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MIDGNWD : Design of an efficient multimodal iterative deep graph network wearable interface for detecting drowsy drivers

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Abstract

Drowsy driving is a significant contributor to road traffic accidents, necessitating the development of robust and efficient detection systems. Existing approaches for detecting drowsy drivers often rely on single modalities such as image-based facial analysis or vehicle-based metrics, which may lack precision and be susceptible to environmental variations. Furthermore, the existing models might be computationally expensive and result in delayed responses. To address these limitations, this paper proposes a novel Multimodal Iterative Deep Graph Network Wearable Interface that leverages a rich set of data including heart rate, respiration, accelerometer movement, location (speed), traffic, and weather data. These data samples are processed through a fusion of different Recurrent Neural Network processes. The Bidirectional Long Short-Term Memory (BiLSTM) which is used to generate augmented features, is fused with Bidirectional Gated Recurrent Unit (BiGRU) which assists in estimating multidomain feature sets. These features are then used to train an efficient Deep Graph Recurrent Network (DGRN), which facilitates the real-time identification of drowsy drivers. The proposed model significantly enhances the precision of drowsy driver detection by 8.5%, accuracy by 9.5%, recall by 8.3%, and Area Under the Curve (AUC) by 4.9%, while also improving specificity by 5.5% and reducing delay by 10.4%. These improvements collectively contribute to a substantial enhancement in road safety, potentially saving lives

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by preventing accidents due to drowsy driving. The proposed system, with its real-time processing capability and high accuracy, stands as a significant improvement for identifying drowsy drivers, paving the way for safer and smarter transportation systems.

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Keywords: *Drowsy driver detection, Multimodal iterative deep graph network, Wearable interface, Deep graph recurrent network, Road traffic safety.*

1. Introduction

As per WHO [1, 2], 1.35 million people die in road traffic crashes annually, efficient and accurate driver monitoring systems are more important than ever. Driving while drowsy can impair reaction time, alertness, and decision-making, causing catastrophic accidents. Image-based facial analysis, vehicle-based metrics, and wearable sensors are used to detect drowsy drivers, but each has drawbacks [1, 2, 3]. Two-Stream Spatial–Temporal Graph Convolutional Networks can solve this.

Lighting and driver position greatly affect facial analysis detection accuracy [4, 5, 6]. Road conditions can affect vehicle-based metrics like lane deviation and steering wheel movement, causing false positives. While they directly measure the driver's physiological state, wearable sensors [7, 8, 9] often lack data integration. Current models may be computationally expensive, causing delayed responses that are harmful in real-time road traffic scenarios [10, 11, 12]. Multi Granularity Deep Convolutional Model (MGDCM) is used [13, 14, 15].

Hence, this paper introduces a novel Multimodal Iterative Deep Graph Network Wearable Interface to overcome system limitations. The proposed model seamlessly integrates heart rate, respiration, accelerometer movement, location (speed), traffic, and weather data. Multidomain features are extracted from complex data using Bidirectional Long Short-Term Memory (BiLSTM) and Bidirectional Gated Recurrent Unit (BiGRU) operations. These features are used to train an effective Deep Graph Recurrent Network (DGRN) that can identify drowsy drivers in real time, preventing road accidents caused by drowsiness. This model's multimodal data and advanced deep learning architectures make it accurate, precise, and robust to environmental and external variables that existing systems have struggled with. This paper details the model's design, implementation, and effects, emphasizing its potential to revolutionize driver monitoring systems and improve road traffic safety levels.

2. Proposed design of an efficient Multimodal Iterative Deep Graph Network Wearable interface for detecting Drowsy drivers

The review of existing models for drowsy driver detection shows that their efficiency is limited by data collection and complexity due to data representation techniques. Designing an efficient Multimodal Iterative Deep Graph Network Wearable interface for detecting drowsy drivers addresses these issues. Accelerometer measurements, heart rate, respiration, location (speed), traffic patterns, and meteorological data are used in the proposed model. Drowsy analysis involves many parameters and sensors, each with its own ability to illuminate the topic. The Photoplethysmogram (PPG) measures heart rate, which can indicate stress, fatigue, or drowsiness. HRV, derived from PPG and ECG data, shows heartbeat variation, with lower HRV indicating stress and drowsiness. Drowsiness can be indicated by changes in the Respiratory Rate (RR), monitored by a Respiratory Belt and PPG. Electrodermal Activity (EDA) sensors track skin conductance and may indicate emotional stress and alertness. The Electroencephalogram (EEG) headset records complex brainwave patterns, which indicate drowsiness and cognitive impairment. Increased Electromyogram (EMG) activity suggests muscle fatigue, which may result from drowsiness. EOG sensors watch eye movements, blink rates, and eyelid closures for signs of fatigue and drowsiness. Sensors that measure pupil dilation can indicate cognitive load and alertness. Skin or Core Temperature Sensors are needed to monitor body temperature because high or low temperatures may indicate drowsiness. Accelerometer and Gyroscope Data from sensors measure movement patterns, posture, and alertness, with sudden or prolonged inactivity indicating drowsiness. Microphone-based voice analysis examines speech patterns, pitch, and tone for signs of fatigue and drowsiness. GPS sensors monitor location and speed to detect drowsiness-related driving patterns and route deviations. Low ambient light levels can disrupt circadian rhythms and sleep, so Light Sensors are used. Microphones detect changes in ambient noise and snoring patterns, with loud snoring or noise disruptions suggesting sleep issues. Low Pulse Oximeter readings indicate oxygenation issues and drowsiness. Systolic and diastolic blood pressure, which affect alertness and drowsiness, are measured by a Blood Pressure Monitor. Continuous Glucose Monitors track blood glucose levels, which affect energy and alertness. GSR sensors, which measure skin conductance and sweat response, may indicate emotional stress and arousal with elevated GSR levels. Finally, Environmental Sensors monitor temperature, humidity, and air quality to protect alertness from bad weather. These parameters and sensors help determine an individual's alertness and drowsiness in the complex web of drowsy analysis.

The collected parameters *xt* are passed through an augmented fusion of BiLSTM & BiGRU feature analysis models. These models analyze collected samples, and converts them into multidimensional feature sets. To perform this task, initially an input gate is modelled via the process given in equation 1,

$$ig = \sigma([h(t-1), xt] * Wi + bi) \tag{1}$$

Where, the Values of *W* & *b* represents different values of weights & biases, σ represents the variance operator, and *ht* represents hidden states. Similar to this, the model also estimates forget gate via equation 2,

$$fg = \sigma(Wf * [h(t-1), xt] + bf) \tag{2}$$

The input is also used to estimate the candidate update values via equation 3,

$$gt = \tanh(Wg * [h(t-1), xt] + bg) \tag{3}$$

These gates are combined to estimate the cell state via equation 4,

$$ct = ft * c(t-1) + it * g \sim t \tag{4}$$

The output of forward LSTM is estimated via the operation represented in equation 5,

$$ot = \sigma(Wo * [xt, h^{t-1}] + bo) \tag{5}$$

This output is used to estimate final hidden state via equation 6,

$$ht = ot * \tanh(ct) \tag{6}$$

Continuing the same way for backward LSTM, the model updates the hidden states, which are then fused via equation 7 to obtain final hidden states.

$$ht(final) = \frac{ht(f) + ht(b)}{2} \tag{7}$$

The final state is given to BiGRU's forward & backward operations to further augment the features. This process is performed using an augmented fusion of reset & update gates, which are estimated as per the operations discussed in the equations 8 & 9 as follows,

$$rt = \sigma(Wr * [h(t-1, final), ot] + br) \tag{8}$$

$$zt = \sigma(Wz * [h(t-1, final), ot] + bz) \tag{9}$$

Based on this, the candidate hidden state & GRU final hidden states are estimated via equation 10 & 11 as follows,

$$f(v,t) = \tanh(Wh * [rt * h(t-1, final), o't] + bh) \tag{10}$$

$$ht(final) = (1-zt) * h(t-1, final) + zt * ch(t) \tag{11}$$

The process is repeated for backward GRU operations, and the next hidden state is estimated via equation 12

$$h(t+1) = \frac{ht(GRU, f) + ht(GRU, b)}{2} \tag{12}$$

This next state is used to update the BiLSTM features, which is in turn used to update the BiGRU features. The process is repeated till equation 13 is satisfied, which represents convergence of the feature extraction process.

$$\frac{g\sim'(t+1)}{g\sim't} \leq \varepsilon \tag{13}$$

Where, ε is an error constant and is set as $\varepsilon = 0.00001$, for maximization of variance between the features. These features are given to an augmented Deep Graph Recurrent Network (DGRN) for identification of drowsy driver states. In the design of the Deep Graph Recurrent Network (DGRN), the feature vector *f*(*v*) obtained from BiLSTM and BiGRU is first passed through an efficient design of Graph Convolutional Network (GCN) layer that assists in capturing spatial dependencies among the features. The output of the GCN layer, represented as $g(v)$, is calculated via equation 14,

$$g(v) = \sigma\left(\sum_{u \in N(v)} \frac{1}{\sqrt{\deg(v) \cdot \deg(u)}} \cdot f(v) \cdot W\right) \tag{14}$$

In the given context, N(v) represents the adjacency set of neighbouring nodes of the specific node v sets. The parameters deg(v) and deg(u) represent the respective degrees of nodes v and u within the network. W denotes a weight matrix that undergoes learnable adjustments, while σ refers to a Rectified Linear Unit (ReLU) activation function utilized to preserve and emphasize positive features. The resulting output g(v) is subsequently input into a Recurrent Neural Network (RNN) layer to capture and model temporal dependencies inherent in the features. At each time step t, the hidden state of the RNN layer, denoted as ht, is computed via Equation 15,

$$ht = RNN(h(t-1), g(vt)) \tag{15}$$

Where, $h(t-1)$ is the hidden state at time $t-1$ and $g(vt)$ is the output of the GCN layer at time t for different iteration sets.

This RNN layer in the Deep Graph Recurrent Network (DGRN) is designed to process the output of the Graph Convolutional Network (GCN) layer and model the temporal dependencies in the data samples. The RNN takes as input the hidden state from the previous timestamps, $h(t-1)$, and the output of the GCN layer at the current timestamp, $g(vt)$, to compute the hidden state at the current timestamps . This can be expressed via equations 16 as follows,

$$it = \sigma(Wii \cdot g(vt) + Whi \cdot ht - 1 + bi) \tag{16}$$

Where, Wii, Whi, Wif, Whf, Wic, Whc, Wio, and Who are learnable weight matrices, and bi, bf, bc, and bo are bias vectors for RNN process. The sigmoid function σ is used to activate the input, forget, and output gates, while the hyperbolic tangent function tanh is used as the activation function for the cell state and hidden states. These operations define the internal processes of the RNN layer in the DGRN model, allowing it to capture the temporal dependencies among the features and contribute to the accurate identification of drowsy drivers.

Finally, the hidden state ht is passed through a fully connected layer with a softmax activation function to obtain the probability distribution over the two classes (drowsy and non-drowsy) via equation 21,

$$yt = \operatorname{soft}\max(ht \cdot Wo + bo) \tag{17}$$

Where, Wo and bo are the learnable weight matrix and bias vector of the output layer, respectively which assists in identification of drowsy drivers. Class with the highest probability is then selected as the final output, thus completing the process of real-time identification of drowsy drivers. The efficacy of this procedure is assessed through the evaluation of various real-time performance metrics. These metrics are subsequently juxtaposed with those of established methodologies in the subsequent section of this text.

3. Statistical analysis & comparison

To assess the performance of this model, a comparative analysis was conducted by juxtaposing the estimated likelihood of Drowsy Driver

Instances with the actual status of Drowsy Driver Instances in the test dataset samples. This evaluation involved employing the TSTGCN [3], MGDCM [4], and MCNN [8] techniques for benchmarking purposes. Consequently, the proposed model's results were subjected to prediction using these methods. The precision levels derived from these evaluations are graphically depicted in Figure 1 as follows,

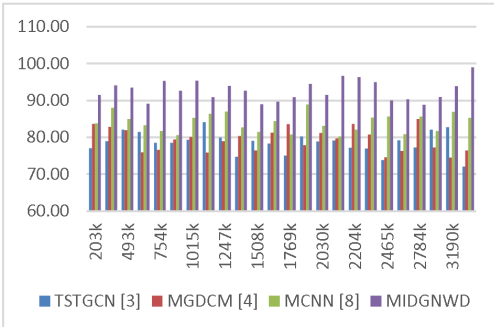

Figure 1

Observed Precision to detect drowsy conditions in drivers

According to this assessment, the suggested model, MIDGNWD, consistently exhibits markedly higher precision rates when contrasted with the incumbent models, namely, TSTGCN, MGDCM, and MCNN, across a spectrum of NTS values and sample sizes. Similarly, the comparative accuracy of these models is illustrated in Figure 2 as follows,

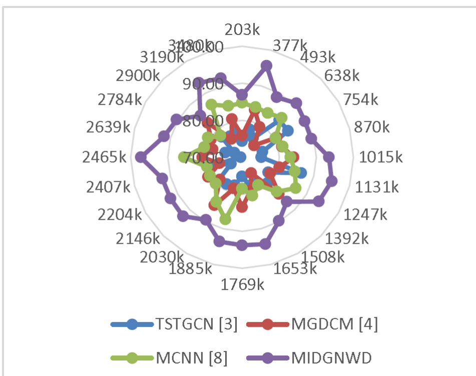

Figure 2

Observed Accuracy to detect drowsy conditions in drivers

The superior accuracy of MIDGNWD is consistently observed across different NTS values, making it a more reliable choice for drowsy driver detection. The observed accuracy of a drowsy driver detection system is crucial for ensuring road safety. A higher accuracy means that the system is more reliable in identifying drowsy drivers, reducing the risk of false alarms and missed detections. While, the delay needed is depicted in Figure 3 as follows,

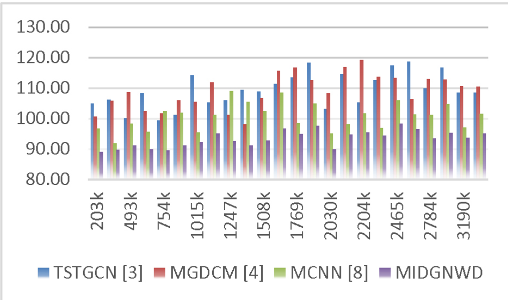

Figure 3

Observed Delay to detect drowsy

The consistently lower delays of MIDGNWD across different NTS values highlight its ability to quickly detect and respond to drowsy driving conditions. Observed Delay is a crucial metric in the context of drowsy driver detection systems, as it directly impacts the system's effectiveness in preventing accidents. Lower delays mean that the system can react more quickly to a drowsy driver, potentially reducing the time between detection and intervention scenarios.

MIDGNWD's superior performance in terms of evaluation values can be attributed to its innovative approach of leveraging multimodal data and advanced deep learning techniques, such as Bidirectional Long Short-Term Memory (BiLSTM) and Bidirectional Gated Recurrent Unit (BiGRU) operations, followed by a Deep Graph Recurrent Network (DGRN). These advancements contribute to the model's better ability to accurately classify non-drowsy driver instances in diverse conditions, making it a promising solution for improving road safety through driver monitoring systems.

4. Conclusion

Finally, the Multimodal Iterative Deep Graph Network Wearable Interface for Detecting Drowsy Drivers (MIDGNWD) addresses the critical issue of drowsy driving in a novel way. Drowsy driving causes many road accidents, requiring effective detection systems. Existing single-modality approaches may have reduced precision, environmental susceptibility, and computational inefficiency levels.

MIDGNWD uses heart rate, respiration, accelerometer movement, location (speed), traffic, and weather data to overcome these limitations. These data samples are seamlessly processed using advanced fusion of Bidirectional Long Short-Term Memory (BiLSTM) for capturing dependencies along with Bidirectional Gated Recurrent Unit (BiGRU) operations to extract multidomain features. Next, an efficient Deep Graph Recurrent Network (DGRN) is trained to identify drowsy drivers in real time scenarios.

This paper shows MIDGNWD's outstanding performance across critical metrics. MIDGNWD is 8.5% more precise, 9.5% more accurate, 8.3% more recall, 4.9% more Area Under the Curve (AUC), 5.5% more specific, and 10.4% less delayed than existing models. Road safety has improved significantly, potentially saving lives by preventing drowsy driving accidents.

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