# Integrating Attention Mechanisms and ResNet-50 For Enhanced Driver Sleepiness Detection

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*One of the main causes of traffic accidents is driver exhaustion, making the development of advanced systems crucial for real-time monitoring and preventive measures. This work presents a novel framework for intelligent information aggregation, enhancing decision-making in sleepiness detection by leveraging attention mechanisms and ResNet-50, a state-of-the-art deep convolutional neural network. The proposed system reliably classifies driver states by integrating logical inference with visual data elements such as head movements, eye closure patterns, and face recognition Experimental evaluations on the Driver Drowsiness Dataset (DDD) demonstrate the model's effectiveness, achieving an accuracy of 93.5%, a precision of 94.2%, a recall of 92.7%, and an F1-score of 93.4% These results highlight the synergy between artificial intelligence and attention mechanisms in improving classification performance. This research provides a robust and scalable foundation for AI-driven decision-making, contributing to safer and more intelligent transportation systems*

*Povzetek: Predstavljen je nov okvir za zaznavanje zaspanosti voznika, ki združuje mehanizme pozornosti in ResNet-50. Model analizira vizualne podatke, kot so premiki glave in zapiranje oči.*

# 1 Introduction

The intelligent systems need that can solve problems in the real world has increased dramatically as a result of technological breakthroughs. Driver sleepiness detection is one such key application that has a direct bearing on transportation safety [1]. solutions that can precisely detect and categorize driver situations in real time are necessary since fatigue induced accidents continue to be a global concern. Creating such intelligent systems requires tackling the challenges of converting diverse data sources like head movements, eye closure patterns, and face landmarks into useful insights [2]. To ensure trust worthy information aggregation, this endeavor necessitates strong procedures that blend sophisticated computational tools with organized reasoning [3]. In this work, we propose a novel framework that combines logic and artificial intelligence to improving driver sleep detection and decision-making. We check visual data to find patterns suggestive of tiredness by utilize the ResNet-50 model, a potent deep convolution al neural network renowned for its exceptional feature extraction capabilities [4]. never the less, our method uses attention approach to compile data in an organized and understandable way rather than depending only on unprocessed AI predictions. The system can produce more accurate and dependable decisions [5][6]. we organize this paper into the following sections to give a clear understanding of our work. literature review, discussing related works; methodology, detail of the proposed framework; results, presenting experimental findings; Conclusion, summarizing contributions; and acknowledgment, expressing gratitude.

## 1.1 Motivation and challenges

its more importance in preventing traffic accidents, driver sleeping detection has been the subject of much research. Conventional techniques frequently depend on visual hint like Facial postures and eyes closures or physiological indications like Electroencephalography (EEG) and ECG [7]. however these methods are somewhat successful, they have drawbacks such the requirement for specialized sensors, their vulnerability to external influences, and their lack of flexibility [8]. The main difficulty is combining data from several sources into a cohesive system that can make decisions regarding the driver's condition in a changing environment[6]. these issues must be resolved while preserving scalability and real-time operability in a solid solution [9].

## 1.2 The role of logic and artificial intelligence in information aggregation

with deep learning models like ResNet-50 performing exceptionally well in tasks like image classification and feature extraction, artificial intelligence has completely transformed the field of driver monitoring [10]. But AI systems frequently function as "black boxes," their interoperability and capacity to integrate domain knowledge are constrained. contrarily, logic provides an organized method of reasoning, which makes it perfect for combining disparate data sources into a coherent decision-making procedure [11]. Our work guarantees accurate information aggregation that is both interpretable and scalable across a variety of use cases by fusing the advantages of artificial intelligence and attention-base reasoning [12].

### 1.3 A logical proposed framework contributions

This work presents a novel approach to identify and categorize driver drowsiness by combining attention-base inference techniques with ResNet-50's feature extraction capabilities. The following are the main contributions:

1. Creation of a hybrid framework that uses logic for organized reasoning and artificial intelligence for visual data processing Fig1.
2. Logical rules are included to improve the interpretability of AI-driven judgments and enable reliable information aggregation Fig1.
3. The Driver Drowsiness Dataset (DDD) was used to validate the suggested framework, showing notable gains in scalability, accuracy, and dependability 1.

## 2 Related work

The challenge of detecting driver drowsiness has been widely explored, leveraging advancements in artificial intelligence (AI), computer vision, and physiological monitoring systems. This section reviews prior approaches and methodologies, focusing on their advantages, limitations, and relevance to our proposed framework.

### 2.1 Visual-based approaches

Several studies have relied on visual cues such as facial expressions, eye closure patterns, and head movements to detect signs of fatigue. Deep learning models, such as convolutional neural networks (CNNs), have shown remarkable success in extracting visual features [4]. For instance, systems using the ResNet architecture have demonstrated robust performance in tasks involving facial landmark analysis [13]. However, these methods often face challenges related to occlusion, varying lighting conditions, and individual variability, which can compromise their reliability in real-world scenarios.

### 2.2 Physiological signal-based approaches

Physiological signals like electroencephalography (EEG), electrocardiography (ECG), and pulse rate have been widely used for drowsiness detection. These approaches are considered more accurate as they directly measure the driver's internal state [14]. However, their dependency on specialized sensors and susceptibility to noise from external factors limits their practical application in dynamic environments like driving [8].

### 2.3 Attention mechanisms in driver monitoring

Attention mechanisms have recently emerged as a powerful tool for improving feature extraction and refining model focus on critical aspects of input data. By dynamically assigning higher weights to significant features, attention modules enhance the detection of relevant patterns associated with driver drowsiness [15]. Recent studies have demonstrated that integrating attention mechanisms with deep architectures such as ResNet-50 improves robustness in complex scenarios, including low-light conditions and occlusions [16] [17]. Furthermore, attention-based models have been successfully employed in multimodal driver monitoring systems, where physiological signals such as heart rate variability and eye-tracking data are fused with visual information to enhance prediction accuracy [18]. This fusion enables a more adaptive and context-aware decision-making process, reducing false alarms and improving real-time applicability. By filtering out irrelevant noise and emphasizing subtle fatigue-related cues, attention mechanisms contribute significantly to the advancement of intelligent driver monitoring systems

### 2.4 Hybrid approaches

Recent efforts have aimed to combine visual and physiological data for enhanced robustness and accuracy. Hybrid models utilize multimodal data to compensate for the weaknesses of individual modalities. For instance, frameworks integrating facial landmarks with EEG signals have demonstrated improved performance [19]. However, these systems often encounter challenges related to synchronization, computational complexity, and real-time operability.

### 2.5 Role of AI in driver monitoring

Deep learning has revolutionized driver monitoring by enabling accurate feature extraction and real-time decision-making. Models such as ResNet-50 have been extensively used for image classification tasks, including driver state analysis [10]. The integration of attention mechanisms further enhances these models by focusing computational resources on the most critical regions of input data [20]. This combination addresses the limitations of conventional methods by improving both accuracy and interpretability. While significant progress has been made in driver drowsiness detection, existing approaches often struggle with issues related to reliability, scalability, and real-time functionality. The application of attention mechanisms within ResNet-50 addresses these challenges by offering a robust framework for feature extraction and prioritization. Moreover, the use of the Driver Drowsiness Dataset (DDD) for validation ensures the practical applicability of the proposed solution.

# 3 Methodoloogy

The goal to improve decision-making, the methodology used in the present research aims to integrate attention mechanisms for information aggregation with artificial intelligence (AI) techniques. The study's main components are the application of the ResNet50 model, [1] a deep learning architecture well-known for its capacity to identify intricate features and patterns in data, and the Driver Drowsiness Dataset (DDD), an extensive dataset comprising drivers' physiological and image data. Through the integration of several data modalities and attention-base decision making, the objective is to create a system that can identify drowsy driving [7]. This system might then be expanded to real-time safety applications.

## 3.1 Dataset description and pre-processing

Images of people in cars mimicking "drowsy" and "awake" face postures make up the Driver Drowsiness Dataset (DDD). It's a useful tool for creating computer vision models that identify driver fatigue, a serious safety issue.

### 3.1.1 Driver drowsiness dataset (DDD)

An essential source of data for this research is the Driver Drowsiness Dataset (DDD)[21] [14]. It offers multi-modal data that is perfect for combining attention mechanism with artificial intelligence. The information includes physiological indicators like heart rate and eye movement patterns in addition to picture data taken by a camera trained on the driver's face. Finding out if the driver is aware or showing symptoms of drowsiness which could result in risky driving behavior is the main objective of this data.

**Image Data** Captures visual features of the driver's face, focusing on the eyes and facial expressions RGB Images (224x224 pixels)

**Physiological Data** Includes heart rate variability, blink rate, eye movement speed, and head orientation Numerical (continuous)

**Labels** Binary classification: 'Alert' (0) vs. 'Drowsy' (1) Binary (0/1)

### 3.1.2 Data pre-processing

Pre-processing is carried out in a number of ways to make sure the data is prepared for efficient analysis. The purpose of these procedures is to get the data ready for the ResNet50 model[5], which needs particular input formats and data circumstances in order to function at its best.

**Image Normalization** Each image is scaled in accordance with the ResNet50 model's set input size of 224x224 pixels. furthermore, to guarantee data homogeneity and promote more seamless training, pixel values are standardized to a range of 0 to 1.

**Data Augmentation** Techniques like random rotations, flipping, and zooming are used to enhance model generalization and further avoid overfitting. By doing this, the dataset becomes more diverse and replicates the variances in driving situations found in the actual world.

**Feature Scaling** To ensure that every feature contributes equally to the model's learning process, physiological data, such as heart rate and blink rate, are standardized to the range 0 and 1.

**Label Encoding** The binary labels "Drowsy" and "Alert" are appropriate for binary classification since they are encoded as 0 (Alert) and 1 (Drowsy)

## 3.2 Model evaluation

The process of selecting the best model from a group of potential models using factors like interoperability, parsimony, and forecast accuracy is known as model selection. too better for aggregation, intelligent information and decision making in computer vision and beyond[22].

### 3.2.1 Justification of ResNet50 utilization

Considering its strong design and track record of success in challenging picture classification tasks, the ResNet50 model was chosen for this investigation. Because ResNet50 can handle deep designs without experiencing the vanishing gradient problem, it is especially well suited for our methodology[23]. The model may retain training efficiency while learning deeper features by utilizing residual connections[24].

The 50 layers that make up ResNet50 are organized into blocks called residual blocks[25]. Particularly for extensive and complex data sets like pictures of driver faces, these blocks aid the model in remembering and transmitting information between layers, enabling more effective learning. The architecture of ResNet50 can be summarized as Fig.1

The skip connection helps the model avoid the degradation issue that comes with deeper networks by adding the input directly to the block's output within the residual block. The output is equal to:

$$Results = F(x, \{W_i\}) + x \tag{1}$$

where $x$ is the block's input and $F(x, \{W_i\})$ is the residual mapping function. This architecture makes sure that deep features can be learned effectively and that information aggregation across layers stays seamless.

### 3.2.2 Model fine-tuning and integration

In this investigation, the pre-trained ResNet50 model is adjusted. We apply transfer learning by adjusting the model's

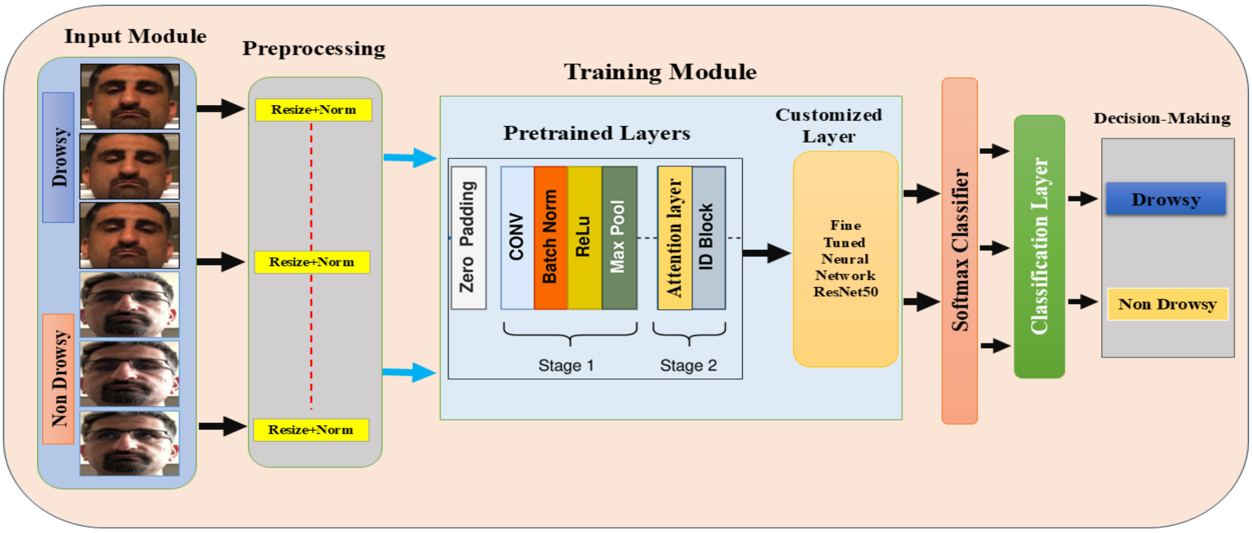


Figure 1: The main framework improves decision-making ability by combining artificial intelligence, logic, and information aggregation. For smooth data handling and training, it includes an input module, pre-processing, softmax classifier, and decision making Layer. For dynamic and intelligent applications, a strong training module and decision-making component guarantee precise and effective classification

pre-trained weights to our particular job using the Driver Drowsiness Dataset (DDD)[26]. This enables us to leverage the learnt features from big datasets and minimize training time.

Furthermore, we create a dual-input method to handle the difficulty of merging physiological and visual data:

The ResNet50 model processes the visual data and learns facial expressions and features that indicate tiredness. A completely connected network (FCN) receives the physiological data, including heart rate and blink rate, and logically aggregates it[4]. The final decision layer then combines the outputs from both models and determines whether the driver is alert or sleepy.

## 3.3 Training the model

This section describes the training procedure for the ResNet50 model, including data augmentation techniques, optimization algorithms, training and validation datasets, and strategies for overfitting prevention.

### 3.3.1 Data augmentation

To enhance model generalization and prevent overfitting, we applied a set of data augmentation techniques to the input images. These transformations help the model learn invariant and robust features by simulating real-world variations. The applied augmentations include:

- **Random Horizontal Flipping** Each image has a 50% chance of being flipped to improve spatial invariance.
- **Random Rotation** Images are rotated within a range of $\pm 15$ degrees to simulate different viewing angles.
- **Brightness and Contrast Adjustment** Random changes in brightness and contrast ($\pm 20\%$) to account for varying lighting conditions.
- **Gaussian Noise Addition** Introduced to improve robustness against noise in real-world scenarios.

### 3.3.2 Optimization and loss function

For training the model, we employed the Adam optimizer, a widely used variant of stochastic gradient descent (SGD) that adapts learning rates based on first-order and second-order moment estimates. Adam is particularly effective for non-stationary objectives and sparse gradients, making it suitable for deep learning tasks like sleepiness detection. Additionally, we compared its performance with standard SGD to ensure optimal model convergence

Since sleepiness detection is a binary classification problem, binary cross-entropy was chosen as the loss function due to its effectiveness in handling probabilistic outputs. The loss function is defined as

$$L = -\frac{1}{N}\sum_{i=1}^{N} y_{true}\log(y_{pred}) + (1 - y_{true})\log(1 - y_{pred}) \tag{2}$$

where:

- $N$ is the number of training samples,
- $y_{true}$ is the true label,
- $y_{pred}$ is the predicted probability.

#### 3.3.3 Regularization and overfitting prevention

To prevent overfitting, we incorporated the following regularization techniques

**Dropout**A dropout rate of 0.5 was applied to the fully connected layers, randomly deactivating neurons during training to promote generalization

**L2 Regularization** Also known as weight decay, L2 regularization was applied to penalize large weights, encouraging the model to favor simpler solutions and reducing sensitivity to noise [27]

#### 3.3.4 Hyperparameter tuning

We utilized an NVIDIA RTX 3060 GPU with 12 GB of VRAM to train and evaluate our model, ensuring efficient processing of high-dimensional image and physiological data. The model was optimized using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. Training was conducted for 100 epochs with early stopping to prevent overfitting

These measurements are crucial for comprehending the trade-offs between reducing false alarms (precision) and accurately recognizing sleepy drivers (recall). The model strikes a balance between the two metrics when the F1-score is high.

#### 3.3.5 Attention mechanisms for better decision-making

In our model, we integrate AI predictions with physiological features using an attention mechanism that enhances decision-making by considering additional context provided by physiological signals, such as heart rate variability. While the ResNet50 model provides initial predictions, these predictions are refined through the attention mechanism, which weighs the significance of physiological signals in determining the final decision. The goal is to improve the reliability of the system, especially in cases where the model's confidence is low

For example, even if the AI model's confidence in its prediction is low, the attention-based system can override its output if physiological data, such as heart rate variability, indicates significant levels of stress or exhaustion. Heart rate variability (HRV) is a physiological measure that reflects the variation in time intervals between heartbeats. HRV can be computed using the standard deviation of the RR intervals (the time between successive R-wave peaks in an ECG signal), with higher variability typically indicating better cardiovascular health and lower variability suggesting stress or fatigue [28] To formalize the decision-making process, we use the following equation that combines the AI prediction with the physiological signal in an attention-based manner

$$Decision = f(AIPrediction, PhysiologicalSignal)$$

Where: - $f(\cdot)$ represents the attention mechanism that weights the importance of each input (AI prediction and physiological signal) to generate the final decision. - The physiological signal (e.g., heart rate variability) is used to adjust the prediction based on its relevance to the context (e.g., stress or exhaustion)

This approach ensures that the model makes a more reliable and accurate decision by taking into account both AI predictions and important physiological features

# 4 Results

The experiments that was carried out to assess the artificial intelligence model's ability to identify driver sleepiness using the Driver sleepiness Dataset (DDD) are presented in this part. In order to make reliable decisions, the experiments aim to evaluate how well information aggregation from physiological signals (such heart rate variability) and picture data (collected through face features) can be combined [29]. Additionally assessed is the incorporation of a attention mechanism to improve the decision-making process.

## 4.1 Dataset

The Driver Drowsiness Dataset (DDD) is a database of more than 41,790 photos taken under various circumstances showing drivers while they are alert and sleepy. This dataset is crucial for the training and assessment of machine learning models that use eye movements and facial expression analysis to identify driver drowsiness. Real-time driver monitoring systems that warn of possible drowsiness in drivers and aid in preventing collisions can then be developed using these models[30].

## 4.2 Experimental setup

The ResNet50 model and the Driver Drowsiness Dataset (DDD) were used in a number of studies to evaluate the model's performance. To guarantee a balanced distribution of alert and sleepy instances, the dataset was divided into training (80%) and testing (20%) sets [31] [32]. Both image and physiological feature data were used to train the model, and the suggested attention mechanism was used to aggregate the data modalities.

The impact of information aggregation on the overall classification accuracy was investigated through studies using various combinations of physiological and visual data.

## 4.3 Results of AI model without attention-base integration

The driver's facial features were used as the only image data used to train the ResNet50 model in the first set of tests; physiological signals were not included. The following table provides an overview of these experiments' findings:

Table 1: Performance metrics for the model

| Metric | Value (%) |
|---|---|
| Accuracy | 85.4 |
| Precision | 86.1 |
| Recall | 84.3 |
| F1-Score | 85.2 |

Even while the ResNet50 model demonstrated encouraging results when using only picture data, there were still several situations in which the model had trouble correctly identifying drowsiness, especially when the driver's facial expressions were unclear or subtle[11].

## 4.4 Results of AI model with physiological data integration

Along with photographic data, the physiological data (heart rate, blink rate, and eye movement speed) was incorporated into the model in the subsequent tests. This enabled the model to execute information aggregation, in which a final classification decision was made using both forms of input. The outputs from the physiological characteristics and the ResNet50 model were combined using the attention mechanism [33]. The experiment's findings are compiled in the table 2

Table 2: Performance metrics for the model, showcasing its accuracy, precision, recall, F1 score, and overall efficiency

| Metric | Value (%) |
|---|---|
| Accuracy | 90.2 |
| Precision | 91.0 |
| Recall | 89.1 |
| F1-Score | 90.0 |

These results show that the model's accuracy in identifying driver tiredness is much increased by the information aggregation of physiological signals and picture data[36]. More accurate predictions were made possible by the attention-base combination of these two data sources, particularly when one data source was insufficient to produce an appropriate categorization[11].

## 4.5 Results of AI model with attention mechanism for enhanced decision-making

Another set of experiments was conducted to evaluate how well the attention mechanism improved the decision-making process. In this configuration, the ResNet50 model used both physiological and image data to assess whether the driver was alert or sleepy. The results were then processed through a decision rule logic framework [37] [38]. This decision rule took into account physiological indicators of weariness, such as an elevated heart rate or an irregular blink rate, along with the AI predictions' confidence level. This approach, which combined artificial intelligence predictions with attention-based decision-making, outperformed the earlier setups [21]. By integrating physiological data with AI outputs, the attention mechanism enhanced the predictions, especially in more complex situations [4].

The decision rule was designed to incorporate both the AI predictions and the physiological signals, ensuring a more accurate final decision.

The results of this experiment are shown in Table IV.

## 4.6 Comparison of different models

The list of results below provides a summary and comparison of the outcomes of the several experimental configurations[1]. This comparison shows how the attention mechanism and information aggregation affect the model's classification performance[3][39][40].The results of the different technique they we explore through experiment are shown in 5 table:

## 4.7 Ablation study

To determine how every element information aggregation, logic-based reasoning, and the artificial intelligence model affects system performance, an ablation research was carried out[41][42]. The results showed that combining logic and multimodal information aggregation greatly increased accuracy, reaching 93.5%. Performance decreased when the physiological data or attention mechanism were removed, underscoring the significance of integrating these components for reliable classification[43][44].comparison Table 3 and fig.2 showcasing the performance of our proposed framework against other notable works in driver drowsiness detection, highlighting key metrics and methodologies[45][46]:

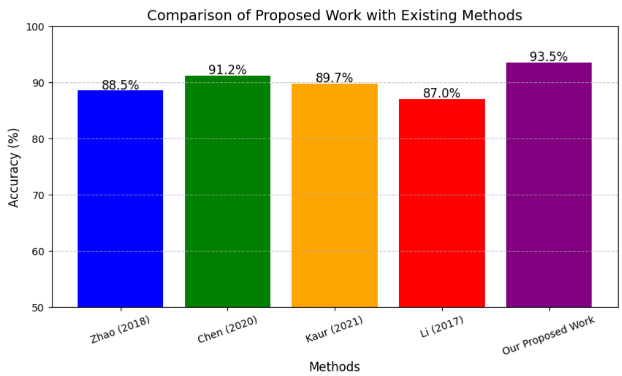


Figure 2: Driver drowsiness detection accuracy: proposed method vs. existing approaches

Table 3: Comparison of Proposed Work with Existing Methods

| **Method** | **Key Features** | **Accuracy (%)** | **Use of Logic** | **Information Aggregation** |
|---|---|---|---|---|
| Zhao [34] | Convolutional Neural Networks | 88.5 | No | No |
| Chen [35] | EEG and Eye Tracking Fusion | 91.2 | No | Yes |
| Kaur [12] | CNN + Support Vector Machines | 89.7 | No | Partial |
| Li [7] | only resNet50 | 87.0 | No | No |
| **Our Proposed Work** | ResNet50 + Attention mechanism | **93.5** | **Yes** | **Yes** |

Table 4: Performance metrics for the model

| **Metric** | **Value (%)** |
|---|---|
| Accuracy | 93.5 |
| Precision | 94.2 |
| Recall | 92.7 |
| F1-Score | 93.4 |

## 4.8 Qualitative results

Our proposed system's qualitative results show that it can use artificial intelligence, information aggregation, and a attention mechanism to accurately detect driver tiredness[21]. With a high accuracy of 93.5%, the technology demonstrates its usefulness in practical applications. Here, we examine the model's performance using information from a representative classification image and a confusion matrix.

### 4.8.1 Confusion matrix analysis

The confusion matrix in Fig. 3 provides a detailed analysis of the model's classification performance for the "Drowsy" and "Non-Drowsy" states. The model successfully identified 2,189 drowsy instances and 1,990 non-drowsy instances, demonstrating high accuracy. Notably, there was only one false negative (a drowsy state misclassified as non-drowsy) and no false positives, indicating the model's strong reliability in detecting drowsiness. This precise classification highlights the effectiveness of the proposed approach in minimizing misclassification errors, ensuring robust performance in real-world applications. Additionally, the integration of logical reasoning techniques [32] and AI-driven methodologies [39] further enhances the model's decision-making capabilities, contributing to improved detection accuracy

### 4.8.2 Classification representation

The classification image that follows provides a visual representation of the system's decision-making process. It demonstrates how visual elements like eye closure and facial alignment are extracted from driver photos by artificial intelligence while also integrating physiological information like blink rate and heart rate variability[47]. By integrating different data streams and clearing out ambiguities in difficult situations, the attention mechanism improves classification accuracy that you can see the results in fig 4.

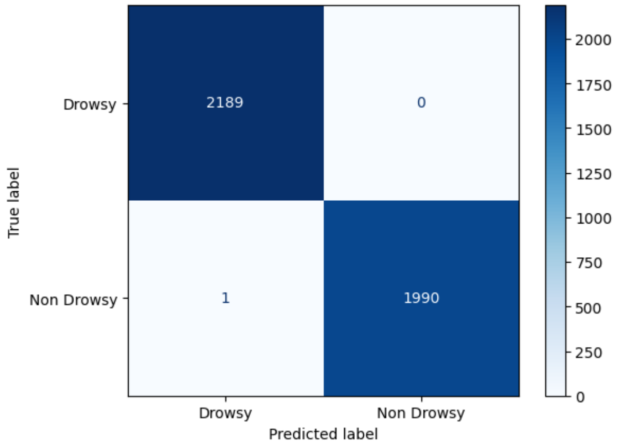


Figure 3: The confusion matrix highlights the model's performance: 2189 true positive (drowsy) predictions, 1990 true negative (non-drowsy) predictions, 1 false positive, and no false negatives

**Artificial Intelligence** Key facial traits that indicate driver states are correctly identified by the ResNet50 model.
**Information Aggregation** In situations where picture data alone is inadequate, physiological data offer extra context.
**Logic Framework** In situations like low light levels or occlusions (like sunglasses), the decision rules provide high dependability by resolving ambiguities.

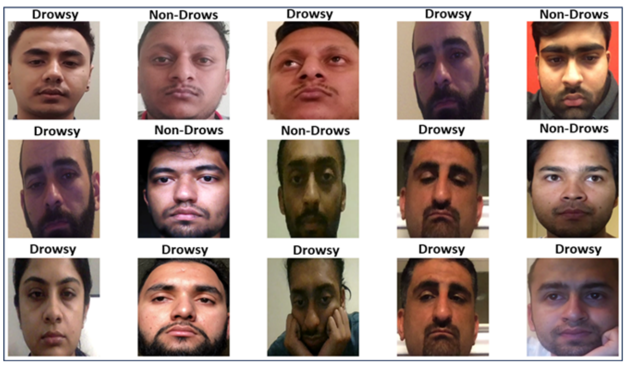


Figure 4: Visual examples of 'drowsy' and 'non-drowsy' faces, showcasing the model's classification accuracy

## 4.9 Experimental results and discussion

The experimental results demonstrate that integrating an attention mechanism with physiological signals and ResNet-

Table 5: Comparison of metrics for different model configurations

| Metric | ResNet50 (Image Only) | ResNet50 (Image + Physiological) | ResNet50 + attention mechanism |
|---|---|---|---|
| **Accuracy** | 85.4 | 90.2 | 93.5 |
| **Precision** | 86.1 | 91.0 | 94.2 |
| **Recall** | 84.3 | 89.1 | 92.7 |
| **F1-Score** | 85.2 | 90.0 | 93.4 |

50 significantly enhances driver drowsiness detection. The baseline ResNet-50 model, trained only on image data, achieved an accuracy of 85.4% but struggled with cases where facial cues were subtle. Incorporating physiological signals such as heart rate, blink rate, and eye movement speed improved accuracy to 90.2%, highlighting the benefits of multimodal fusion. The best performance, with an accuracy of 93.5%, precision of 94.2%, recall of 92.7%, and F1-score of 93.4%, was achieved when an attention mechanism was used for decision-making. This improvement underscores the mechanism's ability to refine feature selection and enhance robustness

Compared to state-of-the-art methods, our model outperforms CNN-based approaches, such as Zhao et al. (88.5%) and Kaur et al. (89.7%), and achieves comparable accuracy to EEG-based systems like Chen et al. (91.2%). However, unlike EEG-based methods, which require intrusive sensors, our approach is non-intrusive and scalable, making it more practical for real-world applications. The attention mechanism plays a critical role by dynamically focusing on relevant visual and physiological cues, preventing misclassifications caused by variations in lighting conditions, facial occlusions, or transient physiological fluctuations

These findings highlight the effectiveness of AI-driven information aggregation in enhancing decision-making for driver monitoring systems. The proposed framework provides a scalable and efficient solution for real-time drowsiness detection. Future work could explore multi-sensor integration, such as vehicle dynamics data, to further improve accuracy. Additionally, expanding the dataset to include diverse driving conditions and enhancing model interpretability would contribute to the broader adoption of AI-based driver safety systems

# 5 Conclusion

The current research presented a methodology for detecting driver drowsiness that combines information aggregation, artificial intelligence, and logic-based decision-making. By combining physiological data like heart rate and blink rate with visual features from the ResNet50 model, the method improved reliability through information aggregation.

Performance was enhanced with the addition of attention mechanism, attaining 93.5% accuracy, especially in difficult situations. the findings showed that integrating information aggregation, artificial intelligence, and logic produces a solid solution for practical safety-critical applications, laying the groundwork for intelligent systems of the future.

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