Driving behavior analytics: an intelligent system based on machine learning and data mining techniques

Areen Arabiat, Muneera Altayeb
Department of Communications and Computer Engineering, Faculty of Engineering, Al-Ahliyya Amman University, Amman, Jordan

Article Info

Article history:

Received Aug 2, 2024
Revised Oct 19, 2024
Accepted Nov 26, 2024

Keywords:

AdaBoost
CN2 rule inducer
Driver behavior
Machine learning
Orange3 data mining tool

ABSTRACT

One of the most common causes of road accidents is driver behavior. To reduce abnormal driver behavior, it must be detected early on. Previous research has demonstrated that behavioral and physiological indicators affect drivers' performance. The goal of this study is to consider the feasibility of classifying driver behavior as either aggressive (sudden left or right turns, accelerating and braking), normal (average driving events) or slow (keeping a lower-than-average speed). Innovation in data mining and machine learning (ML) has allowed for the creation of powerful prediction tools. ML techniques have shown potential in predicting driver behavior, with classification being a critical study area. The data set was gathered using the Kaggle platform. This study classifies driver behavior using Orange3 data mining tools and tests several classifiers, including AdaBoost, CN2 rule inducer, and random forest (RF) classifiers. The results showed that AdaBoost was superior in predicting driver behavior, with 100% accuracy, while the classification accuracy in CN2 rule inducer and RF was 99.8% and 95.4%, respectively. These results demonstrate the possibility of early and highly accurate driver behavior prediction and use it to create a ML-based driver behavior detection system.

Corresponding Author:

Areen Arabiat
Department of Communications and Computer Engineering, Faculty of Engineering
Al-Ahliyya Amman University
Al-Salt, Amman, Jordan
Email: a.arabiat@ammanu.edu.jo

1. INTRODUCTION

Every year, millions of people are injured or killed in car incidents worldwide. Human drivers' difficulties, including cognitive overload, judgment, and operational errors, are the primary causes of traffic accidents. Drivers impact traffic by operating their cars by traffic regulations and allowing themselves to drive [1]. Road safety is a global concern, causing 1.3 million deaths and injuries annually. Factors like human conduct, road layout, vehicle safety, environmental conditions, and socioeconomic differences contribute to accidents. The European Union and WHO aim to reduce fatal traffic accidents by 2030, with emerging technology expected to play a crucial role [2].

Driver behavior is one of the most essential parameters that influence road safety. As a result, monitoring and identifying driver behavior systems has lately been a popular subject in the study [3]. However, human drivers engage in a variety of activities, such as road usage, transportation use, social contact, and psychobiological organisms. Their distinct characteristics, including mental abilities like attention and decision-making, lead to accidents. Reduced behavioral features can lead to accidents; hence, automation is a viable alternative [4], [5]. Driving is a complicated activity that demands both physical and psychological changes. Intelligent vehicles can educate drivers, but confusion can lead to differences.

Efficient driver-vehicle cooperation solutions based on driving behavior prediction and mental state inference are critical for improved driver-vehicle understanding [6]. In order to improve road accident mitigation and avoidance systems, driver models were developed; however, existing models do not take user interactions into account, despite advances in control theory models and data-driven applications [7].

Research relies heavily on artificial intelligence (AI) technology. Machine learning (ML) and deep learning (DL) are strong technologies widely employed in various settings and applications, including robotics [8]. However, ML and DL approaches have considerably enhanced the efficiency of intelligent transportation systems (ITS), notably in the areas of traffic anomaly prediction, accident detection, and severity prediction. Human factors play an important part in traffic accidents, accounting for 95% of all incidents. As a result, monitoring and analyzing driver behavior is critical for detecting safety issues and designing accident prevention techniques. Driver behavior can be difficult to precisely characterize and assess due to psychological, social, cultural, environmental, and individual aspects [9].

Yang *et al.* [10] examined the connections between driving aggression, driving behavior, and driving competence among 239 licensed drivers. Driving ability, everyday driving habits, and aggressive driving behaviors were the main topics of the questionnaire study. Five components were extracted using factor analysis, and the link between these factors and the societal characteristics of the drivers was investigated using correlation analysis. Drivers' driving aggression was divided into tiers using the K-means cluster algorithm. To forecast driving aggression levels, an ordinal regression model was created. According to the findings, male drivers exhibited greater anger while driving, while experienced drivers reported improved driving conduct. Elassad *et al.* [11] demonstrated that neural networks (NN) are among the most exact ML methods for evaluating the driving events dimension. When studying driver behavior using ML approaches, this dimension has been the focus of active research, with additional emphasis paid to physiological and psychological states. According to the evaluation of the driving events dimension, ML models have arithmetic means of accuracy ranging from 73% to 98%, recall from 82% to 96%, and specificity from 84% to 97%. Malik *et al.* [12] explored that various methodologies can be used to identify the target driver's behavior, depending on system capabilities and desired effects. NN methods were used to examine current driver behavior and styles. This proposed method assessed various parameters that were important in determining particular driver behavior and driving styles. The Python experiment found that the driver model achieved 90% accuracy in logistic regression.

Ansari *et al.* [13] suggested a modified bidirectional long short-term memory deep NN was built, trained, and evaluated on 15 healthy participants utilizing 3D time-series head angular acceleration data for sequence-to-sequence categorization. The research describes a unique technique for evaluating driver mental tiredness and sleepiness via head position changes. The solution, which used a modified bidirectional deep NN, outperformed cutting-edge techniques and traditional ML tools. The study discovered that the total training accuracy was 99.2%, the sensitivity was 97.54%, the precision was 97.38%, and the F1 score was 97.46%. William *et al.* [14] proposed a real-time detection and monitoring system for weary drivers that employs DL and behavioral techniques. The system records real-time driving behavior and trains it with a convolutional neural network (CNN) that has a 99.8% accuracy rate, as well as a MATLAB prototype model. On the other hand, the work in [15] describes a web-based system for real-time driver sleepiness detection that employs facial landmarks, metrics such as eye aspect ratio (EAR) and eye closure ratio (ECR), and adaptive thresholding. The you only look once (YOLO) v5 classifier is integrated and achieves 91% accuracy, indicating its potential to improve driver safety through effective sleepiness detection.

In this study, a registered dataset from Kaggle is used to classify and determine the driver into the following types: normal, slow, and aggressive, using ML techniques that include AdaBoost, CN2 rule inducer, and random forest (RF). It is expected that the proposed model will leverage the study's findings to identify the driver's behavior. The novel aspect of this work is developing a predictive model to identify different types of driver behavior using the Orange3 data mining tool, in addition to using a huge data set of driver behaviors that are collected by the Android data collector application. The dataset includes 3,084 instances, with critical features including subtraction of gravitational acceleration, accelerometer and gyroscope sensors, acceleration, rotation, classification labels, and timestamps. These features will lead to accurate prediction and classification.

2. METHOD

The proposed model uses several ML techniques to predict driver behavior. This method part will use Orange3 to create ML models. The dataset was first acquired via the Kaggle platform, and it was then preprocessed and transformed to a comma-separated value (CSV) format that Orange3 could read. The dataset is then passed into Orange3, which uses AdaBoost, CN2 rule inducer, and RF to generate the needed model. Because there were a large number of records (3085) in the dataset, random selection with a 70%

training and 30% testing set size produced a satisfactory result. In addition, 10-fold cross-validation is used to improve performance and avoid overfitting. After constructing the trained model, the dataset is assessed in terms of accuracy, f-measure, precision, and sensitivity using the confusion matrix generated by Orange3. Furthermore, a comparison study will be carried out to determine which ML model has the best performance metrics. The findings reveal which ML algorithms are superior at predicting driver behavior, among other things, as shown in Figure 1, which displays the design of a driver behavior prediction system. The model of the driver behavior prediction system is depicted in Figure 2.

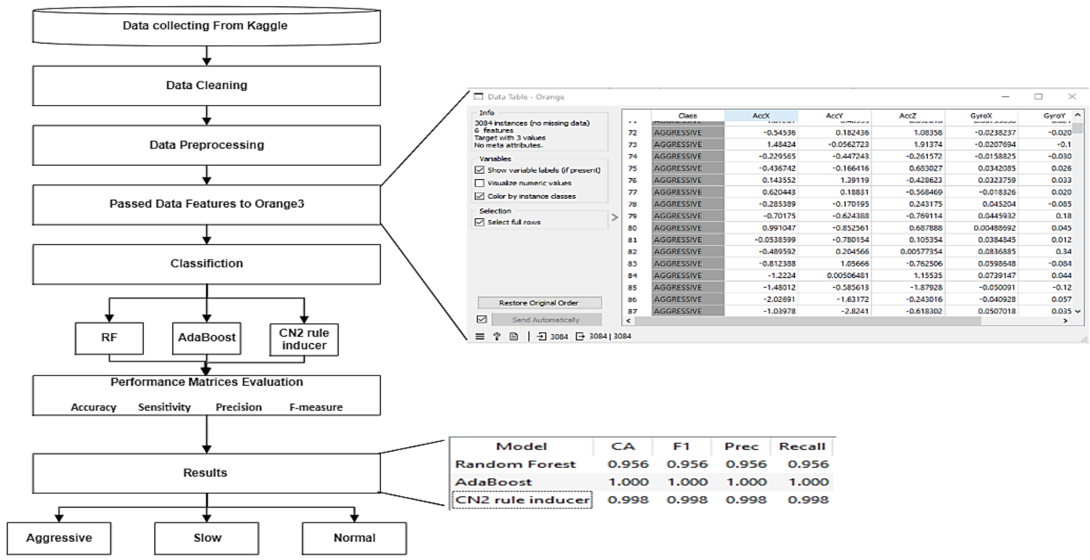


Figure 1. Driver behavior prediction system structure

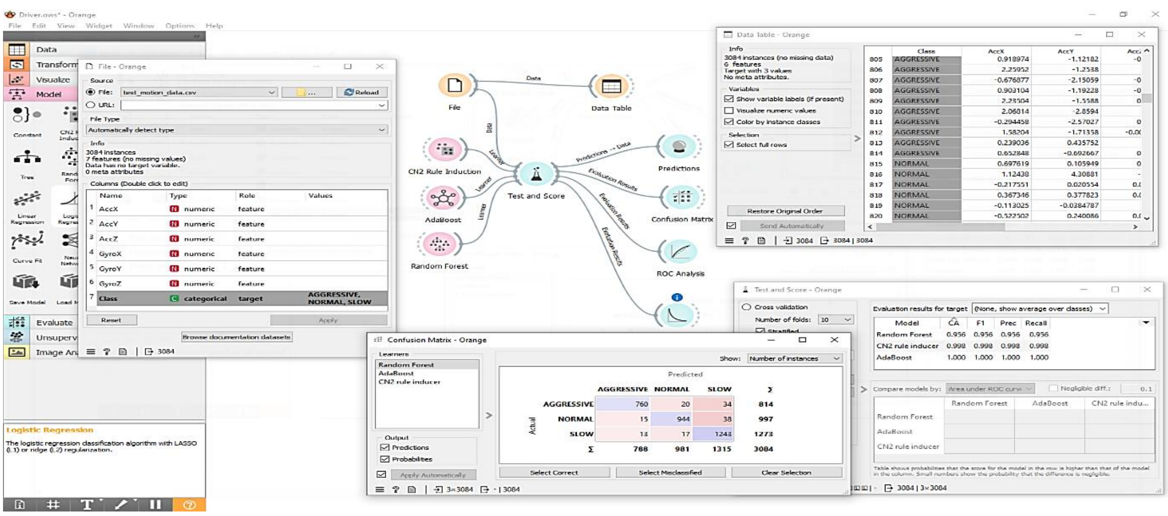
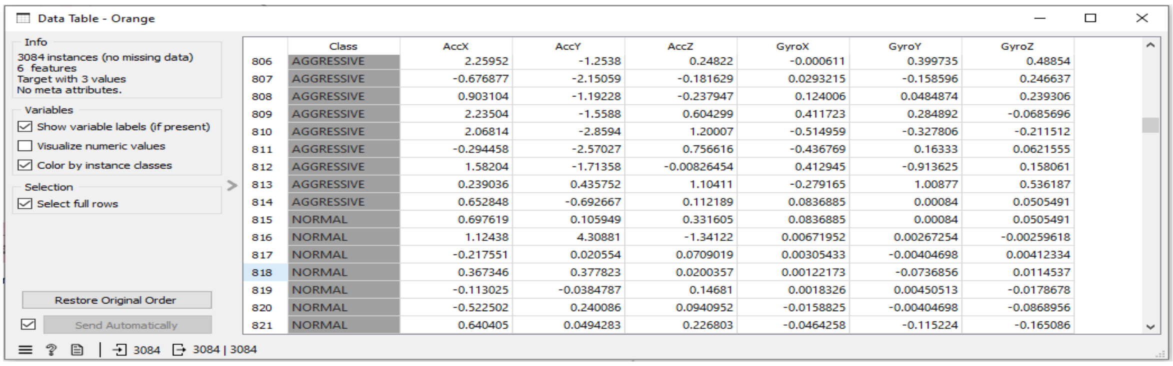


Figure 2. Driver behavior model using Orange3

2.1. Dataset and data preprocessing

One unique dataset of driver behavior was obtained from Kaggle [16]. A data collector application in Android has been designed to collect data from accelerometer and gyroscope sensors. The data set includes 3,084 instances. The configuration of the data set was set as follows to enhance the quality of the collected data on driver behavior. The gravitational acceleration is subtracted, the sensors utilized were the accelerometer and the gyroscope, the data acceleration was (X, Y, Z axes in meters per second squared), the data rotation was (X, Y, Z axis in degrees per second (°/s), and the classification labels were slow, normal, and aggressive. Finally, the timestamp was in seconds according to the used device, which is a Samsung Galaxy S21. The features of the data set are demonstrated in Figure 3 as a data table for driver behavior analysis using Orange3.



	Class	AccX	AccY	AccZ	GyroX	GyroY	GyroZ
806	AGGRESSIVE	2.25952	-1.2538	0.24822	-0.000611	0.399735	0.48854
807	AGGRESSIVE	-0.676877	-2.15059	-0.181629	0.0293215	-0.158596	0.246637
808	AGGRESSIVE	0.903104	-1.19228	-0.237947	0.124006	0.0484874	0.239306
809	AGGRESSIVE	2.23504	-1.5588	0.604299	0.411723	0.284892	-0.0685696
810	AGGRESSIVE	2.06814	-2.8594	1.20007	-0.514959	-0.327806	-0.211512
811	AGGRESSIVE	-0.294458	-2.57027	0.756616	-0.436769	0.16333	0.0621555
812	AGGRESSIVE	1.58204	-1.71358	-0.00826454	0.412945	-0.913625	0.158061
813	AGGRESSIVE	0.239036	0.435752	1.10411	-0.279165	1.00877	0.536187
814	AGGRESSIVE	0.652848	-0.692667	0.112189	0.0836885	0.00084	0.0505491
815	NORMAL	0.697619	0.105949	0.331605	0.0836885	0.00084	0.0505491
816	NORMAL	1.12438	4.30881	-1.34122	0.00671952	0.00267254	-0.00259618
817	NORMAL	-0.217551	0.020554	0.0709019	0.00305433	-0.00404698	0.00412334
818	NORMAL	0.367346	0.377823	0.0200357	0.00122173	-0.0736856	0.0114537
819	NORMAL	-0.113025	-0.0384787	0.14681	0.0018326	0.00450513	-0.0178678
820	NORMAL	-0.522502	0.240086	0.0940952	-0.0158825	-0.00404698	-0.0868956
821	NORMAL	0.640405	0.0494283	0.226803	-0.0464258	-0.115224	-0.165086

Figure 3. Data table for driver behavior analysis using Orange3

The subsequent phase is data cleaning, which entails repairing or removing inaccurate, corrupted, badly formatted, duplicated, or missing information from a dataset. We used Excel's eliminate duplicates function to eliminate unnecessary data from our driver behavior prediction system. Structural issues were corrected by creating a new rule that uses conditional formatting to solve inaccurate classifications. The third stage is data preprocessing, the essential initial step in developing an ML classifier and ensuring that the data fits the analytical requirements. Typically, the driver behavior dataset is saved as a CSV file.

2.2. Machine learning classification methods

ML-based classification models are used for a wide range of classification applications. To produce good predictions, these models often use advanced ML approaches and a large amount of historical data [17]. Because of their remarkable performance, DL and ML approaches are being employed to create intelligent systems that manage data across different fields; these algorithms are essential. Reinforcement learning, unsupervised learning, semi-supervised learning, and supervised learning are examples of ML approaches. However, data classification using ML consists of two steps: training, also known as learning, and testing, or evaluation, which compares an instance's predicted class to its actual class. The model will be verified using 10-fold cross-validation, with 30% of the data utilized for testing and 70% for training via AdaBoost, CN2 rule inducers, and RF classifiers. If the hit rate is deemed acceptable by the analyst, the classifier is judged capable of classifying future occurrences of unknown classes. The data in this inquiry should be categorized into three categories: aggressive, slow, and normal [18], [19].

2.2.1. AdaBoost

The AdaBoost technique is a good classification solution, although it might be better at dealing with unbalanced data [20], it is also based on supervised learning. It classifies situations into positive and negative categories [21]. The AdaBoost weak classifier, which employs weighted majority voting criteria, is an ensemble learning technique that blends weak and strong classifiers. However, it has difficulty with generalization and overfitting. To overcome these concerns, a novel weak learning method is suggested that classifies instances using multiple thresholds, increasing accuracy. This strategy constructs a model by giving equal weight to all data items. Incorrectly classified points are given more weight. The model prioritizes points with higher weights. It will train models until a smaller error is achieved. The AdaBoost algorithm provides a straightforward and flexible approach for classification issues that do not need regular refining. It's simple to construct and adjust, doesn't require much parameter adjustment, and decreases the risk of overfitting by repeatedly reducing the weight of invalid data. It works with simple classifiers such as decision trees and NN and can manage imbalanced data sets by adjusting the weights [22]-[24]. The AdaBoost algorithm is schematically represented in Figure 4.

As indicated in (1), each time a new tree model is added to the system, the general tree is removed and only the strongest tree is added. In this approach, as repeated computations accumulate, the overall model performance steadily improves.

$$Fn(x) = F_{m-1}(x) + argminh_h \sum_{i=1}^{n} L(y_{i,}\ F_{m-1}(x_i) + h(x_i) \quad (1)$$

where $Fn(x)$ is the overall model, F_{m-1} is the previous round's overall, $y_{i,}$ is the ith tree prediction result, and $h(x_i)$ is the newly inserted tree [25].

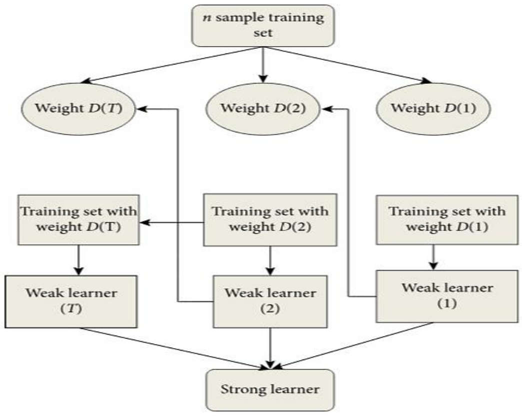


Figure 4. AdaBoost algorithm schematic representation [26]

2.2.2. CN2 rule inducer

The CN2 learning algorithm is an iterative approach for finding complicated rules across a large number of samples from a single class C plus a few additional classes. It assesses the predictability and dependability of the rule and, if successful, adds it to the rules list. An indirect search is used to investigate specializations of this set, and a new conjunctive word or disjunctive element is added or deleted [27] However, the CN2 rule inducer generates straightforward output; if a condition exists, it anticipates a class, even when noise is present. Furthermore, it creates a class distribution depending on the number of instances covered and distributes them throughout the classes [28]. In other words, it shows the total number of class representatives. The Laplace estimate has been defined as an alternative measure of the quality of the rule to rectify unwanted entropy (downward bias) as (2):

$$\text{Laplace Estimation (R)} = \frac{\text{P}+1}{\text{P}+n+k'} \quad (2)$$

'R' is the rule, 'p' is the number of positive instances in the training set, 'n' is the number of negative examples, and 'k' is the number of classes in the training set [29].

2.2.3. Random forest

RF is a geotechnical engineering, ensemble classification, and regression computing tool. Breiman invented the combinatorial classifier method in 2001, which consists of numerous decision tree classification models. The voting mechanism determines discriminant outcomes, which leads to a better prediction model with less accuracy. As shown in Figure 5, the fundamental idea is to randomly choose X attributes from Y properties at each node of the tree, lowering the purity of each node before choosing one to mature [30]. Here is the equal-representation RF (3). denotes N as the number of features used to identify similar accounts, where Fi is the value received from the system and yi is the original value utilized for feature I [31]-[33].

$$Random\ forest = \frac{1}{N}\sum_{N=1}^{N} (F_i - y_i)2 \quad (3)$$

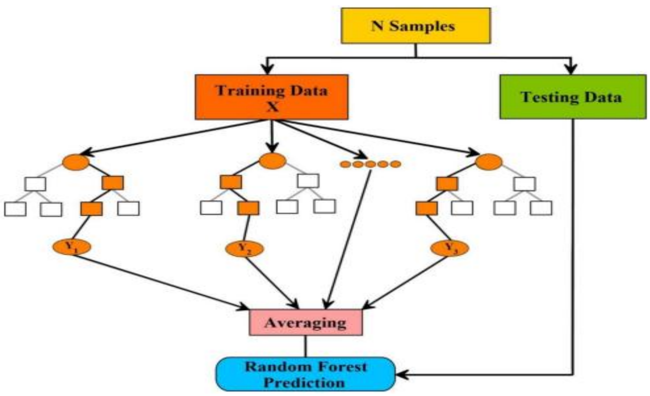


Figure 5. RF flow chart [31]

2.3. Orange3 data mining tool

Is an open-source data mining toolkit for exploratory data analysis and visualization. It is based on Python, serves as a platform for experiment selection, and is beneficial when innovation, dependability, or quality are required. Orange may be used on command lines or in any Python environment to provide a well-structured overview of many capabilities [34], [35].

3. RESULTS AND DISCUSSION

After testing the primary model assumptions, it is critical to assess the proposed model's efficacy and predictive potential. As a consequence, the assessment measures were used to assess the usefulness of the proposed models [36], [37]. The confusion matrix is a useful tool for assessing how well an algorithm works. It computes the quantities of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) in accuracy rate computations [38]-[42]. The suggested model's efficiency was evaluated using the F-measure, accuracy, precision, and sensitivity as specified in (4) to (7):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{6}$$

$$\text{F} - \text{Measure} = \frac{2*\text{Precision}*\text{Sensitivity}}{\text{Precision}+\text{Sensitivity}} \tag{7}$$

The dataset of driver behaviors was classified using many approaches, including AdaBoost, CN2 rule inducer, and RF algorithms. The classification results revealed that AdaBoost excels with 100% accuracy across all performance metrics. Accuracy, sensitivity, and the F-measure. For the CN2 rule inducer, the classifier obtained a CA of 99.8% across all performance metrics. However, RF attained CA 95.4% across all performance parameters. According to area under curve (AUC), AdaBoost had the greatest value of 1.000, CN2 rule inducer achieved 0.999, and RF had the lowest AUC of 0.995. Table 1 demonstrates the classifier's performance in driving behavior and classification using the Orange3 tool, while Figure 6 compares the performances of several classifiers. In this study, the precision of the results revealed is superior to earlier research. As in Elassad *et al.* [11], accuracy ranged from 73% to 98%, recall from 82% to 96%, and specificity from 84% to 97%; in Malik *et al.* [12], the accuracy rate was 90%; and in William *et al.* [14], the accuracy rate was 91%. However, in this study, the accuracy rate was achieved at 100%. Table 2 shows the result comparison of the classifier's performance evaluation of previous studies and the proposed model.

Table 1. Performance comparison of different ML classifiers

Model	AUC	Accuracy	F-measure	Precision	Recall
AdaBoost	1.000	1.000	1.000	1.000	1.000
CN2 rule inducer	0.999	0.998	0.998	0.998	0.998
RF	0.995	0.954	0.954	0.954	0.954

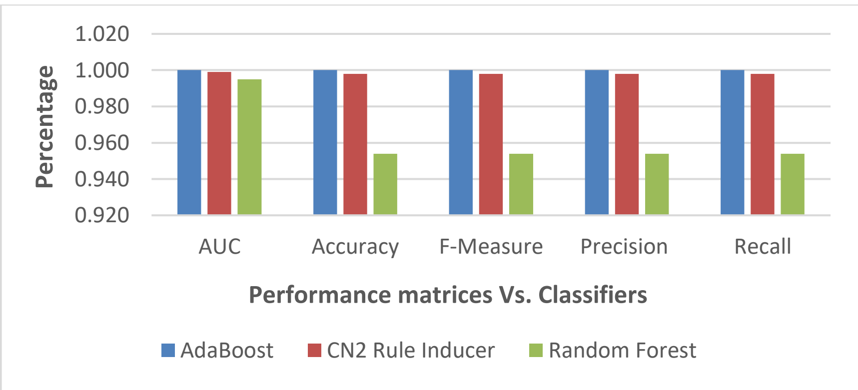


Figure 6. Performances comparative analysis of different classifiers'

Table 2. Result comparison of classifier's performance evaluation of previous studies and proposed model

Study/year	Methods/model	Performance metrics	Percentage (%)
[11]/2020	NN	Accuracy Recall Specificity	73-98 82-96 84-97
[12]/2022	RF, support vector machine, Gaussian Naïve Bayes, and logistic regression using Python	Accuracy	90
[14]/2022	CNN using MATLAB	Accuracy	99
Proposed model	RF, Adabbost, and CN2 inducer using Orange3 datamining tool	Accuracy	100

The receiver operating characteristic curve (ROC curve) is a graphic that shows a true positive rate (TPR) or sensitivity on the y-axis and a false positive rate (FPR) or 1-specificity on the x-axis. Classifiers with ROC curves closer to the upper left corner outperform others [43]. To compare classifiers or predict accuracy, utilize the area under the ROC curve to characterize their performance as shown in Figure 7. Figure 7(a) shows the ROC analysis of all classifiers using Orange3 according to target, Figure 7(b) shows the analysis according to aggressive status, and Figure 7(c) shows the ROC analysis according to slow status. It emphasizes its characteristics, meaning, and value in comparing various tests or predictor variables, as well as its significance in assessing binary predictors [44], [45]. In this study, the receiver operating characteristic (ROC) curve is also used to evaluate the performance of driver behavior predictors.

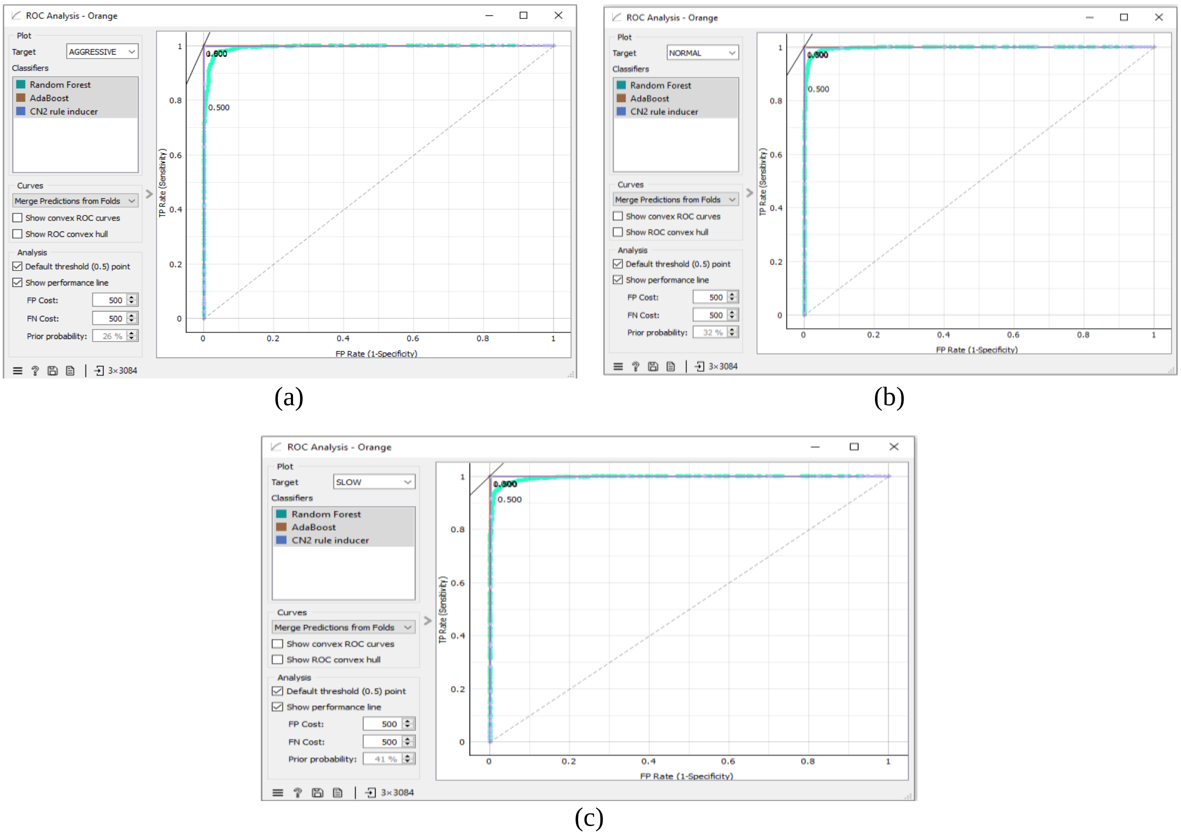
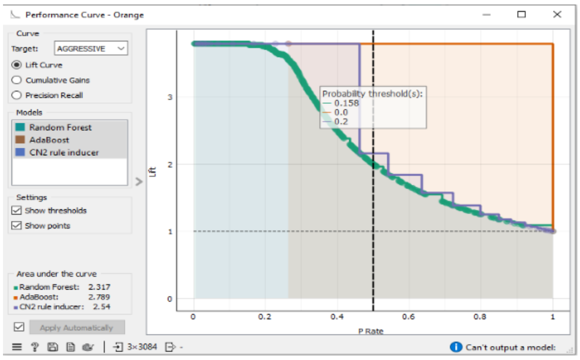
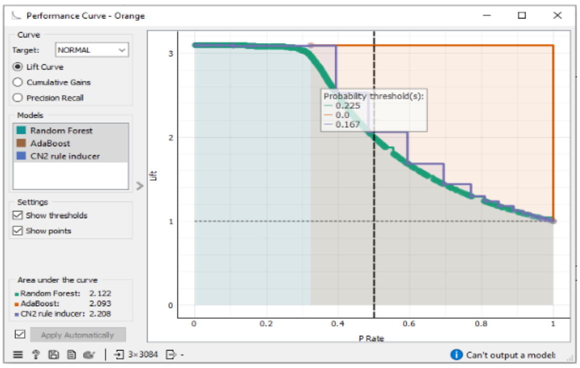


Figure 7. ROC analysis of all classifiers using Orange3 according to target; (a) ROC analysis according to aggressive status, (b) ROC analysis according to normal status, and (c) ROC analysis according to slow status

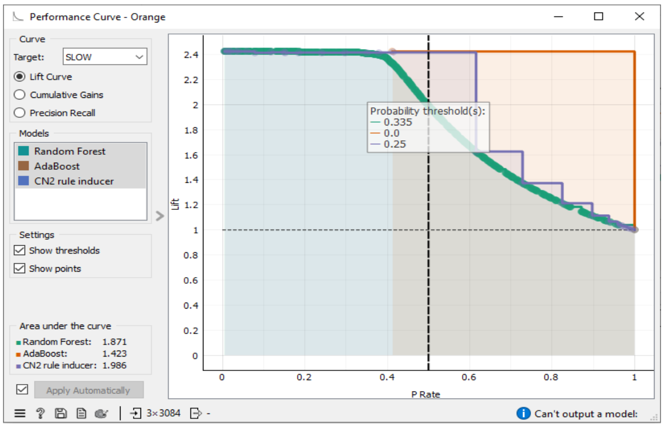
On the other hand, the performance curve is also used to evaluate the performance of classifiers, as shown in Figure 8. Figure 8(a) shows performance curves of classifiers using Orange3 according to target. Figure 8(b) shows performance curves according to normal status, and Figure 8(c) shows performance curves according to slow status. It compares the fraction of TP data instances to the classifier's threshold and is divided into three types: lift curves, cumulative gains, and precision-recall curves. A larger beginning curve and longer flatness enhance the model [46].



(a)



(b)



(c)

Figure 8. Performance curve of classifiers using Orange3 according to target; (a) performance curve according to aggressive status, (b) performance curve according to normal status, and (c) performances curve according to slow status

4. CONCLUSION

Road accidents are a worldwide problem caused by human driving behavior, resulting in fatalities among people. In a dynamic environment, safe driving necessitates acute awareness and fast cognitive judgments. Monitoring, identifying, and forecasting driving behavior is critical. This study predicts and classifies driver behavior and explores how to identify it using various criteria. In this study, we used the best dataset obtained from Kaggle to train the algorithm to identify driver behavior. To get the best possible result for our investigation, we used the ML methods AdaBoost, CN2 rule induction, and RF. The model was verified using 10-fold cross-validation, with 30% of the data utilized for testing and 70% for training. Following training, each of these algorithms completed testing. Finally, the Orange3 data mining tool generated a confusion matrix to evaluate and compare the algorithm's performance. The results were discussed, and the AdaBoost algorithm was superior with an accuracy rate of 100% for all metrics, while the accuracy reached 99.8% for CN2 and 95.4% for RF.

5. FUTURE WORK

It is recommended that future studies on driver behavior take into account a variety of driving scenarios and real-time data from vehicle sensors. Long-term studies of ML and DL can improve prediction accuracy through knowledge that can be obtained from behavioral factors such as stress and distractions. Nonetheless, the idea's effectiveness is demonstrated by using it in the real world with driving classes and insurance companies. Additionally, the use of user-friendly software promotes safer driving behaviors. When adopting new features, it's critical to consider the implications of regulatory and ethical concerns. Furthermore, by working with the auto industry, predictive models can be integrated into automobile safety systems.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Areen Arabiat	✓	✓	✓	✓	✓	✓		✓	✓		✓			
Muneera Altayeb	✓					✓		✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The dataset that supports the findings of this study is openly available in Kaggle at https://www.kaggle.com/datasets/outofskills/driving-behavior reference number [16].

REFERENCES

[1] S. Jaradat, T. I. Alhadidi, H. I. Ashqar, A. Hossain, and M. Elhenawy, "Exploring Traffic Crash Narratives in Jordan Using Text Mining Analytics," in *2024 IEEE 3rd International Conference on Computing and Machine Intelligence, ICMI 2024 - Proceedings*, IEEE, Apr. 2024, pp. 1–6, doi: 10.1109/ICMI60790.2024.10586010.

[2] S. Roussou, T. Garefalakis, E. Michelaraki, T. Brijs, and G. Yannis, "Machine Learning Insights on Driving Behaviour Dynamics among Germany, Belgium, and UK Drivers," *Sustainability*, vol. 16, no. 2, pp. 1–23, Jan. 2024, doi: 10.3390/su16020518.

[3] M. Shahverdy, M. Fathy, R. Berangi, and M. Sabokrou, "Driver behavior detection and classification using deep convolutional neural networks," *Expert Systems with Applications*, vol. 149, pp. 1–12, Jul. 2020, doi: 10.1016/j.eswa.2020.113240.

[4] J. Chen, H. Chen, X. Lan, B. Zhong, and W. Ran, "A Method to Develop the Driver-Adaptive Lane-Keeping Assistance System Based on Real Driver Preferences," *Sensors*, vol. 24, no. 5, pp. 1–24, Mar. 2024, doi: 10.3390/s24051666.

[5] N. M. Negash and J. Yang, "Driver Behavior Modeling Toward Autonomous Vehicles: Comprehensive Review," *IEEE Access*, vol. 11, pp. 22788–22821, 2023, doi: 10.1109/ACCESS.2023.3249144.

[6] Y. Xing, C. Lv, D. Cao, and E. Velenis, "Multi-scale driver behavior modeling based on deep spatial-temporal representation for intelligent vehicles," *Transportation Research Part C: Emerging Technologies*, vol. 130, pp. 1–20, Sep. 2021, doi: 10.1016/j.trc.2021.103288.

[7] P. Thalya, J. Kovaceva, A. Knauss, N. Lubbe, and M. Dozza, "Modeling driver behavior in interactions with other road users," *Proceedings of 8th Transport Research Arena TRA 2020,* Helsinki, Finland, 2020, pp. 1–16, Feb. 28, doi: 10.31234/osf.io/wu4z9.

[8] Y. H. Bhosale and K. S. Patnaik, "IoT Deployable Lightweight Deep Learning Application For COVID-19 Detection With Lung Diseases Using RaspberryPi," in *2022 International Conference on IoT and Blockchain Technology, ICIBT 2022*, IEEE, May 2022, pp. 1–6, doi: 10.1109/ICIBT52874.2022.9807725.

[9] S. Bouhsissin, N. Sael, and F. Benabbou, "Driver Behavior Classification: A Systematic Literature Review," *IEEE Access*, vol. 11, pp. 14128–14153, 2023, doi: 10.1109/ACCESS.2023.3243865.

[10] L. Yang, X. Li, W. Guan, and S. Jiang, "Assessing the relationship between driving skill, driving behavior and driving aggressiveness," *Journal of Transportation Safety and Security*, vol. 14, no. 5, pp. 737–753, May 2022, doi: 10.1080/19439962.2020.1812785.

[11] Z. E. A. Elassad, H. Mousannif, H. A. Moatassime, and A. Karkouch, "The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review," *Engineering Applications of Artificial Intelligence*, vol. 87, pp. 1–27, Jan. 2020, doi: 10.1016/j.engappai.2019.103312.

[12] M. Malik, R. Nandal, S. Dalal, V. Jalglan, and D. N. Le, "Deriving driver behavioral pattern analysis and performance using neural network approaches," *Intelligent Automation and Soft Computing*, vol. 32, no. 1, pp. 87–99, 2022, doi: 10.32604/iasc.2022.020249.

[13] S. Ansari, F. Naghdy, H. Du, and Y. N. Pahnwar, "Driver Mental Fatigue Detection Based on Head Posture Using New Modified reLU-BiLSTM Deep Neural Network," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 10957–10969, Aug. 2022, doi: 10.1109/TITS.2021.3098309.

[14] P. William, M. Shamim, A. R. Yeruva, D. Gangodkar, S. Vashisht, and A. Choudhury, "Deep Learning based Drowsiness Detection and Monitoring using Behavioural Approach," in *Proceedings of International Conference on Technological Advancements in Computational Sciences, ICTACS 2022*, IEEE, Oct. 2022, pp. 592–599, doi: 10.1109/ICTACS56270.2022.9987728.

[15] P. V. Sri, S. Aathilakshmi, and A. S. B. Sam, "Machine Vision for Driver Safety: YOLOv5-powered Real-time Drowsiness

Detection," in *2023 International Conference on Data Science, Agents and Artificial Intelligence, ICDSAAI 2023*, IEEE, Dec. 2023, pp. 1–5, doi: 10.1109/ICDSAAI59313.2023.10452555.
[16] Cojocaru, "Driving behavior," Kaggle, 2024. [Online]. Available: https://www.kaggle.com/datasets/outofskills/driving-behavior (Accessed: Mar. 10, 2024).
[17] S. Badillo *et al.*, "An Introduction to Machine Learning," *Clinical Pharmacology and Therapeutics*, vol. 107, no. 4, pp. 871–885, Apr. 2020, doi: 10.1002/cpt.1796.
[18] R. H. Jhaveri, A. Revathi, K. Ramana, R. Raut, and R. K. Dhanaraj, "A Review on Machine Learning Strategies for Real-World Engineering Applications," *Mobile Information Systems*, vol. 2022, pp. 1–26, Aug. 2022, doi: 10.1155/2022/1833507.
[19] B. Mahesh, "Machine Learning Algorithms - A Review," *International Journal of Science and Research (IJSR)*, vol. 9, no. 1, pp. 381–386, Jan. 2020, doi: 10.21275/art20203995.
[20] X. Huang, Z. Li, Y. Jin, and W. Zhang, "Fair-AdaBoost: Extending AdaBoost method to achieve fair classification," *Expert Systems with Applications*, vol. 202, Sep. 2022, doi: 10.1016/j.eswa.2022.117240.
[21] W. Wang and D. Sun, "The improved AdaBoost algorithms for imbalanced data classification," *Information Sciences*, vol. 563, pp. 358–374, Jul. 2021, doi: 10.1016/j.ins.2021.03.042.
[22] J. Zheng, D. Lin, Z. Gao, S. Wang, M. He, and J. Fan, "Deep Learning Assisted Efficient AdaBoost Algorithm for Breast Cancer Detection and Early Diagnosis," *IEEE Access*, vol. 8, pp. 96946–96954, 2020, doi: 10.1109/ACCESS.2020.2993536.
[23] Y. Ding, H. Zhu, R. Chen, and R. Li, "An Efficient AdaBoost Algorithm with the Multiple Thresholds Classification," *Applied Sciences*, vol. 12, no. 12, pp. 1–13, Jun. 2022, doi: 10.3390/app12125872.
[24] T. R. Mahesh *et al.*, "AdaBoost Ensemble Methods Using K-Fold Cross Validation for Survivability with the Early Detection of Heart Disease," *Computational Intelligence and Neuroscience*, pp. 1–11, Apr. 2022, doi: 10.1155/2022/9005278.
[25] C. Wang, S. Xu, and J. Yang, "Adaboost algorithm in artificial intelligence for optimizing the IRI prediction accuracy of asphalt concrete pavement," *Sensors*, vol. 21, no. 17, pp. 1–16, Aug. 2021, doi: 10.3390/s21175682.
[26] H. Zhou and G. Yu, "Research on fast pedestrian detection algorithm based on autoencoding neural network and adaboost," *Complexity*, no. 1, pp. 1–17, Jan. 2021, doi: 10.1155/2021/5548476.
[27] N. Kumar and U. Kumar, "Comparative analysis of CN2 rule induction with other classification algorithms for network security," *Multimedia Tools and Applications*, vol. 81, no. 26, pp. 37119–37135, Nov. 2022, doi: 10.1007/s11042-022-13542-3.
[28] R. Hasan, S. Palaniappan, S. Mahmood, A. Abbas, K. U. Sarker, and M. U. Sattar, "Predicting student performance in higher educational institutions using video learning analytics and data mining techniques," *Applied Sciences*, vol. 10, no. 11, pp. 1–20, Jun. 2020, doi: 10.3390/app10113894.
[29] H. M. Al-Ahmadi, A. Jamal, K. A. Al-Ofi, M. Zahid, and Y. Chen, "Adopting machine learning and spatial analysis techniques for driver risk assessment: Insights from a case study," *International Journal of Environmental Research and Public Health*, vol. 17, no. 14, pp. 1–16, Jul. 2020, doi: 10.3390/ijerph17145193.
[30] M. A. Mohammed *et al.*, "Benchmarking Methodology for Selection of Optimal COVID-19 Diagnostic Model Based on Entropy and TOPSIS Methods," *IEEE Access*, vol. 8, pp. 99115–99131, 2020, doi: 10.1109/ACCESS.2020.2995597.
[31] A. Niyogi, T. A. Ansari, S. K. Sathapathy, K. Sarkar, and T. N. Singh, "Machine learning algorithm for the shear strength prediction of basalt-driven lateritic soil," *Earth Science Informatics*, vol. 16, no. 1, pp. 899–917, Mar. 2023, doi: 10.1007/s12145-023-00950-8.
[32] A. Arabiat and M. Altayeb, "Assessing the effectiveness of data mining tools in classifying and predicting road traffic congestion," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 2, pp. 1295–1303, May 2024, doi: 10.11591/ijeecs.v34.i2.pp1295-1303.
[33] M. K. I. Ibraheem, A. A. J. Al-Abadi, M. B. Mohamed, and A. Fakhfakh, "A Security-Enhanced Energy Conservation with Enhanced Random Forest Classifier for Low Execution Time Framework (S-2EC-ERF) for Wireless Sensor Networks," *Applied Sciences (Switzerland)*, vol. 14, no. 6, pp. 1–22, Mar. 2024, doi: 10.3390/app14062244.
[34] R. Ratra and P. Gulia, "Experimental evaluation of open source data mining tools (WEKA and orange)," *International Journal of Engineering Trends and Technology*, vol. 68, no. 8, pp. 30–35, Aug. 2020, doi: 10.14445/22315381/IJETT-V68I8P206S.
[35] Orange Data Mining library, "Orange Data Mining Library - Orange Data Mining Library 3 documentation," orange3.readthedocs.io, 2024. [Online]. Available: https://orange3.readthedocs.io/projects/orange-data-mining-library/en/latest/ (Accessed: Mar. 13, 2024).
[36] J. H. J. C. Ortega, "Analysis of Performance of Classification Algorithms in Mushroom Poisonous Detection using Confusion Matrix Analysis," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 1.3, pp. 451–456, Jun. 2020, doi: 10.30534/ijatcse/2020/7191.32020.
[37] J. Gwak, A. Hirao, and M. Shino, "An investigation of early detection of driver drowsiness using ensemble machine learning based on hybrid sensing," *Applied Sciences (Switzerland)*, vol. 10, no. 8, pp. 1–13, Apr. 2020, doi: 10.3390/APP10082890.
[38] S. Nafaa *et al.*, "Advancing Roadway Sign Detection with YOLO Models and Transfer Learning," *2024 IEEE 3rd International Conference on Computing and Machine Intelligence (ICMI)*, Mt Pleasant, MI, USA, 2024, pp. 1-4, doi: 10.1109/ICMI60790.2024.10586105.
[39] N. Teffo, P. Bokoro, L. Muremi, and T. Paepae, "Performance evaluation of selected machine learning techniques in the detection of non-technical losses in the distribution system," in *Proceedings of the 32nd Southern African Universities Power Engineering Conference, SAUPEC 2024*, IEEE, Jan. 2024, pp. 1–5, doi: 10.1109/SAUPEC60914.2024.10445037.
[40] M. Altayeb and A. Arabiat, "Crack detection based on mel-frequency cepstral coefficients features using multiple classifiers," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 3, pp. 3332–3341, Jun. 2024, doi: 10.11591/ijece.v14i3.pp3332-3341.
[41] A. Al-Ghraibah and M. Al-Ayyad, "Automated detection of leukemia in blood microscopic images using image processing techniques and unique features: Cell count and area ratio," *Cogent Engineering*, vol. 11, no. 1, pp. 1–10, Dec. 2024, doi: 10.1080/23311916.2024.2304484.
[42] M. M. Abualhaj, Q. Y. Shambour, A. Alsaaidah, A. Abu-Shareha, S. Al-Khatib, and M. O. Hiari, "Enhancing Spam Detection Using Hybrid of Harris Hawks and Firefly Optimization Algorithms," *Journal of Applied Data Sciences*, vol. 5, no. 3, pp. 901–911, Sep. 2024, doi: 10.47738/jads.v5i3.279.
[43] J. N. Mandrekar, "Receiver operating characteristic curve in diagnostic test assessment," *Journal of Thoracic Oncology*, vol. 5, no. 9, pp. 1315–1316, Sep. 2010, doi: 10.1097/JTO.0b013e3181ec173d.
[44] F. Movahedi, R. Padman, and J. F. Antaki, "Limitations of receiver operating characteristic curve on imbalanced data: Assist device mortality risk scores," *Journal of Thoracic and Cardiovascular Surgery*, vol. 165, no. 4, pp. 1433–1442, Apr. 2023, doi: 10.1016/j.jtcvs.2021.07.041.
[45] N. Alzboun, M. Alhur, H. Khawaldah, and M. T. Alshurideh, "Assessing gastronomic tourism using machine learning approach: The case of google review," *International Journal of Data and Network Science*, vol. 7, no. 3, pp. 1131–1142, 2023, doi:

10.5267/j.ijdns.2023.5.010.
[46] Performance curve, "Performance Curve-Orange Visual Programming 3 documentation," orange3.readthedocs.io. [Online]. Available: https://orange3.readthedocs.io/projects/orange-visual-programming/en/latest/widgets/evaluate/performancecurve.html (Accessed: Mar. 13, 2024).

BIOGRAPHIES OF AUTHORS

Areen Arabiat earned her B.Sc. in Computer Engineering in 2005 from al Balqaa Applied University (BAU), and her M.Sc. in Intelligent Transportation Systems (ITS) from Al Ahliyya Amman University (AAU) in 2022. She is currently a computer lab supervisor and (part time) lecturer in the Department of Communications and Computer Engineering at Al-Ahliyya Amman University since 2013. Her research interests are focused on the following areas: machine learning, data mining, image processing, internet of things (IoT), and artificial intelligence. She can be contacted at email: a.arabiat@ammanu.edu.jo.

Muneera Altayeb earned a bachelor's degree in computer engineering in 2007, and a master's degree in communications engineering from the University of Jordan in 2010. She has been working as a lecturer in the Department of Communications and Computer Engineering at Al-Ahliyya Amman University since 2015. She currently holds the position of Assistant Dean at the Faculty of Engineering at Amman Al-Ahliyya University. Her research interests focus on the following areas: digital signals and image processing, machine learning, robotics, and artificial intelligence. She can be contacted at email: m.altayeb@ammanu.edu.jo.