Study of Drowsiness Detection Applications in Vehicle Drivers and Implementation of an Innovative Solution

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***Abstract*—This project aims to develop a robust solution based on connected objects for the early detection of drowsiness in vehicle drivers. The potential social and economic impact of addressing this issue is significant, as fatigue-related road accidents remain a leading cause of fatalities worldwide. The developed solution holds the potential to enhance safety and save lives by contributing to the prevention of accidents. Furthermore, the technological transfer of such solutions to automotive manufacturers will be facilitated. Preliminary implementations of such systems are already integrated into vehicles by some manufacturers, such as Volkswagen. However, these implementations rely on monitoring irregular driving profiles, such as erratic steering movements and lane deviations indicating driver drowsiness, often detected only at advanced stages. In this project, the focus is on leveraging modalities that enable the detection of drowsiness in early phases, using, for example, onboard cameras or continuous monitoring through heart rate sensors.**

***Index Terms*—Fatigue, Drowsiness, Driving, Driving Monitoring, Road Accidents, Deep Learning**

I. Introduction

NOWADAYS, car accidents constitute one of the leading causes of mortality [1]. These accidents can be attributed to various factors such as fatigue, speeding, drug consumption, non-compliance with seatbelt use, and distracted driving [2]. Drowsiness, defined as a state of altered consciousness associated with a desire or tendency to sleep [3], can result from intense fatigue, drug or alcohol consumption. Drowsiness while driving accounts for approximately 20% of road accidents worldwide [4], increasing the risk of an accident by 4 to 5 times [5]. It becomes imperative to develop drowsiness detection systems to significantly reduce the number of road accidents.

In this perspective, numerous research efforts and commercial products have been proposed in the field of drowsiness detection. These contributions rely on the use of measures such as car-related measures (position, deviation, acceleration, etc.), behavioral measures (facial expressions, head position, etc.), and physiological measures (heart rate, respiration, etc.) [6], [2], [7]. Others focus on subjective measures such as the Karolinska Sleepiness Scale (KSS) and others [8]. Solutions vary in their approach, employing either a single measure or a combination of two or more measures.

While there have been notable contributions, there is still potential for enhancements in the field. This is justified by the presence of several challenges, including:

- What types of measures to use? Single or multiple?
- How to deploy sensors for these measures?
- What type of architecture to choose (cloud or local)?
- Opt for a generic solution or a personalized solution for each driver?
- In the case of using multiple measures, how to perform data fusion?

This work implements an automatic drowsiness detection system for driving based on the use of cameras, heart rate sensors from smartwatches, and contextual information during driving (driving duration, temperature, time, etc.). Machine learning is employed for drowsiness detection using data from these sensors. The drowsiness decision-making of the system is facilitated by an ontology built on the results obtained from the sensors and additional contextual information.

A state-of-the-art review of existing research and commercial tools will be detailed in Section 1. Section 2 will be dedicated to presenting our design and describing its implementation. Section 3 covers the implementation and evaluation of our solution in comparison to existing approaches. Finally, Section 4 concludes our work and offers insights into potential future research endeavors.

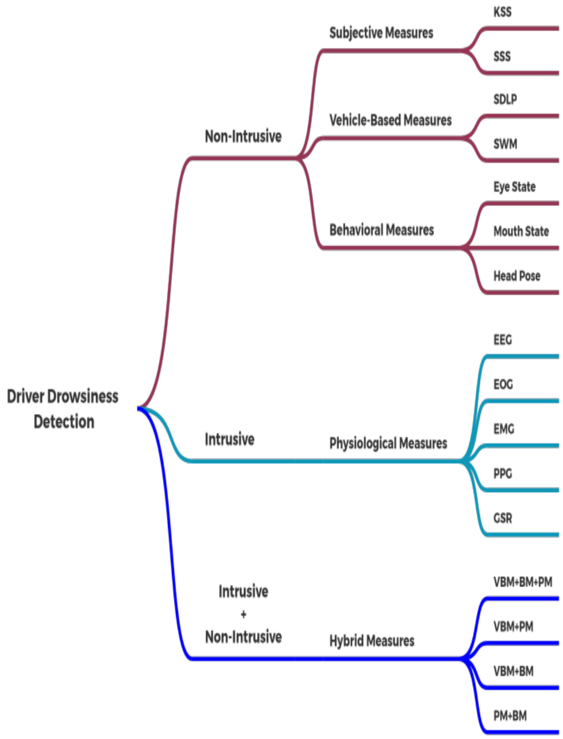
II. State-of-the-Art

This section outlines all the research work and commercial products identified in the field of drowsiness detection. *The solutions presented are based on the utilization of various types of measures. The first type of measure is physiological, encompassing all physiological characteristics related to the human body, including heart rate, respiratory rate, and others. The second type of measure is behavioral, involving observable and measurable behaviors related to an individual's state of alertness, such as eye blink frequency, eye movements, and others. Vehicle-based measures utilize vehicle characteristics, such as trajectory, speed, and others. The last measure is subjective, relying on individual drivers' responses and perceptions. It may include questionnaires on perceived fatigue levels, self-assessment of vigilance, and others.* Figure 1 illustrates the measures and their types.

A. Commercial Products in Drowsiness Detection

Numerous products are marketed for drowsiness detection while driving, generally provided by car manufacturers. These products are typically integrated during the manufacturing process, but optional installable products are also available on the market. These diverse products can be categorized based on the type of measure used, including:

Fig. 1. Synthesis of measures and their types for drowsiness detection [9].



- Commercial products based on physiological measures;
- Commercial products based on behavioral measures;
- Commercial products based on vehicle measures;
- Commercial products based on hybrid measures.

1) Commercial Products Based on Physiological Measures: The main drawback of these products is their high cost and intrusive nature. However, they offer high precision for drowsiness detection. The most commonly used sensor is the GSR (Galvanic Skin Response). EEG (electroencephalogram) sensors are also employed. Table I summarizes these products.

TABLE I
PRODUITS COMMERCIAUX BASÉS SUR LES MESURES PHYSIOLOGIQUES. SOURCE: [2], [10].

Product	Manufacturer	Description
Anti Sleep alarm Vigiton	Neurocom	Skin Resistance (GSR)
StopSleep Device	StopSleep	Dermal Activity (EDA)(GSR)
STEER	STEER	Heart Rate (HR) + EDA (GSR)
SmartCap	SmartCap	EEG (ElectroencEphaloGram)

2) Commercial Products Based on Behavioral Measures: They generally rely on the use of cameras and are the most widely used in the field. They are non-intrusive and more affordable. Some solutions also use motion sensors. They detect drowsiness based on attributes such as eye blink frequency, head movements, and others. The list of products is described in Table II.

TABLE II
COMMERCIAL PRODUCTS BASED ON BEHAVIORAL MEASURES. SOURCE: [2], [10].

Product	Manufacturer	Description
Delphi DSM	Delphi	Uses a near-infrared camera
Eagle light	Optalert	Uses glasses to detect blinks
AntiSleep	SmartEye	Eye and head tracking
EyeAlert	LumeWay	Rate and duration of eye closure
Eyetracker System	Fraunhofer	Dual-camera for eye tracking
Siemens IR-LED	Siemens	Detects microsleep
Operator alertness system light vehicle	HxGN (Mine-Project)	Eye and face tracking
Guardian	Seeing Machines	General tracking using a camera
Saab Driver Attention Warning System [49]	SAAB	Uses 2 infrared cameras to detect eyes, gaze, and head position
DADS	InterCore	Bluetooth monitoring to a smartphone
DriveAlert+	DriveRisk	Eyes, facial features, and movements
Driver fatigue monitoring system	STONKAM	General monitoring via camera
Driver fatigue monitor DFM2	Transport Support	PERCLOS
Anti Sleep Alarms	NO-NAP	Head movement
Anti Sleep Pilot	Danish Systems	Reaction time
EyeAlert System	LumeWay	Eye closure
InSight System	SensoMotoric Instr. (SMI)	Face + eye closure

3) Commercial Products Based on Vehicle Measures: These products are generally based on road monitoring (camera) and steering wheel movements, acceleration, and others. Table III presents these products.

4) Commercial products based on hybrid measures: These solutions combine measures to enhance the performance of their system for drowsiness detection. These products are described in Table IV.

The figure 2 presents a synthesis of commercial products by types of measures.

We notice that the majority of products focus on the use of behavioral measures. Drowsiness is detected using cameras, which is a non-intrusive solution and much easier to implement in terms of cost and comfort. Vehicle-based measurement solutions are more commonly used by car manufacturers and are primarily focused on lane departures and steering wheel movements. These solutions are not exactly drowsiness detection solutions but rather address distraction. On the other hand, it is also evident that physiological measurement-based solutions are not used at all by car manufacturers; instead, they

TABLE III
COMMERCIAL PRODUCTS BASED ON VEHICLE MEASURES. SOURCE: [2], [10].

Product	Manufacturer	Description
FAS 100	Albrecht	Lane departure
Driver alert	Ford	Lane departure
Driver Drowsiness Detection	Bosch	Steering wheel movement
Attention Assist	Mercedes, Nissan, BMW	Steering wheel movement
Driver alert control system	Volvo	Lane departure
SafeTRAC	Cognex	Lane departure
Safety System+	Lexus	Lane departure warning
EyeSight driver assist	Subaru	Lane-keeping and object detection
ASTiD	fmi	Time of day + Steering wheel movement
Iteris Safety Direct	Iteris	Lane departure warning
Rest Assist	Volkswagen, Skoda	Steering wheel movement
SafeTrac	Cognex Corporation	Lane departure
Vision/Radar Sensor	Mobileye NV	Lane departure
ASTiD	Pernix	Steering wheel movement

TABLE IV
COMMERCIAL PRODUCTS BASED ON HYBRID MEASURES. SOURCE: [2], [10].

Product	Manufacturer	Description
Interior monitoring systems	Bosh	behavioral + vehicle
Driver attention monitor	Lexus and Toyata	behavioral + vehicle

are more installable by the driver. Hybrid measurement-based solutions, interestingly, do not utilize physiological measures.

B. Research Work in Drowsiness Detection

We followed a systematic approach in developing the state of the art. The database used for paper searches is **Mendeley database**. The keywords for the search were **"driver" and "drowsiness" and "detection"**. Figure 3 outlines the methodology for selecting works for the state of the art. Various research works on drowsiness detection have been published in recent years. They rely on subjective measures, vehicle-based measures, behavioral measures, and physiological measures. They utilize sensor technologies and data processing approaches based on machine learning (ML) and artificial intelligence (AI) [10]. These diverse works can be categorized into two main groups:
On one hand, there are studies employing a single-measure (monomodal). The majority of these studies use behavioral measures, with some also incorporating physiological measures. However, studies utilizing subjective measures and vehicle-based measures are nonexistent. These details are presented in Table V.

Fig. 2. Synthesis of commercial products

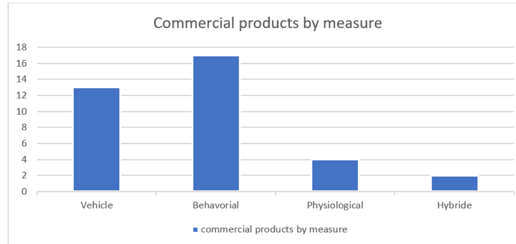


Fig. 3. Methodology for State of the Art in Research Works

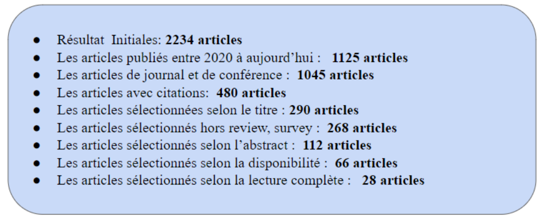


TABLE V: Measures used by single-measure research studies.

Studies	Type of Measure			
	Behavioral	Physiological	Vehicle	Subjective
[11]	X			
[7]	X			
[12]	X			
[13]	X			
[14]	X			
[15]	X			
[16]	X			
[17]	X			
[18]		X		
[19]	X			
[20]	X			
[21]		X		
[22]	X			
[23]		X		
[24]	X			

TABLE VI: Model used by single-measure research studies.

Studies	Models
[11]	LWN
[7]	AlexNet, VGG-FaceNet, FlowImageNet, ResNet
[24]	LSTM

Continued on next page

TABLE VI: Model used by single-measure research studies. (Continued)

Studies	Models
[12]	Inception v3, LSTM
[13]	CNN
[14]	NB
[15]	VGG, CNN, ResNet
[16]	KNN, SVM
[17]	KNN, SVM, KNN+SVM
[18]	RF
[19]	Dlib
[20]	SVM
[21]	SVM, DT, LR, GBM, Extra Tree Classifier, Multilayer Perceptron
[22]	lightweight deep learning network
[23]	RF, boosting, bagging
[24]	LSTM

TABLE VII: Single-measure Research studies addressing specific issues.

Studies	Issues
[11]	Fatigue threshold setting
[7]	Night / day detection, Indoor / Outdoor detection
[12]	Lightness of the model
[14]	Eye region detection
[17]	Hypovigilance
[18]	The influence of being adult and young on detection
[19]	Model latency
[20]	Processing capacity, energy consumption
[21]	Invasiveness
[22]	Privacy issues
[24]	Power consumption, smartphone location

On the flip side, the table VIII illustrates works that employ a hybrid (multimodal) approach. Relying on the amalgamation of two or more measurements, these works in the literature primarily focus on combining physiological and behavioral measures. Integrating multiple measures poses a challenge, leading to the identification of various fusion methods, including upstream fusion and downstream fusion. For decision-making, the authors of papers [9], [25], [26], [8], [27], [28], [29], [30] adopt an upstream fusion approach, consolidating various modalities into a characteristic vector before subjecting them to the model for learning.

On the other hand, in other works, downstream fusion is employed, involving the use of a separate model for each measure. To amalgamate the results of each model, the document [6] addresses the issue using a condition with a conjunction operator for decision-making. For decision-making, the authors of the papers [31], [4], [32], [29] propose integrating the results of different models into a global model.

In the article [33], an upstream fusion strategy is employed for measures of the same type, followed by downstream fusion for the previously obtained merged data.

Tables VI and IX describe the models used by the works in the two categories. We observe the use of a single model in some cases and multiple models in others. Both machine learning and deep learning are utilized. In each of the works, the occurrence of the model is presented.

Beyond drowsiness detection, some works have focused on specific issues. A presentation of these issues is found in tables VII and **??**. For example, the lightweight nature of the model is an additional concern in [12].

The complete set of measures classified by type, along with the state-of-the-art works that use these measures, is presented in Table XI. It is noteworthy that the use of cameras is much more prevalent in these works.

Beyond the detection of drowsiness, some studies have focused on specific issues. These issues are presented in Tables VII and X. For example, model lightweightness is an additional challenge discussed in [12].

Table XI presents all the measures classified by type and the set of state-of-the-art studies using these measures. It is noteworthy that the use of cameras is much more prevalent in these studies.

An overview of the datasets identified in various studies is provided in Table XII. The majority of studies (18) utilize their own datasets developed for their specific research. Among existing datasets, NTHUDDD is the most frequently used. Image datasets include Facemask, HFFD, NTHUDDD, YAWDD, while Drozy comprises images, signals, and other data. In studies developing their own datasets, a combination of image, signal, and other datasets is observed.

The analysis of the studies presented in this section raises several considerations. Among the use of single measures, various issues have been identified. Despite the precision of physiological measures, sensors are costly and highly invasive. Behavioral measures yield good results but also face problems such as brightness and camera positioning. Vehicle measures generally detect only advanced stages of drowsiness, which is something to avoid. Subjective measures, by their nature, are inherently subjective. In the case of multimodal approaches, the question of fusion remains a major challenge. Some studies adopt upstream fusion by grouping modalities into a characteristic vector, while others choose downstream fusion with separate models for each measure. Despite these varied approaches, decision-making remains a topic of discussion.

Therefore, our proposal is a solution based on physiological and behavioral measures to ensure the accuracy of drowsiness detection. For decision-making, we plan to use an ontology, which is not present in the literature mentioned above.

TABLE VIII: Measures used in mult-measure research studies.

Studies	Type of Measure			
	Behavioral	Physiological	Vehicle	Subjective
[6]	X	X		
[31]	X	X	X	
[9]	X	X		X
[25]	X	X		
[4]		X	X	
[26]	X	X	X	
[33]	X	X		
[8]	X	X		
[27]		X		X
[28]	X	X		
[32]	X	X		
[29]	X	X		
[30]		X		

TABLE IX: Model used by multi-measure research studies.

Studies	Models
[6]	Threshold, CNN
[31]	CNN, LSTM
[9]	MTCNN
[25]	CNN-LSTM
[4]	BPNN
[26]	RF
[8]	RF, KNN
[33]	XGB
[27]	complex tree, linear discriminan, logistic regression, fine KNN, fine Gaussian SVM and ensemble subspace KNN
[28]	CNN
[32]	DNN
[29]	DT
[30]	KNN, SVM

TABLE X: Multi-measure research studies addressing specific issues.

Studies	Issues
[6]	Wearing a mask, gender of driver, distance from camara
[31]	distribution and privacy
[25]	level of drowsiness
[4]	impact of each indicator individually, impact of dominant hand, impact of driving experience
[26]	Feature priority, level of drowsiness
[27]	the impact of driver age
[32]	managing multimodality

TABLE XI
LIST OF STUDIES WITH THEIR MEASURES

Type of measure	Measure	Studies
Physiological	Heart rate	[6], [18], [28], [27]
	Thermal Camera	[16]
	IR Camera	[16]
	Skin Conductance	[33], [29], [9], [23]
	Blood Volume Pulse	[33], [29]
	Skin Temperature	[33], [29]
	Respiration rate	[33], [29], [21]
	PPG	[4]
	ECG	[26], [25], [8], [30]
	EEG	[30], [32]
Behavioral	Camera	[6], [7], [15], [14], [11], [13] [12], [19], [28], [32], [29] [20], [9], [22], [31]
	IR Camera	[17]
	Thermal Camera	[33], [25], [29]
	Movement	[16]
	Seat pressure	[26]
	Audio	[24]
Vehicle	Accelometer	[31], [26]
	Gyroscope	[31], [32], [26]
	Steering wheel movement	[8]
	Lane deviation	[8]
	Movement	[4]
Subjective	tablet/smartphone	[27], [9]

TABLE XII
DATASETS USED IN RESEARCH STUDIES.

Dataset	Studies
Facemask[34]	[6]
HFFD[35]	[11]
NTHUDDD[36]	[7], [31], [9], [12], [13], [14], [15]
YAWDD[37]	[12]
Drozy[38]	[30]
Dataset developped by auteurs for the study	[16], [25], [17], [18], [33], [4], [26], [8], [19], [27], [28], [32], [29], [20], [21], [22], [23], [24]

C. Ontology in Drowsiness Detection

In the context of proposing an ontology for decision-making in our system, it is important to review the existing literature

on the use of ontology in the field. There are few works on the subject.
The paper [39] presents a drowsiness detection system using ontologies. The system relies on the use of two ontologies, the first one to represent the vehicle and the second one to represent the driver. Drowsiness is detected based on visual behaviors (camera), including eyelid movement (percentage of eye closure PERCLOS, eye blink rate), face orientation (facial pose), and gaze movement (pupil movement). Decision-making is performed using ontologies, and the system is implemented on a smartphone. The main drawback of their system is its reliance on eye recognition, which has various limitations (brightness, wearing glasses, etc.[7]). These limitations are not addressed in the paper.
A fatigue detection system based on ontology using vehicle data, physical, and physiological driver data is presented in the work [40]. Decision-making relies on ontology. Only one use case (vehicle data) has been implemented and tested on a simulator. However, no method has been defined for the fusion of all data.

III. Proposed Solution

This section describes the design of our proposed solution as well as the performance indicators (KPI) that we will use to evaluate our solution. Our solution comprises two parts: Ontology-based data fusion for drowsiness decision-making and IoT-Based Non-Invasive low-cost for drowsiness detection.

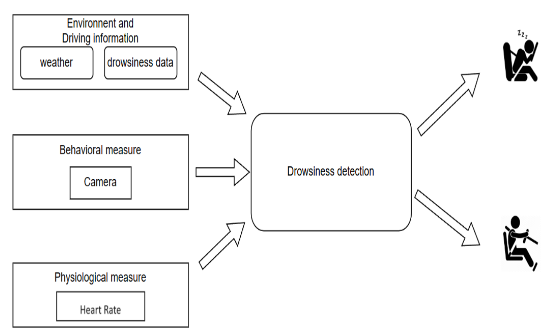
1) Ontology-based data fusion for drowsiness decision making: Our solution is based on monitoring the driver's heart rate and visual characteristics. We use a specific classification model for each type of measurement. The result of each model is then passed to the ontology for decision-making. On the other hand, we gather information about the environment and driving, which is provided to the ontology to enhance its decision-making. This information includes weather conditions, driving duration, and time. The set result of the heart rate model, result of the visual characteristics model, weather conditions, driving duration, time is used for reasoning, at the end of which the level of drowsiness is determined.
System operation is described in the figure 4.

The developed ontology model (Figure 5) consists of five main classes: "Driver" (information about the driver's drowsiness level), "Event" (dangerous events that can impact the driver's drowsiness level), "Sensors" (sensors integrated into the smartphone and smartwatch), "Environment" (parameters characterizing the driving environment), and "Driving" (parameters characterizing the driving behavior). All classes are used to detect driver drowsiness.
The decision-making using the ontology employs a set of SWRL rules and considers:

- The occurrence of a failure in one of the sensors;
- The unavailability of environmental and driving information.

When developing the ontology, information in the field of driver drowsiness was utilized. This includes statistical information about peak hours for drowsiness-related accidents,

Fig. 4. Functional Description of the Solution

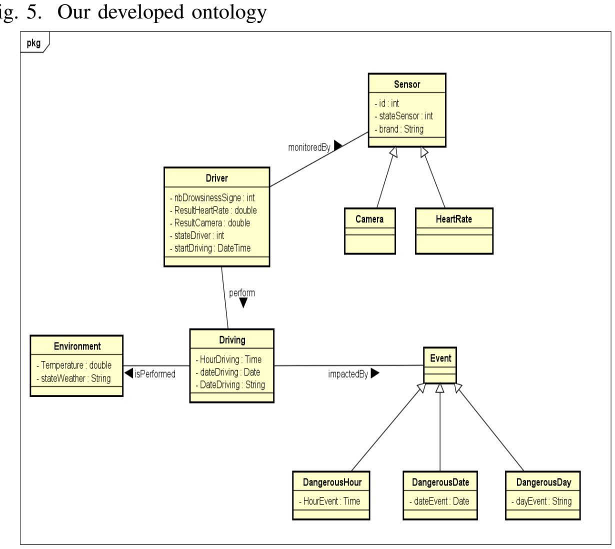


high-risk days of the year for drowsiness, and other relevant data. Examples of how this environmental and driving information can be used are described below:

- When the normal threshold for triggering an alert is N signs of drowsiness, this threshold could be reduced to N/2 on holidays like New Year's, when the number of drowsiness-related accidents is higher.
- The time between 00:00 and 05:00 could be considered as red alert hours, triggering the alarm at the first sign of drowsiness.
- In case of exceeding the legally allowed driving hours, the system could also escalate to a red alert to warn the driver of potential drowsiness.

An important note regarding the use of our ontology is that no sensitive user information is employed. Thus, the system ensures the user's privacy.

Fig. 5. Our developed ontology



2) IoT-Based Non-Invasive low-cost for drowsiness detection: The objective of our work is to propose a drowsiness detection solution, and it must adhere to criteria such as: - Ensuring real-time drowsiness detection; - Avoiding false detections; - Non-intrusiveness of detection sensors; - Lightweight resource utilization for the solution; - Low-cost.

To meet these objectives, the proposed IoT-based solution is characterized by:

- The use of behavioral (facial features) and physiological (heart rate) measures to increase the model's accuracy and minimize false detection issues;
- For heart rate measurement, the solution utilizes the sensor present on the smartwatch. Smartwatches can be used inside and outside the car, providing a less invasive option for drivers who already own one. This leverages existing devices and ensures ease of use. Additionally, heart rate sensors are basic features of all smartwatches.
- For facial feature measurement, we had the choice between using a microcontroller with a camera or the driver's smartphone. We opted for the smartphone to avoid additional costs associated with purchasing other equipment. Even if a microcontroller is used, the smartwatch would still need to be connected to the smartphone to send data to the microcontroller [41]. However, using the smartphone may present challenges such as resource consumption.
- To ensure real-time processing, the analysis is performed locally on the smartphone.
- The solution employs lightweight classification models specifically designed for smartphones, minimizing resource consumption (CPU and energy).

The figure 6 depicts the overall architecture of the solution. It illustrates the sensors, modules, triggers, APIs, and interconnections enabling the system's operation. Communication between the smartphone and the smartwatch occurs via Bluetooth. Finally, the hardware description of the system is presented in figure 7.

Fig. 6. General architecture of the solution

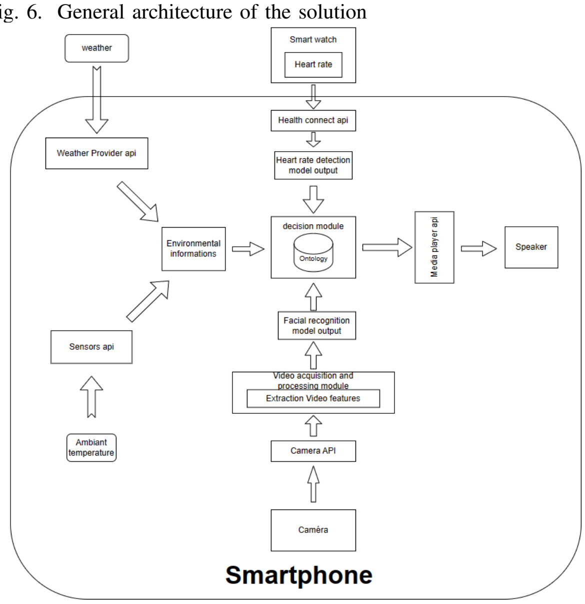
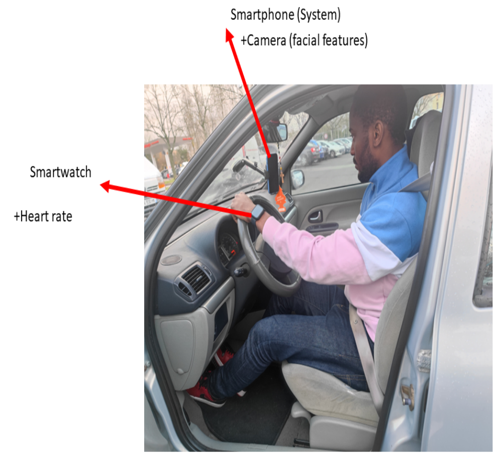


Fig. 7. Hardware architecture of the solution



A. Use scenario of the solution

The description of the use of the solution by the driver is as follows:

1) The driver enters the car and starts our solution (application) on their smartphone;
2) At the start of the application, the system checks the availability of the camera and the smartwatch;
3) In case of unavailability of both, the system sends an alert to the driver;
4) If at least one of the two devices is available, the system moves to the analysis state;
5) The system retrieves, depending on availability, the result of detection by heart rate and by vision, as well as driving and environmental information;
6) All information is stored in the ontology, and the ontology is reasoned;
7) In case of drowsiness detection, the driver is alerted to their state;
8) Otherwise, the system returns to step 2.

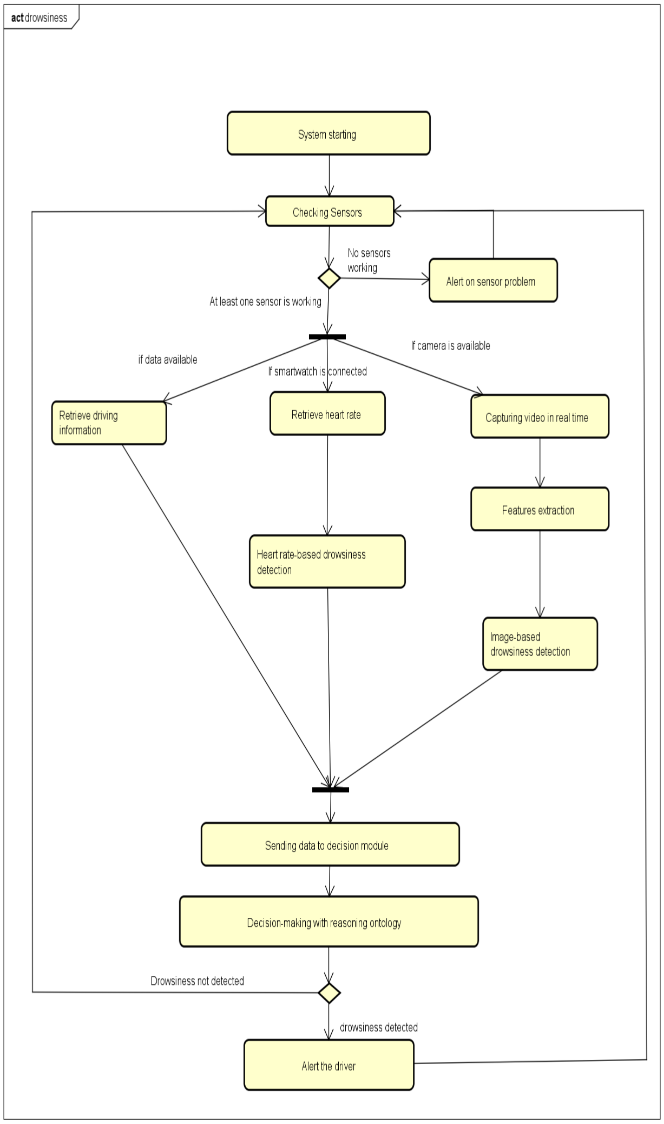
An important note is that when using the camera, the driver must ensure that their face is within the camera's field of view. Figure 8 presents the activity diagram describing the use scenario of the solution.

B. Performance indicators (KPI)

To evaluate the quality and effectiveness of our solution, it is essential to define metrics. This allows us to identify the advantages and disadvantages of our solution. In the majority of works identified in the state of the art, accuracy is the most commonly used metric. The level of intrusiveness is also considered. The set of identified metrics includes:

- Precision: The percentage of correct detection of drowsiness regardless of the brightness of the environment, gender, or age of the driver.
- Intrusiveness: Direct or indirect monitoring of the internal functions of the organism.

Fig. 8. Activity diagram of the system



- Privacy Protection: The possibility of identifying drivers from the collected data or collecting their sensitive data.
- Cost: The cost of implementing the solution.
- Robustness: The ability of the solution to consistently provide accurate results in case of sensor failures measuring the modalities.

IV. Conclusion

Our study provides a comprehensive analysis of various approaches adopted in drowsiness detection among vehicle drivers, while exploring existing research works and commercial products in the market. The findings underscore a predominance of solutions focused on behavioral measures, attributed to their affordability and ease of implementation.

Furthermore, this work presents a detailed design of a drowsiness detection solution, based on the integration of heart rate and facial features. The significant contributions of this solution include an ontology-based data fusion for drowsiness decision-making and a non-invasive, cost-effective IoT (Internet of Things) approach for drowsiness detection. Notably, the solution is designed for deployment on smartphones, leveraging their cameras and the heart rate sensor integrated into smartwatches.

Future perspectives of this work will concentrate on the practical implementation of the proposed solution and its real-world evaluation. This will involve field tests to assess the effectiveness and accuracy of drowsiness detection in actual driving situations, contributing to the validation and continuous improvement of our approach.

Appendix A
Abreviations List

- **API**: Application Programming Interface
- **BPNN**: Back Propagation Neural Network
- **BM**: Behavioral Measures
- **CNN**: Convolutional Neural Network
- **CPU**: Central Processing Unit
- **DNN**: Deep Neural Network
- **DT**: Decision Tree
- **drozy**: ULg Multimodality Drowsiness Database
- **ECG**: Electrocardiograms
- **EDA**: Dermal Activity
- **EEG**: Electroencephalograms
- **EMG**: Electromyograms
- **EOG**: Electrooculograms
- **GBM**: Gradient Boosting Machine
- **GSR**: Galvanic Skin Response
- **HM**: Hybrid Measures
- **HFFD**: Hybrid Fake Face Dataset
- **IoT**: Internet of Things
- **KNN**: K-Nearest Neighbors
- **KPI**: Key Performance Indicator
- **KSS**: Karolinska Sleepiness Scale
- **LR**: Linear Regression
- **LSTM**: Long Short Term Memory
- **LWN**: Lightweight Neural Network
- **MTCNN**: Multi-Task Cascaded Convolutional Neural Networks
- **NB**: Naive Bayes
- **NTHUDDD**: National Tsing Hua University Drowsy Driver Detection
- **PERCLOS**: Percentage of Eye Closure
- **PM**: Physiological Measures
- **PPG**: Photoplethysmography
- **RF**: Random Forest
- **SDLP**: Standard Deviation of Lane Positioning
- **SSS**: Stanford Sleeping Scale
- **SWN**: Steering Wheel Movement
- **VBM**: Vehicle-Based Measures
- **VGG**: Visual Geometry Group
- **XGB**: eXtreme Gradient Boosting
- **YAWDD**: Yawning Detection Dataset

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