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EEG-Based TNN for Driver Vigilance Monitoring

Justin Sia
Faculty of Engineering and Information Technology
University of Technology Sydney
Sydney, Australia
justin.sia@student.uts.edu.au

Yu-Cheng Chang
GrapheneX-UTS Human-centric Artificial Intelligence Centre
University of Technology Sydney
Sydney, Australia
Yu-Cheng.Chang@uts.edu.au

Chin-Teng Lin
GrapheneX-UTS Human-centric Artificial Intelligence Centre
University of Technology Sydney
Sydney, Australia
Chin-Teng.Lin@uts.edu.au

Yu-Kai Wang
Faculty of Engineering and Information Technology
University of Technology Sydney
Sydney, Australia
yukai.wang@uts.edu.au

Abstract—**Transformer neural network (TNN) has demonstrated its remarkable capacity to analyze and discern complex sequential datasets. This approach has achieved unprecedented success, particularly in the domain of natural language processing (NLP). TNN has since consistently proven to perform remarkably in other fields where long-term dependencies in the data are prevalent. Electroencephalography (EEG) data has historically posed a challenge for even modern deep neural networks to classify as EEG is notably complex and noisy, making training laborious and time-consuming. Though, there has been significant research done recently into the application of TNNs in EEG classification, often the task involved does not infer the TNN's ability for long-term dependencies. In this paper, we propose a TNN-based model for EEG-based driver vigilance monitoring, emphasizing the classification of driver vigilance states. This study utilized the data of 11 subjects taken from a public EEG dataset, focusing solely on single-channel analysis. Results indicate that the proposed TNN model can achieve average accuracies of up to 92.69% for Single-Subject analysis, 94.09% for Cross-Subject analysis and 74.74% for Leave-One-Subject-Out analysis, which surpasses state-of-the-art methods. The proposed TNN model's potential lies in not only driver vigilance state monitoring but also paving the way for broader applications of biosignal processing.**

Keywords— Transformer Neural Networks, Electroencephalogram, Driver Vigilance, Classification

I. INTRODUCTION

The detection and classification of driver vigilance has become increasingly important as it offers enhanced road safety by mitigating drowsy-driving accidents. Developing a real-time detection system that can monitor and assess a driver's vigilance level represents a crucial advancement in this sphere [1]. Among the myriads methods, electroencephalography (EEG) -based detection has garnered interest due to the valuable insights that brain activity measurements offer, amplified by its widespread applications in neuroscience, clinical diagnostics, and brain-computer interfaces (BCI) [2]. Yet, the intricacies of EEG data present hurdles for traditional deep neural networks, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) [3]. Conventional EEG data analysis techniques often rely on manually designed feature extraction and filtering methods, which are both intricate and resource-consuming.

The landscape of deep learning models was transformed by the advent of the Transformer Neural Networks (TNNs) by Google Brain, which leverages the self-attention mechanism for sequential data analysis [4]. The innovation has sparked development of groundbreaking pre-trained models such as GPT-4 and T5 which have completely revolutionized the field of natural language processing and generation [5], [6]. TNNs have also proven their versatility by demonstrating their efficacies in other domains, such as image recognition and human pose estimation [7], [8]. In each case, the TNN was specifically designed and trained for the tasks and surpassed traditional methods.

Models like EEGNet, CNNs, and LSTMs have been employed for driver vigilance classification using EEG signals, yielding satisfactory results [9]. Nonetheless, there remains room for improvement in handling the complexities inherent in EEG data. Inspired by the shared time-dependent characteristics between auditory signals and EEG data, both of which record dynamic changes over time and demand accurate temporal analysis, we propose the usage of TNNs for this time-sensitive EEG signal classification [10]. The self-attention mechanism within TNNs, which emphasizes relevant data segments while minimizing noise, offers a promising avenue for EEG data processing. This can potentially reduce or remove the need for hand-crafted feature extraction and automatically filtering EEG data [11]. Additionally, the long-term dependency handling ability of TNNs is particularly advantageous for large sequential data, such as driver vigilance recordings, where context is crucial [12].

Despite TNN's infancy, its applicability to EEG data classification, has been substantiated. One study applied a variant of Google's BERT TNN for EEG data, though accuracies fell short of existing models [13]. Other research demonstrated 'gated transformers' outperforming conventional methods on BCI tasks, and the synergistic power of combined CNN and transformer networks for time series data [14], [15]. A distinct study classified raw EEG data using TNN, indicating potential for automated feature extraction, and hinted at performance enhancement through TNN specific modifications for EEG data [11]. Cumulatively, these findings underscore the potential of TNNs in EEG data classification. While these studies have highlighted the effectiveness of TNNs for extracting temporal features like in emotion recognition and short stimuli tasks such as motor imagery, there remains an evident lacuna in assessing TNNs capability for long-dependent features in EEG data.

Addressing this gap, the paper contributes to the growing body of research on EEG data classification. Specifically, we are the first to harness TNNs for the nuanced, time-sensitive task of driver vigilance state monitoring. While previous studies have explored the use of TNNs for EEG data for other tasks, the application to the specific problem of driver vigilance classification presents a novel contribution. Through

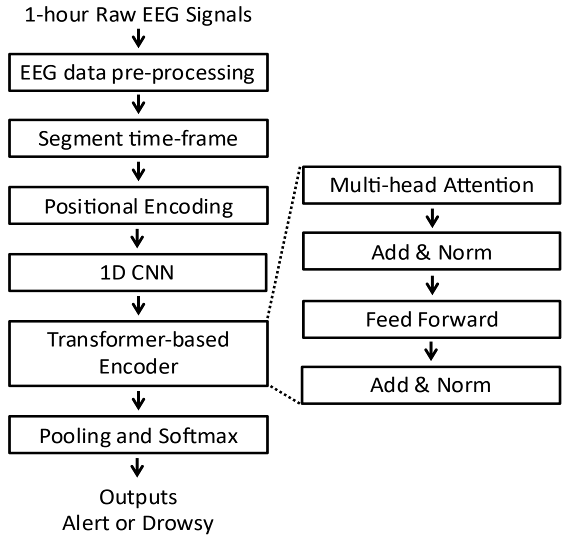

Figure 1. EEG-based TNN Model: The figure presents the architecture of a TNN model designed for EEG data analysis. The model begins with a positional encoder that assigns unique positions to each data point in the EEG data, enabling the model to recognize the sequence of the data. Following the positional encoding, a one-dimensional convolutional layer (Conv1D), activated by a Rectified Linear Unit (ReLU), is applied to extract local features from the EEG data. The processed data is then passed through stacks of encoders, each consisting of multi-head self-attention and feed-forward network sub-layers, for further transformation and analysis. Finally, the output of the TNN model is passed through a pooling layer and a softmax function for classification. This sequential architecture effectively harnesses the potential of TNN for EEG data analysis.

this, we aim to leverage the power of TNNs to potentially improve the accuracy, efficiency, and reliability of vigilance detection systems, thereby enhancing road safety.

II. Methodology

A. TNN Model

The TNN model used, shown in Figure 1, consists of stacks of encoders with two sub-layers, multi-head self-attention and feed forward network. To effectively harness the potential of TNN for EEG data analysis, our model incorporates two key additions: a positional encoder and a one-dimensional convolutional layer (Conv1D).

Unlike traditional methods such as the LSTM, the TNN model inherently lacks a mechanism for capturing the sequential information of the input data, which is critical to be able to understand the context of a data series. In the field of NLP, a tokenizer is typically employed prior to the positional encoder to breakdown sentences into separate text data, called ‘tokens’. These tokens subsequently serve as a basis for position assignment. However, EEG data lacks explicit textual differentiators such as letters, words, or punctuation marks. To address this, our model subdivides the EEG data into epochs representing discrete data points that mirror the temporal progression of brain wave patterns. A unique position is assigned to each point via a positional encoder, permitting the model to learn the positional relationships within the EEG data. This approach imparts the necessary sequence recognition capabilities to the TNN model, making it more effective for EEG data analysis.

A Conv1D layer is also introduced prior to the input data being processed by the TNN encoders. Activated by a Rectified Linear Unit (ReLU) function, the Conv1D layer serves a critical role in the extraction of local features from the input data and thereby enhancing the EEG data representation and improving the model's ability to recognise critical patterns in the data.

B. Dataset

We utilised a public EEG dataset involving a simulated driving task designed to induce different states of vigilance. A sustained attention driving task was designed in a virtual reality driving simulation [16]. Twenty-seven participants were instructed to drive the car while maintaining its position in the centre of the lane with assistance of cruising control at fixed speed 100 km/hour. To mimic minor alterations in road curvature or obstacles like stones that cause the car to drift, random lane-departure events were introduced, which shifted the car to the left or right of the central lane. The subjects were required to stay attentive throughout the experiment and promptly respond to lane-departure events by steering the car back to the centre of the lane. Each lane-departure event constituted an "epoch" consisting of a baseline period, deviation onset (when the car begins drifting), response onset (when the participant starts turning the wheel), and response offset (when the car repositions in the central lane). During driving, the drivers’ brain dynamics were recorded via 32-channel EEG equipment.

The data is then further processed as detailed in [17], the baseline alert response time (RT) is set at the 5th percentile of all session RTs. Epochs are labeled either 'alert' when both local and global-RT are less than 1.5 times the alert-RT, and 'drowsy' when they exceed 2.5 times the alert-RT. This is done to exclude the transitioning states. Out of 27 subjects, data from 11 were selected based on how balanced they were. Each data was then further filtered by selecting the most representative from the majority class. Shorter reaction times (RTs) were chosen for the alert class and longer RTs for the fatigue class, ensuring an equal number of each label in the final data used in the training.

C. Experiment Setup

An essential facet of the experiment preparation was data processing. We started by down-sampling and bandpass filter our EEG data to 128Hz and 1-50 Hz, taking 3-second epochs prior to each epoch's deviation onset. We performed single-channel analysis, focusing on the central channels – Fz, FPz, Pz, CPz, Cz, Oz, which cover areas over the major brain regions including frontal, central, parietal, and occipital regions. These areas are associated with motion and cognitive functions in driving tasks [3], [9], [17-18]. This allowed us to investigate the efficacy of using single-channel EEG classification as it is more cost-effective, less intrusive, and more comfortable for participants. However, we acknowledged that while single-channel analysis has these benefits, it offers a more limited view of brain activity compared to multi-channel EEG.

In this study, we conducted three distinct predictive modelling experiments to classify the driver’s states. These experiments, structured around different training and testing paradigms, served to explore the diverse facets of vigilance classification from EEG data. All experiments were done with and without the one-dimensional convolutional layer to

TABLE 1. TEST ACCURACY

CHANNEL NAME	*Single-Subject*	*Cross-Subjects*	*Leave-One-Subject-Out*	*Single-Subject (W/O 1D-CNN)*	*Cross-Subjects (W/O 1D-CNN)*	*Leave-One-Subject-Out (W/O 1D-CNN)*
Fz	88.47	86.04	70.15	74.81	70.09	70.53
FCz	91.33	79.22	71.64	76.42	67.52	72.15
Cz	91.70	81.65	73.49	76.48	69.39	**72.66**
CPz	92.47	89.87	**74.73**	**77.16**	75.61	69.79
Pz	**92.62**	**94.09**	72.88	76.77	**83.78**	67.45
Oz	90.32	82.65	71.74	74.77	77.96	68.08

TABLE 2. F1 SCORE

CHANNEL NAME	*Single-Subject*	*Cross-Subjects*	*Leave-One-Subject-Out*	*Single-Subject (W/O 1D-CNN)*	*Cross-Subjects (W/O 1D-CNN)*	*Leave-One-Subject-Out (W/O 1D-CNN)*
Fz	88.28	85.04	71.05	69.44	71.22	72.57
FCz	91.08	78.09	71.87	72.79	65.95	**73.69**
Cz	91.46	80.59	71.83	74.42	69.88	73.41
CPz	92.36	89.18	**74.34**	**74.88**	74.37	70.97
Pz	**92.62**	**93.64**	74.08	73.28	**83.78**	68.29
Oz	90.29	82.32	71.35	71.59	79.68	67.41

TABLE 3. ROC-AUC METRIC

CHANNEL NAME	*Single-Subject*	*Cross-Subjects*	*Leave-One-Subject-Out*	*Single-Subject (W/O 1D-CNN)*	*Cross-Subjects (W/O 1D-CNN)*	*Leave-One-Subject-Out (W/O 1D-CNN)*
Fz	0.9411	0.9187	0.8027	0.8240	0.7884	0.7924
FCz	0.9685	0.8763	0.8132	0.8482	0.7666	0.7906
Cz	0.9694	0.9016	0.8324	**0.8623**	0.7867	**0.7998**
CPz	0.9711	0.9515	**0.8384**	0.8532	0.8569	0.7905
Pz	**0.9726**	**0.9834**	0.8108	0.8527	**0.9116**	0.7769
Oz	0.9553	0.9279	0.7806	0.8243	0.8723	0.7840

quantify the layer's contribution to feature extraction and pattern identification.

The first experiment, "Single-Subject Prediction", involves training and testing using each subject's individual EEG data. The objective is to leverage the model's capacity to discern and predict unique vigilance-associated patterns and characteristics inherent to each subject. This investigation primarily answers how effectively an individual's vigilance state can be modelled from their exclusive physiological patterns using a TNN neural network.

The second experiment, "Cross-Subject Prediction", involves a comprehensive approach, where the model is trained and tested on the collective EEG data from all eleven subjects. This investigation explores the ability of the model to identify and predict vigilance-related features from a larger, more diverse dataset, encompassing the vigilance patterns of all participating subjects. The objective here is to assess the model's efficacy when exposed to a broad array of vigilance-related EEG patterns and its capacity to generalize over a wider spectrum of individual variations.

The third experiment, referred to as "Leave-One-Subject-Out Prediction", adopts a generalized methodology. Under this paradigm, the model is trained on EEG data from ten subjects, and subsequently, its performance is evaluated on a distinct held-out subject. The aim here is to probe the model's generalizability and its capacity to extract and apply broad vigilance-associated features across a heterogeneous group of subjects. This approach is designed to answer whether common indicators of vigilance can be extracted from a diverse dataset and successfully applied to a separate individual.

Altogether, these three experiments provide a holistic evaluation of the capabilities of TNNs in vigilance state prediction. This multi-tiered approach enables a more comprehensive understanding of the model's versatility and adaptability in handling varied and complex data, thus enhancing its potential applications in real-world scenarios.

For performance evaluation, we employ multiple metrics including accuracy, F1 Score, and Receiver Operating Characteristic Area Under Curve (ROC-AUC). These metrics are chosen to provide a well-rounded view of the model's performance. While accuracy measures the overall correctness of the model's predictions, the F1 score offers insights into its precision and recall, useful in contexts of uneven class distributions. Additionally, ROC-AUC measures the model's discriminative power across varying classification thresholds. These indices are calculated for each EEG channel and averaged over multiple iterations, providing a comprehensive assessment of our model's performance.

III. Results and Discussion

Table 1 details the accuracy of our model across Single-Subject, Cross-Subjects, and Leave-One-Subject-Out classifications, with and without the Conv1D. In both Single-Subject and Cross-Subjects classifications, the Pz channel proved most optimal, yielding accuracies of 92.69% and 94.09%, respectively. In the Leave-One-Subject-Out classification, the CPz channel achieved the highest accuracy

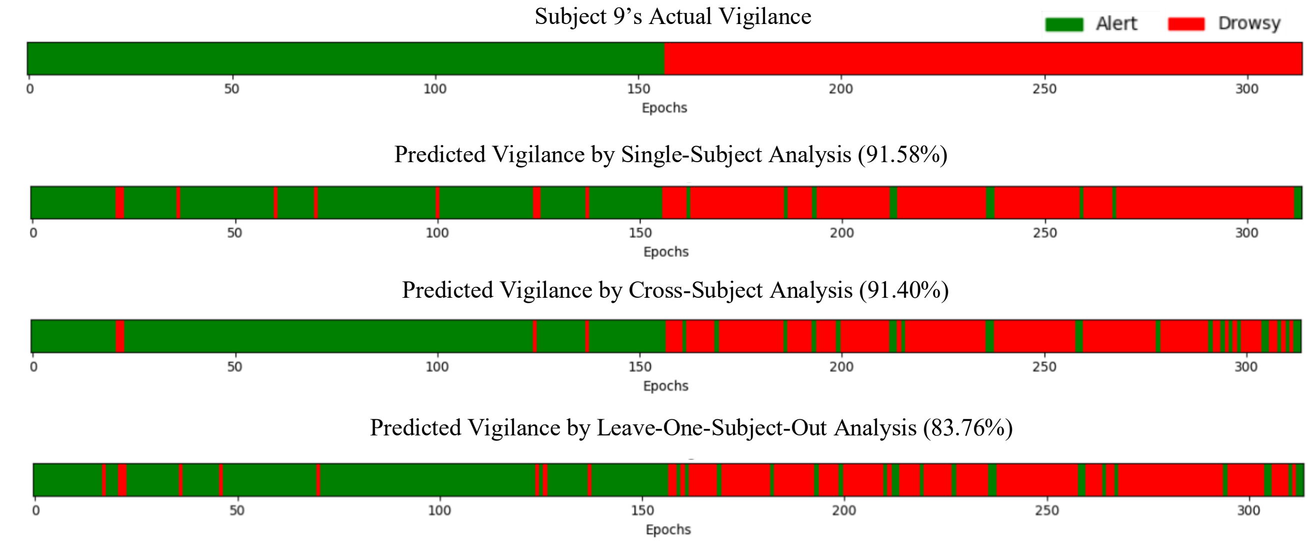

Figure 2. The outcomes of TNN-based EEG Analysis for Driver Vigilance Monitoring. The first line shows the selected subject 9's actual vigilance. The following lines shows the predicted vigilance across Single Subject, Cross Subject, and Leave-One-Subject-Out analysis.

of 74.73%. The Fz channel generally showed lower accuracy, with the lowest being 70.15% in the Leave-One-Subject-Out classification. The use of the Conv1D typically improved accuracy across all classifications.

We also observed that the individual channel differences could play a significant role in the model's performance as highlighted by the range of accuracy rates across subjects and channels. This prompts further investigation into the factors that may contribute to such variation, such as differences in individual brain wave patterns and how they're captured by different EEG channels. Certain EEG channels, particularly the Pz and CPz channels, consistently yielded higher accuracy rates in Single-Subject, Cross-Subjects, and Leave-One-Subject-Out classifications. This could be due to these channels' specific scalp locations, potentially capturing more relevant neural activity for the task at hand.

In comparing our findings to a similar study mentioned earlier, we found that our TNN model has performed slightly better than conventional methods such as EEGNet and Deep CNN and also outperformed their proposed model which had the highest accuracy in their paper of 73.22% [17]. It's worth noting that the difference, though modest, could be significant considering the challenges associated with Leave-One-Subject-Out EEG analysis, such as inter-individual variability in brain activity patterns and EEG signal quality.

However, our study has limitations. While our sample size was sufficient to demonstrate our model's potential, larger and more diverse datasets are needed to verify its effectiveness across a broader range of individuals. Furthermore, our single-channel approach, while beneficial in simplifying data collection and computation, may limit the model's ability to capture the full complexity of brain activity.

IV. Conclusion

The application of transformer-based models for driver vigilance monitoring is a promising approach. This research demonstrated its potential by delivering high accuracy rates across different classifications, with the highest being 94.09% in the Cross-Subjects classification at the Pz channel. While these initial results are promising for real-time monitoring of driver alertness, further investigation is required to enhance the model's universality across diverse individuals and to evaluate the amalgamation of multiple channels for even greater precision in detecting different states of vigilance.

The integration of TNN architecture in EEG analysis heralds a novel paradigm in driver vigilance systems. As advancements continue, transformer-based models are poised to revolutionize the tools available to offer more nuanced insights into a driver's alertness and cognitive state.

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