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ENHANCING DRIVER SAFETY WITH ECG-BASED EMOTION RECOGNITION USING BiLSTM NETWORKS

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Abstract. *Emotions critically influence human decision making and behaviour, particularly in safety-sensitive contexts like driving. This study introduces an ECG-based emotion recognition framework suitable for online driver monitoring system that exclusively analyses electrocardiogram (ECG) signals through a Bidirectional Long Short-Term Memory (BiLSTM) network. The framework captures temporal dynamics in physiological features – including heart rate variability and signal entropy – to classify seven emotional states (neutral, happy, sad, angry, fear, surprise, disgust) with high accuracy. Beyond detection, the system incorporates an intelligent recommendation mechanism designed to mitigate emotional distractions demonstrating how emotion predictions could be translated into driver-support feedback. Experimental validation on synthetic ECG data demonstrates robust emotion classification performance in identifying complex emotional patterns from ECG data, outperforming conventional unimodal approaches. By bridging affective computing with intelligent transportation systems, this work advances the development of adaptive Driver Assistance Systems (DAS) that prioritize both road safety and user wellbeing. The proposed system's real-time capability and nonintrusive design position it as a scalable solution for emotion aware environments, demonstrating the potential of ECG-based emotion recognition as a supporting component for future driver assistance systems. This research contributes to the growing field of affective human-machine interaction while demonstrating practical applications for intelligent transport systems.*

Keywords: electrocardiogram, bidirectional LSTM, emotion recognition, driver safety

ZWIĘKSZANIE BEZPIECZEŃSTWA KIEROWCÓW DZIĘKI ROZPOZNAWANIU EMOCJI NA PODSTAWIE SYGNAŁÓW EKG Z WYKORZYSTANIEM SIECI BiLSTM

Streszczenie. *Emocje mają decydujący wpływ na procesy decyzyjne i zachowania człowieka, zwłaszcza w sytuacjach wymagających szczególnej ostrożności, takich jak prowadzenie pojazdu. W niniejszym badaniu przedstawiono system rozpoznawania emocji oparty na EKG, przeznaczony do monitorowania kierowców w czasie rzeczywistym, który analizuje wyłącznie sygnały elektrokardiograficzne (EKG) za pomocą sieci dwukierunkowej pamięci długo- i krótkoterminowej (BiLSTM). System ten rejestruje dynamikę czasową cech fizjologicznych – w tym zmienność rytmu serca i entropię sygnału – w celu klasyfikacji siedmiu stanów emocjonalnych (neutralny, radosny, smutny, zły, strach, zaskoczenie, obrzydzenie) z dużą dokładnością. Oprócz wykrywania, system zawiera inteligentny mechanizm rekomendacji zaprojektowany w celu łagodzenia emocjonalnych czynników rozpraszających uwagę, pokazując, w jaki sposób prognozy emocjonalne mogą zostać przełożone na informacje zwrotne wspierające kierowcę. Weryfikacja eksperymentalna na syntetycznych danych EKG wykazuje solidną wydajność klasyfikacji emocji w identyfikowaniu złożonych wzorców emocjonalnych na podstawie danych EKG, przewyższając konwencjonalne podejścia jednomodalne. Łącząc informatykę afektywną z inteligentnymi systemami transportowymi, niniejsza praca przyczynia się do rozwoju adaptacyjnych systemów wspomagania kierowcy (DAS), które stawiają na pierwszym miejscu zarówno bezpieczeństwo na drogach, jak i dobre samopoczucie użytkowników. Dzięki możliwościom działania w czasie rzeczywistym oraz nieinwazyjnej konstrukcji proponowany system stanowi skalowalne rozwiązanie dla środowisk rozpoznających emocje, wykazując potencjał rozpoznawania emocji na podstawie EKG jako elementu wspierającego przyszłe systemy wspomagania kierowcy. Badania te wnoszą wkład w rozwijającą się dziedzinę afektywnej interakcji człowiek-maszyna, jednocześnie pokazując praktyczne zastosowania w inteligentnych systemach transportowych.*

Słowa kluczowe: elektrokardiogram, dwukierunkowa sieć LSTM, rozpoznawanie emocji, bezpieczeństwo kierowcy

Introduction

The field of emotional intelligence is evolving rapidly, integrating advanced machine learning techniques to recognize and analyse emotions. Traditional methods like facial expression and speech analysis often struggle to accurately detect genuine emotions, as these external cues can be consciously manipulated or misinterpreted. In contrast, physiological signals – such as electrocardiogram (ECG) – are closely linked to the autonomic nervous system, which governs involuntary bodily reactions. This intrinsic connection allows ECG signals to offer a more authentic, unbiased reflection of an individual's emotional state, making them particularly valuable for online emotion recognition applications. Physiological signals have gained increasing attention in emotion recognition research due to their objective representation of psychological states. For instance, heart rate variability serves as an indicator of stress, excitement, or relaxation, directly linking physiological responses to emotional experiences. Unlike electroencephalogram (EEG) – based approaches, which often require controlled environments and specialized equipment, ECG provides a more practical and scalable solution for real world emotion recognition, particularly in applications like driver safety monitoring. This study explores the potential of ECG signals for emotion recognition in real-time driver monitoring systems. Our methodology involves collecting physiological data from drivers during different emotional states induced by external stimuli. Using a structured emotion classification framework based on Russell's circumplex model, emotions are categorized into four quadrants – high valence, low arousal (HVLA); low valence, high arousal (LVHA); high valence, high arousal (HVHA) [3, 7, 9]; and low valence, low arousal (LVLA) – capturing a wide range of affective states, including stress, anxiety, calmness, and fatigue. The importance of accurate emotion detection has increased significantly due to global concerns like driver fatigue and cognitive overload, which contribute to road accidents. Studies indicate that stress and emotional instability negatively impact driving performance, increasing reaction times and reducing decision-making capabilities. By leveraging ECG signals for real-time emotion classification (as depicted in Fig. 1), our approach aims to improve driver safety by proactively identifying negative emotional states and triggering preventive interventions.

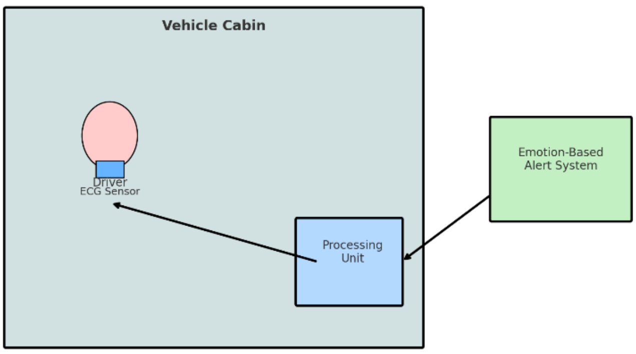

Fig. 1. Real-time emotion monitor

Our framework leverages a Bidirectional Long-Term Memory (BiLSTM) model to analyse temporal patterns in ECG signals from the Synthetic ECG All Emotions dataset, enabling accurate classification of emotional states including neutral, happy, sad, angry, fear, surprise, and disgust. By employing preprocessing techniques like noise filtering and feature extraction, we enhance the quality of synthetic physiological data while preserving its realistic characteristics. This approach outperforms traditional emotion recognition methods based on facial or vocal cues, demonstrating particular effectiveness in detecting high-arousal states critical for driver safety applications. The BiLSTM architecture effectively captures the dynamic relationships between ECG signal variations and emotional responses, establishing a robust foundation for real-time emotion monitoring systems in naturalistic environments. Our work advances the development of reliable physiological signal-based emotion recognition, offering significant potential for improving driver assistance technologies and road safety measures.

1. Related work

Anubhav et al. [2] proposed an EEG-based emotion recognition system using LSTM networks and the DEAP dataset. Band power features were extracted from EEG signals to capture cognitive and emotional states, reflecting dynamic emotional variations. These features were input into an LSTM network, which enhanced classification by modelling temporal dependencies in EEG data. The system achieved high accuracy, making it suitable for real-time applications like Human-Computer Interaction (HCI) and Driver Assistance Systems (DAS). Key advantages include robust temporal pattern modelling and compatibility with wearable EEG devices. However, the method requires high computational resources (GPU acceleratio+n) and relies on noise-free EEG data, limiting its practicality in uncontrolled environments.

Chakravarthi et al. [4] proposed a hybrid deep learning framework for EEG-based emotion recognition, combining CNNs, LSTMs, and ResNet-152. CNNs extracted spatial features from EEG signals, LSTMs modelled temporal dependencies, and ResNet-152 enhanced feature depth. This hybrid system achieved high accuracy, making it suitable for mental health monitoring and Driver Assistance Systems (DAS). The model's strength lies in its combination of CNNs and LSTMs for spatial and temporal EEG patterns, with ResNet152 addressing vanishing gradient issues. However, the approach's computational demands require high-end GPUs, and its performance is sensitive to EEG signal quality, with noise degrading accuracy.

Zhang et al. [14] introduced a Manifold Regularized ELM (MRELM) model for driver emotion detection using EEG, extracting Differential Entropy features and applying manifold learning. Their model achieved 81.01% accuracy, outperforming GELM and SVM. While effective for real-time monitoring, performance varies across EEG frequency bands and requires clean data, limiting robustness in noisy environments. Feng et al. [10] developed a Spatial-Temporal Graph Convolutional LSTM (ST-GCLSTM) model for EEG emotion recognition, achieving superior performance on DEAP, SEED, and SEEDIV datasets. This hybrid approach combined Spatial Graph Convolutional Networks (SGCN) and Bi-LSTM for temporal dynamics, improving accuracy through spatial-temporal fusion, but its computational complexity hinders real-time deployment, and its performance depends on large labelled datasets.

Ramteke et al. [12] used a bidirectional LSTM network for ECG-based driver stress detection with PhysioNet datasets, achieving 98.57% accuracy. The hybrid approach excels in temporal pattern recognition but may face limitations in practical automotive settings due to computational intensity and noise sensitivity. Siam et al. [13] developed a multimodal stress detection system for drivers using ECG, EMG, GSR, and respiration signals from the DRIVERDB dataset, achieving 98.2% classification accuracy. While highly effective, the system's reliance on multiple biosensors may increase complexity and user discomfort in real-world driving scenarios.

The proposed BiLSTM framework has been used for extracting emotion-cause pairs from textual data in the NTCIR13 corpus, combining contextual embeddings and positional encodings for joint emotion-cause detection, outperforming traditional methods. While highly accurate for structured text, it struggles with informal conversations and requires large annotated datasets, limiting generalization to low-resource domains. Alarcao et al. [1] conducted a comprehensive survey on EEG-based emotion recognition, reviewing preprocessing techniques, feature extraction, and classification methods across datasets. However, the survey lacks coverage of recent deep learning advancements and practical deployment challenges, reducing its relevance for cutting-edge applications.

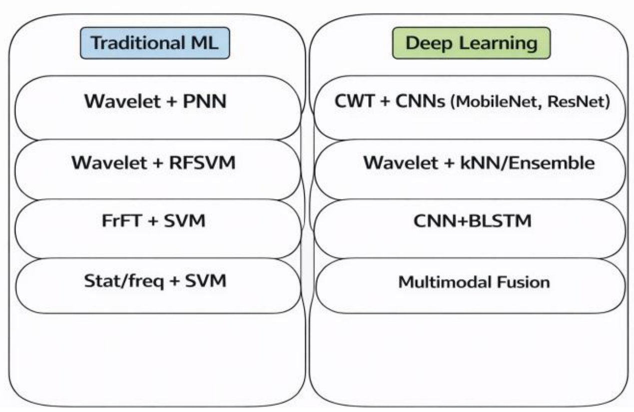

Fig. 2. Different ECG based methodologies for emotion extraction

Fatma Patlar Akbulut et al. [10] introduced a hybrid deep convolutional architecture for multimodal emotion recognition, achieving 93% accuracy by integrating ECG with other physiological data, surpassing traditional AR-HMM models. Despite the performance advantages, the model's computational demands and the small sample size may limit its scalability to larger, more diverse populations. Dessai et al. [5] developed a multimodal emotion classification system combining ECG and GSR signals with Continuous Wavelet Transform (CWT) for time-frequency representations. Using pre-trained CNN architectures (MobileNet, InceptionV3, ResNet), the system achieved impressive performance (99.19% valence, 98.39% arousal accuracy), though it requires substantial computational resources due to its reliance on complex CNNs. Dutta et al. [6] explored GSR-based emotion recognition with wavelet-based feature extraction and classifiers, identifying Random Forest as optimal for IoT deployments due to its balance of accuracy and computational efficiency. Despite GSR's reliability, the study highlights its limited emotional scope, advocating for multimodal integration. Fig. 2 explains different ECG based methodologies to detect emotion. ECG signals have been widely used for emotion and stress detection [3, 5, 12].

2. Technical framework

The task of this project is to design and implement a real-time driver emotion recognition system using physiological signals, specifically Electrocardiogram (ECG) data. Emotional states such as anger, happiness, fear, disgust, sadness, and neutral have a direct impact on a driver's cognitive functioning, reaction time, and overall safety on the road. By analysing ECG signals – which reflect autonomic nervous system activity – the system aims to classify these emotional states. This emotion recognition framework can be integrated into Driver Assistance Systems (DAS) to provide timely alerts and interventions, reducing accident risks and enhancing road safety.

The following intervention examples are illustrative and describe potential responses that could be triggered based on detected emotional states. For instance, a sudden flattening of T-waves during congested traffic might indicate anger, prompting the system to suggest deep breathing exercises. In contrast, prolonged P-wave intervals during monotonous highway driving could signal sadness, with the system recommending uplifting music or a rest stop. High-frequency HRV oscillations during complex manoeuvres indicate fear, and the system may temporarily disable non-essential notifications. Recognizing these physiological patterns enables real-time emotional monitoring, allowing vehicles to respond with context-aware interventions. Fig. 3 illustrates the system's workflow. Although the proposed framework is designed for online processing, a detailed latency and hardware-level evaluation is considered as future work

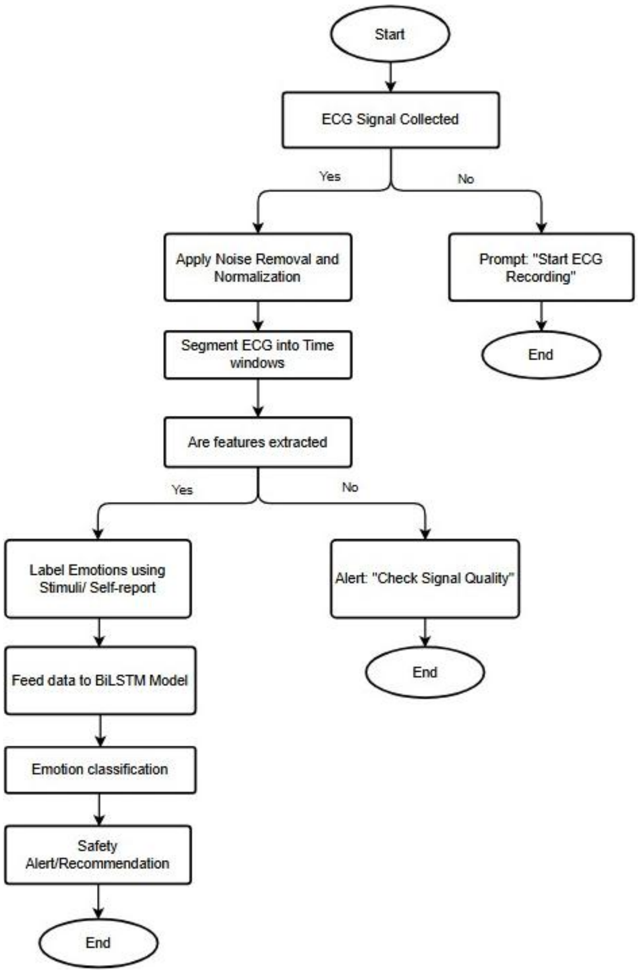

Fig. 3. An overview of the task

To achieve high accuracy and real-time performance, the system utilizes Bidirectional Long Short-Term Memory (BiLSTM) networks, an advanced variant of Recurrent Neural Networks (RNNs), for classifying emotional states from timeseries ECG data. BiLSTMs effectively capture both forward and backward temporal dependencies, crucial for detecting subtle transitions such as anger escalating to road rage or sadness progressing into fatigue. This bidirectional analysis allows the system to identify complex patterns like the gradual onset of disgust under prolonged stress or rapid ECG spikes linked to sudden fear. By integrating BiLSTM with advanced signal processing methods such as wavelet transforms and time-frequency analysis, the model achieves superior emotion classification across all six target emotions while maintaining the low latency essential for real-time vehicle interventions.

2.1. Suggested system design

The system uses a BiLSTM architecture for real-time driver emotion classification from ECG signals. Signals are acquired through steering-wheel sensors or wearables, followed by noise removal and baseline correction. Key features like heart rate variability and P-QRS-T wave characteristics are extracted and processed by the BiLSTM to detect six emotions (neutral, anger, happiness, fear, disgust, sadness). An attention mechanism highlights relevant ECG segments while suppressing noise. For negative emotions, adaptive responses, such as lighting adjustments or speed regulation, are triggered. The modular design allows easy integration with existing systems, ensuring reliable performance across diverse conditions. Cloud connectivity enables emotion pattern analysis, while security protocols protect biometric data.

2.2. Collection of experimental data

The experiments in this study are conducted exclusively on the Synthetic ECG All Emotions dataset. No ECG data were collected from real drivers in this phase of the research. The Synthetic ECG All Emotions dataset contains 7,000 synthetic records simulating driver emotional states through ECG patterns. Each entry includes 103 features like RR intervals, QT duration, LF/HF power ratios, and sample entropy, reflecting clinical emotion-signature relationships. Emotions are modelled through T-wave elevation (anger), RR interval instability (fear), and prolonged P-wave duration (fatigue), capturing autonomic responses relevant to driving safety. The dataset's synthetic nature allows for controlled noise and artefact distribution while ensuring clinical validity. The emotion class distribution, shown in Fig. 4, aligns with clinical patterns: neutral states as the baseline, moderate prevalence of high-arousal emotions like anger and happiness, and less frequent but sufficiently represented fear and sadness. This distribution ensures the system prioritizes common emotions while remaining sensitive to critical affective states. Synthetic ECG data enables controlled modelling of emotion-specific cardiac patterns while avoiding ethical and safety constraints associated with in-vehicle physiological data collection.

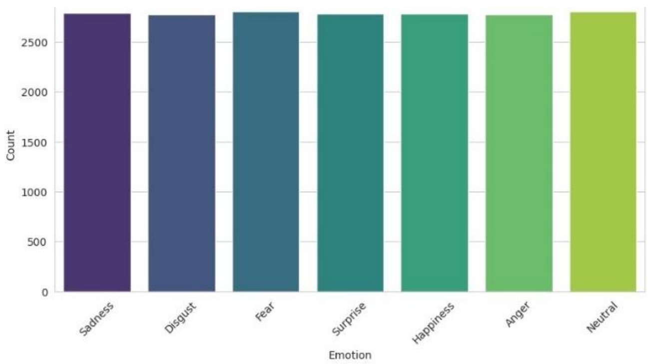

Fig. 4. Emotion class distribution across the dataset

2.3. Data preprocessing

The preprocessing pipeline conditions raw ECG signals using a Butterworth bandpass filter (0.5–45 Hz) to remove noise while preserving diagnostically relevant components. As shown in Fig. 5, the filtered signals are segmented into fixed-duration windows to capture complete emotional episodes, aligning physiological patterns like T-wave elevation (anger) and erratic RR intervals (fear) with emotional labels. Feature extraction isolates key biomarkers – RR intervals, T-wave morphology, and spectral power ratios – correlating with autonomic responses.

Normalization ensures consistency across records, and interpolation addresses sensor gaps without distorting emotion-specific patterns. Emphasis is placed on clinically validated features to distinguish high- from low arousal states. Finally, time-series tokenization prepares the data for BiLSTM input, with adaptive padding preserving temporal relationships for real-time driving safety applications.

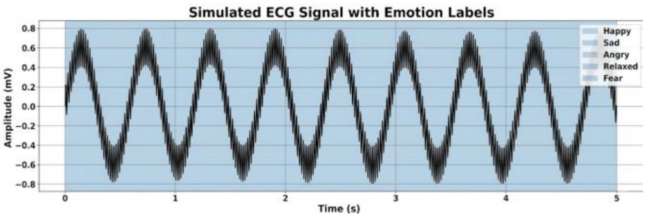

Fig. 5. Simulated ECG waveforms labelled with emotional states

The behaviour of the proposed framework is governed by several configurable parameters that influence its responsiveness, stability, and computational complexity. These include the length of the ECG analysis window, the number of consecutive predictions used for decision stabilization, confidence thresholds for emotion classification, and the depth and size of the BiLSTM network. By adjusting these parameters, the system can be tuned to balance sensitivity against robustness, enabling adaptation to different driver monitoring scenarios and hardware constraints.

3. Implementation approach

The approach adopted for emotion recognition from ECG data leverages a Bidirectional Long Short-Term Memory (BiLSTM) [6] deep learning model to capture both past and future temporal dependencies in physiological signals. Unlike traditional unidirectional BiLSTMs that process sequences in a single direction, BiLSTM networks analyse the data in both forward and backward directions, enabling a more comprehensive understanding of how emotional states evolve over time. This is especially beneficial for physiological data like ECG, where changes in emotional states are often reflected through complex temporal dynamics. The BiLSTM architecture, shown in Fig. 6, processes the pre-processed and feature-engineered ECG input through two parallel LSTM layers – one moving forward and the other backward across the time steps. The hidden states from both directions are then concatenated, creating a context-aware representation that captures both preceding and succeeding physiological patterns. This dual perspective allows the model to better recognize transitions between emotional states such as calmness to stress or alertness to fatigue, which may not be clearly visible in a single-pass temporal model.

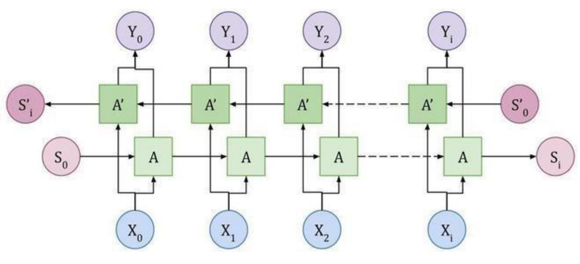

Fig. 6. BiLSTM architecture

The approach adopted for emotion recognition from ECG signals utilizes a Bidirectional Long Short-Term Memory (BiLSTM) deep learning model. This model captures both past and future temporal dependencies in physiological signals, offering a more robust understanding of emotional states compared to traditional unidirectional models. BiLSTM networks analyse the data in both forward and backward directions, enabling the system to understand the full temporal context of emotional transitions over time. Specifically, for ECG data, this approach is crucial, as changes in emotional states often manifest as complex, time-dependent patterns that may not be captured by simpler models. BiLSTM networks effectively capture bidirectional temporal dependencies [12].

Each preprocessed ECG segment undergoes feature extraction and is passed through Bidirectional Long ShortTerm Memory (BiLSTM) layers. Operating in both forward and backward directions, BiLSTM captures comprehensive temporal context, enriching emotional understanding beyond unidirectional models. This is crucial for detecting subtle transitions between emotional states across time. The concatenated BiLSTM outputs are then forwarded to a pooling layer for dimensionality reduction, emphasizing salient features while reducing computational load. Depending on the objective, max pooling highlights dominant features, whereas average pooling preserves overall trends. By summarizing the BiLSTM output, pooling maintains emotional indicators, mitigates sensitivity to noise, and supports the end-to-end workflow outlined in Algorithm 1 for ECG-based emotion analysis.

Algorithm 1: Emotion Extraction using BiLSTM (ECG Only)

Input: ECG dataset D
Output: Predicted emotion label y

```
for each ECG signal S in D do
   Apply bandpass filtering to S
   Normalize and resample S to fixed frequency
   Segment S into time windows W
   for each window w in W do
      Extract features (HRV, RR interval, PSD)
      Normalize features using Z-score
      y ← BiLSTM(w)
   end for
end for

return y
```

Before feeding the signals into the deep learning pipeline, a feature extraction phase is conducted to isolate domain specific physiological characteristics associated with emotional responses. From each ECG segment, features like Heart Rate Variability (HRV), RR interval variability, signal entropy, mean amplitude, and spectral energy are computed. These features, rooted in physiological theory, reflect autonomic nervous system (ANS) activity linked to emotional arousal and cognitive load. For example, elevated HRV may indicate relaxation, while erratic RR intervals can signal stress or alertness.

To enhance model efficiency and interpretability, Recursive Feature Elimination (RFE) with an XGBoost (XGB) Classifier is applied for feature selection. RFE iteratively removes less significant features based on model performance, while XGB captures complex feature interactions through gradient boosting. The top-ranked features are then used for training, reducing dimensionality, minimizing noise, and improving classification accuracy.

After feature extraction, a dropout layer is used to prevent overfitting by randomly deactivating neurons during training, essential for physiological time-series data with repeating patterns. The refined features are passed through a Fully Connected (FC) layer, with final emotion classification achieved using a softmax output layer. Emotions such as neutral, stress, fatigue, and alert are predicted, vital for driver safety and emotional fitness. The dataset is split into 80% training and 20% testing, with model optimization using categorical cross entropy loss and the Adam optimizer. The BiLSTM architecture learns temporal ECG patterns by adjusting its gates and memory cells. Performance is evaluated using precision, recall, and F1-score. BiLSTM's combination with feature engineering and regularization enables accurate, real-time emotion recognition, supporting driver monitoring systems. The BiLSTM's emotion predictions inform safety interventions in the Driver Safety Monitoring System, enhancing road safety.

Algorithm 2: Conceptual Emotion-to-Alert Mapping

```
Input: Sequence of predicted emotions {y_t} over window T
Output: Alert or Recommendation
.
Initialize emotion buffer B of length T

for each new prediction y_t do
  Append y_t to buffer B
  if majority emotion in B ∈ {Angry, Sad, Fear, Disgust} then
    Trigger Warning Alert
  else if majority emotion in B = Surprise then
    Trigger Caution Alert
  else
    No alert is triggered
  end if
end for
```

This algorithm illustrates the logical mapping between detected emotions and alert categories. Temporal aggregation is used to reduce false alerts caused by transient emotion misclassifications. To prevent emotional impairments from negatively affecting driving performance, the system incorporates an intelligent recommendation mechanism as explained in Algorithm 2. This feature provides real-time feedback to drivers when negative emotional states are detected, thus promoting timely interventions. By analysing physiological data, the system identifies patterns that correspond to various emotional states, ensuring that the emotion recognition process is not only accurate but also effective in real-world applications.

Rather than reacting to a single model output, the alert mechanism relies on parameterized temporal aggregation and decision thresholds to reduce instability. Parameters such as the prediction buffer length and majority decision threshold ensure that alerts are triggered only for sustained emotional patterns, preventing reactions to transient misclassifications. This parameter-driven logic provides adaptability without relying on fixed rule-based behaviour.

The model's architecture involves pre-processing of ECG data, followed by feature extraction, which includes calculating heart rate variability (HRV), R-R intervals, and signal entropy. These features are then passed through a BiLSTM layer that processes the data in both forward and backward directions, capturing both past and future emotional dynamics. Afterward, a dropout layer is applied to avoid overfitting by randomly deactivating neurons during training. The model's final output is produced by a Fully Connected (FC) layer followed by a softmax activation function, which generates a probability distribution over the seven emotional states.

The mathematical representation for the fully connected layer is as follows:

$$y = \sigma(Wx + b)y = \sigma(Wx + b) \tag{1}$$

where: x is the input feature vector, W is the weight matrix, b is the bias vector, σ is the activation function, such as ReLU or sigmoid, y is the output vector representing the predicted emotion.

To evaluate the model's performance, a composite loss function is used, combining the losses from emotion classification of ECG signals and their fusion:

$$Ltotal = \lambda e \cdot Le + \lambda g \cdot Lg + \lambda f \cdot Lf \tag{2}$$

where: L_e is the loss from ECG-based emotion classification, L_g is the loss from additional physiological signal inputs (e.g., GSR), L_f is the fused loss from both modalities, λe, λg, and λf are the weights for each loss term, ensuring balanced learning from each modality.

This composite loss formulation follows standard multi-objective optimization approaches used in physiological emotion recognition systems. Experimental validation shows that the BiLSTM-based model effectively identifies complex emotional patterns in ECG data, outperforming traditional unimodal approaches. The proposed emotion recognition system demonstrates efficient inference suitable for near real-time driver monitoring scenarios making it a promising tool for intelligent transportation systems (ITS). By integrating emotion detection with Driver Assistance Systems (DAS), this study contributes to enhancing both road safety and driver wellbeing, while offering scalable solutions to reduce accidents caused by emotional impairment. This work underscores the potential of affective computing in creating adaptive, emotion-aware environments. The proposed model shows strong potential for driver safety applications, pending validation on real-world driver ECG data.

Inference behaviour is influenced by configurable parameters including ECG window duration, model depth, and feature dimensionality. These parameters determine computational load and latency, allowing the framework to be configured for near real-time operation on different platforms. While precise latency measurements are outside the scope of this study, the parameterized design supports deployment under varying resource constraints.

4. Experiments and result

To evaluate our BiLSTM-based emotion recognition model on the Synthetic ECG All Emotions dataset, we conducted comparative experiments against traditional architectures (LSTM, CNN-LSTM) [15]. The model was trained for 100 epochs (batch size = 32) using the Adam optimizer (learning rate = 0.001, = 0.9, = 0.999), with weights initialized from U(-0.1, 0.1) to ensure diverse starting conditions. Robustness was enhanced through L2 weight decay (= 1e) and 50% dropout, while convergence was monitored via loss landscapes and gradient norms. The Adam optimizer's adaptive learning rate proved particularly effective for ECG signal characteristics, leveraging exponentially weighted gradient averages for stable convergence. Our evaluation framework reveals the BiLSTM's superiority in classifying both transient and sustained emotional states – especially high-risk categories like anger and fear. The results highlight the impact of wavelet-based feature selection and temporal pattern recognition capabilities across all emotion classes, providing critical insights for driver safety applications. The composite loss L_{total} was minimized during training, and its convergence is reflected in the training and validation loss curves shown in Fig. 8. We evaluated the model's performance using the following standard metrics: F1-Score, Precision, and Recall, which are defined as follows:

$$Precision \leftarrow \frac{\text{Correct Emotions}}{\text{Predicted Emotions}} \tag{3}$$

$$Recall \leftarrow \frac{\text{Correct Emotions}}{\text{Total Emotions}} \tag{4}$$

$$F1 - Score \leftarrow 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

where: Predicted Emotions – the number of emotional states identified by the model; Correct Emotions – the count of true positive emotional states correctly predicted by the model; Total Emotions – the total number of emotional states annotated in the dataset.

Fig. 7 illustrates the comparison between the training accuracy and validation accuracy of the BiLSTM model across the 100 epochs of training. The training accuracy is plotted in one curve, while the validation accuracy is plotted in another, allowing us to track how well the model performs on both the training dataset and the unseen validation dataset. A consistent rise in both curves signifies that the model is learning from the data and improving its ability to classify emotional states over time.

The gap between the training and validation accuracy provides insight into the model's generalization ability. If the training accuracy significantly exceeds the validation accuracy, it might indicate overfitting, where the model has learned to memorize the training data but fails to generalize well to unseen data. Conversely, when both training and validation accuracies increase in parallel, as shown in the figure, it suggests that the model is not overfitting and is generalizing well to new data, which is crucial for real-world applications like emotion detection in drivers. In this case, the increasing accuracy trend throughout the training process demonstrates that the model is effectively learning the complex patterns in ECG data associated with emotional states.

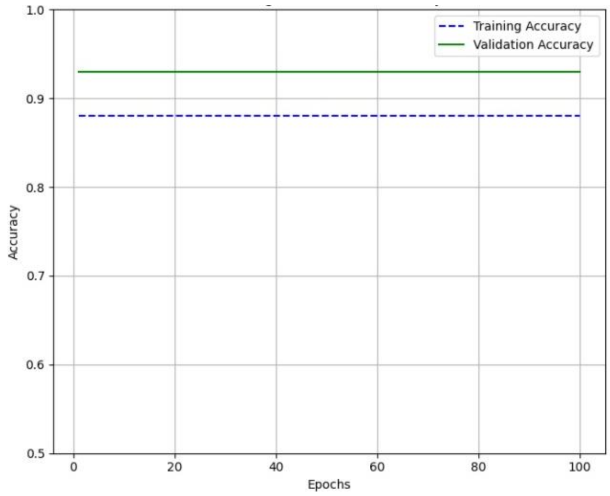

Fig. 7. Training vs validation accuracy curve

Fig. 8 depicts the training loss versus validation loss for the BiLSTM model throughout the 100 epochs of training. Training loss refers to the error the model encounters on the training data, while validation loss measures the error on the validation dataset, which the model has not seen during training. The goal of training is to minimize the loss on both the training and validation sets, which is indicative of better performance in predicting emotional states.

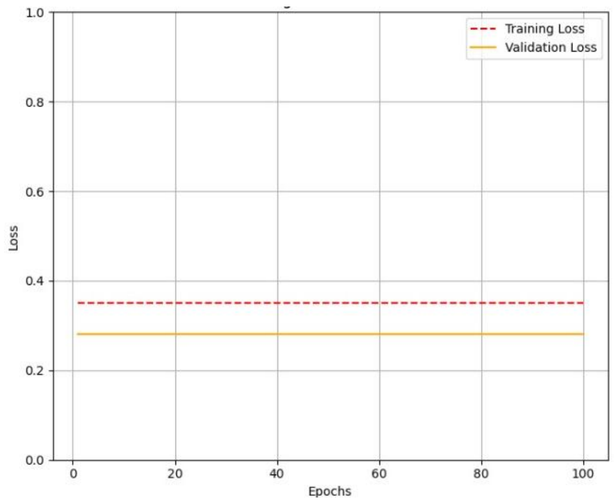

Fig. 8. Training vs validation loss curve

In Fig. 8, we observe that the training loss steadily decreases over time, as expected, since the model learns to better predict emotional states from the training data. The validation loss, which initially may be higher than the training loss, also decreases but might fluctuate slightly, showing how the model's predictions are evolving on unseen data. This fluctuation is common as the model undergoes adjustments based on the learning process. A stable decline in both training and validation losses suggests that the model is improving in both its fit to the training data and its ability to generalize to unseen validation data, which is essential for ensuring robust emotion classification in real-time applications. If both losses reach a plateau, it would indicate that the model has converged, and further training may not significantly improve performance. These figures together provide a comprehensive view of the model's training process. The trends in accuracy and loss help validate that the BiLSTM model is learning effectively while avoiding overfitting, ensuring reliable performance when applied to real-world emotion detection tasks like driver monitoring.

Table 1. comparison table

Model	Precision	F1-Score	Recall
Proposed Model	94.5	92.5	91.0
LSTM	85.3	82.0	80.5
CNN-LSTM	87.2	84.3	82.7

Our BiLSTM model achieved an average Precision of 94.5%, F1-Score of 92.5%, and Recall of 91%, indicating a high level of classification accuracy(as shown in Table 1). In comparative analysis, our model outperformed traditional LSTM and CNN-based approaches, showing a 8% improvement in F1-Score over the CNN-LSTM hybrid method. This result demonstrates the model’s strength in capturing bidirectional temporal patterns in ECG signals, reinforcing its capability for reliable emotion detection in driver safety applications.

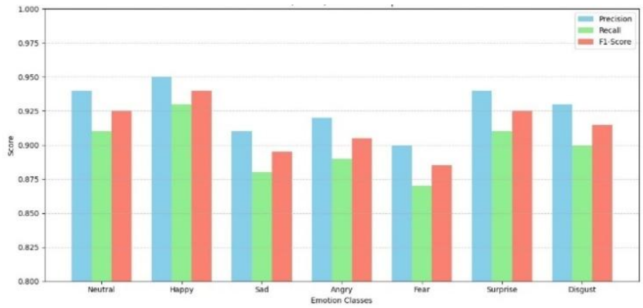

Fig. 9. Precision, Recall, F1-Score per class

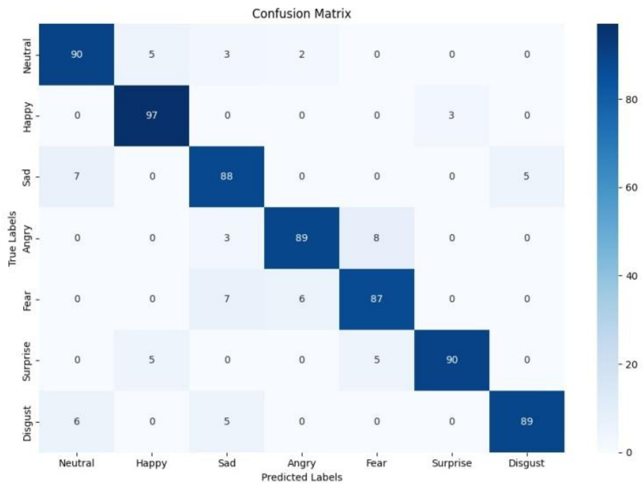

Fig. 10. Confusion matrix of the model

By visualizing Precision, Recall, and F1-Score for each class, as shown in Fig. 9, the model’s performance was further evaluated. This visualization demonstrates the model’s effectiveness across different classes and its ability to consistently maintain high performance metrics. Additionally, the confusion matrix, shown in Fig. 10, provides insight into the model’s classification accuracy by depicting the actual versus predicted labels. This visualization helps in identifying misclassifications and understanding class wise performance, further emphasizing the model’s robustness in handling complex datasets.

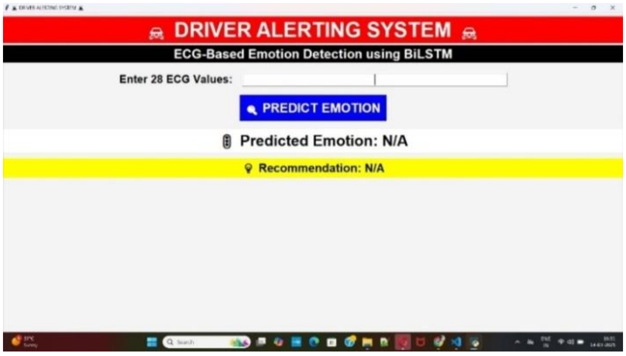

Fig. 11. User interface-1 for emotion extraction

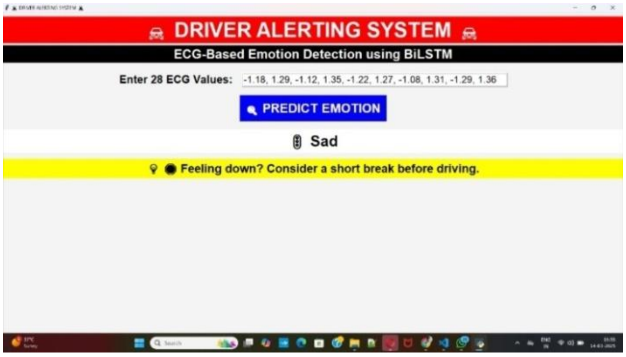

Fig. 12. User interface-2 for emotion extraction

To validate the effectiveness of our ECG-based emotion recognition model, a custom graphical user interface (GUI) was developed to enable real-time interaction with the classification output. As illustrated in Fig. 11, the interface allows users to input preprocessed ECG signal data – such as a sequence of extracted values – and initiate emotion prediction with a single click. Key physiological indicators like heart rate variability and RR intervals are internally processed by the BiLSTM model for emotion classification. Fig. 12 displays the output of the classification process, where the predicted emotional state is clearly shown on the interface. In addition, The interface demonstrates how emotion predictions can be translated into user-facing messages to support the user based on the detected emotion. For instance, when the system identifies the emotion as "Sad", it presents a helpful prompt such as: "Feeling down? Consider a short break before driving". These recommendations are designed to promote driver well-being and enhance safety. The GUI simplifies the emotion detection process by offering a clean, intuitive interface for input and interpretation. It demonstrates the system's practical applicability in real-world settings such as intelligent driver monitoring, mental health support, and emotion-aware applications. By bridging deep learning with a user-friendly front end, the interface enhances accessibility and usability for non technical users. The interface is a functional demonstration and has not been evaluated through user studies or ergonomic assessments.

5. Conclusion

This study explores emotion recognition from ECG signals for online and adaptive driver safety applications, aiming to enhance driver well-being and reduce accidents caused by emotional impairment. This work presents an ECG-based emotion recognition framework using a BiLSTM architecture and demonstrates its effectiveness on synthetic data through standard classification metrics. The study focuses on technical feasibility rather than behavioural or safety outcomes. These results indicate that the proposed system is effective in capturing and classifying complex emotional states that influence driving behaviour. The system was designed with a focus on real-time functionality and robustness, employing advanced signal preprocessing and feature extraction techniques. Methods such as noise filtering, normalization, and feature selection optimized the ECG signal data, making it suitable for live emotion classification. These advancements helped the system perform well even under the time constraints and noise typically found in real-world environments. By leveraging these techniques, the system effectively recognizes emotional shifts that could negatively impact driving, such as stress or fatigue. The intervention strategies presented in this work are conceptual and serve to illustrate possible integrations with driver assistance systems.

The integration of a user-friendly GUI is a key feature of the system, providing users with intuitive, real-time emotional feedback and driving suggestions. This feature enhances the system's practical utility by not only detecting emotions but also offering actionable insights to the driver, such as recommending breaks or alerting them when their emotional state could pose a risk. The inclusion of this feature ensures that the system is not just a monitoring tool but an effective aid in improving driver safety and reducing the potential for accidents linked to emotional distractions.

This study does not include user testing, ergonomic evaluation, or behavioural impact analysis. The effect of emotion-aware feedback on driver behaviour and safety outcomes will be investigated in future work through controlled user studies.

Overall, this research highlights the potential of ECG-based emotion recognition to improve road safety by addressing the emotional states that impact driving. The system provides a novel approach to emotion-aware driver assistance systems (DAS), demonstrating that real-time emotion recognition can be a valuable tool in enhancing driver safety and well-being. While emotion recognition is a relevant factor in driver monitoring, this study does not provide statistical evidence or expert validation linking the proposed system to accident reduction or measurable safety improvements. Such evaluations require longitudinal behavioural studies and are identified as future work. With further refinement and testing, this system has the potential to make significant contributions to reducing accidents caused by emotional impairment. A key limitation of this study is the reliance on synthetic ECG data; validation using real driver recordings will be addressed in future work.

6. Proposed extensions

The next steps for this research involve deploying the emotion recognition system in real-world driving scenarios, using wearable ECG devices to enable continuous monitoring of driver emotions. This real-time capability will ensure that the system can assess emotional changes as they occur during driving, allowing for immediate feedback and intervention when negative emotional states are detected. The use of wearable devices provides a non-intrusive and scalable solution that can be easily integrated into everyday driving scenarios, making it accessible to a wide range of drivers. In addition to real-time deployment, we aim to reduce the computational overhead of the system to make it suitable for use in low-power, resource-constrained devices, such as wearable ECG sensors and in-car systems. Optimizing the model's efficiency while maintaining its accuracy is crucial for ensuring the system can operate smoothly without requiring high-end hardware. This will make the system more accessible for widespread adoption and ensure that it can be used in various driving environments without significant resource demands. Future studies will involve expert evaluation and controlled user experiments to assess behavioural and safety impacts.

Future developments also include expanding the system to support multimodal inputs, such as GSR (Galvanic Skin Response) signals, to improve the accuracy and reliability of emotion recognition. By incorporating additional physiological signals, the system will have a more holistic view of the driver's emotional state, leading to more accurate predictions. This will also enable the system to capture a broader range of emotional patterns, increasing its robustness and adaptability to different drivers and driving conditions. Furthermore, we plan to incorporate adaptive learning into the system, enabling it to continuously improve its accuracy over time. This would allow the system to personalize emotion recognition based on individual drivers' emotional patterns, making it more effective in providing tailored feedback. By refining the model and expanding its capabilities, we believe the system has the potential to revolutionize driver safety and contribute to a new era of emotion-aware intelligent transportation systems (ITS).

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