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"Development of a Smart Driver Drowsiness Detection Model with Cloud Integration"

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Abstract

Early detection of driver drowsiness plays a crucial role in minimizing road accidents and enhancing transportation safety. Fatigue usually develops progressively, making it difficult for drivers to recognize the decline in their alertness and reaction capability at the initial stage. Recent advancements in monitoring technologies, such as computer vision techniques and physiological signal analysis, have shown significant potential in identifying early symptoms of drowsiness. These methods analyse parameters including eye blink duration, yawning frequency, head posture variations, and heart rate fluctuations to detect fatigue before it leads to critical driving mistakes. This research presents "Driving Alertness to the Cloud: Intelligent Drowsiness Detection with Cloud-Assisted Machine Learning," an advanced framework designed to identify real-time indicators of driver fatigue through facial and physiological monitoring. The proposed system captures features such as extended eye closure, irregular blinking behaviour, yawning patterns, and abnormal head movements. The acquired information is pre-processed and transferred to a cloud-supported machine learning environment, where intelligent algorithms analyse behavioural patterns and classify the driver's alertness condition with high accuracy. The integration of cloud computing enables scalable storage and processing capabilities, continuous enhancement of machine learning models, and seamless implementation across multiple vehicular platforms. Experimental results demonstrate that the system can effectively provide timely warnings to drivers, thereby reducing the likelihood of fatigue-related accidents. Consequently, the proposed cloud-based framework delivers a reliable, adaptive, and intelligent solution for improving safety in modern transportation systems. In addition, this work evaluates the effectiveness of multiple machine learning algorithms for detecting driver drowsiness using facial and physiological characteristics. Auto Colour Correlogram (ACC) features were extracted from driver images, and six classifiers—Additive Regression (AR), Naive Bayes (NB), Linear Regression (LR), Attribute Selected Classifier (ASC), Naive Bayes Multinomial (NBM), and Logistic Regression—were analysed and compared. Among these models, the Additive Regression classifier achieved superior performance across different evaluation parameters, demonstrating its suitability for real-time drowsiness detection applications.

Keyword: Driver Drowsiness Detection, Cloud-Assisted Machine Learning, Transportation Safety, Computer Vision, Physiological Signal Analysis, Auto Colour Correlogram (ACC), Fatigue Detection, Intelligent Transportation Systems

1.Introduction

Driver drowsiness is considered one of the leading causes of road accidents worldwide, frequently resulting in serious injuries, loss of life, and significant financial damage. Factors such as long driving durations, irregular sleeping habits, and repetitive driving environments contribute heavily to fatigue, which negatively affects a driver's concentration, awareness, and reaction speed. Unlike external risk factors like unfavourable weather or poor road infrastructure, drowsiness originates internally and may remain undetected until driving ability is severely impaired. Therefore, identifying the early symptoms of fatigue is essential for enhancing overall road safety.

Traditional vehicle safety mechanisms, including airbags and seat belts, are primarily intended to reduce the severity of injuries after an accident has occurred. However, driver drowsiness detection systems focus on accident prevention by recognizing fatigue symptoms before they lead to hazardous driving situations. Research studies have shown that drowsy drivers exhibit noticeable behavioural and physiological changes that can be monitored and analysed using modern sensing and intelligent technologies. Generally, driver drowsiness detection techniques are grouped into three major categories: vehicle-based, physiological-based, and behavioural-based approaches. Vehicle-based methods monitor driving characteristics such as steering wheel movement, lane deviation, and unusual braking behaviour. Physiological-based techniques evaluate biological signals including Electroencephalogram (EEG), Electrocardiogram (ECG), and heart rate variability to determine fatigue conditions. Behavioural-based systems rely on visual observation of facial expressions and eye activities, detecting indicators such as frequent blinking, prolonged eye closure, yawning patterns, and variations in head posture.

Advances in computer vision, artificial intelligence, and machine learning have significantly improved the performance of behavioural-based systems. Deep learning algorithms, in particular, are capable of processing large volumes of visual data in real time, identifying subtle indicators of drowsiness with high accuracy. Similarly, AI-driven analysis of physiological signals has proven effective in providing reliable fatigue detection even under challenging conditions, such as varying light or road environments. Computer-aided detection (CAD) systems are increasingly being developed to combine multiple data sources, integrate sensor inputs, and deliver real-time alerts. Such systems can notify drivers through auditory, visual, or haptic feedback when signs of fatigue are detected, encouraging timely preventive actions such as resting or pulling over.

Embedding drowsiness detection technologies into modern vehicles holds tremendous potential to reduce fatigue-related accidents. Automakers and researchers are actively working toward incorporating these systems into advanced driver-assistance systems (ADAS). With the advent of smart vehicles and Internet of Things (IoT) integration, continuous monitoring of driver states has become more practical and efficient. The present study investigates machine learning models for driver drowsiness detection using both behavioural and physiological indicators. By applying methods such as feature extraction, data preprocessing, and classifier optimization, the goal is to enhance detection accuracy while reducing false alarms. Ultimately, the adoption of intelligent monitoring systems can significantly improve road safety, safeguard lives, and support the broader vision of accident-free transportation.

2.Literature Review

This systematic review provides a comprehensive synthesis of peer-reviewed studies investigating the use of deep learning models for driver drowsiness detection in both simulated and real-world contexts. Drawing on 81 eligible studies published between 2015 and 2025, the review analyses key aspects of model development, evaluation, and applicability, offering critical insights into the current state of research and practice in this field [1]. The findings indicate that a wide range of DL architectures—most notably CNNs, RNNs, LSTM networks, and hybrid models—have been employed to detect drowsiness based on behavioural, physiological, and multimodal inputs. While many models report high accuracy and F1-score values, especially in controlled environments, real-world performance remains dependent on data diversity, input robustness, and contextual adaptability. This paper explored real-time DDD using ML and CV techniques, focusing on facial analysis. The research assessed the efficacy of several methods for identifying drowsy driver behaviour by employing diverse public datasets. Vision-based systems still dominate practice, leveraging eyelid dynamics, blink rate, yawning, and head pose to infer alertness [2]. Majeed et al. [3] developed a deep CNN-based model for detecting driver drowsiness focused on the Mouth Aspect Ratio (MAR), achieving 96.69% accuracy using the YawDD and data augmentation techniques. Bai et al. [4] introduced a two-stream spatial–temporal graph convolutional network (2s-STGCN), capturing spatial and temporal features from facial landmarks, with accuracies of 93.4% and 92.7% on the YawDD and NTHUDDD datasets, respectively. Weng et al. [5] employed a Hierarchical Temporal Deep Belief Network (HTDBN), combining Deep Belief Networks (DBNs) and Hidden Markov Models (HMMs) for drowsiness detection, and tested it on a diverse custom dataset. Phan et al. [6] integrated DL networks with IoT technologies for real-time driver fatigue detection, achieving up to 98% accuracy. Finally, Bekhouche et al. [7] developed a hybrid framework using YOLO for face detection and ResNet-50 for feature extraction, refined by a novel algorithm (FCFS), achieving 86.74% accuracy on the NTHUDDD dataset. FL enhances data isolation during model training, protects data privacy, and enables efficient collaborative learning among multiple participants. It allows both the storage of data and the model training phases to occur locally, thereby promoting collaborative training of globally optimal models. Through exclusive reliance on central server interactions for model updates, FL has shown great potential in improving the efficiency and security of machine learning within ITS applications, leading to extensive research and development in recent years [8]. An objective method [9] for detecting drowsy driving in an EEG-based framework was suggested in this study. Five classifiers were utilized for training and testing data: Diagonal Linear Discriminant Analysis (DiagLDA), Support Vector Machine (Linear and Radial Basis Functions), K-Nearest Neighbour (KNN), and Random Forest Classifier (RF). Data were pre-processed before extracting features, and an easily electrode chosen technique was utilized to optimize electrodes and demonstrate the efficacy and robustness of the proposed method. Many useful indicators [10,11,12] can be used to track and assess driver drowsiness. Indicators that are objective Electro-oculogram (EOG), facial expressions and shifts, yawning, eye movement, heart rate, breathing rate, skin conductance, and steering wheel grip are all examples of brain signals. Subjective techniques, such as KSS, are used during, before, and after the driving task. Lane lateral deviation and steering wheel movement rates are two other metrics that measure the vehicle's driving efficiency. Drowsiness and alertness were measured and graded in real-world driving, simulated driving tasks in simple setups, and simulated driving in complex setups in specialized laboratories [13,14]. One of the physiologic markers that can track human actions, etiquette, and mental state is brain signals. In recent years, the electroencephalograph (EEG) has been designed to record brain signals without the need for complicated setups, which has stifled the use of brain signals in brain-computer interfaces [15].

3 Materials and methods

For this study, a publicly available Driver Drowsiness Detection Dataset was utilized, borrowed from the Kaggle data repository. The dataset comprises driver facial images categorized into two primary states: Drowsy and Non-Drowsy. Each image was captured under varying lighting conditions and with different driver postures to ensure diversity. The dataset contains 1,466 images, divided into two main categories:

Drowsy Drivers: 687 images

Non-Drowsy Drivers: 779 images

All images were resized to 224 × 224 pixels during preprocessing, ensuring consistency in input format for machine learning models. This normalization step facilitated efficient training while preserving key visual features such as eye closure, yawning, and head orientation.

Table 1 provides a detailed description of the dataset distribution after preprocessing:

Table 1: Decription about Driver Drowsiness Detection Dataset

S.No	Images	Count	Size (After preprocess)
1	**Drowsy**	687	224x224 pixel
2	**Very Drowsy**	779	224x224 pixel

The images were further augmented using random rotations, horizontal flips, brightness adjustments, and zooming to increase dataset variability and improve the robustness of the trained models. Following preprocessing and augmentation, the dataset was split into training (70%), validation (15%), and testing (15%) subsets to evaluate model performance effectively.

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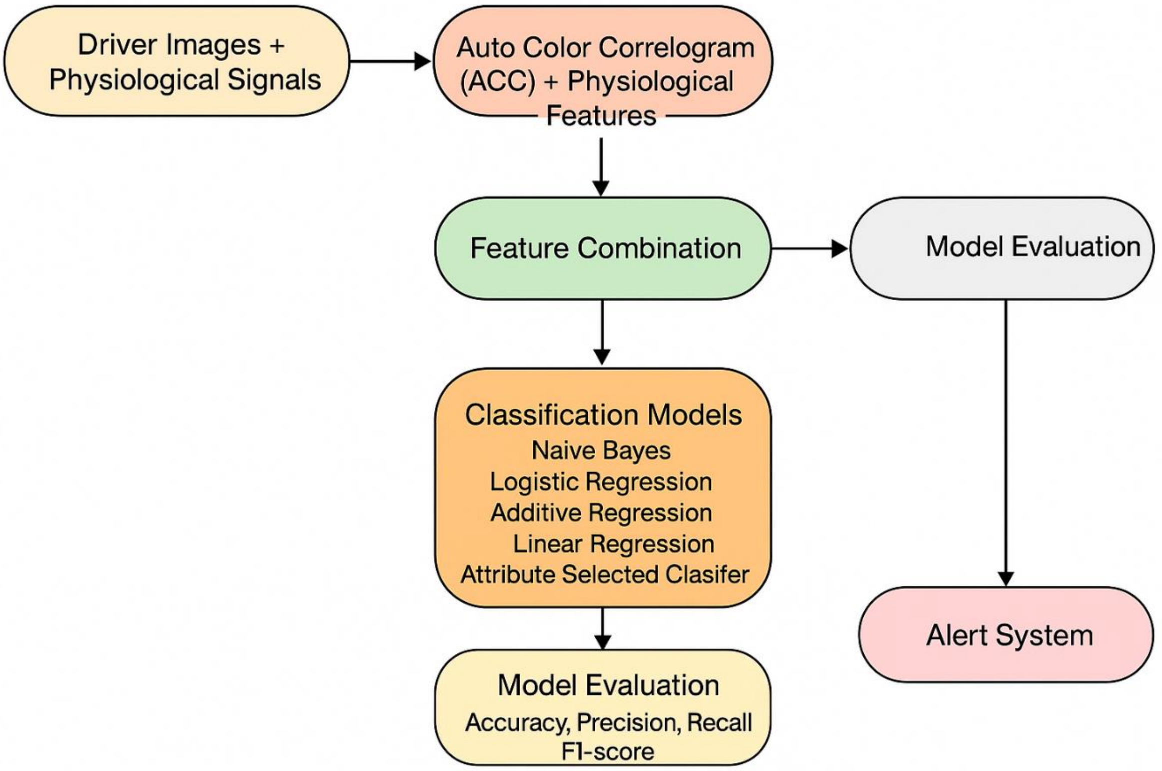

Figure 1: Proposed Architecture

The detection of driver drowsiness begins with the acquisition of driver-related information, such as eye movements, facial expressions, yawning frequency, and head orientation, through camera-based or sensor-driven monitoring systems. The collected data is then subjected to image preprocessing, where techniques like noise reduction, normalization, and enhancement are applied to improve quality and emphasize critical features associated with drowsiness.

Following preprocessing, sampling methods are employed to address dataset imbalance, ensuring sufficient representation of both drowsy and non-drowsy states. This step enhances the effectiveness of training machine learning models. Subsequently, machine learning algorithms are utilized to analyse the processed data and detect behavioral patterns linked to fatigue. To further improve prediction accuracy, hyperparameter optimization is performed, fine-tuning the models for greater robustness. The trained models are evaluated using performance measures such as accuracy, precision, recall, and F1-score to verify their effectiveness in practical scenarios. The most suitable model is then chosen and deployed for real-time monitoring, capable of issuing timely alerts when signs of drowsiness are detected.

This systematic workflow establishes a reliable foundation for developing intelligent driver monitoring systems, ultimately contributing to the prevention of fatigue-induced accidents and enhancing overall road safety.

Algorithm for Driver Drowsiness Detection

Input: Driver facial images and physiological signals (e.g., eye closure, yawning frequency, head position, heart rate variability)

Output: Efficient model for detecting drowsiness in real time

1. Data Representation

Let $J = \{J_1, J_2, ..., J_n\}$ be the set of input driver image signals.

Let $Z = \{z_1, z_2, ..., z_n\}$ be the set of corresponding labels where $z_i \in$ {Drowsy, Alert}

2.Auto Color Correlogram Filter: For each image J in the dataset:

$$ACC(J) = \{\gamma^{(k)}_c(J)\}(c \in C, k \in K) \text{ where:}$$

- C is the set of quantized colors
- K is the set of distance values

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- $\gamma^{(k)}_c(I)$ is the probability of finding a pixel of color c at distance k from a pixel of the same color

Mathematically, $\gamma^{(k)}_c(I)$ is defined as: $\gamma^{(k)}_c(I) = Pr(p_2 \in I_c \mid p_1 \in I_c, \|p_1 - p_2\| = k)$ where:

- Pc is the set of pixels with color c in image P
- p_1 and p_2 are pixels in P
- $\|p_1 - p_2\|$ is the distance between p_1 and p_2

3.Feature Extraction: $X = ACC(J) \cup P(J)$

$= \{ACC(J_1), ACC(J_2), ..., ACC(J_n)\} \cup \{\text{physiological features}\}$

where P(J) represents features like eye closure rate, yawning frequency, head tilt, and heart rate variability.

4. Data Split: (X_train, y_train), (X_test, y_test) = split (X', Y)

5.For each classifier:

a) Naive Bayes: $P(y|x) = P(x|y)P(y) / P(x)$

b) Linear Regression: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon$

c) Additive Regression: $f(x) = f_0(x) + \beta_1 f_1(x) + \beta_2 f_2(x) + ... + \beta_m f_m(x)$

d) Naive Bayes Multinomial: $P(y|x) = P(y) \prod_i P(x_i|y) / P(x)$

e) Logistic Regression: $P(y=1|x) = 1 / (1 + e^{(-z)})$ where $z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n$)

6. Model Evaluation:

   Accuracy = (TP + TN) / (TP + TN + FP + FN)

   Precision = TP / (TP + FP)

   Recall = TP / (TP + FN)

   F1-score = 2 * (Precision * Recall) / (Precision + Recall)

7. Model Selection: $M *= argmax_M Evaluation_M etric(M)$

IV Outcome and Interpretations

This section focuses the outcome of ACCF + AR, ACCF+NB, ACCF+LR, ACCF+ASC, ACCF+NBM, and ACCF+Logistic models. The below table 2 shows the various outcomes of ACCF+AR, ACCF+NB, ACCF+LR, ACCF+ASC, ACCF+NBM, and ACCF+Logistic models.

Table 1: Classifiers Vs Classification Outcomes

S.No	Classifier	Accuracy	Precision	Recall	ROC	PRC
1	ACCF + AR	92.10%	0.93	0.90	0.98	0.97
2	ACCF + NB	86.96%	0.90	0.86	0.93	0.93
3	ACCF + LR	87.82%	0.89	0.87	0.95	0.91
4	ACCF + ASC	83.19%	0.87	0.83	0.83	0.77
5	ACCF + NBM	87.27%	0.83	0.86	0.96	0.94
6	ACCF + Logistic	84.98%	0.91	0.85	0.93	0.92

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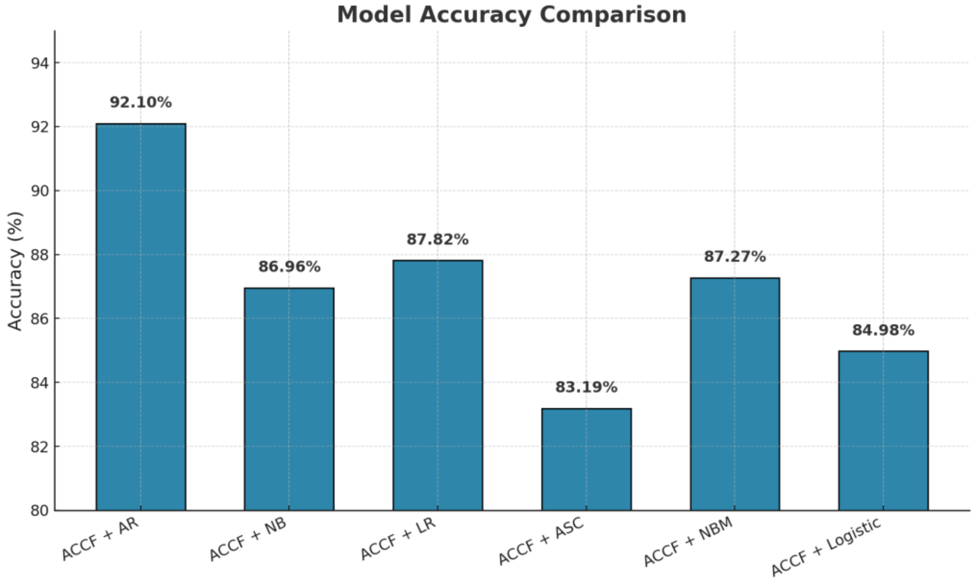

Figure 2 : Model Vs Accuracy

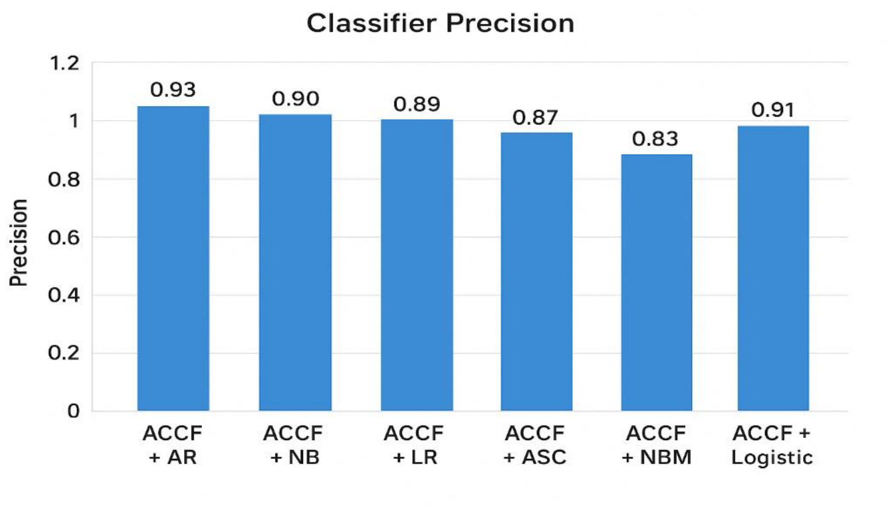

Figure 3: Model Vs Precision

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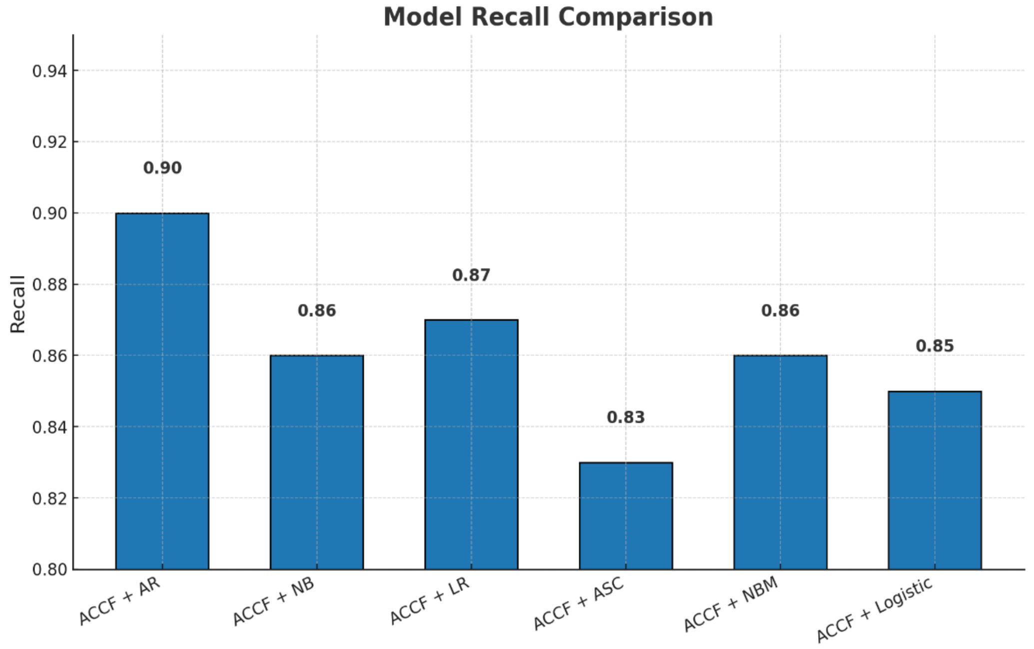

Figure 4 : Model Vs Recall

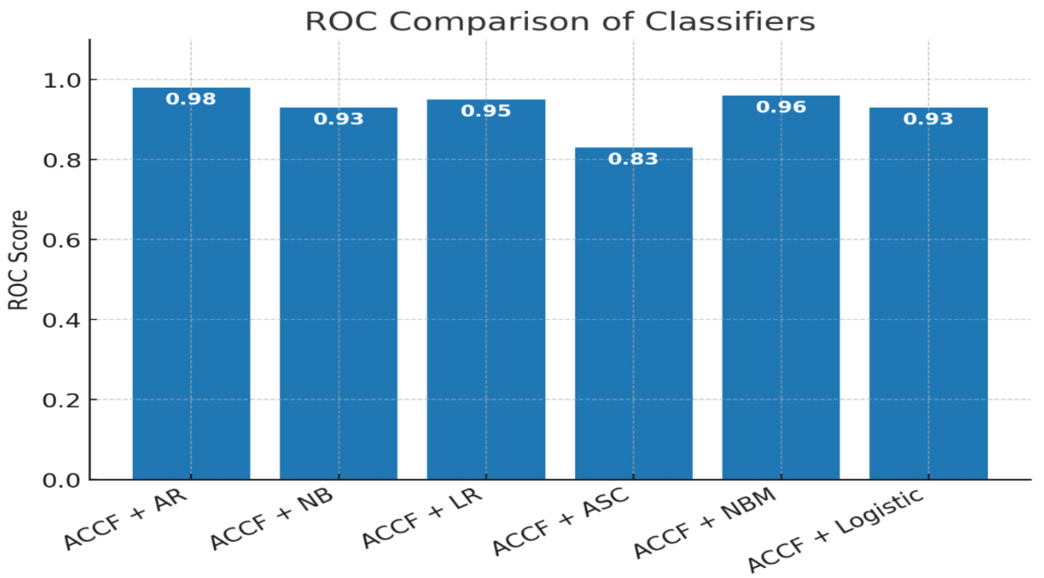

Figure 5: Model Vs Roc

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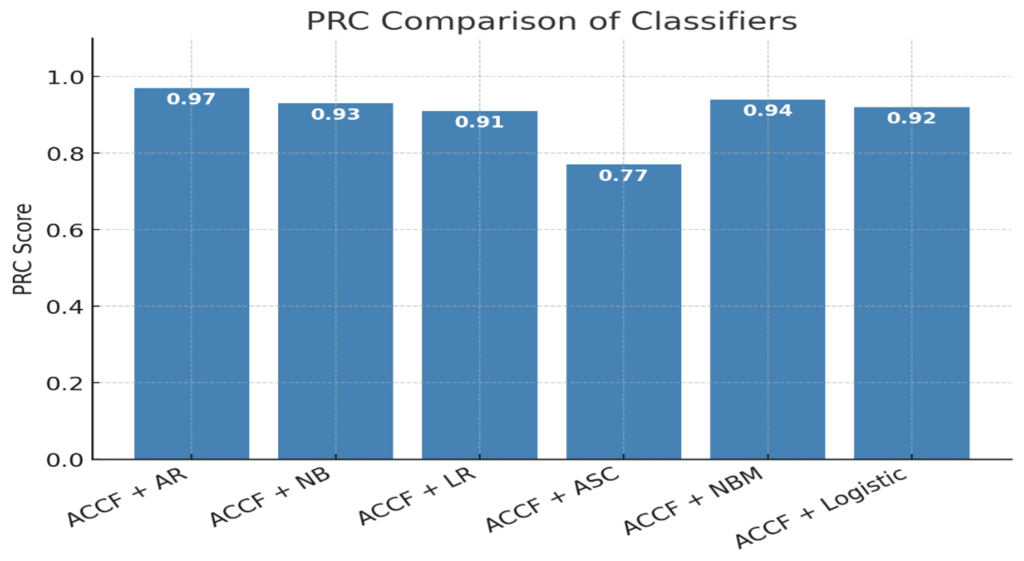

Figure 6: Model Vs PRC

Table 2: Classifiers Vs Statistical outcome

S.No	Classifier	Time	Kappa	F-Measure	MCC
1	ACCF + AR	0.19	0.64	0.89	0.64
2	ACCF + NB	0.14	0.61	0.84	0.62
3	ACCF + LR	0.16	0.62	0.85	0.61
4	ACCF + ASC	1.01	0.55	0.81	0.52
5	ACCF + NBM	2.95	0.58	0.44	0.59
6	ACCF + Logistic	0.12	0.62	0.83	0.60

The table 2 above illustrates the time consumption, Kappa, F-Measure, and Matthews Correlation Coefficient (MCC) values for the ACCF+AR, ACCF+NB, ACCF+LR, ACCF+ASC, ACCF+NBM, and ACCF+Logistic models.

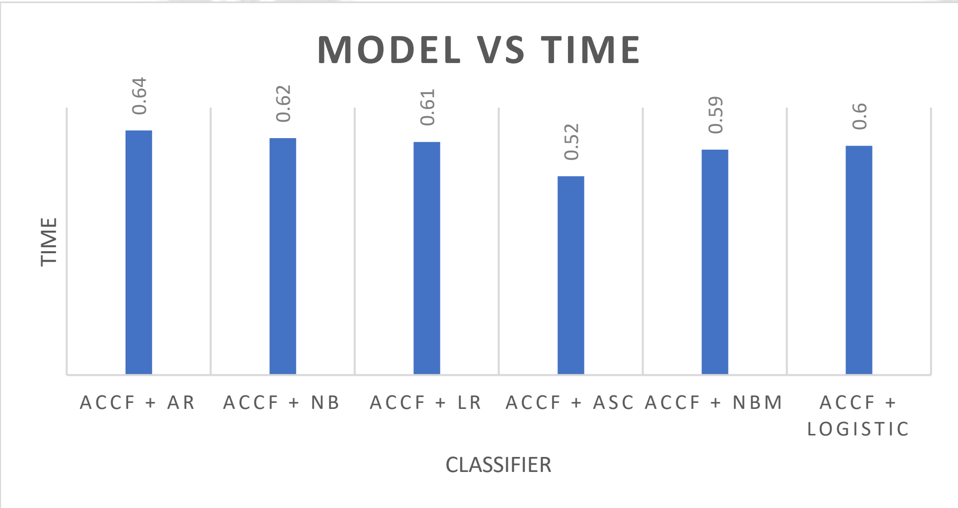

Figure 7: Model Vs Time

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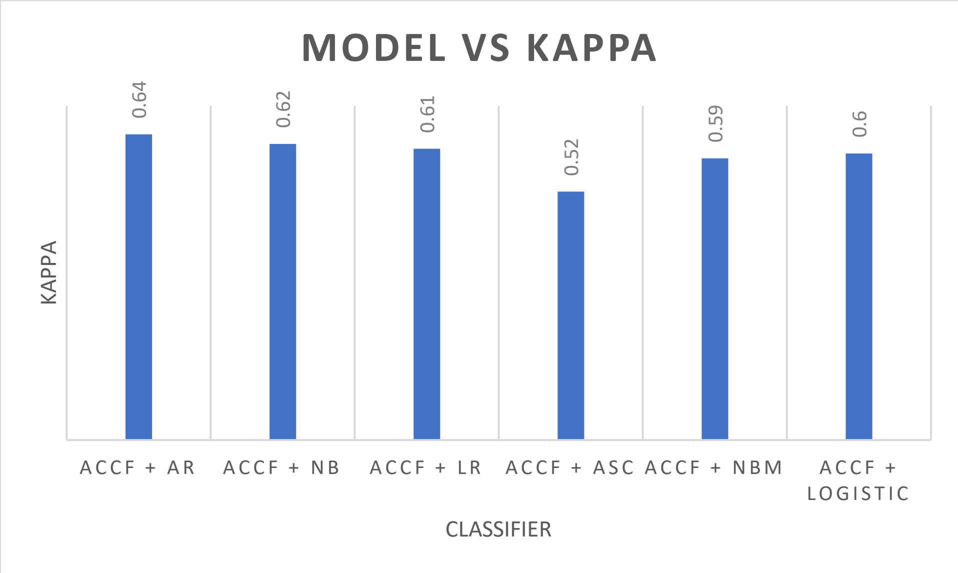

Figure 8: Model Vs KAPPA

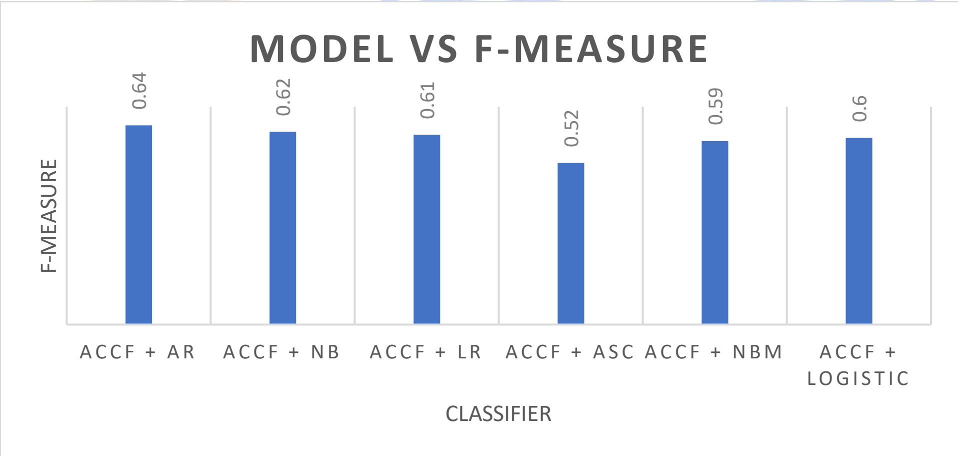

Figure 9: Model Vs F-MEASURE

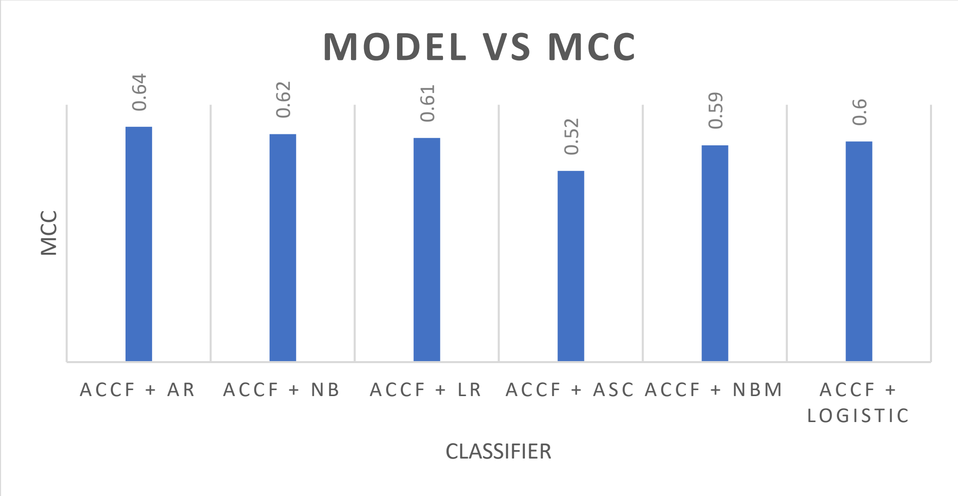

Figure 10: Model Vs MCC

Table 3: Classifiers Vs MCC

Classifier	MCC
ACCF + AR	0.64
ACCF + NB	0.62
ACCF + LR	0.61
ACCF + ASC	0.52
ACCF + NBM	0.59
ACCF + Logistic	0.60

Conclusion

This research presented an intelligent driver drowsiness detection framework integrated with cloud-assisted machine learning techniques to improve transportation safety and reduce fatigue-related road accidents. The proposed system utilized behavioural and physiological indicators such as eye closure, yawning frequency, head movement, and facial expressions to identify signs of driver fatigue in real time. Auto Color Correlogram Filter (ACCF) features were extracted from driver facial images, and multiple machine learning classifiers including Additive Regression (AR), Naïve Bayes (NB), Linear Regression (LR), Attribute Selected Classifier (ASC), Naïve Bayes Multinomial (NBM), and Logistic Regression were implemented and evaluated.Experimental analysis demonstrated that the ACCF + AR model achieved superior performance compared to the other classifiers, obtaining 92.10% accuracy, 0.93 precision, 0.90 recall, 0.98 ROC value, and 0.97 PRC value. The model also achieved a high F-measure of 0.89 and MCC value of 0.64, indicating strong classification capability and reliability for real-time driver monitoring applications. The results confirm that integrating ACCF feature extraction with machine learning classifiers significantly improves drowsiness detection accuracy while minimizing false alarms.

Furthermore, the integration of cloud computing enhanced the scalability, storage capability, and continuous learning performance of the proposed framework, enabling efficient deployment in modern intelligent transportation systems. The proposed system provides timely warning alerts to drivers and contributes toward reducing fatigue-induced accidents and improving road safety. Overall, this research demonstrates that intelligent machine learning–based drowsiness detection systems can serve as an effective solution for next-generation smart vehicle safety applications.

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