Data Fusion and Artificial Neural Network-Based Classification for Deforestation Monitoring in the Brazilian Amazon

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***Abstract*—The Amazon rainforest is widely recognized as one of the most biodiverse ecosystems on the planet, playing a fundamental role in global climate regulation. However, illegal deforestation continues to have profound international consequences, compromising Brazilian biodiversity and contributing to climate change. In this work, we present a classification approach based on artificial neural networks for analyzing spatial imagery and identifying deforested and non-deforested areas. The research incorporates geoprocessing methodologies, including the Linear Spectral Mixture Model, alongside advanced machine learning techniques such as Data Fusion. Experimental results demonstrate that both Multilayer Perceptron (MLP) and Convolutional Neural Networks (CNN) achieve high classification performance, with a ROC curve area exceeding 95%. In addition, data fusion techniques further improved the classification accuracy, enabling three of the developed models to correctly classify all samples presented to the network. These findings underscore the importance of continuing research on the Amazon biome and highlight the potential of artificial intelligence in supporting scientific investigations of this complex environmental system.**

***Index Terms*—Artificial Neural Networks, Geoprocessing, Brazilian Amazon, Deforestation, Image Processing, Data Fusion**

I. Introduction

The Amazon rainforest is recognized as a global natural heritage site and the largest tropical forest in the world due to its vast size and rich natural resources. However, this biome is increasingly threatened by illegal activities that have attracted international concern. Economic interests in northern Brazil have led to local population growth, agricultural expansion, and extraction of timber and minerals, factors that have contributed significantly to deforestation in the Amazon region [1].

To address this issue, the Brazilian National Institute for Space Research (INPE) plays a key role in monitoring deforestation using satellite imagery, particularly from the China-Brazil Earth Resources Satellite (CBERS). INPE implements two main programs for this purpose: the Legal Amazon Forest Monitoring by Satellite (PRODES) and the Real-Time Deforestation Detection System (DETER) [2]. The growing availability of remote sensing data, enhanced by technological advancements in satellite sensors with multiple spectral bands, has created new opportunities for more detailed and frequent analyses of the Amazon biome.

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A persistent challenge in processing satellite images is the issue of spectral mixture. Since each pixel in an image represents a combination of surface elements, even high-resolution images are affected by mixed signals from components such as vegetation, soil, water, or shadows [3]. To address this, the Linear Spectral Mixture Model (LSMM) is widely used to decompose each pixel into fractional abundances, offering a clearer representation of surface composition [4], [5]. These fractional images have been instrumental for INPE in identifying and classifying degraded or deforested areas, especially through tools such as the TerraAmazon geoprocessing platform [6].

Given the complexity and scale of the Amazon, the detection and classification of deforestation remain a challenging task. In this context, Artificial Neural Networks (ANNs) have emerged as powerful tools to address classification problems in satellite data. Previous work has explored the use of ANNs for the detection of deforestation in various parts of the Amazon [7], [8], often integrating remote sensing with machine learning and ecological perspectives to improve monitoring results.

Among ANN architectures, the Multi-Layer Perceptron (MLP) has proven effective for structured data classification tasks [9], while Convolutional Neural Networks (CNNs) are particularly suited for image-based problems due to their ability to extract hierarchical features from data [10]. Moreover, data fusion strategies, such as methods such as early, intermediate, and late fusion, offer the potential to improve model accuracy and robustness [11].

In this work, we propose a classification approach for deforested areas in the Amazon using MLP and CNN architectures, combined with data fusion techniques leveraging images coming from the fractions of the Linear Spectral Mixture Model. Our goal is to improve classification accuracy and provide more effective monitoring tools to support the preservation of this critical ecosystem.

The structure of this paper is organized as follows: Section 2 presents related work; Section 3 describes the dataset used in this study; Section 4 details the proposed method based on Artificial Neural Network models; Section 5 discusses the preliminary results; Section 6 presents a brief discussion of the proposed work; and Section 7 concludes the paper with final remarks and future work directions.

II. Amazon Biome and Related Work

The Brazilian Amazon is rich in biodiversity. The biome is home to over 3 million species, including 2,500 types of trees, and shelters more than 180 Indigenous peoples, totaling around 440,000 individuals in the northern region. In addition to its rich biodiversity and cultural diversity, the forest plays a vital role in regulating the global climate, though it is negatively impacted by human activities such as burning and deforestation. For this reason, it is considered an irreplaceable natural treasure of the biosphere [12]–[14].

Due to illegal activities that threaten biodiversity and the global climate, research focused on biome preservation continues to grow. Several studies have proposed technological solutions for monitoring and detecting deforestation in the Amazon region. A recent approach involves the use of Uncrewed Aerial Vehicles (UAVs), whose effectiveness has been analyzed through a socio-ICT model that evaluates environmental impacts such as annual deforestation rates and CO_2 emissions, highlighting important trade-offs in the design of such systems [15]. Reference [16] combines technologies like LiDAR data and PlanetScope satellite imagery, showing that integrating these sensors improves the detection of forest disturbances caused by selective logging, especially in small clearings, thus contributing to more accurate and effective forest management. Additionally, methods based on MODIS imagery with moderate spatial resolution have proven promising for rapid and near real-time deforestation assessments, showing good agreement with Landsat data and enabling quicker policy responses [17]. These efforts underscore the growing role of remote sensing technologies and computational modeling in the preservation of Amazonian ecosystems.

The Linear Spectral Mixture Model (LSMM) has been explored in various studies as a potentially useful approach for environmental monitoring tasks, such as mapping forest disturbances and fire scars. One study utilized surface reflectance images from the Wide Field Imager (WFI) onboard CBERS 4 and CBERS 4A satellites, combined with data cubes from the Brazil Data Cube Project, to detect burned areas. The application of LSMM enabled the generation of shadow fraction images, which were compared to a manually created reference map. The results showed a statistically significant correlation ($p < 0.05$) and an overall similarity of 70%, demonstrating the effectiveness of the method despite a 12.30% overestimation of the burned area. Additionally, the use of data cubes helped reduce the volume of imagery to be processed, improving efficiency [18]. Another study focused on the region of Boca do Acre, a new logging frontier in the Amazon. LSMM was employed to derive soil fraction images, which were then used for visual interpretation of selective logging over a time series from 2007 to 2019. By integrating these results with MapBiomas data, the study revealed that approximately 2.4% of primary forest had been subjected to logging activities by 2019. The findings emphasize the increasing pressure from logging, particularly from access routes in the neighboring state of Acre, and underline the urgent need for stronger surveillance and forest protection strategies [19].

In recent years, the integration of Artificial Intelligence (AI), particularly deep learning techniques, has significantly enhanced the ability to monitor and predict deforestation in the Amazon rainforest. Several studies have demonstrated the effectiveness of AI models in processing satellite imagery to detect forest degradation with high precision. For instance, one approach employed the Mask2Former architecture, which leveraged multisatellite data and cloud-aware training strategies to achieve 91.1% pixel accuracy and an F1 score of 88.8% in deforestation segmentation tasks [20]. Another study proposed a recurrent deep learning model for monthly prediction of deforestation events using seven years of data from the Brazilian Real-Time Deforestation Detection System (DETER), indicating promising results in recall performance [21]. Furthermore, convolutional neural networks (CNNs), such as 1D-CNNs and architectures like VGG16 and MobileNetV2, have been applied to hyperspectral and optical satellite data, reaching classification accuracies above 93% and even up to 98.92% in some cases [22], [23]. The results highlight AI's potential to support remote sensing and spectral models, offering scalable and accurate insights for environmental protection and policy-making.

III. Dataset Description

Our dataset was composed of two classes: deforestation and non-deforestation. The deforestation class, illustrated in Fig. 1, includes areas with exposed soil, indicating total loss of primary vegetation, as well as illegal mining sites.

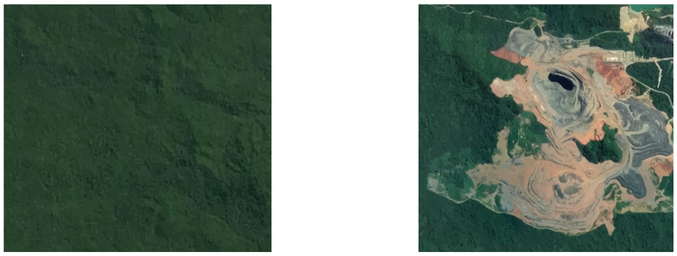
(a) Deforestation with exposed soil/pasture in the state of Acre.

(b) Mining in the Kayapó indigenous region, in Pará.

Fig. 1: Images considered deforested for training the neural network.

The non-deforestation class, illustrated in Fig. 2, comprises areas with primary vegetation—that is, regions within the

Amazon where the forest remains intact with minimal human intervention—as well as large-scale mining areas, considered legal and government controlled, such as the Carajás and Azul mines located in eastern Pará.



(a) Amazon rainforest located in the state of Pará.

(b) Salobo mine located in the state of Pará.

Fig. 2: Images considered non-deforested for training the neural network.

A. Image Source: CBERS Satellite Imagery

The dataset was built using images from the China–Brazil Earth Resources Satellite 04A (CBERS-04A), provided by the Brazilian National Institute for Space Research (INPE). We chose images captured by the Wide-Field Imager and Panchromatic Multispectral Camera (WPM), which offers four spectral bands (Blue, Green, Red, and Near-Infrared) at an 8-meter resolution, as well as a panchromatic band (PAN) with a 2-meter resolution.

B. Dataset Construction

The multispectral maps were built using the Mosaic tool in QGIS software, which allows for the combination of various spectral bands into a single multispectral image. For this project, the four spectral bands provided by CBERS-04A were combined, as made available through INPE's Image Catalog.

The dataset was divided into two groups: (I) true color composite images, and (II) colored images generated from fraction images. All images were exported from QGIS in GeoTIFF format, with a maximum dimension of 529 × 637 pixels. Given the CBERS spatial resolution of 8 meters, each image covered approximately 4,232 × 5,096 meters of territory.

To generate the true color composite images, bands 3 (Red), 2 (Green), and 1 (Blue) were mapped to RGB channels, forming a 3-2-1 band composition.

To produce the fraction-based colored images, the multispectral maps created in QGIS were transferred to TerraAmazon, where the Linear Spectral Mixture Model was applied. TerraAmazon offers three mathematical principles for the mixture model: least squares, constrained least squares, and principal component analysis (PCA).

We selected the constrained least squares method, as it allows the use of four input bands and three components—an essential feature given that the satellite provides four spectral bands. The three selected components, or endmembers, were water, soil, and vegetation. Figure 3 shows a reflectance graph generated during the selection of these endmembers, closely resembling typical reflectance profiles found in the literature.

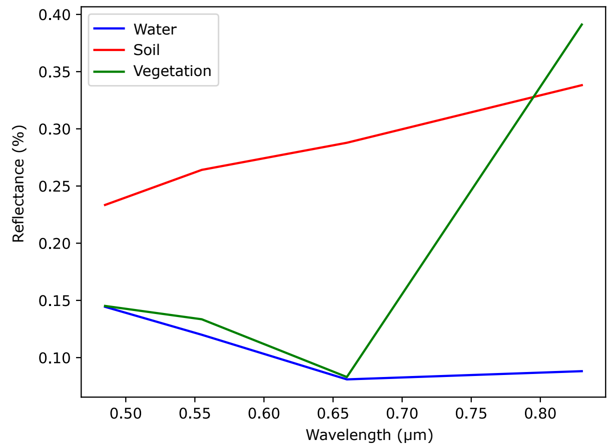


Fig. 3: Reflectance of water, soil and vegetation components.

In the considered spectral range, soil exhibits a continuous increase in reflectance, while water shows a decreasing trend due to absorption and transmission of incident radiation. Vegetation, on the other hand, absorbs visible light for photosynthesis and reflects strongly in the near-infrared band, resulting in a marked rise in its reflectance curve. This behavior confirms that the selected endmembers are consistent with those reported in the literature.

TerraAmazon software also supports the creation of colored compositions from the three fraction images, as illustrated in Fig. 4. These compositions were reimported into QGIS to allow them to be exported as RGB fraction-based images.

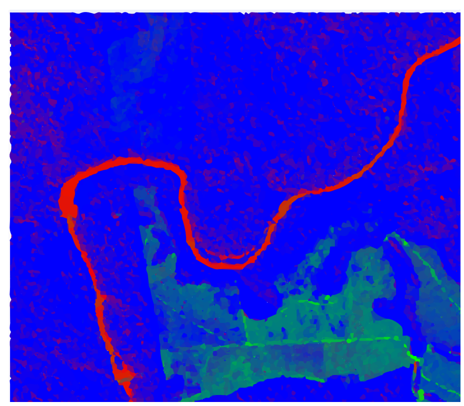


Fig. 4: RGB image composed of fractional components: Water in the R channel, Soil in the G channel, and Vegetation in the B channel.

The final dataset contained 4,000 images, split evenly into two subsets: 2,000 true color composite images and 2,000 fraction-based images. Each subset includes 1,000 images labeled as "deforestation" and 1,000 labeled as "non-deforestation".

The final step of the image preprocessing pipeline was implemented in Visual Studio Code. Since neural networks require data to be preprocessed before training, Python scripts were used to convert images into lists and arrays, assign labels, and shuffle the dataset. Image shuffling is crucial to prevent the model from learning patterns based solely on sequence. Key Python libraries used in this phase included cv2, os, numpy, and pandas. Visual Studio Code was also the chosen development environment for training the neural networks, with Python as the primary programming language. The Keras library—widely used in deep learning and integrated with TensorFlow—was used to construct the neural models in this project.

IV. Proposed Method: Artificial Neural Network Model

The literature presents three main types of data fusion for training: early, intermediate, and late fusion. In early fusion, data are combined at the input stage for the application of a single neural network model. In intermediate fusion, the data pass through a machine learning architecture before being fused and processed again by another architecture. Finally, late fusion occurs after the initial models have been trained, with the output (classifier) directly resulting from the fusion.

The model applied in this work is based on the principles of late fusion. Two image groups - one composed of true-color images and the other of fraction images from spectral components - were individually trained using two different neural network architectures: CNN and MLP. After validating the neural networks, a data fusion process was performed. In this case, since there are two network architectures for each image type, four possible data fusion combinations can be created. Table I shows the four possible combinations of late fusion between models trained on different image groups and architectures. Group A refers to true color composite images, while Group B refers to fractional image compositions. Finally, the architecture resulting from the data fusion was responsible for classifying the two possible classes: deforestation or non-deforestation.

TABLE I: Possible combinations of late fusion between architectures trained on different data groups

Group A / Group B	CNN (Fraction)	MLP (Fraction)
CNN (True Color)	F1	F2
MLP (True Color)	F3	F4

Fig. 5 illustrates the operation of the system. Using two distinct datasets, we trained CNN and MLP neural networks separately for each dataset. For the MLP, the images were vectorized prior to being used as input for neural network training. After training, we froze the final layer of each architecture, the layer responsible for producing the classification output, and concatenated the last layer hidden using a layer concatenation strategy. Based on this, we constructed a new classification layer composed of two neurons: one for identifying deforestation and the other for identifying the absence of deforestation. Finally, we trained only the weights of this new output layer to obtain the final classification result.

The neural network was trained on a Lenovo Ideapad Gaming notebook equipped with an Intel Core i7-11370H processor, 16GB of RAM, and a dedicated Nvidia GeForce GTX 1650 GPU with 4GB of memory.

The neural network parameters were determined through trial and error. Both the CNN and MLP models, for the true-color composite images and the fraction-derived composite images, were trained using 1,800 images. The remaining 200 images were set aside for future testing. The main characteristics of the architectures can be seen in Tables II and III.

TABLE II: CNN Architecture Characteristics

Characteristic	Value
Convolutional layers (Conv2D)	2
Activation function	ReLU
Pooling layers	2
Pooling operation	Max
Neural network input	1 Image 529x637x3
Hidden layers (Fully connected)	1
Neurons in hidden layers	128
Neurons in output layer	2
Activation function in output layer	softmax
Loss function	sparse-categorical-crossentropy
Learning rate	0.0001
Epochs	15

TABLE III: MLP Architecture Characteristics

Characteristic	Value
Epochs	30
Neural network input	1 Image 529x637x3
Hidden layers	1
Neurons in hidden layers	512
Activation function in hidden layers	ReLU
Neurons in output layer	2
Activation function in output layer	softmax
Loss function	sparse-categorical-crossentropy
Learning rate	0.00001

For the data fusion stage, due to memory limitations of the machine, the fusion models were trained with 480 images from each input branch, while 200 images per branch were reserved for future testing. The main characteristics of the architecture can be seen in Table IV.

TABLE IV: Data Fusion Network Characteristics

Characteristic	Value
Neural network input	2 Images 529x637x3
Epochs	30
Neurons in output layer	2
Activation function in output layer	softmax
Loss function	sparse-categorical-crossentropy
Learning rate	0.0005

The validation of the trained neural networks in this study was performed using the ROC curve, and the separability histogram. These evaluation methods are widely used in binary

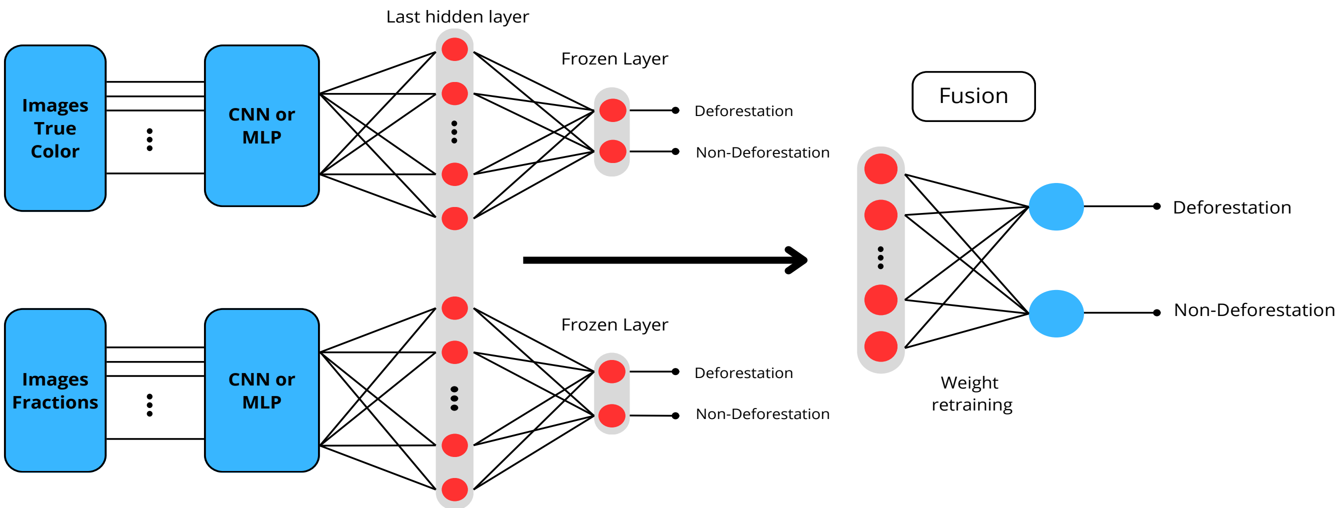


Fig. 5: Data fusion architecture

classification problems, in this case to distinguish between deforested and non-deforested areas. The histogram bin width was fixed at 2.5%, and the decision threshold was set at 0.5 to ensure a balanced approach for both classes.

V. Preliminary Results

This section is divided into three parts: the first will present the results obtained from the CNN and MLP architectures using the true-color image dataset. Similarly, the second will present the results of the architectures applied to the dataset composed of fraction-based images. Finally, the results of the data fusion are presented.

A. *Training with true-color composite images*

Fig. 6 illustrates the ROC curve obtained from the CNN and MLP architectures for the true-color images. The results indicate a good ability of the neural networks to distinguish between the classes, as the areas under the curve (AUC) are close to 1. Based on the AUC, it can also be stated that the CNN architecture demonstrates superior classification performance compared to the MLP architecture, since the area under the CNN curve is greater than that of the MLP. The graph also supports this observation, as the blue curve is closer to the ideal curve than the orange one.

As illustrated in histogram (a) of Fig. 7, the CNN architecture demonstrated a good classification performance, misclassifying only 5 out of the 200 input images. Specifically, three deforestation images were incorrectly classified as non-deforestation, while two non-deforestation images were classified as deforestation. For the MLP architecture, shown in histogram (b), although the model correctly classified the majority of the samples, its performance is clearly inferior to that of the CNN. The MLP misclassified 13 images—8 deforestation images as non-deforestation and 5 non-deforestation images as deforestation.

These results provide further support to the conclusions drawn from the ROC curve, as well as findings reported in the literature, confirming that CNNs are generally more effective for image-based tasks compared to MLPs. Nevertheless, considering the total number of input images, the MLP still performed reasonably well, correctly classifying 185 out of 200 images.

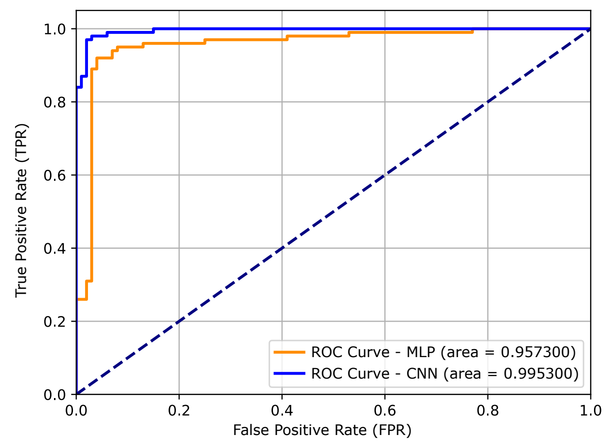
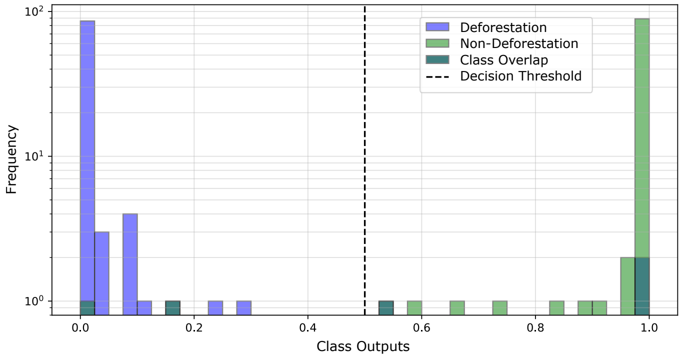


Fig. 6: Curve ROC - True color images.

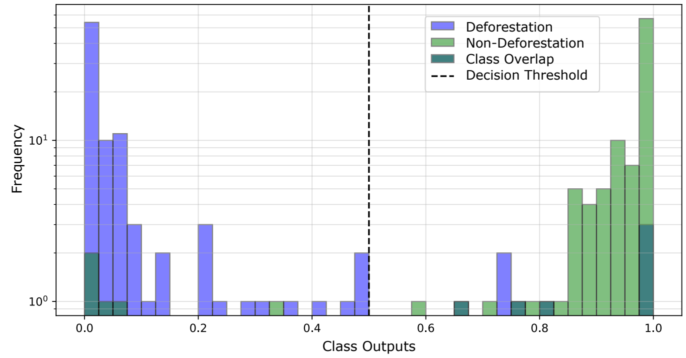
B. *Training with fraction-based images*

The ROC curves obtained for the CNN and MLP architectures using the images composed of fractions are shown in Fig. 8. The area under the curve (AUC) values, which are close to 1, indicate that the trained neural networks achieved a high true positive rate and a low false positive rate, reflecting strong capability in distinguishing between deforestation and non-deforestation classes.

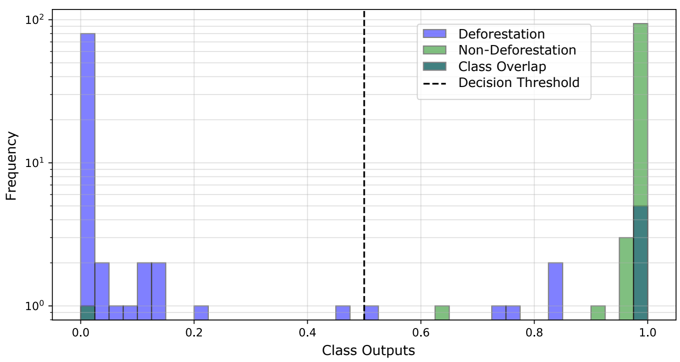
Although the CNN architecture exhibits slightly superior classification performance—evidenced by a larger AUC—it can be stated that both architectures perform similarly in terms of classification. This is because the difference between their AUC values is minimal, with only a 0.006 margin.



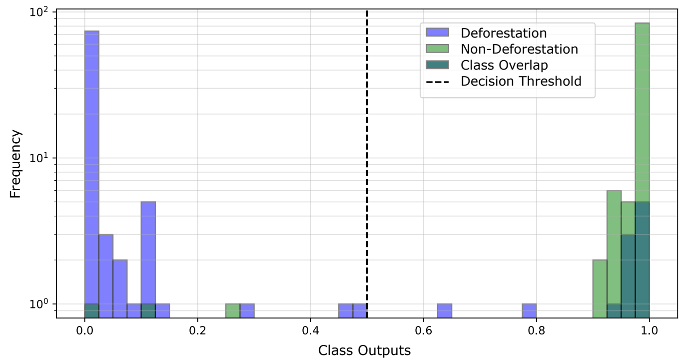
(a) CNN arquitecture for true-color images



(b) MLP arquitecture for true-color images



(c) CNN arquitecture for fraction images



(d) MLP arquitecture for fraction images

Fig. 7: Separability Histogram of the CNN and MLP architectures used for classifying images from the true color and fraction component datasets.

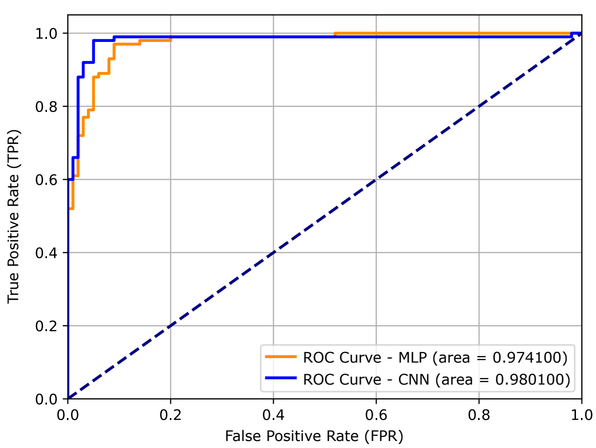


Fig. 8: Curve ROC - Fraction images.

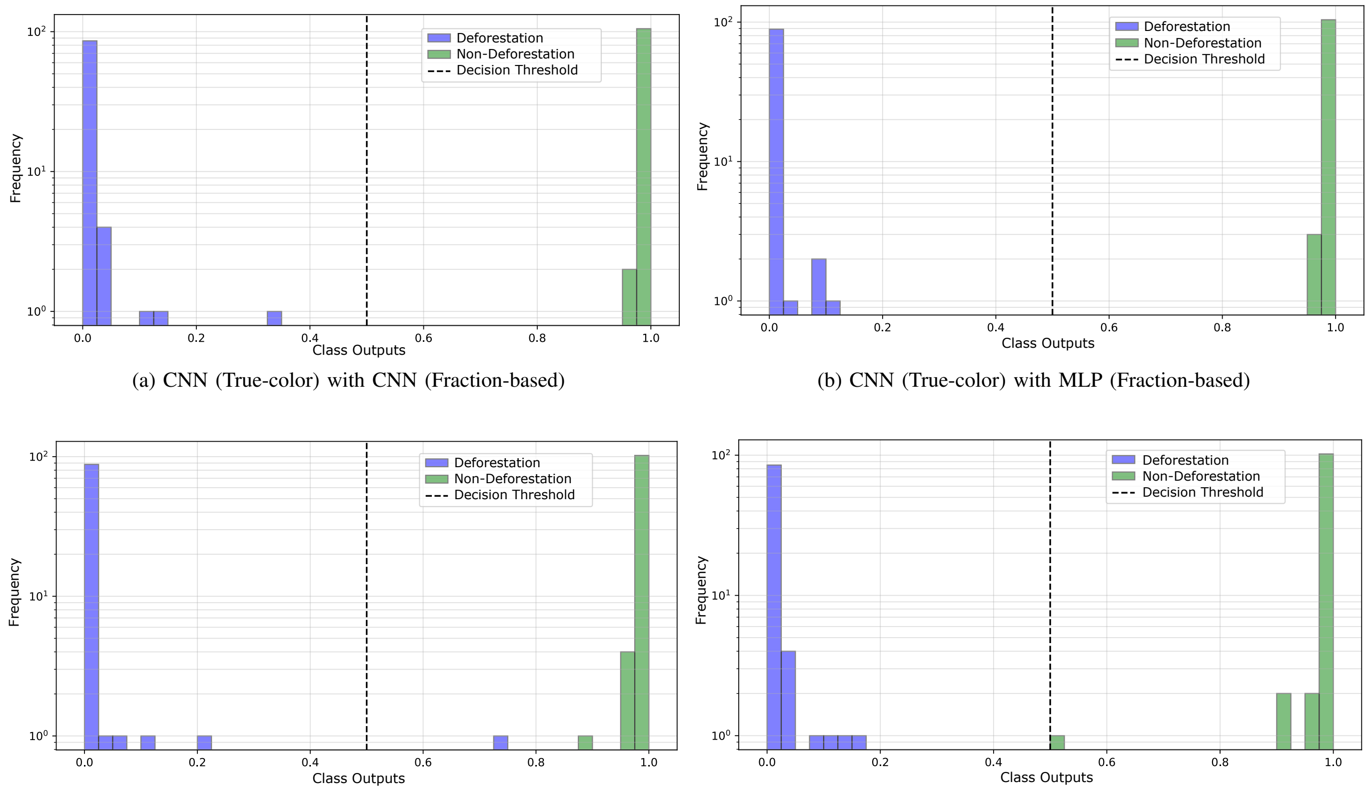
Similar to the results obtained with the true-color composite image dataset, histograms (c) and (d) in Fig. 7 show that both CNN and MLP architectures were able to classify the fraction-based images. The CNN misclassified 10 out of 200 images, demonstrating high precision for the non-deforestation class, as only one image from this class was incorrectly labeled. The MLP, in turn, misclassified 14 images: 3 non-deforestation images were classified as deforestation, and 11 deforestation images were classified as non-deforestation.

As illustrated by the ROC curve and supported by the histogram results, both architectures achieved comparable performance in classifying the fraction-based images.

Once again, as observed in the training on true-color composite images, the results indicate that both architectures face challenges in accurately distinguishing between the two classes, despite presenting generally good precision. However, a closer analysis of the predictions—particularly for the deforestation class—reveals a noticeable dispersion. The models tend to produce more false negatives (i.e., deforested areas incorrectly predicted as non-deforested) than false positives. This behavior suggests a bias in the classification toward the non-deforestation class, potentially affecting the model's effectiveness in real-world applications where the accurate detection of deforestation is critical.

C. Data Fusion

The plots in Fig. 9 illustrate how data fusion between architectures enhances the classification performance of neural networks. When combining the CNN trained on true-color images with the CNN trained on fraction-based images, the architecture achieved perfect classification of all 200 samples.



(a) CNN (True-color) with CNN (Fraction-based)

(b) CNN (True-color) with MLP (Fraction-based)

(c) MLP (True-color) with CNN (Fraction-based)

(d) MLP (True-color) with MLP (Fraction-based)

Fig. 9: Separability Histogram of the Data Fusion architecture

Notably, the non-deforestation class was predicted with over 95% confidence, as each bin in the histogram corresponds to 2.5%.

In the fusion of the CNN (true-color) with the MLP (fraction-based), the non-deforestation class achieved the same performance, while all deforestation samples had confidence scores above 87.5%. In the fusion of the MLP (true-color) with the CNN (fraction-based), only one deforestation sample was misclassified, and all non-deforestation predictions were made with over 90% confidence. Finally, the fusion of the MLPs trained on both image types also achieved 100% classification accuracy, although one sample—still correctly classified—had a confidence value close to 50%.

These findings underscore the importance of the decision threshold. For instance, a threshold of 0.6 would classify the sample near 0.5 in histogram (d) as deforestation, whereas a threshold of 0.2 would make the network more sensitive to the non-deforestation class. Similarly, in histogram (c), a threshold of 0.8 would correctly classify all samples, while a lower threshold would shift the network's sensitivity toward the alternate class. In other words, threshold selection governs the sensitivity of the system. Therefore, the environmental analysis context plays a critical role in defining how sensitive the network should be for detecting and classifying deforestation, allowing for calibration based on specific monitoring objectives.

VI. Discussion

Previous studies have demonstrated the potential of Artificial Intelligence to support the monitoring of deforestation in the Amazon, as discussed in Section II. Building upon this foundation, the methodology proposed in this work highlights the advantages of integrating data fusion techniques in studies on deforestation in the Northern region of Brazil. Our results show that all considered fusion strategies outperformed individual architectures (CNN and MLP) when applied separately, reinforcing the benefit of combining different sources of information.

In qualitative terms, our study demonstrates that merging two distinct spectral compositions—true color and LSMM-derived fraction images—through late fusion leads to more robust and flexible classification strategies. This approach not only improves accuracy but also enhances generalization by leveraging the complementary characteristics present in each data group.

VII. Conclusion and Future Work

The vastness and diversity of the Amazon rainforest make deforestation monitoring an exceptionally complex task, requiring advanced approaches to achieve effective results. This work studied the classification of deforested areas in the

Amazon by comparing the performance of two artificial neural network (ANN) architectures and exploring data fusion to enhance classification accuracy.

The methodology proved effective for both project development and result generation. However, the computational resources used in this research imposed constraints on the size of the dataset that could be processed. Given this limitation, even with a suitable methodology, the use of more advanced computing infrastructure is recommended to enable the handling of larger datasets, which is essential for dealing with the complexity of the Amazon rainforest and for generating more robust and comprehensive results.

The Linear Spectral Mixture Model (LSMM) played a crucial role in estimating the fractions of surface components present in the satellite images. As evidenced by the results, both MLP and CNN architectures demonstrated competence in classifying deforested areas using fraction images derived from the LSMM.

The findings also indicated solid performance of both MLP and CNN architectures in the classification task, despite challenges associated with misclassifications in certain image samples. It is recommended that further analysis be conducted on images that were misclassified, in order to understand the causes of these errors and to identify potential improvements through the application of alternative techniques. In addition, it is recommended to use techniques already consolidated in the literature, such as AlexNet or VGG16, for more promising results.

Data fusion significantly improved classification performance across all evaluated scenarios. This enhancement suggests that fusing outputs from different architectures not only leveraged their complementary strengths but also highlighted the benefits of integrating multiple data representations.

An important consideration in this study is the decision threshold. A threshold of 0.5 was adopted to maintain balanced class assignment. However, in practice, this parameter should be adjusted based on the cost of misclassification. In real-world applications, inaccurate classification can incur significant consequences, and thus, the threshold must be fine-tuned to ensure the neural network properly alerts the system to potential deforestation areas.

The challenges inherent to deforestation monitoring in the Brazilian Amazon remain complex. The wide variety of deforestation patterns and the sheer scale of the biome make detection and monitoring a continuous and demanding task. Therefore, ongoing advancement in machine learning techniques is essential to maintain accuracy and reliability in this field.

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