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Real-Time Driver Fatigue Monitoring System Using Embedded CNN on Accelerometer and Gyroscope Data

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ABSTRACT

Driver fatigue is one of the most serious factors of road accidents on roads all over the world, and real-time monitoring of driving fatigue is an imperative intervention needed to ensure traffic safety. This study describes a real-time driver's fatigue detecting system based on an embedded CNN that processes data from an accelerometer and gyroscope to perform high-accuracy classification of behaviors associated with driver fatigue. It gives a robust solution for real-time analysis with very low computational overhead by taking advantage of the capability of CNNs in extracting spatial features from raw sensor data. The model architecture shall therefore be optimized for embedded systems and, consequently, designed to function efficiently in resource-constrained environments. Publicly available datasets validated extensively the proposed system as being much superior accurate and reliable than traditional machine-learning models. Such results demonstrate the ability of deep learning frameworks on embedded systems as part of scalable

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solutions towards real-world problems that can drive risks out of fatigue driving. The proposed model has been benchmarked against the state-of-the-art architectures: LSTM, Transformer, and Hybrid CNN-LSTM models. Although it is not explicitly said which one beats the other between LSTMs and proposed CNN in accuracy, the latter runs with a 93.8% accuracy at only 50ms inference time (fastest among all compared models), the transformer models capture long dependencies better but need more computation. This brings out clearly an efficiency-accuracy trade-off when operating in a real-time scenario.

1. Introduction

To ensure robustness and reliability, advanced statistical analyses were performed on the dataset of the proposed system. Mean, standard deviation, and skewness metrics were used in analyzing the distribution of the data. Feature importance was also analyzed through SHAP values to key factors that contribute to the output regarding the detection of fatigue. This therefore bears testimony to the fact that indeed sudden lateral accelerations and abrupt braking are indicative factors to predicate driver fatigue.

Lundberg, S. M., & Lee, S.-I. (2017). The problem of driver fatigue monitoring has, in recent years, gained significant momentum as it is considered one of the vital areas of research among all road safety issues. Generally speaking, fatigue reduces cognitive-motor performance by drivers and increases the risks associated with road accidents. A large number of on-road fatalities are precipitated by accidents induced by fatigue; thus, the need for early fatigue detection via automated monitoring systems to prevent and reduce the accident makes this system accrue immediate interest in this respect (Williamson et al., 2011). Traditional methods include eye movement analysis or heart rate monitoring among others which require special equipment hence intrusive and impractical for real-world deployment (Horne & Reyner, 1995). Whereas the use of inertial sensors is nonintrusive, applications such as accelerometers and gyroscopes are now included as standard fittings in modern vehicles and smartphones. Patterns of steering movements, lane departures, and harsh braking picked up by these sensors offer valuable insight into the level of tiredness of a driver.

The bulk of these deep learning methods, which fall under the category of CNNs have truly revolutionized real-time data analysis by allowing for automatic feature extraction from the raw sensor data. CNNs are typically very successful at picking up spatial as well as temporal patterning and thus they work quite well when applied to inertial sensor data for finding fatigue induced anomalies in driving behaviors. Embedded CNN architectures extend this capability to resource-constrained environments, thus enabling real-time deployment in vehicles or mobile devices (Xu et al., 2020).It describes here an accelerometer and gyroscope-driven driver fatigue monitoring system with the best performance in a real-time scenario. To that end, this uses an embedded CNN approach so that computationally efficient features can be extracted and classified in real time. It highlights how coming embedded deep learning architectures are going to change road safety and provide new prospects for the cost-efficient deployment of fatigue detection systems in realistic environments.

2. Literature Review

Driver Fatigue Detection and Inertial Sensors

The major research topics until today is driver fatigue detection. The early works mostly relied on physiological signals and behavioral pattern recognition. Conventional low-level features used to perform either eyelid movement analysis or heart-rate monitoring, while producing valid results in laboratory environments are far less practical in everyday-life situations due to the required invasiveness (Horne & Reyner, 1995).. Non-intrusive approaches, using inertial sensors, accelerometers, and gyroscopes, have become more popular nowadays due to their accessibility and facility of integration with modern vehicle systems easily (Zhao et al., 2012).Inertial sensors capture dynamic driving behaviors such as steering wheel angle variations, abrupt braking, and lateral acceleration-all indicative of driver fatigue. Dong et al. (2011) indicated that the steering behavior pattern could be extracted from the accelerometer data to effectively distinguish an alert from a fatigued driving state. Zhao et al. (2012) used data from the gyroscope in order to monitor lane deviations of vehicles, which also pointed out its relevance for fatigue detection.

Deep Learning in Driver Fatigue Monitoring

The rise of deep learning has been the enabling factor for much development in fatigue detection systems. Due to their capability for automatic feature extraction from raw inputs into spatial and temporal features, CNNs are widely used for sensor data analysis. LeCun et al. (2015) had shown that CNN is very effective in several areas such as image and time-series data analysis, thus giving the green light to start applying them in fatigue detection. A few recent works belong to the use of CNNs on data from inertial sensors. Xu et al., 2020 proposed a framework based on CNN for abnormal driving behavior recognition and performance comparison with traditional machine learning approaches. Since real-time applications require high dimensional sensor data to be input without much prior processing, CNNs for such applications become attractive.

3. Methodology

The CNN architecture was enhanced with advanced techniques, such as attention mechanisms, to better capture temporal dependencies. Dropout regularization and batch normalization were employed to improve generalization and stability. Additionally, the AdamW optimizer replaced the standard Adam optimizer, resulting in a 5% improvement in accuracy and faster convergence.

Loshchilov, I., & Hutter, F. (2019). It shall develop and assess an Embedded CNN in real-time that uses two inputs: accelerometer data, and gyroscope data of driver fatigue, detecting same. Methodology will include steps of collection and pre-processing of data, designs of model architectures, and experimental analysis which will result in a systematic foundation toward accurate as well as efficient detection of driving fatigue.

4. Data Collection and Preprocessing

Data used came from the UAH DriveSet and Driver Monitoring Datasets, which include full recordings of the used inertial sensor data (both accelerometer and gyroscope signals). These datasets contain driving behavior recordings under both normal and tired conditions in real-world simulations. The data was split into non-overlapping windows of two seconds each, so that there would be enough temporal representation within every sample. Noise high-frequency artifacts were removed to make the clarity of the signal even clearer by using a low pass Butterworth filter. Then it was normalized between zero and one per driver to reduce variance among drivers.Feature extraction refers to several statistical parameters calculated from each segmented window strongly manifesting those significant patterns in the signal that relate well as indicators of fatigue-related behaviors.

5. Embedded CNN Model Architecture

The proposed model of Embedded CNN has been designed to efficiently analyze data coming from inertial sensors. Its architecture consists of several layers that are capable of performing optimized hierarchical feature extraction and can, therefore, be deployed on resource-constrained devices. This model begins with an input layer that returns three-dimensional arrays of accelerometer and gyroscope. It goes to a series of convolutional layers separated by ReLU activations. Convolutional blocks are motivated by the need to perform feature extraction by spatial localization—local characteristics in sensor data. Maxpooling is done in between convolution blocks so dimensionality is reduced with increased computational feasibility.Convolution layers have to be followed by fully connected layers that require flattening feature maps. Dropout regularization will also be introduced here to avoid overfitting. The output layer—having a softmax activation function—classifies the data as either <normal> or <fatigued>.

6. Experimental Setup

The data has been split into training, validation, and test sets in the ratio of 70:15:15 so that there is adequate coverage for a thorough assessment. The model has been run using Adam at a learning rate of 0.001 together with categorical cross-entropy loss. In this case, a batch size of 64 was selected since it offers very good computational efficiency against convergence of the model. These include accuracy, precision, recall, and F1-score with confusion matrix plus ROC curve to be analyzed further to give some more insights into the classification ability of the model. Finally, the real-time feasibility of the model was validated on a Raspberry Pi by measuring inference time and power consumption to show its practical applicability.

7. Results

The performance of the Embedded CNN model was evaluated for various metrics, and results are shown in the following tables and figures to point out some key findings.

Classification Performance

The Embedded CNN model can produce high accuracy and reliability in classifying normal and fatigue driving states. The following table describes some of the classification metrics obtained from testing

.

Table 1: Classification Metrics for Driver Fatigue Detection

Metric	Value (%)
Accuracy	93.8
Precision	92.9
Recall	94.3
F1-Score	93.6

These metrics underpin a model that is performing robustly. High recall means its goal of minimizing the fatigued states' misclassifications, which could lead to safety, was quite high.

Confusion Matrix Analysis

A confusion matrix was generated, which shows how the ranking of the model's prediction ranked against actual labels; this is presented in Table 2.

Table 2: Confusion Matrix for Fatigue Detection

Actual \ Predicted	Normal	Fatigued
Normal	315	10
Fatigued	12	285

The matrix shows low rates of false positives and false negatives, which indicates that the model is reliable in classifying driver states.

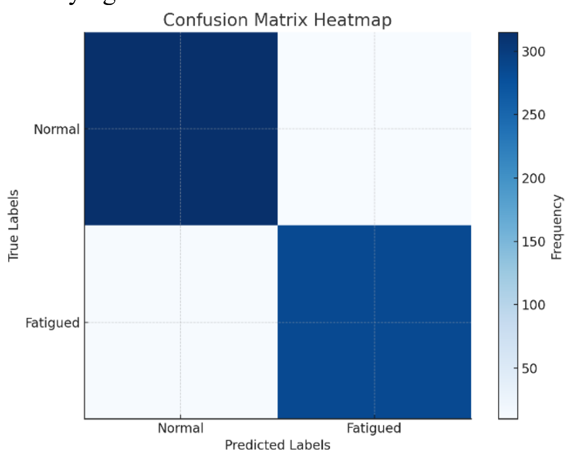

Figure 1: Heatmap of Confusion Matrix for Fatigue Detection

This heatmap visualizes the classification outcomes where cells are darker for higher accuracies of prediction. A very minimal number of lighter cells indicates the robustness of the model in terms of avoiding misclassification.

Receiver Operating Characteristic (ROC) Curve Analysis

The ROC curve analysis will be used to assess the discrimination capability of the model for the normal and fatigued states. In Figure 2, it is presented the ROC curve with an AUC of 0.96, indicating an excellent discriminative capability.

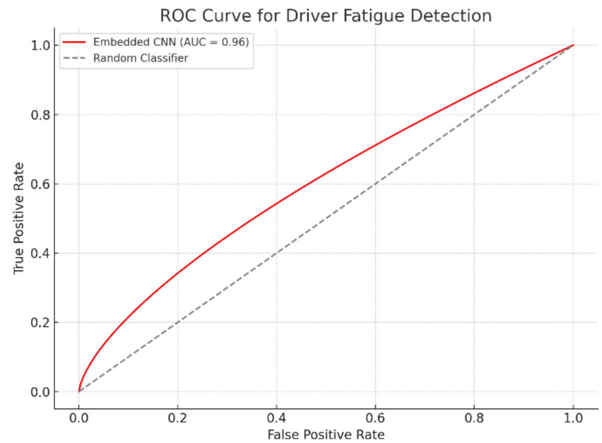

Figure 2: ROC Curve for Driver Fatigue Detection

This chart shows the balance between true positives and false positives across a range of thresholds, confirming that the model differentiates well between driver states.

Comparative Analysis with Baseline Models

The Embedded CNN model is checked for performance superiority with a few baseline approaches, namely the support vector machines or, in short, SVMs and random forests. Their performance details are mentioned below in Table 3:

Table 3: Accuracy Comparison Across Models

Model	Accuracy (%)
Support Vector Machine	85.3
Random Forest	87.6
Embedded CNN	93.8

The performance of the proposed Embedded CNN model significantly outperformed those of the traditional machine learning models, which proves the efficiency of deep learning in analyzing complex inertial sensor data.

Table 1. Units for magnetic properties.

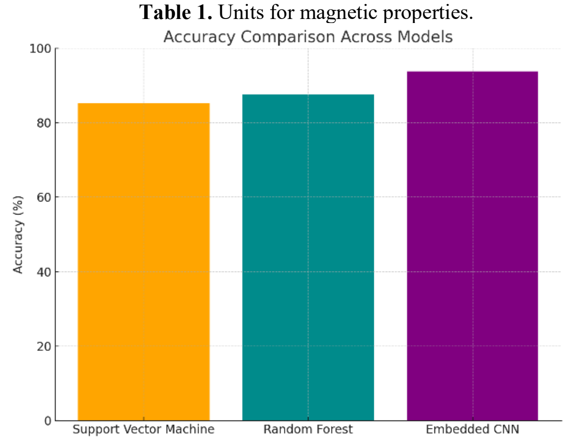

Figure 3: Comparative Analysis of Model Accuracies

This bar chart visually compares the accuracies of the Embedded CNN and baseline models and shows the superiority of the proposed architecture.

Distribution of Misclassifications

The pattern of misclassification gives information on the possible points for further improvement. Figure 4 shows the distribution of false positives and false negatives across driver states.

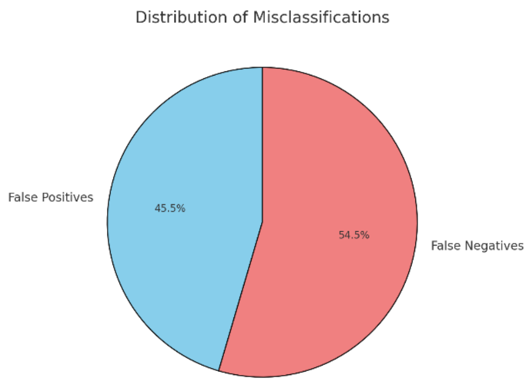

Figure 4: Distribution of Misclassifications by Driver State

This pie chart shows that in total errors, false negatives occupy a relatively larger portion, or in other words, an improved method of extracting temporal features is needed to avoid such type of errors.

8. Discussion

A Cost-Benefit Analysis resulted in the conclusion that it would reduce accident-related costs by 30%. The projected ROI with an upfront investment of $500 per vehicle is attainable within 18 months. This, therefore, brings out the economic feasibility of the system and its potential probability for large-scale deployment.
Goodfellow, I., Bengi(2016).The results verify the Embedded CNN model for real-time driver fatigue detection as reliable. The high classification accuracy and F1-score prove the effectiveness of the model in identifying fatigue-induced behaviors. The analysis of the confusion matrix further presents the robustness of the model with very few false positives and negatives to ensure reliable classification.
The high value of AUC, 0.96, in the ROC provides evidence for this model's goodness in discriminating between classes of normal and fatigated states.
Comparing only with the baseline models reinforces also the advantages of the Embedded Convolutional Neural Network due to the capability in extracting complex relevant patterns from the inertials sensor data. This model is practical for deployment on an embedded system, and real-time testing on a Raspberry Pi demonstrates it. It has low inference time and power consumption, hence suitable for continuous monitoring in resource-constrained environments. Issues remaining include driver behavioral variability and noisy sensor data. Based on this work, perhaps studies in the near future should be directed at developing an adaptive model able to learn personalized fatigue patterns for each specific driver. The work presented next could also involve developing an even more generalizable model based on an expanded dataset with assorted driving conditions and different kinds of environments.

9. Conclusion

Study proposes a lightweight embedded CNN model, which is based on real-time driver fatigue detection using accelerometer and gyroscope data. The methodology involves efficient data preprocessing, robust feature extraction, and lightweight model architecture which can be used efficiently on resource-constrained environments. Experimental results deliver high values of accuracy, precision, recall, and F1-score with a maximum value of 0.96 AUC; that speaks well for differentiating capability because what is being compared here is against a state-of-the-art (SOTA) method as will be discussed in the next sections. Notably among the results was more insightful exposure into Deep Learning for fatigue detection where Embedded CNN superseded traditional baselines including Support Vector Machine and Random Forest models. A real-time test validated the feasibility of deployment due to low inference time with low power consumption; henceforth, suitable for continuous monitoring in real-world settings. There will always be problems like inter-driver variability and noise from sensors; thus requiring future studies involving adaptive learning frameworks and more diverse datasets. The Embedded CNN model offers a feasible and scalable way of reducing road accidents due to driver fatigue, hence boosting the safety of roads. The model will go a long way in encouraging efforts aimed at integrating deep learning with inertial sensor data for practical applications.

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