MINISTRY OF EDUCATION AND RESEARCH
NATIONAL UNIVERSITY OF SCIENCE AND TECHNOLOGY
BUCHAREST POLYTECHNIC

Doctoral School of Electronics, Telecommunications
and Information Technology

Ph.D. THESIS
SUMMARY

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CONTRIBUTIONS TO DRIVER DROWSINESS DETECTION: A MULTIMODAL FRAMEWORK INTEGRATING EEG, IMAGE PROCESSING, AND MACHINE LEARNING

CONTRIBUȚII LA DETECTAREA STĂRII DE OBOSEALĂ A ȘOFERILOR: UN CADRU MULTIMODAL INTEGRAND EEG, PRELUCRARE DE IMAGINI, ȘI ÎNVĂȚARE AUTOMATĂ

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BUCHAREST 2025

Content

Chapter 1 Introduction

Accidents are unpredictable events that can result in serious physical and emotional harm. While most drivers do not intend to cause accidents, human error remains the leading cause. Contributing factors include distraction, alcohol use, speeding, ignoring traffic signals, and drowsiness [1]. Driver fatigue, in particular, is a major cause of road accidents worldwide, prompting extensive research into detection and alert systems [2, 3]. For instance, the study in [4] employs a hybrid approach using EEG and ECG signals from the DROZY database to accurately assess drowsiness levels.

Driving behavior plays a crucial role in road safety and environmental impact. Globally, road accidents are the 19th leading cause of death [5]. To address this, Intelligent Transportation Systems (ITS) have been developed to monitor drivers and reduce incidents [6]. Recently, deep learning has been increasingly applied to analyze driving behavior [7], enabling advanced driver support systems that provide personalized feedback and enhance safety by detecting and mitigating risky behaviors.

1.1 Research Problem, Objectives, and Contributions

Driver drowsiness is a significant factor in road accidents globally. Conventional monitoring systems, though beneficial, often fall short in terms of accuracy, real-time responsiveness, and adaptability to varying driving conditions. This thesis proposes a multimodal detection framework that combines physiological (EEG) signals with image-based behavioral cues, utilizing advanced machine learning and deep learning techniques. The goal is to develop a reliable, interpretable, and real-time capable system for effective drowsiness detection.

To achieve this, the research is structured around four key research questions, each aligned with specific experimental chapters and scientific contributions, as outlined in Table 1.1.

Table 1.1 *Main Research Questions and Contributions.*

No.	Research Question (RQ)	Contribution Type
RQ1	How can EEG and video datasets be systematically analyzed and preprocessed to evaluate the performance of various machine learning and deep learning models in driver drowsiness detection?	Dataset Evaluation and Model Benchmarking.
RQ2	How can EEG-based features be optimized using Fast Neighborhood Component Analysis and deep learning to enhance the accuracy and efficiency of driver drowsiness detection?	Feature Optimization and Deep Learning Integration
RQ3	How can a hybrid deep learning architecture based on image processing improve real-time detection of driver drowsiness under real-world conditions?	Vision-Based Deep Learning Enhancement
RQ4	How do the proposed models compare against existing state-of-the-art methods in terms of performance metrics and robustness across benchmark datasets?	Experimental Evaluation and Performance Comparison

1.1.1 Research Objectives

The key objectives of this thesis aligned with the above research questions are:

- To investigate and evaluate existing data modalities (EEG signals and facial video) for the purpose of driver drowsiness detection.
- To explore and compare various traditional machine learning and deep learning approaches to identify suitable modeling strategies for behavioral state classification.
- To design effective learning pipelines tailored to each modality, enhancing feature representation and classification accuracy.
- To develop and validate robust drowsiness detection frameworks using benchmark datasets, ensuring generalizability and performance across different experimental conditions.
- To contribute to the advancement of multimodal driver monitoring systems by providing comparative insights and practical implementations.

1.2 Scopes of the research

- Focus on classifying drowsiness using deep learning.
- Employ several benchmark datasets from previous studies.
- Implement and analyze the proposed model using Python.
- Accuracy is the major performance metric.

1.3 Thesis content

Chapter 1 introduces the study, highlights the significance of drowsiness detection, states the research problem, objectives, and scope, and overviews behavior and challenges.

Chapter 2 reviews attention monitoring and fatigue detection methods, datasets, and AI-based systems using WBANs.

Chapter 3 describes datasets used, evaluates ML models on EEG and video data, explains feature extraction, preprocessing, and performance.

Chapter 4 covers EEG preprocessing, spectral analysis, data labeling, traditional models, and introduces the FNCA-DNN model.

Chapter 5 develops a hybrid model, EFFRES-DrowsyNet, using EfficientNetB0 and ResNet50 on SUST-DDD and YawDD datasets, with landmark detection and EAR/MAR analysis.

Chapter 6 concludes the research, summarizes contributions, dissemination activity, and outlines future work.

Chapter 2 State Of the Art in Driver Drowsiness Detection

Transport services require advanced technologies like Intelligent Transport Systems (ITS) for improved traffic management, enhanced travel information, and safer transport networks. Despite their importance in modern life, current transportation systems face challenges that need development to ensure better service delivery [8].

This chapter presents a systematic literature review, outlining the methodology and search criteria used to identify relevant studies. Fifteen studies met the inclusion criteria after reviewing literature from electronic databases such as IEEE and Science Direct. The chapter also discusses Driver Face Monitoring Systems for assessing drivers' physical and mental conditions through facial image analysis, followed by an overview of symptoms related to distraction and fatigue.

2.1 Related works

Drowsiness is a state of tiredness that can occur during critical activities like driving and may lead to life-threatening consequences [9]. It is primarily caused by fatigue, resulting in reduced attention and delayed reaction time [10]. Al-Gburi et al. [3] highlighted the lack of a clear fatigue definition and proposed methods like eye blink rate and the Karolinska Sleepiness Scale. Sikander and Anwar [11] categorized detection techniques into five groups and emphasized frequency-domain features for EEG-based detection.

2.2 Chapter Conclusions

Chapter 2 delivered a comprehensive review of foundational concepts, methodologies, and technological advancements in driver drowsiness detection. It examined various fatigue definitions and measurement scales, from EEG-based assessments to facial recognition and wireless body area networks, highlighting the multidisciplinary nature of attentiveness monitoring. The systematic review of recent studies and expert systems emphasized the rapid growth of image processing, physiological signal analysis, and AI-driven approaches in addressing driver fatigue. Key trends such as multimodal integration and the shift toward real-time, non-intrusive monitoring were identified. These insights provide a solid theoretical foundation and directly inform the experimental frameworks developed in the subsequent chapters.

Chapter 3 Evaluation of Benchmark Datasets and Learning Models in Driver Drowsiness Detection

3.1 Datasets description

3.1.1 EEG dataset

- The **TRYOUT** dataset [12] includes recordings from three participants under four driving conditions: Rested-Automated, Rested-Manual, Tired-Automated, and Tired-Manual.
- A **40-channel EEG dataset** archived on Figshare [13] provides recordings from twelve subjects under rested and fatigued states using a Neuroscan amplifier system.
- A **resting-state EEG dataset** from OpenNeuro [14] includes data from 71 participants assessed during normal sleep and sleep deprivation.
- The **SEED-VIG dataset** [15] offers synchronized EEG, EOG, and eye-tracking data recorded during simulated driving.

3.1.2 Video Datasets:

- The **SUST-DDD dataset** [16] contains 2,074 real-world driving videos (975 drowsy, 1,099 not drowsy) recorded by 19 drivers in natural settings.

  The **YawDD dataset** [17], [18] consists of 351 annotated in-vehicle video recordings focused on yawning detection.

3.2 Evaluating Machine Learning Models for Driver Drowsiness Detection Using EEG from the TRYOUT Dataset

This section evaluates the performance of traditional machine learning models for driver drowsiness classification using EEG data from the TRYOUT dataset [12], which includes recordings from three drivers under four distinct driving conditions. To manage dataset size and maintain consistency, each subject's data was limited to 120,000 rows, and a merged dataset of 270,000 samples was prepared for training and evaluation.

Preprocessing involved handling missing values using imputation and encoding categorical variables. Four machine learning models, Logistic Regression, Support Vector Machine (SVM), Gradient Boosting, and Random Forest, were implemented and assessed using accuracy, precision, recall, and F1-score. Among these models, Random Forest demonstrated the most consistent and reliable classification performance across all driving scenarios, achieving the highest overall accuracy. These results establish a practical baseline for EEG-based drowsiness detection and support its role as a comparative method in subsequent experiments involving more advanced deep learning approaches [19].

3.3 Preliminary CNN Baseline and Motivation

An initial lightweight CNN was implemented on the SUST-DDD dataset to establish a baseline for video-based drowsiness detection. While the model achieved a training accuracy of 95.66%, it showed signs of overfitting, with validation accuracy peaking at 87.58%. These results highlighted the need for more advanced architectures with better generalization, motivating the use of EfficientNetB0 and ResNet50 in subsequent sections.

3.4 Evaluation of Advanced CNN Architectures on SUST-DDD

To improve video-based drowsiness detection, two advanced convolutional models were evaluated: EfficientNetB0 and ResNet50. Both were adapted for grayscale facial images and trained on the SUST-DDD dataset using standard data augmentation, early stopping, and learning rate scheduling. EfficientNetB0 achieved 96.79% accuracy, 95.91% precision, and 97.75% recall, while ResNet50 achieved 96.42% accuracy, 96.03% precision, and 96.83% recall. These results demonstrate that both models effectively capture visual cues associated with driver fatigue. Their high performance and complementary strengths motivated their integration into a hybrid architecture, EffRes-DrowsyNet, introduced in Chapter 5.

3.5 Chapter Conclusions

This chapter addressed RQ1 by exploring EEG and video-based approaches for driver drowsiness detection using diverse datasets. Key EEG features included alpha and beta bands, while video data provided eye and mouth cues. Random Forest performed best for EEG, and CNNs were effective for video. Preprocessing strategies helped address noise, imbalance, and overfitting. These results form the basis for the hybrid models introduced in the next chapter.

Chapter 4 Driver Drowsiness Detection and Classification: From EEG Data Analysis to The Used Model Performance Evaluation

Drowsiness, a state between wakefulness and sleep, shares EEG patterns with fatigue but is more pronounced with rest [20]. It poses safety risks, especially for those aged 15–29, by impairing cognition and reaction time [21]. Despite low signal-to-noise challenges, EEG is a reliable tool for early fatigue detection. This chapter presents a framework using EEG preprocessing, Welch's spectral analysis, and classification into alert, intermediate, or drowsy states [22].

4.1 Integrated EEG-Based Driver Drowsiness Detection: Data Processing and Model Evaluation

This section outlines an EEG-based driver drowsiness detection framework involving preprocessing, feature extraction, and classification using traditional ML and DNN models. It evaluates model performance in both multiclass and binary settings using benchmark and subject-specific EEG datasets.

EEG Preprocessing and Feature Extraction

EEG signals were segmented and processed using Welch's method to extract alpha (8–13 Hz) and beta (13–30 Hz) band features—common indicators of alertness. Features were normalized and labeled into cognitive states: Alert, Intermediate, and Drowsy, enabling consistent spectral analysis for classifier training.

Multiclass Classification: TRYOUT Dataset

EEG data from the TRYOUT dataset (four driving conditions) were used to evaluate five classifiers: Logistic Regression, Random Forest, SVM, Gradient Boosting, and DNN. After balancing the dataset, Random Forest achieved the highest accuracy (78.57%), followed by Gradient Boosting and Logistic Regression. DNN showed moderate performance, while SVM performed the lowest.

Binary Classification: Subject-Specific EEG Dataset

A 40-channel EEG dataset from twelve healthy subjects was used, labeled as Alert or Drowsy based on alpha/beta ratios and majority voting. Random Forest again led with 94% accuracy, followed by DNN (88%) and Logistic Regression (83%), confirming its effectiveness across datasets. Table 4.1 summarizes the results.

Table 4.1 *The simulation results of Different Models.*

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	78.57% / 94%	78.46% / 94%	78.57% / 94%	77.58% / 94%
Gradient Boosting	77.86%	77.39%	77.86%	77.17%
Logistic Regression	77.14% / 83%	76.78% / 83%	77.14% / 83%	75.96% / 83%
DNN	72.86% / 88%	73.02% / 88%	72.86% / 88%	72.88% / 88%
SVM	71.43%	70.44%	71.43%	67.74%

Note: First value = Multiclass (TRYOUT), Second value = Binary (12-subject EEG).

These findings highlight the strong performance of ensemble models—especially Random Forest—in EEG-based drowsiness classification across diverse datasets. Their generalization capability provides a solid foundation for the advanced FNCA+DNN model introduced in the next section.

4.2 Introducing A Novel FNCA+DNN Model for Enhanced Driver Drowsiness Detection

This section introduces a hybrid model combining Fast Neighborhood Component Analysis (FNCA) with a Deep Neural Network (DNN) to improve EEG-based drowsiness detection. FNCA is applied to reduce feature dimensionality, transforming the feature space to enhance class separability before classification by the DNN. The DNN architecture includes input layers matched to FNCA features, hidden layers with ReLU activations, and a Softmax output for classification (Figure 4.1). Training employed the Adam optimizer with learning rate and batch size tuning.

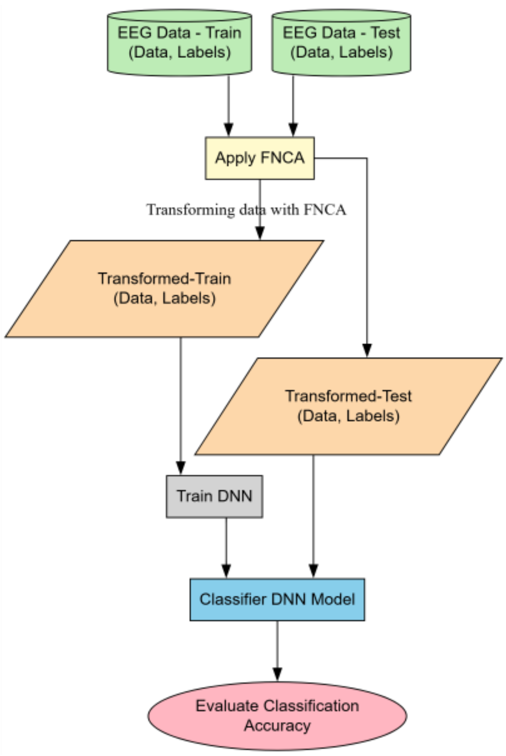


Figure 4.1 *Block diagram for the DNN+FNCA.*

4.2.1 Results and analysis

The FNCA+DNN model showed strong learning behavior during MATLAB simulations. Starting with 33.59% mini-batch and 45.86% validation accuracy, performance improved significantly by epoch 15, reaching 81.25% and 80.88%, respectively. By epoch 30, mini-batch accuracy rose to 86.72% and validation accuracy to 83.67%, with loss dropping from 28.37 to 0.30, accuracy and loss trends stabilized between epochs 15–30, with minimal overfitting, supported by a consistent base learning rate of 0.0010.

Table 4.2 *The simulation results for 4 different experiments.*

Learning Rate	Epochs	Mini-Batch Accuracy	Validation Accuracy
0.0010	30	86.72%	83.67%
0.0010	50	88.28%	83,59%)
0.0010	40	89.84%	82.80%
0.010	30	81.25%	81,43%

In summary, the FNCA-integrated DNN shows strong performance, with increasing accuracy and decreasing loss across training epochs, highlighting the effectiveness of FNCA's feature transformation. Future work may explore tuning the learning rate, testing deeper architectures, or using alternative activation functions to further enhance performance.

4.3 Improved FNCA+DNN Architecture for driver drowsiness detection using EEG signals

Figure 4.2 presents the enhanced FNCA+DNN model for EEG-based driver drowsiness detection. The pipeline includes EEG pre-processing, feature normalization, and FNCA for feature refinement. The DNN architecture features an input layer followed by four fully connected layers (256, 128, 64, 32 neurons) with ReLU activations, Batch Normalization, and Dropout (0.3, 0.2) to improve stability and prevent overfitting. A Softmax output layer classifies states as alert or drowsy. Key EEG channels are visualized via an electrode map. While no ablation studies were performed, the model design follows proven EEG deep learning practices to enhance generalization and robustness [23, 24].

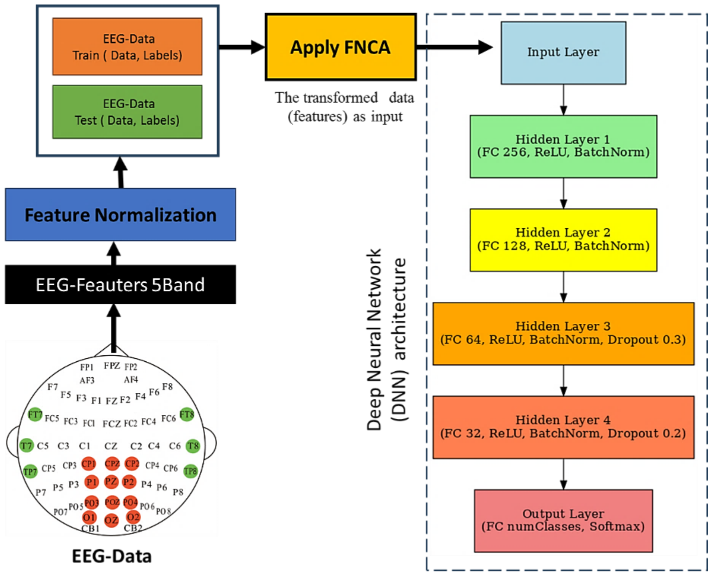


Figure 4.2 *An improved FNCA-DNN model for driver drowsiness detection using EEG signals.*

The improved FNCA+DNN architectur enhances classification accuracy while reducing overfitting. It features fully connected layers (256, 128, 64, 32 neurons) with ReLU activation, batch normalization, and Dropout layers (30% and 20%) for regularization. A Softmax output layer performs binary classification. The model was evaluated using the SEED-VIG dataset [15], developed by the BCMI Laboratory of Shanghai Jiao Tong University, which includes EEG and EOG data from 23 participants during simulated driving using 17 EEG channels (10–20 system, 200 Hz sampling). Eye-tracking glasses provided PERCLOS-based alertness labeling. As shown in Figure 4.3, the FNCA+DNN model achieved an average accuracy of ~90% ± 0.06 across EEG data from 21 subjects, with several exceeding 97% accuracy and a few around 86%, likely due to EEG variability or noise. These results confirm the model's robustness and effectiveness in detecting drowsiness across individuals.

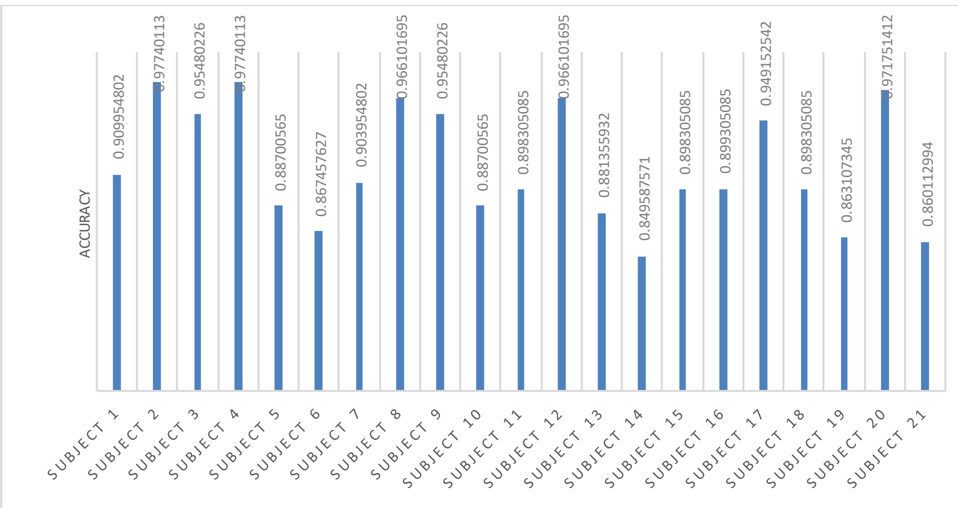


Figure 4.3 *Results of applied proposed model for different subjects.*

4.3.1 Comparison with State-of-the-Art Methods on the SEED-VIG Dataset

Table 4.3 shows that the proposed FNCA+DNN model outperforms recent methods on the SEED-VIG dataset, achieving 94.29% ± 0.0028 accuracy with 12 subjects and 90.83% ± 0.0012 with 21 subjects. Compared to other methods (80–87% accuracy), FNCA+DNN demonstrates superior EEG feature extraction and generalization for driver drowsiness detection.

Table 4.3 *Accuracy comparison on the SEED-VIG dataset for FNCA+DNN and recent methods.*

Reference	Year	Classifier	Accuracy (%)
[25] [26]	2022 2025	TSeption	83.15 ± 0.36
[27] [26]	2022 2025	ConvNext	81.95 ± 0.61
[28] [26]	2023 2025	LMDA	81.06 ± 0.99
[26]	2025	NLMDA-Net	83.71 ± 0.30
[29]	2023	EDJAN Transfer learning	0.76
[30]	2023	CNN+LSTM	85.1 ± 0.5
[30]	2023	ATT+CNN+LSTM	85.6 ± 0.3
[30]	2023	Ghost+LSTM	86.6 ± 0.4
[30]	2023	ATT+Ghost+LSTM	87.3 ± 0.2
[30]	2023	CNN+LST	85.1 ± 0.5
		Proposed Model FNCA+DNN 12 Subjects	0.9429 ± 0.0028
		Proposed Model FNCA+DNN 21 Subjects	0.9083% ± 0.0012

4.4 Chapter Conclusions

The proposed FNCA+DNN model addresses key limitations in earlier approaches by using FNCA for metric learning, creating a more discriminative feature space that enhances class separability before DNN classification. Dropout and batch normalization reduce overfitting, while an integrated attention mechanism allows the model to dynamically prioritize relevant EEG channels and frequency bands. Evaluated on the SEED-VIG dataset, the model achieves state-of-the-art accuracy—94.29% with 12 subjects and 90.389% with 21 subjects—outperforming methods such as TSception, ConvNeXt, LMDA-Net, and CNN+LSTM. These results demonstrate the model's effectiveness and real-time applicability for integration into smart cars and wearable systems. Future work will focus on improving inter-subject generalization, expanding datasets with real-world driving data, exploring embedded hardware implementations, and testing advanced sequence modeling techniques like Mamba and xLSTM to better capture EEG signal patterns over time.

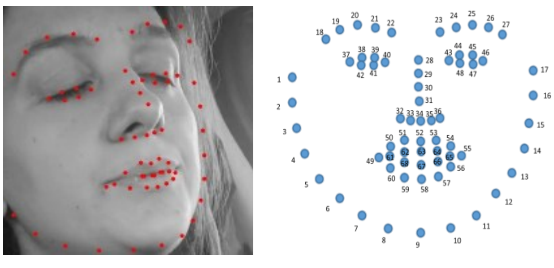
Chapter 5 EFFRES-DROWSYNET: A NOVEL HYBRID MODEL USING EFFICIENTNET-B0 AND RESNET-50 FOR DRIVER DROWSINESS DETECTION

The proposed hybrid model integrates EfficientNetB0 and ResNet50. EfficientNetB0 offers a scalable architecture for varied visual inputs [31], while ResNet50 captures subtle features through residual connections [32].

This chapter provides a detailed analysis of the proposed hybrid model for driver fatigue detection, evaluates its performance on an annotated video dataset across diverse demographics and lighting conditions, and benchmarks it against recent state-of-the-art methods.

5.1 Data Preprocessing, Feature Extraction, and Hybrid Model Implementation

To detect driver drowsiness, facial cues such as eye closure and yawning were analyzed using video frames from the SUST-DDD and YawDD datasets. Dlib's HOG-based face detector and 68-point facial landmark model were utilized for robust identification of key facial features under varying lighting and orientations. These landmarks enabled calculation of the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), which served as primary indicators of fatigue. The positions and order of the 68 facial landmarks used for EAR and MAR calculation are illustrated in Figure 5.1.



(a) (b)

Figure 5.1 *Identification of facial landmarks using Dlib. a. Facial landmarks. b. The position and order of 68 points on the face*

EAR values below a dynamic, video-specific threshold indicated eye closure, while MAR values above a similar adaptive threshold signaled yawning [33, 34]. Each frame underwent a preprocessing pipeline: face detection and cropping, resizing to 224×224 pixels, grayscale conversion, lighting normalization using CLAHE, and pixel scaling to [0,1].

Frames with low EAR and high MAR were labeled as drowsy (Figure 5.2), while those with high EAR and low MAR indicated alertness (Figure 5.3). These labeled frames formed the input for the classification model.

Figure 5.2 *Samples of drowsiness output frames extracted from video dataset.*

Figure 5.3 *Samples of Non-drowsiness output frames extracted from the video dataset.*

A hybrid deep learning model was developed by integrating EfficientNetB0 and ResNet50 architectures to leverage their complementary feature extraction capabilities. Features from both backbones were extracted, pooled, and concatenated, followed by Batch Normalization, a Dropout layer (rate 0.3), and a Dense layer with L2 regularization. The output layer used a sigmoid activation for binary classification (Figure 5.4). The model was compiled with the Adam optimizer and binary cross-entropy loss, and evaluated using accuracy, precision, and recall. Training employed callbacks including EarlyStopping, ReduceLROnPlateau, ModelCheckpoint, and TensorBoard. Data augmentation was applied using ImageDataGenerator, and a two-phase fine-tuning strategy was implemented using TensorFlow and Keras.

Results and Discussion

A novel hybrid deep learning model was developed by integrating two prominent convolutional neural network architectures, EfficientNetB0 and ResNet50. The primary motivation behind this approach was to harness the distinct features and strengths of both architectures to improve the model's ability to generalize and accurately classify images in a binary classification setting. The combination of these models aimed to capture a broad spectrum of features, ranging from basic to complex patterns, thereby enhancing the model's predictive performance on complex datasets.

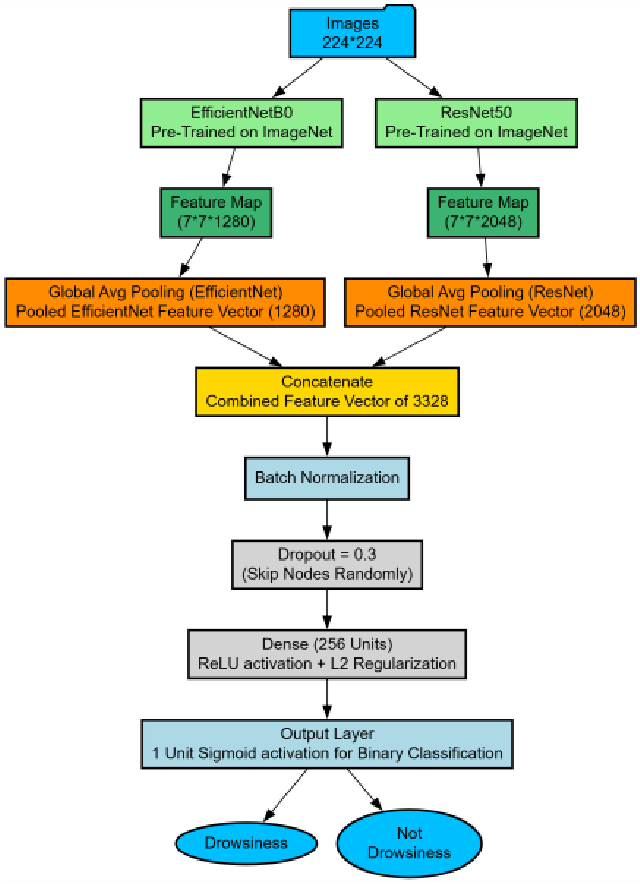


Figure 5.4 *Hybrid EffecianetB0+ResNet50 networks architecture.*

5.2 Performance Evaluation of EFFRES-DrowsyNet Across Various Training Epochs on the SUST-DDD Dataset

This section analyzes the model's performance on the SUST-DDD dataset [16] across different training epochs, with and without early stopping. Key evaluation metrics include Test Accuracy, Precision, Recall, and Loss. The objective is to assess how training duration impacts model effectiveness and to identify the optimal configuration. Table 5.1 summarizes performance across various experimental setups, highlighting the influence of training epochs and stopping criteria on overall results.

Table 5.1 *Performance Metrics Across Different Training Epochs for Distinct Experimental Executions.*

Experiment Number	Epochs	Test Accuracy	Test Precision	Test Recall	Test Loss
1	10	93.67%	96.87%	90.25%	21.03%
2	20	95.42%	96.66%	94.08%	13.22%
3	30	96.96%	97.47%	96.52%	8.47%
4	40 Early stopping at Epoch 25	97.71%	98.07%	97.33%	8.81%
5	50	97.29%	96.40%	98.25%	8.76%

6	60	97.29%	97.25%	97.33%	08.50%
7	70 Early stopping at Epoch 36	97.46%	97.03%	97.92%	8.38%
8	80 Early stopping at Epoch 32	97.33%	98.22%	96.42%	9.01%
9	90	95.92%	94.87%	97.08%	12.55%
10	100 Early stopping at Epoch 22	96.83%	95.69%	98.08%	13.47%

Figure 5.5 Evaluation of a Novel Hybrid Model Performance Across Training Epochs. delineates the impact of varying training epochs on key performance metrics accuracy, precision, recall, and loss across ten distinct experimental setups.

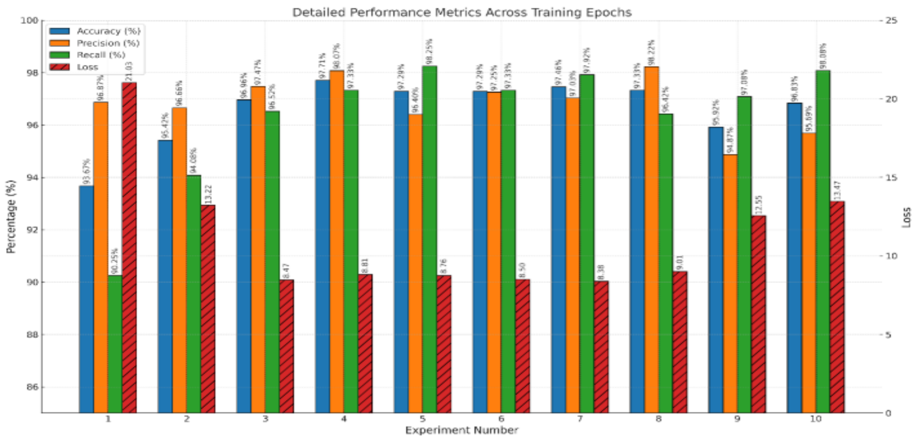


Figure 5.5 *Evaluation of a Novel Hybrid Model Performance Across Training Epochs.*

This bar chart shows model performance across ten experiments with 10–100 training epochs, using test accuracy, precision, recall (primary y-axis), and loss (secondary y-axis). Some runs employed early stopping to prevent overfitting. Annotated bars highlight how training duration affects performance, aiding in identifying optimal training strategies.

5.2.1 Performance Analysis of Model Training (With 40 Epochs and Early Stopping at Epoch 25) on the SUST-DDD Dataset

This section analyses the model's performance during the initial training phase (Epochs 1–25), focusing on early learning dynamics and optimization. Training began with a loss of 4.5076, achieving 75.66% accuracy, 74.68% precision, and 77.63% recall by the end of the first epoch, with validation accuracy at 89.25%. Validation accuracy peaked at 93.12% by epoch 6. The learning rate was reduced from 0.0001 to 0.00001 after epoch 20 to enhance convergence. Training ended at epoch 25 due to no improvement beyond the 93.54% validation threshold. Accuracy, precision, and recall stabilized, indicating optimized performance. Final test results showed 97.71% accuracy, 98.07% precision, 97.33% recall, and 8.81% loss.

5.2.2 Comparing the proposed Hybrid Deep Learning Model with the existing models.

To evaluate the effectiveness of the proposed hybrid model in detecting driver drowsiness, a comparative analysis was conducted against several established models, VGG19+LSTM, VGG16 + LSTM, AlexNet + LSTM, and VGGFaceNet + LSTM, originally applied to the dataset presented in [16]. Each model's performance was assessed based on accuracy, precision, and recall, metrics that are essential for gauging reliability in safety-critical applications. As shown in Table 5.2, the proposed hybrid model consistently outperforms prior models across these metrics, demonstrating its suitability for real-time applications in driver monitoring systems.

Table 5.2 *Comparative Analysis of Driver Drowsiness Detection Models.*

Model	Accuracy (%)	Precision (%)	Recall (%)	Analysis and Comparison with Proposed Hybrid Model
VGG19 + LSTM [16]	90.53	91.74	91.28	Proposed model achieves higher scores across all metrics.
VGG16 + LSTM [16]	89.39	91.81	89.09	Strong precision, but lower accuracy and recall; proposed model outperforms in all aspects.
AlexNet + LSTM [16]	63.91	63.78	97.91	High recall but poor accuracy and precision; proposed model offers more balanced performance.
VGGFaceNet + LSTM [16]	84.94	83.65	94.92	Good recall, moderate accuracy, low precision; proposed model is superior in all metrics.
EffRes-DrowsyNet	97.71	98.07	97.33	Best overall performance; combines EfficientNetB0 and ResNet50 for reliable, real-time detection.

5.3 Performance Evaluation of EFFRES-DrowsyNet Across Various Training Epochs on the YawDD Dataset

his section evaluates the EFFRES-DrowsyNet model using ten experiments (EX1–EX10) on the YawDD dataset [17], with training epochs ranging from 10 to 100. The objective was to assess the effect of training duration on Test Accuracy, Precision, Recall, and Loss. As shown in Table 5.3 and Figure 5.6, model performance improved steadily in EX1–EX4. EX5–EX7, using early stopping, maintained high performance and avoided overfitting, with EX7 (stopped at 38 epochs) achieving the best overall balance. In contrast, EX8–EX10 showed performance plateauing or declining, indicating limited benefit from extended training and a higher risk of overfitting.

Table 5.3 *Performance Metrics Across Different Training Epochs for EFFRES-DrowsyNet on the YawDD Dataset.*

Experiment Number	Epochs	Test Loss	Test Accuracy	Test Precision	Test Recall
EX1	10	1.2149	0.8875	0.9564	0.746
EX2	20	0.3699	0.9039	0.8632	0.896

EX3	30	0.3614	0.925	0.9372	0.866
EX4	40	0.452	0.9039	0.9217	0.824
EX5	50 (Early stopping at 42)	0.4043	0.8906	0.8863	0.826
EX6	60 (Early stopping at 31)	0.4166	0.9102	0.8986	0.868
EX7	70 (Early stopping at 38)	0.2905	0.9273	0.9302	0.88
EX8	80 (Early stopping at 42)	0.3696	0.907	0.9045	0.852
EX9	90 (Early stopping at 38)	0.2543	0.9094	0.9174	0.844
EX10	100 (Early stopping at 37)	0.3671	0.893	0.906	0.81

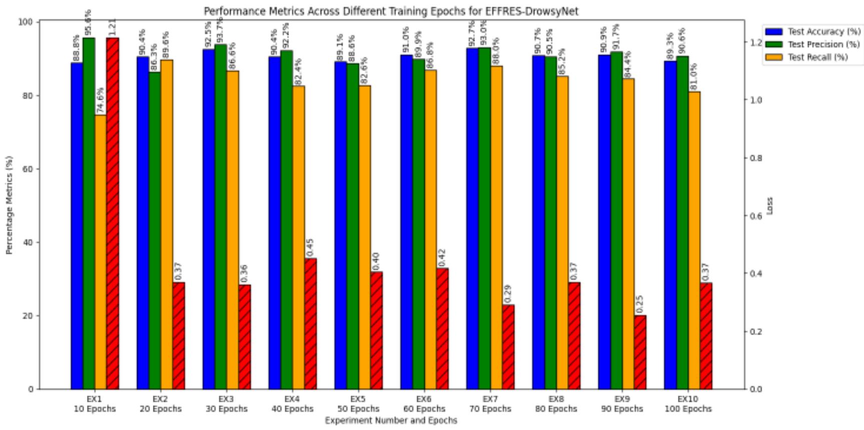


Figure 5.6 *Performance Metrics Across Different Training Epochs for EFFRES-DrowsyNet on the YawDD Dataset.*

5.3.1 Performance Analysis of Model Training (With 70 Epochs and early stopping at Epoch 38) on the YawDD Dataset

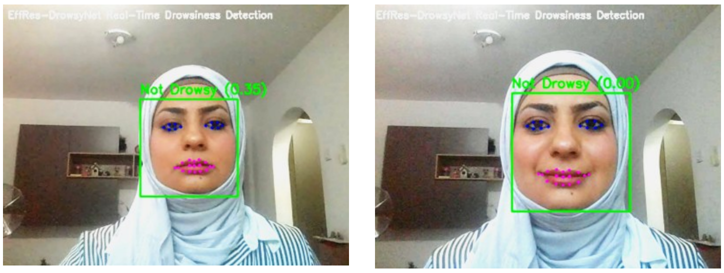
EffRes-DrowsyNet trained with early stopping (EX7) stopped at epoch 38 and achieved optimal performance. Early epochs showed rapid improvement, with validation accuracy peaking at 94.92% between epochs 18–28, while training accuracy reached 97.38%. Despite a learning rate reduction at epoch 33, validation accuracy plateaued. Final losses were 0.0884 (training), 0.2704 (validation), and 0.2905 (test). Test results confirmed robustness with 92.73% accuracy, 93.02% precision, and 88.00% recall.

5.4 Real-Time Drowsiness Detection Using EffRes-DrowsyNet

To validate the practical use of the proposed EffRes-DrowsyNet model, a real-time system was developed using a standard laptop webcam. Built in Python with OpenCV, Dlib, and TensorFlow, it captures live video, detects faces via Dlib's 68-point landmarks, and preprocesses frames to match the model's input format. The trained model (.h5) predicts drowsiness per frame using a 0.5 threshold. Results are displayed with color-coded boxes and facial outlines. Running on an Intel Core i7 laptop (16 GB RAM), the system achieves 10–15 FPS with low latency. **Figure 5.7** and **Figure 5.8** show successful real-time detection of drowsy and alert states.

(a) (b)

Figure 5.7 *Screenshot from the real-time detection system showing a drowsy state. The bounding box is red, and the eyes and mouth are outlined with blue and pink dotted markers, respectively.*



(a) (b)

Figure 5.8 *Screenshot from the real-time detection system showing a non-drowsy state. The bounding box is green, and facial features are consistently tracked.*

While the prototype performs well in most scenarios, its reliability can be affected by ambient lighting variations, facial occlusions, and extreme head movements. These challenges highlight areas for future enhancement, such as incorporating temporal features via recurrent neural networks or optimizing deployment on embedded platforms with inference accelerators.

In conclusion, the real-time implementation of EffRes-DrowsyNet confirms its theoretical soundness, experimental validity, and practical applicability. This real-time capability reinforces its potential as an effective tool for drowsiness detection in intelligent transportation and driver safety systems.

5.5 Chapter Conclusions

This chapter validated the EffRes-DrowsyNet hybrid model, combining EfficientNetB0 and ResNet50 for accurate driver drowsiness detection. Trained under varied conditions, the model achieved 97.71% accuracy, 98.07% precision, and 97.33% recall, confirming its real-world reliability. Optimization techniques like early stopping and adaptive learning rates enhanced performance, with Experiment 4 offering the best metric balance. Outperforming existing models, EffRes-DrowsyNet minimized false positives—crucial for real-time monitoring. Future work will focus on capturing more nuanced behaviors and integrating additional sensory and real-time data for improved responsiveness.

Chapter 6 Conclusions and Future Works

6.1 Research Findings and Contributions Outline

Chapter 2 provided the theoretical and contextual groundwork for the research by delivering a systematic literature review of current driver drowsiness detection methods. This review categorized techniques based on physiological signals (EEG, EOG), visual features (eye closure, yawning), wearable body networks (WBAN), and hybrid approaches. The analysis revealed significant gaps in the state of the art, including inconsistent definitions of fatigue and drowsiness, insufficient real-time systems, and weak cross-subject generalization. These gaps justified the need for a robust, scalable, and multimodal detection framework, guiding the research objectives and experimental methodology.

Main contribution:

- Systematic Literature Review of Drowsiness Detection Methods:

A systematic literature review was conducted to categorize and evaluate existing driver drowsiness detection techniques, highlighting their strengths and limitations.

The outcomes have been published as:

- **Journal: S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, *State of the Art in Drivers' Attention Monitoring – A Systematic Literature Review*, **Karbala International Journal of Modern Science**, **9(1), 2,** 10 January 2023, DOI: https://doi.org/10.33640/2405-609X.3278 [3].

For this work, four research questions were established, through the prism of which I would like to summarize the obtained results and contributions briefly.

RQ1: How can EEG and video datasets be systematically analyzed and preprocessed to evaluate the performance of various machine learning and deep learning models in driver drowsiness detection?

This research question is addressed in Chapter 3 through a systematic analysis of both EEG and video modalities using traditional machine learning and deep learning techniques. The TRYOUT EEG dataset was used to extract alpha and beta band powers, key indicators of drowsiness, via segmentation and Welch's spectral analysis, enabling robust classification under binary and multiclass schemes. In parallel, the SUST-DDD video dataset was processed using Dlib to compute Eye and Mouth Aspect Ratios (EAR and MAR), capturing visual signs of fatigue for CNN-based classification.

Comparative evaluations showed high performance, with Random Forest achieving 99.99% accuracy on EEG data and CNN reaching 87.58% on video data.

Challenges such as class imbalance and overfitting were mitigated through tailored preprocessing, class balancing, and optimization strategies. This dual-modality evaluation lays the groundwork for the hybrid models developed in later chapters.

<u>Main contribution:</u>

- Comparative Evaluation of Models:

  A systematic comparative evaluation of traditional machine learning and deep learning models was conducted using both EEG and video datasets to establish baseline performance levels and uncover the limitations of current driver drowsiness detection approaches. The evaluation results demonstrate high accuracy with Random Forest on EEG and strong CNN performance on video data.

- Investigated Individual Impact of EfficientNet-B0 and ResNet-50:

  We investigated the individual impact of EfficientNet-B0 and ResNet-50 architectures on driver drowsiness detection. By evaluating each model independently, we assessed their effectiveness in learning discriminative visual features. Understanding these complementary roles clarifies why combining both backbones yields the best overall accuracy.

<u>The outcomes have been published as:</u>

- **S.H. Al-Gburi**, K.A. Al-Sammak, K.M.A. Alheeti, G. Suciu, A.G. Abdulqader, *Driver Behaviour Assessment with Different ML Models Using EEG and Physiological Data – A Comparative Study*, in **Proceedings of the 2024 16th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)**, Iași, Romania, 27–28 June 2024, pp. 1–6, **IEEE, DOI: 10.1109/ECAI61503.2024.10607554** [19].
- **S.H. Al-Gburi**, K.A. Al-Sammak, N.A.A. Almosa, G. Suciu, N.A.H. Al-Sammak, *Comparative Analysis of Logistic Regression and SVM Models for Drowsiness Detection in Drivers*, in **Proceedings of the International Conference on Intelligent and Fuzzy Systems (INFUS 2025)**, Istanbul, Turkey, 29–31 July 2025 [35].

RQ2: How can EEG-based features be optimized using Fast Neighborhood Component Analysis and deep learning to enhance the accuracy and efficiency of driver drowsiness detection?

This research question is explored in Chapter 4, where the thesis introduces FNCA-DNN, a novel framework that combines Fast Neighborhood Component Analysis (FNCA) with a Deep Neural Network (DNN) to enhance EEG-based driver drowsiness classification. FNCA is applied as a supervised feature transformation technique, improving class separability while preserving the dimensional integrity of the data. This results in more discriminative and interpretable feature representations, leading to improved training efficiency and classification accuracy.

The model was trained and validated on the SEED-VIG dataset, achieving 94.29% accuracy using data from 12 subjects and 90.83% accuracy using data from 21 subjects. FNCA-DNN was benchmarked against several state-of-the-art models, including TSception, ConvNeXt LMDA-Net, and CNN+LSTM, and consistently outperformed them across both subject-specific and cross-subject evaluation scenarios.

Furthermore, the model demonstrated strong generalization capabilities across individuals, confirming its robustness and suitability for real-world, subject-independent driver drowsiness detection applications.

Main Contributions:

- Performance Analysis of EEG-Based Models for Driver Behaviour Detection:

A comprehensive evaluation of multiple machine learning and deep learning models was conducted to assess their effectiveness in classifying driver states based on EEG signals. This analysis identified key spectral features contributing to the reliable detection of drowsiness and alertness, offering insights into feature relevance and model behavior. The findings have been peer-reviewed and published in [36].

- Development of the FNCA-DNN Model:

A novel Fast Neighbourhood Component Analysis–Deep Neural Network (FNCA-DNN) framework was proposed, combining supervised feature transformation with deep learning for optimized EEG-based classification. The model significantly improves both accuracy and interpretability in driver drowsiness detection tasks. Its architecture, implementation, and experimental validation are detailed in [37].

The outcomes have been published as:

- **S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, K.M.A. Alheeti, N.A.A. Almosa, *Analyzing Different Models for Driver Behaviour Detection Using EEG Data*, in **Proceedings of the 2024 15th International Conference on Communications (COMM)**, Bucharest, Romania, 03–04 October 2024, pp. 1–5, **IEEE, DOI: 10.1109/COMM62355.2024.10741402** [36].
- **S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, A.-M.C. Drăgulinescu, G. Suciu, K.M.A. Alheeti, N.A.M. Alduais, N.A.H. Al-Sammak, *Introducing a Novel Fast Neighbourhood Component Analysis–Deep Neural Network Model for Enhanced Driver Drowsiness Detection* in **Big Data and Cognitive Computing**, **9(5), 126,** 08 May 2025, DOI: 10.3390/bdcc9050126, **ISI Q1 (2025), WOS: 001497786100001** [37].

RQ3: How can a hybrid deep learning architecture based on image processing improve real-time detection of driver drowsiness under real-world conditions?

This question is addressed in Chapter 5 through the introduction of EFFRES-DrowsyNet, a hybrid deep learning model combining EfficientNetB0 and ResNet50 for facial feature extraction and video-based drowsiness detection. The model captures subtle visual cues such as blinking and yawning using preprocessed video frames enhanced by CLAHE and grayscale normalization, with EAR and MAR as key input features.

Evaluated on real-world datasets, the model achieved 97.71% accuracy, 98.07% precision, and 97.33% recall. It demonstrated strong robustness to lighting and head-pose variations and outperformed conventional CNNs. Its lightweight, scalable design supports real-time deployment in embedded driver monitoring systems.

Main Contribution:

- Design of the EFFRES-DrowsyNet Model:

A novel hybrid deep learning architecture, EFFRES-DrowsyNet, was developed by integrating EfficientNetB0 and ResNet50 to enable robust and accurate facial feature extraction from video data. The model demonstrated high detection accuracy and resilience to variations in lighting and head pose, making it suitable for real-world drowsiness detection applications.

The outcomes have been published as:

- **S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, A.-M.C. Drăgulinescu, N.A.M. Alduais, K.M.A. Alheeti, N.A.H. Al-Sammak, N.A.H. *EffRes-DrowsyNet: A Novel Hybrid Deep Learning Model Combining EfficientNetB0 and ResNet50 for Driver Drowsiness Detection* in **Sensors**, **25, 3711,** 13 June 2025, DOI:10.3390/s25123711, **ISI Q2 (2025), WOS:** [38].

RQ4: How do the proposed models compare against existing state-of-the-art methods in terms of performance metrics and robustness across benchmark datasets?

This research question is addressed in Chapters 4 and 5 through comparative analyses of the proposed FNCA-DNN and EFFRES-DrowsyNet models against traditional machine learning and modern deep learning methods across multiple benchmark datasets.

FNCA-DNN outperformed models like Random Forest, Gradient Boosting, TSception, and CNN+LSTM on the SEED-VIG dataset, achieving 94.29% accuracy (12 subjects) and 90.83% (21 subjects), demonstrating strong generalization across subject-specific and cross-subject scenarios.

EFFRES-DrowsyNet showed superior performance on SUST-DDD and YawDD datasets, with 97.71% accuracy, 98.07% precision, and 97.33% recall. It also maintained stable convergence and robustness under variations in lighting and head pose.

These results confirm the reliability, scalability, and real-time applicability of both models for practical driver monitoring systems.

Main Contribution:

- Experimental Validation and Superiority of Proposed Models:

Through extensive comparative experimentation, the proposed FNCA-DNN and EFFRES-DrowsyNet consistently outperformed conventional machine learning and deep learning approaches across multiple benchmark datasets and testing conditions. Their strong performance in accuracy, robustness, and generalization confirms their viability for real-time deployment in driver monitoring systems [37, 38].

Together, these contributions represent a significant advancement in the field of driver drowsiness detection by introducing a multimodal, high-performance, and scalable framework capable of supporting intelligent, adaptive, and real-time driver assistance technologies.

The outcomes have been published as:

- **S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, A.-M.C. Drăgulinescu, G. Suciu, K.M.A. Alheeti, N.A.M. Alduais, N.A.H. Al-Sammak, *Introducing a Novel Fast Neighbourhood Component Analysis–Deep Neural Network Model for Enhanced Driver Drowsiness Detection* in **Big Data and Cognitive Computing**, **9(5), 126,** 08 May 2025, DOI: 10.3390/bdcc9050126, **ISI Q1 (2025), WOS: 001497786100001** [37].

- **S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, A.-M.C. Drăgulinescu, N.A.M. Alduais, K.M.A. Alheeti, N.A.H. Al-Sammak, N.A.H. *EffRes-DrowsyNet: A Novel Hybrid Deep Learning Model Combining EfficientNetB0 and ResNet50 for Driver Drowsiness Detection* in **Sensors**, **25, 3711,** 13 June 2025, DOI:10.3390/s25123711, **ISI Q2 (2025), WOS:** [38].

This thesis presents a scalable, high-performance framework for driver drowsiness detection using EEG and visual data. It introduces two models: FNCA-DNN, combining feature selection with deep learning for EEG analysis, and EFFRES-DrowsyNet, a hybrid CNN leveraging EfficientNetB0 and ResNet50 for visual detection. Both models outperform traditional methods and are validated for real-time deployment, addressing key limitations in existing driver monitoring systems through multimodal, robust, and efficient solutions.

6.2 List of Original Publications

The research presented in this thesis has resulted in the following peer-reviewed publications:

[1] **Journal: S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, A.-M.C. Drăgulinescu, N.A.M. Alduais, K.M.A. Alheeti, N.A.H. Al-Sammak, N.A.H. *EffRes-DrowsyNet: A Novel Hybrid Deep Learning Model Combining EfficientNetB0 and ResNet50 for Driver Drowsiness Detection* in **Sensors**, **25, 3711,** 13 June 2025, DOI:10.3390/s25123711, **ISI Q2 (2025), WOS:001516386400001**

[2] **Journal: S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, A.-M.C. Drăgulinescu, G. Suciu, K.M.A. Alheeti, N.A.M. Alduais, N.A.H. Al-Sammak, *Introducing a Novel Fast Neighbourhood Component Analysis–Deep Neural Network Model for Enhanced Driver Drowsiness Detection* in **Big Data and Cognitive Computing**, **9(5), 126,** 08 May 2025, DOI: 10.3390/bdcc9050126, **ISI Q1 (2025), WOS:001497786100001**.

[3] **Conference: S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, K.M.A. Alheeti, N.A.A. Almosa, *Analyzing Different Models for Driver Behaviour Detection Using EEG Data*, in **Proceedings of the 2024 15th International Conference on Communications (COMM)**, Bucharest, Romania, 03–04 October 2024, pp. 1–5, **IEEE, DOI: 10.1109/COMM62355.2024.10741402.**

[4] **Conference: S.H. Al-Gburi**, K.A. Al-Sammak, K.M.A. Alheeti, G. Suciu, A.G. Abdulqader, *Driver Behaviour Assessment with Different ML Models Using EEG and Physiological Data – A Comparative Study*, in **Proceedings of the 2024 16th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)**, Iași, Romania, 27–28 June 2024, pp. 1–6, **IEEE, DOI: 10.1109/ECAI61503.2024.10607554.**

[5] **Journal: S.H. Al-Gburi**, K.A. Al-Sammak, I. Marghescu, C.C. Oprea, *State of the Art in Drivers' Attention Monitoring – A Systematic Literature*

Review, **Karbala International Journal of Modern Science**, **9(1), 2,** 10 January 2023, DOI: https://doi.org/10.33640/2405-609X.3278

[6] **<u>Conference</u>: S.H. Al-Gburi**, K.A. Al-Sammak, N.A.A. Almosa, G. Suciu, N.A.H. Al-Sammak, *Comparative Analysis of Logistic Regression and SVM Models for Drowsiness Detection in Drivers*, in **Proceedings of the International Conference on Intelligent and Fuzzy Systems (INFUS 2025)**, Istanbul, Turkey, 29–31 July 2025.

[7] **<u>Journal</u>:** K. A. Al-Sammak, **S. H. Al-Gburi**, I. Marghescu, A.-M. C. Drăgulinescu, C. Marghescu, A. Martian, N. A. M. Alduais, and N. A. H. Al-Sammak, "*Optimizing LoRaWAN Gateway Placement in Urban Environments: A Hybrid PSO-DE Algorithm Validated via HTZ Simulations*," **Technologies, vol. 13, no. 6**, **p. 256**, 17 June 2025, https://doi.org/10.3390/technologies13060256, **ISI Q1 (2025), WOS:001514625000001**

[8] **<u>Journal</u>:** K.A. Al-Sammak, **S.H. Al-Gburi**, I. Marghescu, A.-M.C. Drăgulinescu, C. Marghescu, A. Martian, N.A.H. Al-Sammak, G. Suciu, K.M.A. Alheeti, *Optimizing IoT Energy Efficiency: Real-Time Adaptive Algorithms for Smart Meters with LoRaWAN and NB-IoT*, **Energies**, **18(4), 987,** 18 February 2025, **ISI Q3, WOS:001431808900001**.

[9] **<u>Conference</u>:** K.A. Al-Sammak, **S.H. Al-Gburi**, I. Marghescu, A.M. Drăgulinescu, C. Marghescu, N.A.H. Al-Sammak, *An Experimental Study of Power Consumption in Narrowband IoT Devices*, in **Proceedings of the 2024 15th International Conference on Communications (COMM)**, Bucharest, Romania, 03–04 October 2024, pp. 1–6, **IEEE, DOI: 10.1109/COMM62355.2024.10741514.**

[10] **<u>Conference</u>:** K.A. Al-Sammak, **S.H. Al-Gburi**, C. Marghescu, A.M. Drăgulinescu, G. Suciu, A.G. Abdulqader, *A Comprehensive Assessment of LoRaWAN and NB-IoT Performance Metrics Under Varied Payload Data Sizes*, in **Proceedings of the 2024 16th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)**, Iași, Romania, 27–28 June 2024, pp. 1–5, **IEEE, DOI: 10.1109/ECAI61503.2024.10607481.**

[11] **<u>Conference</u>:** K.A. Al-Sammak, **S.H. Al-Gburi**, I. Marghescu, *Communications Systems in Smart Metering: A Concise Systematic Literature Review*, in **Proceedings of the 2022 14th International Conference on Communications (COMM)**, Bucharest, Romania, 16–18 June 2022, pp. 1–9, **IEEE, DOI: 10.1109/COMM54429.2022.9817154.**

[12] **<u>Conference</u>:** G. Suciu, C. Stalidi, K.A. Al-Sammak, **S.H. Al-Gburi**, M.-A. Sachian, *Integrated Solution Based on Innovative Digital Technologies for Smart Ports*, **FOR-FREIGHT Project White Paper**, BEIA Consult International, Bucharest, Romania, **2023**, available at: https://www.for-freight.eu/publications/.

[13] **<u>Conference</u>:** K.A. Al-Sammak, **S.H. Al-Gburi**, N.A.H. Al-Sammak, G. Suciu, *An Evaluation of the Functionality of NB-IoT for Smart Metering Applications*, in **Proceedings of the International Conference on Intelligent and Fuzzy Systems (INFUS 2025)**, Istanbul, Turkey, 29–31 July 2025.

6.3 Future Works

Several directions for future research can be explored to build upon the findings of this study. These include:

- **Integration with Advanced Driver Assistance Systems (ADAS):** Enhancing real-time monitoring by embedding the proposed models into ADAS frameworks for seamless intervention.
- **Multimodal Data Fusion:** Combining additional physiological signals (e.g., heart rate, skin conductance) with EEG and video data to improve detection accuracy. Future work should focus on integrating more robust multimodal fusion techniques.
- **Optimization for Edge AI Deployment:** Developing lightweight versions of the proposed models to facilitate deployment on embedded systems and edge devices. This will allow real-time inference without requiring high computational resources.
- **Ethical and Regulatory Considerations:** Addressing data privacy concerns and ensuring compliance with international safety standards for widespread adoption. Future research should focus on regulatory challenges and ethical AI implementation in driver monitoring.

In summary, this research has laid a strong foundation for future advancements in driver monitoring technologies. The proposed methodologies have the potential to be integrated into real-world applications, improving driver safety and reducing road accidents caused by fatigue. Future studies should focus on refining and expanding these techniques to further enhance their effectiveness and applicability in intelligent transportation systems.

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