Neuro-Fusion: A Unified Approach for Cognitive Workload Classification Using EEG Data

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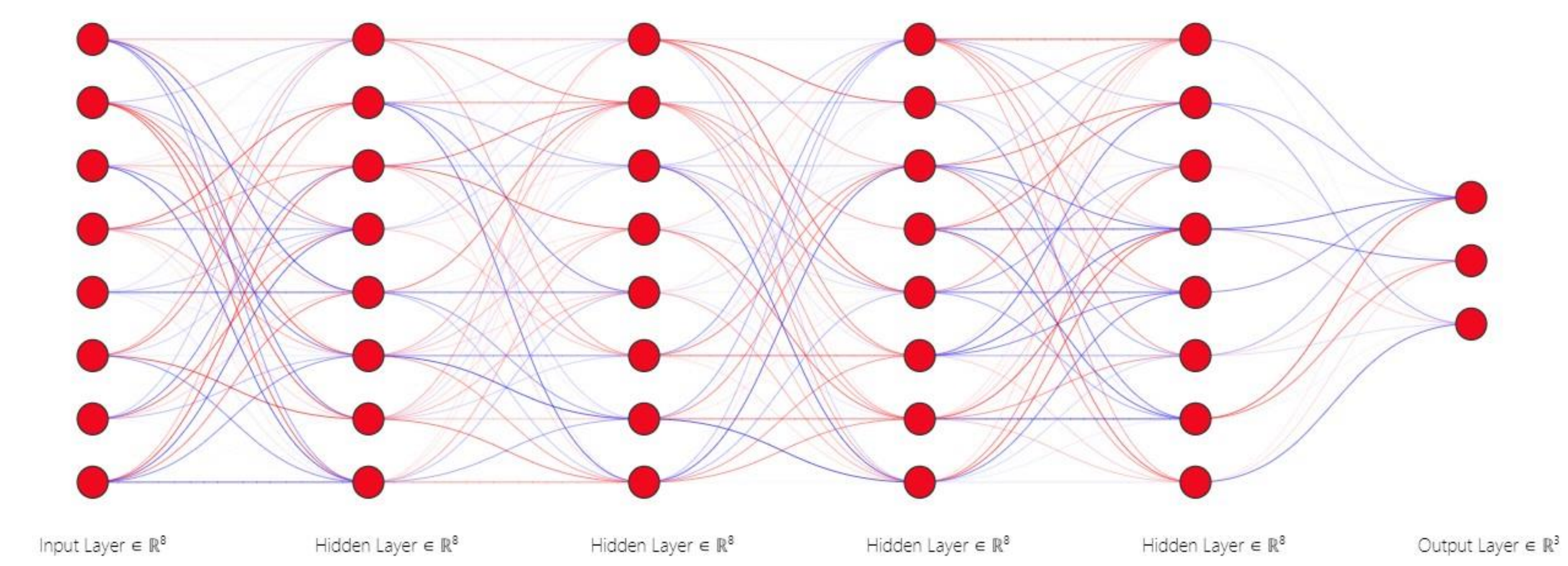
INTRODUCTION

In our dynamic world, optimizing human performance goes beyond conventional limits. Key to this pursuit is the accurate assessment of cognitive workload—a vital aspect of unlocking human potential. Neuro-Fusion, our pioneering approach, integrates advanced neural networks with EEG data, combining LSTM and GRU models for precise workload assessment. Fueled by EEG data from the STEW dataset, our Neuro-Fusion model achieved an impressive 96% accuracy, signaling its potential in precision-demanding scenarios.

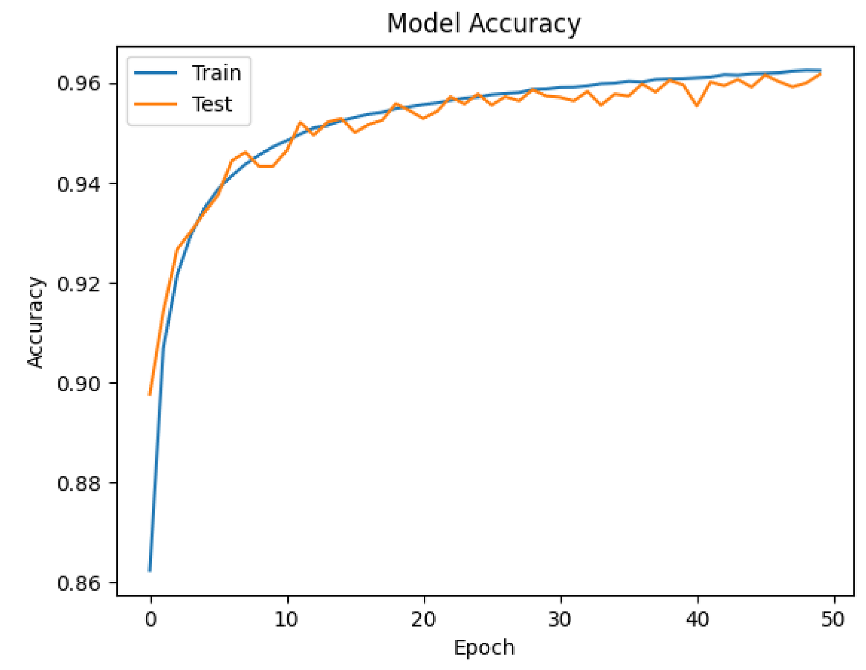
MATERIALS & METHODS

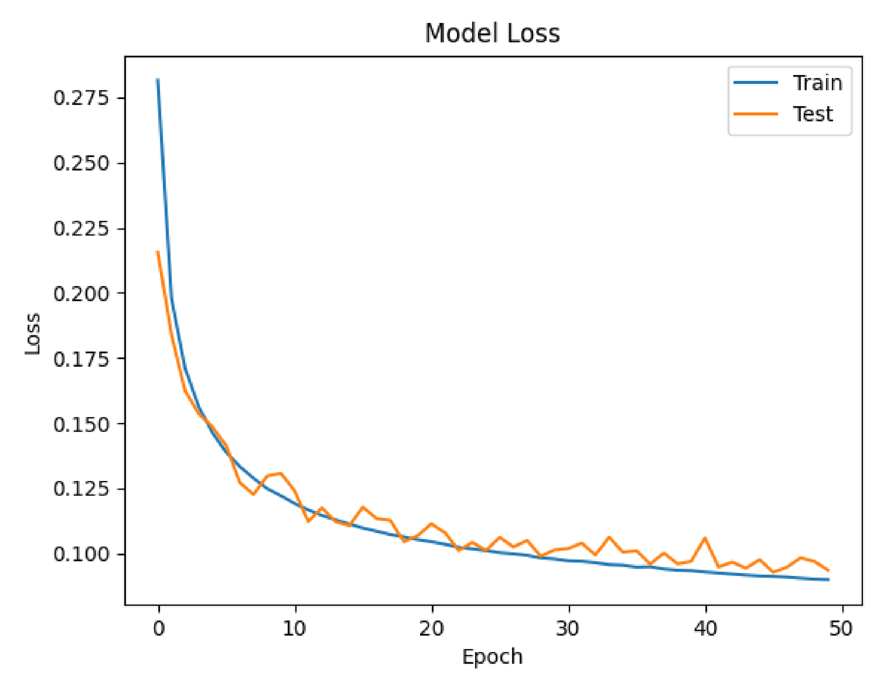
Neuro-Fusion Model: The hybrid deep learning model integrates LSTM and GRU layers. The LSTM and GRU layers are designed to capture temporal dependencies in the EEG data, enhancing the model's ability to assess cognitive workload accurately.

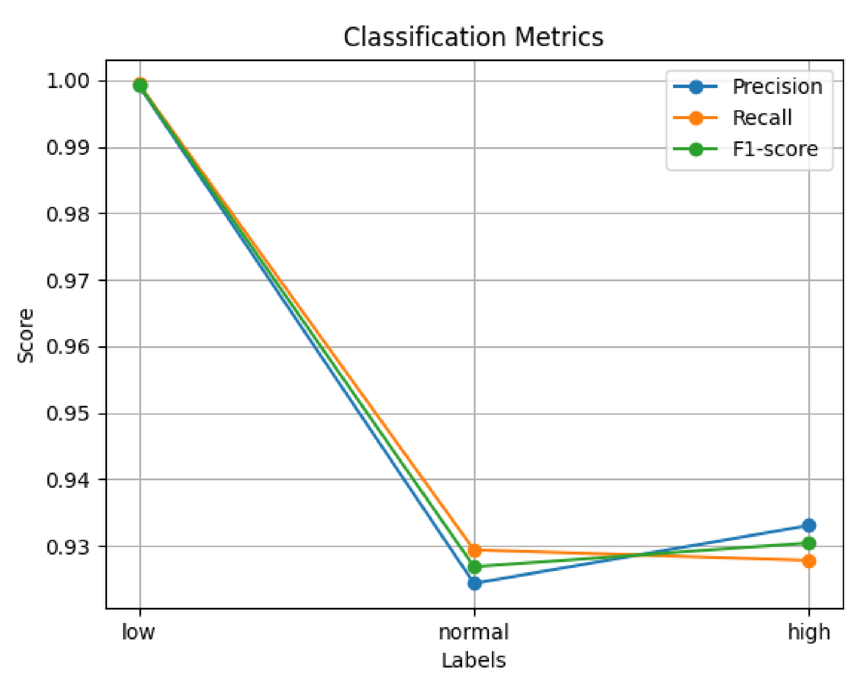


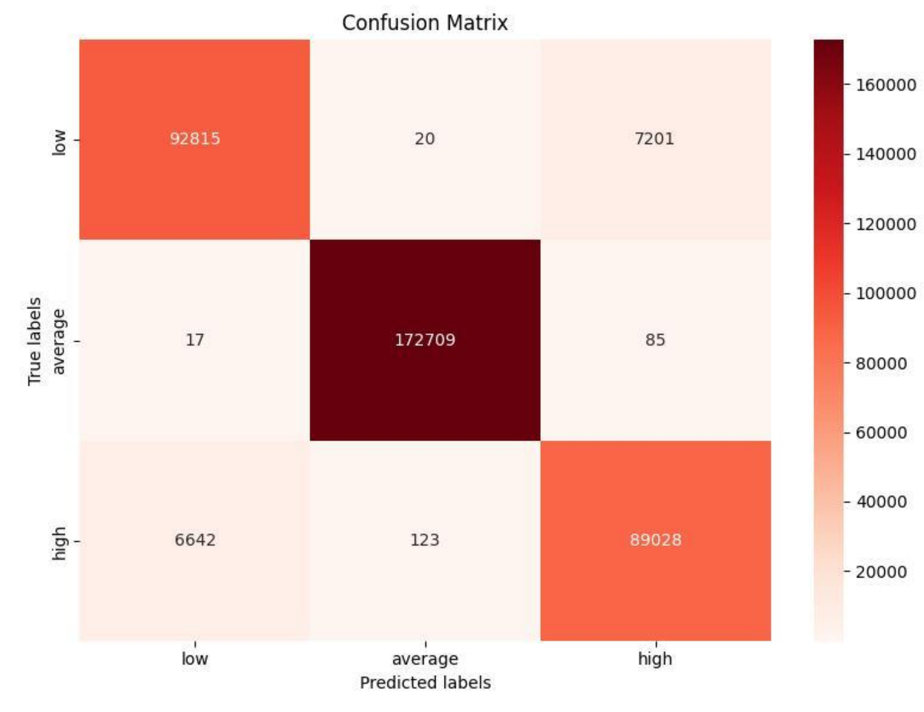
RESULTS

The Neuro-Fusion model excelled with a 96% accuracy and a minimal loss below 0.100 in real-time cognitive workload assessment. Beyond accuracy, evaluation metrics including precision, recall, and F1 score underscore the model's effectiveness.









CONCLUSION

In the ever-evolving landscape of optimizing human performance, our pioneering Neuro-Fusion model emerges as a transformative force in cognitive workload assessment. Seamlessly integrating LSTM and GRU neural networks with EEG data, our approach achieved an exceptional 96% accuracy in real-time cognitive workload assessment using the STEW dataset. This accuracy, coupled with a minimal loss below 0.100, underscores the robustness and reliability of our method, particularly crucial in precision-demanding scenarios.

Our model's efficacy is further validated by the confusion matrix, which demonstrates high correctness in predicting low, average, and high workload levels. The minimal off-diagonal values indicate rare misclassifications, reinforcing the model's proficiency in distinguishing cognitive states. Beyond accuracy, the inclusion of precision, recall, and F1 score as evaluation metrics reveals a well-balanced performance across all levels.

FUTURE RESEARCH

Future research endeavors should delve into refining and expanding the model's capabilities. Enhancing precision and adaptability by exploring advanced neural network architectures and incorporating additional physiological parameters beyond EEG data could elevate the model's performance.

REFERENCES

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