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Driver Identification Via Hybrid Model and Few-Shot Technique Based CAN-BUS Data

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ABSTRACT

Driver identification is vital in connected transport and has various benefits like usage-based insurance, personalized assisted driving, fleet management, etc. The data collected from behind the wheel makes it possible to identify unique driving styles as an alternative to adding extra costs or compromising drivers' biometric fingerprint privacy, such as facial recognition. The variable nature of drivers causes problems for traditional techniques because they become less accurate when faced with new drivers. This paper presents an innovative method of driver identification using few-shot learning techniques based 1D CNN-LSTM Attention model that can effectively solve the N-driver identification problem, given very few training examples on driving. Our findings reveal that this model can be generalized correctly from just a few examples, making it essential in real-life situations. We compare our proposed method with several baseline models such as LSTM Attention, LSTM, CNN, and ANN. Furthermore, applying our model to 3-way and 5-way classification problems using 1-shot and 5-shot methods further evidences its effectiveness in changing environments. Consequently, from this research, it is clear that knowledge based on the training dataset could be applied successfully to new drivers. Impressive results obtaining when trained on all raw databases but still getting correct identifications even with a small number of instances per driver label.

1. INTRODUCTION

Acquiring a distinct representation of driving styles from vehicle in-built sensor (vehicular controller area bus) data in automobiles presents a formidable challenge. This distinctive style is a digital fingerprint for applications requiring driver identification or recognition while upholding privacy concerns. For example, an insurance company offering a pay-as-you-drive program must ensure that the designated driver listed in the policy is driving the insured vehicle. Similarly, a fleet management system overseeing many delivery vehicles must track which driver undertook specific delivery trips to trace any lost cargo.

Numerous methods for driver identification based on unseen features and measurements have been extensively researched. These features include vehicle RPM, accelerator pedal usage, speed, steering angle, and other data obtained from the vehicle's CAN-Bus. Among all the driver identification methods explored in previous studies, the most advanced models have been reported to utilize deep learning techniques combined with windowing strategies. Despite the success of the previous deep learning methods in driver identification, they face significant limitations when dealing with unanticipated scenarios or new drivers not seen during the training phase. Traditional deep learning models typically require large volumes of labelled data to achieve high accuracy. This dependency on vast datasets makes traditional deep-learning models less adaptable to real-world conditions where new drivers are frequently added or removed from the system. The new drivers often carry much less existing data, leading to an imbalanced dataset. This imbalance in data can hinder the model from accurately identifying and adapting to new drivers since it is skewed towards more abundant data from previously seen drivers. Moreover, these models may be computationally expensive and time-consuming to retrain, which poses practical challenges for dynamic environments.

Depth models which can quickly cope with a fluctuating number of drivers (output classes), even if there are only several driving samples. Our method is designed to overcome the problem of data imbalance and insufficiently large training datasets to ensure that the system remains accurate and reliable as new drivers appear. This paper also suggests using a hybrid deep learning model containing one dimension convolution neural network (1D CNN), Attention and Long short-term memory (LSTM) for few-shot driver identification. This method ensures the privacy of individuals by exclusively using data from the CAN-BUS network. The 1D CNN with Attention is employed to extract and emphasize relevant features effectively. At the same time, LTSMs capture temporal dependencies and sequences in driving data. Combining two models enables the utilisation of the strong points of both models, thus enhancing the overall adaptability and accuracy of the driver identification system. The proposed hybrid deep learning model performs superior on public dataset experiments than previous models. Accuracy increases when we use a hybrid approach in driver identification. This is achieved through robust performance for fewer driving samples that solve the challenges posed by constraints such as data imbalance and rapid adaptation to new drivers. This paper makes a significant contribution.

- A new hybrid deep learning model that combines parallel 1D CNN, attention mechanisms, and LSTM cells is presented. 1D CNN extracts the most essential patterns in driving data with Attention, emphasising them and capturing temporal dependencies from LSTM unit, leading to a strong and accurate driver identification system.
- We tested our proposed approach on publicly available driving datasets for three- and five-way classification problems. Five-shot and one-shot learning methods were used to evaluate its usefulness with less data and show it outperforms previous works in such scenarios.

2. RELATED WORK

Drivers have been identified using a variety of techniques based on their behaviors. These techniques can be classified as deep learning (DL), machine learning (ML), or hybrid approaches. The features derived from CAN-BUS data, internal measurement unit (IMU), and smartphone data.

Wakita et al. [1] introduced a driver identification method that relies on analyzing driving behaviour signals observed during car following scenarios. The researchers employed a Gaussian Mixture Model (GMM) to examine and categorize these signals. They gathered driving behaviour signals using a driving simulator, which included inputs, from the accelerator and brake pedals, vehicle velocity and distance, from the car ahead. Meng et al. [2] proposed an intelligent-vehicle security system. The focus of the researchers was centered on creating a dynamic human behaviour family model performed with driving simulation data in reference to acceleration, brake and steering wheel movement. The authors used a classifier hidden Markov model (HMM) which is one of the algorithms that were used to govern and interpret wealth predictions in the acquired data. The system was developed to be able to clearly identify and basically outline what humans do when they are driving their vehicles in an attempt to find out how the behavioral patterns associated with human driving can be improved so as improve vehicle security, reduce losses and eventually avoiding thefts. Del Campo et al. [3] analyzed the signals that were picked up from the CAN-BUS system through Artificial Neural Network (ANN) technique. Authors employs windowing strategy towards the pre-processing data, with the identification accuracy of those drivers reaching 84%. Kwak et al. [4] suggested driver identification model that used CAN-BUS time series signals. The researcher extracted statistical features such as mean, median, and standard deviation from collected CAN-BUS data, to capture important characteristics. Random Forest (RF) algorithm was employed by the authors for driver identification, which proved highly effective. The model achieved high accuracy rate of 99% for ten drivers (Security Driving Dataset). In their research, Zhang et al. [5] discussed how they used window-based support vector machines (SVM) for driver categorisation purposes. Their study also examined any relationships between data sources, such as single phone sensors, single automobile sensors, combined phone and car sensors, and classification accuracy. According to the author's considerations, combining data from several sources yielded the highest accuracy score of 86.67% in driver categorisation. Different processing strategies were completely assessed on various datasets over different time windows by Ezzini et al. [6]. As part of their evaluation, they tried to see if traditional machine learning techniques such as Random Forest, Extra Trees and KNN would do any better. Their study results showed that these algorithms can achieve a good cross-validation score. Specifically, the study identified two distinct attributes for driver evaluation. The first category includes features related to driving behaviour, and the second contains features related to driver heart rate, etc. Li et al. [7] introduced a driver recognition model using data collected from in-vehicle sensors, especially LSM330DLC sensors. Data collected included vehicles' lateral speed, height and position. The authors used four machine learning models in their study: RF, KNN, Adaboost, and ANN. These models were used to classify and identify drivers based on sensor data—the proposed model aimed to accurately distinguish between different drivers using this machine learning algorithm. The study focused on investigating the effectiveness of these models for driver recognition based on collected sensor data. Khan et al. [8] proposed a comprehensive method for driver identification using seven different models, including SVM, Naïve Bayes, Logistic Regression, k-NN, Random Forest, Decision Tree, and Gradient Boosting. The study focused on safe driving databases, particularly two of the 51 available features: fuel consumption and engine speed. Features Used Using machine learning algorithms, the authors aimed to stop these selected items by accurately identifying and differentiating the drivers.

Current methods relying on machine learning exhibit two notable limitations. First, artefacts and prior knowledge must be built, providing more efficient and accurate attribute extractions for only a limited number of drivers. Second, materials technology curriculum types often require iterative adjustments to ensure optimal results. It turns out that many recent scholars have successfully used deep learning models to identify drivers. In addition, many researchers have conducted research using hybrid deep learning models for driver detection, using combined deep learning methods to improve accuracy and efficiency. These models are usually CNNs [9-12] and RNNs [13-15] to capture spatial and temporal features from diverse sensor data sources.

Wang and Ho [16] came up with an innovative approach for driver identification by using large-scale GPS sensor data. The authors provided a joint-histogram-based feature map construction method. Furthermore, Deep Neural Network (DNN) models show highly accurate, exceeding 94% in the driving manoeuvres classification. Moreover, the Long Short-term Memory (LSTM) achieved high accuracy 92% for the driver identification task. Jeong et al. [17] proposed a driver identification system based on CNN deep learning model. In this research study, the author using real-world collected dataset using vehicle CAN-BUS network, which consisting data from four drivers over an average of 30 minutes daily for eight days. The model mention above achieved high accuracy 90% using 4-5 minutes window size for training model. Xun et al. [18] employed Convolutional Neural Networks (CNN) and Support Vector Domain Description (SVDD) as a method for vehicle driver identification. The model was built to enhance the accuracy of identifying. This model achieves high accuracy 98.216% for driver identification within the 300 seconds window period, and total of 20 drivers. Girma et al. [19] used LSTM deep learning model one of the best performing models as an ovel approach for driver identification task. The authors used three public datasets including, Vehicular Data Trace Dataset-1, Security Driving Dataset, and Vehicular Data Trace Dataset-2 to train their model. An exceptional F1 score of 98%, LSTM-based model achieved when evaluated using the Security Driving Dataset using overlapping time windows (120-60) s. El Mekki et al. [20] presented a remarkable hybrid technique for driver identification using fully convolution Neural Network-Long Short-Term Memory (FCN-LSTM) hybrid model. The proposed system trains the model on four public datasets including, UAH-Drive dataset, Security Driving Dataset, OSF and HCILAB. Furthermore, using window size technique (60-30) s to enhance the detection of driver behaviour. The proposed model achieves high accuracy when train using Security Driving Dataset. Zhang et al. [21] presented a novel deep learning framework that seamlessly integrates CNNs and RNNs with conceptual methods into a comprehensive end-to-end solution delivery see the driver. and the standard deviation was subtracted. Remarkably, the proposed model achieved an impressive mean accuracy of 98.36% with a negligible accuracy standard deviation of 0.0015 when employing an overlapping window of (60-54) s with a step size 6. Chen et al. [22] presented the development, architecture, and technological aspects of the cognitive internet of vehicles. The authors covered real-time driver monitoring methods that can significantly lower traffic accidents. Abu-Gellban et al. [23] put out a method that uses Fully Convolutional Networks (FCN) and Gated Recurrent Units (GRU) to efficiently record both short- and long-term trends in driving behaviors. The Segmented Features Generation method was used to segment driving behaviour with an analysis window size, reducing the state space of driving behaviour and increasing training efficiency. Ullah and Kim [24] presented an innovative driver identification method based on a compact hybrid deep learning model. The authors parallelized the LSTM and GRU-based RNN models with a 2D CNN. They employed a public dataset to train their model and utilized an overlapping window of (40-34) for feature extraction. Impressively, the model achieved an outstanding accuracy of 98.72%. Furthermore, the authors conducted experiments on three hardware platforms, namely NVIDIA DOCKER with Xavier, TX2, and Nano, and measured the training time for each device. Azadani and Boukerche [25] created several classification machine learning and deep learning models. Deep Neural Network (DNN), Random Forest, LSTM, Decision Tree, KNN, CNN, and DeepConvLSTM, a hybrid model that fused CNN and LSTM and achieved excellent accuracy—were among the models. Abdennour et al. [26] was utilized Residual Convolutional Network (RCN) as a hybrid model to achieve innovative driver identification approach. The proposed model achieves impressive degree of accuracy 99.3% when using Security Driving Dataset to train and evaluate the model. The authors used window size method (60-54) s as data augmentation method with time step six second. Lu and Xiong [27], three versions of a meta-learning model designed to quickly adapt to varying numbers of drivers, particularly when only a few examples are available. The models were tested on scenarios involving three and five drivers using a public driving dataset and 5-shot and 1-shot learning approaches. The proposed models achieved an accuracy of 68.05% for the 5-shot approach with three drivers and 51.57% for the 5-shot approach with five drivers. Hu et al. [28] present a groundbreaking ensemble DL model that combines a 1-D 1D CNN and Bidirectional Long Short-Term Memory (BLSTM) models. Their approach utilizes two datasets: one collected using CAN-BUS sensors and another from a publicly available dataset. The authors employ four data augmentation methods and incorporate few-shot learning techniques to enhance the model's performance. Remarkably, the proposed model achieves an accuracy of 64.67% when using only 3% of the dataset and 90% when using 50%.

3. METHODOLOGY

3.1 Few-shot learning problem

This study starts with a group of 5 drivers, for whom multiple trips are collected. The driving data is obtained from unobtrusive sensors onboard and transmitted via a CAN bus. The CAN bus data, which includes parameters such as speed, brake pedal usage, and engine torque, indirectly reflects the drivers' behaviour. Previous research has utilized these data to identify drivers without infringing on their privacy, unlike intrusive methods such as facial recognition. Traditional driver identification methods rely on sufficient training data. Still, our focus is on how to adapt a pre-existing 5-driver classification model when an additional driver joins group A and provides only a single trip.

Consequently, a 6-driver classification model can be constructed based on the initial 5-driver model. In real-world engineering scenarios, waiting for sufficient data to establish a robust identification model for the 6-driver problem is impractical, as issues such as vehicle theft or insurance disputes may arise during the waiting period. We seek to develop a model with self-learning capabilities to address the general domain of N-driver identification problems, particularly when insufficient driving examples exist. Unlike conventional deep learning approaches tailored to a specific number of drivers, our challenge is framed as a few-shot problem, specifically the N-driver, few-trip identification problem.

In the context of driver identification, N-way k-shot classification presents a compelling solution for scenarios with limited data. Here, N represents the number of distinct drivers (classes) the model needs to identify, while k denotes the number of example trips (shots) available per driver. The N-way k-shot classification framework is particularly advantageous when dealing with the few-shot learning paradigm, where traditional supervised learning approaches falter due to the scarcity of labelled data. Leveraging state-of-the-art models that can rapidly adapt to new drivers from few data allows for robust and accurate identification of drivers even with a limited number of trips. Thus, the N-way k-shot classification framework is very useful in real-world domains where drivers might be removed or new drivers added to the system. The model's flexibility of the N-way K-shot classification framework also helps to quickly adapt to these changes, thereby maintaining high performance and reliability across various diverse and evolving scenarios. This characteristic is important in its application in areas such as fleet management or personalized insurance, where there must be timely identification of an accurate driver despite dynamic driver rosters. In line with this, the 1D CNN-LSTM attention model seems an excellent match for solving the problem of identifying an N-driver. For instance, information learned by a 3-driver identification model can support the classifier regarding fewer or more drivers being involved in particular contexts. Such ability manifests itself through adapting and suitably capturing any change, thus allowing efficient learning of new patterns, making it suitable for dynamic driver recognition tasks.

3.2 1D CNN LSTM attention model

Deep learning techniques have been developed to tackle difficult applications like driver identification due to the swift progress in artificial intelligence. We provide a novel model that effectively addresses the inherent difficulties associated with driver identification by fusing the power of LSTM with the versatility of attention mechanisms parallel with separable 1D-CNNs with attention units. Figure 1 showcases the proposed driver identification model, which features a 1D CNN LSTM with an Attention mechanism.

The model consists of two parallel components: the first is a 1D Separable CNN with an Attention mechanism, and the second is an LSTM with an Attention mechanism. The outputs from both parts are combined through a concatenation mechanism, merging the strengths of each to enhance the overall performance of the model.

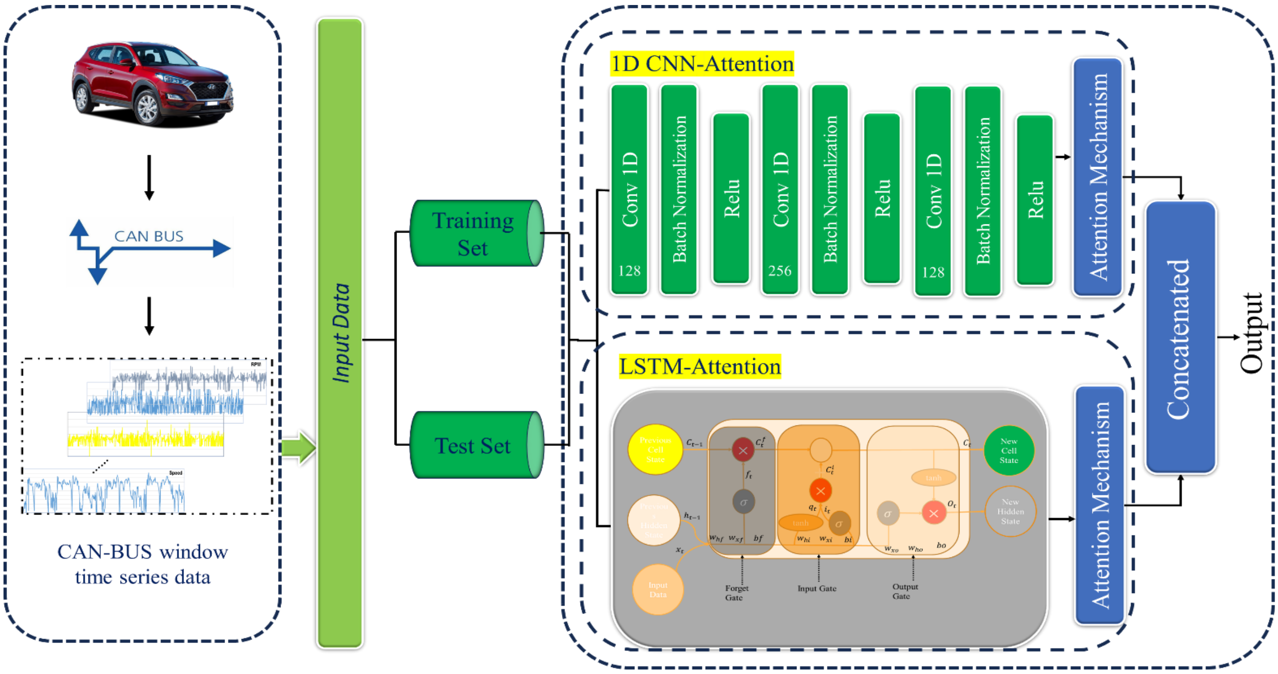

Figure 1. Driver identification proposed model

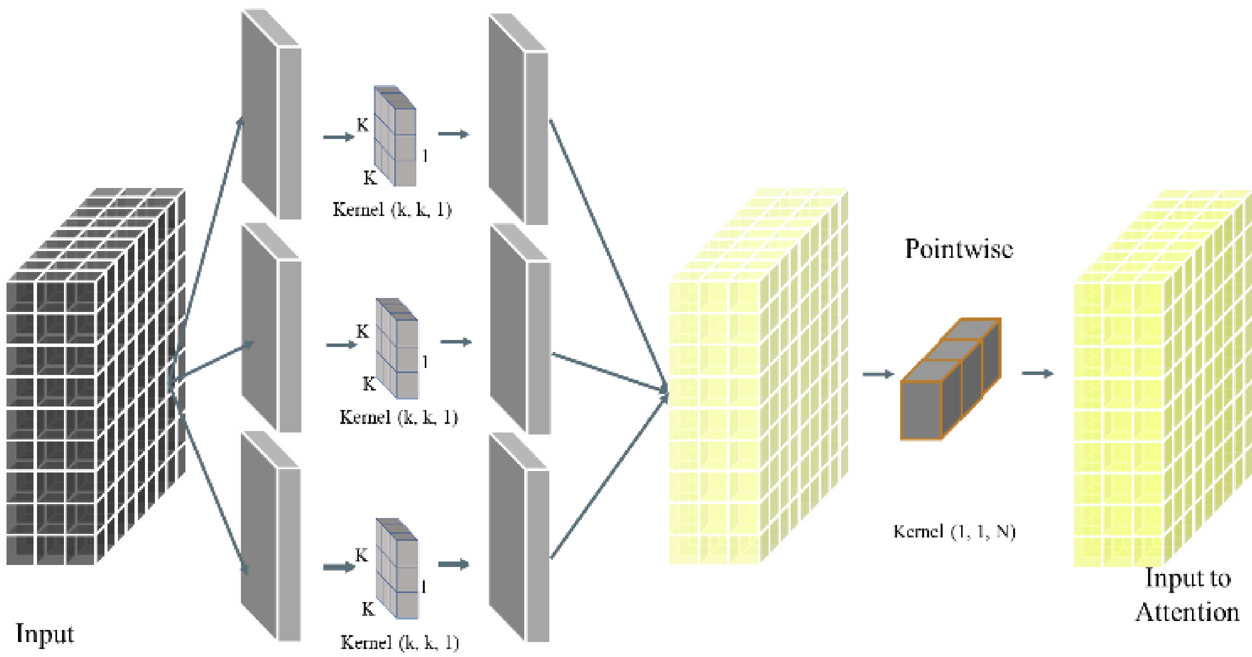

Figure 2. 1D CNN depthwise separable architecture

3.2.1 Depthwise separable CNN

The strength of 1D-CNNs lies in their ability to extract features using separable 1D convolution layers. At this level, we used three Separable 1D layers of convolution, each accompanied by a LeakyReLU activation function and batch normalisation (BN) layer. Separable convolutions are selected because they have better parameter efficiency than traditional ones. The method involves two steps: first, a depthwise separable convolution, and then, a pointwise convolution. This way, the process overcomes overfitting and efficiently extracts fundamental features from the input data. Eq. (1), and (2) present mathematical models for these methods, respectively. At this stage, the LeakyReLU activation function improves it by retaining abnormal patterns in its data and eliminating "dying ReLU", see Eq. (3). The input is denoted as "I", the depth-wise filter is represented by "D", and the pointwise filter is represented by "P", as illustrated in Figure 2.

$$(I * D) = \sum_i \sum_j I\,(x-i, y-j) * D(i,j) \tag{1}$$

$$(I * P)(x,y) = I(x,y) * P \tag{2}$$

$$f(x) = MAX\ (\alpha x, x)\ where\ \alpha =\ 0.15 \tag{3}$$

3.2.2 LSTM

In this stage, we use one layer of LSTM with ten cell neurons. This selection of architecture enables us to perform the temporal dependencies analysis on the driving data time series efficiently. The LSTM layer is the memory block, allowing the model to remember critical information and detect long-term patterns in individual drivers' driving behaviour. With ten cell neurons, we equip the model with enough memory for learning and exhibiting complex driving patterns. This helps in precise feature extraction during the later stages of driver identification.

3.2.3 Multi-head attention

The next phase of our approach involves the Attention System, a revolutionary innovation in DL. Based on the design of the transformeration framework [29], this method provides a robust alternative to conventional recurrent layers, particularly in managing distant dependencies, as Figure 3 illustrates. The ability of the self-attention mechanism to convert a query and a set of key-value pairs into an outcome, where the production, keys, values, and query are all expressed as vectors, is its basic working concept. The result is computed by taking a weighted total of the values, with the weights defined by a compatibility function that quantifies the relationship between the query and each respective key. The attention mechanism equations as:

$$\text{Attention } (Q, K, V) = \text{SoftMax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{4}$$

$$\text{MultiHead } (Q, K, V) = \text{Concat } (head_1, head_h)\ W^O \tag{5}$$

$$head_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{6}$$

where, Q represented for queries, K for keys, and V for values. Furthermore, d_k denoited by the dimension of the keys. Eq. (4) represented the scaled dot product attention component which consists of several key operations. It first analyses the query and key vectors through a matrix multiplication that it calls MatMul. Subsequently, the dot product results are divided by square root of the dimension of the key vector in order to normalize the vector. This scaling is crucial as otherwise it is possible to obtain a very large dot product and hence the attention mechanism will not be very helpful. Next, the scores are passed through the softmax function that converts them into attention weights which sum up to one. The weights are of the attention mechanism and they define the attention given to each of the key-value pairs in the input sequence for the query. Lastly, another dot product, MatMul, calculation is carried out on the attention weights and the respective values. Eq. (6) maps the vectors Q, K, and V into different representation subspaces by use of learnt linear transformations, which are identified as $QW_i^Q, KW_i^K, and\ VW_i^V$, respectively.

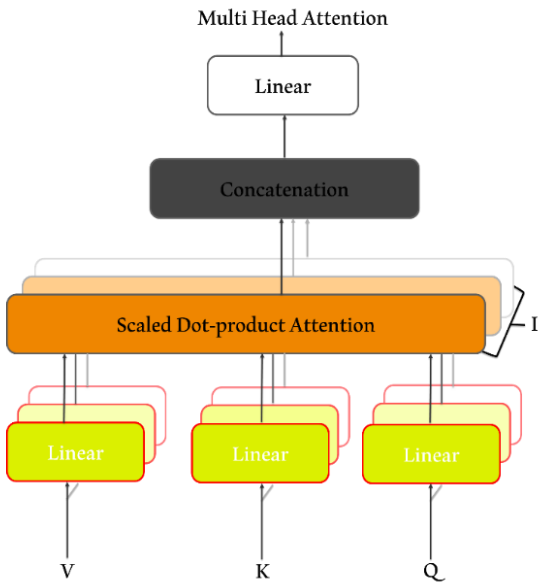

Figure 3. Multi-head attention architecture

Table 1. Proposed model hyperparameter

Layer	Kernal	Output Channel	Other Information
Input	-	-	-
1D CNN-1	8	128	-
BN	-	128	-
Leaky-Relu	-	-	alpha=0.2
1D CNN-2	5	64	-
BN	-	64	-
Leaky-Relu	-	-	alpha=0.2
1D CNN-3	3	32	-
BN	-	32	-
Leaky-Relu	-	-	alpha=0.2
GAP	-	32	-
LSTM	-	10	-
Attention	-	32	
Fully connected	-	10	-

A Global Average Pooling (GAP) layer is added after the concatenation manipulation. The purpose of this layer is to serve as a feature descriptor, which effectively reduces the dimensionality of the model's output by summarising spatial information. GAP is strategically integrated into our architecture to retain the most informative features and reduce the overfitting hazards commonly associated with fully connected layers. This technique decreases the number of parameters by calculating the average of the feature maps to obtain a single value, hence improving the model's capacity to generalise. Unlike flattening processes, GAP preserves essential spatial information, making it especially well-suited for analysing time-series data, such as patterns in driver behaviour.

The last step of the design consists of a completely linked layer equipped with Softmax activation. This layer relates the high-level information retrieved by the preceding layers to specific driver, enabling successful identification. Table 1 showcase the proposed model parameter.

4. PERFORMANCE EVALUATION

In this section, we initially assess the performance of our proposed model on a public driving dataset [4], utilising the entire dataset. We compare its performance against four benchmark models: ANN, LSTM Attention, LSTM, and CNN, as illustrated in Table 2. Subsequently, experiments are conducted on 3-way and 5-way classification tasks using 5-shot and 1-shot approaches to address few-shot learning scenarios. This section compares our proposed model's results against those reported in previous studies.

Table 2. User-defined parameter for proposed model

Model	Parameters
ANN	Five layers, 30 neurons
LSTM	Five Layers, 30 Cell
CNN	Five Layers
LSTM-Attention	Two head Attention

4.1 Dataset description

This study utilised a dataset that included driving data from ten drivers. Each driver completed two round trips from SANGAM World Cup Stadium to Korea University. This equated to around 23 hours of recorded driving information [4]. The driving route encompasses three distinct urban areas, namely regular streets, highways, and parking spaces, spanning 23 kilometres. The experiment commenced on July 28, 2015, with meticulous attention to the time factor. The experiments were conducted within the same time zone to ensure consistency, specifically from 8 p.m. to 11 p.m. on weekdays. Ten skilled drivers participated in the study, completing two full-round trips to establish reliable classifications. The data collection process encompassed various road conditions to ensure a comprehensive representation of driving scenarios. Ninety-four thousand four hundred one data points were obtained from 32 driving excursions using 51 distinct sensor signals.

During the training phase, the input consisted of driving information from one round trip, while data from the other round trip was used during the testing phase. The divide in the experimental design ensured that the performance of our deep learning model was assessed in authentic driving scenarios, using realistic driving data from a diverse group of drivers.

4.2 Data pre-processing

After data collection and before modelling, data preparation is an essential stage in the machine learning (ML) pipeline. The objective is to accelerate the DL model's convergence and simplify learning. Data preparation involves several functions, such as managing absent values, removing outliers, standardising the data, and feature engineering if required. The data was standardised using the standardisation equation, which involves subtracting the mean and dividing by the standard deviation. Standardising the data puts all the variables on a common scale to ensure that no single variable takes control of the analysis and modelling process. It sets the foundation for reliable and significative analysis and modelling. Eqs. (7)-(9) present the data standardisation process.

The standard deviation is denoted by the parameter σ, whereas the mean is represented by μ. Furthermore, M indicates the dataset's size, and d_i shows a datum's value inside the dataset. We implemented the sliding window technique as a data augmentation method to enhance the driver recognition model's ability to capture a wider array of behaviours. This work uses overlapping sliding-window segments with a 6 s step size and a 1 min window size. Thus, every trip segment becomes a 60 × 15 array reformed into a 60 × 15 × 1 tensor. Ten drivers so generate 15004 windowed segments.

$$\mu = \frac{1}{M}\sum_{1}^{M} d_i \tag{7}$$

$$\sigma = \sqrt{\frac{\sum_1^M (d_i - \mu)}{M}} \tag{8}$$

$$d_{standardized} = \frac{d_{actual} - \mu}{\sigma} \tag{9}$$

4.3 Experimental setting

The proposed approach is primarily divided into two sections. The first section addresses the entire dataset, while the second section focuses on experiments involving 3-driver and 5-driver identification problems under two common few-shot scenarios: 1-shot and 5-shot. We adopt Adaptive Moment Estimation (Adam) as the optimiser, with an initial learning rate of 0.001, which is reduced by 0.9 every 100 steps. The experimental setup employed a TensorFlow 2.11 framework on a virtual machine in the Google Cloud Platform, which included four virtual CPUs and 15 GB of RAM. This setup was used for deep learning tasks.

4.4 Driver identification performance evaluation based on a public dataset

Furthermore, the 1D CNN-LSTM Attention method proved to be the driver identification classification method with the highest efficiency. The proposed approach exhibited much superior performance compared to other methods in terms of computational time and demonstrated improved metric performance, namely accuracy and F1-score. These results demonstrate the proposed algorithm's advantage over competing techniques. The performance of five machine learning algorithms (1D CNN-LSTM Attention, LSTM-Attention, LSTM, CNN, and ANN) was compared using accuracy and F1-score measurements. The comparison was done for a window size of 60 seconds with a 54-second overlap and 6-second time step. All the models were consistently outperformed by the 1D CNN-LSTM model with attention. One indicator of precision is the F1 score, which refers to the ability to precisely recognize positive examples and correctly recall or identify all positive situations. The 1D CNN-LSTM Attention model accomplished a better F1 score, showing its effectiveness in achieving a balanced performance in classification. This is due to its ability to extract features, enhance focus on important features, handle sequential dependencies, and learn robust representations. In the Security Driveset dataset context, the multi-head attention-based LSTM-CNN model performs better than other models, as Table 3 illustrates. It attains remarkable results, with scores of 99.93% with 60 window size. Figure 4 shows the average training process in terms of accuracy and loss.

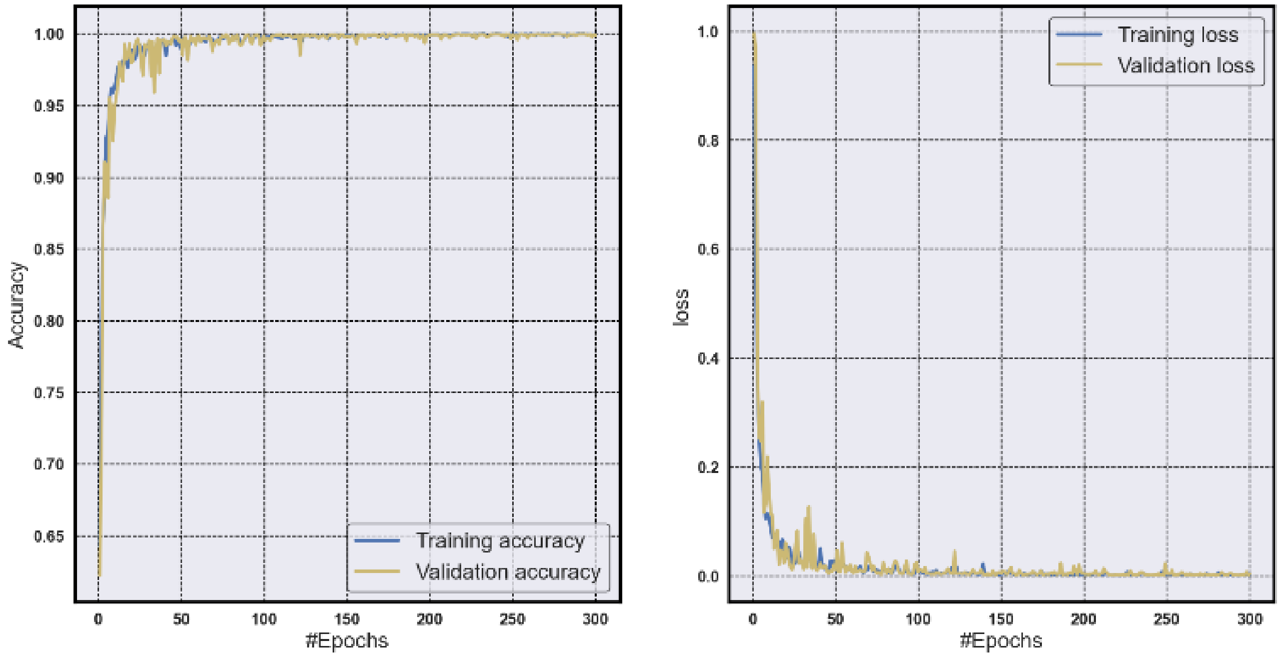

Figure 4. The average training process in terms of accuracy and loss

Table 3. The suggested models' accuracy and macro F1 score-based public dataset

Model	Training		Testing	
	Accuracy	F1-Score	Accuracy	F1-Score
CNN-LSTM Attention	0.9997	0.9997	0.9993	0.9993
LSTM-Attention	0.9993	0.9992	0.9945	0.994
CNN	0.8859	0.8881	0.8858	0.8882
LSTM	0.99	0.99	0.9899	0.9846
ANN	0.8149	0.8144	0.7383	0.7416

4.5 Few-shot learning experiments

Furthermore, the 1D CNN-LSTM Attention algorithm was found to be the most effective method for driver identity classification. Table 4 shows the performance of different models on the 1-shot and 5-shot for the 3-driver identification problem. Each model is evaluated based on accuracy, F1-score, and the time taken for inference. Among these models, the 1D CNN LSTM Attention stands out as the top performer in accuracy and F1 score metrics, exhibiting accuracy and F1 score of 0.6654 for 1-shot and 0.7827 for 5-shot. Notably, even with only one example per driver label, the proposed model surpasses the performance of other suggested models despite a relatively wide confidence interval. Additionally, it shows a comparable or even lower inference time, making it the most effective and efficient model among the options considered in the table. Table 5 showcases the testing performance of the methods above in the context of the 5-way Few-Shot Driver Identification problem. The results of these methods are compared to evaluate their effectiveness. However, the 1D CNN LSTM Attention is the most effective in handling the complexities of the 5-way FSDI problem. It surpasses the performance of the other models, showcasing higher accuracy and F1 scores. While the inference time is slightly longer than some models, it remains within acceptable limits, making it a favorable choice for the 5-way Few-shot Deep learning (FSDL) problem.

Table 4. Driver few-shot result comparison results of five deep learning models in terms of accuracy, F1-score, and training time for three driver configurations

Model	1-Shot			5-Shot		
	Accuracy	F1-Score	Time (s)	Accuracy	F1-Score	Time (s)
ANN	0.368	0.368	27	0.5434	0.5434	28
CNN	0.376	0.376	39	0.364	0.364	38
LSTM	0.4187	0.4187	136	0.68	0.68	145
LSTM Attention	0.5327	0.5327	116	0.7034	0.7034	110
1D CNN LSTM Attention	**0.6654**	**0.6654**	108	**0.7827**	**0.7827**	109

Table 5. Driver few-shot result comparison results of five deep learning models in terms of accuracy, F1-score, and training time for five driver configurations

Model	1-Shot			5-Shot		
	Accuracy	F1-Score	Time (s)	Accuracy	F1-Score	Time (s)
ANN	0.4276	0.4356	27	0.478	0.478	27
CNN	0.4288	0.4193	53	0.4624	0.4428	41
LSTM	0.4348	0.4322	165	0.5704	0.5897	176
LSTM Attention	0.5908	0.6021	108	0.766	0.778	116
1D CNN LSTM Attention	**0.7132**	**0.7040**	119	**0.9192**	**0.9003**	123

Table 6. Comparative table in terms of accuracy of driver identification, 3-driver FSDL, and 5-driver FSDL based security driving dataset [4]

Ref.	Year	Model	Driver Identification Accuracy	Few shot 3-Driver Accuracy	Few shot 5-Driver Accuracy
Proposed	Present	1D CNN-LSTM Attention	99.93%	66.65% for 1-shot 78.27% for 5-shot	71.32% for 1-shot 91.92% for 5-shot
Hu et al. [28]	2023	Ensemble M 1-D CNN with BLSTM	92.72%	64.67% for 3% of all dataset 79.83% for 10% of all dataset 87.32% for 30% of all dataset 90.35% for 30% of all dataset	
Lu and Xiong [27]	2022	MetaARNet	-	53.09% for 1-shot 68.05% for 5-shot	39.21% for 1-shot 51.57% for 5-shot
Azadani and Boukerche [30]	2021	Hybrid DeepConvLSTM	95.03%	-	-
Abdennour et al. [26]	2021	Deep RCN	99.30%	-	-
Azadani and Boukerche [25]	2020	1D-CNN-BLSTM	95.06%	-	-
Ullah and Kim [24]	2020	Depth-wise CONV-LSTM /GRU	98.72%	-	-
Zhang et al. [21]	2019	FCN-LSTM with self-attention	97.01%	-	-
El Mekki et al. [20]	2019	Hybrid FCN-LSTM	95.01%	-	-

Upon comparing the 5-shot and 1-shot scenarios, it becomes evident that all proposed methods exhibit improved classification performance. This outcome aligns with expectations, as having more training examples per label facilitates better learning. Notably, the 1D CNN-LSTM Attention and LSTM-Attention approaches, known for their success in image classification tasks, are also practical in driver identification. However, the performance of the other method fails to demonstrate its superiority in this particular problem.

4.5 Comparative analysis

This work aimed to assess and contrast different models, methods, or strategies for driver identification. It aimed to evaluate their effectiveness and performance in tackling the difficulties related to driver identification. Table 6 thoroughly summarises the most current developments in driver identification methods as described in the literature. It highlights each model's overall driver identification accuracy and few-shot learning accuracy within 3-driver and 5-driver scenarios.

The Proposed model, utilising a 1D CNN-LSTM Attention, stands out with the highest driver identification accuracy of 99.93%. This model also excels in few-shot learning, achieving 66.65% accuracy for 1-shot and 78.27% for 5-shot in the 3-driver scenario, and an impressive 71.32% for 1-shot and 91.92% for 5-shot in the 5-driver scenario. These results indicate the model's robustness and adaptability across different few-shot learning configurations. Hu et al. [28] employ an Ensemble M 1-D CNN with BLSTM and demonstrate a notable gradient in accuracy as the dataset size increases. Starting with 64.67% accuracy for 3% of the dataset, the model's performance improves significantly to 79.83% for 10%, 87.32% for 30%, and peaks at 90.35% for 50%. Lu and Xiong [27] present the MetaARNet model, which shows relatively lower accuracy in few-shot learning tasks. The 3-driver scenario achieves 53.09% for 1-shot and 68.05% for 5-shot; for the 5-driver scenario, it records 39.21% for 1-shot and 51.57% for 5-shot. Other models, such as El Mekki et al. [20], Zhang et al. [21], Ullah and Kim [24] Azadani et al. [25, 30], Abdennour et al. [26], primarily focus on overall driver identification accuracy. These models achieve accuracies ranging from 95.01% to 99.30%, indicating their effectiveness in identifying drivers. However, they do not provide specific data on few-shot learning performance, highlighting a gap in the comparative analysis for scenarios involving limited training samples. In conclusion, the Proposed model demonstrates superior performance in both overall accuracy and few-shot learning scenarios, making it a robust choice for driver identification tasks. Table 5 showcases the comparative our model with previous study in term of accuracy.

5. CONCLUSIONS

This paper presents a novel approach for driver identification using few-shot learning techniques. Our method leverages the power of a 1D CNN LSTM Attention model to address the N-driver identification problem, effectively adapting to scenarios with limited driving examples. Through comprehensive experiments on a public driving dataset, we demonstrated the robustness and accuracy of our model in both traditional and few-shot learning contexts. We validated our proposed method's superior performance and adaptability by comparing our approach with several baseline models, including LSTM Attention, LSTM, and CNN adaptability.

Additionally, our experiments on 3-way and 5-way classification problems using 1-shot and 5-shot approaches further highlight the efficacy of our model in dynamic and Evolve ng environments. When the entire raw dataset was used to train the models, remarkable results were achieved, with the highest accuracy and Macro F1 score reaching an impressive 99.93%. However, when tackling the few-shot learning driver identification problem, the experiments focused on the 3-driver and 5-driver scenarios using one-shot and five-shot approaches. Regarding one-shot learning, the highest accuracy obtained for the 3-driver and 5-driver problems was 66.54% and 71.32%, respectively. Even more promising outcomes were achieved with the five-shot learning approach. The highest accuracy for the 3-driver problem reached 78.27%, while an exceptional accuracy of 91.92% was attained for the 5-driver problem. This study has important practical and societal ramifications. In order to enhance the management of fleets, driver profiling, vehicle security, customized insurance, driving experiences, risk estimation, and traffic safety, the developed model can be put into use in the General Traffic Directorate. The model offers fast and tailored driving experiences in addition to improving overall traffic security and safety by precisely recognizing drivers using few amounts of data. The model can also be used by insurance firms to evaluate driver behavior and set fair insurance rates, encouraging safe driving practices. In general, this study has social and practical ramifications for transportation planning and road safety as well as the automobile sector.

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