IOCBE 2024 Conference

The 1st International Online Conference on Bioengineering

16–18 October 2024 | Online

MDPI

A Machine Learning Approach to Classifying Electromyographic Signals of Cranial Nerves During Neurosurgical Procedures

Sara Quattrocelli, David Perpetuini, Daniela Cardone, and Arcangelo Merla

Department of Engineering and Geology, University G. D'Annunzio of Chieti-Pescara, 65127 Pescara, Italy

INTRODUCTION & AIM

Skull base surgery is a highly complex and delicate practice, as it involves critical neurovascular structures. Cranial nerve injuries are among the most feared complications, as they can lead to permanent neurological deficits and significantly affect patients' quality of life. Therefore, accurate monitoring during surgery is essential.

In this context, monitoring electromyograms (EMGs) emerges as a fundamental technique for assessing muscle activation in real time and identifying potential nerve damage. In recent years, the integration of machine learning (ML) algorithms has shown promising potential to enhance the classification of EMG signals, enabling more precise recognition of muscle activation patterns.

This study aims to investigate the application of ML techniques in EMG monitoring during skull base surgery, with the goal of improving surgical safety and reducing the risk of cranial nerve injuries.

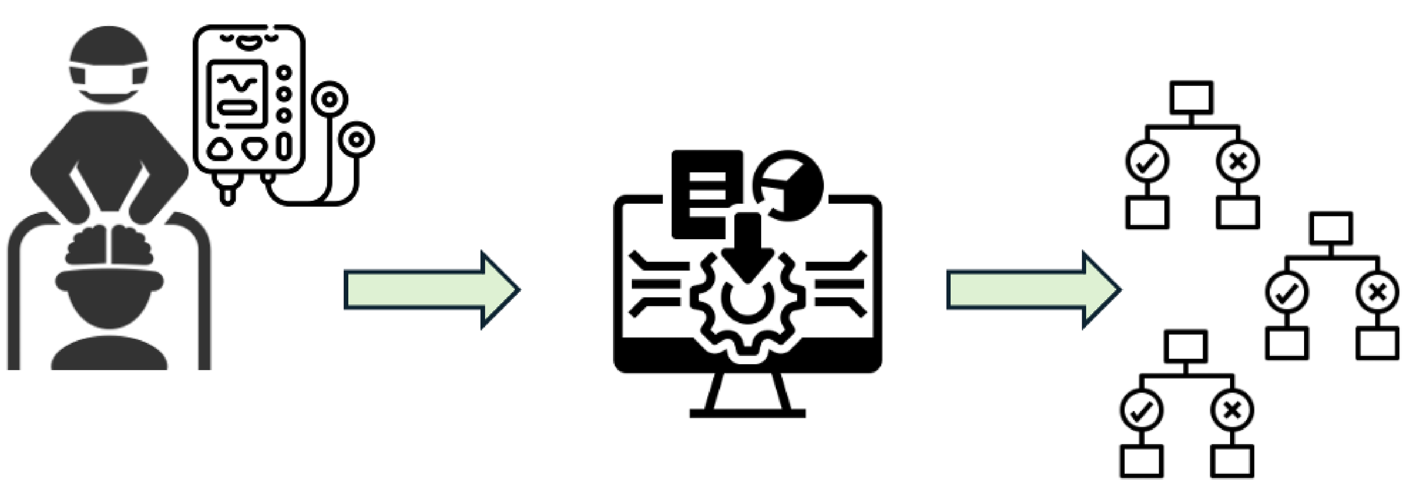

Figure 1. *Processing pipeline of the presented study*

METHOD

This study utilized a publicly available dataset[1] to monitor EMG signals obtained from five cranial nerves in 11 patients undergoing cerebellopontine angle tumor surgery. The EMG data were collected using the Neuromaster G1 MEE-2000 (Nihon Kohden, Inc., Tokyo, Japan) and focused on the V (trigeminal), VII (facial), XI (accessory), X (vagus), and XII (hypoglossal) cranial nerves.

To classify the EMG signals, an ensemble model of decision trees was developed using MATLAB 2023b. The classification categories included 'Injury', 'Artifact', and 'Healthy'. Key features extracted for analysis included the amplitude of the rectified value, root mean square value, median frequency, total power, and mean normalized frequency.

The dataset was divided using a holdout method, allocating 80% of the data for training and 20% for testing. To address class imbalance, synthetic minority oversampling was applied to the training data. The model configuration included a maximum of 800 splits per tree, with constraints of 5 observations per leaf and 10 per parent node. The training process involved 250 learning cycles with pruning enabled to enhance generalization. Finally, the model's performance was validated through 5-fold cross-validation, ensuring a robust assessment of its accuracy.

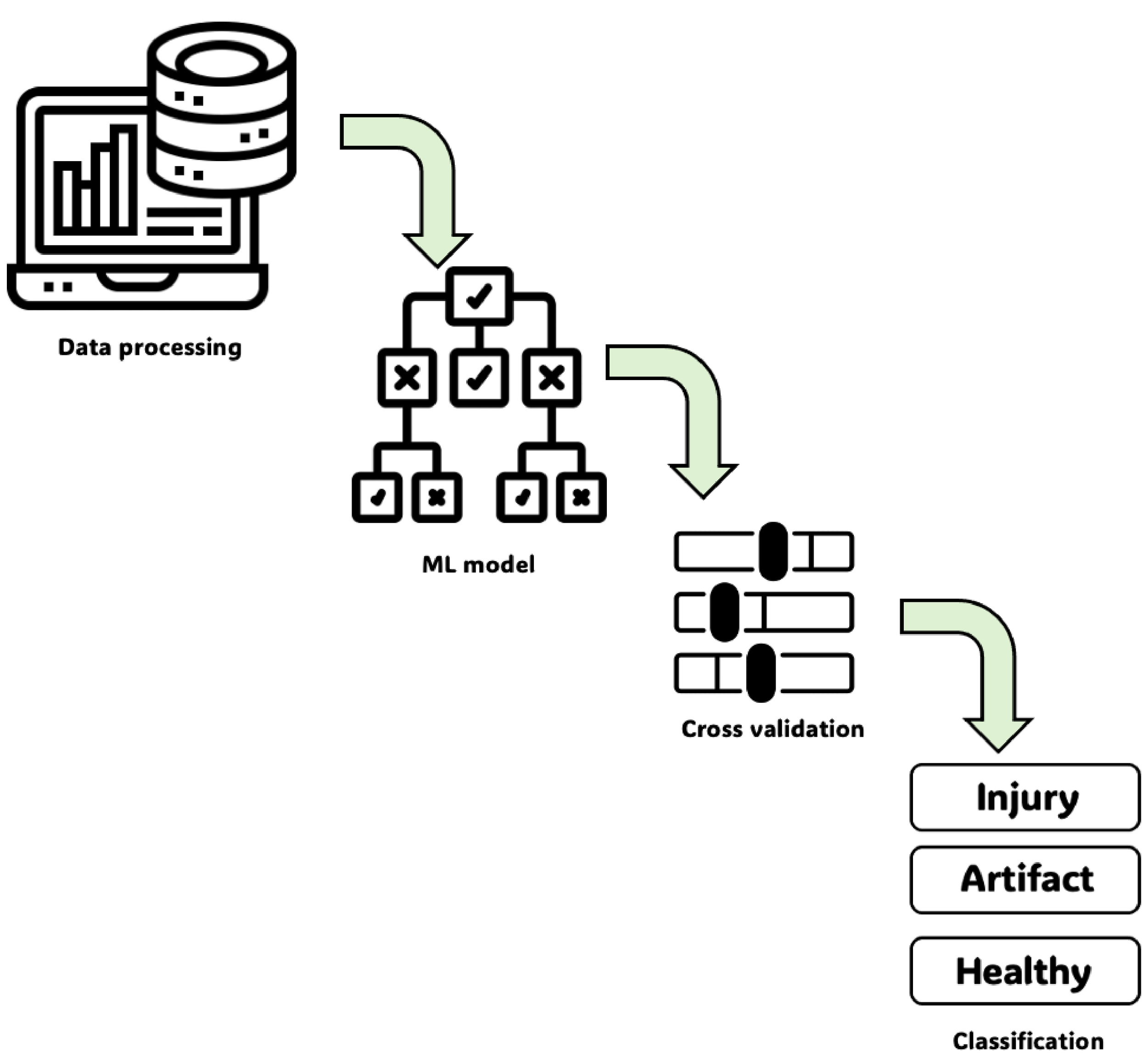

Figure 2. *Machine learning workflow, from data preprocessing and metric calculation to model training and evaluation, concluding with classification results.*

RESULTS & DISCUSSION

The machine learning model demonstrated an overall accuracy of 81.12% on the test set, highlighting its effectiveness in classifying EMG signals from cranial nerves during surgery.

CLASS	PRECISION	RECALL	F1-SCORE
Injury	32.49%	81.01%	46.38%
Artifact	70.00%	75.68%	72.73%
Healthy	97.54%	82.12%	89.17%

Table 1: *Performance metrics of the machine learning model in classifying EMG signals*

These results indicate that while the model performs well overall, there are significant variations in performance across different categories. The low precision for the Injury classification suggests the need for further optimization, potentially through refining feature selection or exploring additional ML techniques. In contrast, the high precision and recall for the Healthy category indicate that the model is particularly effective in distinguishing non-injured states, which is crucial for patient safety during surgical procedures.

Further research should focus on enhancing the model's performance for the Injury classification to reduce the number of false positives and improve clinical applicability. Overall, the findings underscore the potential of machine learning techniques to enhance the monitoring of EMG signals in skull base surgeries, contributing to improved surgical outcomes.

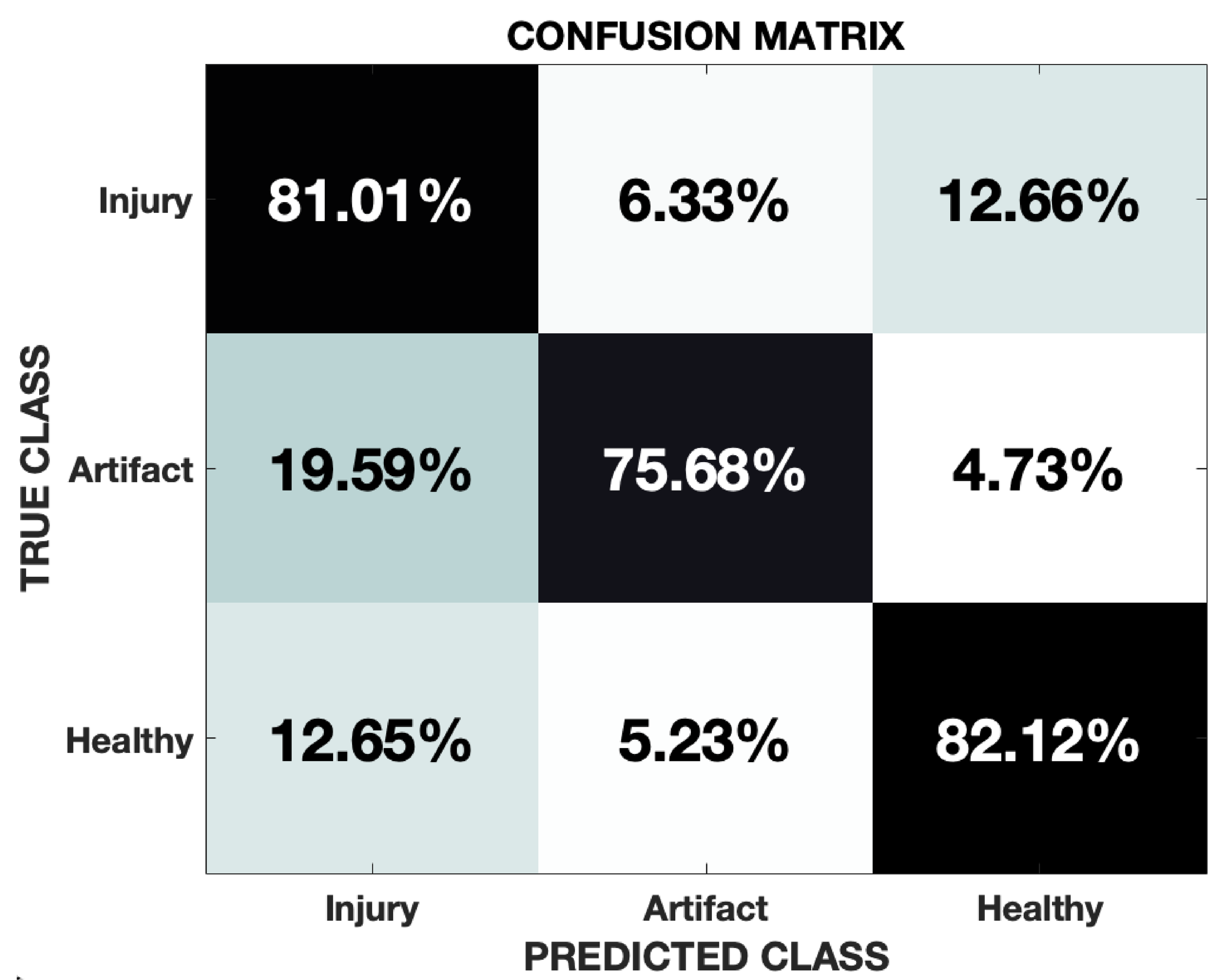

Figure 3. *Confusion matrix showing the performance of the ML model in classifying EMG signals for Injury, Artifact, and Healthy categories*

CONCLUSION

This study underscores the potential of ML in enhancing the intraoperative monitoring of EMG signals from cranial nerves. The findings suggest that ML algorithms can improve diagnostic accuracy and clinical utility. Future efforts should focus on optimizing these models and integrating advanced algorithms to further enhance their effectiveness, ultimately contributing to improved patient safety and surgical outcomes.

REFERENCES

[1]. Ma, Wanting; Chen, Lin; Pang, Xiaofan (2024), "A Multichannel Continuous Clinical Electromyography Dataset from Neurosurgery", Mendeley Data, V2, doi: 10.17632/7hyptcbkkd.2