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E-Key: an EEG-Based Biometric Authentication and Driving Fatigue Detection System

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***Abstract*—Due to the increasing fatal traffic accidents, there are strong desire for more effective and convenient techniques for driving fatigue detection. Here, we propose a unified framework – *E-Key* to simultaneously perform personal identification (PI) and driving fatigue detection using a convolutional attention neural network (CNN-Attention). The performance was assessed using EEG data collected through a wearable dry-sensor system from 31 healthy subjects undergoing a 90-min simulated driving task. In comparison with three widely-used competitive models (including CNN, CNN-LSTM, and Attention), the proposed scheme achieved the best (p $<$ 0.01) performance in both PI (98.5%) and fatigue detection (97.8%). Besides, the spatial-temporal structure of the proposed framework exhibits an optimal balance between classification performance and computational efficiency. Additional validation analyses were conducted to assess the reliability and practicability of the model via re-configuring the kernel size and manipulating the input data, showing that it can achieve a satisfactory performance using a subset of the input data. In sum, these findings would pave the way for further practical implementation of in-vehicle expert system, showing great potential in autonomous driving and car-sharing where currently monitoring of PI and driving fatigue are of particular interest.**

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***Index Terms*—Convolutional Neural Network, Driving Fatigue, EEG, Authentication, Biometric,**

I. Introduction

PROLONGED driving task will typically lead to performance decline of drivers, impairments of control and judgment abilities, even fall into sleep during driving. In fact, driving fatigue is a common experience for most drivers, and it has long been recognized as a serious threat to public safety. Evidence has showed that 15% - 20% of fatal traffic accidents are associated with driving fatigue [1]. Continuous efforts have been made to establish a feasible and practical driving fatigue detection method to prevent driving-fatigue related casualty and economic losses [2].

Most recently, the driving fatigue detection method takes advantage of extracting different features, including *i*) physiological features (i.e., electroencephalogram (EEG) [3]–[5], electrocardiogram (ECG) [6] and electromyography (EMG) [7], [8] and electrooculogram (EOG) [9]), *ii*) measures of driver's performance (i.e., facial morphological features [10], eye blinks [11], [12], yawn motion [13]), *iii*) measures of vehicle's state (i.e., steering wheel motion [14], lane deviation [15]–[17]), and *iv*) the combination of the aforementioned features [18]. Recently, Melnicuk and colleagues presented an excellent review pertaining to the research trends in the area of driver state monitoring through incorporating technologies that are able to record multiple features [19], providing new insights that are relevant for reaching optimal driving performance. Among these features, physiological signals have gained substantial attention for its direct assessment of fatigue status of drivers [2] that are independent of environmental conditions. Particularly, EEG signals have convergently been proven to be a robust biomarker for driving fatigue detection [5], [20]–[23].

It is noteworthy mentioning that most of the aforementioned studies were performed in a fashion of within-subject detection of driving fatigue, largely due to convergent evidences have shown that the perceive of driving fatigue is indeed subject-dependent with substantial individual differences in behavioral performance and brain activities [24]–[26]. It is often a problem that limits the practicability of physiological-signal-based techniques in driving fatigue detection. To this end, accumulating efforts have been made to improve the transferability of the model across different subjects [27], with an implicit assumption of the same distribution of the

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recorded data and same feature space [28], [29]. However, the statistical distribution may vary across subjects [25], [26] and the non-stationary nature of physiological signals may further enlarge the distribution difference among subjects [30]. An alternative approach to improve the practicability of driving fatigue detection method towards in-vehicle expert systems is to apply personal identification (PI) prior to driving fatigue detection, which would simplify the complex issue of cross-subject fatigue detection to within-subject fatigue detection.

Conventionally, authentication was achieved through biometrics including fingerprint [31], iris [32], and face [33]. In 2007, Marcel and Milan introduced a new framework incorporating EEG for person authentication that open new research directions and applications [34]. On that premise, physiological signals like EEG have merits of reliable PI and long-term recording for driving-fatigue detection [34], [35]. It can therefore be inferred that an efficient framework for practical driving fatigue detection based upon EEG signals would benefit from PI. However, there is no study, to the best of our knowledge, has explored the feasibility of utilizing EEG to achieve PI and detect driving-fatigue at the same time. This research gap has been a key motivation for this study, which aims to expand the existing state-of-the-art method in regard to multi-task of PI and driving fatigue detection.

Convolutional neural network (CNN) is a useful tool that has been widely used in the pattern recognition such as image recognition [36], classification of handwritten [37], natural language processing [38] and face recognition [39]. Heuristically, CNN is a specialized kind of neural network for processing input data that has an inherent grid-like topology. That is, the nearby entries for the input data to CNN are correlated and the example of this kind of input is the 2-dimension image. Therefore, CNN has been increasingly applied in various applications ranging from cancer diagnosis [40] to EMG/ECG/EEG signal classification [41], [42]. Particularly, several recent studies utilized CNN model for driving fatigue detection and achieved satisfactory performance [43]–[47]. These studies shed new insights for more feasible and applicable driving fatigue detection system.

In this study, non-invasive EEG signals were recorded using 24 sensors that might have inherent correlation between sensors. Hence, CNN model was used to distinguish the driving fatigue state and perform PI with recorded EEG signals. Conceptually, CNN is superior in automatic feature extraction involving large datasets [48]. However, EEG is temporal sequence signals where two consecutive moments are correlated. Traditional CNN model does not have memory mechanism that can process the correlation of sequential inputs, leading to information loss. In this study, we introduced an analysis framework that combines CNN with the attention mechanism. Such a mechanism has been widely used in natural language processing for the modelling of long-term memory [49]. The underlying logic of our model is that not all channel signals contribute equally to related classification, and the correlation within one channel signal involves in the fatigue state detection or the PI.

With the aim to develop a practical in-vehicle system for driving fatigue detection, the present study introduced a unified CNN-Attention based framework that could concurrently achieve PI and driving fatigue detection using the same EEG data. The arrangement of our study is organized as follows. Section II shows the method and materials of our study, which introduces the characteristics of participants, the experimental protocol, the EEG data acquisition and the preprocessing, the fatigue state determination based on objective behavioral performance, the CNN-Attention model and the classification method. In Section III and IV, we presented the results and discussion. The conclusion of the current work was presented in Section V.

II. Methods & Materials

A. Participants

Participants for this study were 31 healthy subjects (male / female = 18 / 13, age = 23.13 $\pm$ 2.68 years) recruited from National University of Singapore (NUS). Each subject should have considerable driving experience, i.e., as having local driving licence. All participants reported normal or corrected-to-normal vision and had prior experience in simulated driving environment that was confirmed via a self-administered questionnaire prior to the experiment. Participants were additionally prescreened to meet the inclusion criteria, including no history of fatigue-related disorders, chronic physical or mental illness. On the day of the experiment, participants were requested to refrain from caffeine or alcohol consumption and from undertaking strenuous exercise 4-h preceding the recordings. Participants who failed to obtain a full night of sleep (> 7-h) for two nights prior the experiment were re-scheduled. Subjects were further instructed to wash their hair on the day of experiment to facilitate the following EEG recordings. This study was approved by the Institutional Review Board of the NUS an was conducted in accordance wit the Declaration of Helsinki. Written inform consent was obtained from all participants.

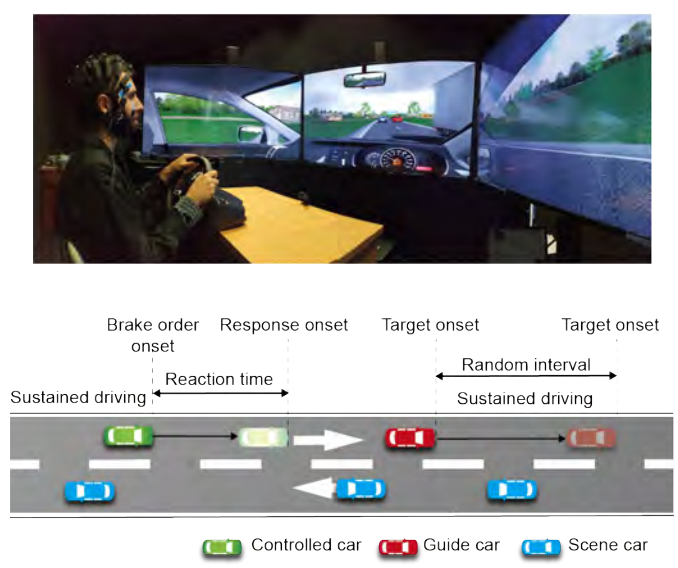

Fig. 1. The experimental setup and protocol.

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B. Experimental Protocol

To effectively represent the driving fatigue state of subjects, we carefully design the experiment so that we can acquire the valuable data efficiently. To achieve a more authentic driving experience, we arrange the environment (i.e., light, sound effect, etc.) as real as possible so that the subject could feel they are indeed in an expressway. In addition, to reduce the complexity of the assessment, we only consider the time factor for each subject rather than other elements like subject's cooperative attitude [46].

Specifically, simulated driving experiment was conducted in a conventional simulation setup (Fig. 1), which includes a simulated driving system (model: Logitech G27 Racing wheel simulator) and three 65-inch LCD screens placed to show one in-front and two-sided rear-view. The simulated driving experiment was customized in the City Car Driving version 1.5 (www.citycardriving.com) and the driving rules complied with Singapore's traffic regulations. Based upon results in previous driving fatigue studies [7], the duration of the task was set at 90 min for salient fatigue effect. The detailed experimental protocol was introduced in our previous study [49], [50]. Briefly, a safe distance paradigm was used. During the experiment, the driver will randomly receive brake signal elicited from the guide vehicle in front of the subject car with the lighting up of the rear lamp, where subjects were required to respond to the brake signal. The brake signal of the guide car was generated with random in-between intervals. The latency between the brake order in the guide car and brake operation made by the participant was considered as the reaction time (RT). The speed variation of the subject car was also collected for the determination of fatigue state. Given the well-known association between circadian rhythm and mental fatigue [51], we have arranged our experiment between $3-5$ pm to control this potential confounding factor.

C. Data Acquisition and Preprocessing

The EEG signal were collected using the remote Cognionics headset (Model: HD-72, Cognionics Inc., USA) with 24 dry-sensors on the subject's scalp according to the international 10-20 system. The reference electrodes were the right and left mastoids. Both horizontal and vertical electrooculogram (EOG) were recorded from electrodes placed at the outer canthi as well as above and below the right eye. The impedance of sensors was kept below 20kΩ throughout the experiment. The collected EEG signal was sampled at 250 Hz. The collected signals were transmitted to a laptop (Toshiba Intel(R) Core (TM) i5-6200U Duo 2.4 GHz) by a Bluetooth module for further data analysis.

A previous-validated EEG preprocessing pipeline was adopted here. Briefly, the raw EEG data were band-pass filtered into $1-40$ Hz using an FIR filter. Main interferences were avoided by anti-aliasing with a 50 Hz notch filter. Then the filtered EEG signal were re-referenced to the average of signals from all channels. Artifacts (including motion and eye movements) removal were performed via independent component analysis [52]. Specifically, the components with high correlation coefficient with EOG signals were removed. Similar to our previous work [22], continuous data rejection was also performed, i.e., data with power over 6 db in high frequencies (20 – 40 Hz) were discarded. EEG data preprocessing were carried out with in-house codes implemented in Matlab (Mathworks Inc., USA) using EEGLAB toolbox [53].

D. Fatigue State Determination

Conceptually, mental fatigue is accompanied by worsening performance, seen in an increased propensity for errors and slowed reaction times [54]. Therefore, the objective behavioral measures were estimated and quantitatively compared to determine the most vigilant and fatigued state. Specifically, the behavioral performance of each subject within a 10-min window was obtained where the first 10-min with the lowest RT and minimum speed variation was considered as the vigilant state whereas the last 10-min with the highest RT and maximum speed variation was determined as the most fatigued state. Following statistical comparison showed that there was statistically significant ($p < 0.01$) difference of the behavioral performance between the two states (Fig. 2). Therefore, the first 10-min and the last 10-min were adopted here to represent the most vigilant and most fatigued state in the current work. Data from these two windows were used for the following driving fatigue detection model.

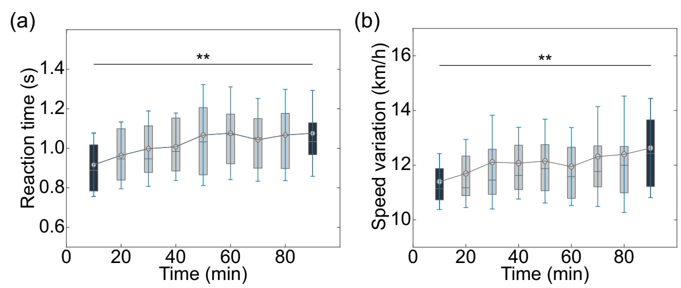

Fig. 2. The (a) reaction time and (b) speed variation in 10-min bin for the simulated driving task. The red metrics within the 1st and last bin were corresponding to the most vigilant and fatigued state respectively. **, $p < 0.01$.

E. CNN-Attention structure

1) Input data: In this study, we develop a unified CNN-Attention model for PI and the classification of driving fatigue state. As it is shown in Fig. 3, same EEG data sets were set as input for PI and driving fatigue detection. Briefly, EEG data within the first 10-min that corresponding to the vigilant state was set as input for PI, EEG data within the last 10-min that corresponding to the fatigued state was additionally included for driving fatigue detection. Specifically, the input data of the network is a 1-sec duration of EEG signal (corresponding to 1 label) with a size of 24×250 without any overlap. The arrangement of the EEG channel were maintained according to the recording setup. Hence, there were 600 labeled EEG signal (i.e., 60 sec $\times$ 10-min with label 1:31 corresponding to different participants) for PI and 1200 labeled EEG signal (i.e., 60 sec $\times$ 10-min of vigilant with label 1 and 60 sec $\times$ 10-min of fatigue with label 2) for driving fatigue detection. A 10-fold cross validation approach was adopted here to assess the

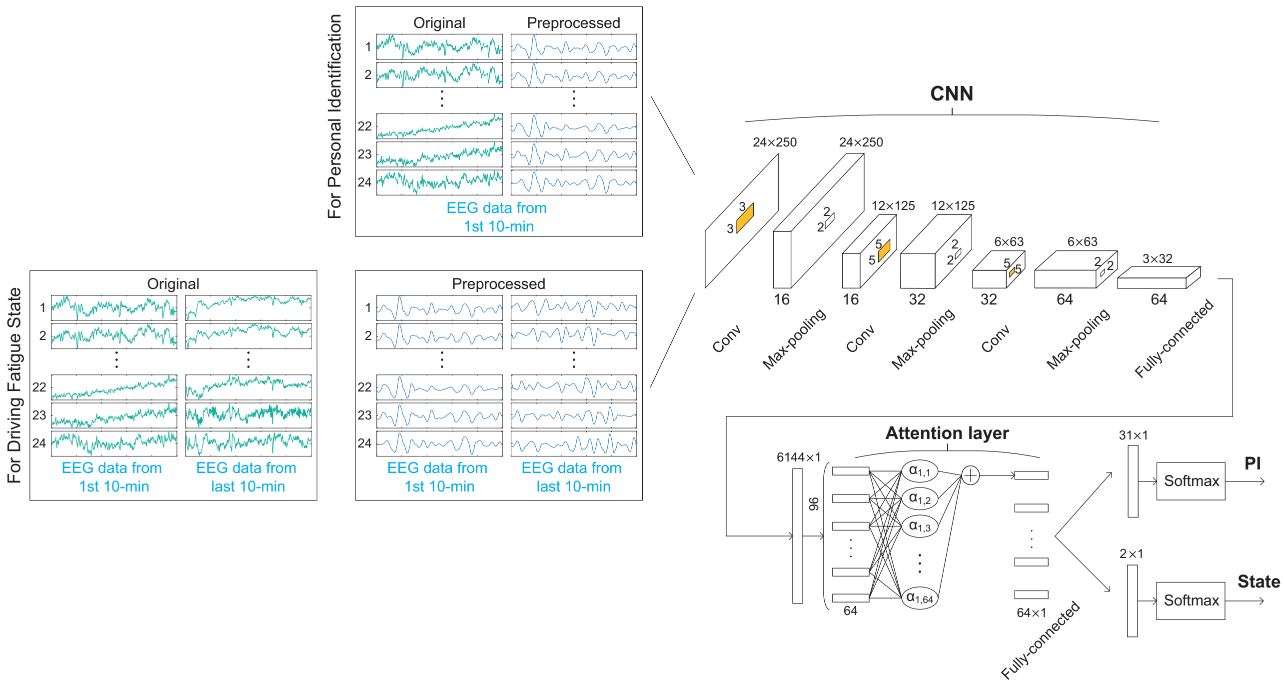

Fig. 3. The structure of the proposed CNN-Attention model. Same EEG signals were used for both PI and driving fatigue detection.

classification performance where 90% EEG signals from the sample data was set as the training dataset and the remaining 10% were used as the testing dataset.

TABLE I
STRUCTURE OF THE PROPOSED CNN-ATTENTION NETWORK

Type	Filters	Size/Stride	Input	Output
Conv1	32	3×3/1	24×250	24×250×16
Max-pool1		2×2/2	24×250×16	12×125×16
Conv2	64	5×5/1	12×125×16	12×125×32
Max-pool2		2×2/2	12×125×32	6×63×32
Conv3	128	5×5/1	6×63×32	6×63×64
Max-pool3		2×2/2	6×63×64	3×32×64
ATT			64×96	64×1
Fully connected			64×1	31×1 or 2×1
Softmax			31×1 or 2×1	a probability

2) Network structure: In the proposed CNN-Attention structure, we have three convolutional layers, three max-pooling layers, two fully-connected layers and one attention layer (Table I). Here, each convolutional layer has different sizes of convolutional kernels that can be regarded as a fuzzy filter, which enhances the original signal characteristics and reduces noise. The representation of each convolutional layer can be written as:

$$x_j^l = f\Big(\sum_{i \in M_j} W_{ij}^l \times x_i^{l-1} + b_j^l\Big) \quad (1)$$

where x_j^l stands for the feature-vector corresponding to the first convolutional kernel of the j convolutional layer with a size of 16×24×250. $f(\dots)$ stands for the activation function, using the *Swish* as it has better nonlinearity than the Rectified Linear Unit (ReLU).

$$f(x) = x \cdot sigmoid(\beta x) \quad (2)$$

where β is a constant that equals to 1. M_j represents the accepted domain of the current neuron and denotes the i^{th} weighting coefficient of the j^{th} convolutional kernel of the first layer. b_j^l denotes the offset coefficient corresponding to the j^{th} product of the l^{th} layer.

In the convolutional layer, the feature vector of the upper layer is convoluted with the convolutional kernel of the current layer. The result of the convolution operation passes through the activation function and then forms the feature map of this layer. Each convolutional layer corresponds to a pooling layer (maximal pooling), which retains useful information while reducing data dimensions. The CNN-Attention structure takes advantage of encode-decode frame where CNN acts as an encoder and attention mechanism as a decoder. In this study, we speculate that EEG is a kind of temporal sequence in which signals are temporally correlated. And attention focuses on the extraction of important segmentation of EEG signals which can represent the feature of the state and/or the person. The structure of attention is shown in Fig. 3.

After the fully connected layer of CNN, the EEG signal is rearranged into a 96×64 matrix (h_i), which is similar to the sentence encoder of sentence attention. Each line of h_i corresponds to i sentences. The attention mechanism can be expressed as:

$$u_i = tanh(W_s h_i + b_s) \quad (3)$$

$$\alpha_i = \frac{exp(u_i^T u_s)}{\sum_i exp(u_i^T u_s)} \quad (4)$$

$$v = \sum_i \alpha_i h_i \quad (5)$$

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b_s is the bias. u_i is a hidden representation of h_i which is fed through a one-layer perceptron with the weight W_s. α_i is a normalized importance weight which is measured by the similarity of u_i with u_s. u_s is a hidden representation of another piece of EEG signal (one line of h_i). After that, we get v which is the summation of the all information of EEG signals.

F. Classification

Softmax that could solve multiple classification problem was employed in the current study to perform PI and driving fatigue detection. According to different input x, the probability value p manifests the classification result. The hypothesis function yields a 31-dimensional vector (participant ID) for PI and a 2-dimensional vector (vigilant or fatigue) for driving fatigue state detection, respectively. The sum of respective vector elements is 1. The function $h_\theta(x)$ is shown below:

$$\begin{aligned} h_\theta(x^i) &= \begin{bmatrix} p(y^i=1|x^i;\theta) \\ \vdots \\ p(y^i=k|x^i;\theta) \end{bmatrix} \\ &= \frac{1}{\sum_{j=1}^{k} e^{\theta_j^T x^i}} \begin{bmatrix} e^{\theta_1^T x^i} \\ \vdots \\ e^{\theta_k^T x^i} \end{bmatrix}, k \\ &= 31(ID) or 2(fatigue) \end{aligned} \tag{6}$$

where $\theta_1, \theta_2, \ldots, \theta_k \in \mathcal{R}^{n+1}$ denote the model parameters, $\frac{1}{\sum_{j=1}^{k} e^{\theta_j^T x^i}}$ normalized the probability distribution so that the summation of probabilities is 1. The one with a higher probability was used as the classification result of the test. To accelerate the training speed, we use the cross entropy as the cost function for this CNN that was estimated as:

$$L = -\sum_{i=1}^{K} y_i log\big(h_\theta(x^i)\big), \tag{7}$$

where L is the loss function, y is the output vector and h_θ is the probability of sample belonging to a category. The learning algorithm for the proposed structure is shown in **Algorithm 1**.

The accuracy of classification rate (CRR) can be expressed as:

$$CRR_f = \big(\frac{1}{u}\sum_{i=1}^{u} N_i\big) * 100 \tag{8}$$

where f equals to 10 (corresponding to the 10-fold cross-validation), u equals to 2 (fatigue state detection) or 31 (PI), respectively. N_i is the number of correct recognition. Finally, CRR_f will be averaged to CRR, which stands for the recognition accuracy of our system. The model is implemented with Keras (Python) on a workstation with an Intel CPU (Model: i7-9700k) and an GIGABYTE GPU (Model: RTX 2080 Ti).

Algorithm 1 Training of CNN-Attention Network

Input
- Labeled training dataset $(\boldsymbol{A}^{(s)}, y_s)_{s=1}^{T}$, $\boldsymbol{A}^{(s)}$ is the s^{th} training dataset and y_s is the label corresponding $\boldsymbol{A}^{(s)}$;
- CNN-Attention model $\overrightarrow{\mathbf{f}}(\boldsymbol{A};\theta)$; θ is the model parameters and $\boldsymbol{A}$ is the all the training dataset.
- Loss function $\mathbf{L}(y,\hat{y})$, y is labels of all training dataset and $\hat{y}$ is the estimated y.
- Number of optimization epochs $\boldsymbol{J}$; N-batch size 256;

Output: Learned parameters θ for the model $\overrightarrow{\mathbf{f}}(\boldsymbol{A};\theta)$.

Initialize parameters θ;

```
for j = 1 : J do
    Extract number of N-batches (256) of samples from A^(s);
    Ã^(s) ← Permute the rows of A^(s);
    for i = 1 : n (n = 31 or 2) do
        Permute the entries of Ã_i^(s);
    end for
    Update θ_(J) via Adam optimizer for the loss function in (4);
end for
for n=1:2 or 31 do
    CRR = Average(CRR_f(f(A;θ)))
end for
```

G. Validations

1) Comparisons with Different Methods: In order to check the performance of the proposed model, we have employed three models, namely CNN, CNN-LSTM, and Attention networks. Here, we briefly introduce some of the details for these compared models. *CNN*: this model use the CNN network structure without the attention layer; *CNN-LSTM*: this model combine the CNN with the deep long short-term memory (LSTM) architecture; *Attention*: this model only use the attention layer. For those who feel interested about the detailed description about the models, please refer to several recent reviews [55], [56].

2) Influence of Kernel Size: In the proposed neural network structure, we use three convolutional layers and the input size of the network is limited at 24×250. Therefore, a proper size of the kernel can guarantee a complete extraction of features as well as reduce the noise during the feature extraction. To investigate the influence of kernel size, we have performed additional analysis with a range of kernel sizes and find the proposed kernel size lead to the best performance (see *Subsection D* of Results for more details).

3) Influence of Input Data: To investigate the reliability of the proposed model, we have performed two additional analysis to quantitatively assess the influence of the input data. 1) PI: A reliable model for PI should have reliable performance independent to input data. Hence, we also use data from fatigue state to assess the reliability of the proposed model (Fig. 3). 2) Fatigue detection: A feasible fatigue detection method should use less input data. Therefore, we have assessed the performance of fatigue detection using portion of the recorded data. Briefly, four subsets of the recorded data were extracted based upon their locations (see *Subsection F* of Results for more details).

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H. Data Availability

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

III. Results

A. PI Classification

We firstly performed the PI with the proposed CNN-Attention model. One-way ANOVA analysis indicates significant differences in classification performance among four methods ($F_{3,120} = 93.36$, $p < 0.001$), where the proposed CNN-Attention model achieved the highest PI performance (98.5%) in comparison with the other three models (i.e., CNN-LSTM: 95.3%; CNN: 91.9%; Attention: 71.2%) (Fig. 4). Further interrogation of the PI at individual level, we showed that the proposed CNN-Attention model performed generally well across all subjects with the lowest mean detection rate of 96.3% in Sub #1. In terms of the operation time, it takes 1.86s for each epoch with the proposed model to reach the classification result, which is less than half of the time to run the second best CNN-LSTM model. Therefore, our CNN-Attention model exhibited apparent superiority in comparison with the widely-used models when taking into account of both accuracy and efficiency.

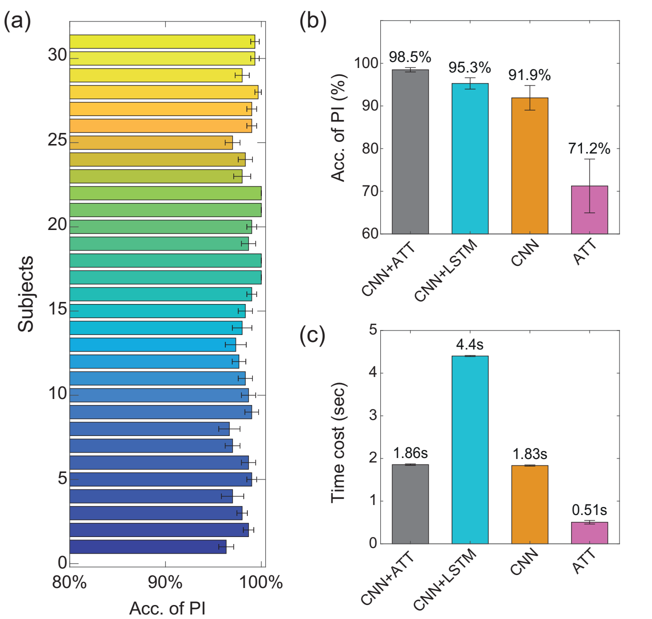

Fig. 4. The results of the PI. (A) Accuracy for all 31 subjects with CNN-Attention network. The error bar manifests that a 10-fold cross validation method applied to such classification. (B) The comparison of fatigue state accuracy with four models. Each bar stands for the averaged accuracy of 10-fold cross validation results of all 31 subjects, and the error-bar indicates standard deviation. (C) The comparison of time cost of PI across four models.

B. Driving Fatigue State Detection

We then performed the driving fatigue detection using the same EEG with the proposed CNN-Attention network and compared the detection rate with three widely-used models. Statistically, the four models exhibited significant differences in performance ($F_{3,120} = 125.6$, $p < 0.001$), with the proposed CNN-Attention model lead to the best performance in driving fatigue detection Fig. 5. Similar to the PI results, the second best detection accuracy was obtained using CNN-LSTM mode. Further interrogation of the fatigue detection performance at individual level, we showed consistently well accuracy among 31 subjects. The lowest detection accuracy was 94% for Sub #12. We also compared the time cost of four methods where we found the proposed CNN-Attention model used only 0.18s to complete the estimation at each epoch. We posit that a good trade-off could be obtained between the classification accuracy and the running time with the proposed CNN-Attention model.

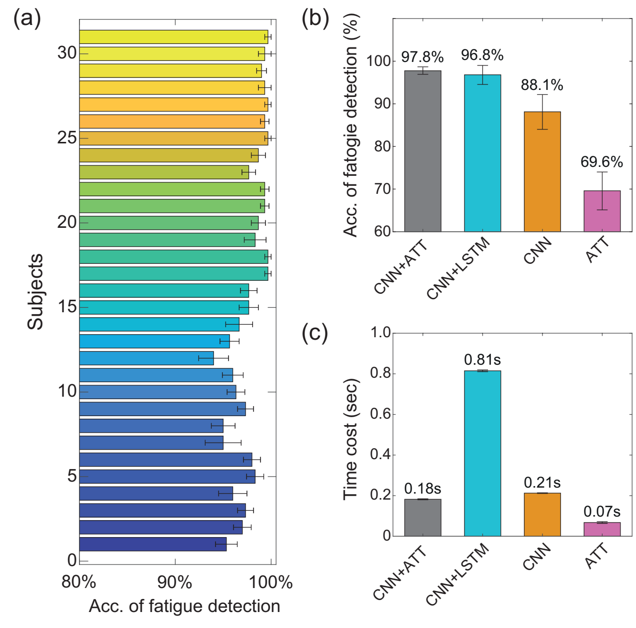

Fig. 5. The results of the driving fatigue detection. (A) Fatigue detection accuracy for all 31 subjects with CNN-Attention network. The error bar manifests that a 10-fold cross validation method applied to such classification. (B) The comparison of fatigue detection accuracy across four methods. Each bar stands for the averaged accuracy of 10-fold cross validation results of all 31 subjects, and the error-bar indicates standard deviation. (C) The comparison of time cost of fatigue detection across four model.

C. Correlation of Performance Between Fatigue Detection and PI

As we have mentioned previously, the performance of driving fatigue detection would be benefit from the PI. Hence, in a practical in-vehicle expert system, the detection performance of PI and driving fatigue detection would be highly correlated. To show the validity of the proposed network structure and to facilitate the practical applications, we perform additional correlation analysis between the mean accuracy of PI and the mean accuracy of driving fatigue state detection at individual level. As expected, statistically significant correlation of classification accuracy between PI and fatigue detection was achieved through using the proposed CNN-attention network ($R = 0.726$, $p < 0.0001$). The other three comparison network models failed to yield significant relationship (Fig. 6).

D. Kernel Size Influence

In the proposed neural network structure, three convolutional layers were used to keep a balance between the

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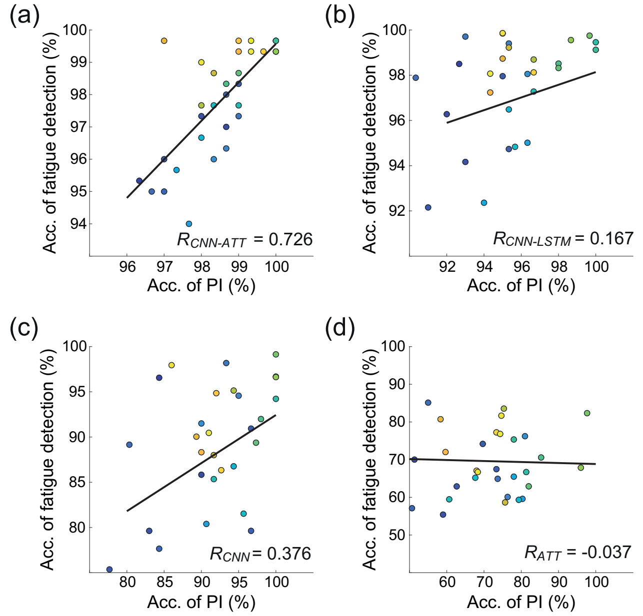

Fig. 6. Pearson correlation between the mean accuracy of PI and the mean accuracy of driving fatigue state detection. (a) CNN-Attention, (b) CNN-LSTM, (c) CNN, (d) Attention.

classification accuracy and the training time. Then, we assessed the influence of different kernel sizes on PI as it has high computation complexity in comparison with the binary classification for fatigue detection. We found the performance for PI is relatively satisfactory across different kernel sizes with the best performance (98.5%) was obtained using the $3\times 5\times 5$ kernel while the minimum accuracy (95%) for the kernel size of $3\times 5\times 3$ (Fig. 7(a)). We then looked into the classification performance at individual level where we get the worst performance across different kernel sizes (Fig. 7(b)). In comparison with other kernel size configurations, the best performance was achieved with a kernel size of $3\times 5\times 5$, where a lower standard deviation was also obtained.

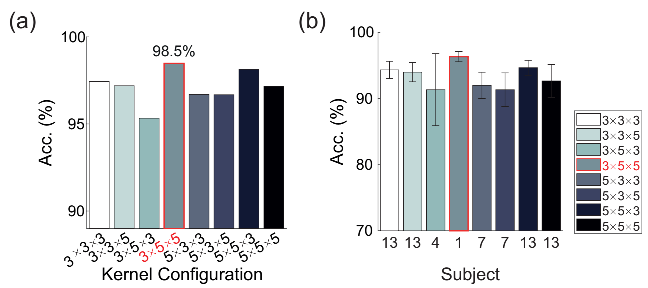

Fig. 7. The comparison of the PI classification accuracy with different CNN structure. (a) The average mean accuracy with different kernel configurations. (b) The lowest mean classification accuracy with its STD at different kernel configuration model.

E. Influence of Input Data

To validate the stability of the proposed CNN-Attention model, we performed additional analyses to show the PI performance when using different input data (Fig. 8). We found relatively stable accuracy for PI when using EEG signal during the fatigue state (mean accuracy = 98% vs. 97.8% using vigilant data). Nevertheless, when using the mixed data (data from both states), the performance of PI (mean accuracy = 88%) was significantly lower ($p < 0.01$) than either single state input date. We further assessed the time cost with three different sets of input data and found comparatively efficient PI classification for both single state input which only took half of the time cost when mixed data was used. We also showed the Pearson correlation between the mean accuracy of state and the mean accuracy of PI with the two types of input data and found significantly higher correlation coefficient when using fatigue data ($R_{fatigue}$ vs. R_{mixed}, p = 0.026).

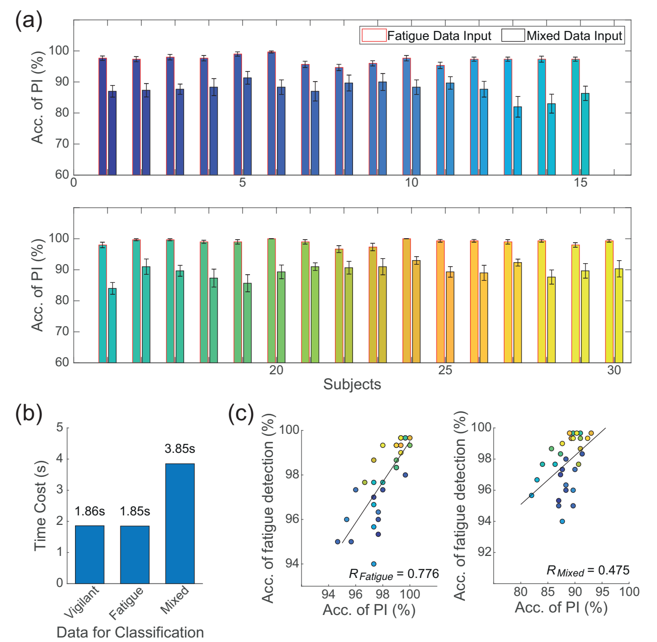

Fig. 8. The comparison of PI classification with fatigue data and mixed data. (a) the comparison of PI classification accuracy. (b) The time cost comparison with different data (awake, fatigue and mixed). (c) Pearson correlation between the mean accuracy of PI and the mean accuracy of driving fatigue state with fatigue and mixed data.

We had also assessed the practicability of the proposed network structure with less input EEG data. Specifically, four subsets of the recorded data were extracted based upon their locations (Fig. 9(a)). As expected, the performance of PI and driving fatigue detection was lower than those when using EEG data from all channels. Specifically, the highest classification accuracy for PI was achieved using data from frontal and parietal channels (ACC_{FP_PI} = 85.2%) (Fig. 9(b)), while accuracy for driving fatigue detection exhibited comparable performance across four subsets of EEG channels with the best performance achieved using data from frontal channels ($ACC_{F\_Fatigue}$ = 94%) (Fig. 9(c)). When combining the performance of PI and fatigue detection, data from FP area lead to a balanced optimal performance (ACC_{FP_PI} = 85.2% & $ACC_{FP\_Fatigue}$ = 93%).

IV. Discussion

In the current study, we introduced a novel unified analysis framework to perform PI and driving fatigue detection via us-

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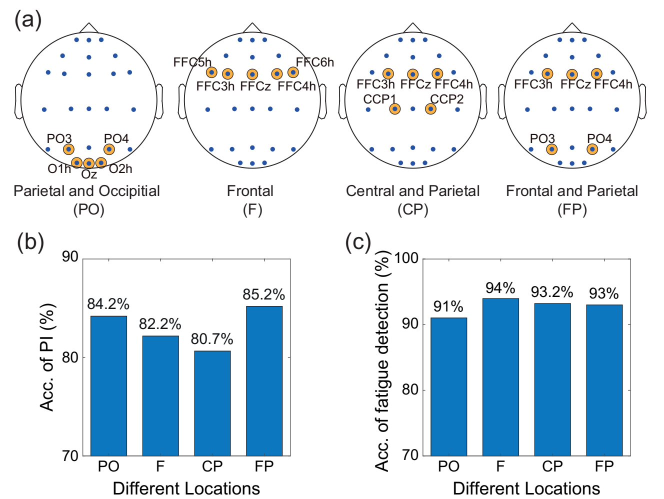

Fig. 9. Different electrode location with its result of classification accuracy. (a) Different locations of electrodes (PO: Parietal and Occipital; F: Frontal; CP: Central and Parietal; FP: Frontal and Parietal). (b) Averaged PI classification accuracy with different sets of channels. (c) Averaged driving fatigue state classification accuracy with different sets of channels.

ing same EEG input data. In comparison with several widely-used neural network models, the proposed model achieved the best performance for both tasks, which is independent of different kernel sizes and input data. Moreover, we further assessed the practicability of the proposed model using subsets of EEG data and showed a satisfactory detection performance for both PI and driving fatigue through using EEG data from frontal and parietal areas. The importance of the effective and efficient driving fatigue detection is evident, and our framework moves a step forward towards a practical in-vehicle system for driving fatigue detection.

A. EEG-based Authentication

EEG signals, as an approach of studying the brain, have been continuously attracting substantial interests coinciding with recent advances in deep learning. Here, we have provided further evidence to demonstrate the feasibility of utilizing EEG for PI. Compared with conventional biometrics used for PI where static pattern was typically adopted (i.e., fingerprint, iris, etc.), EEG-based authentication holds unique advantages including resistance to spoofing attacks and impossibility to use under pressure and coercion states [63]. In Table II, we showed several representative studies of EEG-based authentication. Among them, Mao et al., introduced a CNN-based biometric identification framework using EEG data from driving fatigue experiment and achieved a satisfactory accuracy, i.e., 97% in identifying 100 subjects [57]. More recently, Wilaiprasitporn et al., developed a PI framework using a combination of CNN and recurrent neural networks (i.e., CNN-LSTM) [58]. They demonstrated a mean accuracy of 99% for PI using EEG data recorded when participants were under four affective states. In the current work, we have compared the performance of the proposed CNN-Attention model with the CNN-LSTM model and achieved higher mean PI accuracy with less computation time, indicating the efficacy of the proposed attention structure in improving the PI performance. Heuristically, the attention structure would enhances the important parts of the input data. In the case of EEG-based PI, the characteristic of uniqueness embedded in EEG signals may contribute to the elevated performance. Interestingly, we showed in our validation analysis that PI performance would be modulated by different mental states (Fig. 8), that is, the PI performance is significantly reduced when mixed vigilant and fatigued data was used as input in comparison with vigilant or fatigued alone input. This finding is unlike Wilaiprasitporn's work, which revealed consistent high performance across four affective states [58]. The discrepancies between the two studies could stem from the different experiments, that is, we used a long-term (i.e., 90-min) driving fatigue experimental paradigm instead of a short period (i.e., 60-sec) video induced affective states (i.e., arousal, valence). Heuristically, EEG are emotional state dependent and stress or fear changes the normal brain waves' pattern regardless of the activity [63]. We then speculated that the short video induced affective states used in [58] may not be intense enough to induce dramatic mental state alterations. Nevertheless, further studies examining the generalizability of EEG-based authentication across different mental states are of particular interest to reconcile such apparent inconsistencies.

B. EEG-based Driving Fatigue Detection

EEG-based driving fatigue detection has witnessed a resurgence of interest in recent years, coinciding with recent advances of deep learning techniques and the desire for safe traffic [24]. In Table III, we selectively listed several most recent studies for driving fatigue detection using neural network model on EEG signals. In comparisons with these previous studies, the current work developed a CNN-Attention model and applied on a relatively large number of subjects in

TABLE II
COMPARISON WITH PREVIOUS STUDIES IN EEG-BASED AUTHENTICATION

Reference	Task	Method	EEG channels	Subject num.	Accuracy
Mao et al. 2017 [57]	Driving fatigue	CNN	64	100	97%
Wilaiprasitporn et al. 2019 [58]	VEP	CNN-LSTM	5	32	99.17%
Lan Ma et al. 2015 [59]	REC/REO	CNN	64	10	88%
Arnau-Gonzalez et al. 2017 [60]	VEP	CNN	14	23	94%
Wu et al. 2018 [61]	RSVP	CNN	16	15	97.6%
Chen et al. 2019 [62]	RSVP	CNN	28	157	96%
This paper	**Driving fatigue**	**CNN-Attention**	**24**	**31**	**98.5%**

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TABLE III
COMPARISON WITH PREVIOUS STUDIES IN DRIVING FATIGUE DETECTION

Reference	Method	EEG channels	Subject num.	Accuracy
Chai et al. 2016 [64]	Bayesian Neural Network on PCA analysis of EEG PSD	26	65	76%
Du et al. 2017 [65]	Multimodal (EEG & EOG) with restricted Boltzmann Machine	22	21	85%
Hajinoroozi et al. 2017 [43]	CNN on spatial EEG covariance matrices	64	100	86.14%
Zeng et al. 2018 [44]	CNN with recent deep residual learning	64	10	84.38%
Cheng et al. 2018 [45]	CNN + Image-based EEG	32	37	71.16%
Chai et al. 2019 [66]	Deep belief networks + AR modeling	32	43	90.6%
Gao et al. 2019 [46]	Spatial-temporal CNN	40	8	97.37%
Ma et al. 2019 [67]	PCA network with SVM	32	6	95%
Gao et al. 2020 [47]	Recurrent network-based CNN	40	10	92.95%
This paper	**CNN-Attention**	**24**	**31**	**97.8%**
		5		**94%**

the published studies and achieved high detection accuracy. To further demonstrate the superior performance of the proposed model in driving-fatigue detection, we have also compared the performance between the proposed model and the methods used in Table III on our recorded data Fig. 10. As it can be seen that the proposed method is outperformed other methods in driving-fatigue detection. Interestingly, further validation investigation on the influence of input data showed a better performance for fatigue detection using data from Frontal or Frontal-Parietal areas in comparison with using data from Parietal-Occipital or Central-Parietal areas. These findings were in line with the neural mechanisms of mental fatigue, where the finite neural resources were initially depleted in these areas [23]. Heuristically, thoughts are constrained automatically by the default mode network and deliberately by the fronto-parietal attention network, while the salience network is responsible for modulation [68]. According to the resource-control model of sustained attention [69], increasing time-on-task leads to depletion in executive resources in the salience and attention networks [70]. Collectively, these convergent neuroimaging evidences might lead to the observed sensitive fatigue detection using data from the fronto-parietal areas. Of note, the validation analysis of input data was exploratory in nature for assess the reliability of the model, hence we did not use exhaustive combinations of EEG channels. We believe that optimize electrode selection in advance of analyzing the electrodes involved in the system computation may lead to better opportunity to decrease computational complexity and deserve further investigation [64], [71].

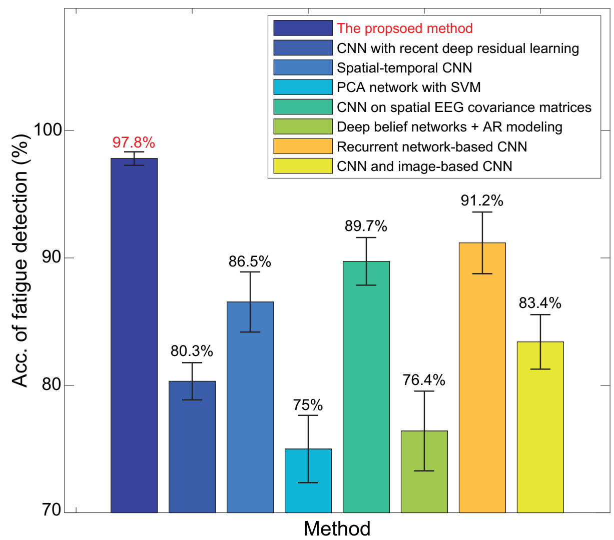

Fig. 10. Comparison of different methods in driving-fatigue detection on our recorded dataset. Each bar stands for the mean accuracy and the error-bar indicates STD.

C. Influence of Network Structure

We found that the performance of CNN with attention structure or CNN with recurrent neural network structure (i.e., LSTM in this work) is much better than that with merely CNN or attention mechanism. These cascade structures work according to the nature of neural networks, where the proceeding layers function as feature extractors for the latter layers [58]. Heuristically, CNN has long been demonstrated to be superior in learning spatial patterns or features [42]. In fact, the key element of CNN is the convolution operation using small kernels (i.e., $3 \times 5 \times 5$ in this work) that are capable of automatically learning local patterns. These patterns could then be combined to form more complex features when stacking multiple CNN layers together (i.e., 3 layers here). The pooling layer was then used to sub-sample the output of the convolution layer on a different scale. The attention or LSTM structure is superior in processing temporal sequence [72], [73], which is a key characteristic of EEG signals. The selective processing nature of attention and LSTM structure may complement the CNN model and collectively lead to the high detection performance in this work. Nevertheless, the proposed CNN-Attention model outperform CNN-LSTM in terms of efficiency, i.e., the time cost of CNN-Attention is significantly less than CNN-LSTM. Our findings therefore further demonstrate the superiority of the cascade structure incorporating both spatial and temporal features and highlight the usefulness of informative EEG signals in terms of spatio-temporal characteristics for EEG-based classification studies.

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D. Merits of This Work and Its Potential Applications

In comparison to previous studies of driving fatigue detection, findings of the current study are of important for the following two reasons. First, in addition to high detection performance, an ideal driving fatigue detection system should be easy to be implemented and comfort for long-term wearing. Through utilizing a wearable dry-sensor EEG system, our work moves a step forward towards real implementation of the driving fatigue detection technique without the need of well-trained experience to setup gel-based conventional EEG device and improve the comforts [74]. Particularly, considering the satisfactory performance for driving fatigue detection using a subset of EEG data, the proposed system shows its readiness for in-field validations. Second, to the best of our knowledge, this is the first study to construct a unified system – *E-Key*, to perform biometric authentication and driving fatigue detection using same EEG data. In practice, we hope the proposed system could be used in several application scenarios including autonomous driving and car-sharing. According to the society of automotive engineers (SAE), the autonomous driving system is categorized into 6 levels of driving automation ranging from fully manual (Level 0) to fully autonomous (Level 5) [75]. The human may control an vehicle not only by sending explicit commands but also by his or her brainwaves. Although fully autonomous driving are predicted to be account for more than 50% of vehicles by 2030 [76], it is still far from feasible with current technology. The driving states (including driving fatigue detection, attention, emotion, mental workload, etc.) could serve as input for smooth switching of driving control to support driver-vehicle adaptivity [19], [77]. However, the substantial individual differences in mental fatigue [25], [26] would in turn significantly influence the performance of fatigue recognition. We then posit that the high detection performance of driving fatigue would be benefit from the PI. Particularly in the insurance industry, concurrently monitoring of driving fatigue and PI are of particular interest [78]. Moreover, coinciding with the recent advent of internet economy, a new and more sustainable way of transportation – car-sharing is blooming [79]. In a recent work [80], Klonovs introduced a two-step authentication through combining traditional methods of authentication and an EEG-based one to further improve the security. The proposed *E-Key* system makes it possible not only reassure the driver's identify but also monitor his/her driving fatigue. In addition to intelligent transportation system, the PI and fatigue detection of on-line workers are also of important to improve the production efficiency and safety provided that the consumer grade portable device can be employed [74].

E. Limitations

Some issues should be considered when interpreting our findings. First, a widely-used within-subject design was applied in the current work for driving fatigue detection. Given that accumulating evidences have showed apparent individual differences in driving fatigue-related brain activities [24]–[26], we opted this framework to maximise the number of existing published studies with which our results could be directly compared [24]. Nevertheless, the allure of subject-independent driving fatigue detection system is strong and continuous efforts have been made to develop cross-subject driving fatigue detection system [28], [81]. We performed additional analyses in a subject-independent manner through applying leave-one-subject out cross-validation on the proposed framework. As expected, the detection performance is significantly reduced, leading to a mean driving fatigue detection accuracy of around 70% (data not shown). One possible reason is that the preprocessed original EEG signals were set as input for the classification. New advances in feature constructions and selection [82]–[84] as well as employment of advanced deep learning methods (including transfer learning [83], adaptive learning [85], multi-task learning [86]), assessing the generalizability and transferability of driving fatigue detection system across subjects are therefore of interest. Second, the advantage of EEG is that they offers rich information on human cognitive and/or emotion states (e.g., trust, workload, attention, etc.), compared to peripheral physiological measures [19], [87]. Here, using a simulated driving as our primary experimental protocol, we demonstrated the feasibility of a unified system – *E-Key* for biometric authentication and driving fatigue detection using same EEG data. In our recent work [77], we developed a simulated driving scenario where subjects were requested to drive a simulated autonomous vehicle under different malfunctions. We found that the inability for human drivers to adaptively mitigate the risk of negative outcomes deteriorate trust, which is reflected in changes in frontal alpha EEG associated with motivational state and action planning, therefore indicating the potential of EEG-based metrics for trust monitoring. In a pioneer work, Smith and Gevins assessed the feasibility of monitoring mental workload and fatigue during operation of a flight simulator [88]. Moreover, we have previously achieved satisfactory performance of mental workload assessments through using connectivity features of EEG signals in a fly simulation experiment [89]. Recently, Chen et al., introduced a transfer learning framework to detect multiple cognitive states (i.e., stress and vigilance) [28]. Promising avenues of future research include developing more practical in-vehicle expert systems for comprehensively monitoring of complex driver status to further improve the driver-vehicle adaptivity through accommodating these new knowledge.

V. Conclusion

In this paper, we developed a unified analysis framework – *E-Key* based upon CNN-Attention network that is able to concurrently perform PI and driving-fatigue detection using the same EEG data with high accuracy (i.e., 98.5% and 97.8% for PI and driving-fatigue detection respectively). In comparison with previous studies, the proposed model makes an optimal balance between the classification accuracy and computation complexity. Subsequent validation analyses on the influence of kernel size as well as input data illustrated the reliability of our *E-Key* framework. Moreover, our results manifest that the proposed model has the potential for multi-task classification with biomedical signals for intelligent

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transportation applications of in-vehicle expert system. With further validation on larger independent study samples and more feasible and remote EEG acquisition hardware in more representative driving environments, our model may represent a promising avenue for real-world drivers whose performance is particularly prone to fatigue.

Appendix

List of Abbreviations and Acronyms

AR	Auto-Regressive Coefficients
CNN	Convolutional Neural Network
CNN-Attention	Convolutional Attention Neural Network
CNN-LSTM	CNN with deep Long Short-Term Memory
CP	Centro-parietal
ECG	Electrocardiogram
EEG	Electroencephalography
EOG	Electrooculogram
F	Frontal
FP	Fronto-parietal
PI	Personal Identification
PCA	Principle Component Analysis
PSD	Power Spectral Density
ReLU	Rectified Linear Unit
RT	Reaction Time
REC	Resting-state eyes-closed
REO	Resting-state eyes-open
RSVP	Rapid Serial Visual Presentation
STD	Standard Deviation
SVM	Support Vector Machine
VEP	Visual Evoked Potential

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