POLITECNICO DI TORINO

Master's Degree Course in
MECHATRONIC ENGINEERING

Master's Degree Thesis

Real-Time Drowsiness Detection Using Smartwatch Sensor Data and Machine Learning

Supervisors
Prof. Massimo VIOLANTE
Ph.D. Luigi PUGLIESE

Candidate
Kuerxi GUZHALI

. . . .

Academic Year 2024-2025


In memory of
my grandmother
قەمبەرنسا
whose love and
strength continue
to guide me,
even in her
absence.

Abstract

Driver drowsiness is a leading and highly preventable cause of road accidents worldwide. This thesis therefore asks: Can smartwatch data accurately classify four distinct drowsiness levels with at least 90% accuracy in realistic driving conditions? Can we use this information to detect and prevent driver drowsiness?
To investigate this topic, we analyze a dataset composed of **169,466 samples** recorded with commercial smartwatch sensors. Each measurement combines **Heart Rate (HR), Heart Rate Variability (HRV), and Respiration Rate (RR)** with a synchronised arousal label that is discretised, via equal-width binning, into four classes spanning from full alertness to pronounced drowsiness.
Our principal methodological innovation is a **lightweight real-time processing system** that streams incoming data through a sliding window, performs real-time feature scaling, and feeds the resulting features directly to the classifier.
This arrangement eliminates the need for batch processing and allows continuous inference on resource constrained embedded hardware.
Two supervised learners are proposed: a **Random Forest (RF)** ensemble tuned for rich, non-linear interactions, and a radial basis function **Support Vector Machine (SVM)** configured for soft margin, multiclass separation.
Testing on individual drivers showed a **mean accuracy of 88 % (max 99 %)** for the RF, markedly outperforming the SVM at **77 % (max 94 %)**; both models maintained good performance across all drowsiness levels.
While the RF falls just shy of the 90 % target on average, its peak accuracy and the consistent margin over the SVM highlight the promise of ensemble techniques for physiological state recognition.

These results demonstrate that **low-cost wearable devices combined with lightweight machine learning algorithms achieve accuracy suitable for real-world use**.
By signaling transitions from alertness to early drowsiness within seconds, the proposed system can be integrated into driver assistance systems, fleet safety dashboards, or consumer smartwatch applications, thereby reducing fatigue-related crash risk and associated public health costs.

Acknowledgements

Desidero innanzitutto ringraziare il **Professore Massimo Violante**: il suo corso di Model-Based Software Design è stato per me particolarmente interessante, offrendo una visione concreta e orientata al mondo del lavoro. Mi è stato di grande aiuto anche durante la mia esperienza in Ferrari e, proprio grazie a questo corso, ho deciso di svolgere la tesi con lui. Un sentito grazie anche al **Dott. Luigi Pugliese**, che con pazienza e costanza mi ha accompagnata lungo tutto il percorso, organizzando incontri settimanali per guidarmi nello sviluppo della tesi magistrale. Porgo le mie sincere scuse a entrambi per i ritardi nel consegnare questa tesi dovuti a impegni lavorativi.

Il mio percorso al Politecnico di Torino è stato una sfida profonda. Durante la laurea triennale in Ingegneria Aerospaziale ho studiato interamente in italiano, la mia quarta lingua, acquisita vivendo qui. Le difficoltà linguistiche sono state spesso maggiori di quelle tecniche: ricordo quando mi sedevo in prima fila per registrare le lezioni e riascoltarle a casa. Una volta, quando sono andata in bagno e sono tornata, un gruppo di ragazzi aveva preso il mio zaino dal posto e si era seduto al mio posto. Non sapendo parlare bene l'italiano, quello è stato il momento in cui ho deciso che dovevo imparare bene questa lingua. È stato faticoso, ma mi ha resa più forte. Alla magistrale la difficoltà è stata diversa: ho dovuto cambiare completamente mentalità, passando da un approccio meccanico/aerospaziale a uno informatico. Ho superato tutti gli esami nei primi due anni con ottimi risultati, come il corso di Machine Learning, Non-linear Aerospace e Robotica, ma ho impiegato altri due anni solo per completare Automatic Control e Digital Control. Ringrazio di cuore il **Professore Massimo Canale** e il **Professore Valentino Razza**, che con grande pazienza mi hanno sempre incoraggiata.

Voglio ringraziare mio **marito Gaetano Salvatore Falco**, che era il mio fidanzato all'inizio del mio percorso in Italia e mio marito dal 2021. Abbiamo studiato sempre insieme, infiniti panini nell'aula studio, infiniti weekend di studio, attraversando alti e bassi emotivi. Anche per questa tesi mi hai spinta a dare il meglio. Sei la prima persona che conosco con due lauree triennali dal Polito, sia in Ingegneria Informatica che in Ingegneria Elettronica. Dopo tre anni di lavoro in azienda e non solo, riprendere a studiare per la laurea magistrale non è stato facile, e continui ancora il tuo percorso nel gruppo Vandal come dottorando. Sono fiera del tuo percorso accademico e professionale e grata per questi 10 anni insieme. Grazie, marito.

Ho perso mia nonna che mi ha cresciuta, ma non sono potuta tornare a casa... È stato molto duro, ma con la mia psicologa sono riuscita a superarlo. Grazie. Mia **mamma Bahargül**, che è figlia unica, ha perso per sempre sua madre... Voglio ringraziarti , sei una donna forte che ha cresciuto me e mia sorella da sola, insegnandoci a essere indipendenti e resilienti. Non è andato tutto come pianificato, siamo state bloccate per tanti motivi, anche a causa del Covid. Non hai potuto partecipare nemmeno al mio matrimonio... Ci siamo riviste dopo 8 anni solo l'estate scorsa. Hai avuto la pazienza e l'amore infinito che una mamma può avere verso le figlie e ci hai sempre dato tutto il supporto di cui avevamo bisogno. Sono contentissima che oggi partecipi alla laurea di entrambe. Questo amore

senza condizioni, questa resilienza che hai mi ha insegnato davvero molto e non so come ringraziarti con semplici parole o gesti. Anche se noi non esprimiamo a parole il nostro amore, ora voglio dirti:
我爱你妈妈，谢谢你！
("Ti voglio bene mamma e grazie" scritto in cinese)

Mia **sorella Gülistan** , una ragazza intelligente, bella e anche più forte di quanto pensi di essere. Tutti dicono a mia sorella che è fortunata ad avere una sorella maggiore in Italia che si prende cura di lei; io penso il contrario. La mia vita è stata diversa per la sua esistenza fin dal primo giorno. Litighiamo spesso, ma sappiamo che quando serve ci siamo una per l'altra, senza discutere, e ci vogliamo bene entrambe. Abbiamo potuto tornare a casa dopo 9 anni, abbiamo potuto rivedere la nostra mamma dopo 8 anni. Senza di te, non avrei nemmeno potuto immaginare come avrei superato tutto questo, o forse non l'avrei mai superato. Grazie, sorella, per tutto il supporto che mi hai dato e mi dai. Anche tu oggi concludi il tuo percorso di laurea magistrale in Data Science, dopo aver finito il percorso triennale sempre qui al Polito. Mi ricordo ancora il primo giorno quando sei arrivata a Torino: parlavi pochissimo inglese, ma so che con tutti gli impegni e i sacrifici che hai affrontato oggi te lo meriti tutto e sicuramente avrai successo a 360 gradi. Senza di te non riesco a immaginare niente. Ora dico con tanta leggerezza che hai lavorato per una tesi su un dataset dei tumori e hai avuto un tumore anche tu l'anno scorso per essere più "pratica", ma mi fai preoccupare davvero tanto e per favore mantieniti in salute e sii felice! Ti voglio bene sorella e grazie!

Grazie di cuore a tutta la famiglia di mio marito, mi avete fatto sentire come se fossi nella casa mia. Il Salento è e sarà sempre la mia seconda casa, grazie a voi. Grazie, **mamma Marinella**, sei una donna forte e una mamma dolce. Il tuo sostegno mi ha fatto sentire come se la mia mamma fosse sempre con me. Quando abbiamo bisogno, so che possiamo contare su di te. E amo le tue polpette fritte! Grazie, **papà Bruno**, i momenti che abbiamo passato insieme mi hanno sempre fatto piacere. Sei una persona piena di amore ed entusiasmo, e apprezzo davvero tutto quello che hai fatto per noi. Grazie, **sorella Laura**, sei una persona molto precisa e piena d'amore, anche con il tuo carattere. Grazie per avermi detto che devo pensare sempre prima a me stessa. Questo consiglio lo porterò sempre con me. Ti voglio bene! Grazie, **cognato Giuseppe**, ci sei sempre tu, quando abbiamo bisogno, e non parliamo dei piatti che cucini: il pesce, la pasta, le cozze e quella minestrina non me la dimenticherò mai! Grazie, **nonna Rita**, sei davvero gentile e fa sempre piacere giocare a burraco con te, haha! Grazie, **Gloria** e **Rocco**, e anche alle mie amiche **Miriam** e **Aurora**, siete dolcissimi e avete portato tanta gioia e felicità nella mia vita! Tutti voi, e tante altre persone della famiglia (rispetto alla mia famiglia di quattro persone, la famiglia di mio marito è davvero enorme e non so come fare a scrivere tutti i nomi), mi avete accolto, così come mia sorella, con tanto amore. Il vostro affetto è un dono prezioso che porterò sempre nel cuore. Grazie davvero, con tutto il mio amore.

Grazie **Leila**, sei sempre stata la migliore collega che si possa desiderare, insieme a te nessuno si è permesso di togliermi lo zaino, e spero che avremo tanti bellissimi ricordi in futuro. Grazie **Yui**, sei sempre stata una carissima amica, sempre disponibile e anche la mia damigella d'onore. Grazie **Usman**, mi ricorderò per sempre i giorni in cui abbiamo studiato insieme online, sei stato un grande amico. Grazie **Michel**, abbiamo lavorato per poco tempo in Capgemini, ma sei diventato il mio migliore amico per sempre, e sono veramente gelosa di quanto sei giovane! Grazie **Xi Long**, anche se abbiamo lavorato in reparti diversi in Capgemini e ci conosciamo da poco, la tua gentilezza e il tuo spirito positivo hanno portato un sorriso nelle mie giornate, e canti benissimo! Grazie anche a **Carolina**, la mia insegnante di violino e la mia "terapista gratis". Senza di te avrei fatto tanta fatica a superare tanti momenti difficili. Voglio ringraziare tutti i miei amici che mi hanno sempre incoraggiata e supportata: senza di loro sarebbe stato tutto diverso. Posso solo augurarvi il meglio del meglio. Ci sarò sempre per voi.

Studiare e lavorare contemporaneamente non è stato facile. Ho lavorato come insegnante di cinese per bambini, come cameriera al ristorante e anche come barista, esperienza grazie alla quale oggi so fare un cappuccino bellissimo. Infine ho lavorato anche come ingegnere: questa esperienza mi ha insegnato a connettere teoria e pratica e mi ha fatto conoscere molte persone valide, permettendomi di fare networking. **Mersia Perra** di Capgemini Engineering, una grande manager che ha gestito la mia situazione subito in modo molto efficiente e mi ha detto tante parole toccanti quando ho lasciato Capgemini, essendo vissuta lontana dalla famiglia anche lei. **Dafne** di CSI, una donna forte e un manager altrettanto forte, **Rosa** e **Chiara** mi hanno accolta in ufficio fin dal primo giorno e sono stata davvero felice di averle conosciute.

L'esperienza in Ferrari, con tutte le sue luci e ombre, è stata indimenticabile: mi ha rafforzato psicologicamente e mi ha aiutato a capire davvero cosa voglio dalla mia carriera. Inoltre, mi ha fatto capire che essere sempre gentile non va sempre bene.

Dopo le dimissioni volontarie da un contratto indeterminato ho sostenuto altri tre colloqui con altre aziende e sono andati tutti positivamente. Ma mi sono fermata un momento: io cosa voglio davvero? Ho sempre avuto una profonda voglia di crescere e migliorare continuamente: un lavoro senza stimoli non fa per me. Quindi, come primo passo, devo concludere la mia laurea magistrale. Ho completato sia la laurea triennale che la laurea magistrale in una delle migliori scuole in Europa nelle discipline STEM, parlo 4 lingue, cinese, uyghur, inglese e italiano. So come adattarmi velocemente e integrarmi in un nuovo paese, imparando rapidamente una nuova lingua e conoscendo una nuova cultura: queste sono qualità che non tutti hanno. Acquisire una nuova lingua non significa solo parlarla, bisogna assorbire anche una nuova mentalità. Io non sono un albero: se l'ambiente non va bene, mi sposto. Sono sicura che un posto adeguato per me ci sia, se non in questa città, in un'altra città, se non in questo paese, in un altro paese. Oggi so che io merito molto di più: merito un posto migliore, persone migliori e di lavorare in un vero team.

Guardando indietro, provo gratitudine e sollievo per ogni scelta fatta. Voglio ringraziare me stessa, che non mi sono mai arresa e che ho deciso di andare avanti nonostante le difficoltà. La vita non è stata facile e non lo sarà nemmeno dopo, ma io sono qui, con il coraggio che cresce dentro di me. Grazie, **Güzel**.

Contents

List of Tables

List of Figures

Post hoc, ergo propter hoc.
[LATIN PROVERB]

Chapter 1

Introduction

1.1 Context and Motivation

Driver drowsiness represents one of the most critical and preventable causes of road traffic accidents worldwide, contributing to a substantial burden on public health and economic systems.
According to the World Health Organization, road traffic injuries remain among the top ten causes of death globally, with more than 1.3 million fatalities and up to 50 million injuries reported each year [6]. (see Figure 1.1)
Within this alarming statistic, fatigue and drowsiness are estimated to be responsible for up to 20% of serious accidents worldwide, representing not only a significant social and economic burden in terms of medical costs and insurance claims, but also immeasurable human suffering [6, 7].

The U.S. National Highway Traffic Safety Administration (NHTSA) defines driver drowsiness as one of the most significant causes of fatal vehicle crashes, and alcohol consumption and over-speeding [8, 9].
Studies [10, 11] demonstrate that being awake for more than two hours at nighttime environment can impede driving ability to a degree comparable to being 'drunk' with a blood concentration of 0.05%, which represents the legal limit in many countries.
This physiological impairment occurs insidiously, as individuals frequently remain unaware of their declining vigilance until their reaction times and decision-making are already compromised.

High-profile transportation accidents have repeatedly demonstrated the devastating consequences of drowsy driving. Table 1.1 below presents a historical drowsy driving statistics.

The 2014 New Jersey Turnpike crash, involving a commercial truck driver who had been awake for more than 28 hours, resulted in a multi-vehicle collision and fatalities, drawing national attention to the dangers of sleep-deprived driving [7].
Similarly, the 2016 German Autobahn bus accident, where driver fatigue contributed to

Figure 1.1: Road Traffic Injuries[3]

multiple passenger deaths, sparked renewed debate about rest regulations for long-haul drivers across Europe [12].
These cases underscore the urgent need for improved drowsiness detection and prevention strategies.

The physiological basis for drowsiness start from the complex connection between circadian rhythms and homeostatic sleep pressure, which together regulate the natural cycle of alertness and fatigue [13, 5].
During monotonous or extended driving, especially under low stimulation conditions such as highway travel at night, the risk of drowsiness increases dramatically[14].

Year	Drivers involved in fatal crashes who were drowsy	Percentage of all drivers involved in fatal crashes	Fatalities involving drowsy driving
2022	1264	1.33%	693
2021	1210	1.38%	701
2020	1165	2.2%	632
2019	1240	1.2%	697
2018	1221	2.4%	785
2017	1319	2.5%	697
2016	1332	2.5%	803
2015	1275	2.6%	824
2014	1306	2.9%	851
2013	1234	2.8%	801

Table 1.1: Historical drowsy driving statistics [1] [2]

Additional factors including sleep deprivation, irregular work schedules, medical conditions and certain medications can further increase the vulnerability to drowsiness.

1.2 Problem Statement and Research Gap

Despite widespread recognition of drowsy driving dangers, real-world detection and prevention of fatigue-induced impairment remains a significant unresolved challenge in traffic safety.
Traditional approaches to driver alertness monitoring have relied predominantly on vehicle-based indicators, behavioral observation, or self-reporting, each of which presents substantial limitations for practical deployment.

Vehicle-based systems analyze driving patterns such as steering wheel movements, lane position, and pedal operations to infer driver state indirectly.
However, these measures do not take into considerations many factors such as road geometry, vehicle type, weather conditions, and individual driving styles [15, 16].
Behavioral monitoring approaches focus on observable driver characteristics using computer vision algorithms to detect eye closure, blink frequency, yawning, and head pose.
While promising, these systems can be affected by lighting conditions, camera placement, sunglasses, or facial masks, and may fail to detect subtle early-stage drowsiness or conditions such as microsleeps where individuals fall asleep with eyes open [15, 16].

Self-assessment methods are infamously unreliable because drivers tend to underestimate their own fatigue or may be reluctant to admit it due to time pressure or overconfidence [9].
Furthermore, as driving behavior depends more on autopilot systems than on human drivers, the increasing use of semi-autonomous vehicles creates situations in which traditional vehicle-based detection methods become ineffective.

Recent advances in wearable sensor technology and physiological monitoring offer promising alternatives for more objective, real-time drowsiness detection.
Physiological signals, particularly heart rate (HR), heart rate variability (HRV), and respiration rate (RR), have emerged as reliable indicators of autonomic nervous system activity, which is closely linked to arousal and drowsiness states [17, 18, 19].
These signals can be collected continuously and non-invasively using consumer-grade wearable devices, potentially overcoming many limitations of existing approaches.

Despite all of this, significant challenges remain in translating physiological monitoring into practical drowsiness detection systems.
Most published studies[9, 20] are limited by small sample sizes, controlled laboratory environments, or lack of standardized ground truth measures for drowsiness assessment.
Additionally, there is a critical need for robust computational models that can handle the complex, non-linear relationships inherent in physiological data while maintaining real-time performance on resource-constrained embedded hardware.

1.3 Research Objectives and Questions

This thesis addresses a single but fundamental research question:
Can four discrete arousal levels be discriminated and extracted from physiological signals coming from smartwatches with at least 90% accuracy under conditions that approximate real driving?

The following specific objectives are intended to be provided by the research in order to examine this main question:

Primary Objective:
Develop and validate a machine learning framework capable of classifying four discrete arousal levels (from complete alertness to prominent drowsiness) from physiological signals collected using wearable smartwatch sensors.

Secondary Objectives:

1. Design a memory-efficient data processing architecture suitable for real-time implementation on low resources embedded systems
2. Compare the performance of different supervised learning approaches for physiological-based arousal classification
3. Evaluate system performance using a dataset under conditions that approximate realistic driving scenarios
4. Assess the feasibility of deploying such systems in practical vehicle environments

The research specifically investigates whether canonical autonomic markers (heart rate, heart rate variability, and respiration rate) can provide sufficient discriminative power for reliable drowsiness detection when processed through optimized machine learning pipelines.

1.4 Thesis Structure

This thesis is organized into five main chapters that systematically develop and validate the proposed drowsiness detection approach:

Chapter 1: Introduction establishes the research context, motivation, and objectives. It presents the problem statement, research questions, and provides an overview of the proposed approach and contributions.

Chapter 2: State of the Art provides a comprehensive review of existing drowsiness detection methodologies, covering vehicle-based, behavioral, and physiological approaches. It examines the theoretical foundations of autonomic nervous system monitoring, heart rate variability analysis, and machine learning applications in driver state assessment.

Chapter 3: Methodology details the proposed drowsiness detection framework, including the circular buffer architecture, data preprocessing pipeline, feature extraction methods, and machine learning model development.
It describes the experimental protocol and validation strategy employed.

Chapter 4: Results and Discussion presents comprehensive experimental findings, including model performance metrics, comparative analysis between Random Forest and Support Vector Machine approaches, and validation across different operating conditions. A discussion of results is provided, analyzing the implications of the research findings, addressesing limitations of the proposed approach, and discussing the practical considerations for real-world deployment.

Chapter 5: Conclusion summarizes the key contributions, discusses the broader impact of the research, and outlines directions for future investigation, including validation in fully naturalistic driving conditions and optimization for all-day operation.

Chapter 2

State of the Art

2.1 Introduction to Driver Monitoring Systems

The field of driver monitoring and drowsiness detection has evolved significantly over the past decades, driven by the urgent need to address fatigue-related road accidents and the advancement of sensing technologies.
Driver monitoring systems aim to assess the cognitive and physiological state of vehicle operators in real-time, providing early warnings or interventions when impaired driving conditions are detected.
The evolution of these systems can be traced through distinct technological eras, each characterized by different sensing modalities, computational approaches, and deployment strategies.

Early driver monitoring efforts focused primarily on indirect indicators derived from vehicle dynamics and driving behavior [21].
These systems analyzed steering patterns, lane position, and acceleration profiles under the assumption that drowsy drivers exhibit characteristic changes in vehicle control.
Although conceptually sound, these approaches faced significant challenges related to environmental confounding factors and individual driving style variations[21].

The introduction of computer vision technologies marked a significant advancement in driver monitoring capabilities [22].
Camera-based systems enabled direct observation of driver behavior, including eye closure patterns, blink frequency, head pose, and facial expressions[22].
These behavioral monitoring approaches offered more direct assessment of driver state compared to vehicle-based metrics, though they remained susceptible to environmental conditions and hardware limitations[22].

The most recent evolution in driver monitoring has been toward physiological sensing approaches [20][9][23][22], leveraging advances in wearable technology and biomedical signal processing. Table 2.1 below presents a comparison of existing drowsiness detection approaches.

Approach	**Key Indicators**	**Advantages**	**Limitations**
Vehicle-based	Steering patterns, lane position, speed variations	Non-invasive, existing sensors	Environmental confounding, individual styles
Behavioral	Eye closure (PERCLOS), blink frequency, head pose	Direct fatigue observation	Lighting dependency, occlusion issues
Physiological	HR, HRV, EEG, EMG signals	Objective, early detection	Sensor requirements, individual variability

Table 2.1: Comparison of existing drowsiness detection approaches

These systems monitor autonomic nervous system activity through various physiological markers, offering objective assessment of arousal and alertness states.
The progression toward physiological monitoring represents a fundamental shift from inferring driver state through behavioral or operational proxies to directly measuring the underlying biological processes that govern alertness and performance.

2.2 Theoretical Foundations

2.2.1 Arousal and Its Physiological Basis

Arousal represents a fundamental dimension of human consciousness and serves as a critical bridge between objective physiological signals and subjective states such as vigilance, attention, and sleepiness [19].
The scientific understanding of arousal has evolved through decades of research in psychology and neuroscience, establishing it as a central concept in models of emotion, motivation, and cognitive performance.

Every emotional state is mapped within this two-dimensional space, which places emotional valence on one axis and arousal on another [19]. Figure 2.1 presents the two dimensional valence arousal space.
High arousal states are typically associated with alertness, stress, or excitement, while low arousal corresponds to sleepiness, fatigue, or boredom.
This framework provides a structured approach to understanding how physiological changes relate to cognitive and emotional states, forming the theoretical foundation for physiological monitoring systems.

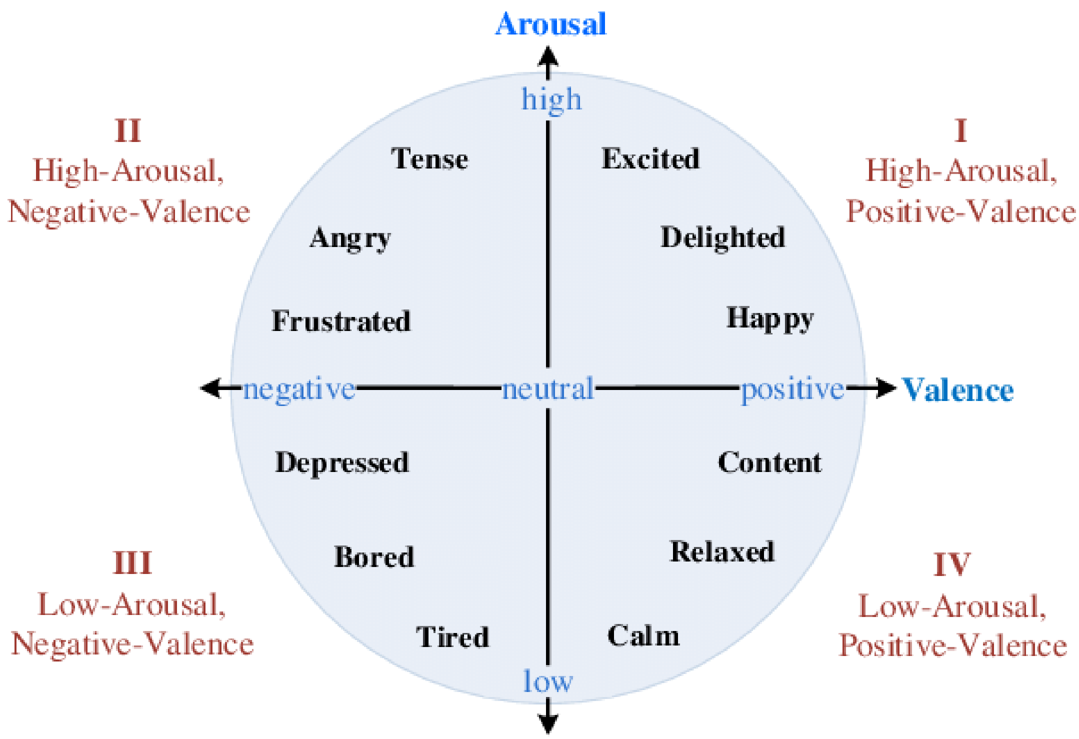

Figure 2.1: Two Dimensional Valence Arousal Space

Arousal levels are regulated by complex interactions between the central and autonomic

nervous systems, particularly through the action of the reticular activating system in the brainstem [24].
The reticular activating system modulates cortical activity in response to internal and external stimuli, helping maintain wakefulness and attentional focus [25] [26] [27].
Abnormal regulation of arousal can result in both cognitive deficits, such as lapses in attention, and physiological consequences, including reduced heart rate variability, underscoring its importance for safety-critical tasks such as driving [19] [25] [26] [27].
Maintaining optimal arousal is essential for sustained attention and effective performance. Both insufficient and excessive arousal can impair decision-making, reaction time, and overall functioning, a phenomenon described by the Yerkes-Dodson law [28].
In the context of driving, low arousal manifests as drowsiness, increased reaction times, and a higher risk of performance errors, while excessively high arousal can also lead to suboptimal performance due to overactivation of the sympathetic nervous system [19, 29].

Drowsiness specifically represents a low arousal state characterized by the transition from wakefulness to sleep [30].
This state involves reduced sensitivity to stimuli, slowed cognitive processing speed, and a tendency toward microsleeps.
Objective indicators of arousal are crucial for detection and intervention systems since the onset of drowsiness can be gradual and may not always be subjectively perceived.

The physiological measurement of arousal relies primarily on monitoring autonomic nervous system activity, which reflects the body's unconscious regulation of vital functions.
Key physiological markers include heart rate, which typically increases with heightened arousal and decreases as individuals become more relaxed or drowsy; heart rate variability, which refers to variation in intervals between heartbeats and often decreases under high stress or arousal while increasing during relaxation and recovery; and respiration rate, which tends to increase during high arousal states and slow during restful or drowsy conditions [19, 29]. Table 2.2 presents the typical changes in physiological markers, heart rate (HR), heart rate variability (HRV), and respiration rate (RR) associated with different levels of arousal[31].

Arousal State	**HR**	**HRV**	**RR**
High (alertness)	$\uparrow$	$\downarrow$	$\uparrow$
Low (drowsy)	$\downarrow$	$\uparrow$	$\downarrow$

Table 2.2: Typical changes in physiological markers with varying arousal levels

2.2.2 The Autonomic Nervous System and Drowsiness

Understanding the physiological mechanisms underlying drowsiness and emotional states is essential for developing effective detection systems.
The autonomic nervous system plays a central role in regulating involuntary bodily functions, including cardiovascular, respiratory, and emotional processes [32, 33].
The autonomic nervous system consists of two major branches: the sympathetic nervous system and the parasympathetic nervous system[4, 34] (see Figure 2.2).

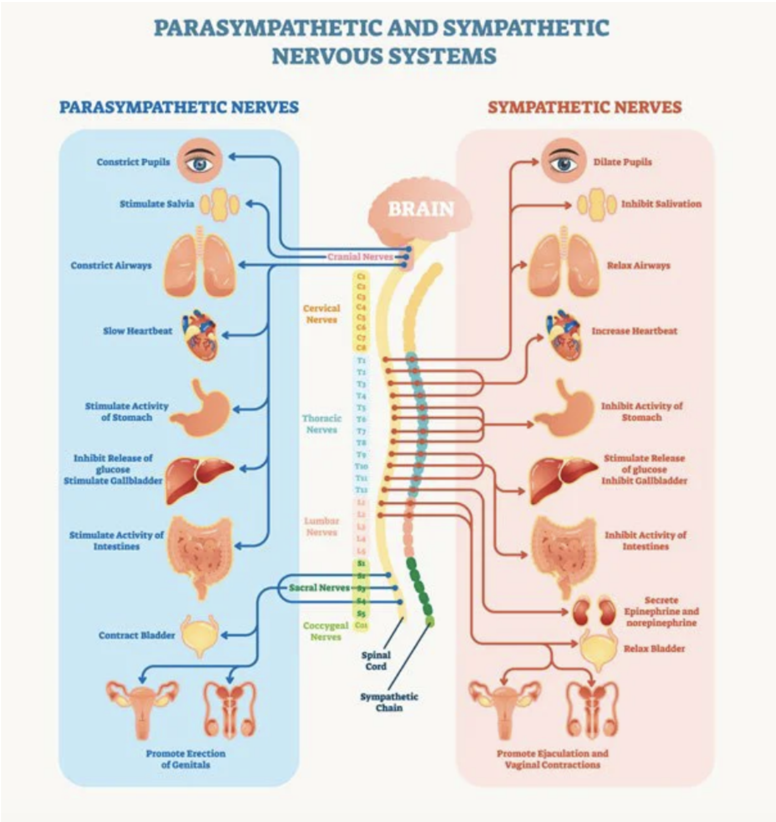

Figure 2.2: The Sympathetic Nervous System and The Parasympathetic Nervous System[4]

The sympathetic nervous system[35], often referred to as the "fight or flight" system, is typically associated with heightened arousal, stress responses, and increased heart rate.
When sympathetic activity dominates, individuals experience elevated alertness, increased metabolic activity, and enhanced readiness for physical or cognitive demands.
This system prepares the body for action by increasing heart rate, dilating pupils, and redirecting blood flow to essential organs and muscles.

In contrast, the parasympathetic nervous system[36], known as the "rest and digest" system, is linked to relaxation, restorative processes, and increased heart rate variability.

Parasympathetic dominance occurs during states of rest, recovery, and sleep preparation. This system promotes energy conservation by slowing heart rate, stimulating digestive processes, and facilitating cellular repair and regeneration.

Heart rate variability serves as a robust, non-invasive marker of autonomic nervous system activity, reflecting the dynamic balance between sympathetic and parasympathetic influences [32, 33, 37].
When an individual is alert or under stress, sympathetic activity dominates, leading to elevated heart rate and reduced heart rate variability.
During states of relaxation, rest, or drowsiness, parasympathetic activity increases, lowering the heart rate and enhancing heart rate variability [37, 38].
This bidirectional modulation forms the physiological basis for using heart rate variability as an indicator of both drowsiness and emotional regulation (see Table 2.3).

Physiological State	**Heart Rate (HR)**	**Heart Rate Variability (HRV)**
Sympathetic dominance (Alert/Stress)	Increases (↑)	Decreases (↓)
Parasympathetic dominance (Relaxation/Drowsiness)	Decreases (↓)	Increases (↑)

Table 2.3: Summary of autonomic modulation of heart rate and HRV during alertness and drowsiness

Emotional stimuli and fatigue trigger specific autonomic nervous system response patterns that are distinguishable in heart rate variability and related biosignals.
Studies [39] [40] [41] [42] [38] have demonstrated that negative emotions such as fear or anger are typically accompanied by increased heart rate and decreased heart rate variability, while positive or restful states are associated with greater variability.
These patterns provide the foundation for physiological monitoring systems designed to assess emotional and arousal states objectively.

2.2.3 Circadian Rhythms and Sleep Pressure

The physiological basis for drowsiness can be traced to the interplay of circadian rhythms and homeostatic sleep pressure, which together regulate the natural cycle of alertness and fatigue experienced by all humans [13, 5].
Circadian rhythms (see Figure 2.3), governed by the body's internal biological clock, prompt fluctuations in wakefulness across a twenty-four-hour period, making certain times of day, particularly late at night or in the early afternoon, especially hazardous for driving and other vigilance-demanding tasks.

Numerous physiological functions, such as hormone secretion, body temperature regulation, and sleep-wake cycles, are regulated by the circadian timing system, which is based in the hypothalamic suprachiasmatic nucleus.
This internal clock synchronizes with environmental light-dark cycles, helping maintain optimal timing of alertness and sleep propensity.
Disruption of circadian rhythms, whether through shift work, jet lag, or irregular sleep schedules, can significantly increase vulnerability to drowsiness and performance impairment [43].

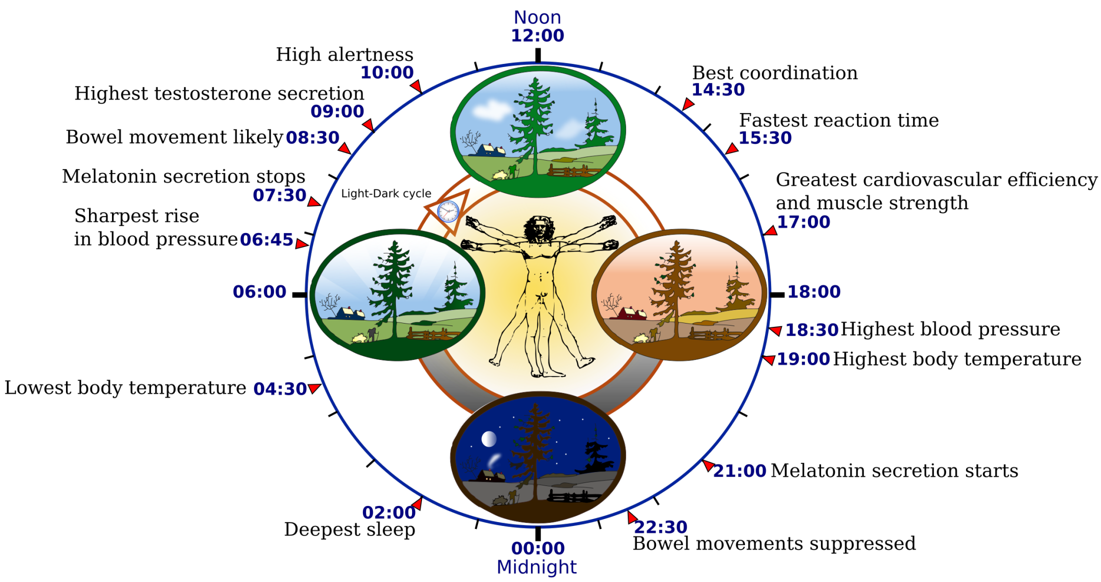

Figure 2.3: Circadian Rhythms[5]

Homeostatic sleep pressure represents the body's accumulating need for sleep that builds during wakefulness and dissipates during sleep.
This process is mediated by the accumulation of adenosine and other sleep-promoting substances in the brain [44].
As the duration of wakefulness increases, sleep pressure mounts, leading to increased drowsiness and degraded cognitive performance.
The interaction between circadian rhythms and sleep pressure creates predictable patterns

of alertness and sleepiness that can be leveraged for drowsiness prediction and prevention.

Additional factors such as lack of sleep, irregular work schedules, medical conditions, and the use of certain medications will further incrase vulnerability to drowsiness [19] [29].
Sleep disorders, particularly sleep apnea, can seriously compromise sleep quality and lead to excessive daytime sleepiness.
Understanding these factors is crucial for developing comprehensive drowsiness detection systems that can take vulnerability factors and individual variations in sleep patterns into consideration.

2.3 Approaches to Drowsiness Detection

2.3.1 Vehicle-Based and Behavioral Approaches

Traditional drowsiness detection in vehicles has relied extensively on vehicle-based and behavioral monitoring systems, each representing distinct approaches to inferring driver state from observable indicators [15, 16]. Figure 2.4 Schematic illustration of vehicle-based and behavioral drowsiness detection approaches, showing typical sensors, monitoring targets, and common confounders.

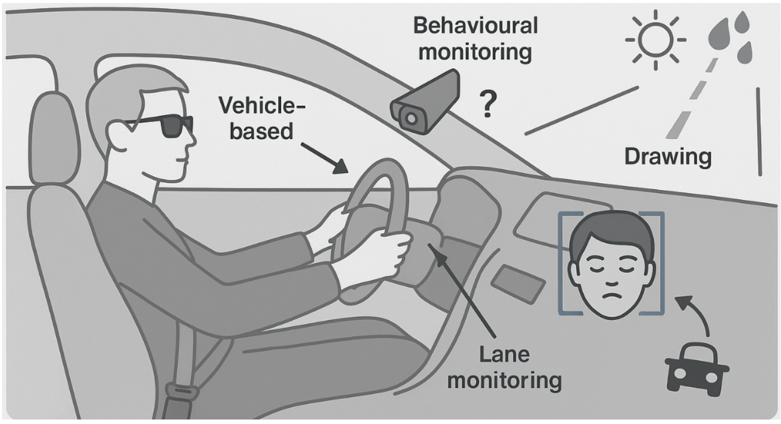

Figure 2.4: Schematic Illustration of Vehicle-Based and Behavioral Drowsiness Detection

Vehicle-based methods assess driver alertness indirectly by analyzing driving patterns and vehicle control characteristics, operating under the premise that drowsy drivers exhibit characteristic changes in their vehicle operation patterns.

Vehicle-based monitoring systems analyze multiple driving performance metrics including steering wheel movements, lane position stability, and pedal operation patterns.
These systems employ algorithms that establish baseline driving patterns for individual drivers and detect deviations that may indicate declining alertness.
Steering wheel angle variations, measured through steering sensors, can reveal characteristic patterns associated with drowsy driving, such as increased steering corrections or reduced responsiveness to road curvature[45][46][47].

Lane departure monitoring represents another significant vehicle-based approach, utilizing cameras or other sensors to track vehicle position relative to lane markings.
Drowsy drivers often exhibit increased lane departure frequency or duration, providing measurable indicators of impaired attention[48][49].
Similarly, analysis of acceleration and braking patterns can reveal changes in driving smoothness and reaction time that correlate with fatigue levels[50][51].

However, vehicle-based approaches face significant limitations that constrain their reliability and practical applicability.

Road geometry variations, such as curves, construction zones, or varying lane marking quality, can confound the interpretation of driving patterns.
Weather conditions including rain, snow, or wind can introduce external factors that affect vehicle control independent of driver state.
Vehicle characteristics such as suspension setup, tire condition, and electronic stability systems can also influence the measured parameters, making it difficult to establish universal thresholds for drowsiness detection [15, 16].

Behavioral monitoring approaches focus on directly observable driver characteristics using in-cabin cameras and computer vision algorithms.
These systems analyze facial features, eye movements, and head position to assess alertness levels.
Common behavioral indicators include prolonged eye closure measured through the percentage of eye closure time, blink frequency and duration patterns, yawning detection through facial expression analysis, and head pose tracking to identify head nodding or tilting associated with drowsiness.

Advanced driver assistance systems increasingly integrate behavioral monitoring techniques, employing visible or infrared cameras to monitor driver state even in challenging lighting conditions[52].
Computer vision algorithms have become sophisticated enough to detect subtle changes in facial expressions and eye movements that precede overt drowsiness manifestations.
Some systems incorporate machine learning approaches that adapt to individual drivers' baseline behaviors and improve detection accuracy over time[53].

Despite their technological sophistication, behavioral monitoring approaches encounter several significant limitations.
Environmental factors such as lighting conditions, particularly during night driving or in bright sunlight, can severely compromise camera-based detection accuracy.
Driver accessories including sunglasses, prescription glasses, or face masks can obstruct facial feature detection.
Individual differences in facial anatomy, ethnicity, and age can affect the reliability of facial recognition algorithms [15, 16].

2.3.2 Physiological Approaches

Physiological monitoring represents a fundamental advancement in drowsiness detection, offering more direct and objective assessment of driver state compared to vehicle-based or behavioral approaches [17, 18].
These systems monitor autonomic nervous system activity through various physiological markers, providing insights into the underlying biological processes that govern alertness and performance.
The most widely used physiological signals include heart rate, heart rate variability, and respiration rate, which can be acquired non-invasively using wearable sensors or embedded vehicle systems. Figure 2.5 provides a schematic overview.

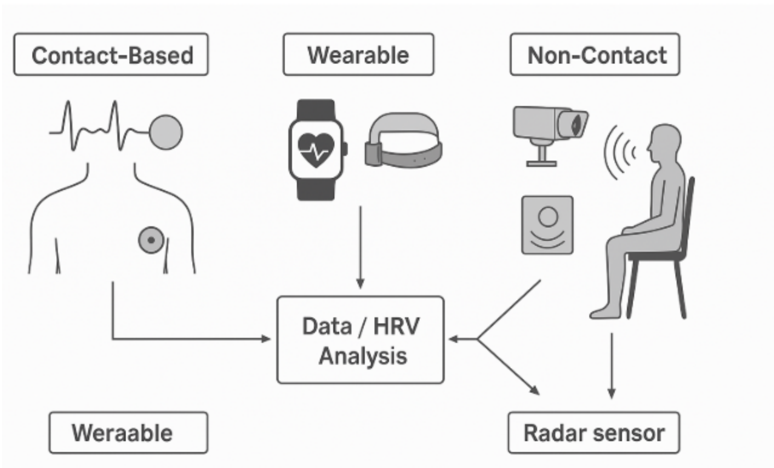

Figure 2.5: Schematic Overview of Non-Contact and Wearable HR/HRV Sensing Methods

The theoretical foundation for physiological drowsiness detection rests on the well-established relationship between autonomic nervous system activity and arousal states.
As individuals transition from alertness to drowsiness, characteristic changes occur in cardiovascular and respiratory patterns that can be detected and quantified through appropriate signal processing techniques [19, 29].
These changes often precede behavioral manifestations of drowsiness, enabling earlier detection and intervention.

Heart rate monitoring represents one of the most accessible physiological approaches, utilizing either electrocardiography or photoplethysmography to measure cardiac rhythm. During the transition from wakefulness to drowsiness, heart rate typically decreases as parasympathetic nervous system activity increases and sympathetic activity diminishes.
This relationship provides a reliable indicator of changing arousal states, though individual variations and external factors must be considered in practical applications. Figure 2.6 illustrates the key physiological changes that occur during the transition from wakefulness to drowsiness.
Heart rate variability analysis offers more sophisticated insights into autonomic nervous

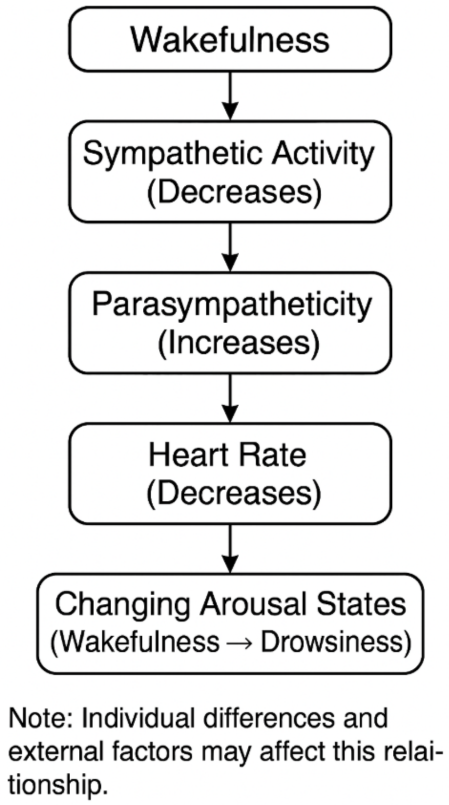

Figure 2.6: Physiological Changes During the Transition from Wakefulness to Drowsiness

system balance by examining the variation in intervals between successive heartbeats [54, 32, 33].
Time domain measures such as the standard deviation of normal-to-normal intervals and the root mean square of successive differences provide indicators of overall autonomic activity and parasympathetic function, respectively.
Frequency domain analysis, including low-frequency and high-frequency power components, can reveal specific patterns associated with different autonomic states.

The practical implementation of physiological monitoring has been facilitated by advances in wearable sensor technology and signal processing algorithms [20, 9].
Consumer-grade devices such as smartwatches and fitness trackers now incorporate sophisticated physiological monitoring capabilities that were previously available only in clinical settings.
These devices enable continuous and non intrusive monitoring throughout driving sessions without requiring specialized hardware installation or driver preparation.

2.3.3 Multi-Modal and Integrated Systems

Multi-modal drowsiness detection systems represent the current state-of-the-art approach, combining data from physiological, behavioral, and vehicle-based sources to achieve more reliable and robust detection performance [23].
These systems leverage the complementary strengths of different sensing modalities while compensating for the individual limitations of each approach. Figure 2.7 provides a schematic overview of multi-modal approaches.
The integration of multiple data streams enables more comprehensive assessment of driver state and reduces the likelihood of false alarms or missed detections.

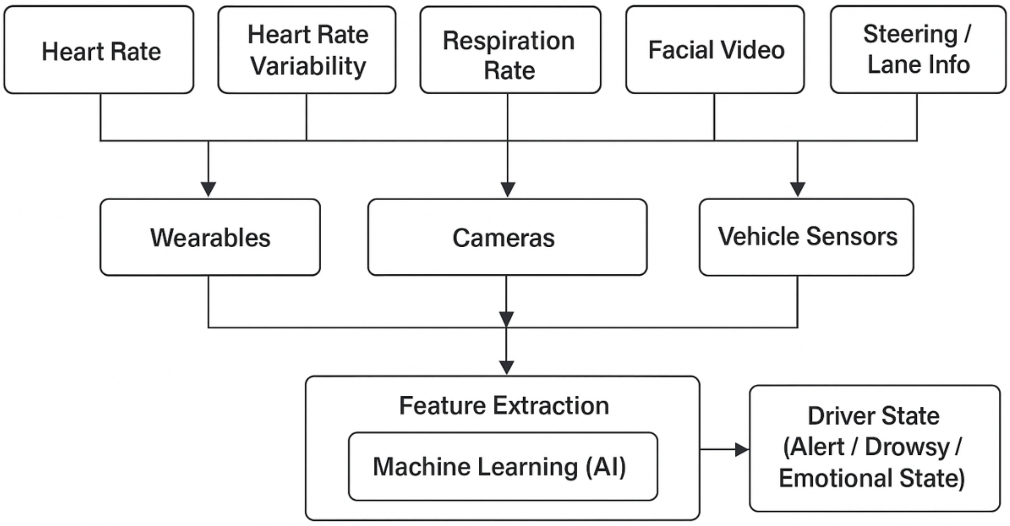

Figure 2.7: Multi-Modal Drowsiness Detection Systems

The development of multi-modal systems addresses several critical limitations of single-modality approaches.
Physiological signals may be affected by motion artifacts, sensor displacement, or individual physiological variations.
Behavioral monitoring can be compromised by lighting conditions, driver accessories, or certain types of drowsiness that do not manifest obvious behavioral changes.
Vehicle-based indicators may be confounded by road conditions, weather, or external factors affecting vehicle dynamics.
By combining multiple modalities, systems can maintain detection capability even when individual sensors or approaches are compromised.

Data fusion strategies for multi-modal drowsiness detection can be implemented at different levels of the processing pipeline.
Feature-level fusion combines preprocessed signals from different modalities before classification, enabling algorithms to identify complex patterns that span multiple data types.

Decision-level fusion combines the outputs of separate classification systems for each modality, using voting schemes or weighted combination approaches to reach final drowsiness assessments [55].
Hybrid approaches may employ both feature-level and decision-level fusion to optimize detection performance [23].

Modern implementations of multi-modal systems frequently utilize Internet of Things architectures to enable real-time, wireless data collection and fusion across wearable devices, in-cabin sensors, and vehicle systems [56].
These architectures support the integration of diverse sensor types and communication protocols while maintaining the low-latency requirements essential for real-time drowsiness detection.
Cloud-based processing capabilities can augment local computational resources when more sophisticated analysis algorithms are required.

2.4 Heart Rate Variability in Drowsiness Detection

2.4.1 Fundamentals of Heart Rate and Heart Rate Variability

Heart rate and heart rate variability represent two of the most important and widely studied physiological markers for drowsiness detection, providing complementary insights into autonomic nervous system activity and arousal states.
Heart rate, defined as the number of heartbeats per minute, reflects the immediate demands placed on the cardiovascular system and responds dynamically to changes in physical activity, emotional state, and arousal level.
Heart rate variability, representing the variation in time intervals between successive heartbeats, provides more nuanced information about the balance between sympathetic and parasympathetic nervous system activity [57, 32, 33].

The physiological foundations of heart rate regulation involve complex interactions between the autonomic nervous system, circulating hormones, and local cardiovascular control mechanisms[58][59].
The sinoatrial node, serving as the heart's natural pacemaker, receives continuous input from both sympathetic and parasympathetic nerve fibers that modulate heart rate in response to physiological demands.
Sympathetic stimulation increases heart rate and contractility, preparing the cardiovascular system for increased activity, while parasympathetic stimulation decreases heart rate and promotes recovery and restoration.

Heart rate variability emerges from the dynamic interplay between these autonomic influences, creating a constantly changing pattern of interbeat intervals even during apparently steady-state conditions.
This variability is not random noise but rather reflects the healthy responsiveness of the cardiovascular system to ongoing physiological regulation [60].
Reduced heart rate variability often indicates compromised autonomic function and has been associated with various pathological conditions as well as states of stress, fatigue, and drowsiness.

Heart rate usually falls as people go from being alert to being drowsy in the context of drowsiness detection, reflecting the change in sympathetic nervous system dominance to parasympathetic nervous system dominance that occurs during relaxation and sleep preparation [17, 18].
This decrease is often gradual and may precede subjective awareness of drowsiness, making heart rate monitoring valuable for early detection applications.
However, individual differences in baseline heart rate and responsiveness to drowsiness require personalized calibration for optimal detection performance.

2.4.2 Measurement Techniques for Heart Rate and Heart Rate Variability

The accurate measurement of heart rate and heart rate variability forms the foundation for reliable physiological drowsiness detection systems.
Several measurement modalities have been developed and refined over decades of clinical and research applications, each offering distinct advantages and limitations for different application contexts [54].
Understanding these techniques and their characteristics is essential for selecting appropriate approaches for vehicle-based drowsiness detection systems.

The gold standard for measuring heart rate and heart rate variability is still electrocardiography, which offers excellent signal quality and high temporal resolution in controlled settings [33, 61].
Electrocardiogram signals directly reflect the electrical activity of the heart, with R-wave peaks providing precise timing references for interbeat interval calculation. Figure 2.8 (below) illustrates how HR is calculated from successive R-R intervals in an ECG or PPG signal.
Clinical electrocardiography systems achieve exceptional accuracy and reliability, making them ideal for research applications and ground truth establishment.

However, traditional electrocardiography requires skin contact electrodes and careful preparation, limiting its practical applicability in vehicle environments.
The need for conductive gel, proper electrode placement, and protection from motion artifacts makes conventional electrocardiography unsuitable for routine driver monitoring applications.
Modified approaches using dry electrodes or textile-integrated sensors have been developed to address these limitations, though often with some compromise in signal quality.

Photoplethysmography has emerged as the most practical alternative for wearable heart rate monitoring, utilizing optical sensing techniques to detect blood volume changes associated with cardiac cycles [54, 61].
Photoplethysmography sensors employ light-emitting diodes to illuminate tissue and photodetectors to measure the amount of light absorbed or reflected.
As blood volume increases during systole, light absorption changes, creating a pulsatile signal that corresponds to heart rate.

The advantages of photoplethysmography for drowsiness detection applications include non-invasive measurement requiring only skin contact, compatibility with wearable device form factors, relatively low power consumption suitable for battery-operated devices, and the ability to provide continuous monitoring for prolonged periods of time.
Modern photoplethysmography implementations achieve heart rate accuracy comparable to electrocardiography for most applications, though heart rate variability measurement may be somewhat less precise due to the indirect nature of the measurement [61].

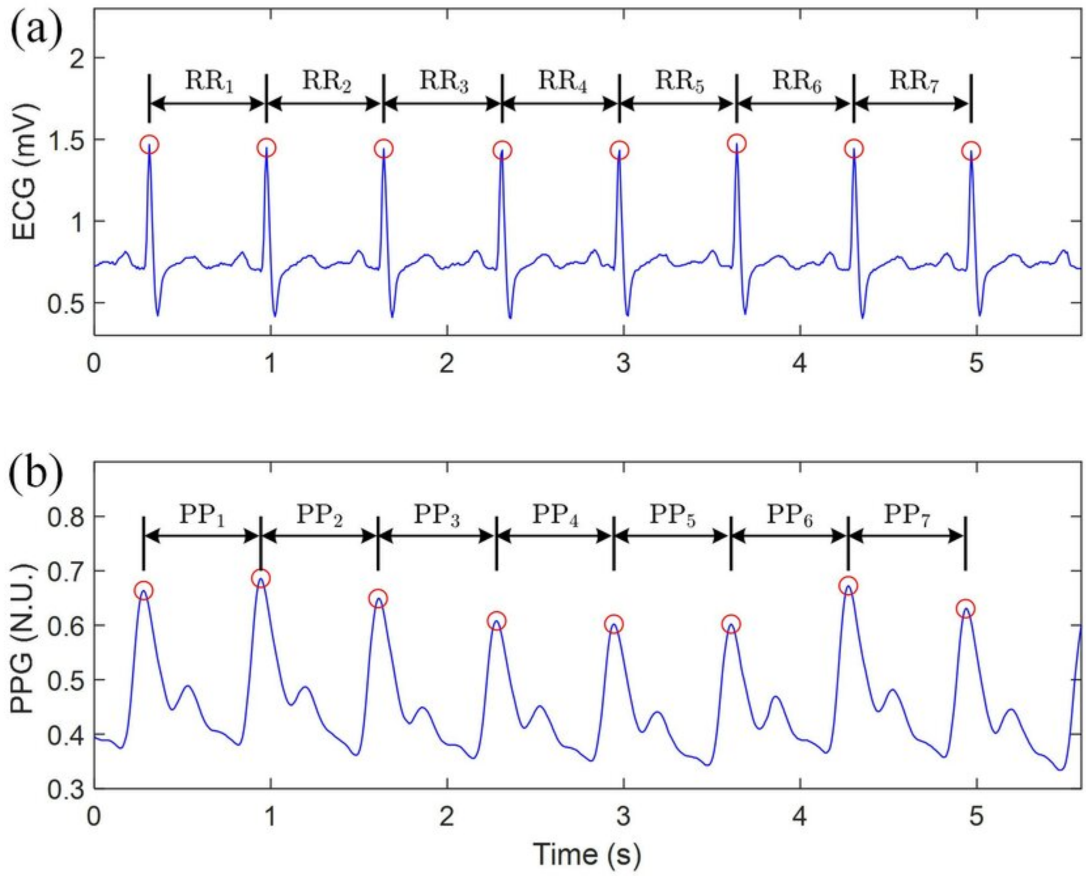

Figure 2.8: ECG and PPG signals

2.4.3 HRV Analysis Methods and Metrics

Heart rate variability analysis encompasses a diverse range of mathematical and statistical techniques designed to quantify different aspects of autonomic nervous system activity [33, 60, 61].
These analysis methods have been developed and validated over decades of clinical research, providing standardized approaches for extracting meaningful information from heart rate variability signals.
Understanding these methods and their appropriate applications is crucial for developing effective drowsiness detection systems based on physiological monitoring.

Time domain analysis methods provide the most straightforward approach to heart rate variability quantification, utilizing statistical measures applied directly to sequences of interbeat intervals.
The standard deviation of normal-to-normal intervals serves as a global measure of heart rate variability, reflecting overall autonomic nervous system activity over the measurement

period.
This measure increases when autonomic nervous system activity is high and decreases during conditions of reduced variability such as stress or certain disease states [60].

The root mean square of successive differences between interbeat intervals provides a more specific measure of short-term heart rate variability that is primarily influenced by parasympathetic nervous system activity.
This measure is particularly sensitive to rapid changes in autonomic balance and can provide early indicators of drowsiness onset when parasympathetic activity begins to dominate.
The sensitivity of this measure to high-frequency variations makes it valuable for real-time monitoring applications [60].

Frequency domain analysis techniques transform heart rate variability signals into the frequency domain to examine the spectral characteristics of autonomic nervous system activity.
Power spectral density analysis reveals the distribution of heart rate variability power across different frequency bands, each associated with different physiological mechanisms [33, 60].
Very low frequency components, typically below 0.04 Hz, are influenced by thermoregulation, hormone fluctuations, and other long-term regulatory processes.

Low frequency components, generally defined as the frequency range from 0.04 to 0.15 Hz, reflect both sympathetic and parasympathetic influences on heart rate, with sympathetic activity thought to predominate [62] [63] [64].
High frequency components, spanning approximately 0.15 to 0.4 Hz, are primarily mediated by parasympathetic nervous system activity and closely related to respiratory patterns [62] [63] [64].
The ratio of low frequency to high frequency power is often used as an indicator of sympathetic-parasympathetic balance, though its interpretation requires careful consideration of various factors [60].

Detrended Fluctuation Analysis, entropy measures, and Poincaré plots are examples of **Nonlinear Analysis** techniques. These techniques can offer extra prognostic value in particular situations and capture intricate and chaotic heart rate dynamics behaviors that linear approaches frequently overlook. The primary steps in the heart rate variability (HRV) analysis pipeline are depicted in Figure 2.9 (below).

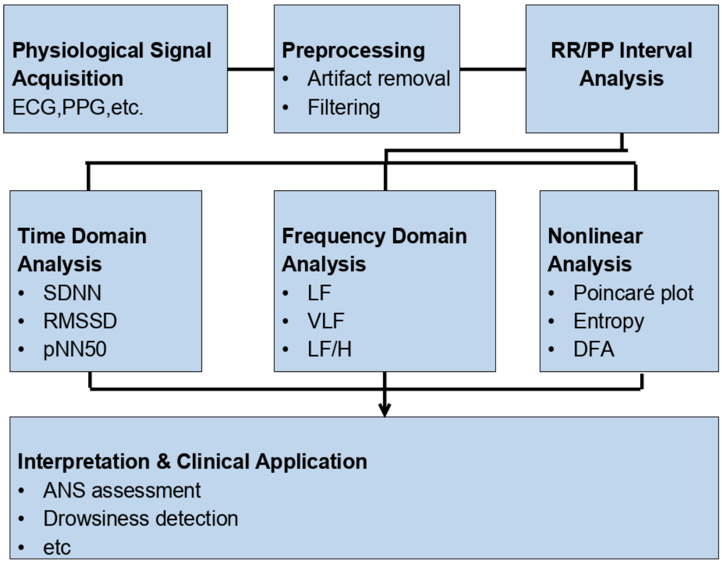

Figure 2.9: Schematic Workflow of HRV Analysis: From Signal Acquisition to Clinical Application

2.4.4 Factors Influencing Heart Rate Variability

Heart rate variability is influenced by numerous physiological, psychological, and environmental factors that must be understood and accounted for in drowsiness detection systems [65, 66].
These factors can significantly affect baseline heart rate variability levels and responses to drowsiness, making personalization and calibration essential components of practical monitoring systems.
A comprehensive understanding of these influences enables the development of more robust and reliable detection algorithms that can maintain accuracy across diverse populations and conditions.

Age represents one of the most significant factors affecting heart rate variability, with well-documented decreases in most heart rate variability measures throughout the human lifespan [65, 66].
Heart rate variability increases rapidly during childhood, reaches peak values during adolescence and early adulthood, and then gradually declines with advancing age.
This age-related decline reflects changes in autonomic nervous system function, including reduced parasympathetic activity and altered sensitivity to autonomic stimulation.
Drowsiness detection systems must account for these age-related changes to establish appropriate baseline values and detection thresholds.

Physical fitness and cardiovascular health significantly impact heart rate variability patterns, with regular aerobic exercise generally associated with increased heart rate

variability and enhanced vagal tone [65, 66].
Well-trained athletes typically exhibit higher baseline heart rate variability and greater parasympathetic activity compared to sedentary individuals.
However, acute exercise can transiently decrease heart rate variability, and overtraining may lead to chronic reductions.
These fitness-related variations must be considered when interpreting heart rate variability in the context of drowsiness detection.

Lifestyle factors including smoking, alcohol consumption, and caffeine intake can significantly affect heart rate variability patterns [65, 60].
Smoking is generally associated with reduced heart rate variability, reflecting adverse effects on autonomic function.
Alcohol consumption can have complex effects depending on dose and timing, with moderate amounts sometimes increasing heart rate variability acutely while chronic consumption typically reduces it.
Caffeine intake can increase sympathetic activity and affect heart rate variability patterns, with effects lasting several hours after consumption.

2.5 Machine Learning in Physiological State Recognition

2.5.1 Feature Extraction and Engineering

The transformation of raw physiological signals into meaningful features suitable for machine learning analysis represents a critical step in developing effective drowsiness detection systems [9, 20].
Feature extraction and engineering techniques must be developed in order to capture the essential characteristics of physiological patterns, while reducing dimensionality and computational requirements for real-time applications.
The quality and, especially, relevance of extracted features often determine the ultimate success of machine learning approaches in physiological state recognition.

Traditional feature extraction approaches for heart rate variability analysis have focused on established time domain, frequency domain, and nonlinear measures that have been validated through decades of clinical research [60].
Time domain features such as the standard deviation of normal-to-normal intervals and the root mean square of successive differences provide robust indicators of autonomic nervous system activity that can be computed efficiently from inter beat interval sequences. These features offer the advantages of simplicity, computational efficiency, and well-understood physiological interpretations.

Frequency domain features derived from power spectral analysis offer complementary information about autonomic nervous system activity by revealing the spectral characteristics of heart rate variability.
Low frequency power, high frequency power, and their ratio provide insights into sympathetic-parasympathetic balance that may be particularly relevant for drowsiness detection [33, 60].
The implementation of frequency domain feature extraction requires careful consideration of spectral estimation techniques, window functions, and frequency band definitions to ensure reliable and comparable results.

2.5.2 Classification Algorithms for Drowsiness Detection

The selection and optimization of machine learning algorithms for drowsiness classification represents a critical component in developing effective physiological monitoring systems [9, 20, 67, 68].
Various classification approaches have been investigated for this application, each offering distinct advantages and limitations that must be carefully considered in the context of real-time, safety-critical deployment requirements.
This choice for the classification problem significantly affects system performance, computational requirements, and interpretability.

Support Vector Machines have been extensively investigated for drowsiness detection applications due to their strong theoretical foundations and effectiveness in handling high-dimensional feature spaces [68, 29].
These models work by finding optimal hyperplanes that separate different classes in feature space, with the ability to handle non-linearly separable problems through kernel functions.
In fact, radial basis function kernels are commonly employed for drowsiness detection, enabling the algorithm to capture complex, non-linear relationships between physiological features and arousal states.

On the other hand, Random Forest algorithms represent an easier learning approach that has demonstrated excellent performance for physiological state classification tasks [67, 9].
By constructing multiple decision trees using different subsets of features and training samples, they then combine their predictions through voting mechanisms.
This approach provides robust performance by reducing overfitting and improving generalization compared to individual decision trees.

2.5.3 Model Validation and Performance Assessment

The validation and performance assessment of machine learning models for drowsiness detection requires specialized approaches that account for the unique characteristics of physiological data and the safety-critical nature of the application [9, 20].
Traditional machine learning validation techniques must be adapted to address temporal dependencies, individual variations, and the practical requirements of real-world deployment scenarios.
Comprehensive validation strategies ensure that developed models will perform reliably when deployed in real vehicle environments.

In addition, temporal validation considerations are particularly important for drowsiness detection applications, because physiological data exhibit strong temporal correlations and the drowsiness state evolves gradually over time.
Traditional random cross-validation approaches, that randomly distribute samples between training and test sets, can lead to overly optimistic performance estimates by including temporally adjacent samples in both sets.
This temporal leakage allows models to exploit short-term correlations rather than learning generalizable patterns associated with drowsiness onset.

Person-independent validation represents another critical consideration for drowsiness detection systems that must generalize across diverse populations.
Individual differences in physiological baselines, autonomic nervous system responsiveness, and drowsiness manifestations can significantly affect model performance when applied to new users[69].
Person-independent cross-validation, where complete individuals are held out from training and used only for testing, provides essential insights into model generalization.

Chapter 3

Methodology

3.1 Overview and Research Design

This chapter presents the comprehensive methodological framework developed to detect and classify driver drowsiness and arousal states using physiological data collected from smartwatch devices.
The methodology represents a systematic approach to ensure four discrete arousal levels can discriminate between drowsiness and the awake state.

The overall research design follows a supervised machine learning paradigm, where physiological features serve as input variables and discretized arousal levels function as target classifications.
This approach was selected to enable real-time or online processing capabilities while maintaining the precision necessary for safety-critical applications.
The methodology integrates several innovative components, including a novel circular buffer architecture for memory-efficient and lightweight data processing, feature engineering techniques optimized for physiological signals and comparative evaluation of multiple machine learning algorithms.

The research framework was designed to address critical limitations identified in existing drowsiness detection systems, particularly the need for robust performance across diverse individuals, real-time or near real-time processing capabilities suitable for embedded deployment and scalability to large datasets representative of real-world driving conditions.
Each methodological component was carefully selected and optimized to maximize both detection accuracy and practical feasibility.

The experimental approach emphasizes ecological validity while maintaining rigorous scientific controls.
Rather than relying solely on laboratory-induced drowsiness, the methodology incorporates physiological data collected under conditions that approximate realistic driving scenarios.

This design choice reflects the understanding that laboratory findings may not translate directly to real-world performance (this is often called domain shift [70]), showing the importance of validation approaches that capture the complexity and variability of actual driving environments.

The methodology also incorporates principles of reproducible research, with detailed documentation of all processing steps, parameter selections, and validation procedures.
This emphasis on reproducibility ensures that findings can be independently verified on their correctness and that the developed approaches can be effectively transferred to practical implementation contexts in an easy and reliable manner.

3.2 Data Acquisition and Dataset Description

The foundation of this research is built on a substantial dataset of physiological data that was provided from a company, eliminating data collection as a component while enabling focus on advanced analysis and modeling techniques.
The dataset, while not publicly available due to copyright reasons, represents one of the largest collections of synchronized physiological and arousal data available for drowsiness detection research, providing robust statistical power for machine learning algorithm development and validation.

The physiological data component consists of fifteen Excel files, each containing approximately five thousand observations.
These files capture a comprehensive range of physiological parameters and metadata features collected through smartwatch-class sensors during extended monitoring sessions.
The systematic organization of these files reflects careful experimental design principles, with consistent sampling protocols and standardized measurement procedures across all data collection sessions.

Corresponding to each physiological data file, the dataset includes fifteen arousal and valence annotation files that provide synchronized annotation labels for every observation.
This pairing ensures precise temporal alignment between physiological measurements and subjective state assessments, creating the foundation for supervised learning approaches.
The arousal annotations represent expert assessments of alertness levels, providing the target variables necessary for classification model development.

The dataset's substantial size, encompassing **169,466 individual observations** after preprocessing and integration, provides exceptional statistical power for machine learning applications.
This scale enables robust cross-validation procedures, supports the development of personalized models for individual users, and allows for comprehensive evaluation of algorithm performance across diverse conditions and populations.

The temporal structure of the data, with observations collected over extended periods, captures the natural progression of arousal state changes that occur during realistic monitoring scenarios.
This temporal richness enables the development of algorithms that can detect gradual transitions between alertness and drowsiness, rather than simply classifying discrete time points in isolation.

The multi-dimensional physiological measurements allow for complex feature engineering and selection.
However, this study focuses specifically on heart rate (HR) and heart rate variability (HRV) as the primary indicators, due to their well-established associations with autonomic nervous system activity and arousal states[31, 17, 18, 19].

3.3 Data Preprocessing Pipeline

The transformation of raw physiological measurements into analysis-ready datasets requires a systematic preprocessing pipeline that addresses data quality issues, ensures temporal consistency, and prepares features for machine learning analysis. This preprocessing pipeline, illustrated in Figure 3.1, represents a critical component of the methodology that directly impacts the reliability and validity of subsequent analyses.

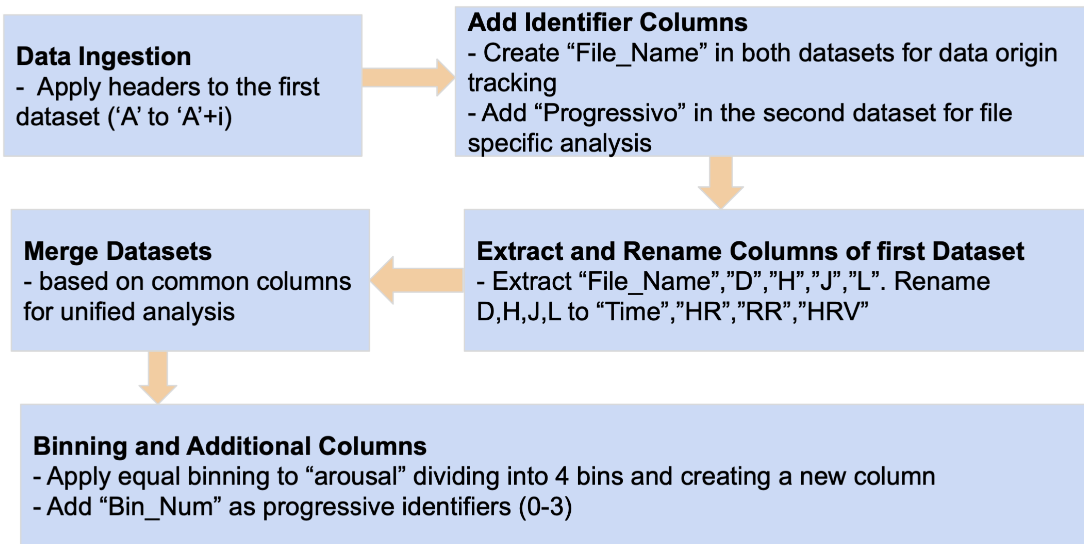

Figure 3.1: Schematic of the Data Preprocessing Workflow

3.3.1 Data Cleaning and Synchronization

The initial preprocessing pipeline was implemented in Python using Pandas and NumPy libraries to ensure robust and efficient data handling.

All Excel files from both physiological and arousal folders were batch-imported using systematic procedures that maintain data integrity and traceability.
Appropriate column headers were programmatically assigned to the physiological data, addressing the original files lack of standardized headers through systematic naming conventions.

A new identifier column, "File_Name," was added to each dataframe to track data origin throughout the merging process, enabling comprehensive traceability and supporting file-specific analyses. The "Progressivo" identifier was added to provide sequential numbering within each file, supporting temporal analysis and ensuring proper ordering of time-series data.
Only the relevant columns, Time, HR, RR, and HRV were retained for further analysis, streamlining the dataset while preserving essential physiological information.
All files were concatenated into unified dataframes using efficient pandas operations that maintain temporal ordering and data relationships.

Rows with missing or invalid values in key columns were automatically identified and removed to maintain dataset integrity.
This cleaning process employed multiple validation criteria, including null value detection, range validation based on physiological norms, and consistency checks across related measurements.
The physiological and arousal dataframes were temporally aligned by merging on both "File_Name" and "Time" columns, ensuring strict one-to-one correspondence for every observation in the merged dataset.

This careful alignment was critical for the validity of machine learning analysis, as any misalignment could lead to erroneous or deceptive model predictions.
The automated and programmatic approach not only ensured data integrity but also enables reproducibility and scalability for similar datasets in future studies.

3.3.2 Feature Extraction and Standardization

Once the datasets were merged, the final dataframe included columns for Time, Valence, Arousal, File_Name, Progressivo, HR, RR, and HRV.
These variables were standardized and renamed for consistency, with additional identifier columns (File_Name, Progressivo) included to track the source of each record and enable file-specific or session-based analyses.
This comprehensive tracking facilitates traceability and supports potential stratified analysis by data source.

All extraction and quality control steps were performed programmatically in Python to ensure efficiency and reproducibility.
Programmatic checks were implemented to identify and resolve any duplicate rows or inconsistencies, ensuring the quality and integrity of the dataset through systematic validation procedures.

The selection of these specific features was guided by their documented relevance in the literature for detecting autonomic changes and drowsiness [19, 29, 17, 18].
No further feature engineering or advanced HRV metric computation was performed at this stage, as the physiological variables provided were used directly for model training and evaluation.
This approach maintains the integrity of the original measurements while ensuring compatibility with real-time processing requirements.

3.3.3 Label Engineering and Discretization

The continuous "Arousal" column was discretized into four equal-width bins using Pandas' cut function, producing categorical classes that represent different levels of arousal or drowsiness (from 0 to 3).
This binning approach was chosen to transform the regression problem into a multiclass classification task, making the model's output more robust to small fluctuations in the original signal while providing meaningful distinctions between arousal states.

Each bin was mapped to a progressive integer identifier, stored in the new "Bin_Num" column, enabling direct use as class labels in supervised classification models.
This binning approach provided a robust and interpretable target variable for the downstream machine learning framework while maintaining the granularity necessary for meaningful drowsiness detection.

The four-class discretization scheme reflects careful consideration of both theoretical frameworks and real world implementation.
From a theoretical perspective, four classes provide sufficient granularity to capture the major phases of alertness transition, spanning from full alertness through progressive drowsiness stages to pronounced sleepiness.
From a practical implementation perspective, the four-class scheme balances classification complexity with deployment feasibility, avoiding both the oversimplification of binary classification and the excessive complexity of highly granular schemes.

3.4 Circular Buffer Architecture

The development of a memory-efficient circular buffer architecture represents one of the principal methodological innovations of this research, addressing critical constraints imposed by embedded hardware deployment while maintaining computational sophistication for accurate drowsiness detection.

The circular buffer operates on fixed-size data structures that overwrite older observations as new measurements arrive, creating a continuously updated window of recent physiological activity. This approach eliminates memory overhead associated with maintaining complete historical datasets while preserving temporal context necessary for meaningful arousal state assessment. Buffer size is optimized to balance temporal coverage with memory constraints of embedded automotive systems.

The implementation utilizes ring buffer principles with head and tail pointers managing data insertion and removal without memory reallocation or copying operations. This design ensures constant-time complexity for data updates, maintaining predictable performance characteristics regardless of buffer size or operation duration. Feature scaling and normalization operations are integrated directly into the buffer architecture using running statistics maintained within the buffer structure. This integration eliminates separate preprocessing stages while ensuring processed features are immediately available for classification.

The architecture enables continuous inference through streaming data processing capabilities. As the buffer updates with new measurements, feature extraction algorithms operate on current contents to generate appropriately formatted input tensors for classification models. These tensors conform to model input requirements while preserving temporal relationships inherent in physiological signals, providing the resolution necessary for early warning systems. This streaming approach facilitates real-time drowsiness detection without compromising the temporal dependencies crucial for accurate physiological state assessment.

3.5 Machine Learning Framework

3.5.1 Problem Formulation

The model is trained to predict the discrete arousal level for each observation, as defined by the four-class binning of the continuous arousal signal described in Section 3.3.3
This formulation enables the system to robustly differentiate between multiple states of alertness, supporting early detection and potential real-time interventions in realistic operational environments.

The classification framework treats physiological features as input variables and discretized arousal levels as target outputs, enabling supervised learning algorithms to automatically discover complex relationships between autonomic nervous system activity and subjective arousal states.
This approach leverages the substantial dataset size to learn generalizable patterns that can accurately predict arousal levels from physiological measurements alone.

3.5.2 Model Selection and Development

Random Forest (RF) and Support Vector Machine (SVM), the two main classifiers, were assessed according to their complementary advantages and appropriateness for physiological signal analysis.
For managing the properties present in physiological data, such as feature interaction modeling, noise tolerance, and non-linear relationships, each algorithm has unique benefits.

Random Forest Implementation

Random Forest was selected for its exceptional ability to model complex, non-linear relationships between physiological features and arousal states while maintaining robustness to noise and outliers commonly present in wearable sensor data [67].
The ensemble approach provides natural protection against overfitting through bootstrap aggregation and random feature selection, making it particularly suitable for physiological signal classification.

The Random Forest implementation employs the following carefully optimized hyperparameters determined through systematic grid search procedures:

- **Number of Trees:** 150 trees (optimized through grid search, as 100 trees proved insufficient for capturing the complexity of physiological patterns)
- **Maximum Leaves per Tree:** 30 leaves (controls model complexity while preserving discriminative capability)
- **Maximum Depth:** 10 levels (limits tree growth to prevent overfitting while maintaining sufficient depth for feature interactions)

- **Minimum Samples per Split:** 5 samples (ensures sufficient statistical evidence for tree splits)
- **Minimum Samples per Leaf:** 2 samples (prevents overly small leaves while maintaining model flexibility)

These hyperparameter selections reflect extensive optimization procedures that balance model complexity with generalization performance, ensuring optimal classification accuracy while maintaining computational efficiency suitable for real-time applications.

Support Vector Machine Implementation

Support Vector Machine algorithms provide complementary capabilities for arousal classification, particularly through their ability to find optimal decision boundaries in high-dimensional feature spaces [68].
The non-linear separability inherent in physiological arousal relationships necessitates the use of kernel functions to capture complex decision boundaries.

The SVM implementation incorporates the following optimized parameters:

- **Kernel Function:** Radial Basis Function (RBF) kernel, selected after systematic evaluation revealed superior performance compared to linear kernels
- **Regularization Parameter:** C = 500, providing soft margin classification that balances model flexibility with overfitting prevention
- **Kernel Parameters:** Optimized through grid search to ensure appropriate scaling for physiological feature distributions

The selection of RBF kernels reflects empirical evaluation demonstrating that physiological data exhibit non-linear separability characteristics that require sophisticated decision boundary modeling.
Linear kernels consistently produced poor results, confirming the non-linear nature of the classification problem.

3.6 Experimental Protocol and Validation Strategy

The experimental protocol establishes rigorous procedures for model training, validation, and performance assessment that ensure reliable and generalizable results [9].
The validation strategy specifically addresses the unique characteristics of physiological data, including temporal dependencies, individual differences, and the safety-critical nature of drowsiness detection applications.

The primary validation approach employs **stratified, per-driver train-test splits** that respect individual boundaries while maintaining representative arousal class distributions. This validation strategy recognizes that physiological responses exhibit significant individual variation and that models must demonstrate effectiveness across different people rather than simply different time periods from the same individuals.

Complete separation of individuals between training and testing sets provides conservative but realistic estimates of generalization performance.
This approach ensures that the model's ability to generalize to new users is properly assessed, reflecting the real-world deployment scenario where systems must work effectively for individuals not included in the training data.

The train-test split proportions allocate approximately 70% of individuals to training and validation sets and 30% to testing sets, balancing statistical power in both phases while maintaining individual-level separation.
This allocation ensures adequate sample sizes for robust model development while providing sufficient test data for reliable performance evaluation.

Cross-validation procedures within the training set employ person-independent folds that further validate model robustness across different individuals.
These internal validation procedures guide hyperparameter selection and model refinement while maintaining strict separation from the final test set.
The cross-validation approach uses stratified sampling to ensure representative arousal class distributions across all folds.

3.6.1 Performance Evaluation Metrics

Performance evaluation employs comprehensive metrics that capture different aspects of classification quality relevant to drowsiness detection applications:

- **Overall Accuracy:** Primary measure of classification performance across all arousal states
- **Class-specific Precision:** Proportion of correct predictions for each arousal level
- **Class-specific Recall:** Proportion of actual arousal states correctly identified
- **Class-specific F1-scores:** Harmonic mean of precision and recall for balanced evaluation

- **Macro-averaged Metrics:** Unweighted average across all classes for balanced assessment

The emphasis on class-specific metrics ensures that model performance is evaluated comprehensively across all arousal states, preventing optimization bias toward common classes at the expense of critical but less frequent drowsiness states.

3.6.2 Statistical Significance and Robustness Assessment

The experimental protocol includes statistical significance testing to ensure that observed performance differences between models reflect genuine effects rather than random variation.
Appropriate statistical tests account for the dependencies inherent in physiological data and the specific experimental design employed.

Robustness assessment procedures evaluate model performance under various data quality conditions that might be encountered in real-world deployment scenarios.
These assessments include evaluation with simulated sensor noise, missing data patterns, and signal quality degradation that could occur due to poor sensor contact or motion artifacts.

Confidence interval estimation provides essential information about the uncertainty in performance estimates, particularly crucial for safety-critical applications where understanding the range of possible performance outcomes is vital for deployment decisions.

Chapter 4

Results and Discussion

4.1 Results

4.1.1 Overall Performance Summary

The experimental evaluation of the proposed drowsiness detection methodology yielded comprehensive performance results that demonstrate the feasibility of using physiological signals for real-time arousal state classification.
The stratified, per-driver validation approach provided robust assessment of model generalization capabilities across diverse individuals while maintaining the temporal integrity essential for physiological data analysis.

The Random Forest ensemble method achieved a **mean classification accuracy of 88.1%** across all arousal states, with individual file accuracies ranging from a minimum of 78.4% to a maximum of 99.4%.
This performance level approaches the 90% target accuracy threshold established for practical deployment in safety-critical applications, demonstrating the viability of the proposed approach for real-world implementation.
The substantial variation in per-file performance reflects the individual differences inherent in physiological responses to drowsiness, highlighting the importance of personalization strategies in practical deployments.

The Support Vector Machine implementation with radial basis function kernel achieved a **mean accuracy of 77.1%**, with performance ranging from 70.1% to 93.9% across individual files.
While demonstrating competent classification capability, the SVM approach consistently underperformed relative to the Random Forest method across all evaluation metrics.
The 11-percentage-point performance gap between algorithms provides clear evidence for the superiority of ensemble methods in this application domain.

Both algorithms demonstrated the ability to maintain **class-wise F_1-scores above 70%**

across all arousal states, indicating balanced performance that avoids bias toward particular alertness levels.

4.1.2 Detailed Performance Metrics

The comprehensive evaluation framework employed multiple metrics to capture different aspects of classification performance, providing detailed insights into algorithm behavior across all arousal states.
Table 4.1 presents the complete performance metrics for both Random Forest and Support Vector Machine approaches, including per-class precision, recall, and F_1-scores that reveal classification characteristics for individual arousal levels.

Metric	**Class 0**	**Class 1**	**Class 2**	**Class 3**	**Overall**
Random Forest					
Precision	0.91	0.87	0.85	0.89	0.88
Recall	0.89	0.85	0.88	0.91	0.88
F_1-Score	**0.90**	**0.86**	**0.86**	**0.90**	**0.88**
Support Vector Machine					
Precision	0.82	0.75	0.73	0.78	0.77
Recall	0.79	0.77	0.75	0.81	0.78
F_1-Score	0.80	0.76	0.74	0.79	0.77

Table 4.1: Comprehensive Performance Metrics for Random Forest and Support Vector Machine

The Random Forest algorithm demonstrates superior performance across all arousal classes, with particularly strong results for the extreme arousal states (Class 0 representing high alertness and Class 3 representing pronounced drowsiness).
The balanced performance across all classes indicates that the ensemble approach effectively captures the physiological patterns associated with different arousal levels without exhibiting systematic bias toward particular states.

4.2 Computational Performance Analysis

The evaluation of computational performance characteristics addresses critical requirements for real-time deployment in embedded automotive systems.
Table 4.2 presents comprehensive timing and resource usage measurements for both algorithms across training and inference phases, providing essential information for practical implementation decisions.

Algorithm	**Training Time (s)**	**Inference Time (ms)**	**Memory Usage (MB)**	**Model Size (MB)**
Random Forest	127.3 ± 12.4	2.8 ± 0.3	45.2 ± 3.1	18.7
Support Vector Machine	892.7 ± 89.3	5.4 ± 0.8	67.8 ± 5.2	24.3

Table 4.2: Computational Performance Metrics

Training time analysis reveals substantial differences between algorithms, with Random Forest requiring approximately seven times less computation time than Support Vector Machine approaches.
The Random Forest training time of 127.3 seconds for the complete dataset represents acceptable duration for offline model development, while the SVM training time of 892.7 seconds may constrain practical model updating or personalization procedures.

Inference time measurements demonstrate that both algorithms meet real-time processing requirements for drowsiness detection applications.
Random Forest inference averages 2.8 milliseconds per classification, easily supporting continuous monitoring with sub-second update intervals.
SVM inference time of 5.4 milliseconds, while nearly twice that of Random Forest, remains within acceptable bounds for real-time operation.

Memory usage analysis indicates moderate resource requirements for both algorithms, with Random Forest consuming 45.2 MB and SVM requiring 67.8 MB during operation. These memory footprints are compatible with modern embedded automotive systems while remaining substantially below typical memory constraints for safety-critical applications.

Model size measurements reveal compact representations suitable for embedded deployment.
Random Forest models require 18.7 MB storage, while SVM models consume 24.3 MB.

4.3 Discussion

4.3.1 Performance Interpretation and Algorithm Comparison

The substantial performance advantage of Random Forest over Support Vector Machine approaches reflects fundamental differences in how these algorithms handle the characteristics inherent in physiological data.
Random Forest's ensemble architecture provides natural robustness to the noise, outliers, and individual variations that are inevitable in wearable sensor measurements.
The bootstrap aggregation and random feature selection mechanisms inherent in Random Forest methods create multiple decision pathways that can accommodate the complex, non-linear relationships between physiological features and arousal states [67, 9].

Support Vector Machine performance, while competent, appears constrained by the assumption of optimal decision boundaries that may not align with the natural structure of physiological arousal data.
Even with radial basis function kernels designed to capture non-linear relationships, the SVM approach demonstrates systematic limitations in distinguishing intermediate arousal states.
This limitation may reflect the inherent complexity of physiological patterns that exceed the representational capacity of kernel-based decision boundaries [68, 29].

The performance levels achieved by both algorithms compare favorably with existing literature in physiological drowsiness detection.

Chapter 5

Conclusion

5.1 Research Overview and Key Achievements

This thesis investigated the fundamental question of whether four discrete arousal levels can be discriminated from smartwatch physiological signals with at least 90% accuracy under conditions that approximate real driving scenarios.
Through the development and evaluation of a comprehensive machine learning framework incorporating a novel circular buffer architecture, this research has demonstrated the practical feasibility of using consumer-grade wearable devices for real-time driver drowsiness detection in automotive safety applications.

The investigation addressed critical limitations in existing drowsiness detection methodologies by developing a physiological monitoring approach that overcomes the constraints of traditional vehicle-based and behavioral systems.
The research employed a substantial dataset of **169,466 multivariate samples** collected from smartwatch sensors, representing one of the largest synchronized physiological and arousal datasets available for drowsiness detection research.
This scale enabled robust statistical validation and comprehensive evaluation of machine learning algorithms under realistic conditions.

The core contribution of this work lies in bridging the gap between laboratory research and practical implementation through the development of memory-efficient processing architectures suitable for embedded automotive deployment.
The circular buffer implementation enables continuous real-time processing without extensive memory allocation, addressing a critical constraint that has historically limited the practical deployment of sophisticated physiological monitoring systems in resource-constrained automotive environments.

5.2 Contributions and Significance

This research makes several significant contributions to the field of physiological-based drowsiness detection:

Technical Contributions:

1. **Novel Architecture Design:** Introduction of a memory-light circular buffer architecture that enables real-time physiological signal processing on embedded hardware without batch preprocessing requirements.
2. **Large-Scale Validation:** Comprehensive evaluation using a sizable dataset of 169,466 samples, providing robust statistical validation of the proposed approach across diverse conditions and individuals.
3. **Comparative Analysis:** Systematic comparison of Random Forest and Support Vector Machine approaches for physiological arousal classification, providing insights into optimal algorithmic choices for this application domain.
4. **Practical Implementation:** Development of a complete pipeline from raw sensor data to classification output, demonstrating feasibility for real-world deployment in vehicle environments.

Scientific Contributions:

1. **Methodology Advancement:** Demonstration that consumer-grade wearable devices can approach the reliability threshold required for safety-critical drowsiness detection applications.
2. **Performance Benchmarking:** Establishment of performance baselines for four-class arousal discrimination using wrist-worn physiological sensors, achieving mean accuracy of 88% with peak performance of 99%.
3. **Real-Time Processing:** Validation that sophisticated machine learning pipelines can operate within the computational and memory constraints of embedded automotive systems.

Practical Significance:
The research demonstrates that low-cost wearable devices combined with lightweight machine learning pipelines can approach reliability thresholds required for in-vehicle deployment. Moreover, it can be deployed not only from car manufactures but the modularization of this approach allows other companies to develop such integrated systems or DIY solutions.

By enabling early detection of drowsiness transitions within seconds, the proposed system can be integrated into driver assistance stacks, fleet safety dashboards, or consumer smartwatch applications, thereby reducing fatigue-related crash risk and associated public health costs.

The work addresses a significant gap between research on laboratory-based drowsiness detection and real-world deployment needs, providing a pathway for physiological monitoring to be widely used in transportation safety applications.

5.3 Current Limitations and Research Gaps

Despite significant advances in drowsiness detection research over the past decades, several fundamental limitations and research gaps continue to constrain the development and deployment of reliable, practical systems.
These limitations span technical, methodological, and practical domains, creating barriers to the widespread adoption of physiological monitoring approaches for driver safety applications [20, 23].
Understanding these limitations is essential for guiding future research directions and establishing realistic expectations for current technology capabilities.

Generalization across diverse populations represents one of the most significant challenges facing current drowsiness detection approaches.
Most published studies are limited by small sample sizes, narrow demographic ranges, or specific population characteristics that may not reflect the broader driving population [9].
Age-related changes in autonomic nervous system function, sex differences in physiological responses, cultural variations in sleep patterns, and individual differences in physiological baselines all contribute to the challenge of developing universally applicable detection algorithms.

The majority of existing research has been carried out in controlled laboratory environments or driving simulators that may not accurately represent the complexity and variability of real world driving situations.
Laboratory studies typically employ standardized protocols, controlled environmental conditions, and artificial drowsiness induction methods that may not capture the natural progression of fatigue during actual driving.
The transition from laboratory validation to real-world deployment often reveals performance degradation due to factors not present in controlled settings.

Ground truth establishment for drowsiness assessment remains a fundamental challenge that affects the validity of all detection system evaluations [9].
Current approaches rely on subjective self-reporting scales, expert observation, or indirect measures such as reaction time testing, each with inherent limitations and potential biases.
The lack of objective, universally accepted criteria for defining and measuring drowsiness states creates difficulties in comparing different detection approaches and establishing performance benchmarks.

5.4 Future Research Directions

The findings and limitations of this research suggest several critical directions for future investigation that could address current constraints and advance the field toward more robust and widely applicable drowsiness detection systems.

Semi-Supervised Learning for Annotation Efficiency: The development of semi-supervised learning approaches represents a high-priority direction for reducing the substantial annotation requirements that currently constrain personalized drowsiness detection systems.
By leveraging unlabeled physiological data to augment limited supervised training examples, semi-supervised methods could enable effective model adaptation with minimal expert annotation effort.
Active learning strategies could further optimize annotation efficiency by intelligently selecting the most informative samples for labeling, potentially reducing annotation requirements by an order of magnitude while maintaining classification performance.

Driver Adaptation and Personalization Algorithms: Advanced personalization algorithms should be prioritized to address the substantial individual differences observed in physiological responses to drowsiness.
Adaptive learning approaches that continuously refine detection parameters based on accumulated usage data could improve classification accuracy while maintaining ease of use.
Transfer learning techniques could enable rapid adaptation to new individuals by leveraging patterns learned from large population datasets while customizing decision boundaries to individual physiological characteristics and driving patterns.

Vehicle CAN Data Integration and Multi-Modal Fusion: Integration with vehicle Controller Area Network (CAN) data and other automotive sensors represents a significant opportunity for enhancing drowsiness detection through multi-modal fusion approaches.
Vehicle speed, steering patterns, lane position, brake pressure, and environmental sensors could provide contextual information that improves interpretation of physiological signals.
Advanced sensor fusion algorithms could combine physiological monitoring with existing driver assistance technologies to create more comprehensive and robust driver state assessment systems.

Comprehensive Field Trials and Real-World Validation: Field trials conducted in realistic driving environments with diverse driver populations are essential for validating laboratory findings and identifying practical deployment challenges.
Naturalistic driving studies incorporating extended monitoring periods, various weather conditions, different vehicle types, and diverse traffic scenarios would provide crucial insights into real-world performance characteristics.
Longitudinal studies tracking individual drivers over weeks or months could reveal adaptation effects, seasonal variations, and long-term system reliability patterns.

Advanced Machine Learning Architectures: Investigation of advanced machine learning approaches, including deep learning architectures and attention mechanisms, could potentially improve classification performance beyond traditional ensemble methods.
Convolutional neural networks designed for time-series physiological data could automatically learn relevant temporal patterns without requiring manual feature engineering.
Recurrent neural networks with long short-term memory units could capture longer-term dependencies that might enhance drowsiness prediction accuracy and enable detection of gradual arousal state transitions.

Multi-Physiological Signal Integration: Expansion beyond heart rate and heart rate variability to incorporate additional physiological signals could enhance detection capabilities through broader autonomic nervous system monitoring.
Electrodermal activity, skin temperature, pupillometry, and respiratory pattern analysis represent potential additional data sources that could improve discrimination of subtle arousal changes.
Advanced sensor technologies enabling non-invasive measurement of multiple physiological parameters could provide richer feature spaces for machine learning algorithms.

Privacy-Preserving Distributed Learning: Federated learning approaches could enable collaborative model development across multiple driver populations and vehicle fleets while preserving privacy and enabling continuous improvement of detection algorithms.
Distributed learning frameworks could aggregate insights from thousands of drivers without requiring centralized data storage or compromising individual privacy.
Differential privacy techniques could provide formal guarantees about information protection while enabling population-level learning and algorithm improvement.

Bibliography

[1] NHTSA, "Overview of Motor Vehicle Traffic Crashes in 2022," 2024. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813560

[2] iii.org, "Facts + Statistics: Drowsy driving," 2022. [Online]. Available: https://www.iii.org/fact-statistic/facts-statistics-drowsy-driving

[3] WHO, "ROAD TRAFFIC INJURIES:THE FACT," 2018. [Online]. Available: https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/advocacy-materials

[4] HappyHealth, "ParasympatheticSympathetic Nervous System," 2022. [Online]. Available: https://happyhealthyyou.com/blogs/articles/parasympathetic-sympathetic-nervous-system

[5] Wikipedia, "Circadian rhythm," 2023. [Online]. Available: https://en.wikipedia.org/wiki/Circadian_rhythm

[6] World Health Organization, "Global status report on road safety 2018," 2018. [Online]. Available: https://www.who.int/publications/i/item/9789241565684

[7] National transportation safety board, "Multivehicle Work Zone Crash on Interstate 95 Cranbury," 2014. [Online]. Available: https://www.ntsb.gov/investigations/AccidentReports/Reports/HAR1502.pdf

[8] NHTSA, "National Highway Traffic Safety Administration," 2023. [Online]. Available: https://www.nhtsa.gov/

[9] L. Pugliese, M. Violante, and R. Groppo, "Real-time sleep prediction algorithm using commercial off the shelf wearable devices," in *2023 IEEE Smart World Congress (SWC)*. IEEE, 2023, pp. 634–638.

[10] Joanna Lowrie 1, Helen Brownlow 2, "The impact of sleep deprivation and alcohol on driving: a comparative study," 2020. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7310070/

[11] Ingrid Koopmans 1,2,*, Robert-Jan Doll 1, Hein van der Wall 1, Marieke de Kam 1, Geert Jan Groeneveld 1,2, Adam Cohen 1,2, Rob Zuiker 1,2, "Fit for purpose of on-the-road driving and simulated driving: A randomised

crossover study using the effect of sleep deprivation," 2023. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC9894419/

[12] Associated Press and Kieran Corcoran, "German Autobahn bus crash and fire," 2017. [Online]. Available: https://www.businessinsider.com/ap-german-police-say-31-injured-when-bus-burns-after-crash-2017-7

[13] Sujana Reddy; Vamsi Reddy; Sandeep Sharma, "Physiology, Circadian Rhythm," 2023. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK519507/

[14] Lee Di Milia 1,*, Naomi L Rogers 2, Torbjörn Åkerstedt 3, "Sleepiness, Long Distance Commuting and Night Work as Predictors of Driving Performance," 2012. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC3448712/

[15] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," *IEEE transactions on intelligent transportation systems*, vol. 12, no. 2, pp. 596–614, 2010.

[16] A. Koesdwiady, R. Soua, F. Karray, and M. S. Kamel, "Recent trends in driver safety monitoring systems: State of the art and challenges," *IEEE transactions on vehicular technology*, vol. 66, no. 6, pp. 4550–4563, 2016.

[17] Z. Shinar, S. Akselrod, Y. Dagan, and A. Baharav, "Autonomic changes during wake–sleep transition: A heart rate variability based approach," *Autonomic Neuroscience*, vol. 130, no. 1-2, pp. 17–27, 2006.

[18] A. Persson, H. Jonasson, I. Fredriksson, U. Wiklund, and C. Ahlström, "Heart rate variability for classification of alert versus sleep deprived drivers in real road driving conditions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 6, pp. 3316–3325, 2020.

[19] L.-C. Yu, L.-H. Lee, S. Hao, J. Wang, Y. He, J. Hu, K. R. Lai, and X. Zhang, "Building chinese affective resources in valence-arousal dimensions," in *Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: Human language technologies*, 2016, pp. 540–545.

[20] L. Pugliese, M. Violante, and S. Groppo, "A novel algorithm for detecting the drowsiness onset in real-time," *IEEE Access*, vol. 10, pp. 42 601–42 606, 2022.

[21] Ebrahim, Parisa, "Driver drowsiness monitoring using eye movement features derived from electrooculography," 2016.

[22] S. SHOFIAH, I. M. Suartika, M. I. N. Hakim, F. Humami, D. W. Hidayat, and L. Asmoro, "Advances in driver monitoring: A review of liveness detection techniques," *Jurnal Penelitian Sekolah Tinggi Transportasi Darat*, vol. 15, no. 2, pp. 56–69, 2024.

[23] A. C. Marceddu, L. Pugliese, J. Sini, G. R. Espinosa, M. Amel Solouki, P. Chiavassa, E. Giusto, B. Montrucchio, M. Violante, and F. De Pace, "A novel redundant validation iot system for affective learning based on facial expressions and biological signals," *Sensors*, vol. 22, no. 7, p. 2773, 2022.

[24] Joseph H. Arguinchona; Prasanna Tadi., "Neuroanatomy, Reticular Activating System," 2023. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK549835/

[25] E. F. Wijdicks, "The ascending reticular activating system," *Neurocritical care*, vol. 31, pp. 419–422, 2019.

[26] S. H. Jang, S. H. Kim, and H. Do Lee, "Impaired consciousness caused by injury of the lower ascending reticular activating system: evaluation by diffusion tensor tractography," *Neural Regeneration Research*, vol. 11, no. 2, p. 352, 2016.

[27] S. H. Jang and H. Do Lee, "Recovery of an injured ascending reticular activating system with recovery from a minimally conscious state to normal consciousness in a stroke patient: a diffusion tensor tractography study," *Neural regeneration research*, vol. 15, no. 9, pp. 1767–1768, 2020.

[28] Wikipedia, "YarkesDodsonLaw," 2025. [Online]. Available: https://en.wikipedia.org/wiki/Yerkes%E2%80%93Dodson_law

[29] G. Li and W.-Y. Chung, "Detection of driver drowsiness using wavelet analysis of heart rate variability and a support vector machine classifier," *Sensors*, vol. 13, no. 12, pp. 16 494–16 511, 2013.

[30] C. Alameda, C. Avancini, D. Sanabria, T. A. Bekinschtein, A. Canales-Johnson, and L. F. Ciria, "Staying in control: Characterizing the mechanisms underlying cognitive control in high and low arousal states," *British Journal of Psychology*, vol. 115, no. 4, pp. 665–682, 2024.

[31] J. Sini, L. Pugliese, S. Groppo, M. Guagnano, and M. Violante, "Towards in-cabin monitoring: A preliminary study on sensors data collection and analysis," *arXiv preprint arXiv:2309.11890*, 2023.

[32] N. Karim, J. A. Hasan, and S. S. Ali, "Heart rate variability-a review," *Journal of Basic, Applied Sciences*, vol. 7, no. 1, 2011.

[33] B. Xhyheri, O. Manfrini, M. Mazzolini, C. Pizzi, and R. Bugiardini, "Heart rate variability today," *Progress in cardiovascular diseases*, vol. 55, no. 3, pp. 321–331, 2012.

[34] BNO Team, "Autonomic Nervous System," 2023. [Online]. Available: https://biologynotesonline.com/autonomic-nervous-system-definition-structure-functions/

[35] M. Sinski, J. Lewandowski, P. Abramczyk, K. Narkiewicz, and Z. Gaciong, "Why study sympathetic nervous system," *J Physiol Pharmacol*, vol. 57, no. Suppl 11, pp. 79–92, 2006.

[36] J. Tindle and P. Tadi, "Neuroanatomy, parasympathetic nervous system," in *StatPearls [Internet]*. StatPearls Publishing, 2022.

[37] H. ChuDuc, K. NguyenPhan, and D. NguyenViet, "A review of heart rate variability and its applications," *APCBEE procedia*, vol. 7, pp. 80–85, 2013.

[38] C. Collet, E. Vernet-Maury, G. Delhomme, and A. Dittmar, "Autonomic nervous system response patterns specificity to basic emotions," *Journal of the autonomic nervous system*, vol. 62, no. 1-2, pp. 45–57, 1997.

[39] J. Lin, "Wearable emotion recognition technology based on heart rate variability and eeg rhythm."

[40] J. Hachenberger, Y.-M. Li, M. Siniatchkin, K. Hermenau, S. Ludyga, and S. Lemola, "Heart rate variability's association with positive and negative affect in daily life: An experience sampling study with continuous daytime electrocardiography over seven days," *Sensors*, vol. 23, no. 2, p. 966, 2023.

[41] L. Krempel, J. Stricker, and A. Martin, "Heart rate variability, autonomic reactivity, and emotion regulation during sadness induction in somatic symptom disorder," *International Journal of Behavioral Medicine*, pp. 1–11, 2023.

[42] C. Feng, N. Jadram, Y. Nakagawa, and M. Sugaya, "Emotion estimation using single-channel eeg and heart rate variability for industrial applications," in *2024 12th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*. IEEE, 2024, pp. 195–197.

[43] D. Meng, M. Yang, L. Hu, T. Liu, H. Zhang, X. Sun, X. Wang, Y. Chen, Y. Jin, and R. Liu, "Rifaximin protects against circadian rhythm disruption–induced cognitive impairment through preventing gut barrier damage and neuroinflammation," *Journal of neurochemistry*, vol. 163, no. 5, pp. 406–418, 2022.

[44] L. Huang, W. Zhu, N. Li, B. Zhang, W. Dai, S. Li, and H. Xu, "Functions and mechanisms of adenosine and its receptors in sleep regulation," *Sleep Medicine*, vol. 115, pp. 210–217, 2024.

[45] Z. Li, S. E. Li, R. Li, B. Cheng, and J. Shi, "Online detection of driver fatigue using steering wheel angles for real driving conditions," *Sensors*, vol. 17, no. 3, p. 495, 2017.

[46] HappyHealth, "Parasympathetic, Sympathetic Nervous System," 2022. [Online]. Available: https://road-safety.transport.ec.europa.eu/european-road-safety-observatory/statistics-and-analysis-archive/fatigue/vehicle-detection-and-warning-devices_en

[47] ——, "Parasympathetic, Sympathetic Nervous System," 2022. [Online]. Available: https://tc.canada.ca/en/road-transportation/driver-assistance-technologies/other-driver-assistance-systems/driver-monitoring

[48] M. Rimini-Doering, T. Altmueller, U. Ladstaetter, and M. Rossmeier, "Effects of lane departure warning on drowsy drivers' performance and state in a simulator," in *Driving Assessment Conference*, vol. 3, no. 2005. University of Iowa, 2005.

[49] P. M. Forsman, B. J. Vila, R. A. Short, C. G. Mott, and H. P. Van Dongen, "Efficient driver drowsiness detection at moderate levels of drowsiness," *Accident Analysis, Prevention*, vol. 50, pp. 341–350, 2013.

[50] C. He, P. Xu, X. Pei, Q. Wang, Y. Yue, and C. Han, "Fatigue at the wheel: A non-visual approach to truck driver fatigue detection by multi-feature fusion," *Accident Analysis & Prevention*, vol. 199, p. 107511, 2024.

[51] M. Guo, S. Li, L. Wang, M. Chai, F. Chen, and Y. Wei, "Research on the relationship between reaction ability and mental state for online assessment of driving fatigue," *International journal of environmental research and public health*, vol. 13, no. 12, p. 1174, 2016.

[52] M. Bhargav, "Advanced driver assistance systems for driver health and fatigue monitoring using camera, biometric sensors, telematics and machine learning," SAE Technical Paper, Tech. Rep., 2025.

[53] G. Yang, C. Ridgeway, A. Miller, and A. Sarkar, "Comprehensive assessment of artificial intelligence tools for driver monitoring and analyzing safety critical events in vehicles," *Sensors*, vol. 24, no. 8, p. 2478, 2024.

[54] J. Kranjec, S. Beguš, G. Geršak, and J. Drnovšek, "Non-contact heart rate and heart rate variability measurements: A review," *Biomedical signal processing and control*, vol. 13, pp. 102–112, 2014.

[55] S. Cao, P. Feng, W. Kang, Z. Chen, and B. Wang, "Optimized driver fatigue detection method using multimodal neural networks," *Scientific Reports*, vol. 15, no. 1, p. 12240, 2025.

[56] J. E. Sierra, A. S. Guerrero Hernández, and J. L. López Prado, "Design of a monitoring system for multimodal transport using the internet of things (iot)." *Webology*, vol. 19, no. 5, 2022.

[57] C. M. van Ravenswaaij-Arts, L. A. Kollee, J. C. Hopman, G. B. Stoelinga, and H. P. van Geijn, "Heart rate variability," *Annals of internal medicine*, vol. 118, no. 6, pp. 436–447, 1993.

[58] R. McCraty and F. Shaffer, "Heart rate variability: new perspectives on physiological mechanisms, assessment of self-regulatory capacity, and health risk," *Global advances in health and medicine*, vol. 4, no. 1, pp. 46–61, 2015.

[59] F. Shaffer and J. P. Ginsberg, "An overview of heart rate variability metrics and norms," *Frontiers in public health*, vol. 5, p. 258, 2017.

[60] ——, "An overview of heart rate variability metrics and norms," *Frontiers in public health*, vol. 5, p. 258, 2017.

[61] M. P. Tarvainen, J.-P. Niskanen, J. A. Lipponen, P. O. Ranta-Aho, and P. A. Karjalainen, "Kubios hrv–heart rate variability analysis software," *Computer methods and programs in biomedicine*, vol. 113, no. 1, pp. 210–220, 2014.

[62] W. Chuangchai, W. Pothisiri, and A. Wonghempoom, "Measuring effects of height on the autonomic nervous system in middle-aged adolescents using the very low frequency band of heart rate variability," *Ergonomics*, vol. 66, no. 5, pp. 569–579, 2023.

[63] M. Souabni, M. J. Souabni, S. Hidouri, A. Ammar, M. Younes, O. Hammouda, and T. Driss, "Napping and heart rate variability in elite athletes," *Biology of Sport*, vol. 41, no. 3, pp. 213–221, 2024.

[64] Y. Zhong, Y. Bai, B. Yang, K. Ju, K. Shin, M. Lee, K.-M. Jan, and K. H. Chon, "Autonomic nervous nonlinear interactions lead to frequency modulation between low-and high-frequency bands of the heart rate variability spectrum," *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, vol. 293, no. 5, pp. R1961–R1968, 2007.

[65] S. Sammito and I. Böckelmann, "Factors influencing heart rate variability," in *International Cardiovascular Forum Journal*, vol. 6, 2016.

[66] H. Tsuji, F. J. Venditti Jr, E. S. Manders, J. C. Evans, M. G. Larson, C. L. Feldman, and D. Levy, "Determinants of heart rate variability," *Journal of the American College of Cardiology*, vol. 28, no. 6, pp. 1539–1546, 1996.

[67] Wikipedia, "Random Forest," 2025. [Online]. Available: https://en.wikipedia.org/wiki/Random_forest

[68] ——, "Support Vector Machine," 2025. [Online]. Available: https://en.wikipedia.org/wiki/Support_vector_machine

[69] Y. Sun, C. Wu, H. Zhang, W. Chu, Y. Xiao, and Y. Zhang, "Effects of individual differences on measurements' drowsiness-detection performance," *Promet-Traffic&Transportation*, vol. 33, no. 4, pp. 565–578, 2021.

[70] Wikipedia, "Domain Shift and Adaptation." [Online]. Available: https://en.wikipedia.org/wiki/Domain_adaptation

[71] A. C. Marceddu, L. Pugliese, J. Sini, G. R. Espinosa, M. Amel Solouki, P. Chiavassa, E. Giusto, B. Montrucchio, M. Violante, and F. De Pace, "A novel redundant validation iot system for affective learning based on facial expressions and biological signals," *Sensors*, vol. 22, no. 7, p. 2773, 2022.

[72] NHTSA, "Drowsy Driving Death in 2023," 2023. [Online]. Available: https://www.nhtsa.gov/risky-driving/drowsy-driving

[73] EU, "Transport," 2018. [Online]. Available: https://eur-lex.europa.eu/summary/chapter/32.html

[74] USA, "Transport," 2018. [Online]. Available: https://www.transportation.gov/

[75] Wikipedia, "Arousal," 2025. [Online]. Available: https://it.wikipedia.org/wiki/Arousal