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EEG-Based Alcohol Detection System for Driver Monitoring

Sistema de detección de alcohol basado en EEG para la monitoreo de conductores

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Abstract.
Today, alcohol drinking frequently accompanies socialising as a routine activity in various groups of society. 84.0% of individuals aged 18 and above in the United States have drunk alcohol at some point in their life (National Institute on Alcohol Abuse & US, 2023). Similarly, 81.7% of Norwegians in the age group 16 to 79 have drunk alcohol in 2021 (Bye, 2018). Driving after the consumption of alcohol is a worldwide problem, causing a large number of deaths and injuries a year. This work proposes the first steps towards developing an electroencephalography (EEG)-based alcohol detector conceived with the idea to prevent people from driving under the influence of alcohol. This includes the design of an experimental protocol for EEG data collection, during which participants performed the Flanker task, and their blood alcohol concentration (BAC) was measured. The resulting data set consists of two sessions per participant, both while they are affected and not-affected by alcohol. Statistical analysis of the Flanker task indicated that participants were affected by alcohol and, therefore, their EEG signals were expected to be affected as well. The collected EEG signals were used as input for intra-subject and inter-subject models, both based on the EEGNet architecture. The intra-subject model obtained a mean classification accuracy of 90.7% and the inter-subject model a mean classification accuracy of 62.9%. The result suggest that alcohol can be detected with high accuracy when developing individual models and above the change accuracy when using a general model. Therefore, the work presented here could be used as the first steps towards the development of an EEG-based alcohol detector for drivers.

Resumen.
Hoy en día, el consumo de alcohol frecuentemente acompaña la socialización como una actividad rutinaria en varios grupos de la sociedad. El 84.0% de las personas mayores de 18 años en los Estados Unidos han consumido alcohol en algún momento de sus vidas (National Institute on Alcohol Abuse & US, 2023). De manera similar, el 81.7% de los noruegos en el grupo de edad de 16 a 79 años consumieron alcohol en 2021 (Bye, 2018). Conducir después del consumo de alcohol es un problema mundial que causa un gran número de muertes y lesiones cada año. Este trabajo propone los primeros pasos hacia el desarrollo de un detector de alcohol basado en electroencefalografía (EEG), concebido con la idea de prevenir que las personas conduzcan bajo los efectos del alcohol. Esto incluye el diseño de un protocolo experimental para la recopilación de datos EEG, durante el cual los participantes realizaron la prueba de Flanker y se midió su concentración de alcohol en la sangre (BAC). El conjunto de datos resultante consta de dos sesiones por participante, tanto mientras estaban afectados como no afectados por el alcohol. El análisis estadístico de la prueba de Flanker indicó que los participantes estaban afectados por el alcohol y, por lo tanto, se esperaba que sus señales EEG también lo estuvieran. Las señales EEG recopiladas se utilizaron como entrada para modelos intra-participantes e inter-participantes, ambos basados en la arquitectura EEGNet. El modelo intra-participantes obtuvo una precisión media de clasificación del 90.7%, y el modelo inter-participantes una precisión media del 62.9%. Los resultados sugieren que el alcohol puede detectarse con alta precisión al desarrollar modelos individuales y con una precisión superior al azar al usar un modelo general. Por lo tanto, el trabajo presentado aquí podría servir como los primeros pasos hacia el desarrollo de un detector de alcohol basado en EEG para conductores.

Keywords.
Electroencephalography (EEG), Alcohol Detection, Convolutional Neural Network (CNN), EEGNet, Flanker Test.
Palabras Clave.
Electroencefalografía (EEG), detección de alcohol, Red Neuronal Convolucional (CNN), EEGNet, Prueba de Flanker.

1. Introduction

Electroencephalography (EEG) is a technique used for capturing brain signals by placing electrodes on the scalp. Today, EEG is a commonly used technique for studying the brain. Many studies (Farsi et al., 2020; Mukhtar et al., 2021; Singhal et al., 2021) have been investigating if it is possible to diagnose alcoholism using EEG data. Several of these studies have been successful, resulting in a high classification accuracy. However, only one study (Ek et al., 2013) has focused on using EEG data for the detection of alcohol in a healthy body. Accurate detection of alcohol in a healthy body is important in the prevention of traffic accidents, caused by drunk driving.

Driving under the influence of alcohol is a worldwide problem. It is estimated to cause the death of at least 273000 road users every year, although the actual number is believed to be higher (Vissers et al., 2018). The legal blood alcohol concentration (BAC) for driving varies for different countries, but, for most, the BAC limit is within the range of .2% to .8% (World Health Organization, 2020).

In order to decrease the number of injuries and deaths, it is important to stop drunk drivers before the accident happens. Today, using breathalysers is the common way of detecting if a person is under the influence of alcohol. The breathalyser estimates the BAC value by using a single breath sample. It is the tool used by the traffic police when they are suspecting that a person is driving under the influence of alcohol.

Although using breathalysers is a quick and inexpensive way of measuring the BAC, it has some disadvantages. Using breath samples is an indirect way of measuring the amount of alcohol in the blood, and inaccurate measurements can occur due to factors such as residual alcohol or juice in the mouth, or temperature and humidity (Nordstrøm-Hauge & Vassbotn, 2023) and due to undetectable alcohol level by breathalyser that can be still relevant on the brain.

Several studies (Celaya-Padilla et al., 2021; Murata et al., 2010; Vijayan & Sherly, 2019) have been proposing an in-vehicle alcohol detector that can inform drivers if their level of alcohol intoxication is above the legal limit, or if their level of drowsiness is considered too high for driving. These factors can be determined by using several different methods. (Celaya-Padilla et al., 2021) is using low-cost alcohol MQ3 sensors together with machine learning, while (Murata et al., 2010) is monitoring biological signals like the body-trunk plethysmogram and respiration of the driver. (Vijayan & Sherly, 2019) is using a neural network for image processing of the face of the driver. However, the use of EEG signals for alcohol detection in driving scenarios has been scarcely reported, and it remains a subject of ongoing research to determine whether utilising EEG signals instead of breath samples could yield a system with higher precision and accuracy than a breathalyser. Therefore, this paper proposes the first step towards the design of an alcohol detector system for onboard detection of the presence of alcohol in drivers.

2. Methods

2.1 Participants

Twenty healthy subjects took part in this study. The selection criteria were being between 20-30 years old, be right-handed, and be a social drinker, so neither abstained from alcohol nor suffered from alcohol use disorders. All participants were healthy young adults with no history of drug or alcohol abuse, no history of drug or alcohol abuse in close family, and no major medical issues or history of psychiatric problems. This was screening in a questionnaire during the recruitment process, potential participants that did not comply with those requirements were excluded from the study. In contrast to previous studies presented in (Cohen et al., 1993; Ehlers et al., 1989; Stenberg et al., 1994) where only males participated, this study aimed to have a gender balanced dataset. Therefore, equal number of males (23.7 years old $\pm$ .78) and females (24.3 years old $\pm$ 1.42) were recruited. The study followed the guidelines of the Helsinki declaration, it was approved by local authority (Norsk Senter for Forskningdata) and all participants gave written informed consent prior to participation.

2.2 Protocol and Data Collection

In order to collect alcohol —and non-alcohol affected EEG data—, each participant took in two sessions. We refer them as alcohol and non-alcohol sessions. In the alcohol session, a vodka-based drink mixed with orange and lime juice was served, the drink had a calculated concentration of ethanol of .45 g/kg. In the non-alcohol session, the alcohol was substituted with a vodka-flavoured mix. The participants were not informed in which session they were given alcohol or not alcohol drink.

During each session, the EEG signals were monitored using 16 channels, for this we used two Unicorn Hybrid Black (gtec, Austria) headsets with eight electrodes each. Lab Streaming Layer (LSL) was used to centralise the data collection and synchronise the EEG measurements from both devices. To monitor the BAC, a breathalyser Alcoscan ALC-1 (Sentech Korea corporation, Republic of Korea) with $\pm$.05% at 1% accuracy and 95% of precision was utilised. Each session started with a measurement of BAC value to ensure the participant has not drunk alcohol before the session. After that, a set of pre-drink recordings took place, where EEG during resting state with eyes open was recorded during five minutes, and then during a Flanker task (see section 2.3) for approximately seven minutes. After this the participant was served with the drink and had 10 minutes for the ingestion. After finishing the drink, a series of two resting state EEG and two BAC measurements

took place. Then, the participants performed a second flanker test, and finalised with BAC measurement, resting state EEG, and a final BAC measurement. Each session lasted approximately 66 minutes. Figure 1 shows the data collection session in detail. A more detailed presentation of the designed protocol and experiments is available in (Nordstrøm-Hauge, 2022; Vassbotn, 2022).

The 16 channels were placed within the 10-10 standard positions in locations Fp1, Fp2, AF7, AF8, FC3, FC4, FC5, FC6, T7, T8, Cz, PO7, PO8, O1, O2, and Oz. The selection of those channels was based on the results presented in (Bavkar et al., 2021), where a discrete harmony search was performed to find which positions in the 10-10 systems were optimal for alcoholism detection, resulting in 12 optimal channels. In order to use the 16 channels available, four channels were added to the optimal set to preserve symmetricity between the two brain hemispheres. The channels displayed in Figure 2 were optimal channels and added channels are coloured in green and orange, respectively.

2.3 Flanker Test

The Flanker test measures the selective attention, accuracy and response time (RT) of the participant (Eriksen & Eriksen, 1974). This is of interest as alcohol is known for affecting both the attention span and the RT of intoxicated people (Steele & Josephs, 1990). The Flanker task also tests a person's ability to ignore irrelevant stimuli around a focal point. This can be compared with how a driver needs to keep their focus on the road, while still retaining an overview of the surroundings.

During this test, participants are shown a sequence of five letters on a screen. They are instructed to press either the A-key or the L-key on the keyboard based on the middle letter. If the middle letter is X or C, they should press A, and if it is V or B, they should press L. The middle letter is surrounded by four identical letters, which are also either X, C, V, or B. This creates 16 possible combinations of letters. If the surrounding letters and the middle letter indicate the same response, it is called a congruent trial; if they indicate different responses, it is called an incongruent trial (Nordstrøm-Hauge & Vassbotn, 2023). Participants see all 16 combinations presented randomly (see Table 1, forming a block. Between each combination, a cross is shown for two seconds before the next combination appears. The entire task consists of 6 blocks, totalling 96 letter sequences shown to the participants. Of these, 48 are congruent and 48 are incongruent. After each block, there is a seven-second break. The RT and the response of the participant are recorded.

2.4 EEG Data Pre-Processing

Before the collected data set was used as input to the classifiers, some preprocessing was applied. First, the 5-minute EEG recordings were split into epochs of 5 seconds.

Table 1

The Stimuli Presented during one Block in the Flanker Task

Congruent	Incongruent
XXXXX	XXVXX
XXCXX	XXBXX
CCCCC	CCVCC
CCXCC	CCBCC
VVVVV	VVXVV
VVBVV	VVCVV
BBBBB	BBXBB
BBVBB	BBCBB

After this, the data was split into a training and a test set. The data set was not subjected to any artifact removal or filtering procedures; only normalisation was performed.

2.5 Classification of EEG Data

To evaluate the possibility of detecting the alcohol-affected EEG signals, two models were trained on the dataset. They were implemented using a Convolutional Neural Network (CNN) architecture made specifically for the classification and interpretation of EEG signal called EEGNet (Lawhern et al., 2018). EEGNet is known for performing well on different types of EEG signals, even when the available data set is very limited (Lawhern et al., 2018). The models were optimised by using the Adam algorithm with a learning rate of .001. The used loss function was *binary cross entropy*. The hyperparameters of EEGNet were chosen to be their default values; $F_1 = 8$, $D = 2$, $F_2 = 16$. The first implemented model was trained only on a single individual data, refereed here as intra-subject model; while the second model was trained based on multiple individual data, refereed here as inter-subject model. Both are presented in the following sections.

2.5.1 Intra-subject Model

This model was trained using only data from the same participant. In this model, all 5-second epochs from the same 5-minute run were placed in the same set. Among the non-alcohol and alcohol sessions there are in total five non-alcohol runs (n_1, n_2,..., n_5) and three alcohol runs (a_1, a_2, a_3) per participant, each one of 5-minutes. One run per each category were selected as test set, and over the remaining data, 3-fold cross validation was used to train and validate the model. Figure 3 presents an example of the data split for training, validation and testing sets in the intra-subject model.

2.5.2 Inter-Subject Model

An inter-subject model is proposed to evaluate generalisation of the detection alcohol- affected EEG signals, in this the model is trained with the data from a population pool and evaluated on an unseen participant. For this particular model, the EEGNet was trained using a leave-

Figure 1

A Detailed Overview of the Data Collection Session (Nordstrøm-Hauge & Vassbotn, 2023)

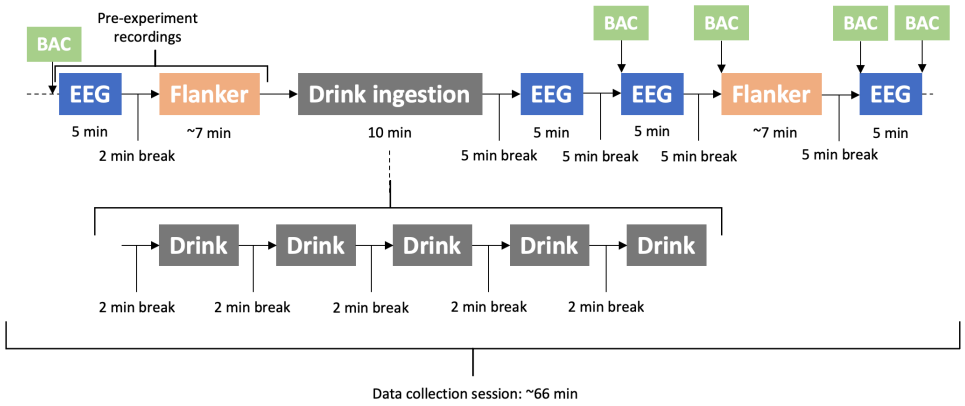
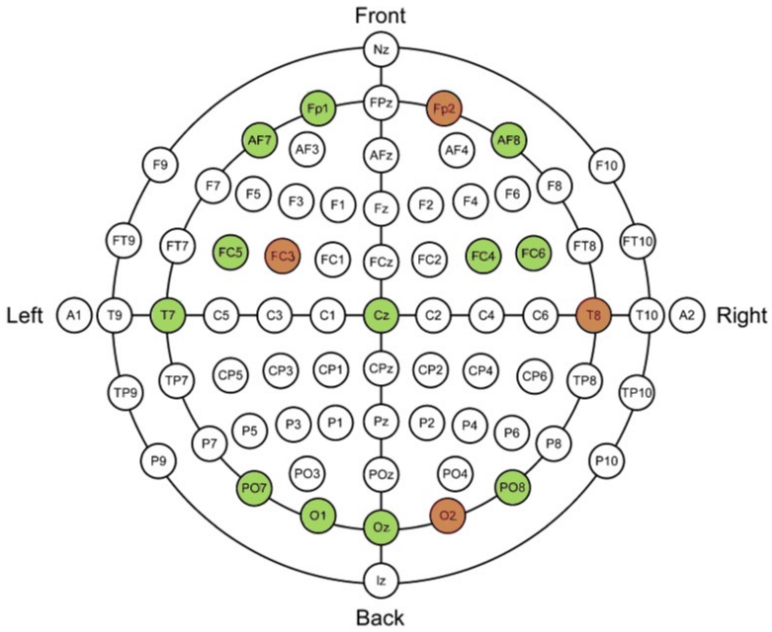


Figure 2

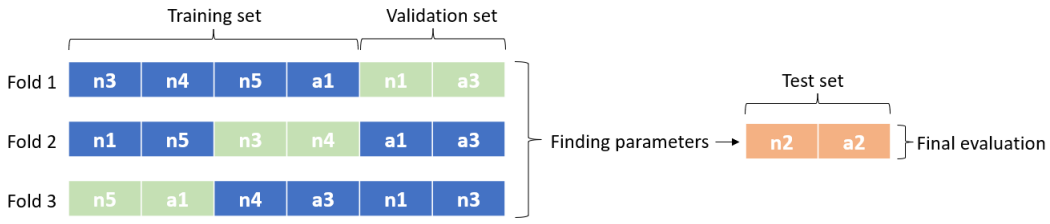
The 16 Channels used for the Recording of EEG Signals



Note. The red channels are the four leftover channels added to the optimal channels for symmetry. Adapted from (Hu & Zhang, 2019).

Figure 3

Example of Individual Data Split for Training, Validation and Testing Sets in the Intra-Subject Model (Nordstrøm-Hauge & Vassbotn, 2023)



one-subject-out strategy, by using data from 19 of the 20 participants. The remaining participant data is used as the test set. During training, the hyperparameters of the model were chosen by using 3-fold cross-validation.

2.6 Performance Metrics

To get an unbiased evaluation of the performance of the models, several evaluation metrics were used: accuracy, precision, recall, F1 score and specificity, these are further described in (Nordstrøm-Hauge & Vassbotn, 2023). These metrics describe the performance of the model on unseen data. As the problem described here is a two-class classification problem we made use of the confusion matrix to represent the performance of the model. It displays the true negative (TN) and true positive (TP) predictions on the diagonal. The anti-diagonal shows the number of false negative (FN) and false positive (FP) predictions. Based on this matrix the performance metrics were computed using the following equations:

$$\text{Accuracy} = \frac{TN+TP}{TN+FN+TP+FP}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

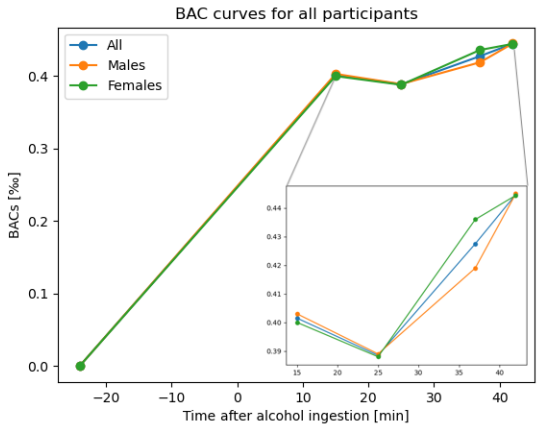
$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1 score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = \frac{TP}{2TP+FP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

Figure 4

Average BAC Values for Males, Females and all Participants during the Alcoholic Recording Session



Note. The inserted window shows an enlarged version of the most relevant area (Nordstrøm-Hauge & Vassbotn, 2023).

3. Results

3.1 BAC Evolution

The measured BAC values after ingestion of alcohol for each participant are presented in Table 2. Before the recordings, all participants had a BAC value of .000%. In the non-alcoholic recording session, all participants had a BAC value of .000% through-out the session. Figure 4 shows the average BAC values for males, females and all participants at each BAC measuring point during the alcoholic recording session.

Table 2

The BACs of All Participants at Approximately 15, 25, 37, and 42 Minutes after (m.a.) Alcohol Ingestion (Nordstrøm-Hauge & Vassbotn, 2023)

Participant	Gender	15 m.a.	25 m.a.	37 m.a.	42 m.a.
P01	Female	.450%	.440%	.430%	.450%
P02	Female	.270%	.330%	.380%	.400%
P03	Female	.420%	.420%	.500%	.540%
P04	Female	.440%	.430%	.490%	.450%
P05	Female	.440%	.450%	.470%	.490%
P06	Male	.310%	.390%	.400%	.430%
P07	Female	.110%	.140%	.190%	.210%
P08	Male	.250%	.260%	.290%	.320%
P09	Male	.420%	.430%	.440%	.450%
P10	Female	.340%	.260%	.260%	.360%
P11	Male	.550%	.530%	.540%	.500%
P12	Male	.390%	.370%	.460%	.480%
P13	Female	.520%	.470%	.490%	**
P14	Male	.430%	.470%	.480%	.480%
P15	Female	.530%	.480%	.570%	.560%
P16	Female	.480%	.460%	.580%	.540%
P17	Male	.250%	.280%	.290%	.380%
P18	Male	.480%	.380%	.470%	.520%
P19	Male	.320%	.310%	.340%	.400%
P20	Male	.630%	.470%	.480%	.490%

Note. ** No measurement due to technical issue with the breathalyser.

3.2 3.2 Behavioural Data from the Flanker Task

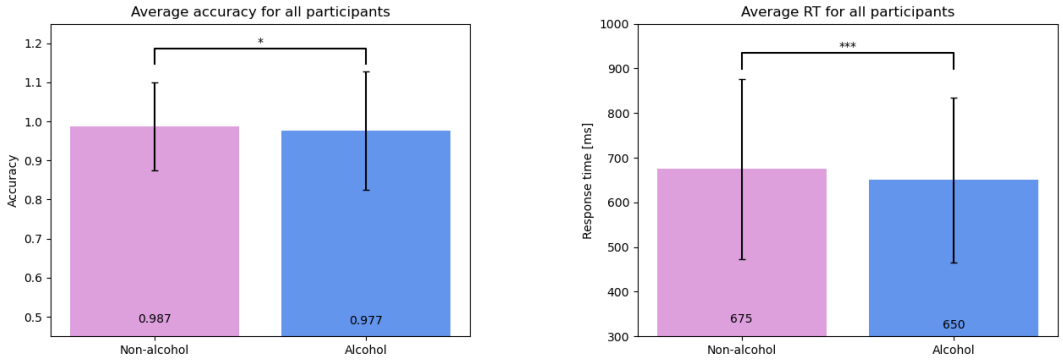
Figure 5 presents the average accuracy results from the Flanker task performed after drink ingestion. As seen in Figure 5a, the average accuracy for all participants decreases with a value of .01 from .987 to .977 when alcohol is present. The difference in accuracy is significant with a p-value of $p = .015836$. Figure 5b shows the average RT for all participants. After ingestion of alcohol, the RT decreased by 25 ms., from 675 to 650 ms. The difference in RT is significant with a p-value of $p = .000091$.

3.3 Intra-Subject Classification

The performance of the intra-subject model is summarised in Table 3. This performance was obtained on the performance of classification of the test set. As shown, 13 of the participants scored perfectly across all metrics, where the lowest accuracy was obtained for P14, with

Figure 5

Average Accuracy and RTs for the Flanker Task (Nordstrøm-Hauge & Vassbotn, 2023)



(a) Average accuracy.

(b) Average RT.

Table 3

The Performance of the Individual Model across Sessions on the test Set when the Data is Split into Epochs of 5 Seconds

Participant	Accuracy	Precision	Recall	F1 score	Specificity
P01	1.000	1.000	1.000	1.000	1.000
P02	1.000	1.000	1.000	1.000	1.000
P03	1.000	1.000	1.000	1.000	1.000
P04	1.000	1.000	1.000	1.000	1.000
P06	1.000	1.000	1.000	1.000	1.000
P09	1.000	1.000	1.000	1.000	1.000
P10	1.000	1.000	1.000	1.000	1.000
P12	1.000	1.000	1.000	1.000	1.000
P13	1.000	1.000	1.000	1.000	1.000
P15	1.000	1.000	1.000	1.000	1.000
P17	1.000	1.000	1.000	1.000	1.000
P18	1.000	1.000	1.000	1.000	1.000
P20	1.000	1.000	1.000	1.000	1.000
P08	.941	1.000	.883	.938	1.000
P11	.908	.845	1.000	.916	.816
P07	.808	1.000	.616	.762	1.000
P16	.808	1.000	.616	.762	1.000
P19	.616	1.000	.233	.378	1.000
P05	.555	1.000	.466	.635	1.000
P14	.508	1.000	.016	.032	1.000
Average	.907	.992	.842	.871	.991

Note. Results marked in green are above the average value of that metric, and those marked in red are below average (Nordstrøm-Hauge & Vassbotn, 2023).

an accuracy of 50.8%. The best-performing metric is precision, with an average of 99.2%, closely followed by specificity with 99.1%.

3.4 Inter-Subject Classification

In Table 4, the results of the inter-subject model on the test set are listed. The participant column shows which participant was leave-out in for the test set. The average accuracy across all participants is 62.9%. The best-performing metric is specificity, with 81.5%. The best accuracy was achieved when P15 and P09 were in the test set, with an accuracy of 94.1% and 90.2%, respectively. The lowest accuracy was obtained using when P04, P19 and P02 where leave out, resulting in accuracy levels of 25.0%, 29.4% and 29.5%, respectively.

4. Discussion

The aim of this study is to pave the way for the design of an EEG-based alcohol detection system for the onboard monitoring of drivers. In this section, the obtained results are discussed. As Figure 4 shows, the average BAC value for all participants decreases from the first to the second measurement after drink inges-

Table 4

The Performance of the General Model on the Test Set

Participant	Accuracy	Precision	Recall	F1 score	Specificity
P15	.941	1.000	.856	.922	1.000
P09	.902	.814	1.000	.897	.829
P13	.875	.750	1.000	.857	.800
P01	.857	1.000	.666	.800	1.000
P16	.760	1.000	.361	.531	1.000
P20	.727	.645	.606	.625	.800
P05	.694	1.000	.267	.431	1.000
P06	.682	1.000	.333	.500	1.000
P10	.682	.000	.000	.000	1.000
P11	.664	.621	.528	.571	.764
P08	.642	1.000	.044	.085	1.000
P07	.625	.500	.333	.400	.800
P03	.625	.500	.666	.571	.600
P17	.619	.000	.000	.000	.887
P12	.550	.000	.000	.000	.880
P14	.500	.000	.000	.000	.800
P18	.394	.000	.000	.000	.630
P02	.295	.000	.000	.000	.615
P19	.294	.000	.000	.000	.470
P04	.250	.000	.000	.000	.400
Average	.629	.492	.333	.360	.814

tion. After this, the average BAC increases. Consequently, the peak BAC value was not reached at 25 minutes after ingestion. Even though the shape of the BAC curve can vary highly during the absorption phase, a decrease in the BAC normally indicates that the peak value has been reached and that the absorption phase is over. Therefore, this dip in value is most likely not due to the unpredictable nature of the absorption phase. A possible explanation can be that this dip is a part of a spike in the BAC value. These can be caused by the sudden opening and closing of the pyloric sphincter (Jones, 2008). Using a breathalyser can also make these spikes more apparent. Therefore, the average dip in BAC value should not be emphasised. To avoid measuring a decrease like this, the BAC could be measured by using another instrument than a breathalyser, or it could be measured in intervals of more than 10-12 minutes.

Considering the increasing trend of the BAC curves (Figure 4), most participants did not reach the peak BAC value. The preferred outcome of the experiment would be to have the participants reach the BAC peak during the alcoholic recording session. This is to enable analyses of the behaviour of the participants while under peak BAC influence (Nordstrøm-Hauge & Vassbotn, 2023). To increase the chances of the participants reaching the peak BAC, they could have been instructed to not eat beforehand, or they could have been served an undiluted alcoholic drink. Otherwise, the length of each experiment session would have to be increased.

In the Flanker results, both the average accuracy (Figure 5a) and the average RT (Figure 5b) decrease from the non-alcoholic to the alcoholic Flanker task. As indicated by their p-values, both of these changes are significant. The decreases can be explained by the disinhibition caused by the alcohol. The participants answer faster due to impulsiveness, and therefore they might not be aware of the correct answer before they press a key. As all participants performed the Flanker task in the pre-experiment recording, the changes between the alcoholic and non-alcoholic Flanker tasks are believed to be caused by alcohol alone, and not nervousness.

The Flanker task was chosen as a part of this experiment to test the participants' ability to filter relevant information from irrelevant. This can be compared to how a driver needs to be aware of both the road they are driving on and their surroundings. As the results in Figure 5 show, the consumption of even a small amount of alcohol seems to significantly affect a person's ability to make the right decision as fast as needed.

The intra-subject model provides a realistic implementation of an alcohol detector tailored for individuals. It is noticeable that the performance was the highest possible for 13 of 20 participants, and only three participants got an accuracy lower than .8. This indicates that an alcohol detector can be tailored for individuals. In the case of the low performance scores an explanation can be the differences in the EEG signals across the recording sessions. These differences can be due to an increased impedance between the sessions, or due to a small change in the EEG cap positions between the two sessions.

The inter-subject model has large differences in its performance (Table 4). These results are not surprising,

as there are differences in the EEG signals across participants (Nordstrøm-Hauge & Vassbotn, 2023). This leads to difficulties when training and testing on different participants. This indicates that the general model was struggling to correctly classify alcohol epochs. Some of the participants where the classifier was struggling present a lower BAC value than the averages. This might lead to less clear alcohol features as the brain is less affected by alcohol, which can make the classification of alcohol-affected signals more difficult. Despite this, the inter-subject model does provide confidence that an EEG- based alcohol detector can become a helpful tool in the future, as it performed above the chance level for 14 of the 20 subjects and obtained an accuracy higher than 0.8 on participants P15, P09, P13, and P01. However, the performance must be significantly improved to use this approach as an alternative to a breathalyser.

The collected data set has some limitations. It was not possible to measure the scalp-electrode impedance while collecting the data. This means the impedance could be higher than desired, and this could have led to the data being more challenging to classify than it could have been with a lower impedance. During the collection of the data, construction work was performed outside the data collection room. The noise from this work could have affected the participants, and, consequently, the noise interference could have affected the classification results negatively.

5. Conclusion

This work shows that it is possible to differentiate alcohol-affected EEG signals from those that are unaffected. The Flanker results indicated that the participants were affected by alcohol, which suggests that the EEG signals might be affected as well. These results are supported by the performance of the classifiers, especially the intra-subject one. The high accuracy indicates that EEGNet can extract features which characterise alcohol-affected signals. The performance of the inter-subject model is not as good as it struggles to correctly classify alcohol-affected signals. There could be numerous reasons for this, and improving the performance should be further explored. Still, the models presented in this paper could be the first step towards creating an EEG-based alcohol detector prevention of drunk-driving.

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