Multi-Model Comparative Study for Bark-Texture Based Tree Species Classification Using Custom Indian Tree Species Dataset

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ABSTRACT

Accurate wood species identification is crucial for biodiversity preservation and forest management. Because traditional identification methods are time-consuming and heavily rely on expert knowledge, automated image-based solutions have become more and more important. This research suggests a hierarchical framework for identifying wood species that makes use of both machine learning (ML) and deep learning (DL) approaches. The dataset of bark images utilized in the testing includes 22 distinct wood species. The ML-based approach evaluates classifiers such as Random Forest, Support Vector Machine, XGBoost, and ensemble models following extensive preprocessing and manually created feature extraction using statistical, color, and texture descriptors. The DL-based technique uses a specially designed CNN architecture in combination with convolutional neural networks that apply transfer learning models, such as MobileNetV2, DenseNet121, and ResNet50. The short dataset size is addressed using data augmentation and fine-tuning techniques. The experimental results demonstrate that Deep Learning models achieve greater classification performance and robustness when compared to Machine Learning models. This study provides a detailed comparison of complex DL algorithms with conventional ML to show the effectiveness of transfer learning for automated wood species identification.

KEYWORDS: *Tree Species Classification, Bark Texture Analysis, Deep Learning, Machine Learning, Transfer Learning.*

Introduction

Identifying wood species is essential for forest management, biodiversity conservation, and regulating timber trade. Automated bark-based identification using deep learning achieves high accuracy, with optimized CNN architectures improving feature extraction and cross-species generalization. Transfer learning further enhances efficiency, especially for small datasets, while practical studies confirm the feasibility of CNN-based identification systems, and visualization methods like Class Activation Mapping improve interpretability.

Traditional approaches rely on handcrafted texture descriptors, which are often time-consuming and sensitive to environmental variations. To improve robustness in real-world conditions, lightweight descriptors such as rotation-invariant and multispectral texture features have been proposed. Multidimensional texture analysis methods also show strong performance, and hybrid feature–classifier techniques enhance classical approaches.

Deep learning addresses many of these limitations by automatically learning hierarchical representations. Accuracy improves with specialized datasets and advanced architectures, while CNN-based descriptors enable dependable identification under a variety of circumstances. Transfer learning has been shown to outperform handcrafted approaches across datasets, lightweight networks support real-time deployment, and patch-based models increase robustness to texture variability. Building on these advances, this work combines CNN architectures and GLCM features to classify 22 wood species, comparing ML & DL methods in order to increase precision and reliability.

Literature Review

Faizal presented an automated method for identifying tree species that makes use of

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convolutional neural networks (CNNs) on bark texture photos from the BarkVN-50 dataset, demonstrating the efficiency of deep learning for bark-based classification. Saengpetch et al. applied a transfer learning-based CNN framework with data augmentation techniques to improve bark image classification accuracy, showing that fine-tuned pretrained models perform well even with limited datasets. Cui et al. proposed an optimized CNN design for bark feature extraction, achieving improved recognition precision and generalization capability across tree species. Kim et al. developed a dedicated bark dataset and CNN model with training, including VGG16 and VGG19, achieving high accuracy for automatic tree identification.

Bhusnurmath and Doddamani evaluated sophisticated deep learning models, such as Wide-ResNet and ConvNeXt, which showed superior bark texture classification performance. Ratajczak et al. explored lightweight, rotation-invariant handcrafted descriptors, enabling efficient bark recognition in real-world outdoor conditions. Boudra et al. and Remes & Haindl focused on handcrafted texture features, proposing radial binary patterns and rotationally invariant multispectral descriptors, respectively, achieving robust classification under varying lighting and orientation.

Barmpoutis et al. applied multidimensional texture analysis with SVM categorization of the WOOD-AUTH dataset, demonstrating effective wood species recognition. Misra et al. proposed a patch-based CNN approach, where aggregating patch-level predictions improved robustness against texture variability and background noise. Wu et al. introduced Deep BarkID, a knowledge-distillation-based lightweight CNN suitable for mobile devices, enabling real-time field identification with high accuracy.

Armi and Abbasi combined color-improved local quinary patterns (CI-LQP) with a stacked MEETG classifier, achieving improved performance over traditional texture-based approaches. Finally, Bhusnurmath and Doddamani demonstrated that deep transfer learning using pretrained CNNs significantly outperforms handcrafted feature methods for bark texture classification across multiple datasets.

Dataset Description

Table 1 displays the dataset used to assess ML and DL models, which consists of 558 JPEG RGB bark photos of 22 wood species.

Table 1: Dataset Description of "Wood Species Bangalore"

Parameter	Description
Dataset Type	Bark Image Dataset
Number of Images	558
Number of Classes	22 Wood Species
Image Format	JPG
Color Space	RGB
Dataset Size	133 MB

Methodology

The suggested methodology employs image-based ML and DL algorithms to systematically categorize wood species. Bark photos are first preprocessed to reduce noise and enhance image quality. The photos are then analyzed using a variety of models, such as machine learning, ensemble techniques, and deep learning networks, to identify significant patterns for classification. Lastly, performance indicators like recall, accuracy, and precision are employed to assess and contrast the efficacy of each strategy.

Figure 1 shows how the machine learning, ensemble, and deep learning approaches are evaluated.

Machine Learning

Through the use of machine learning, systems can automatically identify patterns in data and generate predictions. In order to categorize or forecast fresh, unknown data, algorithms are trained on extracted features. It consists of sequential steps to be followed they are:

Step 1: Input Image and Preprocessing - To enhance image quality and preserve consistency, input bark photos are gathered and preprocessed utilizing scaling, noise reduction, and normalization.

Step 2: Feature Extraction - To record distinctive patterns of several wood species, texture features are retrieved using techniques like GLCM. For every image in this investigation, the GLCM has five Haralick texture features:

- Contrast: reflects texture roughness and quantifies intensity variance between adjacent pixels.
- Correlation: Indicates how correlated a pixel is to its neighbor across the image.
- Energy: depicts the bark surface's consistent texture and recurring patterns.
- Homogeneity: evaluates how closely GLCM elements resemble the diagonal distribution.
- Entropy: measures the texture patterns'

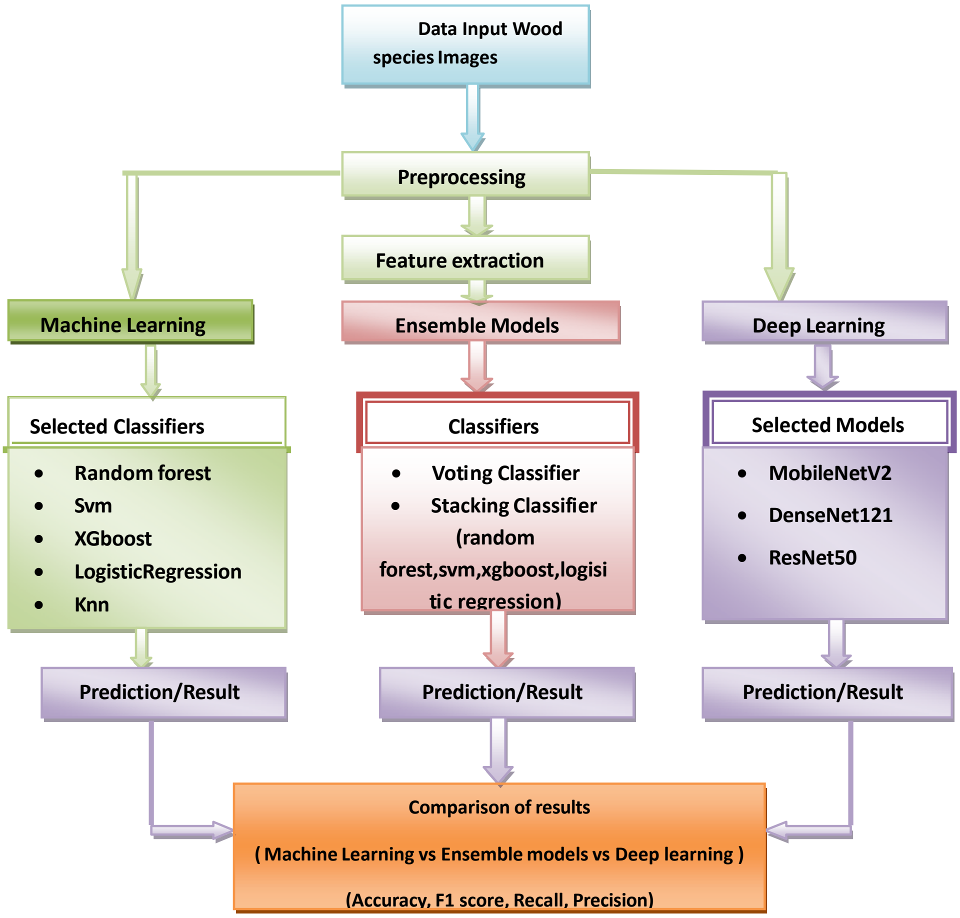

Fig 1 : Flow diagram of Machine learning & deep learning

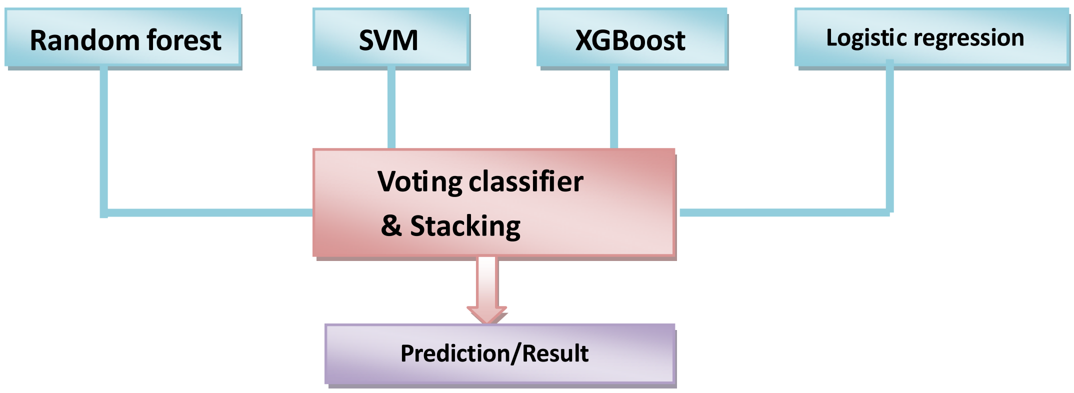

Fig 2: Block Diagram of Ensemble Models

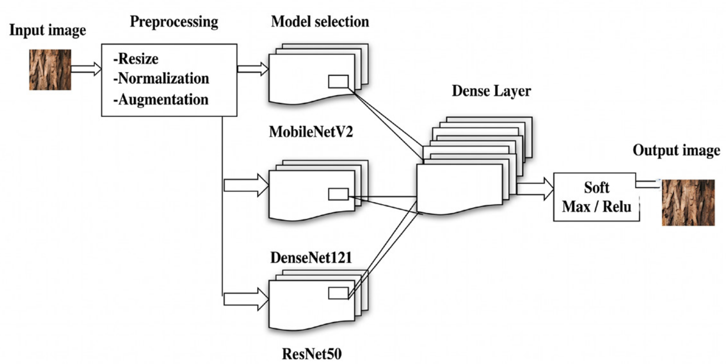

Fig 3: Block Diagram of Deep Learning

complexity or unpredictability.

Step 3: Creating CSV File - Image paths and class labels are stored in a CSV file, which organizes the dataset and facilitates training.

Step 4: Splitting the Dataset (80:20) - To guarantee appropriate model learning and evaluation, the dataset is divided into 80% training data and 20% testing data using the CSV file.

Step 5: Model Training - Machine learning classifiers are trained using the retrieved features to discover correlations between characteristics and species classifications.

Step 6: Model Evaluation - Metrics including accuracy, precision, recall, and F1-score are used to assess the trained model's performance.

Utilizing machine learning classifiers for the proposed experiment are:

- **Random Forest:** An ensemble learning technique that reduces overfitting and increases accuracy by constructing several decision trees and combining their output to provide final predictions.
- **SVM:** An algorithm for supervised learning that uses the best hyperplane to optimize the distance between various classes to classify data.
- **XGBoost:** Gradient boosting is a technique that improves efficiency and effectively handles complex patterns by successively correcting earlier faults.
- **Logistic Regression:** An efficient probabilistic classification approach for linearly separable data that classifies data using a logistic function.
- **K-Nearest Neighbors (KNN):** A non-parametric instance-based classifier that uses distance measurements to assign classes based on the majority of closest neighbors.

Ensemble Models

To enhance performance and generalization, ensemble models were used after evaluating individual machine learning classifiers. They lower mistakes and produce more dependable outcomes by merging predictions from several models. Two ensemble approaches are employed in this investigation.

- **Voting Classifier:** Random Forest, SVM, XGBoost, and Logistic Regression are the basis models used in the Voting classifier. Majority voting is used to choose the final class, increasing accuracy and decreasing individual model bias.
- **Stacking Classifier:** Logistic regression, Random Forest, SVM, and XGBoost are the basis models used in the Stacking classifier. To increase accuracy and generality, their outputs are concatenated using a meta-classifier.

Figure 2 shows ensemble model seen, classifiers such as Random Forest, SVM, XGBoost, and Logistic Regression combine predictions through stacking and voting to increase accuracy.

Deep Learning

Deep learning, which employs multilayer neural networks to automatically identify intricate patterns from bark photos for image classification without the need for human feature extraction, is used in the suggested experiment.

Figure 3 shows the deep learning pipeline is depicted wherein bark images undergo preprocessing, feature learning model analysis, and classification to identify wood species.

Here are steps involved in this:

Step 1: Input Image - Images of the bark of several wood species are fed into the system; these photos may range in size, lighting, and backdrop.

Step 2: Preprocessing - To ensure consistency and enhance model performance, input photos are scaled, normalized, and cleaned to eliminate noise.

Step 3: Model Selection - Deep learning models that automatically learn features for precise categorization, such MobileNetV2, DenseNet121, or ResNet50, are given preprocessed photos.

Step 4: Classified Output - To get the final classification result, the trained model forecasts the wood species label for every input image.

Below listed Deep learning models were used for the proposed experiments:

- MobileNetV2: Using depthwise separable convolutions, this lightweight CNN lowers processing costs without sacrificing accuracy, making it appropriate for real-time and mobile applications.
- DenseNet121: In order to capture fine textures and achieve high classification accuracy, a deep network with dense layer connections enhances gradient flow and feature reuse.
- ResNet50: A deep network with residual connections that effectively extracts complicated characteristics for precise picture classification while preventing vanishing gradients.

Result and Discussion

Using metrics like accuracy, precision, recall, and F1-score, this section evaluates the performance of machine learning, ensemble, and deep learning models for classifying wood species.

Table 1: Results of Machine Learning

Models	Accuracy(%)	Precision(%)	Recall(%)	F1 score(%)
Random forest	84.33	87	84	84
SVM	87.56	90	87	88
XG boost	85.25	87	85	85
Logistic regression	88.48	90	88	89
Knn	82.03	83	82	82

Table 2: Results of Ensemble Models

Models	Accuracy in %
Random forest	89 (Voting Classifier) 82 (Stacking classifier)
SVM	
XGboost	
Logistic regression	

Table 3: Results of Deep Learning

Models	Accuracy(%)	Precision(%)	Recall(%)	F1 score(%)
MobileNetV2	93.23	94	93	93
DenseNet121	94.12	96	94	94
ResNet50	98.22	98	98	98

Table 4: Comparison of Machine Learning and Deep Learning

Models	Machine learning	Ensemble Models	Deep learning	
Random Forest	84.53%	89% (voting classifier) 82% (stacking classifier)	Models	Accuracy(%)
SVM	87.56%		MobileNetV2	93.23
XG boost	85.25%		DenseNet121	94.12
Logistic Regression	88.48%		ResNet50	98.22
KNN	82%			

Table 5: Comparison of State-of-Art Methods

Author	Dataset used	Methods	Accuracy
Saengpetch et al.[1]	BarkVN-50,Bark- 101	Convolutional Neural Network -MobileNet-v2	81%
M. Robert et al.[2]	TRUNK Dataset	CNN-based descriptor models(Deep-Bark & SqueezeBark)	87.2%
Z. Cui et al.[3]	BarkNet 1.0	Convolutional Neural Network	90%
T. K. Kim et al.[4]	BarkNet 1.0	Convolutional Neural Network -EfficientNet, -VGG-16	VGG-16=90.7% EfficientNet=91.0%
S. Boudra et al.[5]	Bark-101	Haralick features.	84.7%
Remes & Haindl[6]	BarkNet	Convolutional Neural Network	91.23%
Gazo, et al.,[7]	BarkNet	Convulational neural network	90.4%
Proposed Method-ology	Wood species (Ban-galore)	- MobileNetV2 - DenseNet121 - Resnet50	MobileNetV2=93.23% DenseNet121=94.12% Resnet50=98.22%

The outcomes show how well deep learning models work for precise classification and compare various methods.

Results of Machine Learning

Table 1 shows the performance of different ML models for wood species classification using 5-fold cross-validation and standard metrics accuracy, precision, recall, F1-score.

According to Table 1, Logistic Regression had the best accuracy (88.48%), followed by SVM (87.56%), and KNN (82.03%). In general, SVM and Logistic Regression outperformed the other models.

Results of Ensemble Models

Table 2 are shown in the results of ensemble methods utilizing classifiers like Random Forest, SVM, XGBoost, and Logistic Regression combined with voting and stacking strategies.

From Table 2 observed that is the ensemble results show that the Voting Classifier with Random Forest achieved higher accuracy (89%) compared to the Stacking Classifier (82%), indicating that voting-based aggregation provided better performance. The remaining models (SVM, XGBoost, and Logistic Regression) can be compared similarly once their accuracy values are included.

Results of Deep Learning

Table 3 shows the presentation of deep learning models for wood species classification, trained for 45–50 epochs, evaluated using accuracy, precision, recall, and F1-score to compare their effectiveness on bark textures.

Table 3 shows that ResNet50 outperformed DenseNet121 (94.12%) and MobileNetV2 (93.23%) in terms of accuracy (98.22%), precision, recall, and F1-score (98%). ResNet50 turned out to be the most successful model overall.

Table 4 presents a comparison of deep learning and machine learning models for classifying wood species from bark photos. To compare classification performance, accuracy (%) is used to assess individual machine learning, ensemble, and deep learning models like MobileNetV2, DenseNet121, and ResNet50.

According to the table, the Voting ensemble attained 89% accuracy, while Logistic Regression (88.48%) outperformed other machine learning models. With an overall performance of (98.22%), ResNet50 outperformed all other models.

Table 5 presents a comparison between the suggested method and cutting-edge techniques for classifying wood species. The suggested models - MobileNetV2, DenseNet121, and ResNet50 - achieved higher accuracy using the Bangalore wood species dataset, demonstrating the potency of deep learning in capturing intricate bark patterns.

Table 5 shows that previous research employing CNN architectures and texture-based techniques produced accuracies ranging from 81% to 91.23%. CNN-based methods, including EfficientNet (91.0%), performed well. On the Bangalore wood species dataset, however, the suggested approach fared better than other studies, obtaining 93.23% with MobileNetV2, (94.12%) with DenseNet121, and the greatest accuracy of (98.22%) with ResNet50.

Conclusion

The classification of wood species using both machine learning and deep learning techniques was investigated in this study. While ensemble approaches increased accuracy and resilience, machine learning models utilized GLCM–Haralick features with classifiers like Random Forest, SVM, and XGBoost. MobileNetV2, DenseNet121, and ResNet50 are examples of deep learning models that automatically extracted features and attained improved accuracy. Deep learning fared better overall than conventional machine learning models, demonstrating its efficacy for accurate identification of wood species.

Future Work:

To enhance model generalization, the dataset can be enlarged in subsequent work with more wood species and a variety of environmental circumstances. More sophisticated optimization and augmentation methods can improve robustness and lessen overfitting. While incorporating features like leaf or grain patterns could further increase classification accuracy and reliability, lightweight architectures might also enable real-time mobile deployment.

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