Exploring Machine Learning and Remote Sensing Techniques for Mapping Pinus Invasion Beyond Crop Areas

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Abstract: The spread of the exotic tree species from the Pinus spp. family has been increasing over the years in the Ponta Grossa region and other areas of southern Brazil, making its monitoring necessary. This study proposes to monitor this spread using deep neural networks trained on satellite images from the Campos Gerais region. For this task, three deep neural network models focused on pixel-by-pixel classification were employed: U-Net, SegNet, and FCN (Fully Convolutional Network). These models were trained on a dataset containing 34 images with a resolution of 2048x2048 pixels, obtained from Google Earth satellites. All images were downloaded using the QuickMapServices extension available in QGIS, and labeled using the same program. Promising results suggest that the U-Net model outperformed the others, achieving 82.49% accuracy, 69.62% Jaccard index, 41.19% recall, and 78.47% precision. The SegNet model showed good accuracy at 82.84%, but underperformed on the Jaccard index at 45.93%, with 58.34% recall and 68.35% precision. Meanwhile, the FCN model produced less reliable results among the three, with 79.37% accuracy, 29.17% Jaccard index, 34% recall, and 67.21% precision.

1 INTRODUCTION

Pinus spp. plantations in southern Brazil have introduced an alternative to the deforestation of trees in native reserve areas. Despite the positive economic impacts, the environmental impacts, on the other hand, have proven to be concerning, as Pinus is an exotic and highly invasive species (Instituto Água e Terra, 2024). The region surrounding the Vila Velha State Park in Paraná, for example, is surrounded by farms with large cultivation areas for this species. As a result, the park, home to around 1376 species of angiosperms and 151 species of pteridophytes (Cervi et al., 2007), has been suffering threats for over two decades. This has compromised soil fertility and the region's biodiversity.

Monitoring the spread of Pinus within the park's boundaries is a challenging task, particularly due to the lack of manpower, the park's vast area, and the presence of wild animals that threaten the safety of the inspectors. Remote sensing via imagery emerges as an efficient alternative, providing information on the location of Pinus plantations and helping governments and forest managers effectively manage forest resources, ecological protection, and timber economic planning, as is already being implemented in China (Li et al., 2020).

Remote sensing image acquisition methods are divided into satellite-based methods (Brandt and Stolle, 2020) and those using remotely piloted aircraft systems (RPAs) (Nascente and Nunes, 2020). In the first case, data is freely available from various space agencies and provides images on a global scale (Brandt and Stolle, 2020), while RPAs require specialized labor for their use.

Monitoring the spread of Pinus spp. must also efficiently identify the species on a large scale. Integrating satellite imagery and machine learning has shown promising results in detecting green areas, especially in identifying tree species (Zhang et al., 2023b).

So, the hypotheses are: the deep neural networks U-Net, FCN and SegNet are effective in the task of classifying Pinus spp. plantations using RGB satellite images, demonstrating distinct capabilities in pixel-wise segmentation? Furthermore, these models are expected to exhibit significantly different performances when evaluated using classification metrics such as precision, recall, accuracy and Jaccard coefficient.

The hypothesis also posits that the U-Net architecture, due to its design optimized for image segmentation, will outperform the other architectures in identifying areas with the presence of Pinus spp. This work seeks to answer these hypotheses.

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2 BACKGROUND AND RELATED WORK

John Brandt (Brandt and Stolle, 2020) proposed the detection of tree canopies outside forests using medium-resolution satellite images. Beloiu et al. (Beloiu et al., 2023) proposed a study on the detection of tree species in heterogeneous forests using RGB satellite images trained on deep neural network models. More recently, Qin et al. (Qian et al., 2023) studied the detection of dominant tree species in urban areas using the Zhuhai-1 satellite. The work of Ortega Adarme et al. (Aparecido de Almeida et al., 2020) evaluates deep learning techniques for detecting deforestation in the Amazon and Cerrado regions of Brazil. Zhan et al. (Zhang et al., 2023b) demonstrated the importance of combining satellite sensor data and machine learning algorithms to map the distribution of tree species in urban areas, particularly in the context of reforestation project management and pest infestations. Li et al. (Li et al., 2019) conducted a study proposing a two-stage convolutional neural network (TS-CNN) for large-scale detection of oil palm plants using high-resolution satellite images in Malaysia, addressing a common challenge in agriculture and environmental monitoring. Zheng et al. (Zheng et al., 2021) developed a method for detecting coconut tree canopies to identify and count coconuts in the Tenarunga region, using high-resolution satellite images acquired from Google Earth. This method involves three main procedures: feature extraction, a multi-level Region Proposal Network (RPN), and a large-scale coconut tree detection workflow. Usman et al. (Usman et al., 2023) assessed the use of high-resolution images from WorldView-2 (WV-2) for classifying tree species in the agroforestry landscape of the Kano Close Settlement Zone (KCSZ) in northern Nigeria. Their method involved geographic object-based image analysis (GEOBIA) to extract individual tree canopies and remotely identify nine dominant species.

This interest is related to the increase in satellite images available at no cost, as well as the ease of implementation. In addition to being a powerful tool for environmental study and preservation, it directly contributes to natural resource management and the fight against environmental crimes. To optimize the use of these images, neural network models have been widely employed, being trained with satellite data for efficient application in various fields, such as fire prevention, deforestation, agricultural area mapping, and soil health monitoring (Handan-Nader et al., 2021). In this context, this work aims to apply deep learning techniques to detect the proliferation of the Pinus spp. tree in various areas of the Ponta Grossa region, where the species has been hindering the growth of native vegetation. For this purpose, images obtained from Google Earth will be labeled to be inserted into three neural network models: U-Net, SegNet, and FCN, which will be evaluated based on the chosen metrics.

3 MATERIALS AND METHODS

This chapter will be divided into subsections that will cover the tools used, the creation of the dataset, the models employed for training, and the evaluation metrics.

3.1 Study Area Characteristics

The vegetation of Vila Velha State Park, composed mainly of woody grassy savanna and mixed rainforest, makes up the Atlantic Forest Biome. With an area of 3,122.11 ha, located in the municipality of Ponta Grossa, state of Paraná (25º 14’ 09” South latitude, and 50º 00’ 17” West longitude).

3.2 Utilized Materials

The training of the algorithms was carried out in the Google Colab PRO environment, which offers the following specifications:

- 53 GB of RAM;
- Nvidia L4 with 22 GB of VRAM;
- 235 GB of storage.

All stages, including training, validation, and testing, were performed using the Python programming language, in conjunction with its machine learning and deep learning libraries, Scikit-Learn, Keras, and TensorFlow.

3.3 Database Creation

For the formation of the database used in the training, validation, and testing stages, satellite images of specific coordinates in the Ponta Grossa region, containing the Pinus spp., were collected in the RGB channels. These images were obtained through the QuickMapServices plugin in the QGIS software, an open-source tool widely used in cartography, which offers several options for labeling and image segmentation (QGIS,). The satellite images were downloaded from Google Earth satellites, including Landsat data, using the QuickMapServices plugin. They were selected based on specific coordinates to encompass a larger number of cases for the database, including areas where the planting of Pinus spp. is regulated, such as the environmental reserve of the Vila Velha Park. Additionally, images were collected from distinct regions where Pinus spp. has spread naturally, such as along roadsides. This decision was made with the objective of understanding the behavior of these plantations in relation to surrounding areas. After downloading, the images were divided into tiles with a resolution of 2048x2048 pixels, totaling 34 images. Then, using the same program, labeling was performed, as illustrated in Figure 1.

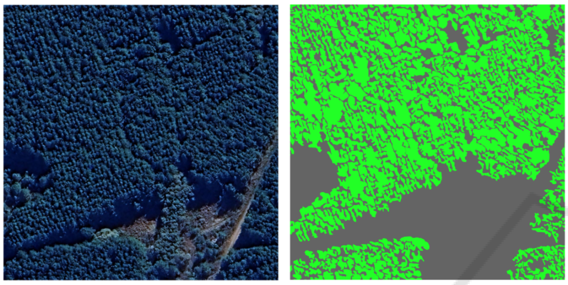

Figure 1: Example of a satellite image and its respective mask.

As shown in the figure above, the entire area containing Pinus in the satellite image was labeled using the color green, while the rest was labeled with the color gray.

3.4 Algorithms Used

Three image segmentation algorithms were used for this work: U-Net, SegNet, and FCN. The models were implemented using the Keras and TensorFlow libraries.

3.4.1 U-Net

The U-Net algorithm was chosen for its ability to use data augmentation layers to achieve superior performance compared to more robust models that require a large amount of data (Ronneberger et al., 2015). Although U-Net is frequently used in medical image segmentation, such as in tumor detection, it can also be adapted for other segmentation domains. Figure 2 illustrates the U-Net architecture as proposed by Ronneberger et al.

Following the same structure as the original model, only a few adaptations were made, such as reducing the number of filters in each layer (the original model ranges from 64 to 1024 filters, while this research used between 16 and 256 filters) due to the reduced size of the dataset. This modification helped

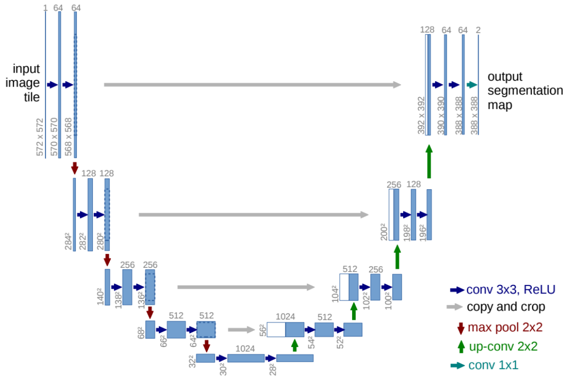

Figure 2: Each blue box corresponds to a multi-channel feature, with its value displayed on top of it.

save time and computational effort.

3.4.2 SegNet

The second model chosen was SegNet, designed for pixel-by-pixel semantic segmentation. SegNet is a trainable segmentation architecture that consists of an encoding network, a corresponding decoding network, and a pixel-by-pixel classification layer. The architecture of the encoding network is topologically identical to the 13 convolutional layers of the VGG16 network (Simonyan and Zisserman, 2015). This model stands out for its robustness, requiring a larger amount of data to achieve optimized performance, and was primarily developed for scene understanding. It is efficient in terms of memory and computational time, even when compared to other robust architectures (Badrinarayanan et al., 2015). Figure 3 shows the original SegNet architecture, as proposed by Badrinarayanan et al.

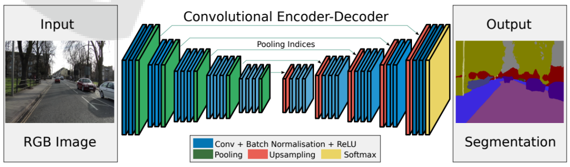

Figure 3: SegNet Architecture. This network is fully convolutional, meaning there are no fully connected layers.

For this research, fewer filters were used in the encoding and decoding layers, starting with 32 filters instead of the 64 filters used in the original version. Additionally, the upsampling method with pooling indices was replaced by Conv2dTranspose to reduce computational cost. The activation function in the output layer was modified to sigmoid, commonly used in binary classifications, while the original model uses softmax, typically used in multiclass classifications.

3.4.3 FCN

The last model chosen was a Fully Convolutional Network (FCN), which is a fully convolutional model designed for pixel-by-pixel segmentation, similar to the SegNet model. FCNs stand out for their ability to handle images of any size, producing segmentation maps with the same dimensions as the input, which is crucial for detailed segmentation (Shelhamer et al., 2015). These networks maintain spatial resolution throughout the segmentation process by replacing fully connected layers with convolutional layers and using upsampling techniques to reconstruct the original resolution of the image. This design allows the FCN to be trained in an end-to-end manner, simplifying the training process and directly optimizing the segmentation task. Figure 4 demonstrates the basic architecture of an FCN.

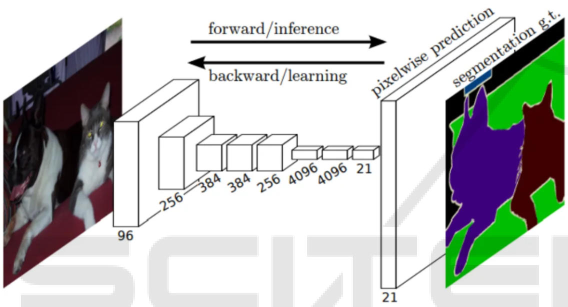

Figure 4: Example of an FCN architecture. All layers are convolutional, forming a pixel-by-pixel final prediction.

In the implemented FCN model, the architecture includes two initial convolutional layers followed by pooling layers, which reduce the image resolution. Then, a fully convolutional part reconstructs the original resolution of the image. The use of Conv2D layers with ReLU activation and UpSampling2D layers helps create a detailed reconstruction of the image's features. The final Conv2D layer with sigmoid activation is used to generate the segmentation map, suitable for binary classification tasks.

3.5 Metrics Used

For this project, four commonly used evaluation metrics in classification were chosen: Accuracy, Jaccard coefficient, recall, precision, and confusion matrix. All the metrics used were implemented using the Scikit-learn library.

3.6 Results and Discussion

After training and prediction on the test dataset, the results suggest a higher accuracy rate for the deep neural network U-Net compared to the other models. As seen in Table 1, the accuracy results of the three models were very close, with the SegNet network achieving the highest result at 82.84%. Regarding the Jaccard metric, the discrepancy between the results became more significant, with the U-Net model achieving 69.62%, the highest result, followed by SegNet at 45.93% and FCN at 29.17%, which was the lowest result. In terms of recall, the results showed some differences, with SegNet achieving the highest result at 58.34%, U-Net at 41.19%, and FCN at only 34%, which again was the lowest result. Finally, the precision results were relatively close, with U-Net achieving 78.47%, SegNet at 68.35%, and FCN with the worst result at 67.21%.

Table 1: Model results on the test database.

Models	Accuracy	Jaccard	Recall	Precision
U-Net	82,49%	69,62%	41,19%	78,47%
SegNet	82,84%	45,93%	58,34%	68,35%
FCN	79,37%	29,17%	34,00%	67,21%

The following figures present the segmentation of the best prediction from each model. It is notable the significant difference in the Jaccard metrics, where U-Net consistently achieves the highest similarity to the ground truth. This model is able to disregard a large amount of vegetation that was not classified as Pinus, in contrast to the competing models.

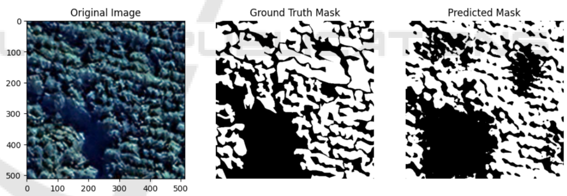

Figure 5: U-Net model segmentation.

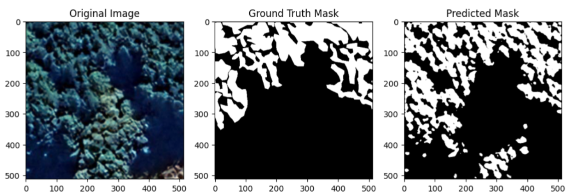

Figure 6: SegNet model segmentation.

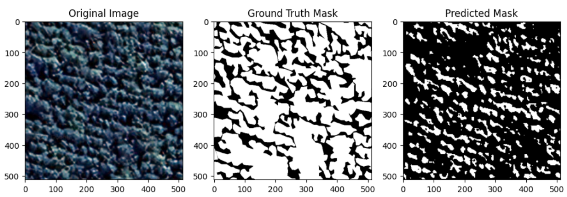

Figure 7: FCN model segmentation.

Finally, by visualizing the following figures containing the confusion matrix for each model, it is evident that U-Net outperforms the others. It is possible to observe that this network correctly predicts 89% of the true negative label samples (non-Pinus spp.) and 63% of the true positive samples.

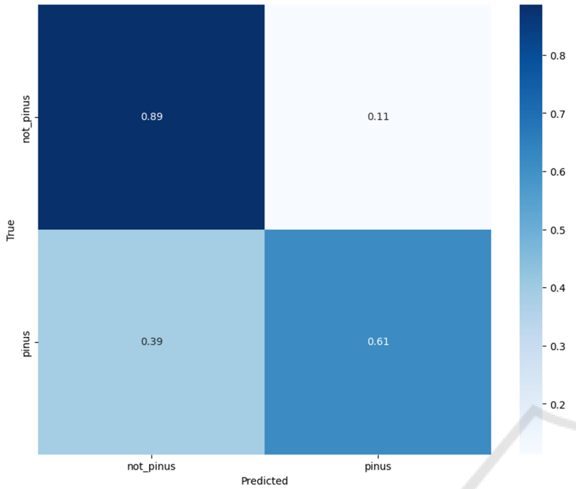

Figure 8: U-Net confusion matrix.

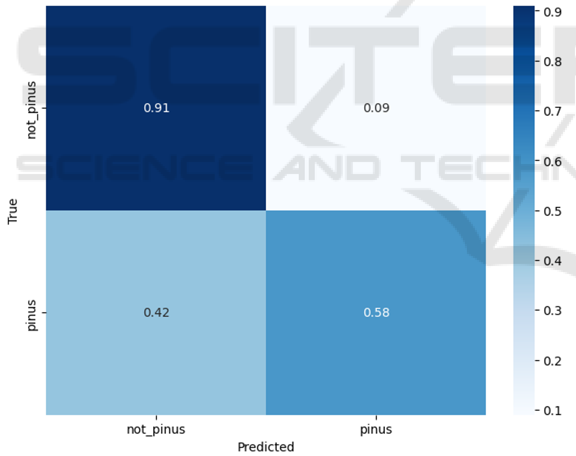

Figure 9: SegNet confusion matrix.

Comparing the results obtained by the U-Net model, which showed the best performance, with studies in similar domains, such as the work by So and Yokota (So and Yokota, 2024), aimed at mapping the distribution of alien species in river embankments, and the study by Zhang et al. (Zhang et al., 2023a), which focused on mapping the distribution of trees in the Beijing Plain reforestation project, a notable difference in the choice of datasets and methodologies for each situation can be observed.

So and Yokota (So and Yokota, 2024) used WorldView-3 satellite images fused with drone imagery, demonstrating how data fusion can enhance spatial resolution and mapping accuracy. This method resulted in high overall accuracy (98.39% for Solidago and 97.78% for Sorghum halepense), proving to be an effective approach for river embankment environments.

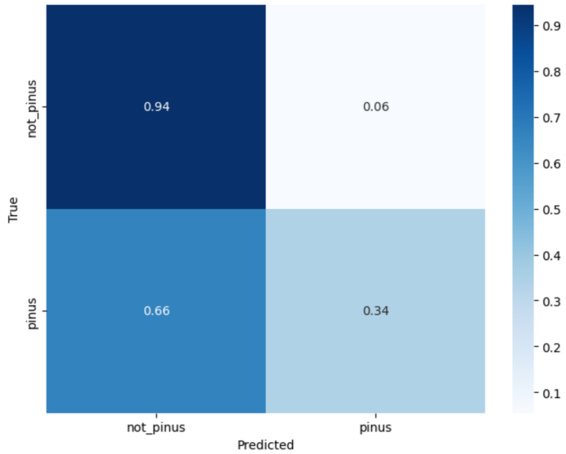

Figure 10: FCN confusion matrix.

On the other hand, Zhang et al. (Zhang et al., 2023a) applied a three-level hierarchical approach, using sources such as Pléiades-1B, WorldView-2, and Sentinel-2 combined with algorithms like SVM and Random Forest. This method achieved varying results depending on forest heterogeneity, with Sentinel-2 being effective for homogeneous forests (OA of 89.29%) and WorldView-2 excelling in mixed forests (OA of 90.91%).

The three studies analyzed demonstrate the effectiveness of remote sensing and machine learning algorithms in different contexts. While So and Yokota emphasize the use of data fusion for high spatial resolution, Zhang et al. explore hierarchical combinations of data and algorithms. This article aims to highlight the usefulness of deep neural networks for mapping specific species.

4 CONCLUSION

The U-Net model demonstrated the best performance among the three, especially excelling in the metrics most relevant to this research, where the primary goal is to correctly classify true positives (Pinus spp.). This is evident from its confusion matrix, which showed the highest number of correct predictions. While the accuracy of all models was satisfactory, it is important to note that a significant portion of this value is attributed to the classification of the true negative class (non-Pinus spp.), which is not the focus of this work.

This imbalance in the dataset highlights an important limitation: the data used in this study is not balanced with the non-Pinus spp. class being disproportionately represented. As a result, the models tend to achieve higher precision and accuracy by correctly identifying the dominant class, even if their performance on the minority class (Pinus spp.) remains less robust.

That limitation is particularly reflected in the Jaccard metrics, which provide a more nuanced evaluation of model performance by considering both false positives and false negatives. Among the models, only U-Net achieved a superior result in this metric, underscoring its effectiveness in identifying areas dominated by Pinus spp. despite the dataset's imbalance.

The dataset used in this project is publicly available for use, making it a valuable resource for researchers interested in advancing methodologies for the classification and monitoring of exotic tree species in similar contexts. For now, the preliminary results are promising, and in the future, new approaches will be explored to improve the results.

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