Fatigue Driving Risk Reduction in Commenced Journey

PROJECT REPORT

Version: 2.0

Date: 06/06/2022

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PROGRAM	
Name	AI for society
Type	Minor
Time	Semester 6
PROJECT	
Title	Fatigue Driving Risk Reduction in Commenced Journey
Document	Report
Version	2.0
Date	06/06/2022

Abstract

This is the report for the project ‘Fatigue Driving Risk Reduction in Commenced Journey’, in which the research question of “How to apply AI for early fatigue detection within 18 weeks and conceptualize deployment for motorists and transporters responsibly?” is answered. In essence, the project makes use of the Real-Life Drowsiness Dataset (UTA-RLDD) made by the University of Texas at Arlington as the source data. By applying computer vision together with deep learning, the physiological blinking patterns of participants can be mathematically extracted as input for a Multi-layer Perceptron model (MLP) to detect the mental state in terms of vigilance, low-vigilance, and fatigued. Although the accuracy only reached 55 percent, the result has proven that there is potential for further research into the field of pre-emptive fatigue detection using endogenous and physiological characteristics. Following this path, the envisioned outlook is a product that can detect early fatigue state in driver and suggest a safe route to a suitable location for recovery or driver change. This product should be independent of a specific car brand and inclusive for all users. This is the base concept of applying the result of the project responsibly. To intuitively grasp key insights, the report can be read in conjunction with the interactive visual dashboard.

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VERSION HISTORY		
Version	Date	Detail
1.0	05/06/2022	Finished adding all content
2.0	06/06/2022	Added appendix

GLOSSARY		
Abbreviation	Full form	Definition
AI	Artificial Intelligence	Intelligence demonstrated by machine for tasks such as subject prediction or object recognition.
EDA	Exploratory Data Analysis	The process of exploring and analyzing initial data to gain insight for better data provision, preparation, and modelling.
GDPR	General Data Protection Regulation	A regulation in European Union's law on data protection and privacy in the European Union and the European Economic Area.
SMART	Specific Measurable Achievable Relevant Time-bound	Acronym for goal setting, encompassing (1) Specific, (2) Measurable, (3) Achievable, (4) Relevant, (5) Time-bound.
TICT	Technology Impact Cycle Tool	A tool that provides prompting questions from ten important perspectives to help developers consider the effects of their technology on society.

1. CONTEXT

FATIGUE DRIVING – DANGER AND PROPOSITION

The first chapter will be outlining the problem and premise of the proposed solution. After which, the chapters for constraints, process, and impact design are available in the mentioned order.

1.1. Problem

As mentioned during the proposal of the project, 15 to 20 percent of road accidents is related to fatigue while driving (SWOV, 2019). Counting indirect cases, studies that used pre-determined crash characteristics (e.g. no skid mark) estimated that the figure can go up to 30 percent. Although, the cause for fatigue driving can be sleep or task-induced, it is clear that this is a genuine issue in the field of traffic control and safety.

With its significance mentioned, it is noteworthy that the solutions for fatigue driving mostly remain at a communication level. Although this is necessary to spread awareness, it is insufficient to solve the problem. In most cases, driving while fatigue is either unintentional (task-induced) or unavoidable (occupational restrictions). Thus, it is clear that a technological application is essential to creating substantial impact.

While such products do exist on the market, most of them make use of an alarm to wake the user up when drowsy. Predictably, this provides a false sense of security due to two reasons. Firstly, mentally fatigued individuals will find it difficult to block distractions and face an increase in decisional error (Faber et al., 2012). Secondly, once the drowsy signs are clear, the driver may already be in a micro-sleep. Thus, prolongment of such state while driving should not be the answer to any risk-reducing product. The most suitable way to deal with fatigue during a commenced journey is to pre-emptively detect the progression of driver's mental state and provide direction to a safe location for temporary rest or change of driver. As NIOSH suggests, "pull over, drink a cup of coffee, and take a 15-to-30-minute nap before continuing" when feeling drowsy (NIOSH | CDC, n.d.).

1.2. Solution premise

With the information from the previous section in mind, envision a device in the front of the seating compartment that can detect the progression of the driver's mental state based on various features including blink attributes (e.g. blink frequency, amplitude, duration). Depending on the vigilance of the user, the product can then suggest a safe route to a safe location via its GPS system. Here, temporary break or driver change can happen. In essence, such product will utilize Artificial Intelligence (AI) to perform the mentioned detection and it is this AI model that is the focus of the project.

2. CONTRAINTS

SCOPE AND IDEA FORMULATION

Having presented the problem and solution premise, this chapter focuses on the scope and a suitable formulation of the project idea.

2.1. Research question

In light of the mentioned premises, it is clear that the project goal is to design an AI model while carefully consider its impact. This model should be able to locate facial features for measurements and detect the user mental state progression. Based on the exploratory nature of such concept, it is most efficient to have a clear application basis to focus on.

Considering all available facial features, most are not dynamic and are only indicative of drowsiness once micro-sleep draws near or is present. To satisfy this condition for pre-emptive detection, the most suitable characteristic is the eyes. More specifically, the blinking attributes of the eyes. To exclude significant anomalies that may stem from external stimuli, the focus should be narrowed down to the endogenous blinking attributes of drivers.

To actualize this idea, the research question of the project can be formulated as **"How to apply AI for early fatigue detection within 18 weeks and conceptualize deployment for motorists and transporters responsibly?"**. Its sub-questions are as follow:

1) What are the early signs of fatigue to become input for detection?
2) What is the method to procure suitable data and capture the determined input?
3) What is the suitable model and its architecture for effective task performance?
4) What is the responsible way to deploy the algorithm for motorists and transporters?

It is not within the scope to find health-remedies for cases of underlying physical and mental issues caused by or leading to sleep deprivation. Any individual with potential health risks should visit professional healthcare services for suitable diagnosis and treatment, both physically and mentally.

2.2. Stakeholders

Having considered the research orientation, it is also important to describe the target and affected groups, i.e. stakeholders. The most relevant primary and secondary parties can be found in table 1 with respective descriptions. Their level of stake is determined by the impact proximity of the envisioned outcome.

Table 1:

Stakeholders and description

STAKEHOLDERS		
Type	Name	Description
Primary	Motorists and truckers	Since fatigue driving risk reduction is the functional goal of the project, motorists and truckers are the direct stakeholder. They have the option to utilize the outcome to reduce their risk of accident. Their benefits are one of the motivators for the project while their response can directly alter the product specifications once commercialized.
Primary	Other traffic participants	Beside the safety of the drivers, the result of the product will also directly affect the safety of other traffic participants (e.g. cyclers, pedestrians).
Primary	Developer/Student	As an internal stakeholder, the developer is responsible for the development of the project.
Primary	Minor Consultants	As the project runs within the Minor program of Fontys University of Applied Sciences, teachers/consultants are available for support and will evaluate the learning curve of the student.
Secondary	Motorists and truckers' family	The family and a driver might be in the vehicle together. Thus, the outcome can directly affect the safety of the family as well as the driver. On the other hand, reducing the danger risk for motorists or truckers will also indirectly affect their families.
Secondary	Societal/government-related parties (e.g. police, hospital)	If the product reduces a substantial proportion of accidents due to fatigue driving, the stress on societal/government-related services may lessen, creating room to deal with other pressing concerns.

2.3. Working constraints

The developer should complete the work for the project by the 12th of June 2022. By this date, the report document, visual report dashboard, and coding notebook series should on Canvas. The deliverables currently contain three must have components :

- An AI model with its result depicted through a visual report.
- Project report to reflect on the development process and deployment depiction.
- AI notebook prototype.

To conduct machine learning tasks within the assignment, the project applied Python – a general-purpose programming language. As the project progresses, other tools also found their role to complete necessary tasks, such as Power BI for dashboard creation and Microsoft Office tools for planning, documentation, and presentation.

3. PROGRESS

APPLICATION OF AI FOR PRE-EMPTIVE DROWSY DETECTION

This chapter will reflect on the working methods, reasonings, and findings acquired throughout the planned stages of the project.

3.1. Methodologies

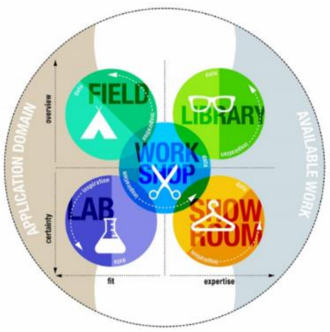
It is now necessary to describe the result and decisions made during the project period. To efficiently complete any given task, the specification of both the method and plan is essential. Thus, this section is a concise description of the methodologies applied.

3.1.1. Research

Due to the exploration nature of the project, research plays a vital role in the context of **"Fatigue Driving Risk Reduction in Commenced Journey."** In order to find, process, and apply information to the working process, the project uses a framework called DOT (Development Oriented Triangulation).

Figure 1:

DOT Framework representation (DOT Framework - ICT Research Methods, n.d.)



This framework takes into account all factors of research that an applied-science project would require. Coupled with the regard to aspects including "what," "how," and "why," DOT provide structure and ease of communication through five different strategies:

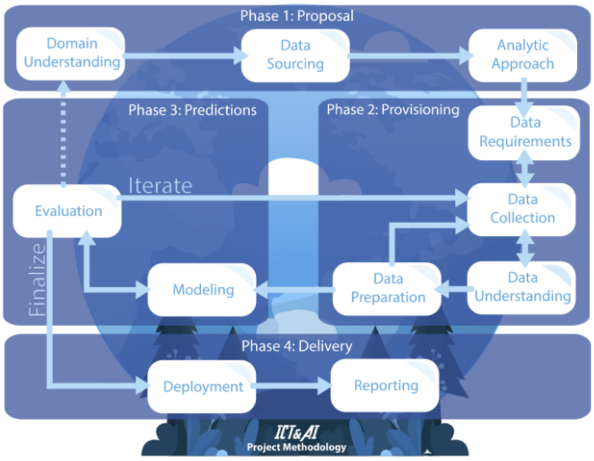
1. Field – to explore the application context of intended product.
2. Library – to explore existing work, guidelines, and theories to support solution design.
3. Workshop – to explore application opportunities via sampling and interaction.
4. Laboratory – to evaluate and derive quality management for intended product.
5. Showroom – consider intended product and samples with regards to existing work.

3.1.2. Working

For working method, the project applied the ICT&AI methodology. It is based on the IBM Foundational Methodology for Data Science (AI Project Methodology, n.d.), with four phases as depicted in figure 2. The project has made multiple loops through the 2^{nd} and 3^{rd} stages to iterate the AI model(s).

Figure 2:

ICT&AI methodology (AI Project Methodology, n.d.)



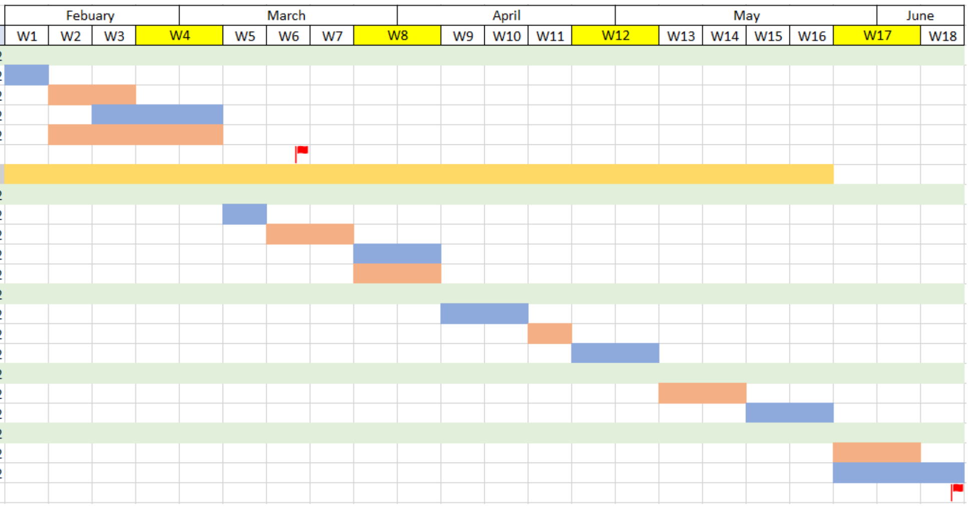
3.1.3. *Planning*

To guarantee value delivery in iteration regardless of spontaneous changes, the project uses sprints as the phasing method. As depicted in figure 3, there are four sprints that compose the entire project.

Figure 3:

Project phasing Gantt chart

ID	Task	Days	Start	End
	INITIATION	28	07/02/2022	06/03/2022
0.1	Subject selection - Prelim research	7	07/02/2022	13/02/2022
0.2	Domain & Technical research	14	14/02/2022	27/02/2022
0.3	Prelim data collection & EDA	14	21/02/2022	06/03/2022
0.4	Document proposal	21	14/02/2022	06/03/2022
	Proposal submission		*20/03/2022*	
0.5	**Fill in report**			
	SPRINT 1	28	07/03/2022	03/04/2022
1.1	Data provision & preparation	7	07/03/2022	13/03/2022
1.2	Models application	14	14/03/2022	27/03/2022
1.3	Tune & analyze	7	28/03/2022	03/04/2022
1.4	Product improvement research	7	28/03/2022	03/04/2022
	SPRINT 2	28	04/04/2022	01/05/2022
2.1	Data provision & preparation (2.0)	14	04/04/2022	17/04/2022
2.2	Models application (2.0)	7	18/04/2022	24/04/2022
2.3	Tune & analyze (2.0)	7	25/04/2022	01/05/2022
	SPRINT 3	28	02/05/2022	29/05/2022
3.1	Deployment research	14	02/05/2022	15/05/2022
3.2	Visual report design	14	16/05/2022	29/05/2022
	SPRINT 4	21	30/05/2022	12/06/2022
4.1	Report wrap-up	7	30/05/2022	05/06/2022
4.2	Final edits	14	30/05/2022	12/06/2022
	Final submission		*12/06/2022*	



3.2. Initiation phase

With the plan and methodologies mentioned above, the developer initiated the first sub-period of the project. The main goal of this phase is to perform research on the different facets of the relationship between blinking attributes and vigilance. Simultaneously, the search for a suitable dataset took place.

3.2.1. *Source data*

Experiments have showed that correlation does exist between endogenous blink attributes and the vigilance level of an individual (McIntire et al., 2014). However, the research that demonstrated this used advance laser for blink monitor and attribute calculation. Thus, the question is how to perform such extraction without the need for advanced machinery. With further community and literature research, the conclusion is that by applying Machine Learning and Computer Vision (a field of AI where machines can see the visual world through training), the attributes of a blink can be determined and modelled.

Keeping in mind the desired input, conventional datasets available online are far from suitable. The common notion implied through these datasets is the usage of images to decide whether or not a driver is in the drowsy state. Such method implicitly assumes that there are only two states – awake and drowsy. In doing so, it makes the same mistake as most product available and will give alert only when micro-sleep has happened. Furthermore, the creator or participants of these images often fake the fatigue state.

After careful selection, the Real-Life Drowsiness Dataset (UTA-RLDD) made by the University of Texas at Arlington seems to be the most suitable source for selection. It contains video recordings of sixty participants, of which forty-three are used in the project. For each participant, there are three videos corresponding to their vigilant states (alert, low vigilance, and drowsy). The collectors of the data have ensured that the participants recorded and labeled the videos as realistically as possible (e.g. real time capturing when experiencing one of the three states). The attempt to increase diversity is also notable in the data as there is a variety of different ethnicities present, with characteristics such as glasses and beard also considered.

3.2.2. Method

There are four attributes available for extraction from the source data. While McIntire et al. (2014) recommended blinking frequency and duration as indicators of fatigue level, a technical study of drowsiness based on blink behavior by Svensson (2004) suggested that amplitude is also a usable attribute. Beside them, the eye-opening velocity has been nominated as the final feature to round off the list by Johns and Hocking (2021). This is also the answer to sub-question one: “What are the early signs of fatigue to become input for detection?”.

To derive the mentioned attributes, the eye aspect ratio (EAR) is an essential concept. This metric measures the ratio between the horizontal and diagonal landmarks of the eyes to determine whether or not they are closed. Using computer vision to read in the videos of the source data frame by frame, the project then applied the prebuilt face detector model from the DLIB library in Python to detect the eye landmarks depicted in figure 4. After which, the formula in figure 5 is used to calculate the EAR sequence of each detected blink.

Figure 4:

Eye aspect ratio sequence and landmarks (Soukupova and Cech, 2016)

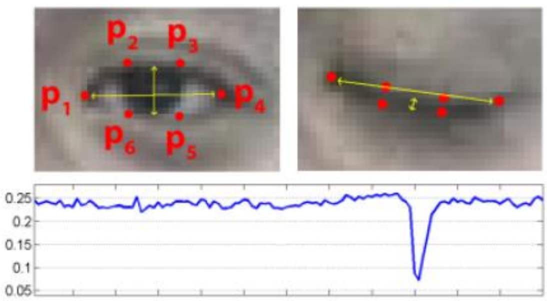


Figure 5:

EAR formula (Soukupova and Cech, 2016)

$$\text{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

While the EAR sequence is essential to calculating the mentioned attributes, there are two approaches available for this task. The first approach is to use insights gathered from previous studies in psychological physiology and computer vision to infer the value of the attributes. This derivation will apply reasonings on the EAR sequence of recorded eye blinks. Key usable information include:

- If the EAR falls below the average threshold for at least three frames, it means that the eyes have closed (McIntire et al., 2014).
- An endogenous blink lasts around 150 - 300ms, which is 5-10 frames in a 30fps video (Stern et al., 1984).
- There is an average of 7-frame-margin and 10-frame-width per blink (Soukupova and Cech, 2016).

By utilizing what these papers have to offer, the project's code can navigate the start, bottom, and emergence points of the EAR sequences. Combined with the recording of frames at which a certain EAR of a blink happens, the attributes can be calculated. Despite being heuristic-based, this is a simple method with straight forward logic that is efficient to implement.

As opposed to the first method, the second approach is to use mathematical calculations to regress between the maxima and minima of the sequences to find the checkpoints of blink-start, blink-bottom, and blink-end. Once the code has determined these values, the calculation of attributes is similar to the first approach. These two methods are also the answer to the second sub-question: "What is the method to procure suitable data and capture the determined input?". To analyze the trade-off between complexity and performance, the project used heuristic reasoning as the primary method until the end of sprint one while the second sprint focused on mathematical calculation for comparison.

3.2.3. Attribute extraction

As the report has described in the previous section, there are four attributes recommended by various research to perform fatigue driving detection. These include amplitude, frequency, duration, and eye-opening velocity. While there is no set definition for them, the widely accepted formulation is as follow:

- Amplitude: the average motion of the eye in EAR
- Frequency: the number of blinks over time (i.e. number of passed frames)
- Duration: the time it takes for a blink in frames
- Eye-opening velocity: speed of eye-opening in EAR/frame

Figure 6:

Attribute formulas (Ghoddoosian et al., 2019)

$$\text{Duration}_i = end_i - start_i + 1 \tag{2}$$

$$\text{Amplitude}_i = \frac{EAR[start_i] - 2EAR[bottom_i] + EAR[end_i]}{2} \tag{3}$$

$$\text{Eye Opening Velocity}_i = \frac{EAR[end_i] - EAR[bottom_i]}{end_i - bottom_i} \tag{4}$$

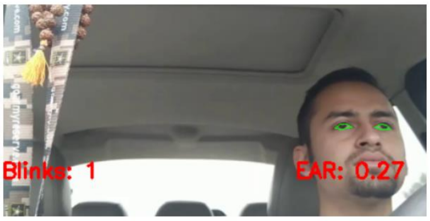
$$\text{Frequency}_i = 100 \times \frac{\text{Number of blinks up to blink}_i}{\text{Number of frames up to } end_i} \tag{5}$$

To extract these features from the videos, the latter must be unison in length and the total size should not exceed the capacity of the local machine[1]. Thus, three minutes became the duration to crop all videos to. This reduced the total memory required from 100GB to 30GB – a sufficient size for a trade-off between performance and local computer storage.

With the videos cropped, the local machine read them frame-by-frame to detect the eye landmarks (figure 7) and calculated the EAR sequences. Using the heuristic method, the bottom EAR of a blink can be determined by looking at the EARs registered while below the dynamic threshold (minima). When the machine determines that a blink is at the EAR above the threshold, it will check 6-frame-span backward for the ideal start point. If a blink takes longer, the code will start at the seventh frame backward until a value is above the threshold. The EAR at this point will be considered alongside three previous frames to see which is the appropriate blink-start (maxima). These reasonings are based on the information that an endogenous blink usually has seven frames margin and a ten-frame-width.

Figure 7:

Eye landmark and EAR tracking sample



The project also made visualizations to explore the attributes collected. The goal is to identify any pattern that is visible to the eye. This may help in the modelling process in terms of data preparation and model selection. However, no special pattern is confirmable with total confidence. While the average values of attributes of the drowsy state is separatable from the low-vigilance and vigilant state (figure 8 and 9), it is difficult to linearly separate the latter pair from each other. Furthermore, the heuristic method is also prone to be misled by eye-closure movements that take longer than the average. The uncertainty lies in the derivation of the blink-end point since the heuristic method is about formulating checkpoints by looking **back** at the

[1] There is no storage resource available in this project other than the local machine.

EAR sequence. There are also various outliers present. However, the project kept them as they may reflect the nature of the mental state shown through blink behaviors.

Figure 8:

Average duration per state

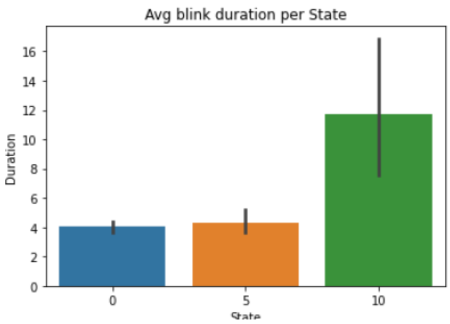


Figure 9:

Amplitude and frequency distribution per state

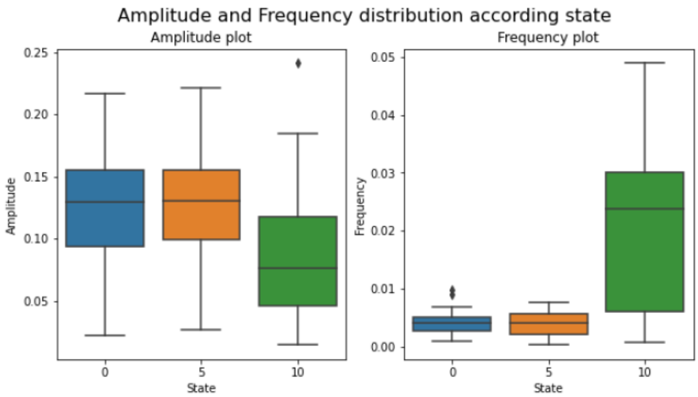


Table 2:

DOT instruments and reasonings for initiation phase

DOT INSTRUMENTS			
Activity	Method	Instrument	Reason
Selecting attributes and research extraction methods	FIELD	Document analysis	By analysing the current situation, a better understanding of fatigue and blink behaviour is available. This helped in the selection of attributes.
	LIBRARY	Literature study	Studying previous research is essential to formulate the heuristic reasoning method.
Explore data extract and check for its applicability regarding task at hand	FIELD	Exploratory data analysis (with system exploration)	The report derived and explored the needed data from the source to find potential issues and recognizable patterns. This is to help with model selection.

3.3. Sprint 1 – Heuristic based

During the first sprint, the main task is to find a suitable model to navigate the data extracted by the heuristic method. Since there is no pattern recognized with confidence by the exploration process, the best approach is to iterate over all major model classes and select popular representatives. From simple to more complex, the list of used models include:

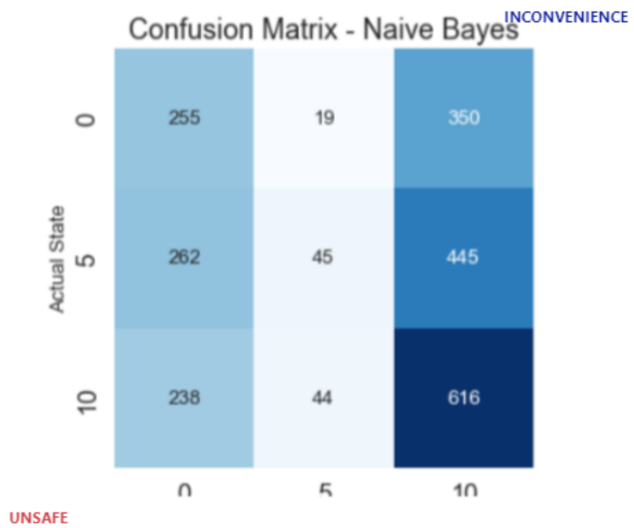
- Naïve Bayes classifier
- K-Nearest Neighbors
- Ensemble models: Random Forest and Gradient Boosting
- Artificial Neural Network: Multi-layer Perceptron

The method of evaluation is to combine the accuracy and confusion matrix of a model. While the former indicates the overall performance, the confusion matrix can analyze the usability in terms of safety and convenience.

Starting with Naïve Bayes classifier – a probabilistic model, while it did return an accuracy of 40 percent – which is higher than the intuitive expectation, the performance is still unfavorable. This is because the classifier is lumping most observations into either the vigilant state or fatigued state. As observable on its confusion matrix, the result is both unsafe and inconvenient.

Figure 10:

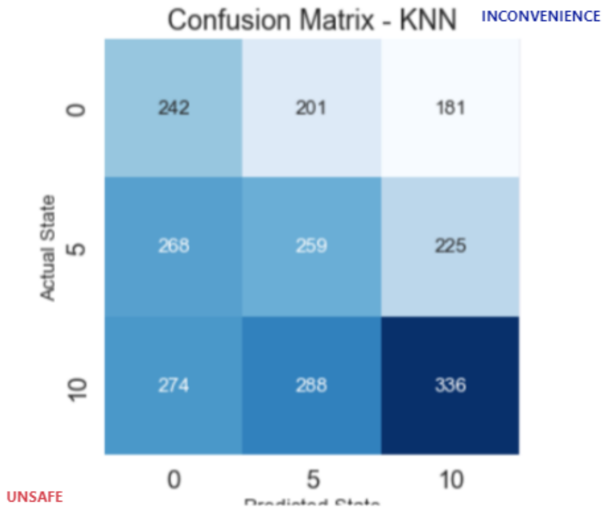
Confusion matrix – NB – Heuristic



Beside Naïve Bayes classifier, the project also expected the result of its antecedent to be low. Being a proximity-based model, K-Nearest Neighbours would not be able to prove itself when there are highly dense and overlapping areas. This is also what the result suggested as the returned accuracy is only 37 percent post-tuning while its confusion matrix indicates that the safety and convenience level are both low.

Figure 11:

Confusion matrix – KNN – Heuristic



The next type of models that was applied is ensemble-based. There were two representatives chosen – Random Forest and Gradient Boosting. While the latter often has higher performance than the former, it is less useful when there are numerous outliers (Glen, 2019). Considering that all potential blinking behaviors are trackable by keeping outliers, the project decided to use both models and compare the result post-tuning.

At the end of this process, the results were similar between these two models. They both give approximately 42 percent accuracy. While this is better than the preceding proximity and probabilistic model, the confusion matrixes indicate that the implication is not yet favorable. Although tuned for the best result, Gradient Boosting still lumps most observations into the fatigued state while Random Forest ignores the vigilant class.

Figure 12:

Confusion matrix – RF – Heuristic

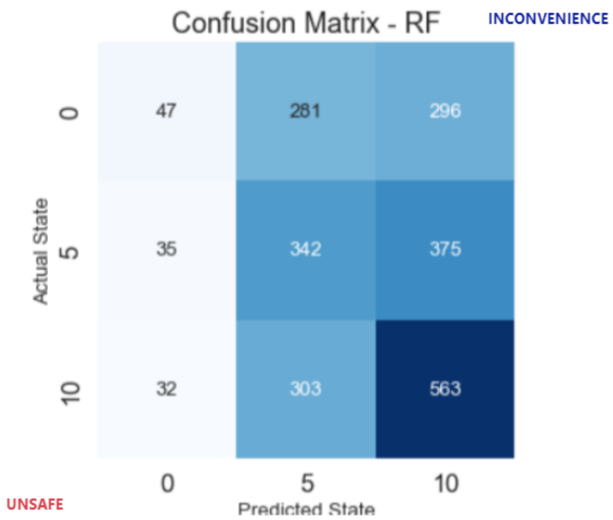
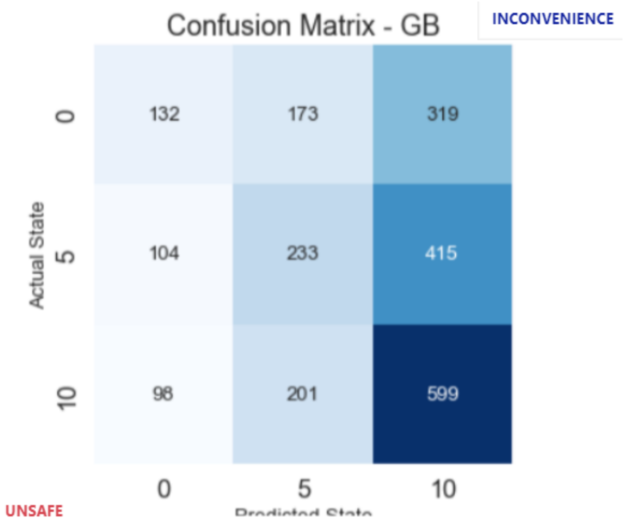


Figure 13:

Confusion matrix – GB – Heuristic

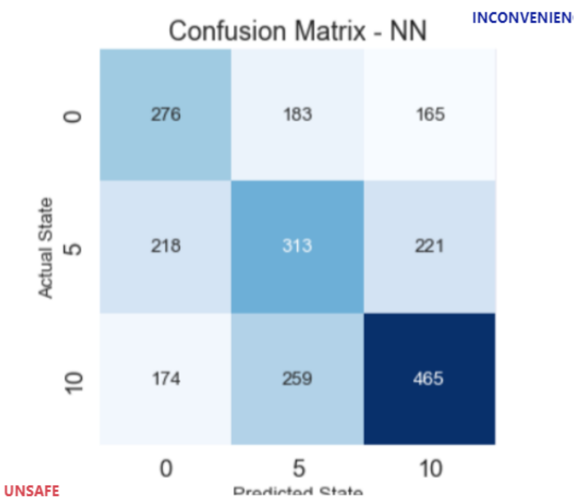


Although supervised and unsupervised learning did not present promising result, community research suggested that deep learning is potentially the most viable method when working with complex issues such as fatigue state detection. After brainstorming, the report found that Multi-layer Perceptron (MLP) is the most suitable deep learning model for the multi-class detection problem at hand.

Through experimenting with the architecture of the model, the best result attained is an accuracy of 46 percent. This is higher than the other models, though still too low to be deemed a favorable result. Regarding the confusion matrix, the ideal situation is a highly concentrated left-to-right diagonal line with light 'unsafe' and 'inconvenience' corner. Although the diagonal is starting to form in the case of MLP, it is still too light.

Figure 14:

Confusion matrix – MLP – Heuristic



Overall, the best performing model while using the heuristic reasoning method for feature extraction is MLP. However, its result is still too low for there to be any applicable implication.

The following steps for sprint two were to re-iterate, extract the blink attributes using the mathematical approach, model, tune, and evaluate the outcomes to find the prototype model.

Table 3:

DOT instruments and reasonings for Sprint 1

DOT INSTRUMENTS			
Activity	Method	Instrument	Reason
Research for suitable algorithms	LIBRARY	Literature study Community research	It is necessary to research about potential algorithms via community and literature. The former is to find inspiration and the latter is to comprehend the mechanism of the model for further design.
Prepare data to get the suitable input format for each model	LAB	Data preparation	This is part of the machine learning workflow and is necessary for model application.
Apply algorithms to the prepared dataset	LAB	Model training	This is part of the machine learning workflow and the main activity of the modelling step.
Evaluate and discuss with domain experts	LAB	Model validation	After modelling, evaluation and validation will help in revealing the legitimacy and actual application value of the model.

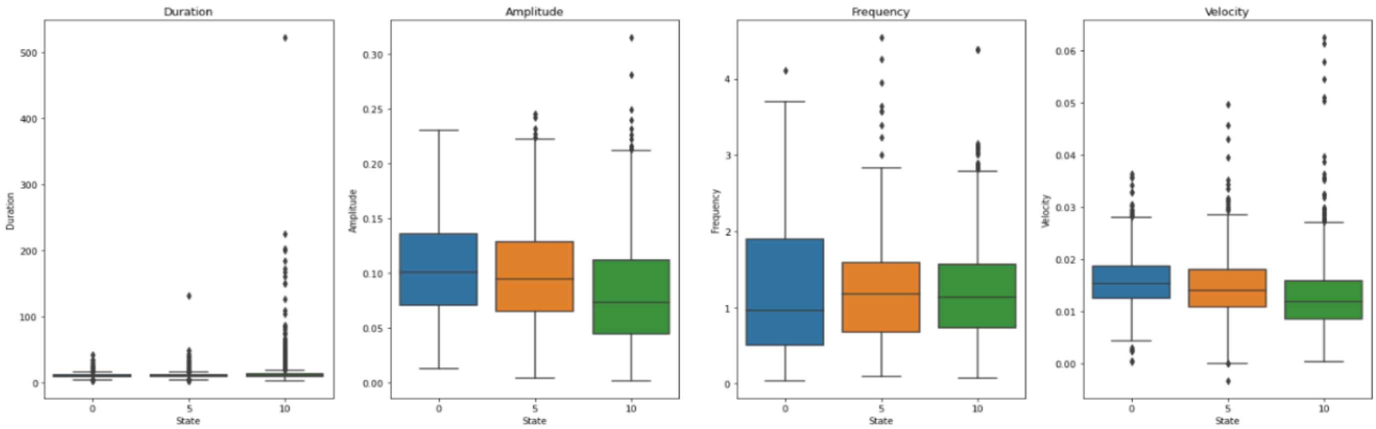
3.4. Sprint 2 – Mathematics based

Compared to the previous phase, the second sprint used the mathematical method for feature extraction. While the formulas to calculate the attributes remain the same, the difference lies in how the methods identifies the checkpoints in the EAR sequence. To perform this derivation, the mathematical calculations from Ghoddoosian et al. (2019) is the reference material and is observable in the appendix. In essence, various regressions are performed to find the points of maxima (blink start and end) and minima (bottom EAR).

One advantage that the mathematical method has over heuristic reasoning is its ability to discern consecutive blinks and prolonged eye closure with confidence. This function is part of the overall code that Ghoddoosian used. Thus, the attribute values have higher certitude and clearer separation as compared to the previous sprint. However, there is still overlapping in terms of their distribution by state (figure 15). Therefore, the project still applied the model-narrow-down approach in this phase.

Figure 15:

Distribution of attributes by state

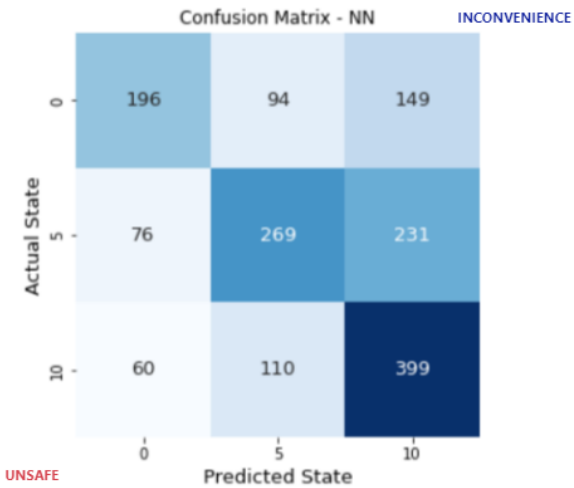


While the Naïve Bayes classifier dropped its performance from 40 percent to 35 percent, the accuracy for K-Nearest Neighbors rose to 46 percent. This is already on par with the best result attained in the first sprint. As the narrow-down approach moved onto the ensemble algorithms, the accuracy also increased pass that of the previous phase. The tuned version of Gradient Boosting did perform slightly better than the Random Forest model with opposing figures of 53 and 51 percent. However, it was still the MLP model that has the best performance.

Using similar architecture to that of the first sprint, the antecedent MLP model achieved an accuracy of 55 percent – the best result in the project thus far. Its confusion matrix also showed potential when the diagonal is much clearer than that of all other models. While there is still a degree of inconvenience, it holds a promising outlook as the 'unsafe' corner is towards the lighter gradient.

Figure 16:

Confusion matrix – MLP – Mathematics



Keeping in mind that there is still improvement available before the model reaches an application level, the result is still very promising as it shows that fatigue state detection through blinking behavior is possible. There is definitely further progression for future development cycles to uncover using more time and resources. However, the attained result has used up all that is available within the constraint of the project.

Combining insights from sprint one and two, the answer for the third sub-question of "What is the suitable model and its architecture for effective task performance?" has been answered. This desired model within the context of the research is MLP, with the architecture shown in figure 17. For sprint three, the tasks were to re-assess the deployment of the envisioned product and design a visual dashboard to report on the results intuitively and interactively. Key ML coding notebooks will also accompany the latter deliverable to demonstrate the outcome of the prototype model.

Figure 17:

MLP architecture

```
# Defining the model
blinkNN = Sequential()
blinkNN.add(Dense(2187, input_dim=4, activation='relu'))
blinkNN.add(Dense(729, activation='relu'))
blinkNN.add(Dense(243, activation='relu'))
blinkNN.add(Dense(81, activation='relu'))
blinkNN.add(Dense(27, activation='relu'))
blinkNN.add(Dense(9, activation='relu'))
blinkNN.add(Dense(3, activation='softmax'))
```

Table 4:

DOT instruments and reasonings for Sprint 2

DOT INSTRUMENTS			
Activity	Method	Instrument	Reason
Research mathematical feature extraction method and suitable modelling process	LIBRARY	Literature study Community research	It is necessary to research the second attribute extraction method via community and literature. The former is to help with versioning/setups and the latter is to comprehend the mechanism for further design.
Extract and prepare the attributes	LAB	Data preparation	This is part of the machine learning workflow and is necessary for model application.
Apply algorithms to the prepared dataset	LAB	Model training	This is part of the machine learning workflow and the main activity of the modelling step.
Evaluate and discuss with domain experts	LAB	Model validation	After modelling, evaluation and validation will help in revealing the actual application value of the model.

3.5. Sprint 3 – Outlook research & Visual report

3.5.1. Deployment research

Although the current performance of the MLP model is not at the real-life application standard, it does show potential for the research path. The detection of fatigue state through blink behavior is only the beginning of a larger domain, which is drowsy detection based on dynamic physiological patterns. In this perspective, a result of 55 percent accuracy is a promising start.

During the third sprint, one of the main tasks of the project is to re-assess the desired deployment method. After research and consideration, the report can now paint a more complete version of the envisioned product as compared to the description in the proposal. The depiction to be described below is also the answer to the fourth sub-question of "What is the responsible way to deploy the algorithm for motorists and transporters?". It is noteworthy that any to-be-mentioned feature not within the scope of the current project is also a potential subject for future development.

In terms of design, the product should be in the form of a device that can be incorporated into any car type. There should be a camera and processing component that can connect to the front of the driver seat at a variety of different angles to prevent the obstruction of driver's vision. Alongside this, there should also be a sensor that can be wrapped around the steering wheel and an external sensor to be placed in the front of the car. This device should have two key modules: fatigue detection and navigation.

Through a camera, the product should be able to detect the facial landmarks of the driver to calculate attributes for fatigue state detection. To support this function and deal with potential obstructor such as face mask or sunglasses, the device should also analyze the head-angle/posture. Combined with the grip strength and steering movement collected by the other two sensors, these features will serve as input for the AI model(s) to determine the fatigue state. Before the driver reach actual drowsiness, the product should pick up early symptoms and the navigation module should activate. As suggested in the proposal, the navigation system will notify the driver of the issue and help them navigate to a safe spot for recovery or to change driver. With careful design of the notice method (audio or visual), word/symbol choice, and design (tone/color), these functions should not be intrusive to the driver. Especially when the given insights are suggestions with the user's safety in mind, not commands.

Additionally, the navigation should also have a user-activation function. Similar to the BMW driver support system (BMW, 2021), the navigation should also be able to perform its task upon the requirement of the user. This is achievable through a specified key-phrase customizable by the user.

Comparing this depiction of the envisioned device to that of the BMW recent assistance systems, the product outlook has advantages in terms of its incorporation ability. There are two main factors behind this: thoroughness and inclusivity.

While the BMW Steering and Lane Control Assistant can sound an alarm when it detects unnatural steering wheel movements, there are other endogenous behaviors that can be capitalized for early fatigue detection. It is understandable that the perspective of BMW is to design assistance systems for their cars, not a fatigue detection product. However, the lack of thoroughness when it comes to potential reduction in accidents is a clear disadvantage as compared to what the project suggests. It is not that BMW do not have functions to track more physiological behaviors. In fact, BMW and other major brands all have newly developed physiological tracking systems. However, they have yet to capitalize everything on fatigue driving risk reduction. As an example, BMW has launched the EASE gaze detection system in 2020 (Lardinois, 2020). However, its main purpose is to help gather insights on what the driver finds interesting on the road. Thus, the issue is not inability but a lack of focus and concern.

Although BMW is the primary example that the report uses, fatigue detection also exists as a minor function in other assistance systems of major car brands. The mentioned points are not to criticize the decisions of these brands, but merely to report on the tradeoffs. In this sense, the nature of assistance system is also a limiting factor beside the lack of focus. Being a built-in system for a certain model of car under a specific brand (often expensive) means that the function will not be accessible to everyone. Drivers choosing to not use a function and the function not being available for all drivers are two different situations. From an inclusivity perspective, the latter is more unfavorable.

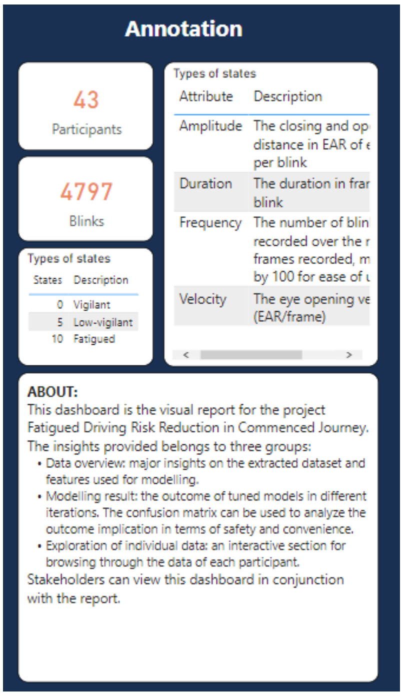
3.5.2. Visual report

As the report have mentioned, the final task of the third sprint is creating a visual dashboard to intuitively and interactively report key insights of the research performed. This is available so that both technical and business-oriented viewers can efficiently comprehend the outcome as well as perform exploration by themselves.

There are four different sections in the dashboard. The first section is annotation, which aims to provide the viewer with a brief context of the project and source data participants. It has been made so that even without spending time to thoroughly read the report, the viewer will still have enough context information to explore the other sections.

Figure 18:

Annotation section



The second section is about the data overview. This section aims to summarize key features of the source data and derived attributes. Through it, the user can gather insights for a better understanding of the data that is used in the modelling process.

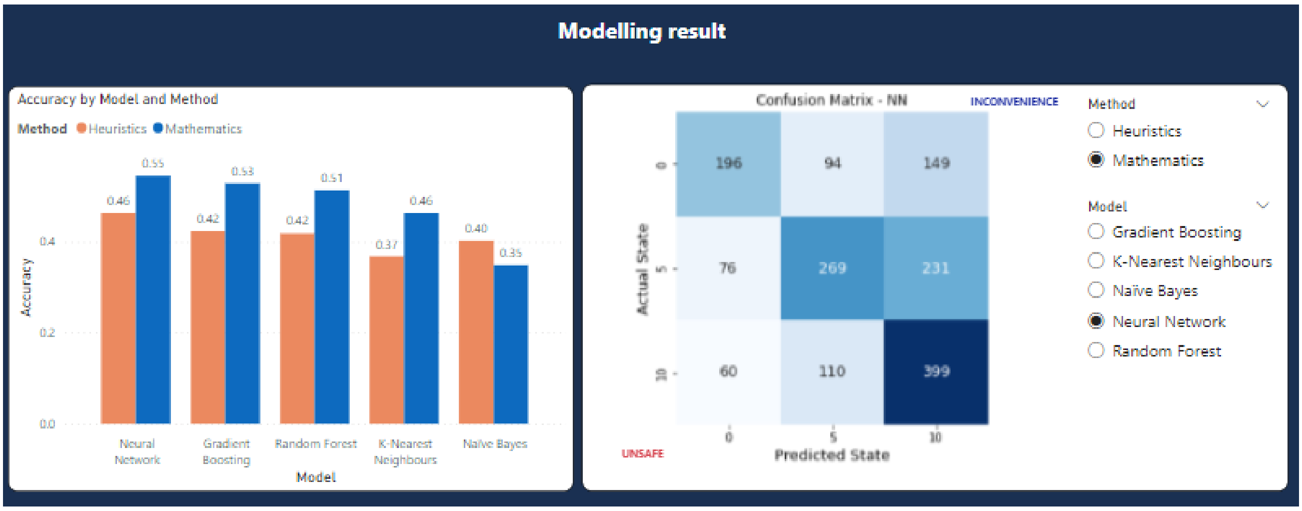
Figure 19:

Data overview section

The third part of the dashboard provides key insights into the modelling result. Here, the viewers can select the extraction method and view each model's analysis metric and performance figure. In doing so, they can explore the different outcomes and compare them to understand the tradeoff between model's complexity and performance as well as the implications in terms of safety and convenience of each model.

Figure 20:

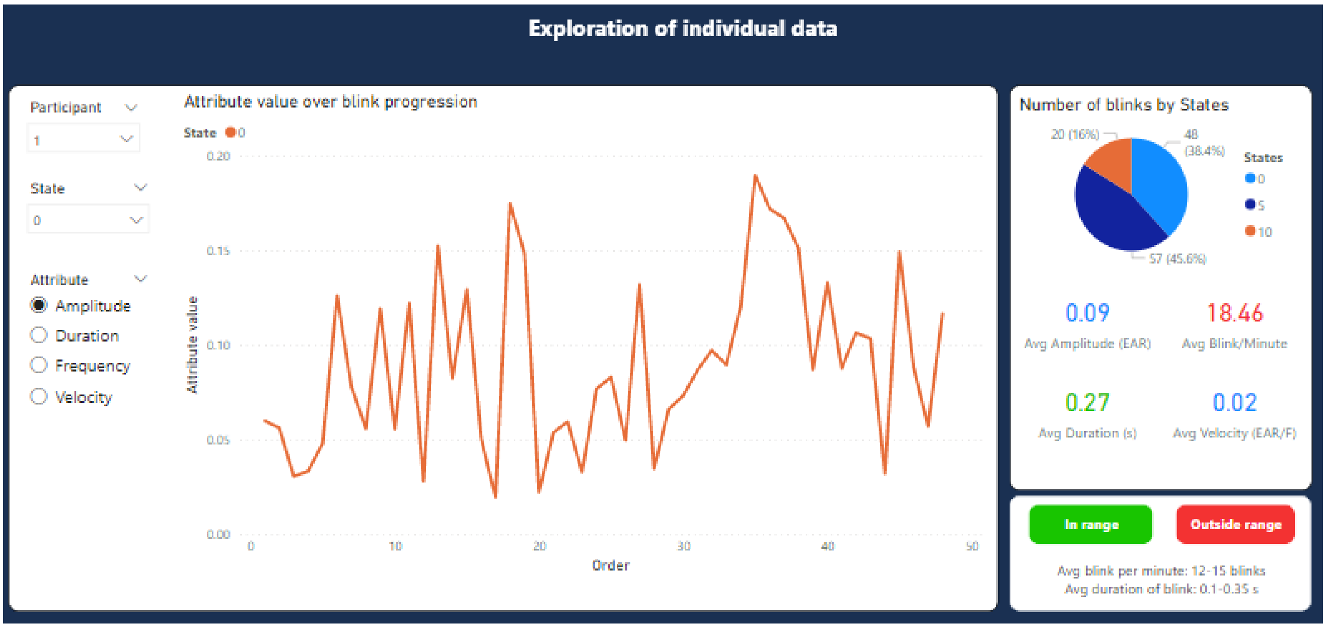
Model result section



The concluding section in the dashboard is reserved for extra exploration into the attributes of each participant and their summarized stats. By browsing this section, the viewer can interact with the dashboard to gain more understanding into the diversified attribute values of each individual as compared to the norm. This can help the viewer to better grasp the units and concepts presented in the report.

Figure 21:

Data exploration section



To demonstrate the prototype model, there are also notebooks of code that the project has selected and trimmed. While it is not necessary for viewers to go through them as all important insights are already in the report and dashboard, they are available as follow:

- Provision v1.0: the initial EDA and feature extraction with static threshold
- Provision v2.0: the heuristic feature extraction code using dynamic threshold
- Provision v2.1: the dynamic threshold extractor to complement Provision v2.0

- Provision v3.0: the mathematical extraction method
- Modelling v1.0: the modelling of heuristic attributes
- Modelling v4.0: the modelling of mathematic attributes

Table 5:

DOT instruments and reasonings for Sprint 3

DOT INSTRUMENTS			
Activity	Method	Instrument	Reason
Compose the new depiction of the envisioned product and perform comparison with similar available systems	WORKSHOP	Brainstorm	It is necessary to note down all viable ways to represent the modelling output, then narrow down for the most thorough design.
	LIBRARY	Available product analysis	Checking available products for inspiration and application advantages or disadvantages helps in creating a unique and valuable outlook.
Rounding up the notebooks and making a dashboard to visualize the prototype model's outcome	WORKSHOP	Prototyping	There is a package versioning difference between the mathematical extraction method and the modelling code. Thus, the project will be using the key notebooks and a visual dashboard to communicate the outcomes as demonstration of the prototype model.
Presenting the visual dashboard to domain experts for discussion	SHOWROOM	Product review	It is important to get feedback on the design and value of the visual report for value delivery

3.6. Sprint 4 – Report & Impact evaluation

The fourth sprint is about wrapping up the project through documentation. As fatigue driving and facial feature collection are complex and sensitive in nature, it is also important to re-assess the possible impacts of the outcome. In a sense, the evaluation of impact can also be considered complementary material for the fourth sub-question as it deals with responsibilities of the developers, both now and in the future. Compared to the outlook-oriented assessment in the proposal, this iteration have additional insights as research on the model has already taken place. The TICT tool will be used to provide structure and thoroughness (TICT, n.d.).

a. Society

Firstly, it is true that fatigue driving is a genuine issue that is often overlooked by the authorities and even traffic participants. Secondly, task and sleep induced drowsiness during an ongoing journey is often unintentional. Thirdly, most products available provides a false sense of security due to the 'alarm approach' described beforehand. From these points highlighted in the previous sections, it is clear that the issue that the product addresses matters. It is one of the keys to reduce fatigue driving risks and increase traffic safety for everyone.

At its current state, the model does not have sufficient performance for application in real scenarios. Furthermore, this project did not address all features of the envisioned product due to the time and context constraint. Thus, the research into fatigue modelling still needs to continue in the future, along with the development of the navigation system to identify and guide drivers to recovery points. This should not cause significant issues as the requirements are straight forward – time and resources.

In terms of the product's outlook, an issue that the proposal previously identified is the criteria to decide on a safe location for recovery when there are unexpected external factors. For example, the product can suggest a route and location for recovery but if natural disaster occurs, it can compromise the safety level identified. Therefore, incrementation is necessary to take into account factors such as that of nature (e.g. from forecast apps). Similarly, this applies to overnight travel on the highway or rural area. Thus, it is clear that defining suitable criteria for recovery location while working on the system in the future is of immense importance.

b. Criminal actors

As the proposal have mentioned, the effects that criminal actors may have on the product lies in future stages of development. In brief, potential issues include criminal activities realized through the hacking of the future product's operating/navigating system and false propaganda to sow social discord based on potential miscommunication between the product and users.

Regarding the first scenario, criminal actors may hack the device's navigating system to use a vehicle as obstruction against law enforcers. It is also possible that the hacking aims to lure and extort an user and their family. Even worse, underlying motives against a community may be present and fuels such activity. This can only be avoided through thorough definition of safety criteria and testing during the commercialization process. Thus, the project recognizes the importance of tackling these issues from a cyber security perspective.

Adding on to the perspective of 'motive against a community,' ethnicity concerns may be invoked if the device cannot recognize features of certain ethnic group. Thus, the project has applied a diverse dataset with dynamic thresholding to take diversity into account. It is noteworthy that such care should be consistent in potential future development cycle.

In the second case, actors of bad intent may hack devices and illegally record data to falsify information in various context to cause turmoil. As the proposal pointed out, actors can falsify that an ethnic group is always leaving later and is overworked as compared to other groups in a targeted company. Thus, implying inequality to cause loss to the target and perform business espionage. This could also be applied to political contexts. Once more, the cyber security scope for future development is highlighted.

c. Privacy

The current model only uses publishable data to not violate the privacy of participants. Thus, there is no concern at this particular stage. However, it gets more complicated as the complexity of the device builds up. This is especially true when the product reaches the commercialization stage and needs a method for continual update of training data. The only solution for this is to invoke users' awareness and ask for permission.

To make it transparent to the users, agreement in terms of data sharing should be drawn up beforehand. Users should know the content of data that is tracked, the purpose, and willingly consent. Only then would the usage of data for service enhancement be possible. Furthermore, data collection should at an equilibrium between quantity and enhancement quality.

According to the General Data Protection Regulation (GDPR), users have the right to erase their data if desired (Wolford, 2020). This is called the "right to be forgotten" and applies to a various scenario. Thus careful consideration is needed at the commercializing stage. Not only would further cycles of development need to keep the mentioned right and security of the data collection method in mind, but also a list of other compliance acts that should be carefully managed before launch. They can be found on the GDPR website. The security check also applies to any interactions with third parties.

The long-term collection of data also means that the habits of users may be logged. Thus, politically ambitious agenda of third parties may present concerns. This should be mitigated through strict management and independent internal development. Agreements should be drawn to bound involved third parties and their scope of influence to the law. It should also be emphasized that regional privacy law adherence is mandatory. If there is a lack of such regulation, responsibility and vigilance of developers still cannot falter.

d. Human values

While drowsiness may be represented by various physiological behaviors, it is important to consider the motorists as more than just that. The feelings and conditions of humans differ between individuals and naturally, there may be those who are uncomfortable with the product or cannot afford it. However, the product is merely a tool to make things easier. True responsibility is about preventing fatigue driving risks and could be achieved through other means, albeit more difficult. Thus, stigmatization may happen when there is generalization against non-users. To deal with such issue would require the marketing team of the future product to think past sale figures. It is important to introduce the product to everyone without capitalizing on stigmatization.

Although not mandatory, most drivers would not deliberately go against the advises of the product as it concerns their safety. Thus, flexible integration of the device into the life of drivers to maximize their autonomy should be considered by the designers. This requires more research upon the development of hardware for the most convenient and responsible integration method. Good integration should also be considered in the sense of impact on humans' reactions. This means finding the right notification method, tone, volume, language, and even word choices.

e. Stakeholders

The report has described all stakeholders and their interaction with the potential product in section 2.2. Overall, the driver holds the most influence and interest as they are the key target. However, the safety or happiness of their family are also affected. Considering the thirty percent of accidents caused by drowsiness, it is clear that civil services such as hospital and police will also receive positive impact once the risk lessen. They will have more resources to spend on other pressing issues, thus increasing life quality for the community as a whole.

f. Data

The project has spent time and consideration to find the most suitable source data. Looking at the description from section 3.2, the criteria of diversity, realism, and compatibility has been met. In terms of outlook, there may exists conditions in the future that exhibit signs similar to endogenous drowsiness. This may trick the device since the attributes are physiological. Thus, future developers need to account for the up-to-date situation regarding healthcare to timely adjust the product.

g. Inclusivity

While the data used within the project is as inclusive as it could get considering the allocated resources, the ratio between ethnicity and age of features' contributors in the future may not be in an equilibrium. Thus, it is necessary to collect a broad range of data to supplement future updates. The hardware design should also consider different car types and diverse device positioning (this has partly been addressed in the data of the project). Furthermore, users who cannot receive audio signal should not be left behind. Finally, sunglasses and other props that obstruct the functionality of the device should be dealt with by incorporating more than just blink behavior in the future. Thus, detection based on EAR sequence is just the start.

h. Transparency

The project has maintained transparency via periodical communication with experts, clear reference to highlight important material used, and a visual dashboard to intuitively communicate key insights with viewers. The report will describe the dashboard in more detail in the following section.

In the future, user manual and product website should describe the solution and its relevant AI functionality truthfully. There should be no withheld information or over-complication of description regarding its certitude. Inquiries should also receive timely and comprehendible answers. As the proposal pointed out, time and quality-adherence of the service team is essential in bridging the gap between the product and users. Furthermore, an action plan or system of question classification and authority to answer should be setup beforehand to methodically support users.

i. Sustainability

By scaling the data and working on the local machine, the project is sustainable in the current context. In future development cycles, it is necessary to have prior planning for the needed material and resources. A balance between production ability (i.e. affordability and realistic lifespan) and environmental sustainability is key. Although plastic is a convenient hardware source, there may be better material in the near future that could adhere to the mentioned tradeoff. Thus, future developers should consider all possibilities with production capability in mind and sustainability as the compass.

Beside the hardware material, data storage and backend facilities are also a concern. It is imperative that future developers can outsource factors such as data center to reliable and sustainable provider(s). It is noteworthy that the development team should also perform a privacy and security assessment on such provider(s).

The final concern has to do with end-to-end logistic process. This includes material provision, production, and collection for recycling. Such process should ensure the follow-through of all stages. Thus, it will deal with any hidden impact of the device before, during, and after usage.

j. Future

The report has applied a future lens to all previously evaluated categories to determine the impact of the project's outlook. It is clear that careful planning and rigorous testing is mandatory prior to the manufacturing process for the most responsible impacts. Upon actual deployment, strict management to conduct planned procedures will guarantee the appropriate usage of the product.

Table 6:

DOT instruments and reasonings for Sprint 4

DOT INSTRUMENTS			
Activity	Method	Instrument	Reason
Re-evaluate the societal impacts of the product and its outlook	WORKSHOP	Brainstorm	It is necessary to re-assess the impact as there are additional insights to be presented after performing the research.

4. CONCLUSION & RECOMMENDATION

THE FINAL ANSWER AND REFLECTION

This closing chapter of the report will conclude with the answer to the research question of the project, as well as recommendations for future development

4.1. Recommendation

In terms of improvement to be made for the blink behavior model, the scope can be formulated in the future to add on a temporal aspect like Ghoddoosian (2019). Instead of trying to detect a certain state of mind, deep learning models can focus on predicting attribute values that may appear in the following moments. After which, they can be inputted into another model to detect potential state to come. This will create more room for experiments in terms of context and also model complexity. For example, HM-LSTM as suggested by Ghoddoosian could be incorporated with an edited version of this project's MLP to create a complete pipeline.

Furthermore, the mathematical calculations of attributes could potentially be updated to use more recent package versions. This will help with demonstration as a continuous process can be visualized through real-time activation. Finally, it goes without mentioning that each of the features described in section 3.5 can become a research topic. They are all necessary to build the envisioned product – an independent and inclusive fatigue-driving risk prevention device.

4.2. Conclusion

The result of the modelling experiments has shown that the detection of fatigue state using physiological attributes is certainly possible. In terms of constraint, the project has been completed on-time with all necessary deliverables and a re-evaluation of societal impact. While the implication of the outlook remains the same as what has been suggested in the proposal, there were added insights that stem from the modelling and product re-envisioning process.

By using computer vision to read the UTA videos and track the EAR sequences, the mathematical feature extraction method can be applied to derive checkpoints and calculate the main inputs for modelling. They include blink frequency, amplitude, duration, and eye-opening velocity. Through the usage of this mathematic derivation method, the attributes are well-defined enough to make a significant 10 percent difference in model performance as compared to the heuristic method. Combined with the depicted architecture and usage of MLP, the best result of the research can be attained. Although this is only the beginning of a bigger domain, an independent and inclusive fatigue-driving risk prevention device as described in section 3.5 is the most responsible way to implement the model and its subsequent features. With these insights, the answer to the research question of "How to apply AI for early fatigue detection within 18 weeks and conceptualize deployment for motorists and transporters responsibly?" has been formulated.

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6. APPENDIX

Below is a snippet showing the logic behind the mathematic feature extraction method (Ghoddoosian et al., 2019):

Algorithm 1 Blink Retrieval Algorithm

Input The initial detected EAR signal $\mathbf{x} \in \mathbb{R}^M$, where M is the size of the $\mathbf{x}$ time series, as a candidate for one or more blinks and epsilon=0.01

Output N retrieved blinks, $N \ll M$

1: $\dot{\mathbf{x}}[n] \leftarrow \mathbf{x}[n+1] - \mathbf{x}[n], \forall\, n \in \{i | i = 0, 1, ..., M-2\}$
2: **if** $\dot{\mathbf{x}}[0] = 0$ **then** $\dot{\mathbf{x}}[0] \leftarrow -1 \times$ epsilon
3: $\dot{\mathbf{x}}[n] \leftarrow \dot{\mathbf{x}}[n-1] \times$ epsilon, $\forall\, n \in \{i | \dot{\mathbf{x}}[i] = 0 \wedge i \neq 0\}$ to avoid zero derivatives for steps 4 and 6
4: $\mathbf{c}[n] \leftarrow \dot{\mathbf{x}}[n+1] \times \dot{\mathbf{x}}[n], \forall\, n \in \{i | i = 0, 1, ..., M-3\}$
5: Define $\mathbf{e} \in \mathbb{R}^{P+2}$, $P \leq M-2$ to store the indices for the P extrema, the first and the last points in $\mathbf{x}$
6: $\mathbf{e}[0] \leftarrow 0$, $\mathbf{e}[P+1] \leftarrow M-1$, supposing the first and last points in $\mathbf{x}$ are maxima
7: $\mathbf{e}[k] \leftarrow n+1, \forall\, (n \in \{i | \mathbf{c}[i] < 0\} \wedge k \in \{i | i = 1, 2, ..., P\})$ ▷ Indices of P+2 extrema, including the first and last points in $\mathbf{x}$ are stored in order
8: Define $THR \leftarrow 0.6 \times \max(\mathbf{x}) + 0.4 \times \min(\mathbf{x})$, as a threshold
9: Define $\mathbf{t} \in \mathbb{R}^{P+2}$, to store +1 or -1 for extrema above and below threshold respectively
10: $\mathbf{t}[0] \leftarrow +1, \mathbf{t}[P+1] \leftarrow +1$, supposing the first and last points in $\mathbf{x}$ are maxima
11: Append +1 in $\mathbf{t}$ for each $n \in \{i | \mathbf{x}[\mathbf{e}[i]] > THR\}$, and append -1 in $\mathbf{t}$ for each $n \in \{i | \mathbf{x}[\mathbf{e}[i]] \leq THR\}$, all in the order of the indices in $\mathbf{e}$
12: Define $\mathbf{z} \in \mathbb{R}^{P+1}$, $\mathbf{z}[n] \leftarrow \mathbf{t}[n+1] \times \mathbf{t}[n]$
13: Define $\mathbf{s}$, to store the indices of all negative values in $\mathbf{z}$, representing the downward and upward movements of eyes in a blink
14: $N \leftarrow \frac{length(\mathbf{s})}{2}$ ▷ N is the number of sub blinks, and $length(\mathbf{s})$ is always an even number
15: **for** $i \leftarrow 0$ to $N-1$ **do** ▷ Define for $blink_i$:
16: StartIndex $\leftarrow \mathbf{e}[\mathbf{s}[2 \times i]]$,
17: EndIndex $\leftarrow \mathbf{e}[\mathbf{s}[2 \times i + 1] + 1]$,
18: BottomIndex $\leftarrow \mathbf{e}[\mathbf{s}[2 \times i + 1]]$
return start, end and bottom points of the N retrieved blinks in $\mathbf{x}$
