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Driver Behavior Classification: A Novel Approach Using Auto-Encoders and Motif Extraction

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Abstract Driver's behavior is expressed by the intentional or unintentional actions the driver performs while driving a motor vehicle. This behavior could be influenced by several factors, such as the driver's fatigue, drowsiness, vehicle surroundings, or distraction state. Monitoring, analyzing, and improving driver behavior can reduce traffic collisions and enhance road safety. Several approaches have been followed for the detection and identification of driver's behavior. Conventional time-series analysis applies forecasting analysis methods for driver's behavior detection, assuming that data are stationary and ergodic; otherwise, data preprocessing is mandatory. Rule-based and deep learning approaches have succeeded in mining the dynamical characteristics of driving time series data. However, they have some challenges, including the selection of efficient architectures and corresponding hyper-parameters, as well as slow training and limited labeled data. In this study, we propose a motif-based approach for categorizing driver behavior as normal or abnormal. Our methodology entails the selection of relevant features, which are encoded using an auto-encoder model, followed by the conversion of the encoded data into an alphabet representation through quantization. Unique patterns of varying lengths are then extracted, and the driver's behavior is classified. Extracted motifs capture significant patterns, which enables us to achieve higher accuracy in classification. The obtained results demonstrate the effectiveness of the proposed approach in accurately categorizing driver behavior, which can significantly contribute to the advancement of intelligent transportation systems and the enhancement of road safety.

Keywords Driver Behavior Detection, Time-Series Data Analysis, Motifs, Machine Learning, AdaBoost.

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1. INTRODUCTION

On the world's roadways, over 1.3 million people die yearly and 20 to 50 million have accidents [1]. Driver behavior classification is a critical task in the field of intelligent transportation systems and driver safety monitoring. By accurately identifying normal and abnormal driving patterns, we can enhance road safety, prevent accidents, and develop effective driver assistance systems.

Several approaches have been investigated for the detection and identification of driver's behavior[9]. Traditional techniques, that apply time series forecasting analysis methods for predicting the driver's behavior [14], face several challenges when applied to driver behavior detection, including data non-stationarity, multi-variate nature, short-term dependencies, seasonality and external factors, etc. Rule-based detection algorithms, used to classify unseen data, would have difficulties to detect periodic or seasonal anomalies since they cannot recognize the temporal dependencies across time stamps [15]. Deep learning (DL) approaches have some challenges, including the selection of efficient architectures, the optimization of hyper-parameters, slow training, and limited labeled data [16].

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Recently, the area of time-series motif discovery has received a lot of attention from the data mining community [17]. Many researchers have investigated the time series motif detection algorithms in different applications, including computational biology, genetics, medicine, seismology, entertainment, etc. Motifs extraction is preferred over ML and DL approaches as it has the advantage of not requiring labels, which is extremely time-consuming to collect. However, few trials have been carried out to investigate the use of time series motifs for studying vehicles driver's behavior.

Several Bench-mark datasets are available for evaluating driver behavior detection algorithms. One of which is the UAH-DriveSet dataset that provides a comprehensive collection of driving scenarios captured from various sensors, including accelerometers, gyroscopes, and GPS [2]. The dataset contains rich, time-stamped raw and preprocessed data necessary to analyze and classify driving activities. It encompasses over 500 minutes of driving sessions involving six drivers, various cars, and three driving styles (normal, aggressive, and drowsy) on two road types (motorway and secondary). Another dataset, similar to UAH-Driveset, is the "Driving Behavior [Data set]"[20] which possesses data from Accelerometer and Gyroscope sensors and categorizes the driver's behavior as Aggressive, Normal, and Slow.

This paper proposes a motif-based approach for categorizing driver behavior as normal or abnormal, using the UAH-DriveSet dataset as the main dataset and "Driving Behavior [Data set]" to validate the applicability of our proposed methodology. The proposed methodology entails the selection of relevant features, which are encoded using an auto-encoder model, followed by the conversion of the encoded data into an alphabet representation through quantization. Unique patterns of varying lengths are then extracted, and classifiers are utilized for behavior classification.

The rest of this paper is organized as follows. Section II summarizes the related work, and Section III introduces the proposed methodology. The results and discussion are presented in section IV, and the conclusions are presented in Section V.

2. LITERATURE REVIEW

The detection of motor vehicle drivers' behavior is an essential task in the field of intelligent transportation systems. It aims to understand and predict driver actions and intentions for improved road safety and traffic management.

Recently, the area of motif discovery has received a lot of attention from the data mining community, however, few trials have been carried out to investigate the use of motifs for studying vehicles driver's behavior. The availability of large-scale driving datasets, such as the "UAH-DriveSet," [2] has facilitated significant advancements in driver behavior analysis and classification.

Silva et al., in [11] proposed an approach for identifying maneuvers from vehicle telematics data, through motif detection in time series. They used a modified version of the Extended Motif Discovery (EMD) method [13] that was applied to the UAH-DriveSet [2]. They attempted to detect acceleration and brakes from the longitudinal acceleration time series, and to recognize turns from the lateral acceleration time series. They noticed that the updated EMD algorithm successfully extracts complicated maneuvers including lane changes and overtaking movements.

The authors in[12] proposed a system (TripMD) that extracts relevant driving patterns from a set of trips. They used Extended Motif Discovery (EMD) algorithm [13] to find their motifs. To evaluate the applicability of TripMD to real tasks, they used the UAH-DriveSet. The three behaviors identified in the dataset (normal, aggressive, and drowsy) were identified.

While these few studies have made significant contributions to driver behavior classification using motifs, several gaps and opportunities for further research remain. More investigations should be carried out, using different datasets and new models for achieving the most possible benefits of this approach. In addition, there is a need

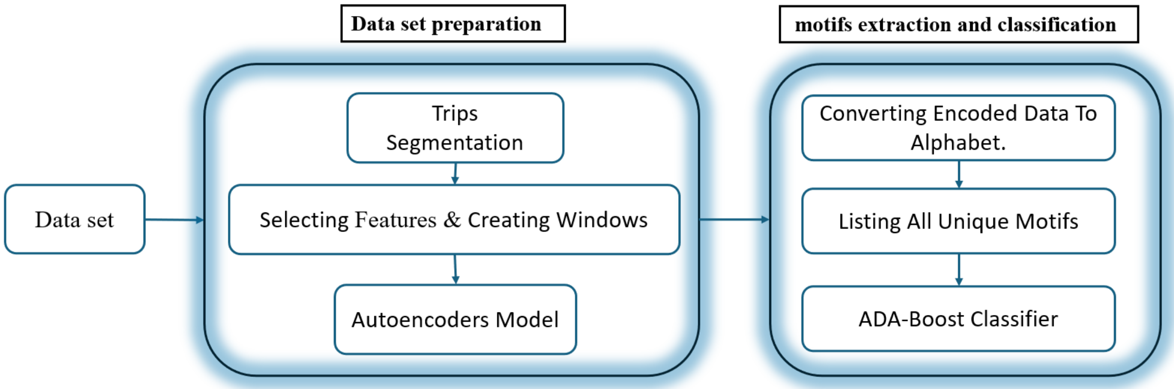

Figure 1. System Architecture.

for comparative studies that evaluate the performance of different feature extraction techniques, including motifs, deep learning, and traditional methods, to determine the most effective approach for driver behavior classification.

Furthermore, the generalization of driver behavior classification models to real-time and real-world scenarios remains a challenge. Future research should focus on developing robust and scalable models that can be deployed in real-time systems, considering factors such as data streaming, computational efficiency, and model interpretability.

3. PROPOSED METHODOLOGY

Benchmark datasets are essential for evaluating driver behavior detection algorithms. One of the public datasets that allow deep driving analysis by providing a large amount of data is UAH-DriveSet [2]. In a previous work by the authors [10] , an investigation of the performance of different machine learning classifiers for the driver's behavior classification using UAH-DriveSet was carried out. The core of the proposed work is carried out applying AdaBoost classifiers on the UAH-DriveSet.

According to Figure 1, a dataset is used to analyze the vehicles' driving behaviors. In our case, two datasets are used: "UAH-DriveSet" [2] as a main dataset, and "Driving Behavior [Data set]" [20] as a secondary one. We pick just a few key pieces, telling us how a driver behaves; how fast the car speeds up and slows down, what way the car is turning, how often the driver switches lanes, and so on. Picking the right pieces of data is super important. It makes our pool of data easier to handle and lets us zone in on what truly matters for detecting driver behavior.

3.1. UAH-DriveSet Preparation

We use the exact features that Saleh et al., used for a balanced comparison [6]. These feature vectors include six features from the inertial measurement sensors: acceleration along x-axis, y-axis and z-axis, roll angle, pitch angle and yaw angle besides two features from the GPS sensor which are the speed and distance to the ahead vehicle, and only one feature from the camera sensor which is the number of detected vehicles.

To ensure accurate trip analysis, we adopt a methodology of segmenting each trip into a series of smaller trips. Specifically, we divide each trip into 5-minute segments with a 3-minute overlap. This approach allows us to capture more granular information and account for variations within the trip duration.

Another segmentation of the trips of UAH-Driveset is carried out to test the proposed approach via small trips. The trips are segmented into 2-minute segments with 1-minute overlap and 3-minute segments with 1.5-minute overlap.

We use a rolling window technique (W) on the 9 aspects taken from the UAH-DriveSet data. Before using the rolling window, these aspects are remodeled and standardized for matching and comparison. This rolling window is

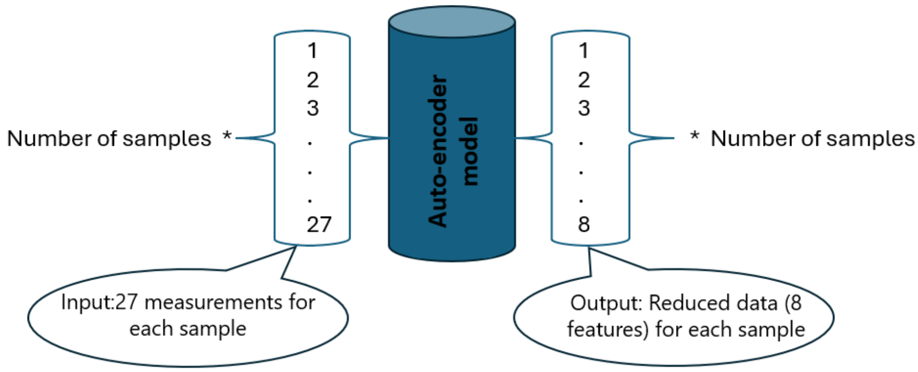

Figure 2. AutoEncoder Model for UAH-Dataset

3 units big, meaning we look at three related aspects together. Importantly, the rolling window uses a 66% overlap, letting us fully examine the data. This method grows the data, crucial for training deep auto-encoder models well.

Once we've picked out which features to look at, we start using an auto-encoder to shrink the data size [4]. We teach the auto-encoder using the features we picked. This lets us get a neat, small version of the data that still holds its main details. This smaller version is important because it shows us the basic patterns and connections in the driver's behavior. The model works with data shaped as (number of samples * 9 features * 3 window size), which can be described as (#numOfSamples * 27) to get encoded data (features) with the shape of (#numOfSamples * 8).

3.2. Driving Behavior [Data set] Preparation

We use all the available features in Driving Behavior [Data set] which are acceleration in x, y, and z axes and Gyroscope in x, y, and z axes. We also use the same rolling window technique used for UAH-Driveset then we use the autoencoder to encode this data. For this dataset, the model encodes data from 18 columns (Input data 6*3 for each sample, to the output of autoencoder: 4 features (columns)).

3.3. Motifs Extraction and Classification

Once we encode the data, we have to find the most effective column (most relevant feature vector), from the output of the autoencoder, so that its numeric value can be converted to an alphabet as it was encoded by all selected features. Thus, creating a Principal Component Analysis (PCA) object with the PCA class providing a good tool for reducing dimensionality in a linear way [3]. This is accomplished through Singular Value Decomposition (SVD), which brings the data into a smaller space. Before SVD is applied, we centralized the data, which gives each attribute an average of zero. However, feature scaling isn't performed on the data.

A quantization technique is applied to convert the most effective column of encoded data into an alphabet representation. Quantization involves mapping continuous numerical values into discrete symbols based on predefined thresholds or quantization levels. The quantization process helps in reducing the data complexity and provides a symbolic representation that is more amenable to classification algorithms. By converting the encoded features into an alphabet representation, we aim to improve the interpretability and generalization of the classification model.

Once we have obtained the resulting alphabetical representation of the converted numeric column using clustering, the next step is to extract a list of all unique motifs of a selected length as explained in Algorithm 1.

To continue, we set out the length of the motifs we aim to extract. Let's say we opt for a length of three; we'll then lookout for patterns made up of three characters within the alphabetical representation. Moving forward, we work through the entire alphabetical representation, with a window of the chosen length sliding along the sequence.

Algorithm 1 Motif Extraction Algorithm

```
Step 1: Convert Numeric Column to Alphabetical Representation using Clustering
Input: Numeric column num_column
Output: converted_alphabetical_column
converted_alphabetical_column ← convert_numeric_to_alphabetical(num_column)
Step 2: Extract Unique Motifs of Selected Length
Input: Motif length motif_length, converted_alphabetical_column
Output: unique_motifs
unique_motifs ← []
for i in len(converted_alphabetical_column) do
    motif ←converted_alphabetical_column_from_i_to_i+motif_length
    if motif not in unique_motifs then
        unique_motifs.append(motif)
    end if
end for
Step 3: Mark Trips Based on the Presence of Unique Motifs
Input: List of trips trips
Output: List of marked trips marked_trips
marked_trips ← []
for trip in trips do
    trip_alphabetical ← get_trip_alphabet(trip_Id, converted_alphabetical_column)
    trip_Motifs ← []                          ▷ Same length as unique_motifs
    for motif in unique_motifs do
        if motif in trip_alphabetical then
            trip_Motifs[motif] ← 1            ▷ Set mark to 1 if motif is present
        else
            trip_Motifs[motif] ← 0            ▷ Set mark to 0 if motif is not present
        end if
    end for
    marked_trips.append(trip_Motifs)
end for
```

As the window comes upon each position, we take note of the motif it captures and add it to a list, as long as it's not already there. This method ensures that the resulting list only contains distinct motifs.

As we slide the window, we diligently cover every single length of the alphabetical representation. This process results in a comprehensive list of unique motifs for the chosen length. From there, our next step is to thoroughly scan through each trip's alphabetical representation. We scrutinize for any of the previously compiled unique motifs. If a trip contains one or more of these motifs, it is marked as 1. However, if no match is found, it is given a value of 0.

With the quantized alphabet representation in hand, we proceed to classify driver behavior using the AdaBoost algorithm. AdaBoost, short for Adaptive Boosting, is a popular ensemble learning algorithm that combines multiple weak classifiers to form a strong classifier [5]. In our experiment, we train the AdaBoost classifier on the quantized features and evaluate its performance in distinguishing between normal and abnormal driver behaviors. The ensemble nature of AdaBoost allows us to leverage the strength of multiple classifiers and improve the overall classification accuracy.

4. Results and Discussion

4.1. UAH-DriveSet

The UAH-DriveSet comprises various road types, including motorways and secondary roads. To analyze each road type, we initially break down every trip into 5-minute segments, with a 3-minute overlap. Consequently, we obtained 93 trips for the secondary road and 118 trips for the motorway road. By applying an autoencoder and subsequently converting the most effective column to alphabetical representation, we obtain a collection of unique motifs, as displayed in Table 1.

Table 1. Number of unique motifs for each motif length

Road type	Motif length	Number of unique motifs
Secondary (93 trips)	From 5 to 10	6106
	From 10 to 20	246184
	100	256175
	200	261356
Motorway (118 trips)	From 5 to 10	11971
	From 10 to 20	226728
	100	336137
	200	262679

Once we acquired the unique motifs, we constructed our AdaBoost model using these motifs as features and the number of trips as the sample size. The data was randomly divided as 80% training set and 20% test set, and we employed 100 estimators in our AdaBoost model, each estimator here being the individual weak learners or base models utilized by the AdaBoost algorithm [5]. To calculate the performance of our methodology we use accuracy and F1-score. We iterate till the accuracy has no change for 5 subsequent iterations. Accuracy is the proportion of correct predictions. F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. The formula for the F1 score is:

$$F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{1}$$

According to Table 2, the obtained classification accuracy is 100% for short motif lengths (5-10) for secondary way and 99.3% for motorway and decreases for longer motif lengths. (For our analysis, we conducted experiments using different motif lengths: 5 to 10, 10 to 20, 100, and 200).

Table 2. Performance of our proposed solution with different motif lengths

Road type	Motif length	Accuracy	F1-Score	Number of iterations
Secondary way (93 trips)	From 5 to 10	1	1	10
	From 10 to 20	1	1	10
	100	0.799	0.845	55
	200	0.341	0.543	40
Motorway (118 trips)	From 5 to 10	0.993	0.991	20
	From 10 to 20	0.98	0.976	30
	100	0.88	0.83	30
	200	0.791	0.658	20

In order to comprehend the impact of individual motif lengths on the effectiveness of our method, we consider motif lengths [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 30, 50, 100, 200, 300, 400] for motorway road type and evaluate the efficiency of each length in the activity one by one.

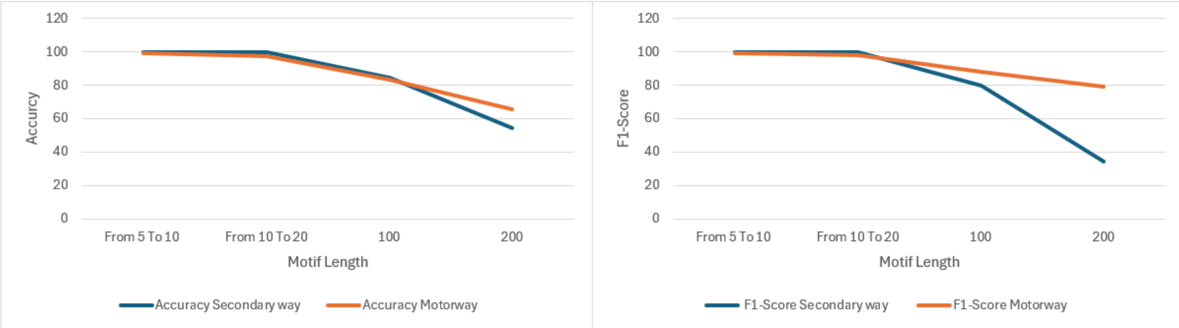

Figure 3. Performance of our approach via selected motifs length

Table 3. Performance of each motif length

Motif length	Motifs count	Accuracy (%)	F1-score (%)
5	239	87.9	90.5
6	489	89.5	91.8
7	968	90.8	92.5
8	1813	90	91.8
9	3189	89.8	91.7
10	5308	92.5	94.2
11	8352	89.5	91.5
12	12439	91.2	92.9
13	17707	89.9	92.2
14	24209	89.7	91.8
15	31984	89.4	91.7
16	40212	89.4	91.8
17	49943	89.2	91.1
18	60322	90.7	92.3
19	72735	90.8	93.1
20	84066	90.9	92.7
30	188935	89.9	91.7
50	290127	85.1	88.8
100	336020	76.4	84.2
200	342875	66.3	79.3
300	343344	67.5	80.3
400	343324	64.6	78.2

According to Table 3, Figure 4, and Figure 5, for short motifs, the performance of each motif is around 90% and decreases for longer motif lengths. With the rate of collection of the dataset of about 10 rows per second, it is logical that one driver will perform better with shorter time intervals. The combination of various lengths gives better performance and results.

For the second segmentation case mentioned before (2-minute with a 1-minute overlap and 3-minute trips with a 1.5-minute overlap), the results are as follows:

Based on the primary experiment outcomes, we identified the most successful motifs with lengths less than 20 characters for the new short attractions to verify our hypothesis with the limitation that this technique will be effective so long as the dataset contains shorter rides with a total duration of not more than 2 minutes. The results of the drive behavior classification revealed that our model can reliably classify driver behavior with an accuracy of 99%.

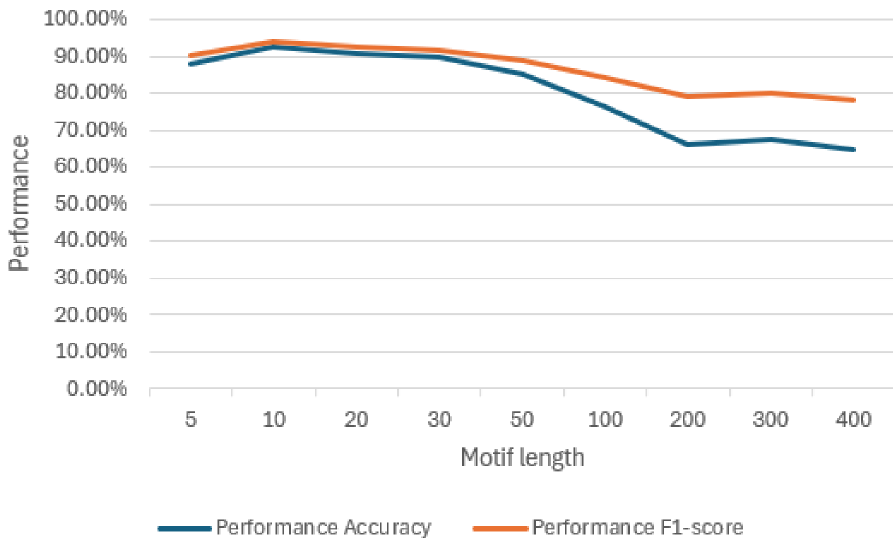

Figure 4. Performance of our approach vs motif length

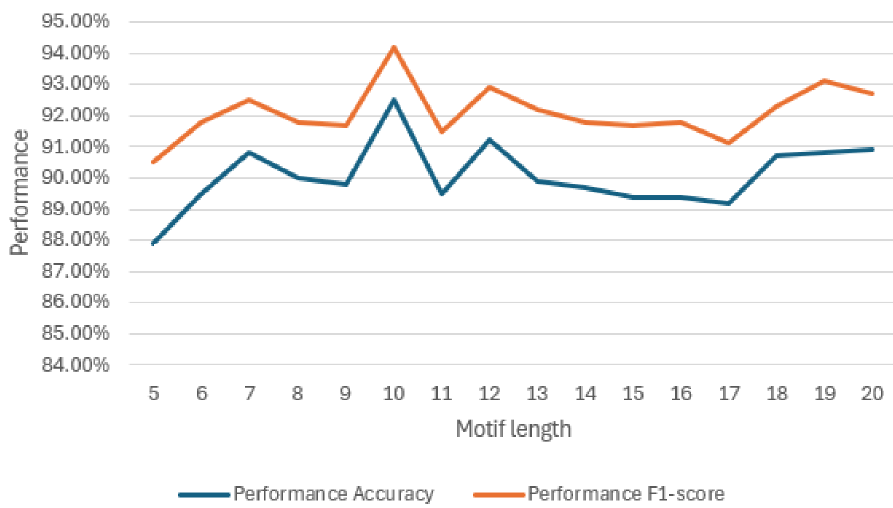

Figure 5. Performance of our approach to individual short motif length

Table 4. Performance of our approach using multi-ride durations

Ride duration	Road type	Rides count	Motif length	Motifs count	Accuracy	F1-score	Number of iterations
2 minutes With 1-minute overlap	motorway	181	From 5 to 10	4995	98.2%	98.5%	15
			From 10 to 20	81532	98.5%	98.9%	15
	Scoundry way	204	From 5 to 10	5681	97.8%	97.6%	30
			From 10 to 20	100020	99.1%	98.9%	45
3 minutes With 1.5 minutes overlap	motorway	167	From 5 to 10	6150	98.5%	98.8%	15
			From 10 to 20	115809	97.8%	98.8%	10
	Scoundry way	141	From 5 to 10	7615	99.2%	99.2%	10
			From 10 to 20	140966	99.8%	99.8%	10

Besides, we make an effort to figure out some useful patterns through radial exploration within the motifs extracted files to match the patterns with the footage of the trip to check if the same pattern is repeated by the driver performing a similar motion. For instance, in the case study, we took a trip from UAH-DriveSet dubbed "(20151111132348-25km-D1-DROWSY-MOTORWAY)", which signifies that the particular trip was undertaken on a Motorway while the driver was acting as drowsy, we discovered that the same motif kept recurring whenever the driver was about to change lanes.

To provide a comprehensive evaluation of our approach, we can juxtapose our findings with those of other studies conducted on the same dataset. As provided in Table 5, Saleh et al. [6], who employed an LSTM model on the UAH-Driveset dataset, achieved an accuracy of 0.95 for secondary way trips, with a slightly lower accuracy of 0.89 for motorway trips, with an overall accuracy of 0.91. This serves as a standard for comparison in our analysis. Furthermore, Sahoo et al. [7], utilizing the UAH-Driveset dataset, applied LSTM-BiLSTM_GRU-GRU models and achieved an overall accuracy of 0.92. Moreover, the findings from Y. Moukafih et al.'s [8] research are worth considering. By utilizing the Stacked-LSTM model, they achieved an impressive accuracy of 99.3% in classifying driver behavior as either normal or not normal, and 99.4% accuracy in classifying it into three distinct categories: normal, aggressive, and drowsy. These results provide valuable context for evaluating our proposed solution and its ability to accurately capture and classify driver behavior patterns.

Table 5. Performance comparison of driver's behavior detection and classification

Reference	Approach	Num of output classes	Evaluation F1-Score (%)
Saleh et al. [6]	LSTM	2: (normal/not normal)	91
Sahoo et al. [7]	LSTM-BiLSTM_GRU-GRU	2: (normal/not normal)	92
Y. Moukafih et al. [8]	Stacked-LSTM	2: (normal/not normal)	99.3
		3: (normal, aggressive, and drowsy)	99.4
Proposed Approach	Motifs & AdaBoost	2: (normal/not normal)	**99.9±0.1**

4.2. Driving Behavior [Data set]

The behavior in this Driving Behavior [Data set] is categorized as AGGRESSIVE, NORMAL, and SLOW. Similar to UAH-DataSet, we also testified for the driver as normal and not normal. In the new dataset, 'AGGRESSIVE' signifies non-normal driving behavior whereas 'NORMAL and SLOW' indicate normal driving behaviors. In The "Driving Behavior [Data set]" there are 2 files for training and testing. The training file is divided into 12 trips, each trip has about 450 rows with 150 rows overlapped for about 3.5 minutes. The test file was also divided into 11 trips while observing the same conditions. Table 6 below shows the obtained results.

Table 6. Accuracy of our approach while using "Driving Behaviour [Data set]"

Motif length	Motif count	Accuracy (%)
3	53	100%
5	353	100%
7	1196	81.8%
9	2455	81.8%
From 3 to 9	6730	100%
20	3611	63.6%

According to Table 6, Figure 6, many datasets can be handled using our method. In particular, the performance achieved by the "Driving Behaviour [Data set]" is similar to that of the UAH-Dataset, although this data set does not contain all the relevant features found in the UAH-Dataset. This points out the efficiency and versatility of our approach against varying data conditions.

For Smart Vehicles coupled with Built-in Sensors and Cameras, the proposed model can be deployed on an Electronic Control Unit (ECU) which is capable of running the model and classifying driver behavior in real-time. This will ensure that alerts are triggered whenever abnormal behavior is detected.

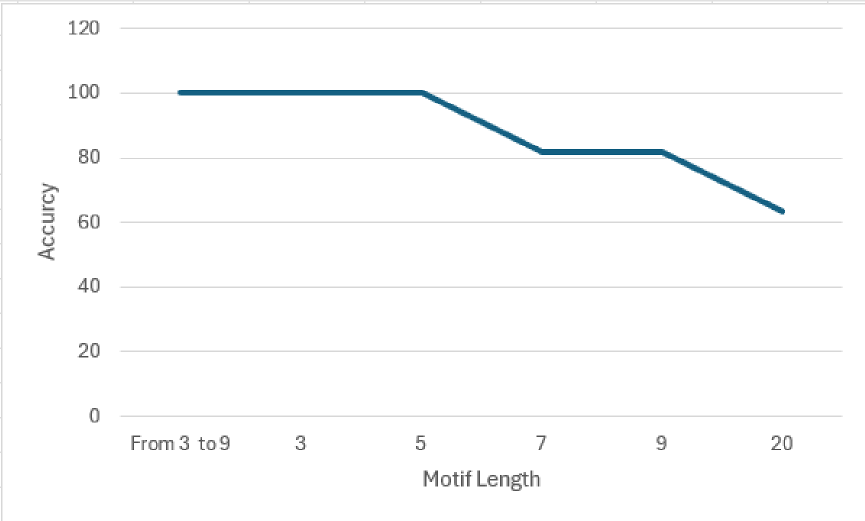

Figure 6. Accuracy of our approach while using “Driving Behaviour [Data set]”

5. Conclusion

This study proposes a motif-based approach for categorizing driver behavior as normal or abnormal, using two datasets. Our methodology entails the selection of relevant features, which are encoded using an auto-encoder model, followed by the conversion of the encoded data into an alphabet representation through quantization. Unique patterns of varying lengths are then extracted, and an AdaBoost classifier is utilized for behavior classification. Extracted motifs capture significant patterns, which enables to achieve higher accuracy in classification.

The proposed approach successfully detected all true instances of the target motifs. This outcome highlights the effectiveness of the proposed methodology in capturing meaningful behavioral patterns. The resulting classification accuracy is 100% for short motif lengths (5-10), for both secondary way and motorway datasets, and decreases for longer motif lengths. By focusing on shorter motifs, we were able to identify and analyze recurring patterns that play a significant role in understanding and categorizing driver behavior.

The obtained results demonstrate the effectiveness of the proposed approach in accurately categorizing driver behavior, which can significantly contribute to the advancement of intelligent transportation systems and the enhancement of road safety.

Compared to published works, the proposed approach outperforms recently published research in this area. Consequently, Motif detection seems to be a valid line of research in driving behavior analysis.

REFERENCES

1. World Health Organization. Global status report on road safety, 2024. https://www.who.int
2. E. Romera, L. M. Bergasa, and R. Arroyo, “Need data for driver behaviour analysis? Presenting the public UAH-DriveSet,” in Proc. IEEE 19th Int. Conf. Intelligent Transportation Systems (ITSC), 2016, pp. 387-392. https://doi.org/10.1109/ITSC.2016.7795584
3. L. G. Kabari and B. B. Nwamae, “Principal component analysis (PCA)-an effective tool in machine learning,” Int. J. Advanced Research in Computer Science and Software Engineering, vol. 9, no. 5, pp. 56-59, 2019.
4. Baldi, Pierre. ”Autoencoders, unsupervised learning, and deep architectures.” Proceedings of ICML workshop on unsupervised and transfer learning. JMLR Workshop and Conference Proceedings, 2012.
5. Y. Freund and R. E. Schapire, “Experiments with a new boosting algorithm,” in Proc. Int. Conf. Machine Learning (ICML), vol. 96, pp. 148-156, 1996.
6. K. Saleh, M. Hossny, and S. Nahavandi, “Driving behavior classification based on sensor data fusion using LSTM recurrent neural networks,” in Proc. IEEE Int. Conf. Intelligent Transportation Systems (ITSC), 2018, pp. 1-6. https://doi.org/10.1109/ITSC.2017.8317835

7. G. K. Sahoo, S. K. Das, and P. Singh, “Two layered gated recurrent stacked long short-term memory networks for driver’s behavior analysis,” Sādhanā, vol. 48, no. 75, 2023. https://doi.org/10.1007/s12046-023-02126-y
8. M. A. Khodairy and G. Abosamra, ”Driving Behavior Classification Based on Oversampled Signals of Smartphone Embedded Sensors Using an Optimized Stacked-LSTM Neural Networks,” in IEEE Access, vol. 9, pp. 4957-4972, 2021. https://doi.org/10.1109/ACCESS.2020.3048915
9. Rabab Gamal, Mirvat Al-Qutt, and Said Ghoniemy, “Driver Behavior Detection in Time Series Decade”, International Journal of Intelligent Computing and Information Sciences (IJICIS), Ain Shams University, Vol.23, No.3, 114-140, 2023. https://doi.org/10.21608/ijicis.2023.192999.1254
10. R. Gamal, M. Al-Qutt, H. Khaled, M. Fayez and S. Ghoniemy, ”Impact of Feature Selection and Interactions on Accuracy of Classical Machine Learning Algorithms: A Driver Behavior Case Study”, 2024 Intelligent Methods, Systems, and Applications (IMSA), Giza, Egypt, 2024, pp. 330-335. https://doi.org/10.1109/IMSA61967.2024.10652676
11. M. I. Silva and R. Henriques, “Finding manoeuvre motifs in vehicle telematics,” Accident Analysis Prevention, vol. 138, p. 105467, 2020. https://doi.org/10.1016/j.aap.2020.105467
12. Silva, M. I., Henriques, R. (2021). TripMD: Driving patterns investigation via motif analysis. Expert Systems with Applications, 184, 115527. https://doi.org/10.1016/j.eswa.2021.115527
13. Yoshiki Tanaka, Kazuhisa Iwamoto, and Kuniaki Uehara. Discovery of Time-Series Motif from Multi-Dimensional Data Based on MDL Principle. Machine Learning, 58(2):269–300, February 2005. ISSN 1573-0565. https://doi.org/10.1007/s10994-005-5829-2
14. Soukaina Bouhsissin, Nawal Sael, Faouzia Benabbou,” Driver Behavior Classification: A Systematic Literature Review”, IEEE Access Volume 11, 2023. https://doi.org/10.1109/ACCESS.2023.3243865
15. Hu, J., Wang, T., Zhang, H. et al. A review of rule-based collision avoidance technology for autonomous UAV. Sci. China Technol. Sci. 66, 2481–2499 (2023). https://doi.org/10.1007/s11431-022-2264-5
16. Alzubaidi, L., Zhang, J., Humaidi, A.J. et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J Big Data 8, 53 (2021). https://doi.org/10.1186/s40537-021-00444-8
17. Zhu, Yan, Abdullah Mueen, and Eamonn Keogh. ”Admissible time series motif discovery with missing data.” arXiv preprint arXiv:1802.05472 (2018).
18. Soukaina Bouhsissin, Nawal Sael, Faouzia Benabbou,’ Classification and Modeling of Driver Behavior During Yellow Intervals at Intersections’, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W3-2022.
19. Y. Ma, Z. Xie, S. Chen, Y. Wu, and F. Qiao, “Real-time driving behavior identification based on multi-source data fusion,” Int. J. Environ. Res. Public Health, vol. 19, no. 1, p. 348, 2021. https://doi.org/10.3390/ijerph19010348
20. Paul-Stefan Popescu, and Cojocaru Ion. (2022). Driving Behavior [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DSV/3748585