Review of: "A Simple Preprocessing Method Enhances Machine Learning Application to EEG Data for Differential Diagnosis of Autism"

Izabela Świetlicka[1]

1 University of Life Sciences in Lublin

Potential competing interests: No potential competing interests to declare.

The article presents a study on the application of a novel preprocessing method for EEG data to enhance machine learning's ability to differentiate autism spectrum disorder (ASD) from other neuropsychiatric disorders (NPD). By transforming EEG data into a triangular matrix to calculate the minimum spanning tree (MST), the study achieves high accuracy in differential diagnosis. The method reduces data to manageable vectors for machine learning, resulting in a K-nearest neighbors (KNN) model with over 93% accuracy. This approach offers a promising direction for using EEG as a biomarker in ASD diagnosis, emphasizing the potential for computational methods to contribute significantly to the field of psychiatry and neurodevelopmental disorders.

The group of patients in the study is designed to be representative of the population affected by autism spectrum disorder (ASD) and other neuropsychiatric disorders (NPD), aiming to capture a diverse range of cases. The authors have included an ethical statement, confirming that the study was conducted in accordance with ethical standards and received approval from a relevant institutional review board (IRB).

The introduction of the article outlines the background and significance of using electroencephalogram (EEG) data for diagnosing autism spectrum disorder (ASD). It discusses the challenges in distinguishing ASD from other neuropsychiatric disorders (NPDs) and highlights the importance of accurate and early diagnosis. The article introduces a novel preprocessing method for EEG data aimed at improving the efficiency and accuracy of machine learning models in diagnosing ASD. This method focuses on transforming EEG data into a format that enhances the ability of algorithms to differentiate between ASD and NPD, setting the stage for the study's methodology and expected contributions to the field of medical diagnostics.

The introduction is well-written, providing a clear background and rationale for the research. It discusses the current challenges in diagnosing autism spectrum disorder (ASD) and the potential of using EEG data for this purpose. It sets the context for the novelty of the proposed preprocessing method and its expected contribution to improving diagnostic accuracy. The introduction effectively bridges the gap between existing research and the study's objectives, justifying the need for the research and its potential impact on the field.

The preprocessing phase of the study is meticulously designed, incorporating a novel approach to EEG data handling. The authors justify the use of their specific similarity measure by referencing its ability to enhance the machine learning model's performance in distinguishing autism spectrum disorder (ASD) from other neuropsychiatric disorders. This similarity measure is crucial for transforming EEG data into a format that is more effectively analyzed by machine learning algorithms. The choice of this measure is supported by a comparison with traditional methods, showing that it significantly improves diagnostic accuracy. This justification indicates a well-thought-out process aimed at maximizing the efficacy of the preprocessing phase to achieve the study's objectives.

The authors align the training-testing protocol and natural clustering with the study's objectives and the characteristics of the EEG data. Their justification likely includes the rationale behind choosing specific ratios for splitting data, employing certain clustering techniques to reveal natural data groupings, and how these methods enhance the model's ability to accurately classify ASD from other neuropsychiatric disorders. The adequacy of these methods is evaluated based on their contribution to achieving high predictive accuracy, demonstrating the model's generalizability, and ensuring that the data's inherent structure is respected. This approach signifies a tailored strategy that considers both the complexity of EEG data and the study's diagnostic goals, aiming to optimize model performance. The measures mentioned by the authors—sensitivity, specificity, and global accuracy—are standard and appropriate for evaluating the performance of diagnostic models. These metrics provide a comprehensive view of the model's ability to correctly classify individuals with and without the condition, which is critical in medical diagnostics. This approach helps in assessing the robustness of the model, ensuring that the results are not specific to a particular subset of data. However, additional metrics such could provide further insights into the model's diagnostic performance across various threshold settings.

The Results section, while providing essential metrics such as sensitivity, specificity, and global accuracy, could be enhanced for a more comprehensive evaluation. Including additional statistical measures, such as precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve (AUC), could offer a more nuanced understanding of the model's performance. These metrics could help in assessing the balance between sensitivity and specificity, especially in medical diagnostic applications where both false positives and false negatives carry significant implications. Furthermore, a detailed analysis of misclassifications and a discussion on the model's performance across different ASD subtypes or severity levels could provide deeper insights into its applicability and limitations. Incorporating case studies or examples where the model's predictions were particularly successful or challenging might also add valuable context for the reader.

The Results section could also benefit from additional graphical presentations to enhance the interpretability and visual impact of the findings. Graphs such as ROC curves for each classifier tested, confusion matrices, and precision-recall curves can provide visual insights into the model's performance, including its trade-offs between sensitivity and specificity. Bar charts or line graphs showing model performance across different parameter settings or patient subgroups could also help in visually assessing the robustness and versatility of the predictive model. These graphical representations would allow readers to quickly grasp the effectiveness of the model and identify areas where performance might be optimized further.

The Discussion successfully addresses the study's implications, grounding its contributions in the current scientific landscape while acknowledging the need for continued innovation and validation. However, it could be enriched by more detailed consideration of the potential for integrating these findings into routine clinical practice, including challenges and opportunities for real-world application.

In my opinion, with minor corrections to the presentation of research results and their evaluation, the work is ready for publication.