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# Tree species detection using hyperspectral and Lidar data: A novel self-supervised learning approach

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Accurate tree identification is essential for ecological monitoring, biodiversity assessment, and forest management. Traditional manual survey methods are labor-intensive and ineffective over large areas. Advances in remote sensing technologies including lidar and hyperspectral imaging improve automated, exact detection in many fields.

Nevertheless, these technologies typically require extensive labeled data and manual feature engineering, which restrict scalability. This research proposes a new method of Self-Supervised Learning (SSL) with the SimCLR framework to enhance the classification of tree species using unlabelled data. SSL model automatically discovers strong features by merging the spectral data from hyperspectral data with the structural data from LiDAR, eliminating the need for manual intervention.

We evaluate the performance of the SSL model against traditional classifiers, including Random Forest (RF), Support Vector Machines (SVM), and Supervised Learning methods, using a dataset from the ECODSE competition, which comprises both labeled and unlabeled samples of tree species in Florida's Ordway-Swisher Biological Station. The SSL method has been demonstrated to be significantly more effective than traditional methods, with a validation accuracy of 97.5 % compared to 95.56 % for Semi-SSL and 95.03 % for CNN in Supervised Learning.

Subsampling experiments showed that the SSL technique is still effective with less labeled data, with the model achieving good accuracy even with only 20 % labeled data points. This conclusion demonstrates SSL's practical applications in circumstances with insufficient labeled data, such as large-scale forest monitoring.

Keywords: self-supervised learning, tree species detection, SimCLR, hyperspectral imagery, lidar data

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**СПЕЦИАЛЬНЫЙ ВЫПУСК**

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# Новый подход к самообучению для обнаружения видов деревьев с использованием гиперспектральных и лидарных данных

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Точное определение деревьев имеет решающее значение для экологического мониторинга, оценки биоразнообразия и управления лесными ресурсами. Традиционные методы ручного обследования трудоемки и неэффективны на больших территориях. Достижения в области дистанционного зондирования, включая лидар и гиперспектральную съемку, способствуют автоматизированному и точному обнаружению в различных областях.

Тем не менее, эти технологии обычно требуют больших объемов размеченных данных и ручной инженерии признаков, что ограничивает их масштабируемость. Данное исследование предлагает новый метод самообучения (Self-Supervised Learning, SSL) с использованием архитектуры SimCLR для улучшения классификации видов деревьев на основе неразмеченных данных. Модель SSL автоматически обнаруживает сильные признаки, объединяя спектральные данные гиперспектральной съемки со структурными данными лидара, исключая необходимость ручного вмешательства.

Мы оцениваем производительность модели SSL по сравнению с традиционными классификаторами, такими как Random Forest (RF), Support Vector Machines (SVM), а также методами обучения с учителем, используя набор данных конкурса ECODSE, который включает как размеченные, так и неразмеченные образцы видов деревьев на биологической станции Ordway-Swisher во Флориде. Метод SSL показал значительно более высокую эффективность по сравнению с традиционными методами, продемонстрировав точность 97,5 % по сравнению с 95,56 % для Semi-SSL и 95,03 % для CNN при обучении с учителем.

Эксперименты по выборке показали, что техника SSL остается эффективной при меньшем количестве размеченных данных, и модель достигает хорошей точности даже при наличии всего 20 % размеченных образцов. Этот вывод демонстрирует практическое применение SSL в условиях недостаточного объема размеченных данных, таких как мониторинг лесов в больших масштабах.

Ключевые слова: самообучение, обнаружение видов деревьев, SimCLR, гиперспектральные изображения, лидарные данные

# Introduction

Accurate detection of tree species is crucial for a wide range of applications, including forest inventory, biodiversity monitoring, and carbon storage assessment [Zhong et al., 2022; Xiao et al., 2019; Gu et al., 2015]. Traditional approaches primarily involve manual surveys and visual assessments, which are labor-intensive, costly, and impractical for large areas [Zhong et al., 2022; Alonzo, Bookhagen, Roberts, 2014; Qin et al., 2022]. These limitations have driven research towards remote sensing technologies, particularly hyperspectral and LiDAR imaging.

Over the past two decades, forest monitoring has increasingly leveraged remote sensing methods, with hyperspectral and LiDAR technologies showing considerable promise, especially in complex ecosystems such as boreal and temperate forests [Mäyrä et al., 2021; Feng et al., 2020; Maschler et al., 2018]. Hyperspectral imaging provides detailed spectral information across hundreds of narrow bands, spanning both visible and non-visible wavelengths. This allows hyperspectral sensors to capture subtle biochemical and physiological differences between plant species, such as chlorophyll, water content, and carotenoid levels, which are often missed by traditional RGB and multispectral images [Mäyrä et al., 2021]. This high spectral resolution has proven beneficial in distinguishing tree species, especially in diverse forested environments [Raczko, Zagajewski, 2017; Modzelewska, Fassnacht, Stereńczak, 2020; Wan et al., 2020; Zhao et al., 2021].

While hyperspectral data offers rich spectral detail, it lacks structural context. LiDAR, on the other hand, provides precise vertical information, allowing for accurate extraction of features such as tree height and canopy shape [Kim et al., 2009; Man et al., 2020]. When combined, hyperspectral and LiDAR data have demonstrated enhanced accuracy in tree species classification by integrating spectral and structural information. However, traditional methods, including Random Forest (RF) and Support Vector Machines (SVM), rely heavily on manual feature engineering and large labeled datasets, which can be limiting in terms of scalability [Mäyrä et al., 2021; Kim et al., 2009]. Deep learning models like Convolutional Neural Networks (CNNs) have alleviated some of these challenges by automating feature extraction, though they continue to rely on labeled data [Sothe et al., 2020; Fricker et al., 2019].

This study introduces a novel approach leveraging Self-Supervised Learning (SSL) with the SimCLR framework to classify tree species using unlabelled hyperspectral and LiDAR data. SSL allows models to learn from unlabeled data through pretext tasks, acquiring features that are transferable to classification tasks with minimal labeled data [Jaiswal et al., 2020; Wang et al., 2023a; Wang et al., 2022]. By leveraging SimCLR's contrastive learning approach, our model can learn robust features from both spectral and structural data without the need for extensive labeled samples [Chen et al., 2020]. In this study, we evaluate the performance of SSL relative to traditional machine learning methods, showing that SSL achieves high accuracy with fewer labeled samples, making it a promising solution for large-scale forest monitoring.

# Related works

**Hyperspectral and LiDAR in tree species classification.** Hyperspectral imaging and LiDAR data have become essential tools in vegetation analysis and tree species classification due to their complementary spectral and structural information. Hyperspectral sensors capture subtle spectral characteristics associated with different plant species, such as chlorophyll, moisture content, and carotenoids [Liu, Wu, 2018; Mäyrä et al., 2021]. LiDAR, in contrast, provides structural details such as canopy height and tree shape, which enhance the spatial context of hyperspectral data. However, the combined use of these technologies has faced challenges due to the need for extensive labeled data and manual feature extraction, limiting their application over large areas [Zhong et al., 2022; Kim et al., 2009].

**Machine learning in remote sensing.** Traditional classifiers, including Random Forest (RF) and Support Vector Machines (SVM), have been widely used in remote sensing for tree species classification, but they often require significant manual feature engineering [Zhong et al., 2022; Alonzo, Bookhagen, Roberts, 2014]. The emergence of deep learning models, such as CNNs, has improved feature extraction by automating the process. CNNs have been successfully applied to hyperspectral and LiDAR data, reducing the dependency on manual feature engineering. Nevertheless, CNNs require large labeled datasets for effective training, which remains a barrier in remote sensing applications with limited labeled samples [Fricker et al., 2019; Sothe et al., 2020].

**Self-supervised learning (SSL).** Self-Supervised Learning (SSL) offers a promising solution to the labeled data challenge by allowing models to learn from unlabelled data through pretext tasks, such as contrastive learning, clustering, and feature prediction [Jaiswal et al., 2020; Wang et al., 2023a]. Although SSL has been successful in fields like medical imaging and general image recognition, it has not yet been widely explored in remote sensing applications. SimCLR, a popular SSL method, has shown effectiveness in learning high-quality representations in computer vision tasks by distinguishing between similar and dissimilar data pairs [Chen et al., 2020]. This approach is particularly suitable for complex datasets, such as hyperspectral and LiDAR data, where subtle spectral and structural differences can signify unique tree species. Our study is among the first to apply SSL to tree species detection in remote sensing, positioning SSL as a valuable approach for data-scarce tasks in ecological monitoring.

## Methodology and study area

### *Study area*

This study used data from the ECODSE group's 2017 competition [ECODSE group, 2017], obtained at the Ordway-Swisher Biological Station (OSBS) in Florida, USA. The research region covers 37 km$^2$ and is dominated by highland forests, including longleaf and loblolly pines with an average canopy height of 23 meters. NEON provides extensive field and remote sensing data, including hyperspectral imaging, LiDAR-derived canopy height models, and high-resolution camera images.

### *Dataset details*

NEON provides extensive field and remote sensing data, including hyperspectral imaging, LiDAR-derived canopy height models, and high-resolution camera images. The hyperspectral data captures 426 spectral bands with a one-meter spatial precision, while the LiDAR data offers structural information on the forest's vertical profile.

The dataset is organized across several files, each contributing different dimensions of information, these files were merged into a single, integrated dataset containing both spectral (hyperspectral bands) and structural (LiDAR) features for each crown. This integrated dataset covers four unique tree species (PIPA, QULA, QUGE, OTHER). Additionally, provide broader taxonomic information represents by genus and genus-id , These information inclusion of both detailed species-specific and genus-level information allows the model to learn hierarchical relationships and refine classification within similar species groups.

### *Data preprocessing*

The dataset consists of two major data types: hyperspectral data and LiDAR data. These datasets contain both high-dimensional spectral information and structural information, and were preprocessed as follows.

**Data cleaning.** Duplicated Recored removed on the integrated dataset to avoid data inconsistency and overfitted during training.

**Normalization and standardization.** The hyperspectral data is composed of hundreds of spectral bands, each indicating the reflectance of a distinct wavelength. To normalize the hyperspectral data to a range of [0, 1], MinMaxScaler from sklearn.preprocessing [Scikit-learn Developers, 2024a] was used. This phase is critical to preventing learning from getting skewed by dominant bands. This transformation can be described numerically as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \tag{1}$$

where $x'$ is the normalized value, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values in the data, respectively.

Furthermore, the LiDAR features, which comprise metrics such as height, diameter, crown dimensions, and canopy height model (CHM), were standardised with "StandardScaler". Standardization ensures that each feature has a mean of zero and unit variance, making the magnitudes of these features comparable, which aids the model in learning effectively from structural metrics. These features were standardized using the StandardScaler [Scikit-learn Developers, 2024b] and formulated as:

$$z = \frac{x - \mu}{\sigma}, \tag{2}$$

where $z$ is the standardized value, $\mu$ is the mean of the feature, and $\sigma$ is the standard deviation.

Using various scalers for hyperspectral and LiDAR data is for accommodate the unique properties of each data source, while MinMaxScaler helps hyperspectral data preserve proportionate contributions across bands, StandardScaler helps LiDAR data standardize the distribution of structural measures. This strategy ensures that the model can learn successfully from both types of input, taking use of their distinct qualities to improve classification performance.

### *Data splitting and augmentation*

To reduce the possibility of bias caused by imbalanced classes, the labeled dataset was partitioned into training and validation sets, with equal representation of all tree species in both sets. During training, data augmentation and Gaussian noise techniques were also used on hyperspectral and LiDAR data. For hyperspectral data, Gaussian noise with a scale of 0.1 was used, whereas for LiDAR features, noise with a scale of 0.05 was applied.

**Hyperspectral data augmentation:**

$$\widetilde{X}_{\text{hyper}} = X_{\text{hyper}} + \mathcal{N}(0,\ 0.1); \tag{3}$$

**LiDAR data augmentation:**

$$\widetilde{X}_{\text{lidar}} = X_{\text{lidar}} + \mathcal{N}(0,\ 0.05). \tag{4}$$

### *Model architectures*

The neural network model employs two branches designed for two different types of input data: hyperspectral images and LiDAR features. These branches are later fused to form one feature for the tree species classification.

The Figure 1 illustrates the model architectures where the hyperspectral data branch uses three 1D convolutional layers ("Conv1D") to effectively capture local spectral dependencies. The use of 1D convolutions is well suited for hyperspectral data since it treats each spectral band as part of a sequence, learning meaningful spectral features, while the LiDAR data branch consists of fully connected ("Dense") layers. This structure is appropriate for learning complex relationships between

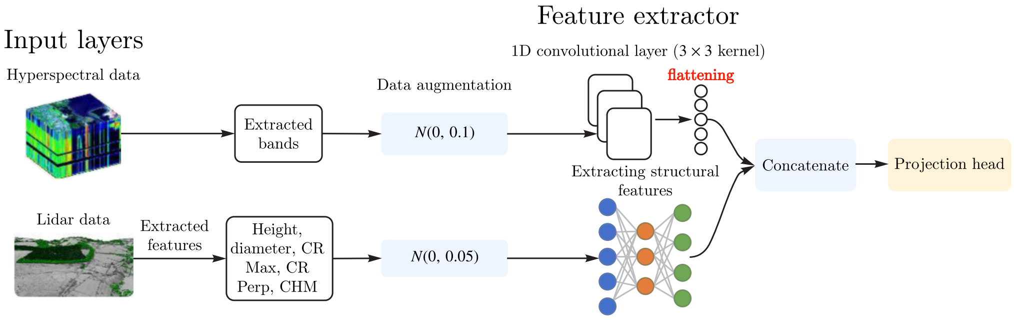


Figure 1. Self-supervised learning architecture for tree species classification

LiDAR features such as tree height, crown diameter, and other structural metrics. The fully connected layers allow the model to capture non-linear interactions among the LiDAR features.

A combined feature vector was formed by concatenating the outputs from both the hyperspectral and LiDAR branches. This fusion allows the model to benefit from both spectral information (hyperspectral data) and structural information (LiDAR data), providing a comprehensive feature set for tree species detection.

### *Self-supervised pretext task (SimCLR)*

The self-supervised learning approach used in this study is based on the SimCLR (Simple Framework for Contrastive Learning of Visual Representations) method. The objective of SimCLR is to train the model without labels by the means of contrastive learning, which forces as strong an agreement as possible over several representations of the same data point.

### *SimCLR framework*

SimCLR learns representations by comparing several enhanced perspectives of the same input. In this context, we generate the augmented views for each data point, and apply random transformations such as Gaussian Noise. This assists the model in learning transformation-invariant features, which means that the model will learn to recognize an item, in this case a tree species, despite minor changes in its spectral or structural qualities. The training goal is to maximize the similarity between these two perspectives in the feature space (similar data points are closer together), while minimise their similarity to all other data points, resulting in negative pairings. This method, known as contrastive learning, allows the model to learn strong and generalizable features by differentiating between similar and dissimilar inputs.

### *Contrastive loss function (NT-Xent loss)*

The model was trained using the NT-Xent (Normalized Temperature-scaled Cross Entropy) loss function, which uses a cosine similarity measure between feature vectors.

$$\ell(i,\ j) = -\log \frac{\exp\left(\frac{\mathrm{sim}(z_i, z_j)}{\tau}\right)}{\sum_{k=1}^{2N} 1_{[k\neq i]} \exp\left(\frac{\mathrm{sim}(z_i, z_k)}{\tau}\right)},$$

where $\mathrm{sim}(z_i,\ z_j)$ is the cosine similarity between two augmented samples, and $\tau$ is a temperature parameter:

$$\mathrm{sim}(z_i,\ z_j) = \frac{z_i \cdot z_j}{\|z_i\| \cdot \|z_j\|}.$$

### *Main task*

Following the training with the SimCLR framework, the model underwent fine-tuning with labeled data for tree species classification. The feature extraction layers learned during the self-supervised phase were frozen, while new dense layers were added for fine-tuning the model for the classification task. The added layers consisted of two dense layers of 512 and 256 units, respectively, followed by dropout layers to prevent overfitting. Dropout layers with a rate of 0.5 were used to ensure that the model remains generalizable by randomly dropping neurons during training, encouraging the model to learn robust representations. L2 regularization 0.001 was used in the dense layers to penalize large weight magnitudes, reducing model complexity and improving generalizability.

The final output layer used a “softmax” activation to classify the input into one of the available tree species categories.

$$\text{Output} = \text{Softmax}(Wz + b), \tag{5}$$

where $W$ and $b$ are learned parameters, and $z$ is the output of the dense layers before the classification layer.

The fine-tuned model was optimized using sparse categorical cross-entropy loss:

$$L = -\sum_{i=1}^{N} y_i \log(\widehat{y}_i), \tag{6}$$

where $y_i$ is the true label, and $\widehat{y}_i$ is the predicted probability.

### *Training setup*

The model was trained for up to 50 epochs with a batch size of 32, allowing early stopping to intervene if necessary. The Adam optimizer was used with its default learning rate and weight decay regularization in the dense layers to prevent overfitting.

A local desktop computer with a 12th Gen Intel® Core™ i7-12650H CPU running at 2.30 GHz was used for training; it lacked a dedicated GPU, therefore all calculations were done using the CPU. This CPU-only configuration showed that the Self-Supervised Learning (SSL) approach is feasible in resource-constrained environments, but it also resulted in longer training periods, especially for deep learning models. Even in the absence of GPU resources, the SSL model’s performance under these circumstances points to encouraging possibilities for scalability in ecological monitoring applications.

### *Evaluation*

After training, the model was evaluated on the validation set, and a confusion matrix was generated to analyze the classification performance across different tree species. The confusion matrix provides insights into specific misclassification patterns, which is particularly valuable when dealing with species with similar spectral and structural characteristics. Morever, a data subsampling experiment was performed To assess the model’s robustness.

### *Models training process*

Each model was trained using the following procedures:

- **Semi-supervised learning (Semi-SSL):** Similar to SSL methods, the Semi-SSL model employed a pseudo-labeling technique, whereby provisional labels were applied to the unlabeled samples according to the model’s confidence in its predictions, and these pseudo-labeled samples were then used in conjunction with the labeled data to train the model. The Semi-SSL model was trained over 50 epochs with the aim of improving the classification capabilities through iterative improvement of the model’s decision boundaries, and the model’s performance improved as it gradually learned from both labeled and pseudo-labeled examples.

- **Supervised learning (CNN):** The CNN was trained with solely labeled data under full supervision. The Adam optimizer was used to minimize the categorical cross-entropy loss function during the 40 period training process. The optimization process was controlled with a batch size of 32 and a learning rate of $10^{-3}$. The model only learned discriminative features for classification using the labeled training data; no data augmentation techniques were used during training.

- **Random forest (RF) and support vector machines (SVM):** radial basis function (RBF) kernel, which is especially well-suited for the high-dimensional, non-linear relationships found in hyperspectral data, the Random Forest (RF) model was set up with 100 trees, each of which used a random subset of features for decision-making to improve generalizability. assessing these models according to how well they classify the labeled validation set.

## Results

In this section, we present and compare the performance of the models employed in this study, including Supervised Learning (CNN), Self-Supervised Learning (SSL) using SimCLR, Semi-Supervised Learning (Semi-SSL), Random Forest (RF), and Support Vector Machines (SVM). We assess their accuracy, precision, recall, and F1-score on the tree species classification task using hyperspectral and LiDAR data. We also analyze the learning curves, confusion matrices, and performance trends during training.

### *Performance comparison across models*

We compared the models based on accuracy, precision, recall, and F1-score on the validation dataset. The table below summarizes the performance of each model.

Table 1. Performance comparison across models

| Model | Accuracy % | Precision | Recall | F1-score | Epochs |
|---|---|---|---|---|---|
| SSL (SimCLR) | 97.5 | 0.96 | 0.97 | 0.96 | 50 |
| Semi-SSL | 95.56 | 0.95 | 0.96 | 0.95 | 50 |
| Supervised Learning (CNN) | 95.03 | 0.95 | 0.95 | 0.95 | 40 |
| Random Forest (RF) | 95.0 | 0.95 | 0.95 | 0.94 | — |
| Support Vector Machines (SVM) | 68.0 | 0.47 | 0.68 | 0.55 | — |

From the table, we observe that the SSL (SimCLR) model outperforms other models in terms of accuracy and F1-score, demonstrating the robustness of Self-Supervised Learning in leveraging unlabeled data to improve classification performance. The Semi-SSL model follows closely, benefiting from the use of pseudo-labeled data. The Supervised Learning model (CNN) achieves strong performance as well, although slightly lower than the SSL and Semi-SSL models. Random Forest (RF) also shows strong performance with an accuracy of 95 %, while SVM struggles with the high-dimensional hyperspectral data, resulting in significantly lower accuracy.

### *Data subsampling experiment*

In addition to the main performance metrics, a data subsampling experiment was carried out to assess the SSL model's reliability when trained on smaller subsets of labeled data. The findings showed that the SSL model was able to maintain a high accuracy (87.58 %) with just 10 labeled data, rising to 92.55 % with 50 % labeled data. These results show how strong SSL is in situations with scarce labeled data, underscoring its usefulness for extensive ecological monitoring.

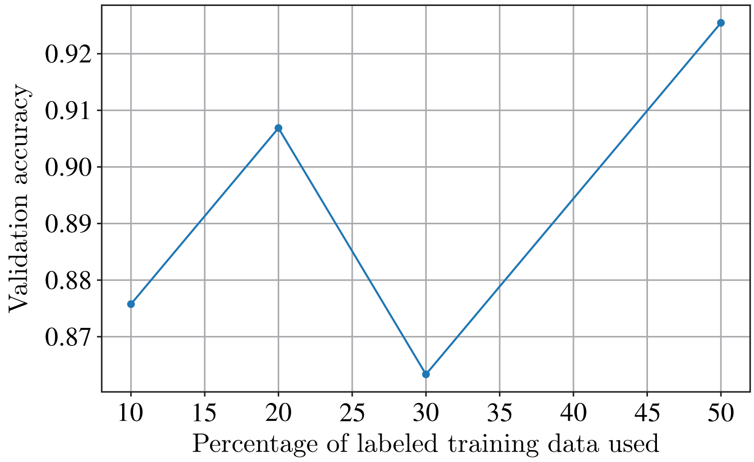


Figure 2. Model performance vs percentage of training data used

Figure 2 shows how the validation accuracy of the SSL model changes based on the amount of labeled training data used. The study shows that the model retains a relatively high level of accuracy, even when the amount of labeled data is greatly reduced. The decrease at 30 can be attributed to variations in the composition of training subsets, as smaller subsets may lack diversity or balance in class representation, Such inconsistencies can lead to temporary declines in model performance, as observed.

## *Model performance analysis*

This section presents the performance analysis for the SSL, Semi-SSL, Supervised Learning (CNN), Random Forest (RF), and Support Vector Machines (SVM) models, combining training curves and confusion matrices for each model.

**SSL (SimCLR) model.** The SSL model demonstrates consistent improvements in both training and validation accuracy, with no signs of overfitting. The final validation accuracy reached 97.5 %, showcasing the model's strong performance. The confusion matrix for SSL reveals minimal misclassifications, confirming the efficacy of self-supervised learning in capturing intricate spectral and structural properties.

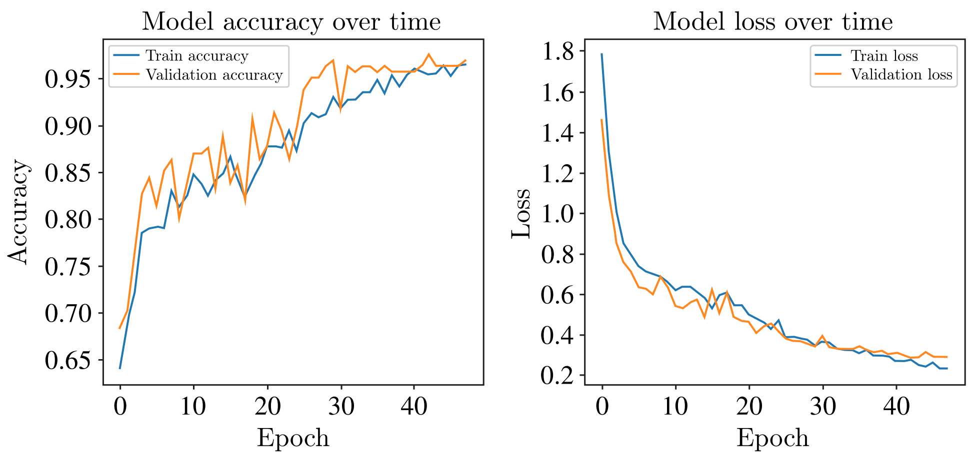


Figure 3. Training and validation accuracy/loss curves for SSL model

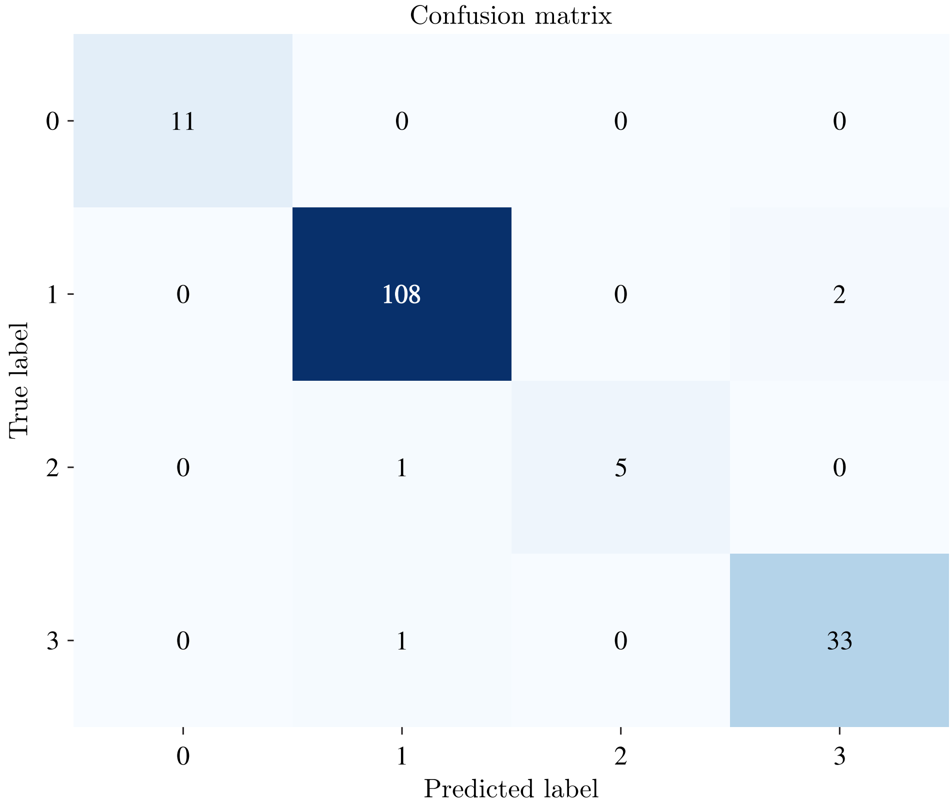


Figure 4. Confusion matrix for SSL model

**Semi-SSL model.** The Semi-SSL model follows a similar accuracy trend but plateaus earlier compared to SSL, indicating that pseudo-labeled data was beneficial yet not as effective as fully self-supervised techniques. The final validation accuracy reached 94 %. The confusion matrix for the Semi-SSL model shows slightly more misclassifications, potentially due to label noise from pseudo-labeling.

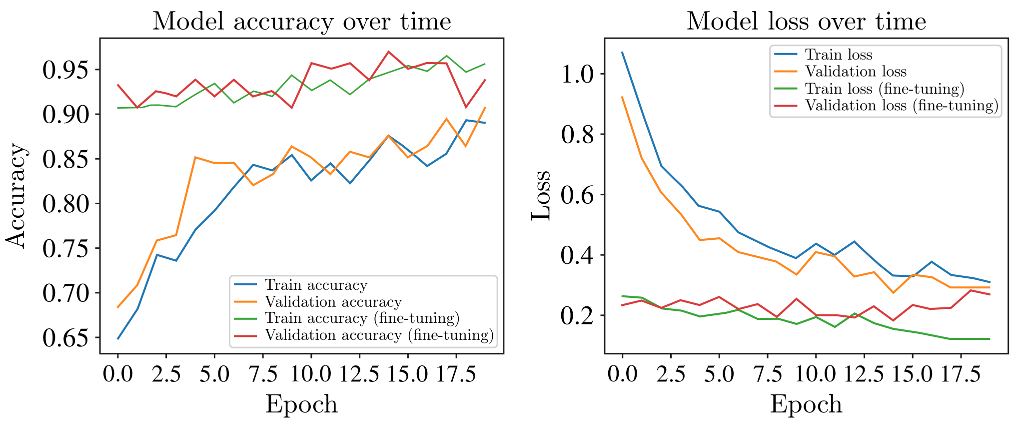


Figure 5. Training and validation accuracy/loss curves for Semi-SSL model

**Supervised Learning (CNN) model.** The supervised CNN model shows steady improvement in validation accuracy, reaching 95.03 %. This performance is strong, though slightly lower than that of the SSL and Semi-SSL models. The confusion matrix indicates that the model struggles with species

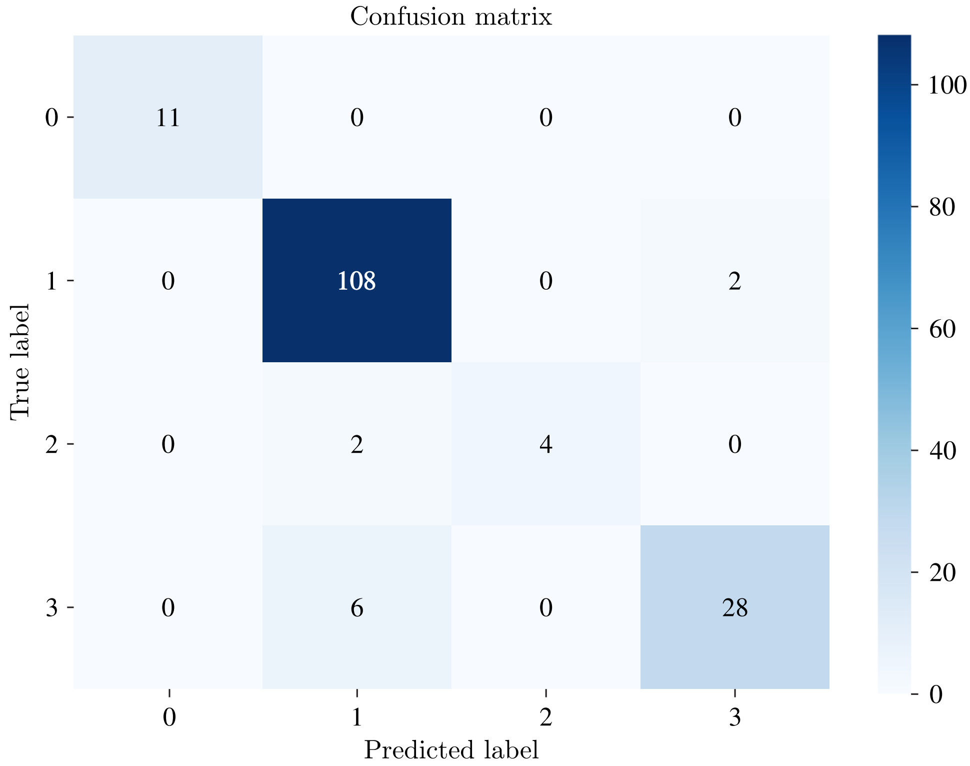


Figure 6. Confusion matrix for Semi-SSL model

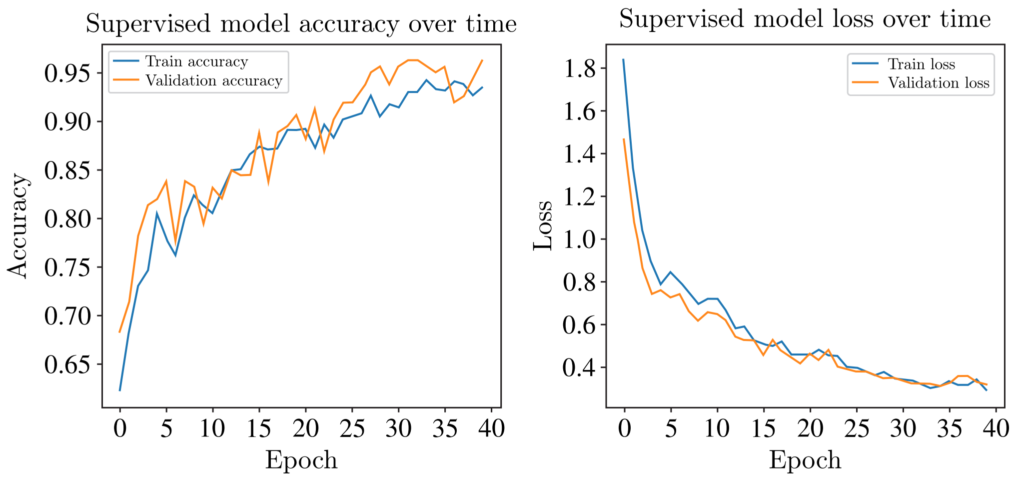


Figure 7. Training and validation accuracy/loss curves for Supervised Learning (CNN) model

that share similar spectral and structural traits, suggesting that more sophisticated feature learning techniques might benefit this model.

**Random Forest (RF) model.** The RF model performs well, with a high classification ability as shown in the confusion matrix. However, it exhibits more misclassifications in species that are difficult to distinguish, likely due to its reliance on manual feature engineering.

**Support Vector Machines (SVM) model.** The SVM model struggles significantly, with a high number of misclassifications for species with overlapping spectral and structural properties. This underscores the limitations of SVM in handling high-dimensional hyperspectral data without advanced dimensionality reduction.


Figure 8. Confusion matrix for Supervised Learning (CNN) model

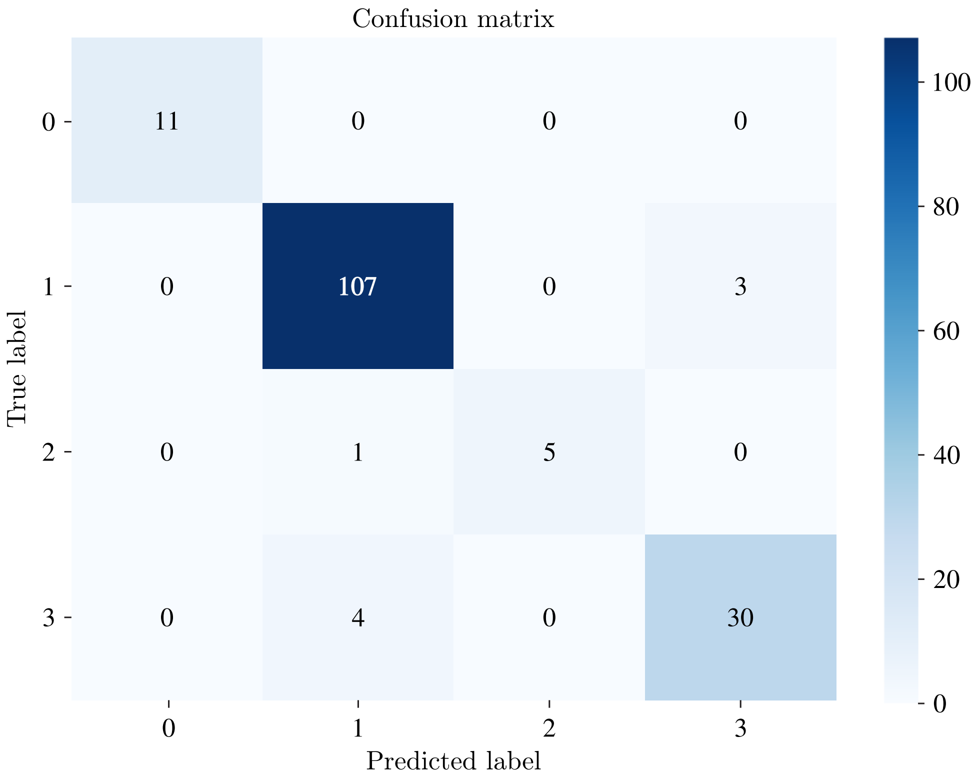


Figure 9. Confusion matrix for Random Forest model

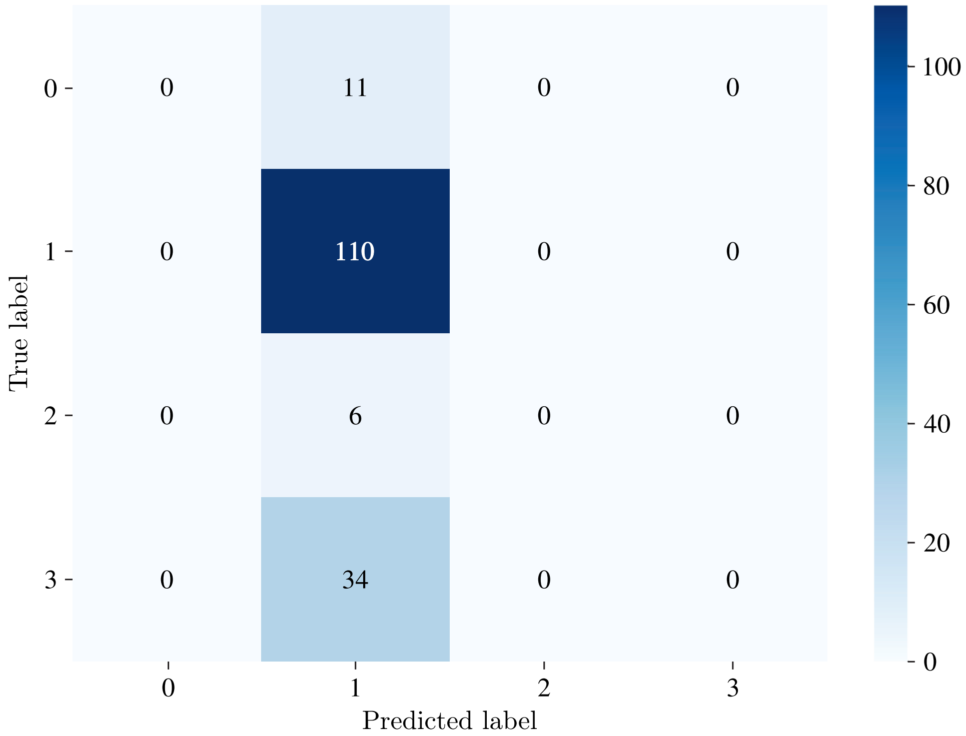


Figure 10. Confusion matrix for Support Vector Machines (SVM) model

By presenting each model's training/validation accuracy and confusion matrix together, this section offers a clear and cohesive comparison of model performances across various aspects.

### *Feature representation*

The SSL model learns feature representations effectively from both hyperspectral and LiDAR data, minimizing the need for manual feature engineering. By projecting the learnt embeddings into lower-dimensional space with SimCLR's projection head, the model captures complex relationships between spectral and structural features. To demonstrate these learnt features and evaluate the representation's quality, t-Distributed Stochastic Neighbor Embedding (t-SNE) was utilized for its ability to capture and highlight local structures within high-dimensional data. t-SNE is a nonlinear approach that excels at preserving local associations between data points. This makes t-SNE very good at visualizing clusters and spotting small differences in feature space, which is critical for determining how effectively the SSL model discriminate between different tree species.

The t-SNE graphic shows that the SSL model successfully learned feature representations that group similar tree species together. There are multiple separate clusters, each of which corresponds to a different tree species. The separation of these clusters demonstrates that the model can distinguish between species using the learned properties. There are areas where clusters overlap, showing that some tree species share spectral and structural traits. This overlap may indicate difficulties in differentiating certain species or regions where the model has to be refined further to improve its discriminative strength.

### *Discussion*

In this section, we evaluate the data to explain why the Self-Supervised Learning (SimCLR) method outperformed other approaches, highlight its practical implications, and indicate prospective areas for further research.

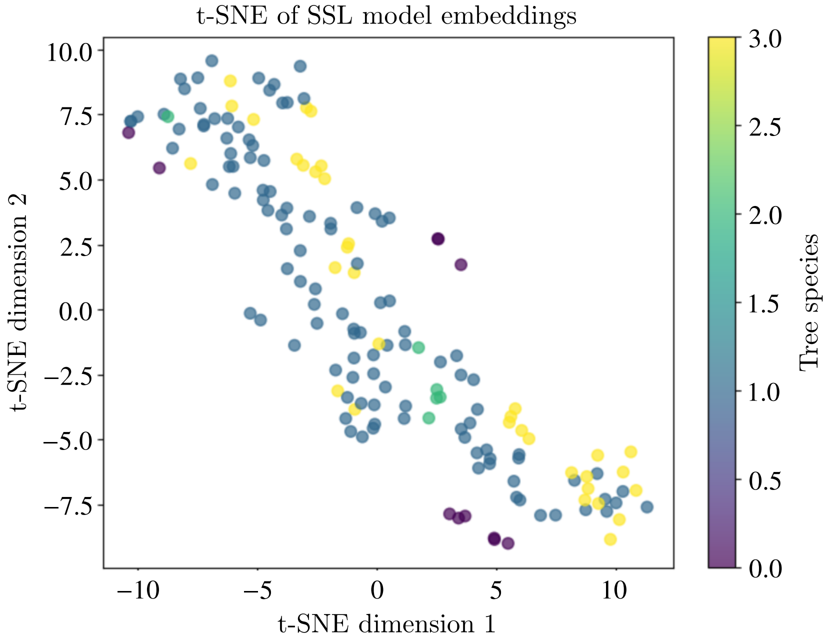


Figure 11. Feature embeddings for SSL model

## *Analysis of results*

**SSL superiority.** The Self-Supervised Learning (SimCLR) model demonstrated superior performance with a validation accuracy of 97.5 %, surpassing both traditional methods like Random Forest (RF) and Support Vector Machines (SVM), as well as the Semi-Supervised Learning (Semi-SSL) approach. The key advantage of SSL lies in its ability to learn from unlabeled data, allowing the model to extract more robust and generalizable features. Through contrastive learning, the SimCLR model effectively aligns similar features while distinguishing dissimilar ones, even without labeled data, which contributes to its enhanced performance in classifying tree species.

**Semi-SSL performance.** The Semi-Supervised Learning model achieved a strong validation accuracy of 95.56 %. This approach benefited from the inclusion of pseudo-labeled data, which enhanced the model's learning process compared to purely supervised methods. However, it did not match the performance of the SSL model. This disparity may be attributed to the introduction of noise through incorrect pseudo-labels, which could have hindered the model's ability to learn optimal representations. Despite this, the Semi-SSL approach still demonstrated the effectiveness of utilizing both labeled and unlabeled data to improve classification accuracy.

**Supervised Learning (CNN) performance.** The Supervised Learning model, trained purely on labeled data, achieved a validation accuracy of 95.03 %. While this is a strong performance, it slightly lags behind the SSL and Semi-SSL models. This result highlights the limitations of relying solely on labeled data, where the model may miss out on the potential patterns and structures present in the unlabeled data that SSL and Semi-SSL methods can capture.

**Random Forest and SVM.** Random Forest (RF) achieved strong performance with a validation accuracy of 95 %, benefiting from its ability to handle complex tabular data and its ensemble nature, which reduces variance and improves generalization. However, RF still required manual feature engineering and did not perform as well as SSL, which can automatically extract useful features from raw data.

On the other hand, Support Vector Machines (SVM) struggled significantly with the high-dimensional hyperspectral data, resulting in a poor accuracy of 68 %. This underperformance is likely due to SVM's limitations in processing large feature sets without extensive hyperparameter tuning and feature selection. The model's inability to efficiently handle the complexity and volume of hyperspectral data highlights the challenges faced by traditional machine learning algorithms in high-dimensional settings.

## Conclusion

The study shows how Self-Supervised Learning (SSL) can effectively classify tree species using unlabeled data, achieving high accuracy even with a limited number of labeled samples. The outcomes demonstrate SSL's promise as a scalable method for ecological monitoring, since obtaining labeled data is costly and time-consuming. The proposed SSL model outperformed supervised deep learning models like CNNs and traditional machine learning techniques like Random Forest and Support Vector Machines by extracting strong, transferable features by utilizing the SimCLR framework.

Furthermore, the experiment with data subsampling demonstrates that SSL is still successful when the quantity of labeled data declines. SSL is a useful technique for applications where labeled data is limited because of its robustness, which highlights its appropriateness for large-scale monitoring and assessment activities in forestry, biodiversity, and environmental sciences.

Despite the promising findings, there are limitations, such as The computational complexity of SSL, particularly with high-dimensional hyperspectral and LiDAR data. Additionally, even though the SSL model's selection of data augmentations worked well in this investigation, it might not apply to other remote sensing scenarios. Advanced augmentation methods and adaptive SSL frameworks that are suited to particular ecosystem features may be investigated in future research.

In conclusion,this study establishes SSL as a potent method for identifying tree species and more general ecological monitoring tasks, providing a practical substitute for fully supervised techniques. Future studies should look into further optimizing SSL for various forest ecosystems, maybe including domain-specific knowledge to increase its adaptability, as remote sensing data continues to increase in volume and complexity, and get closer to automated, scalable solutions for sustainable environmental management by developing SSL in ecological applications.

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