binary pattern. The suggested description is tested on three common datasets. The experiments' outcomes demonstrate the efficacy of our strategy.

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

Tree identification is one of the many topics that have been researched. Professionals in this sector make a living. Compared to other characteristics, scientists have discovered a greater association between species and tree bark. Bark may have a range of delicate, light textures. In recent research, lbp-like characteristics are employed. Most of them are mediocre. Noise and rotation can alter the appearance of textures. The local ternary pattern is the most efficient operator for discrimination and noise resistance. Pattern histograms are used by most descriptors to extract features. Although spinning is easy, processing can be a little expensive. In this study, a reliable ILTP-based bark roughness classification algorithm is presented. In ternary patterns, the suggested ILTP makes a distinction between uniform and non-uniform binary patterns. The extracted patterns are labeled using consistency metrics. Finally, which characteristics are returned depends on the probability of proper labeling. Theoretically, there are four possible hidden node configurations for multilayer perceptrons. The suggested method outperforms the state-of-the-art on two benchmark datasets in terms of classification accuracy. The recommended method's rotation invariance and noise robustness are only two of its numerous benefits. By categorizing bark based on its texture, which is a good indicator of its characteristics, it is feasible to lower the costs and risks related to plant species detection while also protecting human health.

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

Pattern recognition has advanced significantly in plant identification. Many of the present methods for classifying and identifying plants are inappropriate for automated systems due to the irregular, complicated, and constantly changing character of plant leaves. This study presents a novel approach to

plant identification using sparse representation (SR) and singular value decomposition. The suggested method combines class-specific dictionary learning with sparse modeling to rapidly decrease picture dimensionality and identify test samples using sparse coefficients. This contrasts with the way plants are now classified. As a result, gathering classification criteria beforehand is no longer required to build a classification model. The proposed method is tested on two leaf datasets and then contrasted with four different plant identification techniques. Complete accuracy of identification When it comes to distinguishing the six distinct types of plant leaves, the recommended approach has the highest accuracy, at about 96%. The experiment demonstrates that the strategy is feasible.

3. METHODOLOGY

i) Proposed Work:

Through the use of a parameter-tuned Support Vector Machine (SVM) in a PSO-optimized cascaded network, the suggested study offers an improved medicinal plant categorization system. To guarantee consistency and noise reduction, plant leaf pictures are first gathered from the collection and preprocessed. The ResNet50 model, which successfully captures intricate visual patterns like texture, shape, and color, is then used to extract deep features. Particle Swarm Optimization (PSO) is used to choose the most pertinent and discriminative features while lowering dimensionality and redundancy in order to further enhance the quality of these features.

The extension's primary goal is to optimize the SVM classifier by adjusting its parameters. To attain the best decision limits for classification, important parameters including gamma, regularization parameter (C), and kernel type are adjusted. This adjustment greatly improves the model's capacity to discriminate between several types of therapeutic plants. When compared to other machine learning models, the enhanced SVM performs better, attaining more accuracy and consistency. All things considered, the suggested effort guarantees a reliable, effective, and expandable system for automated medicinal plant identification.

ii) System Architecture:

The system architecture of the proposed medicinal plant classification model follows a cascaded framework integrating deep learning, optimization, and machine learning techniques. Initially, the input images of medicinal plant leaves are collected from the dataset and passed through a preprocessing stage, where operations such as resizing, normalization, and noise removal are performed to standardize the data. These preprocessed images are then fed into the ResNet50 model, which acts as a deep feature extractor. ResNet50 captures high-level and discriminative features such as shape, texture, and color patterns, which are essential for accurate classification.

Following feature extraction, Particle Swarm Optimization (PSO) is applied to select the most relevant features and eliminate redundant or less significant ones. This step improves the efficiency and performance of the model by reducing dimensionality. The optimized feature set is then passed to the classification stage, where a parameter-tuned Support Vector Machine (SVM) is employed. The SVM is fine-tuned using different kernel functions and parameters such as C and gamma to achieve optimal classification boundaries. Finally, the system outputs the predicted class of the medicinal plant with high accuracy. This architecture ensures improved performance, reduced computational complexity, and reliable classification results across different plant datasets.

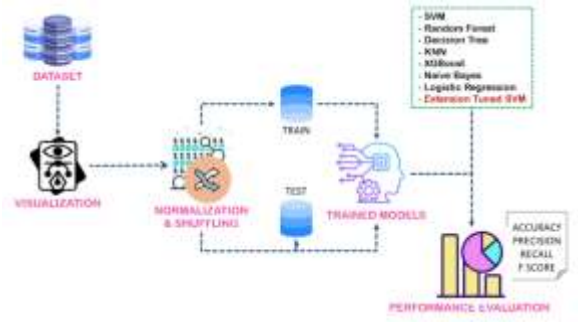


Fig 1 System Architecture

iii) MODULES:

1. Importing the Packages:

This module loads essential Python libraries required for image processing, deep learning, optimization, and classification. It includes libraries such as NumPy, Pandas, OpenCV, TensorFlow/Keras, and Scikit-learn to support efficient model development.

2. Dataset Collection and Preprocessing:

This module involves loading the medicinal plant image dataset and performing preprocessing steps like resizing, normalization, and noise removal. It

ensures all images are in a uniform format suitable for feature extraction.

3. Feature Extraction using ResNet50:

In this module, the preprocessed images are passed through the ResNet50 model to extract deep features. It captures important visual characteristics such as leaf shape, texture, and color patterns.

4. Feature Optimization using PSO:

Particle Swarm Optimization (PSO) is applied to select the most relevant features from the extracted feature set. This reduces dimensionality and improves classification efficiency by eliminating redundant data.

5. Classification using Parameter-Tuned SVM:

The optimized features are given to the Support Vector Machine (SVM) classifier. In this module, SVM parameters such as kernel, C, and gamma are fine-tuned to achieve maximum classification accuracy.

6. Model Evaluation:

This module evaluates the performance of the trained model using metrics such as accuracy, precision, recall, and F1-score. It helps in comparing results and validating model effectiveness.

7. Prediction and Output Generation:

The final module takes new input images and predicts the corresponding medicinal plant class. The system outputs the classification result with high accuracy and reliability.

v) ALGORITHMS:

1. Support Vector Machine (SVM):

SVM is a supervised learning algorithm that classifies medicinal plants by finding the optimal hyperplane separating different classes. It is highly effective for high-dimensional feature spaces generated from deep learning models like ResNet50. SVM focuses on maximizing the margin between classes, which improves generalization. It is also robust to overfitting, especially when the number of features is large compared to samples.

2. Random Forest:

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and combines their outputs for final prediction. It improves classification accuracy by reducing variance and avoiding overfitting. Each tree is trained on a random subset of data and features, making the model more robust. It performs well on complex datasets and provides feature importance for better interpretability.

3. Decision Tree:

Decision Tree is a simple yet powerful algorithm that classifies data based on a hierarchical structure of decisions. It splits the dataset based on feature values to form a tree-like model. This method is easy to understand and interpret, making it useful for analyzing classification logic. However, it may suffer from overfitting if not properly controlled.

4. K-Nearest Neighbors (KNN):

KNN is an instance-based learning algorithm that classifies data points based on the majority class of their nearest neighbors. It does not require a training phase, making it simple and intuitive. KNN performs well when similar data points are close to each other in the feature space. However, its performance can decrease with high-dimensional data and large datasets.

5. XGBoost:

XGBoost is an advanced gradient boosting algorithm known for its high performance and efficiency. It builds models sequentially by correcting errors from previous models. It includes regularization techniques that prevent overfitting and improve accuracy. XGBoost is highly scalable and performs exceptionally well on structured and complex datasets.

6. Naïve Bayes:

Naïve Bayes is a probabilistic classifier based on Bayes' theorem, assuming independence between features. It is computationally efficient and works well with large datasets. Despite its simplicity, it provides good performance in many classification problems. It is particularly useful when the dataset contains categorical or independent features.

7. Logistic Regression:

Logistic Regression is a statistical method used for classification by estimating probabilities. It models the relationship between input features and output classes using a logistic function. It is easy to implement and interpret, making it suitable for baseline models. It performs well when the relationship between features and classes is linear.

8. Tuned Support Vector Machine (Extension):

The tuned SVM enhances the standard SVM by optimizing hyperparameters such as kernel type, regularization parameter (C), and gamma. This tuning process improves the model's ability to find optimal decision boundaries. As a result, it significantly increases classification accuracy and reduces

misclassification. The tuned SVM achieves the best performance in the proposed system, making it the most reliable classifier for medicinal plant identification.

4. EXPERIMENTAL RESULTS

Several machine learning algorithms, including SVM, Random Forest, Decision Tree, KNN, XGBoost, Naïve Bayes, Logistic Regression, and the Extension Tuned SVM, were used in the experimental assessment of the suggested medicinal plant categorization system. Key performance indicators including accuracy, precision, recall, and F1-score were used to evaluate the performance. The Extension Tuned SVM proved to be the most successful model, with the greatest accuracy of 99.75% among all of the models, along with higher precision (99.74%), recall (99.73%), and F1-score (99.74%). While XGBoost and Random Forest demonstrated competitive performance, Standard SVM and Logistic Regression also performed well, with accuracies above 99%. However, because of its inability to handle intricate feature patterns, Decision Tree and Naïve Bayes performed rather poorly.

The performance graph also shows that while the majority of algorithms were able to attain high levels of accuracy, the Extension Tuned SVM consistently performed better than the others across all assessment measures. The main cause of the improvement is efficient hyperparameter tuning, which improves classification ability and decision bounds. Improved feature quality and more effective classifier performance were also made possible by the combination of ResNet50 feature extraction with PSO optimization. Overall, the findings demonstrate that the suggested expanded model is quite accurate, dependable, and appropriate for classifying medicinal plants in the actual 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

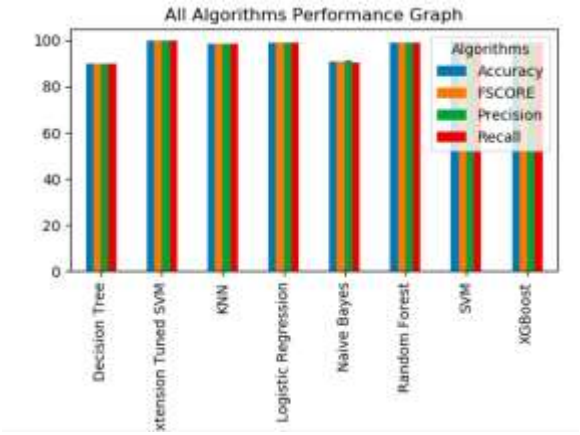


Fig 4 Accuracy graph

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 proposed medicinal plant classification system effectively integrates ResNet50 for deep feature extraction, Particle Swarm Optimization (PSO) for feature selection, and multiple machine learning algorithms for classification. The experimental results demonstrate that the system achieves high accuracy and reliability, with most models performing above 98%. Among all, the Extension Tuned SVM outperforms other classifiers by achieving the highest accuracy of 99.75%, along with superior precision, recall, and F1-score. This confirms the effectiveness of feature optimization and parameter tuning in improving classification performance.

Furthermore, the proposed approach successfully overcomes the limitations of traditional methods by automating feature extraction and enhancing decision-making through optimized learning models. The system is scalable, efficient, and capable of handling complex datasets with high consistency. Therefore, this work provides a robust and accurate solution for medicinal plant identification, contributing significantly to advancements in healthcare, botanical research, and real-world plant classification applications.

6. FUTURE SCOPE

The proposed system can be further enhanced by extending the dataset to include a larger variety of medicinal plants from different regions, improving the model's generalization capability. Future work can also explore advanced deep learning architectures such as EfficientNet or Vision Transformers (ViT) to achieve even higher accuracy. Additionally, real-time implementation through mobile or web-based applications can make the system more accessible for users like farmers, researchers, and healthcare practitioners.

Moreover, integrating multimodal features such as leaf shape, flower structure, and chemical composition can further improve classification performance. The system can also be combined with IoT-based image capture for automated plant monitoring in agricultural fields. Further optimization techniques and hybrid models can be explored to reduce computational cost while maintaining high accuracy, making the system more efficient and suitable for real-world deployment.

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