An Approach Based on Deep Learning for Tree Species Classification in LiDAR Data Acquired in Mixed Forest

Daniele Marinelli, Claudia Paris, *Member, IEEE*, and Lorenzo Bruzzone, *Fellow, IEEE*

***Abstract*—This letter proposes a novel method based on Deep Learning (DL) to forest species classification in airborne Light Detection and Ranging (LiDAR) data. Differently from the state-of-the-art approaches, the proposed method: 1) does not assume any prior knowledge either on the forest to be classified or on the sensor used to acquire the LiDAR data and 2) can be applied to heterogeneous forest characterized by mixed species. First, the 3-D point cloud of each individual tree is decomposed into eight angular sectors to generate a multislice representation of the vertical structure of the tree. This representation models the foliage, the stem, and the branches of the tree crown as well as depicts the internal and external crown properties. Then, a multiview convolutional neural network (MVCNN) DL automatically extracts features used to discriminate the different tree species. This network is pretrained on the massive ImageNet database, thus guaranteeing fast convergence with a relatively small number of ground reference data. Experiments were carried out on high-density airborne LiDAR data collected over a multilayer multiage forest characterized by four conifers and three broadleaf species. The proposed method outperformed the state-of-the-art approaches increasing the Overall Accuracy (OA) up to 16% and 18.9% compared to a DL and a shallow tree species classification methods, respectively. When applied to coniferous or broadlaef forests, the proposed method showed an increase of OA 10.1% and 15.9% (for conifers) and 9.5% and 21.6% (for broadleafs) compared to the DL and shallow methods, respectively.**

***Index Terms*—Deep learning (DL), light detection and ranging (LiDAR), mixed forest, remote sensing (RS), tree species.**

I. Introduction

REMOTE sensing data have been extensively employed to support forest species classification due to the possibility of objectively monitoring wide-area forests. In particular, a large effort has been devoted to develop methods for the classification of tree species on Light Detection and Ranging (LiDAR) data [1]. By taking advantage from the capability of the laser scanner to measure both the inner structure and the 3-D shape of the tree crowns, it is possible to accurately distinguish different forest species [2], [3]. Li *et al.* [2] extracted several LiDAR features to describe the horizontal and vertical structures of foliage and branch distribution (e.g., tree envelop, foliage clustering scale, and gap distribution). Their method has been defined to distinguish four tree species characterized by similar crown structure, i.e., trembling aspen, sugar maple, jack pine, and white pine, when high-density LiDAR data having at least 50 pts/m^2 are available. Similarly, Harikumar *et al.* [3] modeled both internal and external geometric properties of the tree to distinguish four conifer species (i.e., Norway Spruce, European Larch, Swiss Pine, and Silver Fir). By defining an algorithm tailored to the conifer crown structure, their method is able to outperform other state-of-the-art approaches. Indeed, accurate classification results can be achieved with methods based on handcrafted feature extraction by leveraging on prior knowledge of both the forest properties (i.e., species and structure) and sensor characteristics. However, when dealing with mixed heterogeneous forest classification problems, there is the need to use approaches that automatically derive optimal features to model the different crown structures.

Recently, few Deep Learning (DL) approaches have been applied to the tree species classification task considering high-density mobile or terrestrial LiDAR data. Zou *et al.* [4] applied a Deep Belief Network (DBN) to a LiDAR point cloud acquired by terrestrial laser scanning systems for distinguishing four types of trees. First, the 3-D point cloud of an individual tree is projected onto 2-D images using a voxel-based rasterization step. Then, the images are classified according to the DBN model trained from scratch. The authors exploit a DBN model due to its capability of achieving better convergence with small-scale training set compared to other DL models, which typically require a huge number of training samples. Similarly, Guan *et al.* [5] represented the different profiles of the tree LiDAR point clouds as waveforms ingested by deep Boltzmann machines. The method was successfully tested on urban tree species acquired using mobile LiDAR data. In [6], a deep Convolutional Neural Network (CNN) is used to classify individual tree crowns into conifers and deciduous trees. Two discrete representations using leaf-off and leaf-on LiDAR data are used to generate Digital Surface Model (DSM) and 2-D side view profiles. Liu *et al.* [7] focused on the classification of birch and larch by defining the LayerNet deep model made up of a novel layered feature encoding network and the standard PointNet decoding network [8]. The point cloud used in the letter is acquired by an unmanned aerial vehicle (UAV) scanner, which accurately represents the tree stem and the branches needed by the approach to distinguish the two forest species.

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Daniele Marinelli and Lorenzo Bruzzone are with the Department of Information Engineering and Computer Science, University of Trento, 38123 Trento, Italy (e-mail: lorenzo.bruzzone@unitn.it).

Claudia Paris is with the Department of Natural Resources ITC, University of Twente, 7522 NB Enschede, The Netherlands (e-mail: c.paris@utwente.nl).

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Although DL models are promising for individual tree species classification using LiDAR data, most of the methods focus on mobile or terrestrial LiDAR point clouds, while airborne LiDAR data are typically classified with shallow models [1]. This is probably due to similarities of terrestrial data to the ones used in computer vision that allows for methods developed for such field to be applied on terrestrial LiDAR point clouds, thus increasing the use of these data. However, to perform large-scale forest mapping, experiments should be carried out on airborne LiDAR data. The few methods tested on airborne data mainly focus on simple classification task by discriminating broadleaf trees from conifers or focusing on two species, i.e., on binary classification tasks. From the operational viewpoint, it is not feasible to assume the classification of few forest species when a large-scale environmental analysis has to be carried out. To solve this problem, this letter proposes a novel approach to tree species classification based on DL and airborne LiDAR data defined for heterogeneous forest areas characterized by mixed species. In particular, the proposed approach takes advantage from the Multiview CNN (MVCNN) DL model widely used in the computer vision community for 3-D shape recognition [9] to automatically extract semantic abstract features capable of discriminating different tree species. This peculiar DL architecture combines information provided by multiple views of a 3-D shape into a single and compact shape descriptor, thus working in the image domain. The main contribution of this work is to propose a method that: 1) it automatically detects the effective features to distinguished different tree species; 2) it can take advantage, working in the image domain, of a network pretrained on the massive ImageNet database to rapidly boost the performance using a relatively small training set; and 3) it can be applied to heterogeneous mixed forest without the need of manually tuning any model parameter.

II. Proposed Tree Species Classification Approach

The proposed tree species classification approach assumes that: 1) the tree crowns are delineated in the 3-D point cloud space; 2) each segmented tree point cloud has a central stem; and 3) the 3-D structure of the trees (i.e., branch and foliage) is sufficient to discriminate the different tree species. Regarding the first assumption, a reliable segmentation step is necessary for proper training and exploitation of the model. Indeed, errors, such as undersegmentation (typical especially in dense forests), may lead to an incorrect representation of the crown structure and thus an ineffective training. Note that this is a problem common to all single tree methods. The method is based on two main steps: 1) the multislice decomposition of the tree crowns and 2) the DL-based tree species classification. In the following, details are given.

A. Multislice Decomposition of the Tree Crowns

Let $\mathbf{P}_k = \{\mathbf{p}_i\}_{i=1}^N$ be the set of LiDAR points associated with the kth segmented tree and let $\mathbf{t}_k$ be the corresponding tree-top, where $\mathbf{p}_i$ and $\mathbf{t}_k$ are three-element row vectors defined by the x, y, and z coordinates, i.e., $\mathbf{p}_i = (x_i, y_i, z_i)$ and $\mathbf{t}_k = (x_k^t, y_k^t, z_k^t)$. In order to fully take advantage from the capability

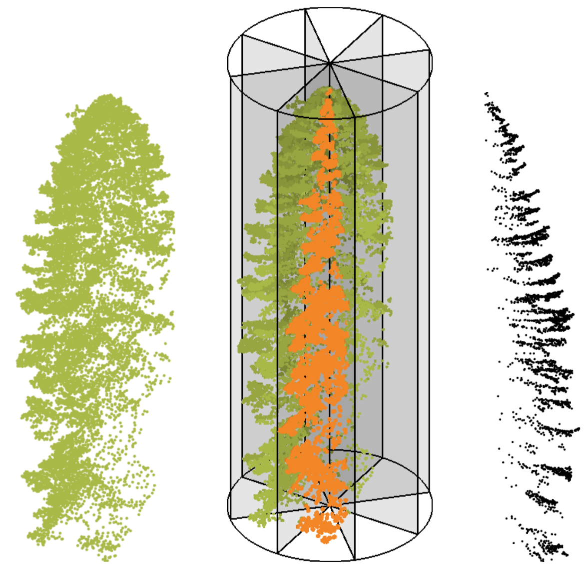

Fig. 1. Example of multislice generation applied to a conifer: (a) original point cloud, (b) sector analysis with the points selected for one slice highlighted in orange, and (c) resulting slice.

of the LiDAR data to accurately represent the structure of the trees, $\mathbf{P}_k$ is first decomposed into N angular sectors to generate a multislice representation of the vertical structure of the tree. Fig. 1 shows a qualitative example of multislice representation of a conifer, where the sectors are defined by the vertical panels. Such decomposition allows us to accurately depict the internal and external crown properties, by properly modeling the foliage, the stem, and the branches of the tree crown.

Let Θ_j be the angular sector defined between $\theta_j = 2\pi j/N$ and $\theta_{j+1} = 2\pi(j+1)/N$, where $j \in [0, N-1]$. The set of LiDAR points belonging to the angular sector $\mathbf{P}_k^{\Theta_j}$, which are represented in orange in Fig. 1(b), can be defined as

$$\mathbf{P}_k^{\Theta_j} = \left\{ \mathbf{p}_i \in \mathbf{P}_k \,\middle|\, \arctan\left(\frac{x_i - x_k^t}{y_i - y_k^t}\right) \in [\theta_j, \theta_{j+1}) \right\}. \quad (1)$$

The 3-D vertical profile of the angular sector can be represented by a 2-D view, by considering the coordinates z_i of the LiDAR points $\mathbf{p}_i \in \mathbf{P}_k^{\Theta_j}$ and their distances from the stem. Let us assume that the tree-top correctly represents the location of the tree stem. The absolute distance of LiDAR points from the stem can be computed as follows:

$$\rho_i = \sqrt{\left(x_i - x_k^t\right)^2 + \left(y_i - y_k^t\right)^2}. \quad (2)$$

To this end, we first apply a circular projection to the points $\mathbf{p}_i \in \mathbf{P}_k^{\Theta_j}$ onto the ρz plane centered in the tree-top coordinates (x_k^t, y_k^t) to map the points from the 3-D space $\mathbf{R}^3$ onto the 2-D space $\mathbf{R}^2$. Let $S_k^{\Theta_j}(\rho)$ be the vertical profile of Θ_j. After the mapping, the LiDAR tree crown $\mathbf{P}_k$ is represented by N 2-D views, i.e., $[S_k^{\Theta_1}(\rho), S_k^{\Theta_2}(\rho), \ldots, S_k^{\Theta_N}(\rho)]$, each one representing one slice. It is worth noting that the production of the 2-D views of the images should: 1) avoid loss of information in the description of the 3-D structure and 2) generate 2-D profiles consistent to each other. The latter aspect is critical since the image properties (e.g., size) must not

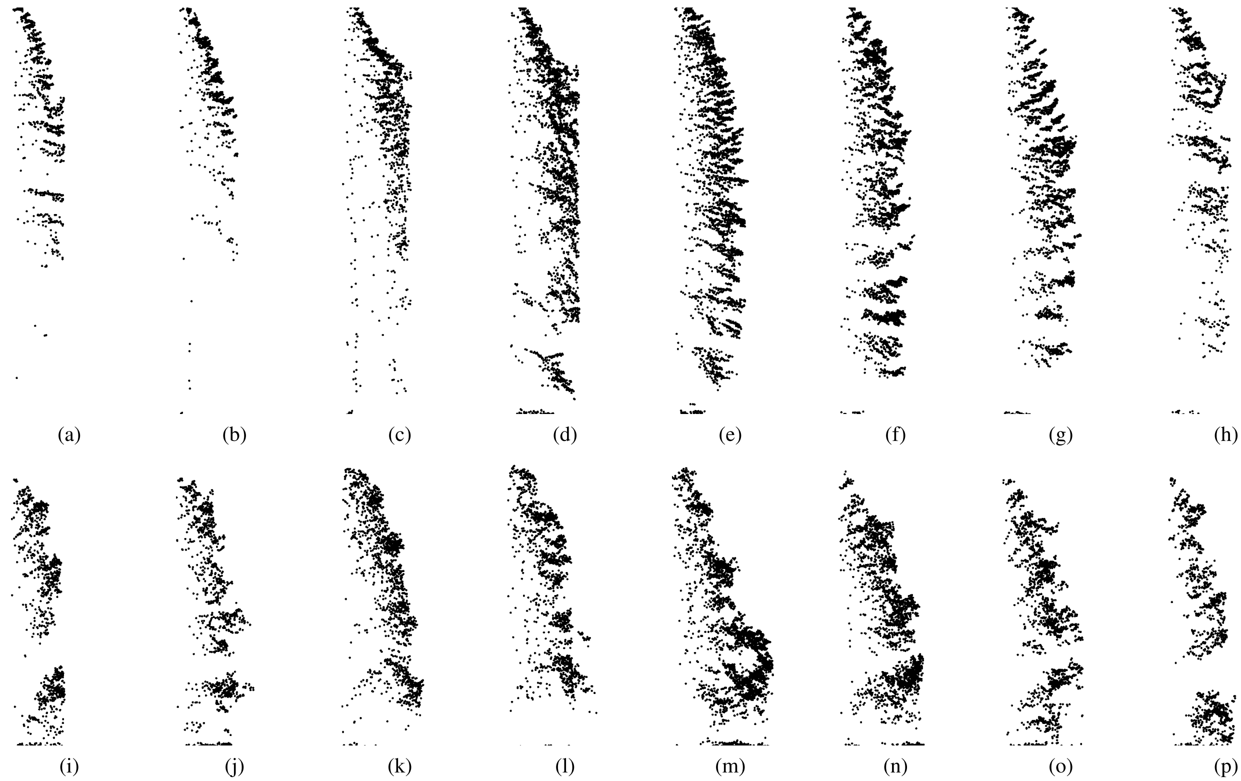

Fig. 2. Qualitative example of multislice decomposition of two tree crowns: (a)–(h) conifer (Silver Fir) and (i)–(p) broadleaf (Aspen). One can notice that the profiles acquired over different angular sectors allow us to capture the irregular structure of the tree crowns.

have an impact on the classification. To this end, the LiDAR points are all rendered as black dots with equal size to drive the MVCNN to focus on the crown structure and enhance the generalization capability of the model. Fig. 2 shows a qualitative example of multislice decomposition of two tree crowns by comparing conifer (silver fir) and broadleaf (aspen) forest species. The figure clearly depicts how the proposed representation effectively captures both the crown shape and internal structure of the trees, by emphasizing the different geometrical properties of the considered tree species.

B. DL-Based Tree Species Classification

DL models proved to be very effective for extracting abstract semantic features to support complex classification task. In particular, CNN models trained on large dataset of natural images such as *ImageNet* or *GoogLeNet* are able to accurately define in a fast and automatic way image descriptors useful for several vision tasks (e.g., object detection, scene recognition, and texture detection) [10]. In this context, the possibility of taking advantage from a pretrained architecture is extremely interesting to address forest species classification of LiDAR data. Indeed, the small training sets typically available for forestry applications are not sufficient to successfully train a DL model from scratch. For this reason, the proposed approach takes full advantage of the capability of the MVCNN model pretrained on the large database of annotated images *ImageNet* [9] to accurately address the considered classification task with a relatively small set of ground reference data.

The MVCNN model is able to synthesize the information from multiple views into a single compact 3-D shape descriptor, which can be used to perform the classification task. In greater detail, each slice $S_k^{\Theta_j}(\rho)$ is passed through a dedicated CNN_j^{Θ}, which is able to automatically extract an informative set of abstract semantic features. In particular, the CNN model is a VGG-11 architecture composed by eight convolutional layers followed by three fully connected layers [11]. It is worth noting that no manual parameter tuning is performed per slice since all the feature extractors $[\text{CNN}_1^{\Theta}, \text{CNN}_2^{\Theta}, \ldots, \text{CNN}_N^{\Theta}]$ share the same parameters. Let us define as $\mathbf{f}_k^{\Theta_j}$ the set of features extracted for the jth view $S_k^{\Theta_j}(\rho)$ of the kth segmented tree. The set of N features $[\mathbf{f}_k^{\Theta_1}(\rho), \mathbf{f}_k^{\Theta_2}(\rho), \ldots, \mathbf{f}_k^{\Theta_N}(\rho)]$ is aggregated into a unique 3-D image descriptor $\mathbf{F}_k$ through a view-pooling layer considering an element-wise maximum operation across the views. The final descriptor $\mathbf{F}_k$ is then used for classification. Also, in this case, the considered DL architecture takes advantage from the capability of a CNN to properly handle this task. To carry out this step, the network is fine-tuned on the considered training set using stochastic gradient descent with backpropagation. Note that the considered network does not require to have the same number of points per segmented crown. This condition allows us to: 1) fully take advantage from the capability of the laser scanner to describe the inner structure of the trees and 2) not impose any constraint on the LiDAR data acquisition. Another advantage of the proposed approach is that it does not require to have a very large number of labeled samples to train the DL model from scratch [4]. Indeed, at the operational level, this may lead to overfitting and curse of dimensionality problems due to the lack of reference data. In particular, the use of a network pretrained on millions of annotated

TABLE I

CLASS DISTRIBUTION AND DENDROMETRIC MEASUREMENTS OF THE DATASET

Class	# Trees			Top Height [m]			Crown Area [m^2]		
	TOT	Train	Test	Min	Max	Mean	Min	Max	Mean
AB	158	117	41	9.7	40.4	26.9	11.4	160.0	58.6
AR	402	300	102	7.2	46.2	27.2	3.9	146.4	48.9
BE	108	82	26	5.2	19.4	13.1	3.9	125.2	30.6
LA	335	251	84	10.3	44.	28.4	10.1	178.5	69.6
ON	65	49	16	4.8	17.2	10.8	5.7	107.2	31.3
PC	67	47	20	7.7	21.2	13.6	4.5	66.1	28.1
PT	81	60	21	7.8	31.4	18.8	9.4	169.3	50.4
Total	1216	906	310						

* AB = Silver Fir; AR = Norway Spruce; BE = Silver birch; LA = Larch; ON = Common Alder; PC = Swiss Pine; PT = Aspen

images allows for a fast boost of the performance with a small training set. Indeed, the size of annotated 3-D models is rather limited compared to image datasets, e.g., ModelNet contains about 150k shapes. Finally, the use of the proposed MVCNN allows for accurate classification results with low computational burden.

III. Dataset and Experiment Description

The proposed method has been tested in a study area of 800 ha located in the southern Italian Alps in the Trento province (central coordinates 46°17’57”, 46°17’57”). This area is characterized by mixed tree species composition with both conifers and deciduous trees. The most common conifers are Silver Fir (AB), AR, LA, and PC, while the most common broadleaf trees are BE, ON, and Aspen (PT). We manually delineated the tree crowns by photointerpretation of the canopy height model and the point cloud for those trees surveyed in the field, i.e., associated with a tree species. This resulted in a dataset composed of 1216 trees associated with seven different forest types. Table I shows the class distribution of the considered datasets and the main dendrometric measurements statistics for each class. The statistics show that we selected a significant diverse set of trees in order to test the proposed approach on challenging multiage multilayer forest area.

The number of slices N (i.e., 2-D views) was set to eight considering the pulse density and the desired result in terms of representation of the crown structure in each slice. To identify the best training parameters, we performed multiple run with different combinations of weight decay (wd) and learning rate (lr) testing the following ranges: wd $\in$ $[0.001, 0.1]$ and lr $\in$ $[5e^{-5}, 5e^{-3}]$. Finally, we set wd and lr equal to 0.01 and 5e^{-5}, respectively. To this end, the training set (see Table I) has been used with a cross-validation strategy, while the independent test set has been used only to assess the model performances. The proposed method has been compared with both a Shallow Method (SM) [12] based on the selection of handcrafted features and the 3-D DL model PointNet++ [8], which is widely used for point cloud classification. The considered SM is the one that provided the best results in [12], which presents an extensive analysis of tree species classification using different combinations of handcrafted features. Since we considered a mixed forest, the features related to the crown base height were neglected as it showed noisy and unstable behavior across the different species. Since no pretrained PointNet++ models are publicly available, in order to have a fair comparison, we also report the classification results obtained by the MVCNN when it is trained from scratch. In greater detail, we tested four different configurations: 1) classification of all the seven tree species (i.e., mixed forest); 2) classification of only the conifers classes (AB, AR, LA, and PC); 3) classification of only broadleaf classes (BE, ON, and PT); and 4) binary classification (broadleaf trees/conifers). The results have been evaluated in terms of Producer Accuracy (PA), User Accuracy (UA), F-score (F1), and overall accuracy (OA).

IV. Experimental Results

Table II shows the quantitative results obtained by the proposed and the baselines methods when applied to the mixed forest. As expected, both the DL approaches outperformed the baseline shallow method due to the possibility of extracting more robust features. The proposed approach obtained the best overall and single classes accuracy proving the effectiveness of the multislice representation. Also, without pretraining, it achieved higher OA and mean F1 with respect to Pointet++, thus proving the effectiveness of the proposed approach. However, as expected, the pretrained MVCNN increases the OA of 8.71% with respect to the non-pretrained model. From the results obtained, it turned out that in the considered dataset, the most challenging classes are the broadleaf trees (BE, ON, and PT) due to the fact that: 1) they are the less represented classes (i.e., few training samples) and 2) their crown structures have a much higher variability with respect to conifers. However, the proposed method (pretrained) achieved good results for all the three classes with the lowest F1 score of 64.52% for the ON class compared to 54.9% and 40.00% obtained with the SM and Pointnet++, respectively. Similar results are also achieved for the BE and PT classes, where the best F1 of 68.97% and 72.22% is achieved by the proposed method, compared to 50% and 51.61% obtained with the SM and 57.69% and 46.67% obtained with the Pointnet++. This is true also for all the conifers classes (AB, AR, LA, and PC), where the proposed method achieved the highest F1 scores compared to the baselines. Focusing on the proposed method, the lowest F1 is related to the ON class, i.e., 64.52%. This is due to the fact that this is the class having the highest variability in terms of crown structure. Indeed, by visually analyzing the tree point clouds associated with different trees, one can notice that they present very different shapes. Moreover, this minor class is the one having the smallest number of samples in the training set.

Table III shows the numerical results for the remaining three configurations. The proposed method (both without pretraining and pretrained) achieved the best result with respect to the two reference methods. As expected, it achieves significantly better results with respect to the mixed forest case (see Table II), which represents the most challenging classification task. Indeed, similar OA and F1 score are achieved when considering homogeneous forest made up of only conifers (F1 of 82.02% and OA of 82.54%) or only broadleaf trees (F1 of 85.72% and OA of 86.64%). The binary classification achieved high OA and F1, thus confirming that the proposed method can distinguish the two macro forest classes.

TABLE II

PA, UA, F1, AND OA OBTAINED ON THE CONSIDERED MIXED FOREST (i.e., FOUR CONIFERS AND THREE BROADLEAF TREE SPECIES) FOR: 1) BASELINE SM [12]; 2) BASELINE DEEP METHOD [8]; 3) PROPOSED METHOD WITH THE MVCNN TRAINED FROM SCRATCH; AND 4) PROPOSED METHOD WITH THE PRETRAINED MVCNN

Class	**SM [12]**			**Pointnet++ [8]**			**Proposed (No Pre-Training)**			**Proposed (Pre-trained)**		
	PA	UA	F1	PA	UA	F1	PA	UA	F1	PA	UA	F1
AB	19.05	29.63	23.19	51.35	46.34	48.72	78.95	36.59	50	82.76	58.54	68.57
AR	83.81	69.84	76.19	70.87	88.24	78.6	77.31	90.2	83.26	85.71	94.12	89.72
BE	57.14	44.44	50	57.69	57.69	57.69	46.51	76.92	57.97	62.5	76.92	68.97
LA	61.8	76.39	68.32	74.39	72.62	73.49	90.28	77.38	83.33	86.36	90.48	88.37
ON	73.68	43.75	54.9	42.86	37.5	40	63.64	43.75	51.85	66.67	62.5	64.52
PC	100	86.96	93.03	66.67	50	57.14	73.08	95	82.61	100	95	97.44
PT	36.36	88.89	51.61	77.78	33.33	46.67	65	61.9	63.41	86.67	61.9	72.22
Mean	61.69	62.84	59.61	63.09	55.1	57.47	70.68	68.82	67.49	**81.52**	**77.07**	**78.54**
OA		64.31			67.10			74.52			**83.23**	

TABLE III

MEAN F1 AND OA OBTAINED BY THE FOUR METHODS WHEN APPLIED TO A CONIFEROUS FOREST, A BROADLEAF FOREST, AND WHEN CONSIDERING THE BINARY CLASSIFICATION

Experiment	**SM [12]**		**Pointnet++ [8]**		**Proposed (No Pre-training)**		**Proposed (Pre-trained)**	
	Mean F1	OA	Mean F1	OA	Mean F1	OA	Mean F1	OA
Conifers	67.62	70.70	71.98	76.52	78.31	82.59	**85.72**	**86.64**
Broadleafs	60.66	60.87	72.86	73.02	70.73	71.43	**82.02**	**82.54**
Binary	89.90	92.92	87.88	92.58	91.48	94.52	**93.32**	**95.81**

V. CONCLUSION

This letter has presented a method based on DL to the classification of tree species in mixed forest with airborne LiDAR data. The method captures the tree crown structure information by slicing the tree point clouds into multiple angular sectors and producing a 2-D view of the vertical profile of each sector. The set of multislice images is given as input to an MVCNN DL model, which extracts robust semantic features that result in good accuracy in mixed forests. The experimental results obtained confirm that the proposed method can effectively model the crown information of different tree species due to the multislice approach that captures the crown structure in different portion of the trees. Moreover, the multiview CNN can learn such representation for a set of diverse tree species using a training set of relatively small dimension. A consistent improvement with respect to both the shallow and deep baseline methods is achieved by the proposed method, both with and without pretraining the network. Indeed, the approach obtained good results on both conifers and broadleaf classes. In particular, the method is able to handle the latter, which is a challenging test case due to the highly irregular and varying structure of the tree crowns.

As future development, we plan to expand the dataset both in terms of number of trees and species to improve the training process. Indeed, since the results presented in this work have been achieved with a relatively small training set (less than 1000 samples), it is reasonable to expect room for improvement, in terms of classification accuracy, with an improved and larger training set. Moreover, we plan to evaluate the proposed approach on other tree types and forests located in different geographical areas. Finally, according to the results of Table III, we aim to explore the possibility of defining a hierarchical approach that first performs a binary classification and then separately classify the tree species of the conifers and broadleaf trees.

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