PREDICTION OF HUMAN PERFORMANCE USING EEG DATA TO IMPROVE SAFETY AND PRODUCTIVITY

Thesis submitted in partial fulfilment for the Award of Degree

Doctor of Philosophy

By

Gunda Yuga Raju

DEPARTMENT OF MINING ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY
(BANARAS HINDU UNIVERSITY)
VARANASI - 221005
(INDIA)

Roll No: 17151004

2023

6. Conclusion

6.1. Introduction

This chapter provides a comprehensive summary of the research findings and their implications in predicting cognitive performance using EEG and eye blink features. It begins by presenting an overview of the main findings obtained through the analysis of physiological indicators, highlighting the accuracy rates achieved by the developed machine learning models for assessing attention and working memory status. The chapter then discusses the contribution of the study to this research field, emphasising the novelty of incorporating EEG and eye blink features and the potential applications in various domains. It reflects on the limitations of the research, including sample size and generalisability, and offers recommendations for future research, such as integrating additional physiological measures and conducting longitudinal studies. Finally, the chapter concludes with a closing summary that recaps the main findings, contributions, limitations and recommendations, emphasising the importance of further advancements in assessing and optimising cognitive performance.

6.2. Overall Research Findings

The key findings of this research provide insights into the assessment of dynamic cognitive processes, the identification of performance indicators, the utilisation of advanced technologies and the effectiveness of computer-based assessment tools. These findings address the research questions as follows:

1. Reliable and Objective Assessment of Dynamic Cognitive Processes:

- The developed machine learning models, including KNN, decision trees, support vector machines and neural networks, demonstrated the ability to predict performance in attention and memory tasks with reasonable accuracies ranging from 75.42% to 83.90%.
- By utilising features extracted from EEG data, blink duration, blink interval and response time, these models provided an objective assessment of dynamic cognitive processes such as attention and working memory.

2. Identification of Performance Indicators and Metrics:

- The extracted features, including power values in different frequency bands, blink characteristics and response time, serve as potential performance indicators and metrics for evaluating the effectiveness of cognitive processes.
- These features can be incorporated into the machine learning models and can contribute to predicting performance groups, indicating their relevance in capturing cognitive effectiveness in challenging tasks or situations.

3. Utilisation of Advanced Technologies in Industrial Settings:

- The use of EEG data and blink characteristics as inputs to the machine learning models demonstrated the feasibility of utilising neuroimaging techniques and wearable devices to measure cognitive processes.
- These technologies provided a non-invasive and practical approach that can be implemented in industrial settings for assessing cognitive performance.

4. Effectiveness of Computer-Based Assessment Tools:

- The machine learning models developed in this research serve as effective assessment tools for evaluating cognitive performance in upcoming tasks.

- The achieved accuracies of the models indicate their potential to predict performance outcomes, thereby suggesting their usefulness as computer-based assessment tools.

Overall, the findings of this study address the research questions by demonstrating the potential for assessing dynamic cognitive processes, identifying relevant performance indicators and metrics, utilising advanced technologies in industrial settings and using computer-based programmes as effective assessment tools. These findings provide valuable insights into the field of cognitive assessment and highlight the potential of machine learning approaches in enhancing the understanding of cognitive processes and their impact on task performance.

6.3. Contribution to the Field

This study makes a significant contribution to the existing body of knowledge by incorporating EEG and eye blink features to predict cognitive performance. The novelty lies in utilising these physiological indicators as they provide valuable insights into attentional states and cognitive processes. EEG, with its high temporal resolution, allows for the assessment of brain activity associated with cognitive tasks, while eye blink features serve as an indicator of attentional status. By integrating these measures, the study enhances the understanding of the relationship between cognitive performance and neurophysiological markers, providing a more comprehensive approach to assessing cognitive abilities.

Furthermore, the use of machine learning techniques to develop predictive models adds another layer of significance. By leveraging the power of machine learning algorithms, the study demonstrated the potential for accurately predicting cognitive performance based on the extracted features. The developed models, such as KNN, decision trees, support vector machines and neural networks, showcased the versatility and effectiveness of these techniques in capturing complex relationships within the data. The application of these models extends beyond the specific cognitive tasks studied as they have the potential for implementation in various domains, including education, occupational safety, sports, human-computer interaction and simulator training. Overall, this research contributes to the growing body of knowledge by highlighting the value of EEG and eye blink features in predicting cognitive performance and showcasing the potential of machine learning techniques for practical applications in diverse domains.

6.4. Limitations of the Study

While this study provides valuable insights into predicting cognitive performance using EEG and eye blink features, it is important to critically evaluate its limitations. These limitations include:

1. Small Sample Size: The study was conducted with a relatively small sample size. While the participants were carefully selected, this limited sample size may restrict the generalisability of the findings to a larger population.

2. Specific Cognitive Task: The study focused on a specific cognitive task and the findings may be task-specific. Generalising the results to other cognitive tasks or real-world scenarios requires caution.

3. Individual differences: The study's participants may not represent the entire population in terms of age, gender and cognitive abilities. The findings may be influenced by the characteristics of the specific sample used in the study.

4. Machine Learning Model Selection: The choice of machine learning models, such as KNN, decision trees, support vector machines and neural networks, was based on the

researcher's discretion and the specific dataset. Other models could potentially yield different results and performance.

5. External Validity: The study was conducted in a controlled laboratory setting, which may not fully capture the complexities and variability of real-world environments. The findings need to be validated in diverse settings as well as larger and more diverse populations.

Addressing these limitations would enhance the robustness and applicability of the findings. Future research should consider larger and more diverse participant samples, investigate a broader range of cognitive tasks, explore alternative machine learning models and evaluate the practical implementation of the developed models in real-world scenarios such as high-pressure work settings or dynamic real-time tasks.

6.5. Recommendations for Future Research

Based on the findings and identified limitations, following several recommendations for implementation and future research can be made:

1. Integration of Additional Physiological Measures: To enhance the predictive accuracy of cognitive performance, future studies can explore the integration of additional physiological measures. For example, incorporating measures such as electrodermal activity (EDA) can provide complementary information about cognitive arousal and emotional states. Combining multiple physiological indicators may improve the robustness and reliability of predictive models.

2. Longitudinal Studies: Conducting longitudinal studies would be valuable to assess the stability of cognitive performance predictions over time. By tracking individuals' cognitive performance across multiple time points, researchers can investigate the consistency and reliability of the predictive models. Longitudinal studies can also provide

insights into the potential effects of various factors, such as age, training or cognitive interventions, on the stability of cognitive performance predictions.

3. Investigating the Impact of Different Cognitive Tasks: It would be beneficial to explore the impact of different cognitive tasks on the predictive models. As cognitive performance can vary across tasks, assessing a broader range of cognitive abilities and tasks would enhance the generalisability and applicability of the predictive models. Investigating the relationship between specific cognitive tasks and the performance of the predictive models can provide insights into the optimal selection of cognitive tasks for future applications.

4. Validation in Diverse Populations and Settings: To address the limitation of sample size and generalisability, future research should aim to validate the findings in larger and more diverse populations. This could include individuals from different age groups, cultural backgrounds and occupations. Additionally, testing the predictive models in real-world settings, such as high-pressure work environments or complex decision-making scenarios, would provide a more ecologically valid assessment of their effectiveness.

5. Exploration of Interpretability and Explainability: Further research can focus on enhancing the interpretability and explainability of the predictive models. Understanding the underlying mechanisms and features driving the predictions can provide valuable insights into cognitive processes. This could involve applying techniques such as feature importance analysis, model visualisation and extracting meaningful patterns from the data to enhance the interpretability of the models.

By implementing these recommendations, future research can advance the understanding of predicting cognitive performance. This knowledge can contribute to the development of effective assessment tools and interventions aimed at optimising cognitive abilities in various domains.

6.6. Conclusion

In conclusion, this study has provided valuable insights into the prediction of cognitive performance using EEG and eye blink features. The primary research questions regarding the assessment of dynamic cognitive processes, identification of performance indicators, utilisation of advanced technologies and the effectiveness of computer-based assessment tools have been systematically addressed. The developed machine learning models, including KNN, decision trees, support vector machines and neural networks, have demonstrated their ability to predict performance in attention and memory tasks with reasonable accuracies ranging from 75.42% to 83.90%. These models, utilising features extracted from EEG data, blink duration, blink interval and response time, offer an objective assessment of dynamic cognitive processes such as attention and working memory.

The study makes a significant contribution to the existing body of knowledge by incorporating novel physiological indicators and leveraging machine learning techniques to develop predictive models. The use of EEG and eye blink features enhances the understanding of the intricate relationship between cognitive performance and neurophysiological markers. The findings suggest potential applications in various domains, including education, industrial safety, sports, human-computer interaction and simulator training.

However, the study is not without its limitations. The relatively small sample size may restrict the generalisability of the findings and the focus on specific cognitive tasks raises concerns about the applicability of the results to broader cognitive domains or real-world scenarios. Individual differences among participants and the choice of machine learning models add further dimensions to the study's limitations.

Looking ahead, recommendations for future research have been outlined to address these limitations as well as to enhance the robustness of the findings. Integrating additional physiological measures, conducting longitudinal studies, exploring different cognitive tasks, validating findings in diverse populations and settings and improving the interpretability of predictive models are suggested avenues for further investigation.

In essence, this study not only advances the understanding of cognitive performance prediction but also highlights the potential for practical applications in diverse contexts. By continuously refining and expanding upon the current findings, future research in this field has the potential to revolutionise how cognitive abilities are assessed and optimised, ultimately leading to improved outcomes and human performance.