SOCIEDAD LATINOAMERICANA EN PERCEPCIÓN REMOTA
Y SISTEMAS DE INFORMACIÓN ESPACIAL
XXI SIMPÓSIO INTERNACIONAL SELPER
4-8 de novembro 2024 - Belém, Brasil

# INTEGRATING AI FOR AIR TRAFFIC SURVEILLANCE: A CASE STUDY USING TABULAR AND GRAPHICAL DATA

Gabriel Dietzsch[1]; Elcio Hideit Shiguemori[2]

[1] Instituto de Estudos Avançados, Departamento de Ciência e Tecnologia Aeroespacial, São José dos Campos, Brasil. dietzschgd@fab.mil.br, https://orcid.org/0000-0001-7241-2416

[2] Instituto Nacional de Pesquisas Espaciais, Pós-Graduação de Computação Aplicada, São José dos Campos, Brasil. elcioesh@fab.mil.br, https://orcid.org/0000-0001-5226-0435

**ABSTRACT**. Illicit activities in the Amazon region, such as deforestation, illegal mining, biopiracy, and drug trafficking, frequently involve the use of aircraft for rapid resource transportation. Effective air traffic control is crucial to addressing this issue. This study investigates the application of neural networks for the automatic classification of suspicious flights using two types of datasets: tabular data containing flight details and graphical data representing planimetric and altimetric trajectories. Various neural network architectures, including BiLSTM, LSTM, Convolutional Neural Networks, Transformers, Gated Recurrent Units, VGG16, VGG19, InceptionV3, ResNet50, and EfficientNetB0, were evaluated for their effectiveness. The results indicate that graphical data models, particularly VGG16 and InceptionV3, provide superior classification accuracy and speed in detecting suspicious flights. However, BiLSTM and LSTM models based on tabular data also showed strong performance. This study enhances air traffic security by demonstrating the potential of integrating neural network architectures with diverse datasets for the detection of suspicious flights.

**Keywords**: Flight Classification; Neural Network; Data Analytics; Deep Learning.

## 1. INTRODUÇÃO

The Amazon, with its vast biodiversity and natural wealth, has been the target of numerous illicit activities, including deforestation, illegal mining, and drug trafficking (Pajolla, 2022). These criminal practices are often facilitated by the use of aircraft, which allow for the rapid transport of supplies and resources necessary to sustain such activities in remote and hard-to-reach areas (Potter, 2023). The vulnerability of the Amazon rainforest was a central theme at the Amazon Summit, held in Belém do Pará in August 2023. The participants recognized the urgent need to protect the region and combat organized crime, highlighting the importance of air traffic control to prevent the advance of these illicit activities (Artaxo, 2023). The Brazilian government proposed the creation of an Integrated Air Traffic Control System to combat illicit air traffic, drug trafficking, and other crimes. Effective air traffic control is crucial for detecting and preventing criminal activities (Potter, 2022). The identification of suspicious flights currently relies on the analysis of tabular and informational data, such as flight plans and radar data, which are processed by human operators (BRASIL, 2020). However, human limitations and the complexity of operations increase the margin for errors and detection failures.

Given this scenario, this study proposes the use of neural networks for the automatic classification of suspicious flights. The approach will explore two types of datasets: tabular data, which includes detailed information on flights in Brazilian territory, and graphical data, generated from the planimetry and altimetry of the same flights. The research aims to determine which type of dataset and neural network architecture offer the best performance in classifying flights as normal or suspicious.

The central problem of this work is to classify suspicious flight routes. The central question of this research is: "Which dataset is better for classifying flights as suspicious or normal, tabular or graphical data?" The general objective is to identify the most effective dataset and neural network for this task. Specific objectives include organizing the two distinct datasets and conducting tests with different neural networks for each dataset. An accurate and efficient identification of suspicious flights is essential to enhance security and combat illicit activities in the Amazon (Valente, 2023) This study will contribute to the development of innovative and technological solutions, boosting the monitoring and response capabilities of the relevant authorities.

## 2. MATERIAL AND METHODS

Detecting suspicious flight routes using artificial intelligence involves various methodologies. Studies highlight the importance of identifying flight route anomalies through deviations from specified waypoints (Pusadan; Buliali; Ginardi, 2016). AI enhances flight safety through automated control systems, engine diagnostics ontology, and air traffic management (Kashyap, 2019). Machine learning models trained on authorization data help determine access authorization and inhibit access to specific resources based on identifiers (Theja, 2019). Combining these insights, a comprehensive approach utilizing AI, machine learning, and anomaly detection effectively identifies suspicious flight routes.

In the early 2000s, researchers explored neural networks to improve air traffic management. , Bosson and Nikoleris, (2004) used supervised learning to classify aircraft trajectories, achieving 90% accuracy in under 40 seconds. This approach aimed to predict future aircraft states and manage complex air traffic systems. In the 2010s and 2020s, deep neural networks predicted likely airspace routes (Naessens et al., 2017), integrating into operational air traffic systems. In 2020, a recommendation tool using multi-agent reinforcement learning and neural networks supported air traffic controllers in complex scenarios, promoting flight efficiency and safety (Dalmau; Allard, 2020). In 2022, machine learning methods predicted air traffic delays (Sangeetha; Andrews; Rajavarman, 2022). Techniques like linear regression, decision trees, and recurrent neural networks improved prediction accuracy and speed. CNNs estimated flight height, relevant for detecting patterns (Dietzsch et al., 2023).

These techniques primarily aimed to improve air traffic management by optimizing flight paths, reducing delays, and enhancing communication rather than detecting suspicious behavior. Thus, this work proposes a solution for better classification of suspicious flight trajectories.

### 2.1. Tabular and graphical data in classification

Comparative analysis between tabular and graphical data in classification is crucial for enhancing accuracy and reliability in various sectors like healthcare (Zaki *et al.*, 2021). Tabular data analysis often overlooks structural correlations within the data, while graphical data representation captures these correlations effectively, providing deeper insights and improved accuracy in classification models (Zaki *et al.*, 2021). In other domains, tabular and graphical data play crucial roles in classification and analysis across various fields. Graphical representations, such as maps and diagrams, are essential for presenting large volumes of data in a visually understandable manner, aiding in easy comparisons, enhancing understanding, and facilitating the identification of patterns in population characteristics (Rachev *et al.*, 2010). On the other hand, tabular classifications are commonly used in medical sciences for numerical dataset analysis, supporting the advancement of linguistic knowledge of diseases through statistical assessments and regression methodologies, emphasizing the importance of assumptions in quantitative evaluations (Isaqova, 2022). Additionally, a user interface allows interaction with graphical displays, presenting quantitative data in both absolute and comparative formats, enabling users to assess data entries relative to specific baselines (Joos *et al.*, 2012). Therefore, the integration of tabular and graphical data is essential for comprehensive and insightful classification and analysis in various domains including the air traffic management (Shankaramma; H V; G. S, 2022).

### 2.2. Description of datasets

This work uses two datasets: one with tabular data from flight spreadsheets including latitude, longitude, altitude, and timestamp information, and another generated from these spreadsheets to graphically represent planimetric and altimetric trajectories. Each flight was classified as suspicious or normal based on its characteristics. The primary data source is FlightRadar24, a global flight tracking service that began in 2006 as a hobby project and expanded in 2009 to allow anyone with an ADS-B receiver to upload data (Flightradar24, 2023). These spreadsheets were used to generate the graphical dataset and were subjected to five different neural networks for classification. Graphs representing planimetric and altimetric trajectories were created from the tabular data. These graphs do not display vertical and horizontal axes to ensure neural networks classify flight behavior independently of the aircraft's location. Figure 1 shows examples of planimetric and altimetric graphs for a normal flight on the left and a suspicious flight on the right.

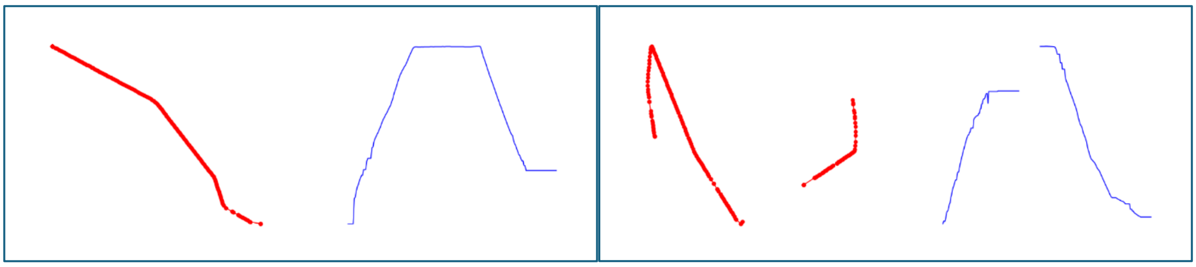

Figure 1. Planimetric (red) and altimetric (blue) graphs of a flight considered normal (left) and Planimetric (red) and altimetric (blue) graphs of a flight considered suspicious (right).

### 2.3. Neural networks used

In this study, five different neural network architectures were evaluated to classify trajectory patterns as normal or suspicious using Tabular data and five well-established convolutional neural network (CNN) architectures were tested for the Graphic dataset. Each of these architectures has unique characteristics that make them suitable for handling sequential data or for image classification tasks:

**LSTM**: LSTMs are a type of recurrent neural network (RNN) capable of learning long-term dependencies. They contain memory cells that can maintain information for long periods, making them suitable for sequence prediction problems (Arifin *et al.*, 2023). **BiLSTM**: BiLSTMs extend the LSTM architecture by processing the input data in both forward and backward directions. This bidirectional approach allows the network to have access to past and future context, improving the model's ability to understand the sequential dependencies in the data (Sun, 2023). **CNN**: traditionally used for image processing but can be adapted for sequential data. They apply convolutional filters to capture local patterns in the data. For time series analysis, 1D convolutions are used to detect patterns across the temporal dimension (Hu; Yue, 2022). **GRU**: they are a simplified version of LSTMs with fewer gates. They retain the ability to handle long-term dependencies but are computationally more efficient, making them suitable for similar tasks where LSTMs are applied (Yigit; Amasyali, 2021). **Transformer**: use self-attention mechanisms to process sequential data, allowing the model to weigh the importance of different parts of the sequence dynamically. This architecture excels in capturing long-range dependencies and has been widely adopted in natural language processing tasks (Nasilloyevich, 2023). The **tabular dataset** was divided into training and testing sets using an 80/20 split. Each model was trained using the training set, and its performance was validated using a portion of the training set (20% of the training data). The centralization and normalization of the data were applied before training to ensure consistency and improve the learning process. The models were trained for 50 epochs with early stopping based on validation loss to prevent overfitting.

**VGG16**: This architecture is 16 layers deep, including 13 convolution layers and 3 fully connected layers. It is known for its simplicity and effectiveness in various computer vision tasks (Yang *et al.*, 2023). **VGG19**: A deeper version of the VGG16, with 19 layers, including 16 convolution layers. Greater depth allows for capture of more complex features (Geeks for Geeks, 2022). In a study comparing VGG16, VGG19, and ResNet50 for suspicious activity detection, VGG19 demonstrated superior accuracy, showcasing its effectiveness in this task (Jain *et al.*, 2023). **ResNet50**: ResNet50 is a 50-layer neural network that uses residual blocks to enable the training of very deep networks. These residual blocks help mitigate the missing gradient problem (Thakur; Chauhan; Gupta, 2023). **InceptionV3**: InceptionV3 is an advanced architecture that uses Inception modules to capture features at multiple scales with parallel convolution layers. It is known for its computing efficiency (Rahman, 2022). **EfficientNetB0**: EfficientNetB0 uses a composite scaling approach to efficiently balance depth, width, and resolution. It is designed to be more compute and memory efficient while maintaining high accuracy (Hoang; Jo, 2021). The training and validation procedures followed the following steps for the **graphical data dataset**: a) Data Preparation: The images were divided into training and validation sets. Samples were balanced to ensure the same number of images (140) in the "normal" and "suspicious" classes. Data generators with data augmentation were used to increase the variability of the data set; b) Configuration of Data Generators: *ImageDataGenerator* was used to normalize pixel values to the range [0, 1] and apply data augmentation (only horizontal flip); c) Training: The model was trained using the fit method, with *steps_per_epoch* and *validation_steps* calculated as the total number of images divided by the batch size. The EarlyStopping condition was used to stop training if the validation loss did not improve after 10 consecutive epochs; and d) Validation: The performance of the model was evaluated in each epoch using a separate validation set. Accuracy and loss metrics were monitored in both the training and validation sets.

To evaluate the performance of all models, the following metrics were used: **Accuracy**: Measure of the proportion of correct predictions in relation to the total number of predictions. **Loss**: Calculated using the binary cross-entropy loss function, providing an indication of how well the model fits the training and validation data. **Validation Accuracy**: Accuracy calculated on the validation set to monitor model performance on unseen data. **Validation Loss**: Loss calculated on the validation set to monitor whether the model is suffering from overfitting.

## 3. RESULTS AND DISCUSSION

The results of all training are expressed in Tables 1 and 2, both the classification conducted with the dataset composed of tabular data, and the dataset composed of graphical data.

| File | Label | BiLSTM | | LSTM | | CNN | | Transformers | | GRU | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Class | Time (sec) | Class | Time (sec) | Class | Time (sec) | Class | Time (sec) | Class | Time (sec) |
| 0ac1aa_1 | S | S | 0,1415 | S | 0,1 | S | 0,0796 | N | 0,1174 | N | 0,1384 |
| 0ac345 | N | S | 0,2156 | N | 0,0924 | N | 0,0747 | N | 0,1658 | N | 0,121 |
| 0ac378_2 | S | S | 0,1292 | S | 0,0985 | S | 0,0766 | N | 0,1524 | N | 0,1239 |
| 1b66a8 | N | N | 0,2491 | N | 0,0967 | N | 0,0809 | S | 0,1489 | N | 0,159 |
| 34718e | N | N | 0,2823 | S | 0,1131 | N | 0,1011 | S | 0,1166 | N | 0,1017 |
| e07211 | S | S | 0,4304 | N | 0,1062 | S | 0,0845 | S | 0,123 | N | 0,1042 |
| e07211_1 | S | S | 0,1364 | N | 0,1305 | S | 0,1127 | S | 0,1893 | N | 0,996 |
| e10000 | N | N | 0,1749 | N | 0,1205 | N | 0,0817 | N | 0,1314 | N | 0,1072 |
| e483b1 | S | S | 0,3332 | N | 0,1136 | N | 0,0768 | N | 0,12 | N | 0,1054 |
| e48e05 | N | S | 0,2467 | N | 0,0979 | N | 0,0802 | N | 0,1125 | N | 0,1 |
| e48f03 | N | N | 0,3912 | N | 0,1012 | N | 0,0844 | N | 0,1251 | N | 0,1027 |
| e493b9_1 | S | S | 0,2544 | N | 0,1022 | S | 0,0813 | S | 0,1516 | N | 0,1131 |
| e493c5_1 | N | N | 0,2511 | N | 0,1047 | N | 0,0906 | N | 0,1619 | N | 0,1048 |
| e49437 | S | S | 0,1553 | N | 0,0971 | N | 0,0812 | N | 0,1774 | N | 0,1062 |
| e49444 | N | N | 1,6684 | N | 0,8959 | S | 0,2255 | S | 0,2323 | N | 1,4483 |
| e495b1_1 | N | N | 0,1693 | S | 0,1376 | N | 0,0897 | N | 0,1467 | N | 0,1034 |
| e495de | N | N | 0,2488 | N | 0,2228 | N | 0,1465 | S | 0,4135 | N | 0,2014 |
| e4961c | S | S | 0,2632 | N | 0,0932 | N | 0,0808 | N | 0,1868 | N | 0,1002 |
| e497e6 | S | S | 0,2085 | S | 0,0979 | S | 0,0793 | S | 0,1723 | N | 0,1192 |

Table 1. Classification based on training and activation of tabular data. S=Suspicious, N=Normal.

| File | Label | VGG16 | | VGG19 | | Inception V3 | | Resnet | | EfficientNetB0 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Class | Time (sec) | Class | Time (sec) | Class | Time (sec) | Class | Time (sec) | Class | Time (sec) |
| 0ac1aa_1 | S | N | 0,0597 | N | 0,0595 | N | 0,0595 | N | 0,0661 | S | 0,0809 |
| 0ac345 | N | N | 0,0592 | N | 0,0635 | N | 0,0635 | S | 0,0659 | S | 0,0948 |
| 0ac378_2 | S | S | 0,0657 | S | 0,0647 | S | 0,0647 | S | 0,07 | S | 0,1105 |
| 1b66a8 | N | N | 0,0598 | N | 0,0626 | N | 0,0626 | N | 0,0657 | S | 0,0862 |
| 34718e | N | N | 0,0667 | N | 0,0602 | N | 0,0602 | N | 0,0663 | S | 0,0813 |
| e07211 | S | S | 0,0591 | S | 0,0614 | S | 0,0614 | N | 0,0655 | S | 0,0951 |
| e07211_1 | S | S | 0,0599 | S | 0,0602 | S | 0,0602 | N | 0,065 | S | 0,0719 |
| e10000 | N | N | 0,0635 | N | 0,8691 | N | 0,8691 | N | 1,484 | S | 3,0147 |
| e483b1 | S | N | 0,059 | N | 0,0591 | N | 0,0591 | N | 0,0663 | S | 0,0793 |
| e48e05 | N | S | 0,0592 | N | 0,0653 | N | 0,0653 | S | 0,0651 | S | 0,0952 |
| e48f03 | N | N | 0,0593 | N | 0,0744 | N | 0,0744 | N | 0,0648 | S | 0,0794 |
| e493b9_1 | S | S | 0,0671 | S | 0,064 | S | 0,064 | S | 0,0656 | S | 0,0849 |
| e493c5_1 | N | S | 0,0587 | N | 0,0597 | N | 0,0597 | S | 0,0649 | S | 0,0788 |
| e49437 | S | S | 0,0601 | N | 0,0594 | N | 0,0594 | N | 0,0726 | S | 0,0758 |
| e49444 | N | N | 0,0598 | N | 0,0679 | N | 0,0679 | N | 0,0743 | S | 0,1811 |
| e495b1_1 | N | S | 0,0586 | N | 0,0628 | N | 0,0628 | S | 0,0651 | S | 0,0782 |
| e495de | N | N | 0,0589 | N | 0,0678 | N | 0,0678 | N | 0,0653 | S | 0,0811 |
| e4961c | S | N | 0,0596 | N | 0,0655 | N | 0,0655 | S | 0,0669 | S | 0,0873 |
| e497e6 | S | N | 0,0603 | N | 0,0689 | N | 0,0689 | S | 0,071 | S | 0,0835 |

Table 2. Classification based on training and activation of graphical data. S=Suspicious, N=Normal.

The results indicate distinct levels of performance between the models tested for detecting suspicious flights, both in terms of accuracy and classification time. Regarding BiLSTM and

LSTM, both models performed well in correctly classifying flights, with BiLSTM superiority, which correctly classified 8 normal flights and 9 suspicious flights, while LSTM correctly classified 7 normal flights and only 3 suspicious flights. The LSTM classification time was slightly faster on average. For the other models used for tabular data, CNN had difficulties classifying suspicious flights, classifying 3 suspicious flights as normal and 1 normal flight as suspicious. The Transformer model presented average hits, missing half of the classifications for each flight class. The Transformer also had faster ratings. The GRU network proved to be unfeasible for this application, at least given the number of training samples. For this network, all examples presented after training were considered normal.

Regarding models intended for training and activating graphical data, VGG16 and VGG19 showed good accuracy, but with some errors in classifying suspicious flights. VGG19 showed a tendency to classify flights as normal, which seems to be a good performance, however, the main objective is to correctly classify suspicious flights. VGG16 presented the fastest classification. InceptionV3 and Resnet showed varied performance with a slight superiority from Inception V3 which correctly classified all normal flights. However, both also showed a tendency to classify flights as normal. EfficientNetB0 presented the worst performance, classifying all flights as suspicious and highlighting the inability to differentiate these behaviors. The results suggest that models based on more complex architectures, such as VGG16, VGG19 and InceptionV3, may be effective for detecting suspicious flights. This may be due to the ability of these models to capture more detailed features in graph data, which is crucial for classification accuracy especially when classification speed is a critical factor. However, models based on LSTM and BiLSTM also showed good performance, especially in terms of classification accuracy, being the models with the highest hit factor.

Next, the confusion matrix of the two best models is highlighted, considering the best model for use on tabular data and the best model for use on graphical data Figure 3.

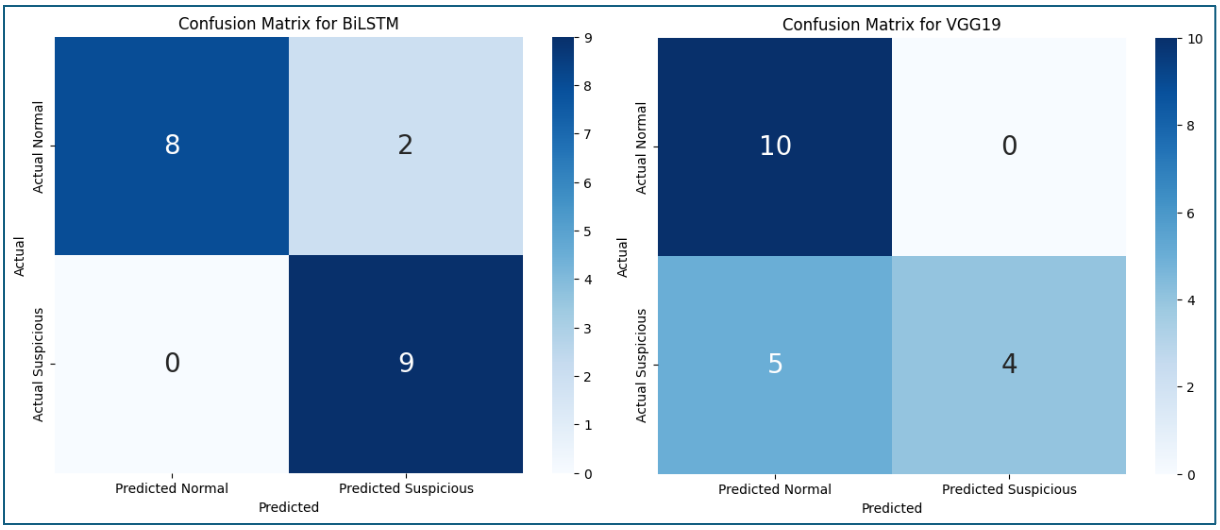


Figure 3. Confusion Matrix of the BiLSTM model (left) and Confusion Matrix of the VGG19 model (right).

This study has some limitations. The first concerns the number of samples in the datasets. the samples were conditioned on the number of suspicious flight samples that were found, fortunately the occurrence of this type of flight is rare and the set may not be representative of all possible scenarios of suspicious and normal flights; The performance of the models can vary significantly with different configurations and hyperparameters, which were not exhaustively explored in this study.

For future research, it is essential to increase samples aiming at a larger and more diverse data set to improve the representativeness of the results, carry out a more comprehensive optimization of the models' hyperparameters to better explore their capabilities, explore other architectures aiming to cover the largest possible scenario to resolve this type of problem.

## 4. CONCLUSION

The results of this study indicate that suspicious flight detection can be significantly improved through the use of neural networks, particularly those with complex architectures such as BiLSTM, LSTM, VGG16, VGG19 and InceptionV3. Models based on graph data, especially VGG16 and InceptionV3, have demonstrated the ability to capture detailed features essential for accurate classification and with shorter classification times, despite tending to misclassify suspicious flights as normal. In contrast, models based on tabular data, such as BiLSTM and LSTM, presented a good overall performance, with BiLSTM showing the best accuracy in classifying suspicious flights.

The central question of this research was to determine which data set, tabular or graphical, is more effective for classifying flights as normal or suspicious. The findings suggest that both types of data have their merits, but models based on graphical data such as VGG16 and InceptionV3 provided better classification time and good accuracy in classifying suspicious flights, while the BiLSTM and LSTM models, based on tabular data, also showed a high hit rate and better performance in terms of classification time.

This study significantly contributes to the field of suspicious flight detection by demonstrating the effectiveness of neural networks in classifying complex data and identifying anomalous behaviors in flight trajectories. The integration of graphical and tabular data with appropriate neural network architectures can improve the security and monitoring capacity of competent authorities, especially in vulnerable regions such as the Amazon.

Although the results are promising, the study faced some limitations, such as the small number of samples and the variability in the performance of models with different hyperparameter configurations. Future research should focus on increasing the dataset and exploring deeper optimizations of the models. The combination of tabular and graphical data should continue to be explored to develop even more robust methods of detecting suspicious flights.

## ACKNOWLEDGMENT

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

## REFERENCES

ARIFIN, Samsul *et al*. **Long Short-Term Memory (LSTM): Trends and Future Research Potential**. International journal emerging technology and advanced engineering, [*s. l.*], 2023. Disponível em: http://dx.doi.org/10.46338/ijetae0523_04.

ARTAXO, Paulo. **Cúpula da Amazônia: frustações, avanços e perspectivas**. Plenamata, [*s. l.*], 2023.

BOSSON, J; NIKOLERIS, A. **Aircraft Trajectory Classification Using Neural Networks**. Journal of Aerospace Computing, Information, and Communication, [*s. l.*], v. 1, n. 1, p. 1–12, 2004.

BRASIL. **Habilitação Técnica para Controle de Tráfego Aéreo**. Instrução do Comando da Aéronáutica 100-18, 2020.

DALMAU, Ramon; ALLARD, Eric. **Air traffic control using message passing neural networks and multi-agent reinforcement learning**. Proceedings of the 10th SESAR Innovation Days, Virtual Event, [*s. l.*], p. 7–10, 2020.

DIETZSCH, Gabriel *et al.* **Estimativa da Altura de Voo de um Vetor Aéreo Por Meio de Reconhecimento de Padrões e Inteligência Artificial**. Anais do XX Simpósio Brasileiro de Sensoriamento Remoto, [*s. l.*], v. 20, 2023. Disponível em: https://proceedings.science/sbsr-2023/trabalhos/estimativa-da-altura-de-voo-de-um-vetor-aereo-por-meio-de-reconhecimento-de-padr?lang=pt-br.

DO, P. H. *et al.* **Graph Neural Networks for Traffic Classification in Satellite Communication Channels:** A Comparative Analysis. Proceedings of Telecommunication Universities, [*s. l.*], v. 9, n. 3, p. 14–27, 2023.

FLIGHTRADAR24. **Flightradar24 AB**. [*S. l.*], 2023. Disponível em: https://www.flightradar24.com/. Acesso em: 22 jun. 2024.

GANESAN, R. *et al.* **Application of Deep Neural Networks for Weed Detection and Classification**. *In*: 2023. 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC). [*S. l.*]: IEEE, 2023. p. 1014–1024. Disponível em: https://ieeexplore.ieee.org/document/10140235/.

GEEKS FOR GEEKS. **VGG-16 CNN model**. [*S. l.*], 2022. Disponível em: https://www.geeksforgeeks.org/vgg-16-cnn-model. Acesso em: 19 jun. 2024.

HOANG, Van-Thanh; JO, Kang-Hyun. **Practical Analysis on Architecture of EfficientNet. *In*:, 2021.** 2021 14th International Conference on Human System Interaction (HSI). [*S. l.*]: IEEE, 2021. p. 1–4.

HU, Kuang; YUE, Kun. **Convolutional Neural Network Based Detection of Seasonal Features in Time Series Data**. [*s. l.*], 2022. Disponível em: http://dx.doi.org/10.1109/GCCE56475.2022.10014257.

ISAQOVA, Xilola. **Numerical and Graphical Diagnosis "Numbers Help to Construct Graphics for Better Understanding"**. *In*: [*S. l.: s. n.*], 2022. Disponível em: http://dx.doi.org/10.2174/9789815050806122010011.

JAIN, Madhur *et al.* **Comparison of VGG-16, VGG-19, and ResNet-101 CNN Models for the purpose of Suspicious Activity Detection**. International journal of scientific research in computer science, engineering and information technology, [*s. l.*], v. 9, p. 121–130, 2023. Disponível em: https://doi.org/10.32628/CSEIT2390124.

JOOS, Derek *et al.* **Comparative graphical data representation**. [*s. l.*], 2012.

KASHYAP, Ramgopal. **Artificial Intelligence Systems in Aviation**. *In*: [*S. l.: s. n.*], 2019. p. 1–26. Disponível em: https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-5225-7588-7.ch001.

MATIJAŠEVIĆ, Nikola; SAMCOVIC, Andreja; ĐOGATOVIĆ, Marko. **Application of Convolutional Neural Networks for the Classification of Human Emotions**. SINTEZA, [*s. l.*], 2022. Disponível em: http://dx.doi.org/10.15308/sinteza-2023-52-59.

MIKHAYLOV, Ilya S *et al.* **Neural Networks Application for the Classification Problem Solving with Domain Constraints**. [*s. l.*], 2023. Disponível em: http://dx.doi.org/10.1109/TELE58910.2023.10184380.

MORINAGA, Makoto; MORI, Junichi; YAMAMOTO, Ippei. **Aircraft model identification using convolutional neural network trained by those noises in a wide area around an airfield**. Acoustical Science and Technology, [*s. l.*], 2023. Disponível em: http://dx.doi.org/10.1250/ast.44.131.

NAESSENS, Herbert *et al.* **Predicting flight routes with a Deep Neural Network in the operational Air Traffic Flow and Capacity Management system**. EUROCONTROL Maastricht Upper Area Control Centre, Maastricht Airport, The Netherlands, Tech. Rep, [*s. l.*], 2017.

NASILLOYEVICH, Urinov Bobur. **Transformadores**: Fundamentos teoricos y Aplicaciones. [*s. l.*], 2023. Disponível em: http://dx.doi.org/10.48550/arxiv.2302.09327.

PAJOLLA, Murilo. **Do tráfico ao trabalho escravo**: rede de atividades ilegais impulsiona devastação da Amazônia. Brasil de Fato, [*s. l.*], 2022. Disponível em: https://www.brasildefato.com.br/2022/04/06/do-trafico-ao-trabalho-escravo-rede-de-atividades-ilegais-impulsiona-devastacao-da-amazonia.

PERIĆ, Staniša Lj *et al.* **Application of convolutional neural networks for road type classification**. Facta Universitatis, [*s. l.*], 2023. Disponível em: http://dx.doi.org/10.22190/fuacr230123001p.

POTTER, Hyury. **As pistas da destruição**. [*S. l.*], 2022. Disponível em: https://www.intercept.com.br/2022/08/02/amazonia-pistas-clandestinas-garimpo/. Acesso em: 25 jun. 2024.

POTTER, Hyury. **Tráfico e garimpo ilegal compartilham aviões e pilotos para lavar dinheiro na Amazônia**. Carta Capital, [*s. l.*], 2023.

PUSADAN, Mohammad Yazdi; BULIALI, Joko Lianto; GINARDI, Raden Venantius Hari. **Anomaly detection of flight routes through optimal waypoint**. [*s. l.*], 2016. Disponível em: http://dx.doi.org/10.1088/1742-6596/801/1/012041.

RACHEV, Svetlozar T *et al.* **Graphical Representation of Data**. *In*: PROBABILITY AND STATISTICS FOR FINANCE. [*S. l.*]: Wiley, 2010. p. 75–99. Disponível em: https://onlinelibrary.wiley.com/doi/10.1002/9781118267912.ch4.

RAHMAN, Md Rezaur. **Convolutional Neural Network (CNN) of Resnet-50 with Inceptionv3 Architecture in Classification on X-Ray Image**. *In*: [*S. l.: s. n.*], 2022. Disponível em: http://dx.doi.org/10.1007/978-3-031-35314-7_20.

SANGEETHA, V; ANDREWS, S Kevin; RAJAVARMAN, V N. **Air traffic control using machine learning and artificial neural network**. Journal of Positive School Psychology, [*s. l.*], v. 6, n. 2, p. 4737–4746, 2022.

SHANKARAMMA; H V, Supreetha; G. S, Prof. Nagaraj. **Analysis of Air Traffic Management Models**. International Journal of Innovative Technology and Exploring Engineering, [*s. l.*], v. 11, n. 3, p. 47–50, 2022. Disponível em: https://www.ijitee.org/portfolio-item/c97520211322/.

SUN, Hongguang. **Supplementary Features of BiLSTM for Enhanced Sequence Labeling**. [*s. l.*], 2023.

THAKUR, Aditya; CHAUHAN, Harish; GUPTA, Nikunj. **Efficient ResNets**: Residual Network Design. [*s. l.*], 2023. Disponível em: http://arxiv.org/abs/2306.12100.

THEJA, Birur. **Detection of operational threats using artificial intelligence**. [*s. l.*], 2019.

VALENTE, Rubens. **Controle 'efetivo' do espaço aéreo é fundamental para terra Yanomami, diz diretor da PF**. [*S. l.*], 2023. Disponível em: https://apublica.org/2023/04/controle-efetivo-do-espaco-aereo-e-fundamental-para-terra-yanomami-diz-diretor-da-pf/. Acesso em: 22 jun. 2024.

VINCENT-BOULAY, Nicolas; MARSDEN, Catharine. **A new approach to aircraft categorization using machine learning to analyze aircraft behaviour**. [*s. l.*], 2023. Disponível em: http://dx.doi.org/10.2514/6.2023-4214.

YANG, Leong Qi *et al.* A new model based on improved VGG16 for corn weed identification. **Frontiers in Plant Science**, [*s. l.*], 2023. Disponível em: http://dx.doi.org/10.3389/fpls.2023.1205151.

YIGIT, Gulsum; AMASYALI, Mehmet Fatih. **Simple But Effective GRU Variants**. [*s. l.*], 2021. Disponível em: http://dx.doi.org/10.1109/INISTA52262.2021.9548535.

ZAKI, Nazar *et al.* **From Tabulated Data to Knowledge Graph**: A Novel Way of Improving the Performance of the Classification Models in the Healthcare Data. **medRxiv**, [*s. l.*], 2021. Disponível em: http://dx.doi.org/10.1101/2021.06.09.21258123.

ZANG, Haipei; ZHU, Jinfu. **Deep Learning Architecture for Flight Flow Spatiotemporal Prediction in Airport Network**. Electronics, [*s. l.*], 2022. Disponível em: http://dx.doi.org/10.3390/electronics11234058.