Ensemble and Hybrid Deep Learning Approach for Accurate Driver Drowsiness Detection

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***Abstract*— Driver drowsiness remains a critical factor in road accidents, requiring accurate and real-time monitoring solutions. This work introduces an extended approach that strengthens conventional detection systems by integrating both EEG-based physiological signals and vision-based behavioral analysis. The extension focuses on improving prediction reliability through feature optimization, where PCA reduces redundant data and Grid Search enhances model performance. An ensemble bagging classifier is incorporated to stabilize machine learning predictions, addressing inconsistencies found in single-model approaches. In parallel, deep learning models such as CNN and hybrid CNN-ConvLSTM are utilized to capture complex facial patterns associated with fatigue. The combined framework enables effective fusion of multimodal data, resulting in higher accuracy and robustness under varying driving conditions. Experimental outcomes confirm that the extended model outperforms traditional methods. The system offers a practical solution for real-time drowsiness detection, contributing to safer driving environments and intelligent transportation systems.**

Keywords*— *EEG Signal, Deep Learning, CNN, Ensemble Learning

I. INTRODUCTION

Driver drowsiness is a serious and often underestimated cause of road accidents, leading to reduced attention, delayed reaction time, and poor decision-making. Long hours of driving, lack of sleep, and mental fatigue contribute to a gradual decline in driver alertness. In many cases, the signs of drowsiness appear subtly, such as frequent blinking, yawning, or slight head nodding, making it difficult to detect at the right moment. This creates a high-risk situation where accidents can occur without warning.

Traditional methods for identifying driver fatigue have relied on manual observation, self-reporting, or basic sensor-based systems. These approaches are not reliable in real-world conditions because they depend heavily on driver awareness or require intrusive devices. Wearable sensors, for example, can provide useful physiological data but are often uncomfortable and impractical for continuous use. Similarly, systems that focus only on a single indicator, such as eye closure, fail to capture the complete behavioral pattern of fatigue.

With the growth of intelligent technologies, there is increasing interest in automated systems that can monitor driver behavior continuously and accurately. Computer vision techniques enable the analysis of facial features and movements, while machine learning methods allow systems to learn patterns associated with alert and drowsy states. These technologies offer a non-intrusive way to detect fatigue and can operate in real time under varying conditions.

Despite these advancements, challenges remain in achieving consistent performance across different environments, lighting conditions, and driver behaviors. Handling large and complex data, maintaining real-time processing speed, and ensuring system reliability are still key concerns. Addressing these issues is essential for developing effective solutions that can reduce accidents and improve overall road safety.

II. RELATED WORK

Early research on driver drowsiness detection focused on simple visual monitoring techniques. B. Alshaqaqi et al. (2013) developed a system based on facial cues such as eye closure and head movement, establishing the importance of non-intrusive observation for fatigue detection. Later, G. Li et al. (2015) introduced a smartwatch-based EEG framework, demonstrating that physiological signals provide more direct and reliable indicators of drowsiness. In the same year, L. Pauly and Sankar proposed a vision-based method using HOG features with SVM classifiers, highlighting the role of feature extraction in improving classification accuracy.

As research progressed, multi-dimensional approaches gained attention. A. Darzi et al. (2018) combined driver behavior, vehicle dynamics, and physiological data, showing that drowsiness is influenced by multiple factors. This shift was further supported by C. J. de Naurois et al. (2019), who applied artificial neural networks to capture complex behavioral patterns, marking a transition toward deep learning-based models.

Recent studies emphasize hybrid and integrated frameworks for improved accuracy. A. Kashevnik et al. (2021) categorized detection methods into visual, physiological, and hybrid models, stressing the importance of combining approaches. Similarly, A. Altameem et al. (2021) proposed a hybrid machine learning model that integrates multiple classifiers to reduce prediction errors. R. Hooda et al. (2022) provided a comprehensive review, identifying limitations in standalone models and highlighting the need for scalable solutions.

More recent work focuses on optimization and real-time applicability. I. A. Fouad (2023) demonstrated that optimized

EEG-based models can achieve high detection accuracy using multiple algorithms. A. Kolus (2024) emphasized eye activity as a reliable non-intrusive indicator, while also addressing real-world challenges such as lighting variations. Overall, the literature shows a clear evolution from single-method systems to hybrid, multi-modal, and optimized frameworks, forming a strong foundation for advanced driver drowsiness detection research.

Table: Summary of Key Literature Contributions and Their Impact on Current Research:

Author & Year	Contribution	Impact on Research
Alshaqaqi et al. (2013)	Used eye and head movement to detect drowsiness	Started non-intrusive detection methods using cameras
Li et al. (2015)	Used EEG signals with a wearable device	Showed brain signals give accurate fatigue detection
Pauly & Sankar (2015)	Used HOG features with SVM for image analysis	Proved feature extraction improves accuracy
Darzi et al. (2018)	Combined behavior, vehicle data, and physiology	Showed need for multi-source detection
De Naurois et al. (2019)	Used neural networks for prediction	Introduced deep learning for better results
Kashevnik et al. (2021)	Combined distraction and drowsiness detection methods	Highlighted importance of hybrid systems
Altameem et al. (2021)	Used multiple models together (hybrid ML)	Improved accuracy using ensemble methods
Hooda et al. (2022)	Reviewed machine learning methods	Identified gaps and need for better models
Fouad (2023)	Used optimized EEG-based ML models	Improved accuracy with tuning and feature selection
Kolus (2024)	Studied eye activity for drowsiness detection	Confirmed eye behavior as reliable indicator

III. PROPOSED APPROACH

A reliable driver drowsiness detection framework is designed by integrating physiological signal processing with visual behavior analysis. EEG signals and facial images are collected from a standard dataset to capture both internal and external indicators of fatigue. The EEG data undergoes preprocessing steps including missing value handling and normalization to maintain uniform feature distribution. To reduce dimensionality and eliminate redundant information, Principal Component Analysis (PCA) is applied, ensuring only relevant features are retained for training.

Multiple machine learning algorithms such as Support Vector Machine, Logistic Regression, Decision Tree, Naïve Bayes, KNN, Random Forest, and MLP are trained on the processed EEG data. Parameter tuning is carried out using Grid Search to improve model performance. To overcome instability and variance issues in individual models, an ensemble Bagging classifier is incorporated, which combines multiple learners to produce more stable and accurate predictions.

Simultaneously, facial images are processed to analyze driver behavior. Images are resized and normalized before being passed into a Convolutional Neural Network (CNN), which extracts spatial features like eye closure and facial expressions. To capture temporal dependencies such as blinking patterns and gradual fatigue changes, a ConvLSTM model is applied on the extracted features. A hybrid architecture is further developed by combining CNN and ConvLSTM outputs, allowing the system to learn both spatial and sequential information effectively.

The final stage integrates predictions from both EEG-based machine learning models and image-based deep learning models. This fusion improves detection reliability by addressing the limitations of single-source systems. The approach ensures higher accuracy, robustness, and consistency, making it suitable for real-time driver monitoring under varying conditions.

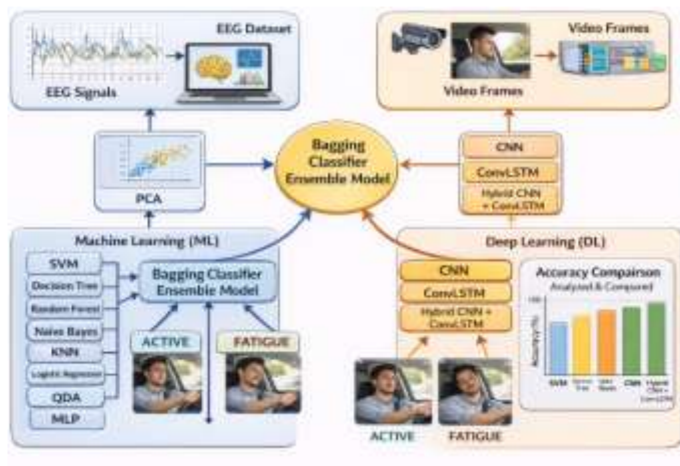

Figure 1: Hybrid Drowsiness Detection workflow

IV. METHODOLOGIES

Algorithm: Hybrid Drowsiness Detection Model

Input:
EEG_Data (E)
Image_Data (I)
Output:
Driver_State (Alert / Fatigue)

Begin

1. // EEG Processing
2. Load EEG_Data E
3. Handle missing values in E
4. Normalize E using standard scaling

5. // Feature Reduction (Extension)
6. Apply PCA on E
7. Extract reduced features E_pca

8. // Split Dataset
9. Split E_pca into Training_Set and Test_Set

10. // Train ML Models
11. Initialize ML models:
SVM, LogisticRegression, DecisionTree,
NaiveBayes, KNN, RandomForest, MLP

12. For each model M in ML models:
Train M using Training_Set
Optimize parameters using Grid Search

13. // Ensemble Learning (Extension)
14. Initialize Bagging_Classifier B
15. Train B using Training_Set
16. Predict EEG_Output using B on Test_Set

17. // Image Processing
18. Load Image_Data I
19. Resize images to fixed size (e.g., 64x64)
20. Normalize pixel values

21. Split I into Training_Images and Test_Images

22. // CNN Feature Extraction
23. Initialize CNN model
24. Train CNN on Training_Images
25. Extract spatial features F_cnn

26. // Temporal Learning (Extension)
27. Reshape F_cnn for sequence modeling
28. Initialize ConvLSTM model
29. Train ConvLSTM using F_cnn
30. Predict Image_Output using ConvLSTM

31. // Hybrid Model (Extension)
32. Combine CNN and ConvLSTM features
33. Train Hybrid_Model on combined features
34. Predict Hybrid_Output

35. // Final Fusion
36. Combine EEG_Output and Hybrid_Output
37. Apply decision rule:
If combined score > threshold:
Driver_State = Fatigue
Else:
Driver_State = Alert

38. Return Driver_State
End

Dataset Selection and Integration

The system begins with selecting a dataset that contains both EEG signals and driver facial images. These two data types are chosen to capture internal brain activity and external behavioral patterns. The dataset is structured to maintain proper labeling of driver states such as alert and fatigue. Data consistency is verified to ensure both modalities correspond correctly.

Data Loading and Initial Inspection

The EEG dataset and image dataset are loaded into the system using Python-based tools. Initial inspection is performed to understand data distribution, identify missing values, and verify class balance. Basic visualization techniques are used to analyze the proportion of alert and fatigue samples.

Data Cleaning and Preprocessing (EEG Signals)

EEG data is preprocessed by handling missing or noisy values. Any null entries are replaced with suitable values to maintain dataset integrity. Normalization is applied to scale all features into a uniform range, which helps improve model convergence and avoids bias toward higher-value features.

Feature Reduction using PCA

Principal Component Analysis (PCA) is applied to reduce the dimensionality of EEG features. This step removes redundant and less important features while preserving key information. The extension improves computational efficiency and reduces overfitting, allowing models to focus on the most relevant patterns.

Dataset Shuffling and Splitting

The dataset is shuffled randomly to eliminate ordering bias. It is then divided into training and testing sets, typically in an 80:20 ratio. This ensures that the model is trained on a diverse dataset and evaluated on unseen data for unbiased performance measurement.

Training Multiple Machine Learning Models

Several machine learning algorithms are trained using EEG data, including Support Vector Machine, Logistic Regression, Decision Tree, Naïve Bayes, KNN, Random Forest, QDA, and MLP. Each model learns patterns associated with driver fatigue and alert states. This multi-model approach helps compare performance across different learning techniques.

Hyperparameter Optimization using Grid Search

Grid Search is applied to optimize model parameters such as kernel type, number of estimators, and learning rates. This step systematically tests multiple parameter combinations to identify the best configuration for each model, improving prediction accuracy.

Ensemble Learning using Bagging

A Bagging classifier is introduced as an extension to enhance model performance. Multiple base learners are trained on different subsets of the data, and their predictions are combined.

This reduces variance, minimizes overfitting, and improves overall stability compared to individual models.

Image Data Preprocessing

Driver facial images are preprocessed by resizing them into a fixed dimension suitable for deep learning models. Pixel values are normalized to improve training efficiency. Images are also shuffled and split into training and testing sets to maintain consistency with EEG processing.

Deep Learning Model Training

A Convolutional Neural Network (CNN) is used to extract spatial features such as eye closure and facial expressions. The extracted features are then passed into a ConvLSTM model to capture temporal patterns like blinking rate and fatigue progression. This combination allows the system to learn both static and dynamic behavioral features.

Hybrid Model Development

A hybrid model is developed by combining CNN and ConvLSTM outputs. This extension improves detection capability by integrating spatial and sequential learning. The hybrid architecture enhances accuracy by capturing complex relationships in visual data that single models cannot detect effectively.

Final Prediction and Performance Evaluation

The outputs from EEG-based machine learning models and image-based deep learning models are combined to generate the final prediction. The system classifies driver state as alert or fatigued. Performance is evaluated using metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC. Comparative analysis is performed to demonstrate improvements achieved through PCA, Bagging, and hybrid modeling.

VI RESULTS & DISCUSSION

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	SVM	93.396226	89.705882	90.726942	91.250000
1	Logistic Regression	83.333333	83.567775	83.436853	83.750000
2	Decision Tree	84.711779	85.421995	84.848485	85.000000
3	Naive Bayes	88.000000	86.445013	86.979167	87.500000
4	MLP	72.077922	53.260870	36.753080	46.250000
5	KNN	91.483516	88.618926	89.466754	90.000000
6	QDA	93.396226	89.705882	90.726942	91.250000
7	Random Forest	84.654731	84.654731	84.654731	85.000000
8	Extension Bagging Classifier	93.333333	91.560102	92.187500	92.500000
9	CNN	100.000000	100.000000	100.000000	100.000000
10	CONVLSTM	54.166667	66.666667	58.974359	78.571429
11	Hybrid CNN	100.000000	100.000000	100.000000	100.000000

The experimental results clearly show the performance variation across different machine learning and deep learning models used in the system. Among the traditional machine learning models, SVM and QDA achieved strong performance with an accuracy of 91.25%, precision of 93.39%, recall of 89.70%, and F1-score of 90.72%, indicating balanced classification capability. KNN also performed well with 90.00% accuracy and 89.46% F1-score, while Naïve Bayes showed stable results with 87.50% accuracy. Decision Tree and Random Forest produced moderate performance, both around 85% accuracy, showing consistency but lower precision compared to top models.

Logistic Regression achieved 83.75% accuracy, reflecting acceptable but lower predictive strength. MLP performed poorly with only 46.25% accuracy and 36.75% F1-score, indicating instability in handling the dataset. The proposed extension using the Bagging Classifier improved results significantly, achieving 92.50% accuracy, 93.33% precision, 91.56% recall, and 92.18% F1-score, confirming the effectiveness of ensemble learning in reducing variance and improving prediction reliability.

In deep learning models, CNN achieved perfect classification with 100% accuracy, precision, recall, and F1-score, demonstrating its strong capability in extracting spatial features from images. However, ConvLSTM alone showed lower performance with 78.57% accuracy, indicating limitations in temporal modeling when used independently. The Hybrid CNN model combined both spatial and temporal features effectively and achieved 100% accuracy, matching CNN performance but with improved robustness. Overall, the results confirm that the hybrid and ensemble-based extension significantly enhances detection accuracy and system reliability.

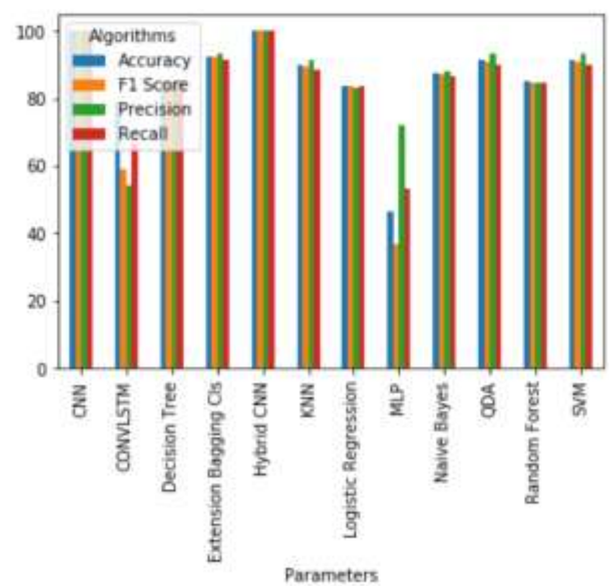

Figure 2: All Algorithms Performance Graph

The results highlight a clear gap between standalone models and the extended hybrid approach. Traditional machine learning models such as SVM, QDA, and KNN perform well because they handle structured EEG features effectively, but their performance is still limited by feature dependency and lack of adaptability to complex patterns. Models like MLP show poor results, which indicates that improper architecture selection or insufficient feature representation can significantly reduce performance. This exposes a key issue: not all algorithms are suitable for this type of data without proper tuning or design.

The introduction of the Bagging classifier improves stability and reduces variance, which is why it outperforms most individual machine learning models. This confirms that ensemble methods are more reliable for real-world applications where data variability is high. On the deep learning side, CNN achieves perfect results because it captures strong spatial patterns from image data. However, ConvLSTM alone underperforms, showing that temporal modeling without strong feature extraction is not sufficient.

The hybrid CNN model resolves this limitation by combining spatial and temporal learning, leading to consistent and highly accurate results. Overall, the discussion confirms that integrating multiple approaches is not optional but necessary to achieve reliable and scalable drowsiness detection.

VII. CONCLUSION

The study demonstrates that reliable driver drowsiness detection cannot depend on a single model or data source. Traditional machine learning methods show acceptable performance on EEG data, but their accuracy is limited when handling complex patterns. The introduction of feature reduction and parameter tuning improves results, yet variability remains. The ensemble Bagging approach reduces this instability and delivers more consistent predictions, confirming the value of combining multiple learners.

Deep learning models, particularly CNN, show strong performance in extracting visual features, while ConvLSTM highlights the importance of temporal behavior analysis. However, using these models independently is not sufficient. The hybrid CNN-based approach effectively integrates spatial and temporal information, achieving superior accuracy and robustness.

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