

Wood Type Classification Based on Hybrid Feature Integration with Optimized Bagging Ensemble Approach

Optimizasyonlu Bagging Ensemble Yaklaşımıyla Hibrit Özellik Entegrasyonuna Dayalı Ahşap Türü Sınıflandırması

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Abstract

Images of oak (*Quercus petraea* L.), chestnut (*Castanea sativa* M.) and Scots pine (*Pinus sylvestris* L.) tree species, which are widely used in Türkiye and around the world, were obtained in this study using mobile devices. The primary objective of this study is to automatically and reliably distinguish these wood species using image processing techniques and statistical classification methods, thereby enabling tree species identification at the genus level. In this context, colour and edge-based features such as HSV (Hue, Saturation, Value), LAB (Lightness, A (green-red), B (blue-yellow)), LBP (Local Binary Pattern) and Sobel (Sobel Edge Detection Operator) were extracted from the images. These features were evaluated using Random Forest, XGBoost, CatBoost, and Extra Trees algorithms to test classification performance. The experimental results show that colour-based features such as HSV and LAB achieved 97.5% accuracy with the Extra trees algorithm, while 100% accuracy was achieved with an optimisation-based bagging ensemble approach using all features together. Achieving such high accuracy on real-world data collected in the field using mobile devices demonstrates that the proposed method can be used as a reliable species identification tool in practical applications.

Özet

Türkiye’de ve dünyada yaygın olarak kullanılan meşe (*Quercus petraea* L.), kestane (*Castanea sativa* M.) ve sarıçam (*Pinus sylvestris* L.) ağaç türlerine ait görüntüler bu araştırmada mobil cihaz kullanılarak elde edilmiştir. Çalışmanın temel amacı, bu ahşap türlerini görüntü işleme teknikleri ve istatistiksel sınıflandırma yöntemleri aracılığıyla otomatik ve güvenilir şekilde ayırt ederek ağaç türü tespitini cins bazında gerçekleştirmektir. Bu doğrultuda, görüntülerden HSV (Hue, Saturation, Value), LAB (Lightness, A (green-red), B (blue-yellow)), LBP (Local Binary Pattern) ve Sobel (Sobel Edge Detection Operator) gibi renk ve kenar tabanlı özellikler çıkarılmıştır. Elde edilen bu özellikler, Random Forest, XGBoost, CatBoost ve Extra trees algoritmalarıyla değerlendirilerek sınıflandırma başarıları test edilmiştir. Deneysel sonuçlar, özellikle HSV ve LAB gibi renk tabanlı özelliklerin Extra trees algoritmasıyla %97.5 doğruluk sağladığını; tüm özelliklerin birlikte kullanıldığı, optimizasyon temelli bagging ensemble yaklaşımıyla ise %100 doğruluk elde edilmiştir. Mobil cihazlarla sahada toplanan gerçek dünya verileri üzerinde bu derece yüksek doğrulukların elde edilmesi, önerilen yöntemin pratik uygulamalarda güvenilir bir tür tespit aracı olarak kullanılabileceğini göstermektedir.

INTRODUCTION

The importance of wood classification and identification extends far beyond illicit trade and ecological problems. Wood identification is crucial to the woodworking industry, forest industry, civil engineering, criminology, art history, archaeology, ethnography, restoration, conservation, and many other disciplines (Silva et al. 2022). Its sustainability and widespread availability in nature, combined with advances in material science and technology, are increasing the use of wood in different application areas. It possesses numerous natural advantages, including high strength, low density, low cost, and high aesthetic appeal. Wood is also the subject

of scientific research for its multifunctional purposes, such as enhanced strength properties, sound absorption, thermal insulation, translucency, energy and electromagnetic shielding, and storage (Chen et al. 2020). These scientific advances have led to the widespread use and preference of wood in many areas, including automotive, construction, packaging, and more. Wood's versatility stems from its unique properties, both its natural structural diversity and its workability, which allow it to be used in a wide variety of engineering and industrial applications (Feng et al. 2024).

The development of computer technology is rapidly evolving and growing. Artificial intelligence, particularly machine learning and computer vision, which includes image processing, is making a wide range of contributions to various areas of life and industry (Pratondo et al. 2014, Pratondo et al. 2020). Wood identification is a crucial requirement for many forest and woodworking industries. It can aid in quality control across all production processes and eliminate uncertainty. It also has the potential to stop fraud in the wood trade. Computer vision has simplified and accelerated the process of identifying unusual woods. However, traditional methods remain important because they often provide greater convenience and efficiency, especially for typical commercial woods (Venugopal et al. 2024).

Machine learning and artificial neural networks are increasingly used in various areas in wood science and engineering, such as analyzing processes, monitoring the health of the structure, determining material properties, and quality control (Nasir et al. 2019).

Over the past decade, numerous studies (Hu et al. 2015, Ibrahim et al. 2017, Silva et al. 2022) have been developed aiming at automating wood species classification and identification. Many studies utilize macroscopic and microscopic images of wood using traditional pre-designed feature extraction.

Ibrahim et al. (2017) present a methodology for the classification and recognition of 48 tropical wood species. The proposed method consists of a two-level classifier focusing on computational efficiency. First, a fuzzy pre-classifier is used to classify images into four broad categories based on their pore sizes. Second, a support vector machine (SVM) classifier is used to perform the final classification based on the texture characteristics of the Gray Level Aura Matrix and the statistics of the pore distribution. The proposed method achieves 98.9% accuracy on a database of 25 species and 98.5% accuracy on a database of 48 species.

Khalid et al. (2011) developed an automatic wood recognition system to classify tropical wood species. Wood features are extracted using two feature extractors: the Basic Gray Level Aura Matrix (BGLAM)

technique and the Statistical Pore Distribution Characteristics (SPPD) technique. Due to the nonlinearity of tropical wood species separation boundaries, a pre-classification step consisting of K-means clustering and kernel discriminant analysis (KDA) is proposed. Finally, for comparison purposes, the Linear Discriminant Analysis (LDA) classifier and K-Nearest Neighbor (KNN) classifier are applied. The study includes a comparison of the system with and without pre-classification using the KNN classifier and the LDA classifier, and achieves a classification accuracy of 96.99%.

Hu et al. (2015) propose a wood species recognition method based on the bag-of-words concept, combined with scale-invariant feature transformation (SIFT), k-means, and k-means++ clustering algorithms. The authors evaluated the performance of artificial neural network (ANN), SVM, and kNN classifiers, and also compared the proposed descriptor with gray-level co-occurrence matrix (GLCM) and local binary patterns (LBP). The results reported that the proposed method achieves an accuracy of up to 90.2% for a dataset of 28 wood species captured by a camera.

Yadav et al. (2013) evaluated different combinations of Gabor filters and gray-level co-occurrence matrix (GLCM) feature extractors to classify 25 wood species using microscopic wood images. They reported an accuracy of 92.6% using an artificial neural network (ANN) as the classifier. Rosa da Silva et al. (2017) presented a cross-sectional dataset of 77 different wood species obtained at a standardized 2.5x zoom using microscopic wood images. Local phase quantization (LPQ) was used as the feature extractor, and linear discriminant analysis (LDA) was used to reduce the number of features. In the analysis performed with the kNN classifier, accuracy was 87.42% for species, 88.79% for genus, and 90.46% for family.

In a study conducted by Khalid et al. (2008), they proposed an automatic classification method for 20 different tropical wood species. They used high-pass spatial filtering, contrast enhancement, and histogram equalization to highlight the anatomical features of the woods. They achieved approximately 95% accuracy using

GLCM for feature extraction and ANN as a classifier. Martins et al. (2013) conducted experiments using pre-designed features (LBP and GLCM) with LDA, SVM, and ANN as classifiers for wood species recognition and identification. They introduced a microscopic dataset consisting of 112 species in two groups: 75 hardwood species (broadleaf) and 37 softwood species (conifer). The results reported classification accuracy of 98.6% within groups and up to 86% within species.

The machine learning process generally consists of two primary stages. The first is feature processing, also known as feature extraction. In this stage, meaningful and distinctive features are extracted from the input images. The second stage is classification. In this stage, the model is trained using the extracted features, and new images are classified. However, there is a step before image processing (Silva et al. 2022). Preprocessing aims to transform the image into data that a specific algorithm can use to extract the necessary features, thereby reducing computational confusion and simplifying subsequent processing (Kour et al. 2013). Splitting the dataset into training, validation, and test subsets is a critical step for accurately assessing the model's generalization ability. This process is not preprocessing but rather part of the model evaluation process. Data splitting is used to create a training set, a validation set, and a test set for later evaluation of model performance (Silva et al. 2022).

Once the extracted features are learned, a classification model is generated by a classifier, and a test set is created to evaluate the system's learning. Images are then input, allowing the classification model to complete the identification by feeding back the predicted classes of each image (Hwang and Sugiyama 2021). Machine learning generally selects the types of features to extract, in many cases, texture and local features (Silva et al. 2022).

In this study, macroscopic images of oak, chestnut, and Scots pine, which are frequently used in the forest industry and wood construction applications, were obtained using a mobile device. Feature extraction from the obtained images was performed using LBP, Sobel, HSV, and LAB feature extractors. Classification was then performed using optimized classification algorithms such as Random Forest, CatBoost, XGBoost, and ExtraTrees. Within the scope of the research, a hybrid feature integration-based wood species identification method was developed using a newly developed optimized bagging ensemble approach for high-accuracy wood species identification and classification.

MATERIALS AND METHODS

Data Set

The oak (*Quercus petraea* L.), chestnut (*Castanea sativa* M.), and Scots pine (*Pinus sylvestris* L.) samples used in this study were obtained from local lumber dealers in the Siteler district of Ankara. Species identification was carried out by expert woodworking engineers based on macroscopic anatomical features described in the literature. To ensure the smoothness of the wood surfaces, sanding was performed manually with 400-grit sandpaper. Photographs were taken in JPG format from a fixed distance of 15 cm, in the same lighting and room environment, with a 12-megapixel, f/1.8 aperture iPhone SE 2020 mobile device used in daily life. A total of 120 photographs were obtained, 40 from each tree species.

Before machine learning, the photographs were resized to 300×300 pixels in Jupyter Notebook using the Python programming language in the Anaconda environment, and the raw dataset was created (Kluyver et al. 2016). Wood samples were prepared from various orientations, including radial and tangential sections, to represent the tree's anatomical structure. This allowed the displayed samples to be analyzed from various angles, reflecting the wood's multifaceted characteristics. Images of the dataset are shown in Figure 1.

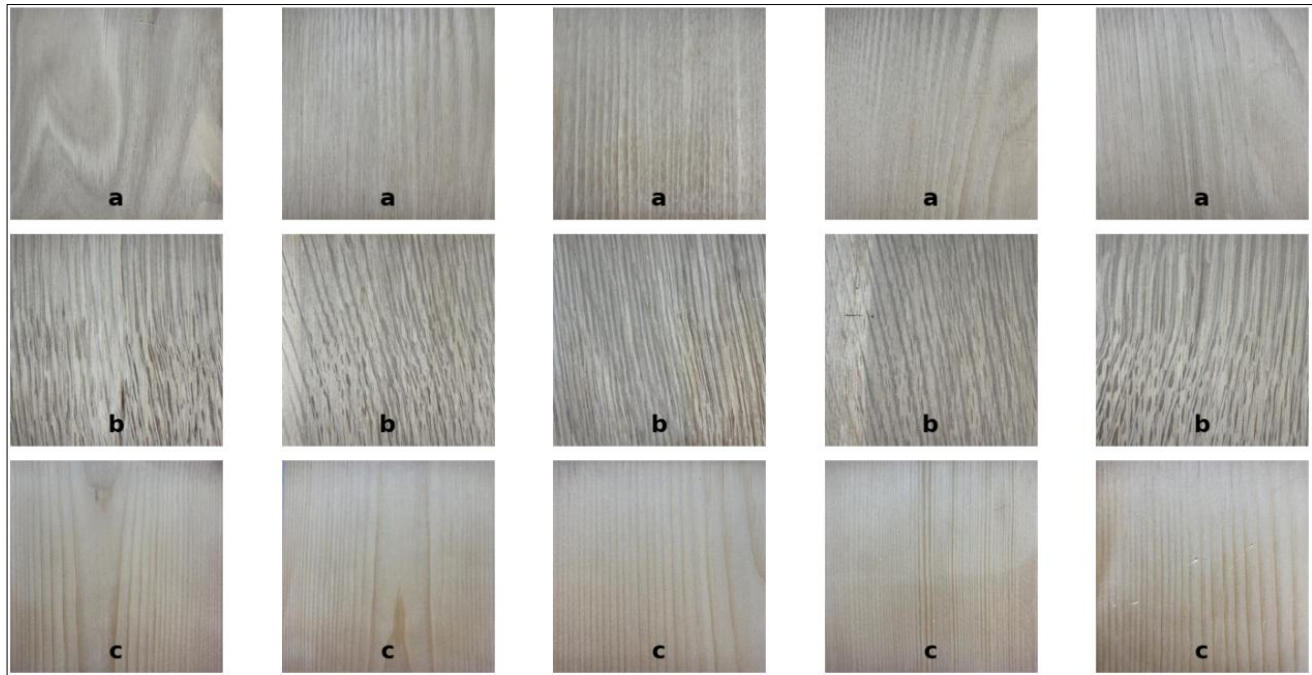


Figure 1. Images of the dataset: (a) Chestnut, (b) Oak, (c) Scots pine

Method

Feature Extraction

The goal is to provide more effective decision-making with low-dimensional data by representing the image with the fewest but most meaningful values. The classification success of algorithms depends on the quality and significance of the extracted features. Geometric, texture, statistical, and color-based features are widely used in the classification of wood species (Mutlag et al. 2020). Additionally, there are different classification approaches that include color, density,

texture, human, fingerprint, conceptual, and textual features (Salau and Jain 2009). Extensive studies on texture features are also available in the literature (Humeau-Heurtier 2019).

In this research, Local Binary Pattern (LBP), Sobel, HSV, and LAB color spaces were used to extract features from images. LBP is a grayscale-independent texture analysis method and produces binary patterns consisting of 1s and 0s by comparing the center pixel with neighboring pixels (Ojala et al. 2002). A total of 10 features were extracted with this method, and an example image obtained with the LBP method is presented in Figure 2.

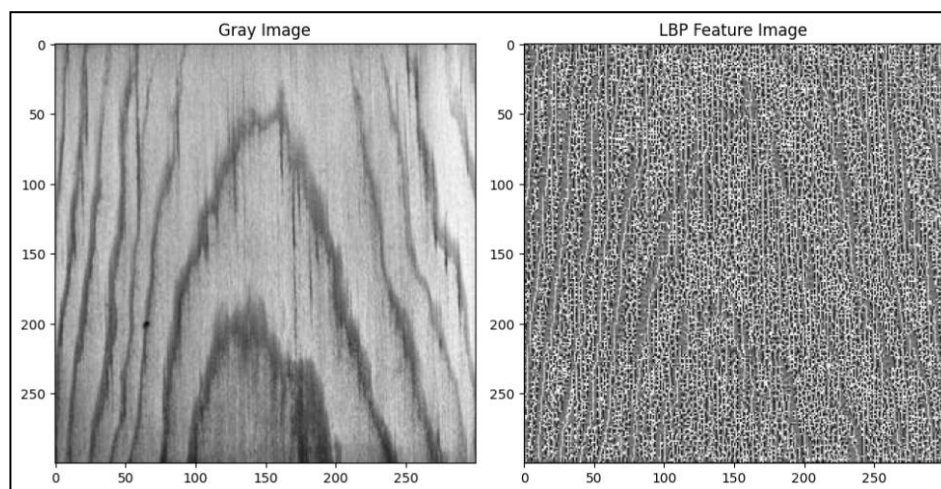


Figure 2. Sample image obtained with LBP feature extraction

Sobel filtering is a filtering method used for edge detection. It determines the direction and intensity of edges by calculating pixel intensity gradients in an image

(Szeliski 2022). In this study, nine features were extracted using the Sobel operator, and the resulting sample image and orientation histogram are shown in Figure 3.

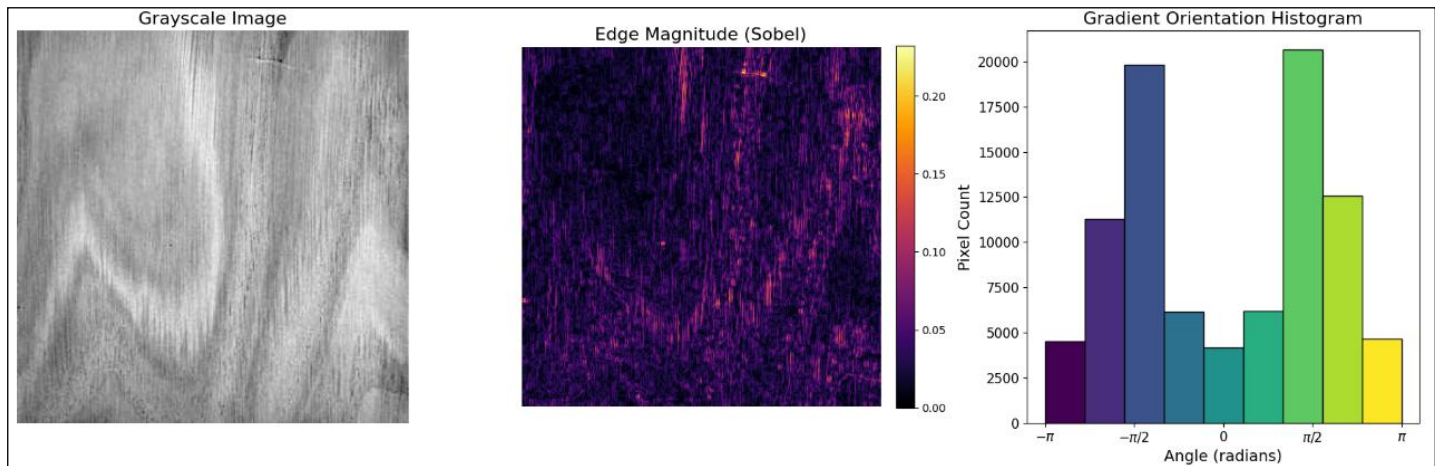


Figure 3. Example image and orientation histogram of the Sobel feature extraction

The HSV (Hue, Saturation, Value) color space is a model that expresses colors more closely to human perception. Hue (H) represents the hue of a color, Saturation (S) represents its saturation, and Value (V) represents its

brightness (Ryszard 2007, Sudhir and Baboo 2011). In this study, 12 features were extracted using HSV, and a sample image is shown in Figure 4.

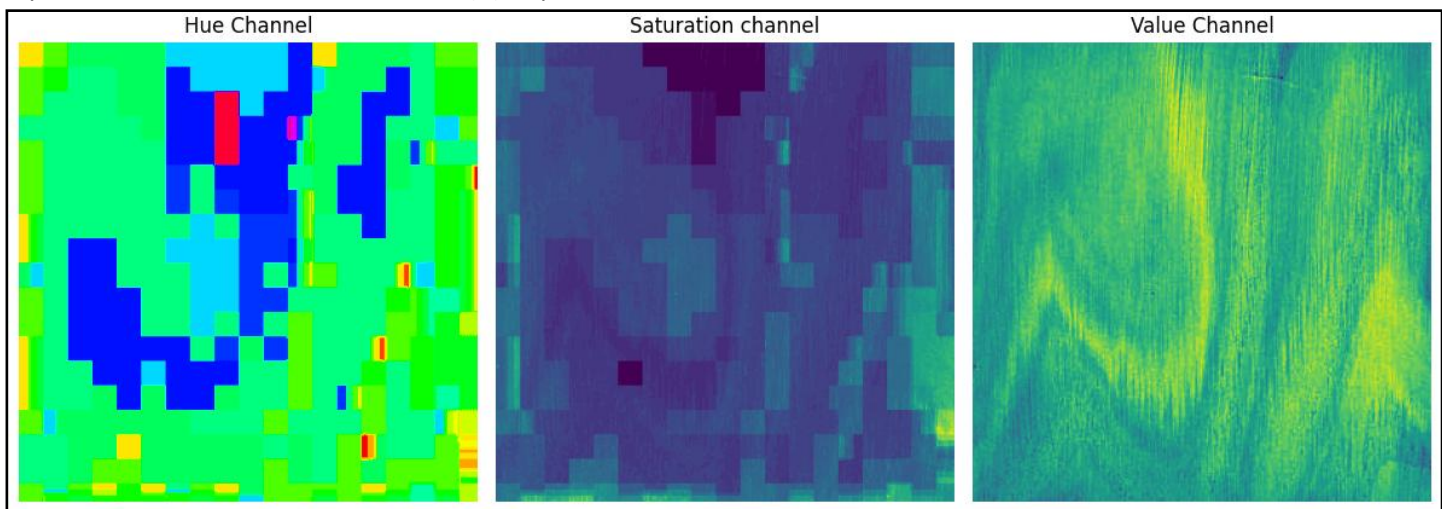


Figure 4. Example image of feature extraction with HSV

LAB, the CIE Lab* color space, is a model developed by the International Commission on Illumination (CIE) to better reflect the human eye's color perception. L* represents brightness (0 black - 100 white), a* represents the green-red axis, and b* represents the blue-yellow axis (Margulis 2005).

In this study, 12 features were extracted using LAB, and a sample image is shown in Figure 5.

Feature extraction methods and parameters used in the study are presented in Table 1.

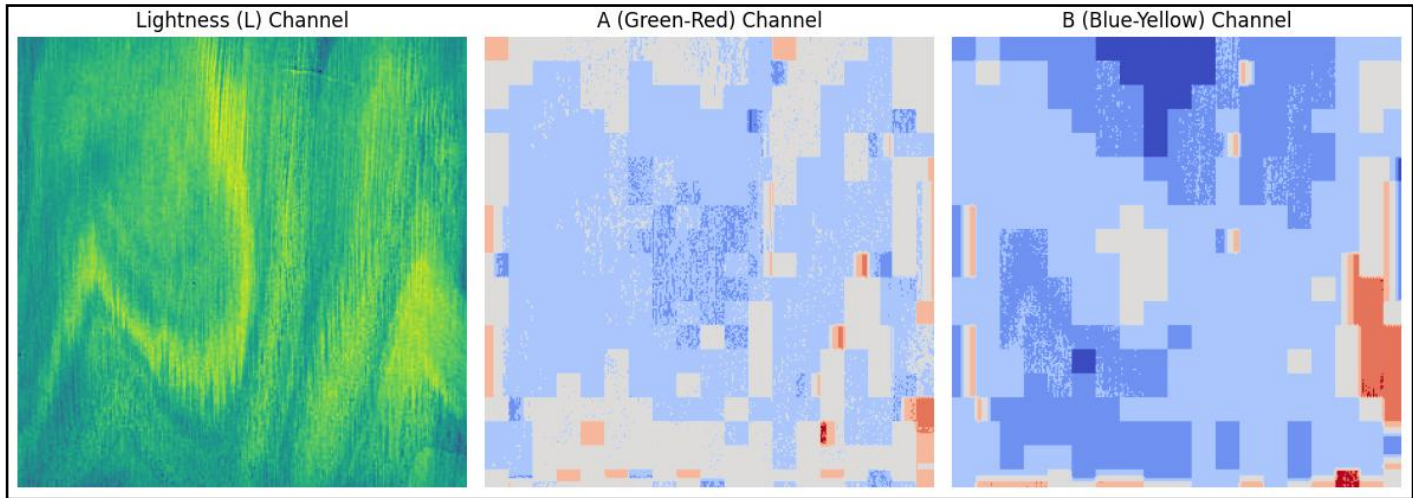


Figure 5. Example image of feature extraction with Lab

Table 1. Feature extraction methods and parameters used in the study

Method	Number of features	Parameters Used	Parameters Used	Description
Sobel	9	dx=1, dy=0 ve dx=0, dy=1 + statistical summaries	Gradient statistics (mean, std, min, max)	It numerically summarizes the gradient magnitudes in the image according to the edge directions.
HSV	12	HSV color space (H, S, V)	Channel-based statistics (mean, std, min, max)	4 features (12 in total) were extracted for each of the 3 channels containing color information.
LAB	12	LAB color space (L, A, B)	Channel-based statistics (mean, std, min, max)	Color representation close to human perception is represented with statistical summaries for each channel.
LBP	10	radius=1, n_points=8, method='uniform'	Texture histogram feature	A 10-dimensional LBP histogram representing the image texture was extracted.

Classical Machine Learning Classification Algorithms

Within the scope of the research, four different algorithms, namely Random Forest, XGBoost, CatBoost, and Extra Trees, were used for classification.

Random Forest is one of the ensemble learning methods that combines decision trees. It is robust against overfitting, can work with incomplete data, and offers high accuracy; however, it is difficult to interpret and has high computational costs on large datasets (Breiman 2001).

XGBoost is an optimized version of the Gradient Boosting algorithm and operates quickly and with low memory usage on large and complex datasets; however, its parameter settings are complex and the risk of overfitting is high (Chen and Guestrin 2016).

CatBoost is a gradient boosting library that can work effectively with categorical data. It stands out with its fast training, low risk of overfitting, and strong performance. However, because it is newer than other methods, its resource support may be limited (Prokhorenkova et al. 2018).

Extra Trees is similar to Random Forest but uses higher randomness in feature selection and splitting points. This prevents overfitting, increases generalization, and reduces training time; however, it has lower interpretability (Geurts et al. 2006).

Hyperparameters of all algorithms were optimized with GridSearchCV, and the most suitable parameters were determined using cross-validation. The most suitable parameters for each algorithm were determined using the GridSearchCV method; hyperparameters and their value ranges are presented in Table 2.

Table 2. Hyperparameters and values used in GridSearchCV

Algorithm	Hyperparameter	Values
Random forest	n_estimators	[100, 200, 300]
	max_depth	[None, 10, 20]
	min_samples_split	[2, 5]
	min_samples_leaf	[1, 2, 3]
XGBoost	n_estimators	[100, 200, 300]
	max_depth	[3, 6, 10]
	learning_rate	[0.01, 0.1, 0.2]
	subsample	[0.8, 1.0]
CatBoost	iterations	[100, 200]
	depth	[4, 6, 10]
	learning_rate	[0.01, 0.1]
	l2_leaf_reg	[1, 3]
Extra trees	n_estimators	[100, 200, 300]
	max_depth	[None, 10, 20]
	min_samples_split	[2, 5]
	min_samples_leaf	[1, 2, 3]

The hyperparameter settings of the ensemble learning algorithms used in the study are shown. The number of trees, depth, and node splitting criteria were optimized for the Random Forest and Extra Trees models, while the number of iterations, depth, learning rate, and regularization parameters were optimized for the XGBoost and CatBoost models. These settings were determined using the GridSearchCV method to improve model performance and prevent overfitting.

Experimental Setup

In this research, four different image feature extraction methods and four different classifiers were used to classify wood species commonly used in our country. The experiments were conducted on the Kaggle platform. Kaggle is a cloud-based data science environment that enables effective analysis of large data sets thanks to the computational power provided by CPU and GPU resources (URL-1).

The dataset contains images of three different wood types: chestnut, oak, and pine. Various feature extraction methods were applied to each image. These methods included LBP, Sobel, statistical features in the HSV color space, and basic statistics in the LAB color space. Each feature extraction method was tested with different classification algorithms.

The GridSearchCV method was used to improve the performance of classification models and identify the most appropriate hyperparameter combinations. Grid Search is a method that systematically scans all possible combinations within specified parameter ranges to select the parameter set that yields the best accuracy. These experiments increase the experiment time because each combination is tested separately. This helps minimize problems such as overfitting or underfitting of the model.

To more reliably assess the model's overall performance, a 5-fold cross-validation method was applied. This method divided the dataset into five equal parts, one of which served as test data and the remaining four as training data. This allowed the model to be tested on different subsets of data, yielding more robust results regarding its generalization ability.

This two-stage approach ensured that the model was trained with optimal parameters and showed consistent performance on different data subsets, thus contributing to the reliability of the study.

All experiments were conducted in the cloud using a Kaggle kernel. The performance of this processor enabled the research to be completed quickly and efficiently. At the end of the experiments, the performance of each method and classifier combination was evaluated using metrics such as accuracy, precision, sensitivity, and F1 scores. These results were compared to determine the

most suitable methods for classifying wood species. Furthermore, a hybrid feature method was developed using an optimized bagging ensemble approach to achieve high-accuracy classification.

Evaluation Metrics

In this research article, the commonly used metrics F1-Score, Accuracy, Precision, and Sensitivity are used to

evaluate the performance of machine learning classification algorithms. The values of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) used in calculating these metrics are obtained from the confusion matrix generated by the outputs of the classification model. An example of the confusion matrix is given in Table 3. The formulas for these metrics are given in Equations (1-4).

Table 3. Example of a confusion matrix

	Predict Class 1	Predict Class 2	Predict Class 3
Actual Class 1	TP ₁	FP	FP
Actual Class 2	FP	TP ₂	FP
Actual Class 3	FP	FP	TP ₃

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (1)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (4)$$

RESULTS

The performances of LBP, HSV, LAB, Sobel, and Hybrid Feature extraction and machine learning classification

algorithms are given in Tables 4, 5, 6, 7, and 8, respectively.

Table 4. Performance of LBP feature extraction and machine learning classification algorithms

Feature, Algorithms	Precision	Recall	F1-Score	Accuracy
LBP Random Forest	0.9195	0.9167	0.9172	0.9167
LBP XGBoost	0.9083	0.9083	0.9083	0.9083
LBP CatBoost	0.9099	0.9083	0.9088	0.9083
LBP Extra trees	0.9349	0.9333	0.9337	0.9333

Table 4 presents the performance comparison of four different machine learning algorithms trained with LBP features. Extra trees demonstrated consistent performance, achieving the highest precision values of 0.9349, sensitivity of 0.9333, F1-score of 0.9337, and accuracy of 0.9333. The Random Forest algorithm also produced results similar to Extra Trees, but was slightly inferior in all metrics. The XGBoost and CatBoost

algorithms performed almost similarly. However, these two models also lagged behind Extra Trees and Random Forest. Tree methods, especially the Extra Trees algorithm, were more effective in LBP-based classification. Algorithms such as XGBoost and CatBoost, however, failed to provide the expected advantage on this dataset.

Table 5. Performance of HSV feature extraction and machine learning classification algorithms

Feature, Algorithms	Precision	Recall	F1-Score	Accuracy
HSV Random Forest	0.9500	0.9500	0.9500	0.9500
HSV XGBoost	0.9415	0.9417	0.9420	0.9417
HSV CatBoost	0.9500	0.9500	0.9500	0.9500
HSV Extra trees	0.9752	0.9750	0.9750	0.9750

When Table 5 is examined, the Random Forest and CatBoost algorithms in feature extraction with HSV achieve very similar results across all metrics, with a performance of 0.9500. XGBoost performed slightly lower compared to the other models. For metrics such as precision, sensitivity, and F1-score, results of 0.9415, 0.9417, and 0.9420 were obtained, respectively. While these results indicate that XGBoost has slightly lower classification accuracy than the other algorithms, they are still quite satisfactory and generally acceptable.

In particular, the Extra Trees algorithm demonstrated the highest performance across all metrics. It achieved a value of 0.9750 in all four key evaluation metrics: precision, sensitivity, F1-score, and accuracy. This result demonstrates that the Extra Trees algorithm achieved very high accuracy and balance in the classification task, and the model made highly effective predictions for both classes.

Table 6. Performance of LAB feature extraction and machine learning classification algorithms

Feature, Algorithms	Precision	Recall	F1-Score	Accuracy
LAB Random Forest	0.9425	0.9517	0.9420	0.9417
LAB XGBoost	0.9341	0.9333	0.9336	0.9333
LAB CatBoost	0.9167	0.9167	0.9167	0.9167
LAB Extra trees	0.9756	0.9750	0.9750	0.9750

Table 6 shows that the Extra Trees algorithm demonstrates the best performance in LAB feature extraction, achieving the highest values across all metrics. Precision, sensitivity, F1-score, and accuracy values are 0.9756, 0.9750, 0.9750, and 0.9750, respectively. This demonstrates that the model is quite stable and performs classifications with high accuracy.

Looking at the other algorithms, Random Forest performs very closely, achieving strong results for precision 0.9425 and sensitivity 0.9517, but lags behind Extra Trees in terms of F1-score and accuracy. XGBoost performs less well with metrics around 0.9333. CatBoost achieves the lowest results, maintaining a consistent performance of 0.9167 across all four metrics.

Table 7. Performance of the Sobel feature extraction and machine learning classification algorithms

Feature, Algorithms	Precision	Recall	F1-Score	Accuracy
Sobel Random Forest	0.7347	0.7417	0.7334	0.7417
Sobel XGBoost	0.7252	0.7333	0.7256	0.7333
Sobel CatBoost	0.7918	0.7750	0.7559	0.7750
Sobel Extra trees	0.8138	0.8000	0.7922	0.8000

Table 7 shows that the Extra Trees algorithm performed best in all metrics for Sobel feature extraction, achieving the best results in terms of precision 0.8138, sensitivity 0.8000, F1-score 0.7922, and accuracy 0.8000.

CatBoost also demonstrated strong performance, achieving high results with precision of 0.7918 and a sensitivity 0.7750, but slightly lower performance than Extra Trees. Random Forest and XGBoost performed worse, achieving lower values for precision and sensitivity, 0.7347 and 0.7252, respectively.

Table 8. Performance of hybrid feature extraction and machine learning classification algorithms

Feature, Algorithms	Precision	Recall	F1-Score	Accuracy
Hibrit Random Forest	0.9754	0.9750	0.9751	0.9750
Hibrit XGBoost	0.9630	0.9583	0.9589	0.9583
Hibrit CatBoost	0.9833	0.9833	0.9833	0.9833
Hibrit Extra trees	1.0000	1.0000	1.0000	1.0000

Table 8 shows the performance evaluation of the method developed for this research, based on hybrid feature integration with the optimized bagging ensemble approach, at 100% accuracy. The Extra Trees algorithm achieves excellent results across all metrics, reaching 1.0000 for precision, sensitivity, F1-score, and accuracy. This indicates that the model achieves full accuracy for both true positive and true negative predictions, achieving an excellent balance without overfitting. The CatBoost algorithm also demonstrates strong performance, reaching 0.9833 for all metrics. Random Forest, on the other hand, achieves high results for precision 0.9754, sensitivity 0.9750, and F1-score 0.9751,

but performs slightly lower compared to CatBoost and Extra Trees. Finally, XGBoost lags behind the other algorithms, achieving slightly lower results in metrics such as precision 0.9630 and sensitivity 0.9583. Extra Trees achieved the highest performance in all metrics, while CatBoost and Random Forest achieved very similar results, with XGBoost showing slightly lower performance than the others.

The confusion matrices of LBP, HSV, LAB, Sobel feature extraction, and Random Forest, XGBoost, CatBoost, and Extra Trees machine learning classification algorithms are given in Tables 9, 10, 11, 12, and 13, respectively.

Table 9. Confusion matrix of LBP feature extraction and classification algorithms

Feature, Algorithms	Actual/Predict	Chestnut	Oak	Scots pine
LBP Random Forest	Chestnut	36	1	3
	Oak	0	37	3
	Scots pine	1	2	37
LBP XGBoost	Chestnut	37	0	3
	Oak	1	37	2
	Scots pine	2	3	35
LBP CatBoost	Chestnut	37	0	3
	Oak	0	37	3
	Scots pine	1	4	35
LBP Extra Trees	Chestnut	38	0	2
	Oak	0	37	3
	Scots pine	2	1	37

When Table 9 is examined, all algorithms were able to distinguish wood species with high accuracy. The Extra Trees algorithm, in particular, achieved the most success with 38 correct classifications for chestnut. All models achieved a similar level of success with 37 correct predictions for oak. Some minor misclassifications were observed for Scots pine; particularly in the CatBoost and XGBoost models, Scots pine samples were occasionally classified as oak or chestnut. This suggests that visual or textural similarities between species complicate model decisions.

An examination of Table 10 shows that classification algorithms trained with features based on the HSV color space demonstrate very high performance. The Extra Trees algorithm stands out as the most successful model, with 38 correct classifications for Chestnut, 39 for Oak, and 40 for Scots pine. Other algorithms also demonstrated similarly high accuracy. For example, Random Forest achieved 37 correct classifications for Chestnut, 38 for Oak, and 39 for Scots pine. While there were minor deviations in the CatBoost and XGBoost models, the overall success rate was high. Scots pine, in.

particular, was largely accurately classified by all algorithms, demonstrating the high effectiveness of HSV-based features in distinguishing wood species.

Table 10. Confusion matrix of HSV feature extraction and classification algorithms

Feature, Algorithms	Actual/Predict	Chestnut	Oak	Scots pine
HSV Random Forest	Chestnut	37	2	1
	Oak	2	38	0
	Scots pine	1	0	39
HSV XGBoost	Chestnut	37	3	0
	Oak	3	37	0
	Scots pine	1	0	39
HSV CatBoost	Chestnut	37	2	1
	Oak	2	38	0
	Scots pine	1	0	39
HSV Extra Trees	Chestnut	38	2	0
	Oak	1	39	0
	Scots pine	0	0	40

An examination of Table 11 shows that the classification algorithms trained with features obtained using the LAB color space generally yielded successful results. All models classified Scots pine quite accurately, each with 39 correct classifications and only one error. For Chestnut, the CatBoost and Extra trees algorithms performed best; both made 38 correct classifications. In

contrast, the XGBoost algorithm performed slightly worse on Chestnut, with 36 correct predictions and 4 incorrect predictions. For Oak, the Extra trees algorithm notably classified all 40 examples correctly, without any errors. The other algorithms experienced between 1 and 3 incorrect classification.

Table 11. Confusion of the LAB feature extraction and classification algorithms

Feature, Algorithms	Actual/Predict	Chestnut	Oak	Scots pine
LAB Random Forest	Chestnut	37	3	0
	Oak	3	37	0
	Scots pine	1	0	39
LAB XGBoost	Chestnut	36	4	0
	Oak	3	37	0
	Scots pine	1	0	39
LAB CatBoost	Chestnut	38	2	0
	Oak	2	38	0
	Scots pine	1	0	39
LAB Extra Trees	Chestnut	38	2	0
	Oak	0	40	0
	Scots pine	1	0	39

An examination of Table 12 reveals that the classification accuracy rates using features obtained with the Sobel edge detection method are lower than those of other color-based approaches. Scots pine, in particular, was the class with the highest confusion across all models. For example, the Random Forest algorithm correctly classified only 21 Scots pine samples, confusing 11 with Chestnut and 8 with Oak. For the Chestnut class, the CatBoost and Extra trees algorithms outperformed the

other models with 36 correct predictions. Oak was generally more accurately classified, with the CatBoost algorithm achieving the best performance in this class with 39 correct classifications. While Sobel-based features highlight edge structure, they limit classification accuracy because they fail to adequately reflect distinctive visual features such as color and texture. This appears to lead to misclassifications, particularly in species with high visual similarity.

Table 12. Confusion matrix of Sobel feature extraction and classification algorithms

Feature, Algorithms	Actual/Predict	Chestnut	Oak	Scots pine
Sobel Random Forest	Chestnut	31	0	9
	Oak	2	37	1
	Scots pine	11	8	21
Sobel XGBoost	Chestnut	33	0	7
	Oak	0	35	5
	Scots pine	13	7	20
Sobel CatBoost	Chestnut	36	1	3
	Oak	1	39	0
	Scots pine	14	8	38
Sobel Extra Trees	Chestnut	36	1	3
	Oak	3	37	0
	Scots pine	10	7	23

When all models and feature extraction algorithms are compared, the Extra Trees algorithm achieves a 100% accurate prediction rate in the hybrid feature extraction

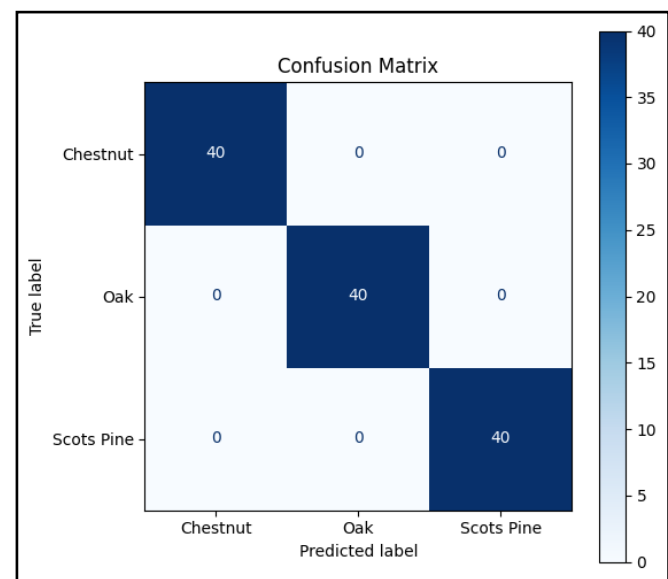
and optimized bagging ensemble approach. The average classification report of the Extra Trees algorithm is given in Table 13.

Table 13. Average mean classification report of the Extra Trees algorithm (5K-fold)

	Precision	Recall	F1-Score	Number of Instances
Chestnut	1.0000	1.0000	1.0000	40
Oak	1.0000	1.0000	1.0000	40
Scots pine	1.0000	1.0000	1.0000	40
Accuracy			1.0000	
Macro avg.	1.0000	1.0000	1.0000	120
Weighted avg.	1.0000	1.0000	1.0000	120

The classification report in Table 13 shows that the Extra Trees model performed very well in the optimized bagging ensemble approach, correctly classifying all classes in the test dataset. Each evaluation metric-precision, sensitivity, F1-score, and accuracy ratio-reached its maximum value of 1.0000. This report demonstrates that the Extra Trees model did not make any errors and correctly classified all classes in the proposed optimized bagging ensemble approach.

The confusion matrix of the Extra Trees algorithm for wood classification with hybrid feature integration with an optimized bagging ensemble approach is given in Figure 6, and the ROC curve is given in Figure 7.

**Figure 6.** Extra trees confusion matrix of the bagging ensemble approach with optimization

The confusion matrix shows that the proposed method classifies each class perfectly. All 40 samples in the classes Chestnut, Oak, and Scots pine were correctly recognized. The proposed method made no misclassifications. This

result means that the model accurately classified each class with 100% accuracy. This type of performance demonstrates that the method performs very well and correctly distinguishes each class.

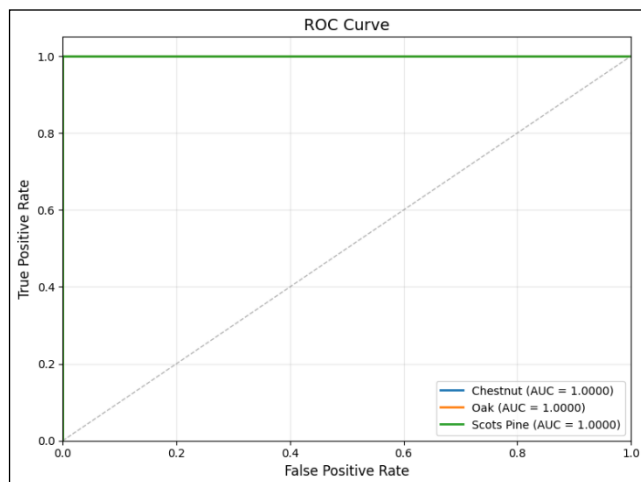


Figure 7. ROC curve of the bagging ensemble approach with optimization, Extra Trees

An AUC=1.0000 and a perfect ROC curve indicate that the model generalizes very well and correctly classifies all classes. This type of result is particularly achievable when there is no discrepancy between the training and test data or when the data is not highly imbalanced. In real-world applications, such excellent results are generally rare on more complex datasets. Consequently, an AUC=1.0000 and a perfect ROC curve indicate that your model performs with excellent accuracy. This indicates that the proposed method is highly reliable.

DISCUSSION

The majority of studies on wood species classification utilize cross-sectional images. This is because cross-sections provide more information about grain structure, pore distribution, and other anatomical features. In this study, a different approach was adopted from traditional approaches by choosing longitudinal and tangential sections. Thanks to the ability of AI-based models to learn patterns and microstructural details in images, high accuracy rates have been achieved from these types of sections. Therefore, the type of section used is not only an alternative approach but also a key factor in enhancing classification success.

The developed hybrid feature integration and optimization-based bagging ensemble approach achieved 100% classification accuracy by combining color-based (HSV, LAB) and texture/edge-based (LBP, Sobel) information. While color features distinguished tonal differences between species, texture and edge information captured the microscopic structure of the surface. The combination of these two types of information produced a much more stable and accurate model than single methods.

When previous studies in the literature are examined, it is seen that high accuracy rates are mostly achieved with cross-sections and single feature extraction methods. For example, Ibrahim et al. (2017) reported 98.9% accuracy with fuzzy pre-classification and SVM approach. Khalid et al. (2011) achieved 96.99% accuracy using KNN and LDA with BGLAM and SPPD features. Hu et al. (2015) achieved 90.2% accuracy with SIFT and k-means-based methods. Yadav et al. (2013) achieved 92.6% accuracy with Gabor filter and GLCM features. The distinguishing feature of this study is that it also surpasses the highest achievements in the literature with longitudinal sections. In particular, the hybrid feature-ensemble approach and the Extra Trees algorithm's 100% accuracy across all metrics stands out as a strong contribution that surpasses existing studies.

Three key elements stand out in the success of this method: (i) feature diversity, i.e., the ability to evaluate color, texture and edge information simultaneously; (ii) the reduction of the risk of overfitting, because the combination of different algorithms and features compensates for the weaknesses of single methods; (iii) applicability, because high accuracy was achieved even on images captured with a mobile device.

However, this high accuracy also has some limitations. The study used only three species (oak, chestnut, and Scots pine) and a limited number of samples. Images were acquired using a single camera model and under similar lighting conditions. Variables such as age, humidity, and surface treatment were not taken into account.

Future studies are recommended to conduct tests with datasets from different geographic regions and with a wider variety of species. Furthermore, performance evaluations should be conducted under different camera types, resolutions, and lighting conditions, and the developed method should be implemented in real-time on industrial production lines. This approach is expected to be widely used in both academic research and industrial applications.

CONCLUSION AND RECOMMENDATIONS

In this study, we comprehensively investigated the performance of different feature extraction methods (LBP, HSV, LAB, and Sobel) used in wood classification and their comparison with machine learning algorithms such as Random Forest, XGBoost, CatBoost, and Extra Trees. Furthermore, we evaluated the effectiveness of the proposed hybrid feature extraction method based on the optimization-based bagging ensemble approach. The results show that among the single feature extraction methods, the HSV and LAB-based methods stand out with their high accuracy rates. Among these two methods, the Extra Trees algorithm was the most successful model with 97.5% accuracy. In contrast, the Sobel-based feature extraction achieved only 80% accuracy and lagged behind the other methods in classification success.

The most striking finding was obtained with the proposed hybrid feature extraction approach. In this method, the Extra Trees algorithm achieved 100% success across all metrics, resulting in a balanced, stable, and highly reliable model. The CatBoost (98.33%) and Random Forest (97.5%) algorithms also demonstrated high performance in this method. In particular, the Extra Trees algorithm's consistent and high accuracy across all experiments makes it the preferred choice for wood classification and feature extraction studies.

Sobel-based methods have been shown to be limited in their use alone, but they can be beneficial when integrated into more complex hybrid systems. It is anticipated that the developed hybrid approach can be used with high success not only in wood classification but also in similar visual classification problems. Future studies are recommended to test this method on

different types of natural materials and industrial surface classification problems.

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