

Abstract

This study explores a machine learning-based neural network system using MATLAB to classify hemiplegia, a condition causing paralysis on one side of the body. Using data from the specialized treatment center “El laboratorio de marcha en el Hospital Ortopédico Infantil” in Caracas, Venezuela, the study developed an algorithm to categorize patients into four established hemiplegia types. Techniques such as Principal Component Analysis (PCA) and Self-Organizing Maps (SOMs) were used for dimensionality reduction and data clustering, while a Convolutional Neural Network (CNN) refined the classification. The algorithm identified distinct subgroups within the categories, indicating a more complex data structure. Despite promising results in aiding clinical diagnosis, time constraints limited the exploration of these subcategories. This research demonstrates the potential of AI to enhance medical diagnostics, especially in resource-limited settings.

Introduction

Hemiplegia, as defined by the Cleveland Clinic, is characterized by paralysis on one side of the body and can be either temporary or permanent, depending on its severity. It commonly results from strokes, traumatic brain or spinal cord injuries, or early childhood injuries. Accurate classification into four categories (Type I, II, III, and IV) is essential for appropriate treatment and its frequency. Misdiagnosis is a significant concern, with over 20% of cases misdiagnosed and 66% of initial diagnoses incorrect (Crandall & Pera Law, LLC, 2023). This research focuses on training artificial intelligence with real case data using supervised and unsupervised machine learning methods to improve the accuracy of hemiplegia classification. By analyzing movement patterns and providing detailed classifications, AI has the potential to reduce misdiagnoses and enhance patient care, particularly in regions with limited specialist access.

Objectives

Develop a model to classify & identify diverse types of hemiplegia.

Train the model using Machine Learning methods with gathered data.

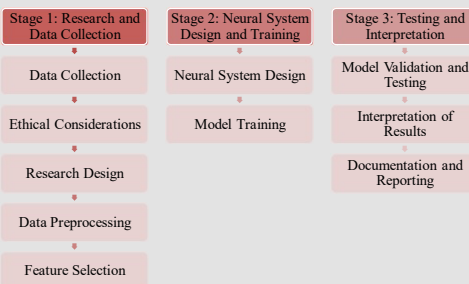
Validate the model's accuracy.

Propose a new classification taxonomy.

Minimize the time required for the classification process.

Aid in areas with limited or no access to specialist.

Methodology and Equipment



The final model was development and trained using the MATLAB Program and language.



Figure 4: MATLAB's Logo (MathWorks, 2023)

Results

The developed algorithm effectively classified diverse types of hemiplegia, reducing the dataset from 612 features to 20 principal components using PCA, which facilitated efficient processing and highlighted key patterns. A Self-Organizing Map (SOM) identified distinct clusters, while the neural network achieved high classification accuracy, successfully differentiating between control groups and hemiplegia subtypes, including uncovering previously unrecognized subgroups. Despite time constraints, the model's performance, evidenced by the confusion matrix and accuracy plots, demonstrated its potential as a valuable diagnostic tool for clinicians with ~90% accuracy.

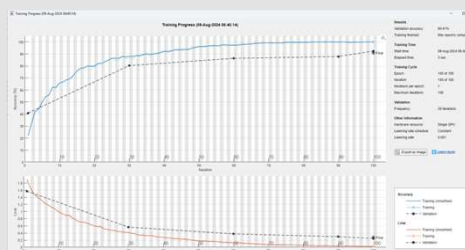


Figure 2: Vazquez Lebron, N. (2024) Accuracy Results of Training vs. Validation URP-HOS-2023-2024.

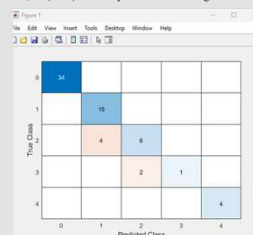


Figure 3: Vazquez Lebron, N. (2024) Classification Results of Training vs. Validation URP-HOS-2023-2024.

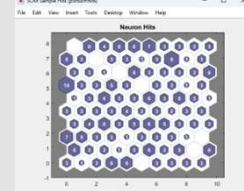


Figure 4: Vazquez Lebron, N. (2024) SOM Results of Sub-Classifications URP-HOS-2023-2024.

Conclusion

This research demonstrates the feasibility and potential of using machine learning techniques, specifically Convolutional Neural Networks, to classify types of hemiplegia. The developed algorithm accurately identified and categorized various hemiplegia types. Principal Component Analysis and Self-Organizing Maps effectively managed the high-dimensional dataset, revealing valuable insights into its structure. The study highlights the potential of artificial intelligence to enhance medical diagnostics by improving accuracy and reducing misdiagnoses. However, limitations include the incomplete exploration of newly identified subcategories, indicating a need for further investigation to understand their clinical relevance. Overall, the findings suggest that machine learning models can uncover patterns not easily detectable by human observation, serving as a complementary tool for healthcare professionals.

Recommendations

- Alternative Dimensionality Reduction
- Alternative Machine Learning Techniques
- Subcategory Exploration
- User-Friendly Implementation

References

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