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Tree Species Classification from TLS Point Clouds Using Multi-Task Learning and Woody-Only Point Cloud Generation

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Highlights

What are the main findings?

- A KPConv-based wood–leaf separation strategy was used to generate woody-only point clouds from leaf-on TLS data, enriching the structural representation available for tree species classification.
- The proposed multi-task learning network achieved strong classification performance on a mixed test set of six typical broadleaf tree species and improved model adaptability across different input representations.

What are the implications of the main findings?

- By jointly learning tree species classification and input-representation discrimination, the shared encoder is encouraged to focus more on relatively stable woody structural features rather than relying excessively on leaf-on appearance cues.
- The proposed framework provides a practical pathway for improving TLS-based broadleaf tree species classification when only leaf-on field data are available.

Abstract

Terrestrial Laser Scanning (TLS) can provide detailed three-dimensional structural information for individual trees and has become an important data source for tree species classification. However, most existing models are trained using leaf-on point clouds and therefore tend to rely heavily on leaf distribution and crown appearance. When the input changes from leaf-on point clouds to woody-dominated representations, classification performance often declines. To address this issue, this study proposes a mixed-input tree species classification framework for six typical temperate broadleaf tree species. First, a KPConv-based wood–leaf separation model was used to extract woody point sets from leaf-on TLS point clouds, thereby generating woody-only representations for subsequent classification. Second, a multi-task learning network based on DGCNN was constructed. In addition to the main task of tree species classification, an auxiliary task for input-representation discrimination was introduced to enhance the model's adaptability to different input forms. Experiments were conducted using a dataset composed of local TLS samples from China and publicly available single-tree point clouds from the BioDiv dataset. The results show that the proposed method achieved an overall accuracy of 94.3% on the mixed test set of six typical broadleaf tree species, with average Precision, Recall, and F1 values of 94.3%, 93.6%, and 93.9%, respectively. These results indicate that integrating woody structural representations with multi-task learning can effectively alleviate overreliance on leaf-on appearance features and improve classification robustness under different input representations.

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Keywords: tree species classification; terrestrial laser scanning (TLS); broadleaf trees; multi-task learning; wood–leaf separation; mixed input

1. Introduction

Accurate tree species identification is a fundamental prerequisite for forest resource inventory, biodiversity conservation, and ecosystem function assessment [1]. Traditional field-based surveys are labor-intensive and time-consuming, which limits their efficiency in large-scale and high-frequency forest monitoring. In recent years, terrestrial laser scanning (TLS), as an active remote sensing technique, has become an important tool for acquiring high-density three-dimensional structural information of trees and for supporting individual-tree species classification [2,3]. Owing to its high geometric accuracy and strong capability for describing trunk, branch, and canopy structures, TLS provides valuable structural information for tree species recognition [4–6]. Compared with conventional two-dimensional observations, TLS point clouds can represent tree architecture more directly and thus offer an important data basis for automated tree species classification.

Before the widespread application of deep learning, tree species classification from TLS point clouds mainly relied on manually designed geometric or structural features combined with traditional classifiers such as support vector machines and random forests [7,8]. With the development of point-cloud deep learning, methods such as PointNet [9], PointNet++ [10], PointCNN [11], and DGCNN [12] have substantially improved the automatic extraction of discriminative features for tree species classification, as also summarized in the review by Guo et al. [13]. Nevertheless, most existing studies are still based on a single-input form, especially leaf-on point clouds collected during the growing season. Under this condition, classification models may rely heavily on foliage distribution, crown appearance, and other surface-level characteristics, while relatively stable woody structural information is not sufficiently exploited. For deciduous broadleaf trees, this problem is particularly evident because leaf-on point clouds preserve abundant canopy morphology but often weaken the expression of internal branch structures due to dense leaf occlusion. As a result, models trained mainly on leaf-on point clouds may show limited adaptability when the input representation changes.

To alleviate this limitation, some studies have attempted to incorporate spectral information or multi-temporal point cloud fusion [14], but such strategies often increase data-acquisition cost and complicate point-cloud registration. Another possible direction is to emphasize geometric information that is less sensitive to differences in input representation, such as woody structural features. Existing wood–leaf separation methods, ranging from geometry-based approaches [15–17] to recent deep learning methods [18,19], can effectively distinguish photosynthetic and non-photosynthetic components in tree point clouds. However, these methods are usually treated only as preprocessing tools for structural analysis or biomass-related applications, while their potential value for improving tree species classification remains insufficiently explored. In particular, few studies have used wood–leaf separation results to construct alternative structural inputs for classification models. Therefore, how to make better use of leaf-on data to simultaneously preserve foliage-related information and enhance woody structural representation remains an important problem in TLS-based broadleaf tree species classification.

To address these challenges, this study proposes a tree species classification framework that combines wood–leaf separation and multi-task learning [20]. First, a KPConv-based semantic segmentation network is used to separate wood and leaf points from leaf-on point clouds, thereby generating corresponding woody-only point clouds for subsequent

classification. Second, a multi-task classification network based on DGCNN is constructed, in which tree species classification is treated as the primary task and input-representation discrimination is introduced as an auxiliary task. This design aims to improve the model's adaptability to mixed-input conditions and to guide the shared feature encoder to focus more on relatively stable woody structural features. Through the joint use of original leaf-on point clouds and generated woody-only point clouds, the proposed framework provides a practical way to improve broadleaf tree species classification when only leaf-on TLS data are available.

This study used a mixed dataset composed of local TLS samples collected in China and publicly available single-tree point clouds from the BioDiv-3DTrees dataset. The experimental samples covered six typical temperate broadleaf tree species, including *Ginkgo*, *Chinese white poplar*, *Norway maple*, *European beech*, *European ash*, and *European hornbeam*. On this basis, the main contributions of this study are summarized as follows:

1. A mixed-input tree species classification framework was constructed by combining original leaf-on point clouds with corresponding woody-only point clouds generated through wood–leaf separation. This strategy enriches the structural representation available for classification under limited leaf-on data conditions.
2. A multi-task learning network based on DGCNN was developed, in which tree species classification and input-representation discrimination were jointly optimized to improve model adaptability under mixed-input conditions.
3. Experiments on six typical broadleaf tree species demonstrate that the proposed method can effectively improve classification performance and provide a practical solution for TLS-based broadleaf tree species recognition when only leaf-on field data are available.

2. Materials and Methods

2.1. Study Area and Dataset

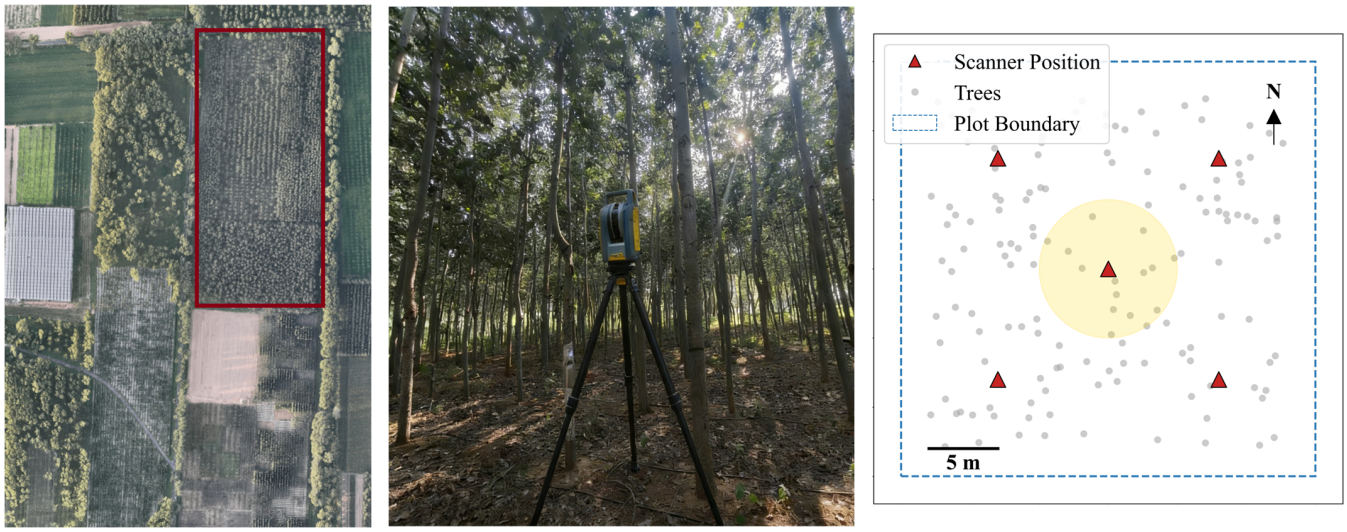
To evaluate the effectiveness of the proposed framework under different species compositions and structural conditions, this study constructed a mixed dataset composed of local TLS point clouds and publicly available single-tree point clouds. The dataset focuses on six typical temperate broadleaf tree species, including *Ginkgo* (*Ginkgo biloba*), *Chinese white poplar* (*Populus tomentosa*), *Norway maple* (*Acer platanoides*), *European beech* (*Fagus sylvatica*), *European ash* (*Fraxinus excelsior*), and *European hornbeam* (*Carpinus betulus*). The local samples were collected in China, whereas the remaining species were selected from the BioDiv-3DTrees public dataset. This combined dataset provides the data basis for subsequent wood–leaf separation and mixed-input tree species classification experiments. The local field scanning strategy is illustrated in Figure 1.

2.1.1. BioDiv-3DTrees Dataset (Germany)

The BioDiv-3DTrees dataset [21] is a publicly available single-tree point cloud dataset collected from temperate forests in Germany. The data were acquired across three Biodiversity Exploratories, namely Schorfheide-Chorin, Hainich-Dün, and Schwäbische Alb, which cover diverse forest environments and provide broad structural variability for tree-level analysis.

In this study, the BioDiv dataset was used to supplement the diversity of broadleaf tree species for subsequent experiments. Considering that the research objective of this paper focuses on broadleaf tree species classification, only broadleaf samples consistent with this objective were retained from the public dataset. Specifically, four representative broadleaf species were selected, namely *Norway maple* (*Acer platanoides*), *European beech* (*Fagus sylvatica*), *European ash* (*Fraxinus excelsior*), and *European hornbeam* (*Carpinus betulus*).

These species differ in crown architecture, branching pattern, and fine-branch complexity and therefore provide useful complementary samples for evaluating the adaptability of the proposed method across structurally diverse broadleaf trees.



(**a**) (**b**) (**c**)

Figure 1. Overview of the data acquisition strategy and field setups. (**a**) Aerial view of the locally collected dataset site (e.g., the plantation forest in Shandong, China). (**b**) On-site field scanning utilizing a Trimble X7 terrestrial laser scanner to acquire high-density point clouds. (**c**) Schematic diagram of the multi-station scanning protocol employed in this study. Five scanning positions (one central and four peripheral, marked by red triangles) were established within each forest plot to maximize coverage and mitigate occlusion.

Unlike the local TLS samples collected in China, the BioDiv data are organized directly at the individual-tree level. Therefore, in the present study, this dataset was mainly used for sample supplementation and species expansion rather than for plot-level preprocessing or single-tree extraction analysis.

2.1.2. Locally Collected Dataset

To complement the public single-tree samples and to provide realistic local TLS data for this study, locally acquired point clouds from two broadleaf tree sites in China were incorporated into the dataset. These local data were obtained from the ginkgo avenue of Beijing Forestry University in Beijing and the *Populus tomentosa* plantation plot in Gaotang County, Shandong Province.

Chinese white poplar (*Populus tomentosa*) is a representative deciduous broadleaf species with a relatively straight main stem and clear branching structure. The corresponding samples provide useful structural information for analyzing broadleaf trees with prominent trunk morphology.

Ginkgo (*Ginkgo biloba*) was collected on the campus of Beijing Forestry University. Owing to its distinctive long-and-short branch morphology and unique crown structure, ginkgo provides an important complementary sample type for the present broadleaf tree species classification task.

The local TLS data were collected using a Trimble X7 terrestrial laser scanner (Trimble Inc., Sunnyvale, CA, USA). To reduce occlusion and improve point-cloud completeness, a multi-station scanning strategy was adopted in the field. The raw point clouds were subsequently registered, preprocessed, and manually segmented into individual-tree samples. These local samples were mainly used for plot-level preprocessing, single-tree sample construction, and supplementation of the broadleaf tree dataset used in later experiments.

The point cloud data of the sample trees were obtained by the terrestrial laser scanner, as shown in Figure 2.

Representative examples of the six broadleaf tree species used in this study are shown in Figure 3. These point cloud samples provide an intuitive illustration of the differences in crown shape, branching pattern, and overall structural organization among the selected species.



(**a**) (**b**)

Figure 2. Visualization of the locally collected dataset (e.g., *Chinese white poplar* plantation) after multi-station co-registration using Trimble X7. (**a**) The true-color (RGB) point cloud of the entire forest plot, demonstrating exceptionally high point density and seamless alignment across multiple scanning positions, which effectively minimizes inherent canopy occlusion. (**b**) The corresponding point cloud after ground filtering and individual tree extraction, highlighting the well-preserved branch and trunk topologies ready for subsequent structural feature analysis.

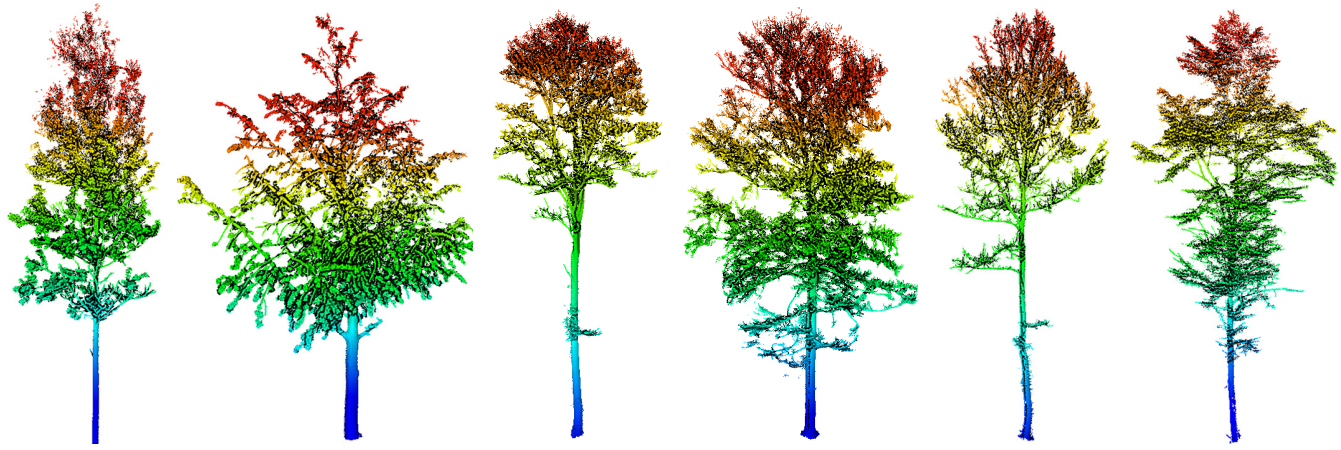


Figure 3. Representative point cloud visualizations of the six broadleaf tree species used in this study (displayed by elevation). From left to right: *Ginkgo* (*Ginkgo biloba*), *Chinese white poplar* (*Populus tomentosa*), *Norway maple* (*Acer platanoides*), *European beech* (*Fagus sylvatica*), *European ash* (*Fraxinus excelsior*), and *European hornbeam* (*Carpinus betulus*).

2.1.3. Dataset Composition and Experimental Use

To clearly describe the source composition and functional roles of the experimental data, the dataset used in this study was organized by combining local TLS samples and

publicly available single-tree point clouds. The final dataset covered six typical temperate broadleaf tree species, namely *Ginkgo* (*Ginkgo biloba*), *Chinese white poplar* (*Populus tomentosa*), *Norway maple* (*Acer platanoides*), *European beech* (*Fagus sylvatica*), *European ash* (*Fraxinus excelsior*), and *European hornbeam* (*Carpinus betulus*). Among them, the local TLS dataset provided samples of ginkgo and *Chinese white poplar*, while the BioDiv-3DTrees dataset supplied samples of the other four broadleaf species.

In total, 386 individual-tree samples were included in the subsequent experiments, including 56 ginkgo samples, 70 *Chinese white poplar* samples, 65 *Norway maple* samples, 70 *European beech* samples, 59 *European ash* samples, and 66 *European hornbeam* samples. These samples jointly formed the data basis for the wood–leaf separation task and the subsequent mixed-input tree species classification task.

The two data sources played different but complementary roles in this study. The local TLS data were mainly used for plot-level preprocessing, single-tree sample construction, and supplementation of representative local broadleaf species. By contrast, the BioDiv dataset was mainly used to enrich species diversity and structural variability at the individual-tree level. Based on this combined dataset, leaf-on point clouds and their corresponding woody-only point clouds were further organized into mixed-input samples for the following classification experiments.

To further clarify the source composition, sample size, and experimental organization of the dataset, the detailed statistics of the six broadleaf tree species used in this study are summarized in Table 1.

Table 1. Detailed statistics of the experimental dataset used in this study. The dataset includes original leaf-on point clouds and the corresponding woody-only point clouds generated through wood–leaf separation.

Species	Origin	Original Samples (Leaf-On)	Generated Samples (Woody-Only)	Training Set (60%, Mixed)	Test Set (40%, Mixed)	Total
Ginkgo	China (Local)	56	56	68	44	112
Chinese white poplar	China (Local)	70	70	84	56	140
Norway maple	Germany (BioDiv)	65	65	78	52	130
European beech	Germany (BioDiv)	70	70	84	56	140
European ash	Germany (BioDiv)	59	59	70	48	118
European hornbeam	Germany (BioDiv)	66	66	80	52	132
Total	—	386	386	464	308	772

Note: Each original leaf-on sample was paired with one corresponding woody-only point cloud generated by the proposed wood–leaf separation method. The training and test sets were first split at the original individual-tree level and then expanded into mixed-input samples by pairing each original leaf-on point cloud with its corresponding woody-only representation.

As shown in Table 1, the final dataset consists of 386 original leaf-on individual-tree samples from six typical broadleaf tree species. By applying the proposed wood–leaf separation method, one corresponding woody-only point cloud was generated for each original sample, resulting in a total of 772 mixed-input samples for subsequent classification experiments. In terms of data source composition, the local TLS dataset contributes ginkgo and *Chinese white poplar* samples, while the BioDiv dataset provides four additional broadleaf species, thereby expanding both species diversity and structural variability. This dataset organization not only preserves representative local samples but also provides a broader broadleaf sample base for evaluating the proposed method under mixed-input conditions.

2.2. Data Preprocessing

The original point cloud data used in this study differed in acquisition scale, point density, and data organization. The local TLS samples were derived from plot-level scans, whereas the BioDiv data were already organized at the individual-tree level. In addition, the raw point clouds generally exhibited high density and non-uniform spatial distribution. Directly feeding these raw data into deep learning networks would increase computational burden and may also affect the stability of feature learning. Therefore, a unified preprocessing procedure was applied to prepare the point clouds for the subsequent wood–leaf separation and tree species classification tasks.

Voxel Grid Downsampling: A voxel-based downsampling filter with a grid size of 0.02 m was applied to the individual-tree point clouds. This resolution was selected to balance computational efficiency and the preservation of structural details required for subsequent analysis. Through voxel grid downsampling, the number of points in each sample was effectively reduced, while the overall spatial distribution of the point cloud was made more uniform. This step provided a more suitable input form for the subsequent wood–leaf separation and tree species classification networks.

Coordinate Normalization: To reduce the influence of differences in spatial position and scale among samples, the coordinates of each individual-tree point cloud were normalized before being fed into the network. Specifically, the geometric centroid of each sample was translated to the origin, and the point coordinates were scaled to a unified range. This normalization step helps the downstream models focus more on relative structural patterns, such as branching arrangement and spatial distribution, rather than on irrelevant positional differences across samples.

Ground Truth Annotation for Segmentation: Training the wood–leaf separation network requires high-quality point-wise annotations. To construct the segmentation dataset, 120 individual-tree samples were selected from the six broadleaf tree species used in this study, with 20 samples per species. During sample selection, differences in tree form, crown structure, and branching complexity were considered to ensure the representativeness of the annotated subset. All selected point clouds were manually annotated in CloudCompare by assigning each point to either the “Wood” or “Leaf” class. The annotated dataset was then divided into 72 training samples, 24 validation samples, and 24 test samples. Because point-wise annotation is highly labor-intensive, this manually annotated subset was used specifically for training, validating, and testing the KPConv-based wood–leaf separation model. The trained model was subsequently applied to the remaining leaf-on samples to generate the corresponding woody-only point clouds required for the following classification experiments.

2.3. Wood–Leaf Separation and Woody-Only Point Cloud Generation Based on KPConv

To enhance woody structural representation for subsequent tree species classification, this study introduces an automated point-cloud processing strategy based on deep learning for wood–leaf separation and woody-only point cloud generation.

2.3.1. Network Selection and Mathematical Formulation of KPConv

To address the semantic segmentation task of wood–leaf separation, KPConv (Kernel Point Convolution) [22] was adopted as the backbone network in this study. KPConv has shown strong performance in point-cloud semantic segmentation tasks [23]. Unlike conventional 3D convolutional networks that require unstructured point clouds to be converted into voxel grids, KPConv performs convolution directly in continuous three-dimensional space. This characteristic is advantageous for tree point cloud analysis because

it helps preserve local geometric details and reduces the loss of structural information caused by voxelization.

Mathematically, given a point cloud $P \subset \mathbb{R}^3$ with corresponding node features $F \in \mathbb{R}^{N \times d_{in}}$, the continuous convolution for a target point $x \in \mathbb{R}^3$ defined by KPConv is formulated as:

$$(F * g)(x) = \sum_{x_i \in N_x} g(x_i - x) f_i \tag{1}$$

where $\mathcal{N}_x$ is the spherical neighborhood of point x defined by a radius r, $f_i \in \mathbb{R}^{d_{in}}$ is the input feature of the neighboring point x_i, and $g(y)$ is the continuous filter weight function applied to the centered coordinates $y = x_i - x$.

To parameterize the continuous function $g(y)$, KPConv introduces a set of K fixed kernel points $\{\tilde{x}_k | k = 1, \ldots, K\}$ within the spherical neighborhood, each carrying a trainable weight matrix $W_k \in \mathbb{R}^{d_{in} \times d_{out}}$. The weight function is then calculated by interpolating the weights of these kernel points based on their distance to the input point y:

$$g(y) = \sum_{k=1}^{K} h(y, \tilde{x}_k) W_k \tag{2}$$

where $h(y, \tilde{x}_k)$ is a linear correlation function defined as:

$$h(y, \tilde{x}_k) = \max\left(0, 1 - \frac{||y - \tilde{x}_k||}{\sigma}\right) \tag{3}$$

Here, σ denotes the influence distance of the kernel points. By operating on a continuous receptive field, KPConv can better preserve sensitivity to the local spatial distribution of points, which is beneficial for describing complex structural boundaries between dense foliage and thin branches. This characteristic helps reduce the loss of fine structural information that may occur in voxel-based representations.

To improve the separability between wood and leaf points in leaf-on broadleaf tree point clouds, explicit geometric prior features were introduced together with the raw three-dimensional coordinates at the input stage. These prior features provide additional local structural cues for the network and help strengthen the representation of woody components in complex canopy scenes. In this study, two representative geometric priors were considered:

Relative Height: Points at the canopy top are more likely to belong to leaves than those at the bottom.

Linearity: The linearity coefficient $L_\lambda = (\lambda_1 - \lambda_2)/\lambda_1$ is calculated using the eigenvalues (λ_1, λ_2, λ_3) of the covariance matrix. Branches typically exhibit high linearity, while leaves show scattered or planar characteristics.

2.3.2. Loss Function Optimization

To address the class imbalance between wood points and leaf points in leaf-on broadleaf tree point clouds, standard cross-entropy loss was replaced with weighted focal loss [24]:

$$FL(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t) \tag{4}$$

where α_t is the class weighting factor (assigning higher weight to wood classes), and γ is the focal parameter, which increases the model's attention to difficult-to-classify samples (e.g., the junction between twigs and petioles).

2.3.3. Woody-Only Point Cloud Generation

After training, the wood–leaf separation model was applied to all leaf-on samples in the dataset. By removing the points predicted as "Leaf", the remaining points were retained as the corresponding woody-only point clouds. In this way, each original leaf-on

sample was paired with a structurally simplified woody representation. These paired samples were subsequently used to construct the mixed-input dataset for the tree species classification experiments.

2.4. Multi-Task Learning Framework

The core classification model in this study is a multi-task learning network designed for mixed-input tree species classification. By jointly learning tree species information and input-representation information, the network is intended to improve model adaptability under different input forms and to reduce overreliance on leaf-on appearance cues. The detailed architecture of the proposed multi-task learning network is illustrated in Figure 4.

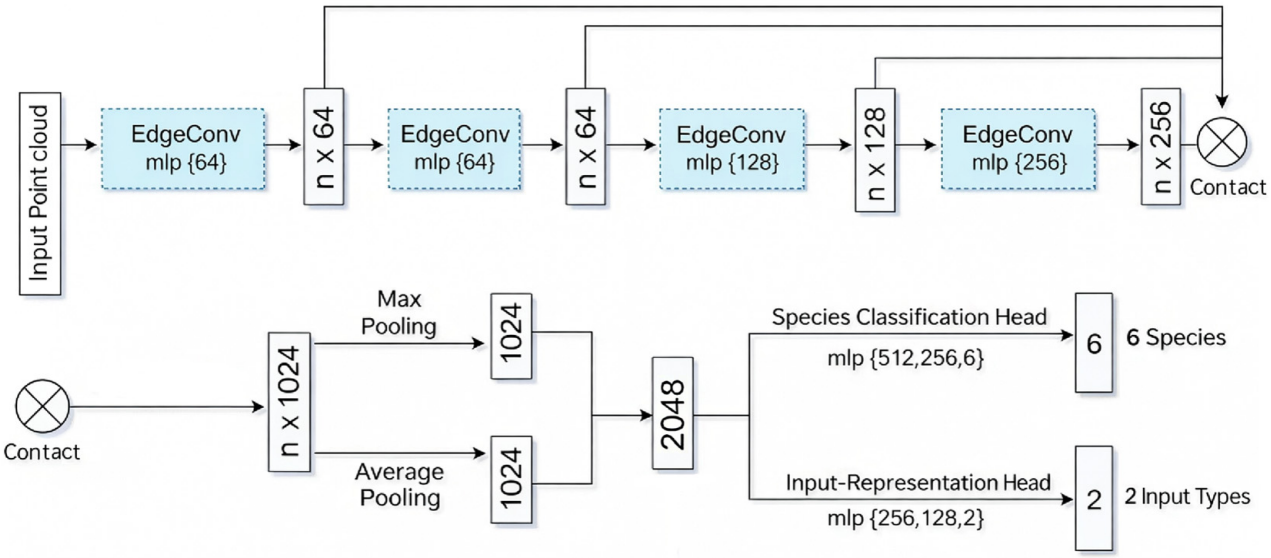


Figure 4. Detailed architecture of the proposed multi-task learning network for mixed-input tree species classification. The shared encoder is built upon a DGCNN backbone and uses stacked EdgeConv modules to extract multi-scale structural features from the input point clouds. The intermediate features are concatenated and aggregated through max pooling and average pooling to form a 2048-dimensional global feature vector. This shared representation is then fed into two parallel branches: the primary species classification head for tree species recognition and the auxiliary input-representation discrimination head for distinguishing leaf-on point clouds from woody-only point clouds.

As shown in Figure 4, the proposed network adopts a shared-feature learning strategy followed by dual-task output branches. The shared encoder is responsible for extracting global structural representations from the input point clouds, while the two output heads respectively focus on tree species recognition and input-representation discrimination. Through this design, the model is expected to improve its adaptability to mixed-input conditions and to reduce excessive dependence on leaf-on appearance information. The auxiliary task therefore serves as a complementary constraint on representation learning, helping the network retain structural cues that remain useful across different input forms.

2.4.1. Shared Feature Encoder and EdgeConv Formulation

A Dynamic Graph Convolutional Neural Network (DGCNN) [12] was employed as the shared feature encoder in the proposed multi-task learning framework. Compared with point-based methods that rely mainly on fixed Euclidean neighborhoods, DGCNN dynamically updates neighborhood relationships in feature space through its core EdgeConv operation. This mechanism allows the network to capture local structural dependencies more effectively and is therefore well suited for representing the complex branching orga-

nization of individual-tree point clouds. For mixed-input tree species classification, such a shared encoder provides an effective basis for learning structural features from both leaf-on point clouds and their corresponding woody-only representations.

The input to the encoder is a mixed data batch $X_{mixed} \in \mathbb{R}^{N \times F}$, consisting of the original leaf-on point clouds and their corresponding woody-only point clouds. For a given layer, let the input be represented as a directed graph $G = (V, E)$, where $V = \{x_1, \ldots, x_N\}$ represents the vertices (points) and E represents the edges. For each point x_i, a local neighborhood graph is constructed by finding its $k-$ nearest neighbors (k-NN) $\{x_{i_1}, \ldots, x_{i_k}\}$ within the current feature space.

The EdgeConv module computes edge features e_{ij} between the central point x_i and its neighbor x_j using a nonlinear asymmetric function h_Θ:

$$e_{\{ij\}} = h_{\Theta(x_i,\, x_j - x_i)} \tag{5}$$

where h_Θ is parameterized by a Multi-Layer Perceptron (MLP) with learnable parameters Θ. The term x_i captures the global spatial position (or global semantic feature) of the point, while the term $(x_j - x_i)$ explicitly encodes the local geometric relationship and structural variations within the neighborhood.

Subsequently, a symmetric aggregation function (e.g., max pooling) is applied over all the neighborhood edge features to generate the updated point representation x_i':

$$x_i' = \max_{j:(i,j)\in E} e_{ij} \tag{6}$$

Because the k-NN graph is dynamically recomputed at each layer based on the updated features x_i', the network can progressively group points with similar structural characteristics in feature space. For mixed-input tree species classification, this property is beneficial for capturing structurally related patterns from both leaf-on point clouds and woody-only point clouds.

Through stacked EdgeConv layers, the shared encoder maps the input to a highly discriminative, high-dimensional global feature vector F_{global}. This shared representation contains information related to both tree structural characteristics and input representation patterns, and is subsequently fed into the two task-specific branches for tree species classification and input-representation discrimination.

2.4.2. Dual-Task Branch Design

The network backend comprises two parallel task heads:

1. Primary Task: Tree Species Classification Head:

Composed of a Multi-Layer Perceptron (MLP) that maps F_{global} to N tree species categories. Outputs pass through a Softmax layer to yield tree species prediction probabilities.

2. Auxiliary Task: Input-Representation Discrimination Head:

The auxiliary branch is designed as a binary classifier to determine whether the input point cloud is a leaf-on point cloud or a woody-only point cloud.

Design Rationale: By jointly learning tree species categories and input representation types, the shared encoder is encouraged to preserve structural cues that remain useful under different input forms, while reducing excessive dependence on leaf-on appearance information. In this way, the auxiliary task serves as a complementary constraint on feature learning and helps improve the model's adaptability under mixed-input conditions.

2.4.3. Joint Loss Function

The total network loss L_{total} is defined as:

$$L_{total} = L_{species} + \lambda L_{input} \tag{7}$$

where $L_{species}$ and L_{input} represent the cross-entropy losses for the primary and auxiliary tasks, respectively, and λ is the balancing coefficient used to adjust the weight of the auxiliary task's influence on feature learning. In our experiments, the balancing coefficient λ was empirically set to 0.5 to ensure that the auxiliary task provides sufficient regularization without overwhelming the primary species classification task.

2.5. Experimental Implementation Details

The experiments were implemented using the PyTorch 2.2.2 deep learning framework on a single NVIDIA GeForce RTX 4090 GPU.

Training Strategy: The Adam optimizer was employed with an initial learning rate of 0.001, decaying by 0.5 every 20 epochs.

Dataset Partitioning: For the tree species classification task, the original individual-tree samples were divided into a training set and a test set at a ratio of 60% to 40%. Based on this split, each original leaf-on sample and its corresponding woody-only point cloud were jointly organized into mixed-input samples for subsequent experiments. For the wood–leaf separation task, the manually annotated dataset was divided into 72 training samples, 24 validation samples, and 24 test samples.

Evaluation Metrics:

Segmentation Performance: Segmentation performance was evaluated using Intersection over Union (IoU), mean Intersection over Union (mIoU), and Overall Accuracy (OA) to assess the quality of wood–leaf separation.

Classification Performance: Classification performance was evaluated using Overall Accuracy (OA), Precision, Recall, F1-score, and Kappa coefficient to assess tree species recognition effectiveness under mixed-input conditions.

Metric Formulation: For the wood–leaf separation task, Intersection over Union (IoU) was used to evaluate the overlap between predicted labels and reference annotations for each class. For a given class, IoU is defined as:

$$IoU = \frac{TP}{TP + FP + FN} \tag{8}$$

where TP, FP, and FN denote true positives, false positives, and false negatives, respectively. The mean Intersection over Union (mIoU) is calculated as the average IoU across classes. Overall Accuracy (OA) is defined as:

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

For the tree species classification task, Precision, Recall, and F1-score were used to evaluate class-wise classification performance, and are defined as:

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{12}$$

In addition, the Kappa coefficient was used to assess the consistency between predicted and reference labels beyond chance agreement.

$$Kappa = \frac{p_o - p_e}{1 - p_e} \tag{13}$$

where p_o denotes the observed agreement and p_e denotes the expected agreement by chance.

3. Results

3.1. Wood–Leaf Separation Performance and Woody-Only Point Cloud Generation

To evaluate the quality of the generated woody-only point clouds, the KPConv-based wood–leaf separation model was tested on a manually annotated subset. The experimental results indicate that the model achieved stable segmentation performance across the six broadleaf tree species used in this study. As summarized in Table 2, the model yielded a mean Intersection over Union (mIoU) of 89.5% and an overall accuracy (OA) of 93.9%, indicating that the proposed method can provide reliable woody structural representations for subsequent classification experiments.

Table 2. Quantitative evaluation results of wood–leaf separation across six broadleaf tree species. The metrics include Intersection over Union (IoU) for wood and leaf classes, mean IoU (mIoU), and Overall Accuracy (OA).

Species	IoU_{Wood} (%)	IoU_{Leaf} (%)	mIoU (%)	OA (%)
Ginkgo	92.4	96.1	94.3	96.8
Chinese white poplar	85.6	91.8	88.7	93.4
Norway maple	85.5	92.2	89.0	93.2
European beech	85.7	92.4	89.2	93.3
European ash	85.3	92.0	88.8	93.0
European hornbeam	85.0	91.9	88.6	92.8
Total	86.6	92.3	89.5	93.9

As shown in Table 2, the proposed KPConv-based method achieved stable wood–leaf separation performance across all six broadleaf tree species. Overall, the model obtained an mIoU of 89.5% and an OA of 93.9%, indicating that the generated woody-only point clouds retain the major structural information required for subsequent classification. These results suggest that the proposed method can provide a reliable structural basis for the following mixed-input tree species classification task.

To further illustrate the effect of the proposed method at the sample level, Figure 5 presents representative qualitative results of wood–leaf separation and woody-only point cloud generation for typical broadleaf tree samples.

As shown in Figure 5, the proposed method can effectively separate leaf points from woody components in representative broadleaf tree samples. In the segmentation results, most leaf points are removed, while the main trunk and major branch structures are retained in the generated woody-only point clouds. Although some fine structural details may still be partially omitted in complex canopy regions, the overall woody architecture remains sufficiently preserved for subsequent tree species classification. These qualitative results are consistent with the quantitative evaluation in Table 2 and further demonstrate the practical value of the proposed wood–leaf separation strategy for mixed-input classification.

3.2. Overall Tree Species Classification Performance

We compared the proposed multi-task network with classical single-task baseline models (PointNet++ and DGCNN) on the mixed test set composed of leaf-on point clouds and their corresponding woody-only point clouds. As shown in Table 3, the proposed method achieved the best performance across the main evaluation metrics, with an overall accuracy (OA) of 94.3%, an average Precision of 94.3%, an average Recall of 93.6%, and an average F1-score of 93.9%. Compared with the baseline models, the proposed multi-task framework showed improved classification performance under mixed-input conditions.



Figure 5. Qualitative results of wood–leaf separation and woody-only point cloud generation for representative broadleaf tree samples. The figure shows two typical broadleaf tree examples. From left to right: (**a**) the original leaf-on point cloud; (**b**) the KPConv-based wood–leaf separation result, where leaf points are shown in green and wood points in brown; and (**c**) the corresponding woody-only point cloud obtained after removing the predicted leaf points.

Table 3. Comparison of overall classification performance among different methods on the mixed test set of six broadleaf tree species.

Method	Backbone	Input Data	OA (%)	Precision (%)	Recall (%)	F1 (%)
PointNet++ [10]	PointNet++	Mixed	89.4	89.8	88.7	89.1
DGCNN (Baseline) [12]	DGCNN	Mixed	91.1	91.4	90.6	90.9
Ours (MTL-Net)	DGCNN + MTL	Mixed	94.3	94.3	93.6	93.9

Note: "Mixed" indicates that the test set contains original leaf-on point clouds and their corresponding woody-only point clouds.

To evaluate the overall performance of the proposed method under mixed-input conditions, the classification results of different models on the mixed test set are summarized in Table 3.

As shown in Table 3, the proposed multi-task learning framework achieved the best overall performance on the mixed test set of six broadleaf tree species. Compared with the

two single-task baseline models, the proposed method showed higher OA, Precision, Recall, and F1, indicating that the joint use of leaf-on point clouds and woody-only point clouds can improve tree species recognition under mixed-input conditions. Among the baseline models, DGCNN outperformed PointNet++, suggesting that dynamic graph feature extraction is more effective for capturing structural relationships in individual-tree point clouds. On this basis, the introduction of the auxiliary input-representation discrimination task further improved the classification capability of the model, demonstrating the usefulness of the proposed multi-task design.

To further examine the class-wise classification behavior of the final model, Figure 6 presents the confusion matrix of the proposed multi-task learning network on the mixed test set.

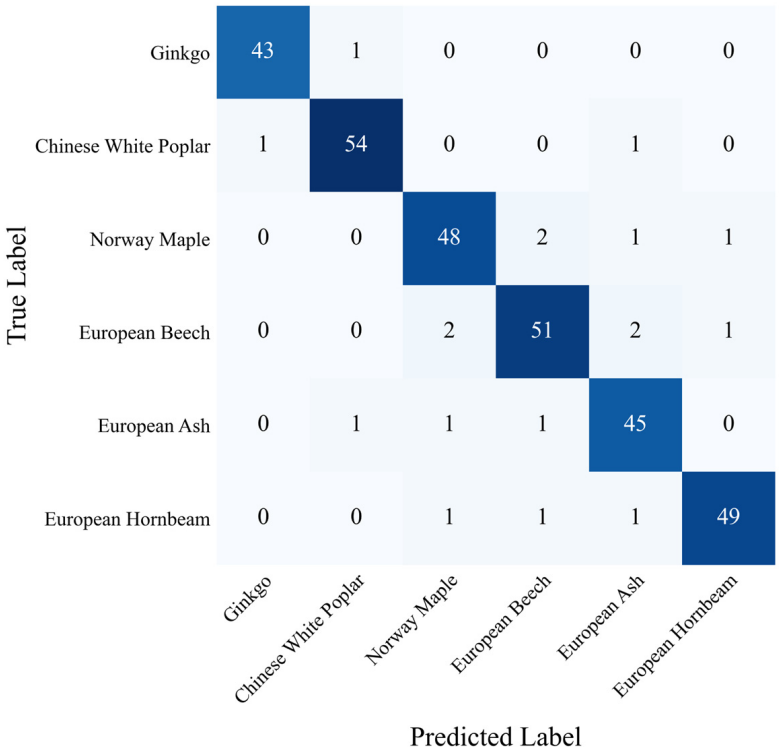


Figure 6. Confusion matrix of the proposed multi-task learning model on the mixed test set of six broadleaf tree species. Values in the matrix represent the number of test samples.

As shown in Figure 6, most samples are concentrated along the main diagonal, indicating that the proposed model can effectively distinguish the six broadleaf tree species under mixed-input conditions. Among the six species, ginkgo shows the most concentrated diagonal distribution and the lowest level of confusion, which is likely related to its relatively distinctive structural characteristics, including its crown form and branch organization. By contrast, the remaining broadleaf species exhibit more obvious mutual confusion, suggesting that their structural differences are less pronounced and therefore more difficult to capture completely even under the proposed framework. Nevertheless, the overall confusion pattern still demonstrates stable classification performance of the proposed method on the mixed test set and indicates that the joint use of leaf-on point clouds and woody-only point clouds helps the model learn discriminative structural cues for broadleaf tree species recognition.

While the above results demonstrate the overall effectiveness of the proposed method, it is still necessary to clarify the respective contributions of woody-only point cloud input and multi-task learning. Therefore, a stepwise ablation study was further conducted.

3.3. Ablation Study

To evaluate the contribution of each key component in the proposed framework, a stepwise ablation study was conducted. Starting from the baseline DGCNN model, woody-only point cloud input and the multi-task learning design were introduced incrementally, and their respective effects were evaluated on the mixed test set.

To further examine the respective contributions of woody-only point cloud input and multi-task learning, the ablation results on the mixed test set are summarized in Table 4.

As shown in Table 4, both woody-only point cloud input and multi-task learning contributed positively to the final classification performance. Compared with Model A, introducing woody-only point clouds in Model B led to a clear improvement in overall accuracy, indicating that additional woody structural information is beneficial for mixed-input tree species classification. On this basis, Model C further improved the classification result after incorporating the auxiliary input-representation discrimination task. This suggests that, beyond expanding the structural information available to the classifier, the multi-task learning design also helps the network better adapt to different input forms. Overall, the ablation results indicate that the effectiveness of the proposed framework arises from the combined contribution of structural input enhancement and multi-task feature learning.

Table 4. Ablation study of the proposed framework on the mixed test set of six broadleaf tree species.

Model	Woody-Only Point Cloud Input	Multi-Task Learning (MTL)	OA (%)	OA Gain (Percentage Points)
A	—	—	76.5	— (Baseline)
B	✓	—	91.1	+14.6
C	✓	✓	94.3	+17.8

Note: Model A denotes the baseline trained using only original leaf-on point clouds. Model B additionally incorporates the corresponding woody-only point clouds. Model C further introduces the auxiliary input-representation discrimination task. OA Gain is calculated relative to Model A. The symbol — indicates that the corresponding module is not used, and ✓ indicates that the module is used.

To further illustrate the limitation of the single-input baseline under mixed-input evaluation, Figure 7 presents the confusion matrix of Model A on the mixed test set.

As shown in Figure 7, the confusion matrix of Model A exhibits a relatively dispersed distribution on the mixed test set, indicating that the classifier trained only on original leaf-on point clouds has limited adaptability under changing input representations. Among the six species, ginkgo shows the most concentrated diagonal distribution and the lowest level of confusion, which is likely related to its relatively distinctive structural characteristics, including its crown form and branch organization. By contrast, the remaining broadleaf species show more obvious mutual confusion, suggesting that their structural differences are less pronounced when the model relies mainly on leaf-on appearance cues. This pattern indicates that, although highly distinctive species such as ginkgo can still be recognized relatively well, the single-input baseline is less capable of distinguishing structurally similar broadleaf species under mixed-input evaluation conditions. Combined with the ablation results in Table 4, the confusion matrix further confirms that the main performance gain of the proposed framework comes from the introduction of woody-only point cloud input.

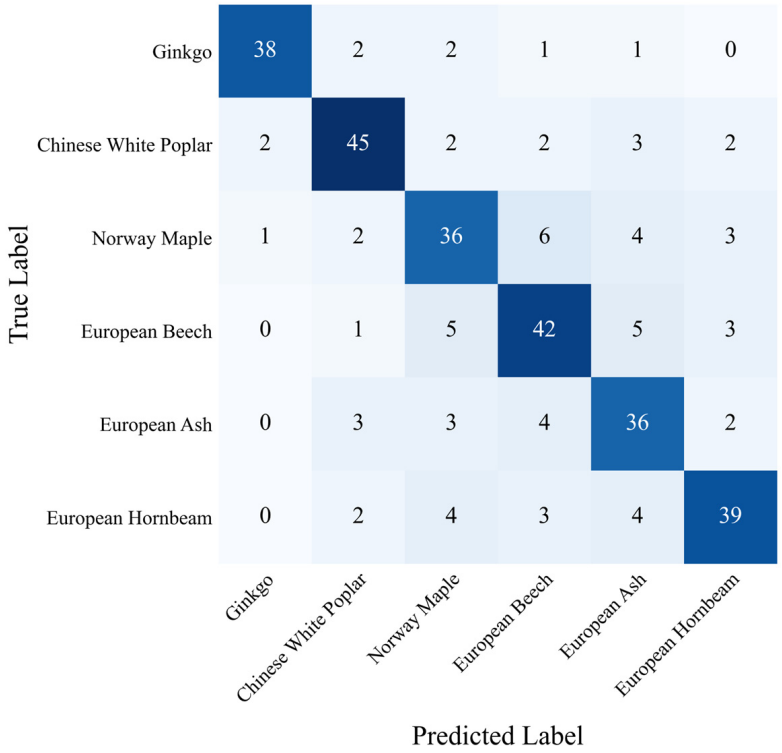


Figure 7. Confusion matrix of Model A (baseline trained using only original leaf-on point clouds) on the mixed test set of six broadleaf tree species. Values in the matrix represent the number of test samples.

4. Discussion

4.1. Effect of Mixed Input and Multi-Task Learning on Tree Species Classification

The experimental results indicate that introducing woody-only point clouds is beneficial for tree species classification under mixed-input conditions. Compared with models trained using only original leaf-on point clouds, the mixed-input setting provides additional woody structural information that complements foliage-related appearance cues. This enrichment of structural representation helps the classifier better distinguish broadleaf tree species with different trunk–branch organization and crown architecture, thereby improving overall classification performance.

On this basis, the multi-task learning design further improves classification performance. By introducing the auxiliary task of input-representation discrimination, the shared encoder is encouraged to retain structural cues that remain useful across different input forms, rather than relying excessively on leaf-on appearance information alone. Therefore, the gain of the proposed framework arises not only from the introduction of woody-only point clouds but also from the additional representation-learning benefit brought by the multi-task learning strategy.

4.2. Comparison with Existing Research

Compared with existing studies on tree species classification from TLS point clouds, the present study differs mainly in two aspects. First, instead of relying only on original leaf-on point clouds, this study constructs a mixed-input classification framework by combining leaf-on point clouds with corresponding woody-only point clouds generated through wood–leaf separation. This design enriches the structural information available to the classifier and provides a practical way to improve broadleaf tree species recognition when only leaf-on data are available [7,8].

Second, existing studies on wood–leaf separation, ranging from geometry-based methods such as LeWos [15] to recent deep learning approaches [25,26], have mainly treated separation as a preprocessing step for biomass estimation, quantitative structure modeling, or related structural analysis tasks [6,27,28]. By contrast, the present study extends the role of wood–leaf separation from a preprocessing procedure to an important component of the classification framework and further combines it with input-representation discrimination in a multi-task learning setting. In this way, the proposed method not only enriches the structural information used for classification but also improves feature learning stability under mixed-input conditions.

4.3. Limitations and Future Work

Despite the encouraging results obtained in this study, several limitations still remain:

1. Incomplete retention of extremely fine woody structures:

The woody-only point clouds used in this study were generated through the proposed wood–leaf separation model rather than directly acquired from real leaf-off scans. Although the main trunk and major branch framework can generally be preserved, some extremely fine woody components may still be omitted during segmentation, especially in structurally complex canopy regions. This may affect the completeness of the generated woody-only representations and limit their ability to fully describe fine-scale branch architecture.

2. Limited validation scope for real leaf-off conditions:

The current evaluation mainly focuses on leaf-on point clouds and their corresponding woody-only point clouds generated through wood–leaf separation. Although the present results support the effectiveness of the proposed method under different input representations, the framework has not yet been systematically validated on an independent real leaf-off test set. Therefore, the conclusions of this study are more appropriately interpreted as evidence of improved adaptability under mixed-input conditions, rather than a complete validation of real cross-seasonal generalization.

3. Limited species and scene coverage, together with computational cost:

The present study focuses on six typical temperate broadleaf tree species, and the experimental data still cover a relatively limited range of species composition and forest conditions. In addition, the KPConv-based segmentation model requires relatively high GPU memory and computational resources compared with lighter point-cloud processing strategies. Future work could further evaluate the proposed framework on broader broadleaf tree datasets, more diverse canopy conditions, and real leaf-off point clouds, while also exploring more efficient learning strategies or complementary data sources to improve both robustness and computational efficiency. In particular, future research may explore integrating UAV laser scanning (ULS) data into the proposed framework. By complementing TLS with top-down canopy information from ULS, such multi-source data fusion may improve structural completeness and further enhance tree species classification in complex forest scenes.

5. Conclusions

This study proposes a mixed-input tree species classification framework for six typical temperate broadleaf tree species based on terrestrial laser scanning (TLS) point clouds. By combining KPConv-based wood–leaf separation with a multi-task learning strategy, the proposed method integrates original leaf-on point clouds and their corresponding woody-only point clouds into a unified classification framework.

Experiments on six representative broadleaf tree species, namely ginkgo, *Chinese white poplar*, *Norway maple*, *European beech*, *European ash*, and *European hornbeam*, lead to the following main conclusions:

1. Effectiveness of woody-only point cloud generation: The KPConv-based wood–leaf separation model achieved stable segmentation performance on the six broadleaf tree species, indicating that the generated woody-only point clouds can preserve the main trunk and branch structures required for subsequent classification.

2. Effectiveness of the mixed-input classification framework: By jointly using original leaf-on point clouds and corresponding woody-only point clouds, the proposed framework achieved strong classification performance on the mixed test set, with an overall accuracy of 94.3% and average Precision, Recall, and F1 values of 94.3%, 93.6%, and 93.9%, respectively. These results indicate that introducing woody structural representations is beneficial for broadleaf tree species classification under mixed-input conditions.

3. Additional benefit of multi-task learning: On the basis of mixed-input classification, the auxiliary task of input-representation discrimination further improved model performance. This suggests that multi-task learning helps the shared encoder retain structural cues that remain useful across different input forms and improves the stability of classification under mixed-input conditions.

In summary, this study demonstrates that, when only leaf-on TLS data are available, integrating woody-only point clouds generated through wood–leaf separation with multi-task learning can effectively improve broadleaf tree species classification under different input representations. The proposed framework provides a practical methodological reference for TLS-based broadleaf tree species recognition and for future research on structural representation enhancement in point-cloud classification.

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