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A Passengers Safety Assistance System during a Transport Riding Event Using Machine Learning

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Abstract: The rise in popularity of ride-sharing services and ride-booking systems has created new opportunities and challenges for security and safety. A useful system for passenger safety assistance using machine learning and mobile applications is missing from the existing work. This paper develops a data set regarding suspicious activity detection using a questionnaire. This paper selects a suitable machine learning model for suspicious activity prediction during a transport ride by examining support vector classifiers (SVC), random forest, MLP classifiers, decision trees, KNN, logistic regression, and Gaussian naive Bayes classifiers. The results showed that the SVC is most suitable, with 97% accuracy, for classifying suspicious activity predictions during transport riding. This paper provides a passenger safety mobile application with passenger and driver verification, application rating, suspicious activity prediction, suggestions regarding safety, location mapping, and trip booking features. The application evaluation results based on users' comments showed that more than 55 percent of users supported the application's usability and effectiveness nature.

Index Terms: Ride-sharing services, ride booking, machine learning, labeled dataset, Smartphone applications, suspicious activity prediction, and passenger safety.

1. Introduction

Road safety and security are critical concerns on a global scale. The international transport forum's road safety annual report 2022 [1] sheds light on road safety performance in various countries, offering a comparative analysis of key indicators. This report serves as a valuable resource for assessing road safety developments and identifying areas for improvement. It is also a significant issue in Bangladesh, and its performance in this area is not only inadequate but also worsening, as reported by the World Bank. According to the same report the number of annual fatalities resulting from road accidents is estimated to range from 2,538 to nearly ten times that figure, reaching approximately 20,736. In the case of ride-booking platforms like Uber, Pathao, Lyft and so on it is not completely safe.

A comprehensive report was published by the authors in [2] that focused on rough ridesharing issues. According to that Uber safety report [2], the authors revealed 5,981 cases of sexual assault documented over two years, with 235 cases classified as rapes. It is noteworthy that 42 percent of the reported sexual assaults were committed against Uber drivers themselves. The co-founder of Legal Rideshare, a law firm specializing in ride-sharing accidents and injuries, emphasizes that crimes against ride-share drivers are significantly underreported. The types of offenses include sexual harassment, sexual battery, stabbings, armed robbery, express kidnapping, grand theft auto, and even murder. The passage also highlights specific incidents such as a Taco Bell executive physically assaulting an Uber driver and a Lyft driver being attacked during a trip. These incidents underscore the need for improved safety measures in the ride-sharing industry. In addition to road accidents, suspicious activities in transportation pose a threat to passenger safety. By collectively working towards creating a safer transportation environment, we can make substantial progress in reducing accidents, improving mobility, and enhancing the overall well-being of individuals and communities.

According to [3], we can see that, a people frequently encounter reckless driving by drivers, while the occurrences of other incidents are relatively negligible in comparison but still happens. The results reveal that as ridesharing services gain popularity in Bangladesh, there is a corresponding increase in security concerns due to various incidents. Both public transportation and ridesharing systems face security challenges, and the study highlights the negative impact of inadequate regulations and monitoring. By addressing these findings, improvements can be made to the transportation system, fostering greater reliance on ridesharing services and building trust between service providers and users. With the rise of ridesharing and transport riding facilities, there exist several threats regarding passenger safety such as hijacking, rude behavior, harassment, life-threat events, sexual assault, robbery, and accident events, among others. To improve passenger safety during a transport ride, different challenges need to be addressed such as suspicious activity prediction during a transport ride, instant help feature, driver and passenger identification, and safety suggestions, among others [1,2,3, 4, 5, 6, 7, 8, 9, 10].

At present, the literature research works (e.g., [11, 12, 13, 14, 15, 16, 17, 18, and 19]) did not investigate passengers safety based mobile application by taking passenger and driver id verification, passenger safety threat detection using machine learning, and instant help features. Most importantly, suitable machine learning model selection with higher accuracy for suspicious activity prediction during a transport riding by examining multiple classifiers such as SVC, random forest, MLP classifier, decision tree, KNN, logistic regression, Gaussian naive bayes classifier is missing in the literature works. To ensure that the drivers of this vehicle are forced to be accountable and responsible this paper has taken the initiative to build an application system to book rides safely and to let the drivers, as well as the passengers, know how a car is being driven only using the most accessible features of a smart phone such as suspicious activity detection, passenger and driver identification number verification, suggestion regarding safety, security and safety tips, and application rating, among others. The important contributions of this paper are described as follows:

(i) This paper develops a reliable and validated dataset for detecting suspicious activity. This paper carefully gathered and curetted data from various sources, including articles and real-life incidents, to ensure the accuracy and dependability of the dataset in capturing diverse occurrences of violent incidents.

(ii) This paper identifies an optimal machine learning model for effectively detecting and classifying suspicious activity during a transport ride. Through rigorous experimentation and evaluation, this paper compared multiple models and selected the one that demonstrated superior performance in accurately identifying suspicious activity and aggressive driving.

(iii) To enhance the overall system's efficiency, this paper also explored better preprocessing techniques and feature selection methods.

(iv) Furthermore, this paper also integrated the trained machine learning model into a mobile application. This application serves as a comprehensive system that not only detects suspicious activity and aggressive driving behavior but also offers additional functionalities such as ride booking, instant suggestions, driver and passenger identification, and other related features. By deploying the trained model within the app, users can benefit from real-time analysis of their situation and convenient access to ride booking services. This paper also offers the user based evaluation results regarding the proposed application features.

The background work is discussed in Section 2. The proposed machine learning-based suspicious activity prediction scheme during transport riding is depicted in Section 3. Section 4 gives the mobile app features with a detailed discussion. Section 5 visualizes the evaluation results. Section 6 describes the key findings of our proposed scheme, along with some challenges.

2. Related Work

This section will present the related works discussion regarding transport safety applications and the use of machine learning-based prediction schemes. There are currently several driving behavior datasets available on Kaggle or Mendeley. Nevertheless, despite the data being gathered, they all have a significant issue: the data is not labeled. In [4], the authors developed a driver behavior dataset and labeled that dataset into three different classes: Slow, Normal, and Aggressive. But the accuracy of their predictions was very low and was not usable. During the year 2019, Wahidur and his contributors launched a system app that provides emergency action for the safety of women inside and outside of their domestication [5].

In August 2021, Hossein Aghayari and his co-authors released a report on their evaluation of different Mobile applications for road traffic health and safety [6]. They evaluated all the found apps from the Google play store in the mirror of Haddon's matrix. Another app was introduced by Tianyu Wang worked on the detection of cars toward pedestrians [7]. But the app works only when static and uses a lot of energy by using both the front and back cameras. An article in [8] published on Autonomous driving systems and the role of warning mobile apps in security cases shows that mobile apps can still help in reducing the hazards to a significant amount. The work in [9] monitors safety threats, disease outbreaks, violent protests, and anything else that might be hazardous during travel. The work in [10] presents a ridesharing service created to make city-to-city hitchhiking quick, secure, and reasonably priced. But, it has limitations too: Limited availability and limited departure times. In [11], the authors developed an Australian ride-sharing service. But it misses other functionalities and it has limited availability and flexibility Even though all those mentioned apps also include driving training, driving feedback, and speed control, all these and other apps have precise and intended applications but very few of them have an accumulated way of performing optimally. They also lack the consideration of organized or other kinds of crimes. Some of them cannot be used for transportation and do not hold anyone accountability scale. The video detection of suspicious activity is also not feasible. Therefore, it is needed to imply these ideas and to build a better way of dealing with unsafe conditions of our transport systems on our roads. As it can be derived from the studies done on alcoholism [12] and pedestrian [13] fatalities, the drivers should be evaluated for their alcohol history and responsibilities. A recent study by Wawage et al. [14] has adopted a similar approach to address the issue of driver behavior detection by utilizing accelerometer and gyroscope data. However, a significant limitation of their work is the lack of labeling in the dataset, rendering it challenging to effectively utilize for implementing deep learning and machine learning models. The dataset is organized into daily folders, each containing seven subfolders. The authors propose that their suggested dataset can be beneficial for the development, testing, and validation of machine learning models aimed at classifying or reforming driver behavior. Carballo et al. presented a multiple 3D LiDAR dataset, which includes data from 10 diverse LiDAR sensors, capturing different environments and configurations [15]. The dataset covers a controlled environment with static targets, adverse weather conditions, and heavy traffic situations. Romera discussed the challenges of studying driver behavior using machine learning techniques and the need for large amounts of data [16]. They addressed these challenges by developing the UAHDriveSet, a publicly available dataset that provides an in-depth analysis of driving behavior. The dataset, created using the DriveSafe app includes data from six drivers exhibiting different driving behaviors on different road types. Although the UAH-DriveSet is considered comprehensive, the authors acknowledged limitations such as the lack of labeling and compatibility with different systems Wang proposes an ensemble learning approach for recognizing aggressive driving behavior, overcoming limitations in previous methods [17]. The study combines self-organizing maps and deep learning methods to construct base classifiers, resulting in improved accuracy compared to conventional deep learning methods. The ensemble classifier based on LSTM and the Product Rule demonstrates optimal performance, highlighting the effectiveness of the proposed approach. This research offers valuable insights into applying ensemble learning techniques for accurate recognition of aggressive driving behavior. Ellison presented a technique for evaluating driver behavior and its correlation with casualty collisions using GPS data [18]. They develop Driver Behavior Profiles to understand the factors influencing driver conduct, considering contextual factors such as time and location. The study demonstrates that Driver Behavior Profiles serve as strong predictors of driver behavior, even when accounting for roadway conditions.

The Honda Research Institute Driving Dataset (HDD) is a comprehensive database for studying driver [19]. It consists of 104 hours of recorded human driving in the San Francisco Bay Area, with detailed sensor and instrumentation data. The publication highlights the challenges of utilizing HDD for external applications and compares it with other driving datasets. The authors propose an annotation approach to interpret driver behavior from the data sequences. In [20], the authors listed examples of suspicious activities and behaviors and also the steps to be taken in case someone detects or witnesses suspicious activity. It also has lists of warning signs of potential violence in someone else and also signs or behaviors that indicate terrorism. There is an article in [21] that delves into the internal factors that pose challenges to detecting suspicious behavior or potential problems. It sheds light on the limitations in observation, including divided attention, fatigue, and distraction, which hinder the accurate perception of events. Additionally, it recognizes the constraints in recalling past events and emphasizes the impact of personal beliefs, biases, and prior experience on the detection process. However, it is important to note that the article primarily focuses on the challenges specific to CCTV monitoring, with a narrower scope. Consequently, there may be other significant aspects of security and surveillance that are not covered in the article. Furthermore, while the article provides a comprehensive overview of the challenges associated with CCTV monitoring, it does not provide specific data or empirical evidence to support its claims. Therefore, caution should be exercised when interpreting the findings, and further research is needed to validate the assertions made. Moreover, the scope of the article’s findings related to different contexts or specific situations is not explicitly addressed. Therefore, additional investigation and contextual analysis are required to determine the extent to which these challenges apply in diverse settings. Another article [22] from the Tennessee government’s public safety department lists some activities that can be considered suspicious and are to be reported immediately if found so. It tells the witness to remember the details like these: What occurred? When and where did it happen? Were there any injuries? What was the time and direction of travel? and so on. The work in [23] conducted a research to investigate the problem of crime on public transport in El Salvador. Drawing on crime opportunity theory, the review aimed to provide a comprehensive understanding of the main forms of crime and disorder affecting the transport system and identify factors contributing to the high levels of criminal incidents. The findings of the review highlighted the need for a program of situational crime prevention measures, including system-wide enhancements and specific interventions targeting crimes on buses and at bus stops. It was emphasized that implementing such measures would require long-term efforts, active involvement of various stakeholders, and substantial government investment. The potential benefits of these measures extend beyond reducing crime on the bus system to positively impact the broader community, with significant implications for public safety and wellbeing. In [24], the authors developed a framework for driver distraction detection scheme using transfer learning. The works in [25] discussed the necessity of safety issues for Saudi women during ridesharing services. The authors in [26] developed a drivers fatigue and drowsiness detection system using open-cv and python programming language. The article in [27] developed a driver safety assistance system using microcontroller and image processing techniques that warns a driver during drowsiness events. The article in [28] developed a machine learning based driver drowsiness prediction scheme by taking heart rate variability into account. The work in [29] utilized both IoT and machine learning technology for driver drowsiness detection. The authors in [30] utilized YOLO-v5 algorithm with CNN architecture for driver drowsiness detection.

However, previous research did not look into predicting suspicious activity during passenger transportation rides using machine learning algorithms. They also did not provide a mobile app for assistance that included driver and passenger ID verification, emergency help or messages, driver ratings, passenger ride booking features, or suspicious activity prediction. In contrast to previous research, this article describes a mobile application for passenger safety assistance and the prediction of suspicious activity during a transportation ride using a suitable machine learning algorithm.

3. Proposed Machine Learning Based Prediction Scheme

In this section, both the machine learning-based suspicious activity prediction and a transport safety assistance mobile application will be discussed in great detail.

3.1. System design

The most important part of our system is the development of a machine learning-based prediction model (see Figure 1). To develop an effective system for detecting suspicious activities during rides, we have carefully selected a set of machine-learning models to test. The chosen models include KNN Classifier, SVC, Decision Tree Classifier, Random Forest Classifier, MLP Classifier, Gaussian Naïve Bayes, and Linear SVC. Each of these models offers unique characteristics and capabilities that make them suitable candidates for our task. As illustrated in Figure 1, we have obtained a validated dataset and are planning to evaluate its performance using the aforementioned machine learning models. To train these models, we will utilize a comprehensive set of features that encompass various aspects of the ride experience. These features include Driver known, Driver verified, Passengers behavior, Quality of driving, Driver taking alternative route, Driver making unplanned stops, Driver talking to mobile frequently, Route is known to the passenger, Occurrences of any incident, Passengers gender, What kind of baggage is the passenger taking, Was the passenger pressurized to do something, Passenger teased?, Route prone to dangerous activity, Driver making the ride was deliberately long, the Driver looking through the mirror frequently, Road quality, Any coordinated activity, Vehicle condition, the Driver's behavior, Did the driver follow traffic rules, The driver asked any inappropriate or personal questions, Is the driver taking detours, the Driver made uneasy or threatening environment, and Classified. The feature selection process for suspicious activity prediction during riding is conducted by collecting passengers' responses. Further, the selected features are verified by theree university professor (transport safety specialist) from CUET.

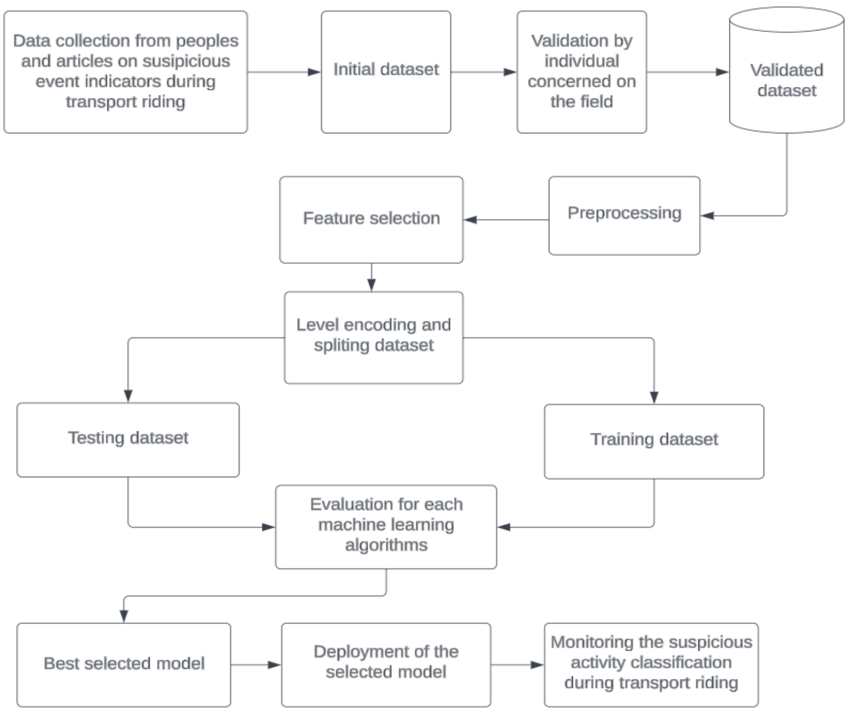


Fig. 1. Machine Learning Model Framework for Suspicious Activity Prediction during Transport Riding

Once the models are trained, we will evaluate their performance using various scores and metrics, such as Confusion Matrix, Precision, Recall, ROC-AUC curve, Mean Absolute Precision Error, R squared error, RMSE error, Specificity, and Accuracy. These evaluations will provide valuable insights into the effectiveness of each model in accurately detecting suspicious activities during rides. By systematically testing and evaluating these machine learning models, along with considering a wide range of relevant features, we aim to develop a robust and reliable system that can effectively identify and address potential safety concerns during rides. This research endeavor will contribute to enhancing the safety and security of passengers in transportation systems. After the selection of the prediction model, our subsequent objective is to develop a mobile application. The diagram outlining the process flow is depicted in Figure 2. The application is built using Android Studio, leveraging the advantages of the cross-platform Flutter framework. The user interface (UI) is designed first, followed by the incorporation of functionalities and features. Upon opening the app, new users are prompted to register by verifying their identity and providing necessary personal information. The main features of our application are account registration, the home page, passenger and driver id verification, suspicious activity detection, application rating, security and safety tips, and ride selection, among others. We used the Sklite package for Flutter to implement the trained model in our mobile application. With the help of this robust package, which supports a variety of algorithms, we were able to easily incorporate the ML model into our application and make predictions even when there was no internet connection.

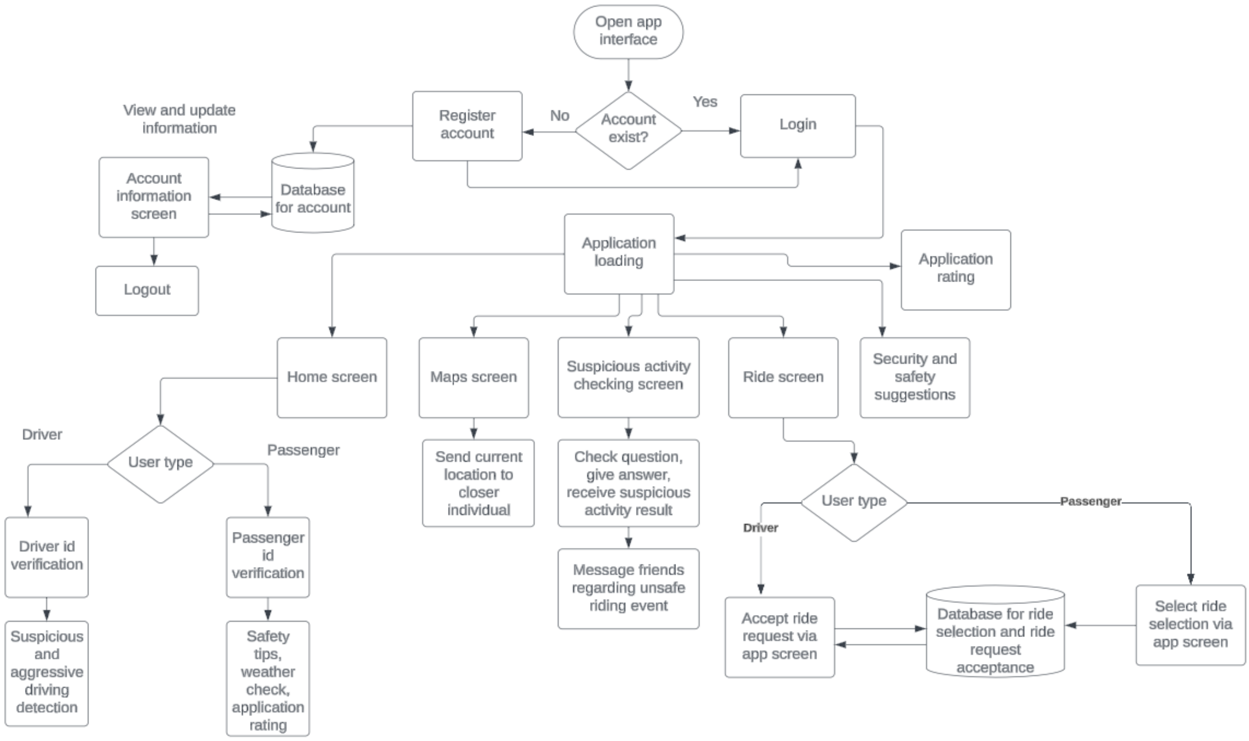
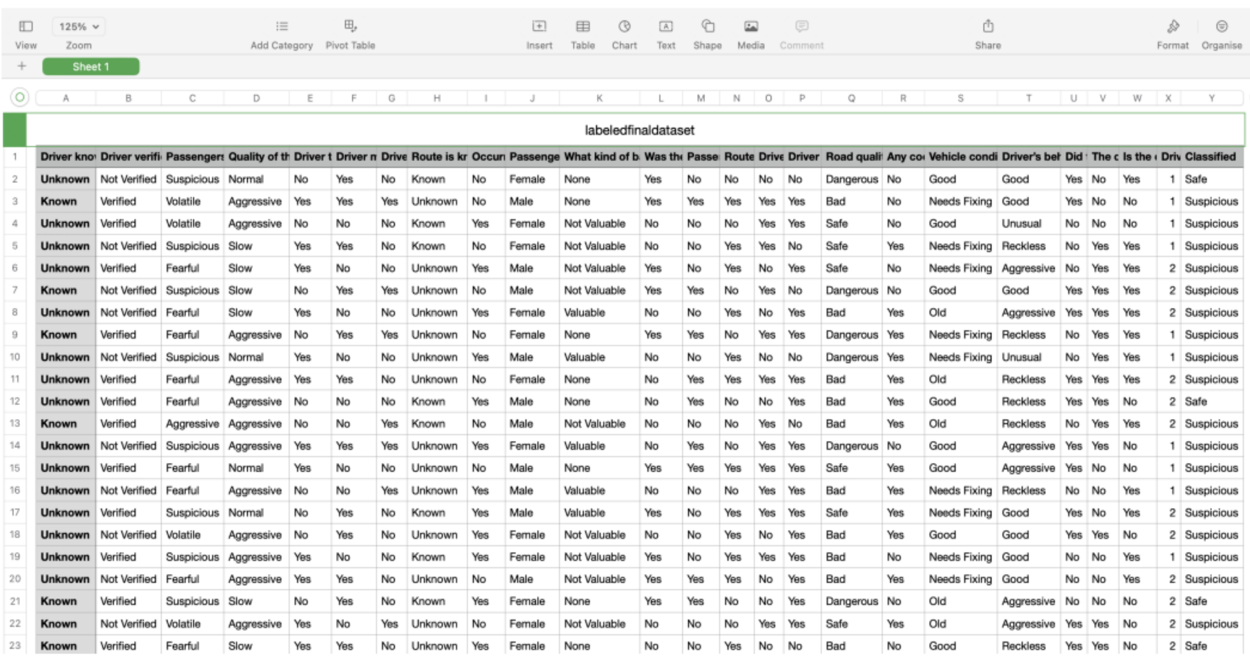


Fig. 2. Process flow diagram of suspicious activity detection app



labeledfinaldataset

	Driver kno	Driver verifi	Passengers	Quality of th	Driver t	Driver n	Drive	Route is kr	Occur	Passenge	What kind of b	Was th	Passe	Route	Drive	Driver	Road quali	Any co	Vehicle condi	Driver's beh	Did	The c	Is the	Driv	Classified
2	Unknown	Not Verified	Suspicious	Normal	No	Yes	No	Known	No	Female	None	Yes	No	No	No	No	Dangerous	No	Good	Good	Yes	No	Yes	1	Safe
3	Known	Verified	Volatile	Aggressive	Yes	Yes	Yes	Unknown	No	Male	None	Yes	Yes	Yes	Yes	Yes	Bad	No	Needs Fixing	Good	Yes	No	No	1	Suspicious
4	Unknown	Verified	Volatile	Aggressive	No	No	No	Known	Yes	Female	Not Valuable	No	No	No	Yes	Yes	Safe	No	Good	Unusual	No	No	No	1	Suspicious
5	Unknown	Not Verified	Suspicious	Slow	Yes	Yes	No	Known	No	Female	Not Valuable	No	No	Yes	Yes	No	Safe	Yes	Needs Fixing	Reckless	No	Yes	Yes	1	Suspicious
6	Unknown	Verified	Fearful	Slow	Yes	No	No	Unknown	Yes	Male	Not Valuable	Yes	No	Yes	No	Yes	Safe	No	Needs Fixing	Aggressive	No	Yes	Yes	2	Suspicious
7	Known	Not Verified	Suspicious	Slow	No	Yes	Yes	Unknown	No	Male	Not Valuable	Yes	Yes	No	Yes	No	Dangerous	No	Good	Good	Yes	Yes	Yes	2	Suspicious
8	Unknown	Not Verified	Fearful	Slow	Yes	No	No	Unknown	Yes	Female	Valuable	No	No	Yes	No	Yes	Bad	Yes	Old	Aggressive	Yes	Yes	Yes	2	Suspicious
9	Known	Verified	Fearful	Aggressive	No	Yes	Yes	Unknown	No	Female	None	Yes	Yes	No	Yes	Yes	Dangerous	Yes	Needs Fixing	Reckless	No	Yes	Yes	1	Suspicious
10	Unknown	Not Verified	Suspicious	Normal	Yes	No	No	Unknown	Yes	Male	Valuable	No	No	Yes	No	No	Dangerous	Yes	Needs Fixing	Unusual	No	Yes	Yes	1	Suspicious
11	Unknown	Verified	Fearful	Aggressive	Yes	Yes	No	Unknown	No	Female	None	No	Yes	Yes	Yes	Yes	Bad	Yes	Old	Reckless	Yes	Yes	Yes	2	Suspicious
12	Unknown	Verified	Fearful	Aggressive	No	No	No	Known	Yes	Male	None	No	Yes	No	No	Yes	Bad	Yes	Good	Reckless	Yes	Yes	No	2	Safe
13	Known	Verified	Aggressive	Aggressive	No	No	Yes	Known	No	Male	Not Valuable	No	No	No	Yes	No	Bad	Yes	Old	Reckless	No	Yes	Yes	2	Suspicious
14	Unknown	Not Verified	Suspicious	Aggressive	Yes	Yes	Yes	Unknown	Yes	Female	Valuable	No	Yes	No	Yes	Yes	Dangerous	No	Good	Aggressive	Yes	Yes	No	1	Suspicious
15	Unknown	Verified	Fearful	Normal	Yes	No	No	Unknown	No	Male	None	Yes	Yes	Yes	Yes	Yes	Safe	Yes	Good	Aggressive	Yes	No	No	1	Suspicious
16	Unknown	Not Verified	Fearful	Aggressive	No	No	Yes	Unknown	Yes	Male	Valuable	No	No	No	Yes	Yes	Bad	Yes	Needs Fixing	Reckless	No	No	Yes	1	Suspicious
17	Unknown	Verified	Suspicious	Normal	No	Yes	No	Known	Yes	Male	Valuable	Yes	No	Yes	Yes	Yes	Safe	Yes	Needs Fixing	Good	Yes	No	Yes	2	Suspicious
18	Unknown	Not Verified	Volatile	Aggressive	No	Yes	No	Unknown	Yes	Female	Not Valuable	No	No	Yes	No	Yes	Bad	Yes	Good	Good	Yes	Yes	No	2	Suspicious
19	Unknown	Verified	Suspicious	Aggressive	Yes	No	No	Known	Yes	Female	Not Valuable	Yes	No	Yes	Yes	Yes	Bad	No	Needs Fixing	Good	No	No	Yes	1	Suspicious
20	Unknown	Not Verified	Fearful	Aggressive	Yes	Yes	No	Unknown	No	Male	Not Valuable	Yes	Yes	Yes	No	Yes	Bad	Yes	Needs Fixing	Good	No	No	Yes	2	Suspicious
21	Known	Verified	Suspicious	Slow	No	Yes	No	Known	Yes	Female	None	Yes	Yes	No	No	Yes	Dangerous	No	Old	Aggressive	No	No	No	2	Safe
22	Known	Not Verified	Volatile	Aggressive	Yes	No	Yes	Unknown	No	Female	Not Valuable	No	No	No	Yes	Yes	Safe	Yes	Old	Aggressive	Yes	Yes	No	2	Suspicious
23	Known	Verified	Fearful	Slow	Yes	Yes	No	Unknown	Yes	Female	None	No	No	Yes	No	No	Bad	No	Good	Reckless	Yes	Yes	No	2	Safe

(a)

Sheet 1

test 3

	Driver kı	Driver '	Passeı	Quạ	Drive	Driveı	Driver	Route	Occurr	Passeng	What k	Was tl	Passen	Route	Driver	Driveı	Road (	Any cc	Vehicle	Driver	Did the	The dri	Is the dı	Driver	Classified
2	**2**	2	1	1	1	2	2	1	2	2	3	1	2	2	1	2	3	2	1	4	1	2	2	1	Suspicious
3	**1**	1	2	2	2	1	2	1	2	2	1	2	2	2	2	2	1	2	2	1	1	2	1	2	Safe
4	**2**	2	4	2	1	2	1	2	1	2	2	2	2	3	1	1	1	1	1	2	1	1	1	2	Suspicious
5	**2**	1	2	3	1	2	2	2	2	1	3	1	2	1	1	1	2	2	1	3	2	1	1	2	Suspicious
6	**2**	1	3	1	1	1	2	1	2	2	3	1	2	3	1	1	3	2	2	3	1	1	2	1	Suspicious
7	**1**	1	3	2	2	1	1	1	1	1	1	2	2	2	2	1	3	2	1	4	2	2	2	2	Safe
8	**2**	2	2	1	2	1	1	1	2	2	1	1	2	3	2	1	2	2	2	1	1	2	1	2	Safe
9	**2**	1	4	2	2	2	1	1	1	1	3	1	1	2	1	2	3	1	1	3	1	1	1	2	Suspicious
10	**1**	1	2	2	1	1	2	2	2	1	1	2	1	2	2	1	2	1	1	1	2	2	2	2	Safe
11	**1**	1	1	2	1	1	1	2	1	2	1	2	1	1	1	1	1	2	1	2	1	1	1	2	Suspicious
12	**1**	2	4	1	2	2	2	1	1	1	3	2	2	3	2	2	3	2	1	4	1	2	2	2	Safe
13	**2**	1	2	2	2	1	1	2	2	1	1	1	1	1	1	2	1	1	2	2	1	1	2	2	Suspicious
14	**2**	1	1	1	2	2	2	1	2	2	2	1	1	1	1	2	2	1	3	2	1	2	1	1	Suspicious
15	**1**	1	1	1	2	2	2	2	2	1	2	2	2	2	1	1	2	2	3	4	1	2	2	2	Safe
16	**2**	2	3	1	2	1	1	2	1	1	1	2	2	1	2	1	3	1	2	4	1	2	1	1	Suspicious
17	**1**	2	3	1	1	2	2	1	2	2	2	2	2	1	2	1	1	2	2	1	1	2	2	2	Safe
18	**2**	1	3	1	2	1	2	2	2	1	2	2	1	3	1	1	3	1	3	1	2	1	1	1	Suspicious
19	**2**	1	4	1	1	2	2	1	2	2	3	1	1	1	1	1	3	1	2	3	1	2	1	2	Suspicious

(b)

Fig. 3. Dataset for Suspicious Activity Detection

3.2. Dataset collection for the suspicious activity detection model

In the first step, we gathered a dataset comprising human psychological symptoms and red flags identified from a range of reliable sources. The collected data was then subjected to validation by expert individuals to ensure its accuracy and reliability. Our dataset consists of 611 rows and encompassed 24 distinct features. A glimpse of the dataset is provided in Figure 3(a), offering a visual representation of the data that is not yet converted into numerical form. Through this meticulous data collection and validation process, we established a robust dataset that serves as the foundation for our subsequent analysis and modeling endeavors. We had duplicate rows. In total, we had 634 rows. The duplicates had to be deprecated and we end up with 611 remaining rows. We also had 34 columns but decided to remove the duplicate meaning and inconsistent columns from further confusing the models. And also after turning the values into a numerical form or in other words encoding the String values into an integer value (see Figure 3(b)).

3.3. Data cleaning and validation

To validate the accuracy and reliability of our dataset, we sought the expertise of three professionals who have extensive knowledge in the field. These experts were carefully selected based on their experience and expertise in dataset evaluation. The specialists are one professor from Chittagong engineering university (CUET), one professor from Chittagong University (transport specialist), and one police officer from Bangladesh road transport authority. Their insight and thoughtful opinions were implemented and we removed redundant rows and columns.

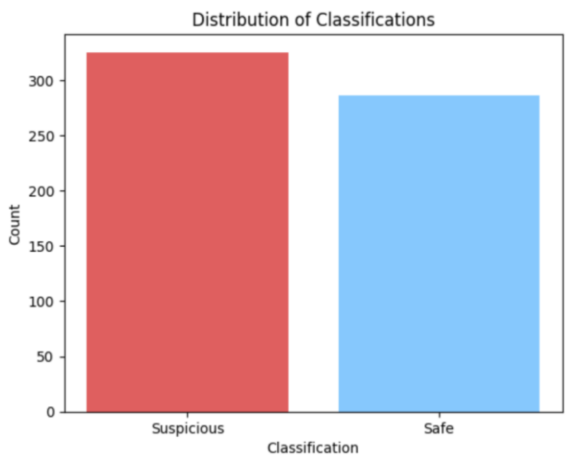


Fig. 4. Frequency of Suspicious and Safe Data

Classifier	Suspicious (1)	Safe (2)
SVC	0.97	0.98
KNeighborsClassifier	0.76	0.63
Logistic Regression	0.95	0.95
DecisionTreeClassifier	0.74	0.74
MLPClassifier	0.87	0.87
GaussianNB	0.97	0.97
linear SVC	0.91	0.92
RandomForestClassifier	0.90	0.91

Fig. 5. Evaluation of performance using F1 score

Classifier	Accuracy
Random Forest Classifier	0.9024
Linear SVC	0.9187
Gaussian NB	0.9675
MLP Classifier	0.8700
Decision Tree Classifier	0.7398
Logistic Regression	0.9512
K Neighbors Classifier	0.7073
SVC	0.9756

Fig. 6. Evaluation of Performance Using Accuracy

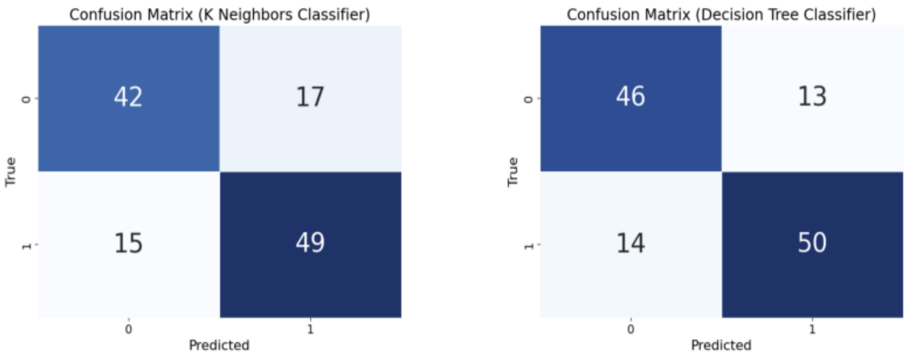


Fig. 7. Confusion Matrix of KNN and decision tree

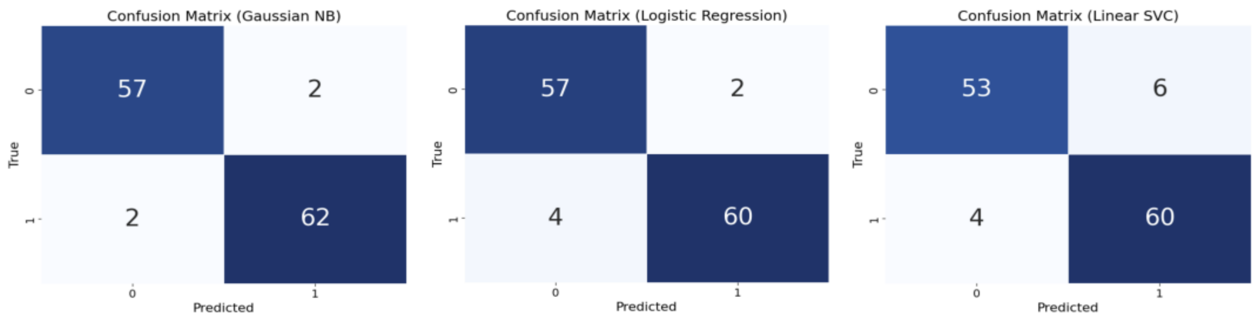


Fig. 8. Confusion Matrix (Gaussian NB, Logistic Regression, Linear SVC)

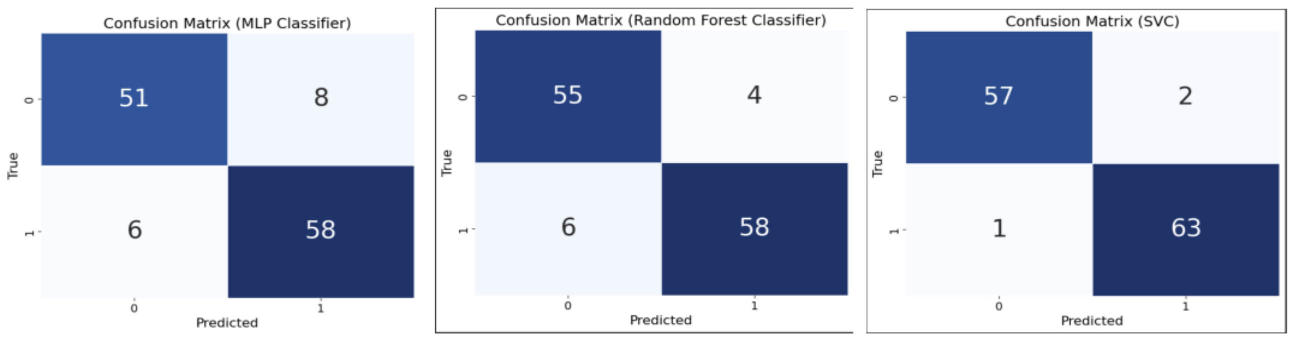


Fig. 9. Confusion Matrix of MLP Classifier, Random Forest, and SVC

Classifier	Suspicious	Safe
Random Forest	0.90	0.91
Linear SVC	0.93	0.91
SVC	0.98	0.97
K Neighbors	0.63	0.91
Logistic Regression	0.93	0.97
Decision Tree	0.71	0.77
MLP Classifier	0.85	0.89
Gaussian NB	0.97	0.97

Fig. 10. Performance Evaluation of ML Models using Precision

Classifier	Suspicious	Safe
Random Forest	0.90	0.91
Linear SVC	0.90	0.94
SVC	0.97	0.98
K Neighbors	0.95	0.48
Logistic Regression	0.97	0.94
Decision Tree	0.76	0.72
MLP Classifier	0.88	0.86
Gaussian NB	0.97	0.97

Fig. 11. Evaluation of performance using recall scores

Classifier	Specificity
Random Forest	0.898
Linear SVC	0.898
SVC	0.966
K Neighbors	0.712
Logistic Regression	0.966
Decision Tree	0.763
MLP Classifier	0.881
Gaussian NB	0.966

Fig. 12. Performance Evaluation of ML Models using Specificity

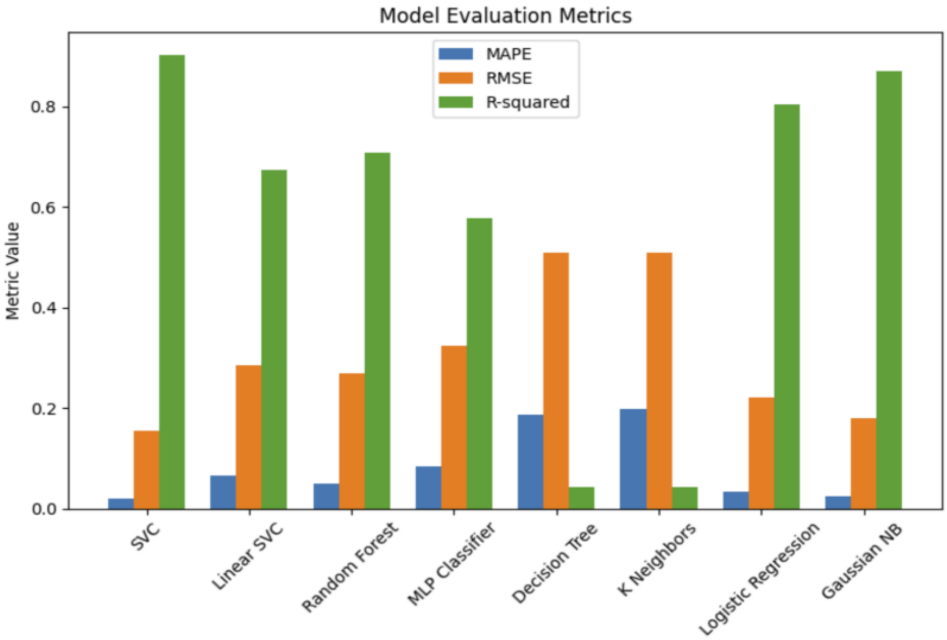


Fig. 13. Performance Evaluation of ML Models using MAPE, RMSE, and R-squared metric

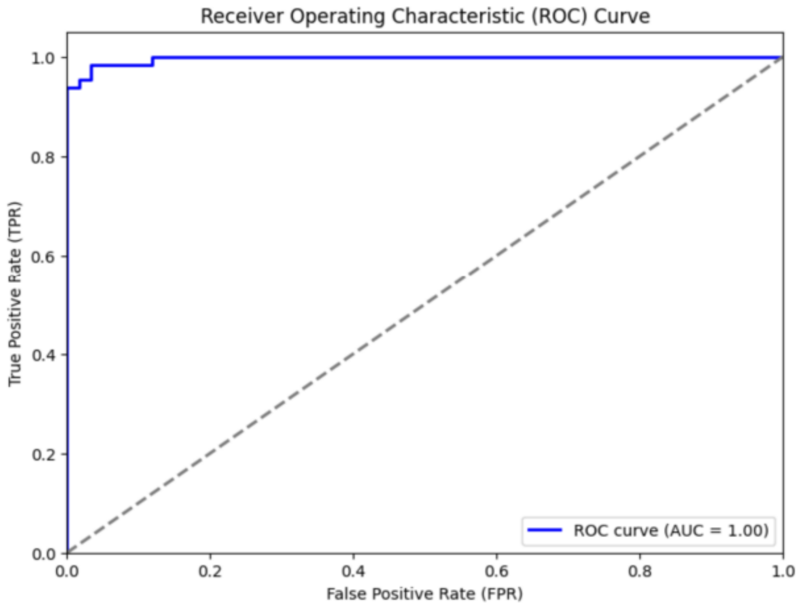
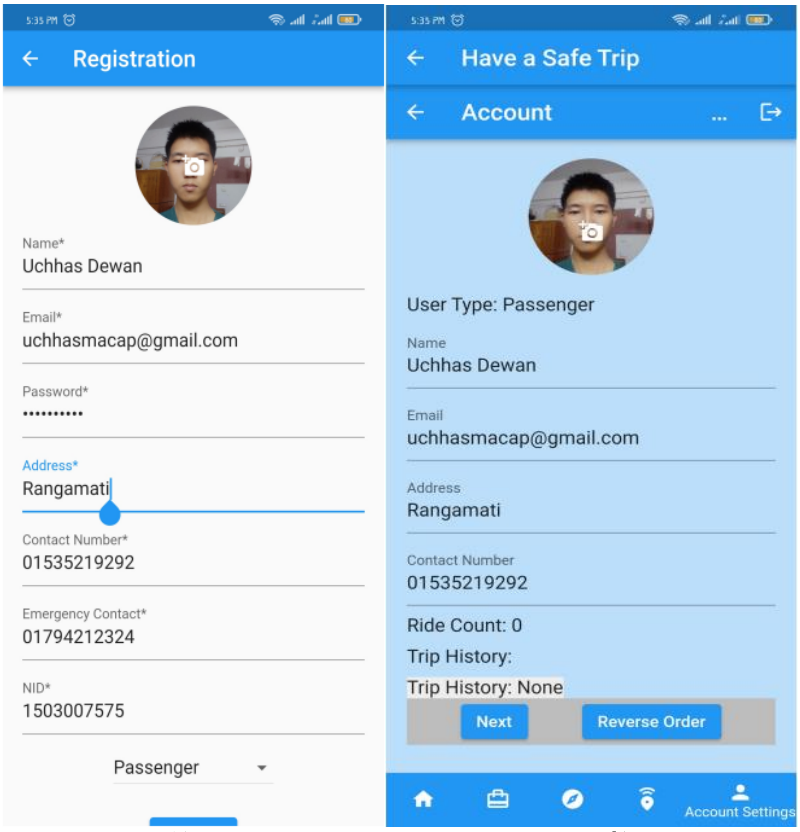
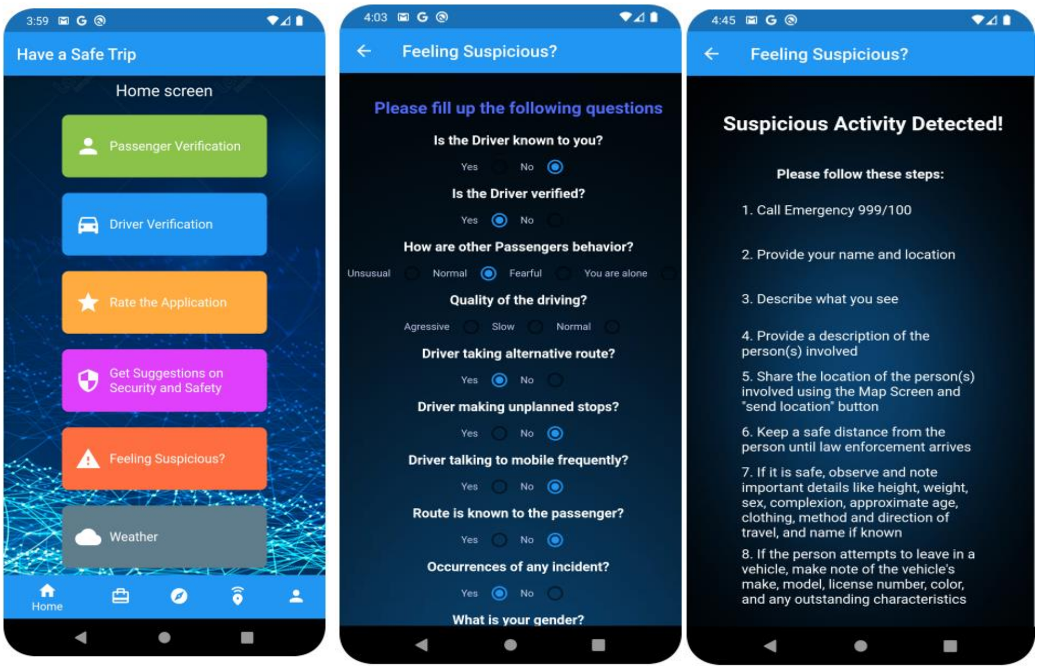


Fig. 14. ROC-AUC Curve of Support Vector Classification Model



(a) (b)

Fig. 15. (a) Registration and (b) Account information of our app

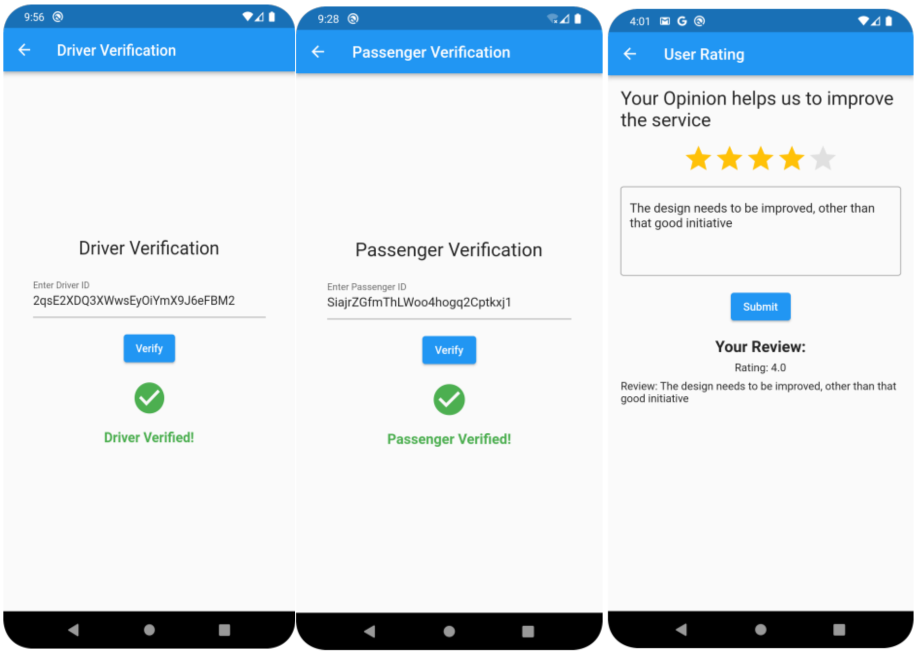


(a) (b) (c)

Fig. 16. Home screen and the suspicious activity detection screen

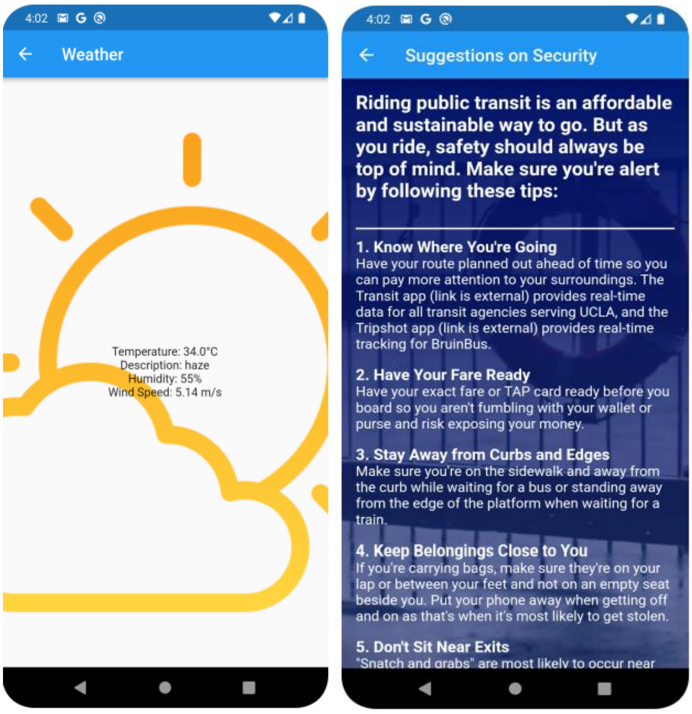
3.4. Important feature selection and data visualization

In the application development process, we performed feature selection to identify the most relevant columns from the original dataset. After a thorough evaluation, we selected 24 columns that were highly associated with detecting suspicious activity and aggressive driving. These chosen columns capture crucial information related to driver behavior, vehicle characteristics, and environmental conditions. The careful selection ensures the application focuses on key factors for accurate analysis and real-time detection. This approach enhances the efficiency and effectiveness of the application in providing valuable insights for improved safety and security. To train the machine learning models, this paper utilized a comprehensive set of features that encompass various aspects of the ride experience. These features include Driver known, Driver verified, Passengers behavior, Quality of driving, Driver taking alternative route, Driver making unplanned stops, Driver talking to mobile frequently, Route is known to the passenger, Occurrences of any incident, Passengers gender, What kind of baggage is the passenger taking, Was the passenger pressurized to do something, Passenger teased?, Route prone to dangerous activity, Driver making the ride was deliberately long, the Driver looking through the mirror frequently, Road quality, Any coordinated activity, Vehicle condition, the Driver's behavior, Did the driver follow traffic rules, The driver asked any inappropriate or personal questions, Is the driver taking detours, the Driver made uneasy or threatening environment, and Classified. The chosen models include K Neighbors Classifier, SVC, Decision Tree Classifier, Random Forest Classifier MLP Classifier, Gaussian NB, and Linear SVC. Each of these models offers unique characteristics and capabilities that make them suitable candidates for our task. Data visualization is the process of representing data in a visual format such as charts, graphs, or maps. It plays a crucial role in conveying complex information concisely and understandably. By visualizing data, patterns, trends, and relationships can be easily identified, enabling users to gain insights and make informed decisions. From Figure 4 we can see that the distribution of Suspicious and Safe Class is Close to even. Having a dataset with 325 instances classified as ”Suspicious” and 286 instances classified as ”Safe” provides a relatively balanced distribution, with approximately 53 percent representing the ”Suspicious” class and 46 percent representing the ”Safe” class. This balanced distribution is advantageous for binary classification as it ensures a reasonable representation of both classes, allowing the model to learn from a diverse set of instances. The presence of a slight class imbalance, in this case, does not pose a significant challenge and is within an acceptable range. It is worth noting that a balanced dataset helps prevent the model from being biased toward the majority class and allows for a more robust and accurate classification process. By considering both the actual numbers and percentages, it is evident that the dataset is well-suited for effective binary classification.



(a) (b) (c)

Fig. 17. Verification of the Driver, Passenger Users and Rating the App



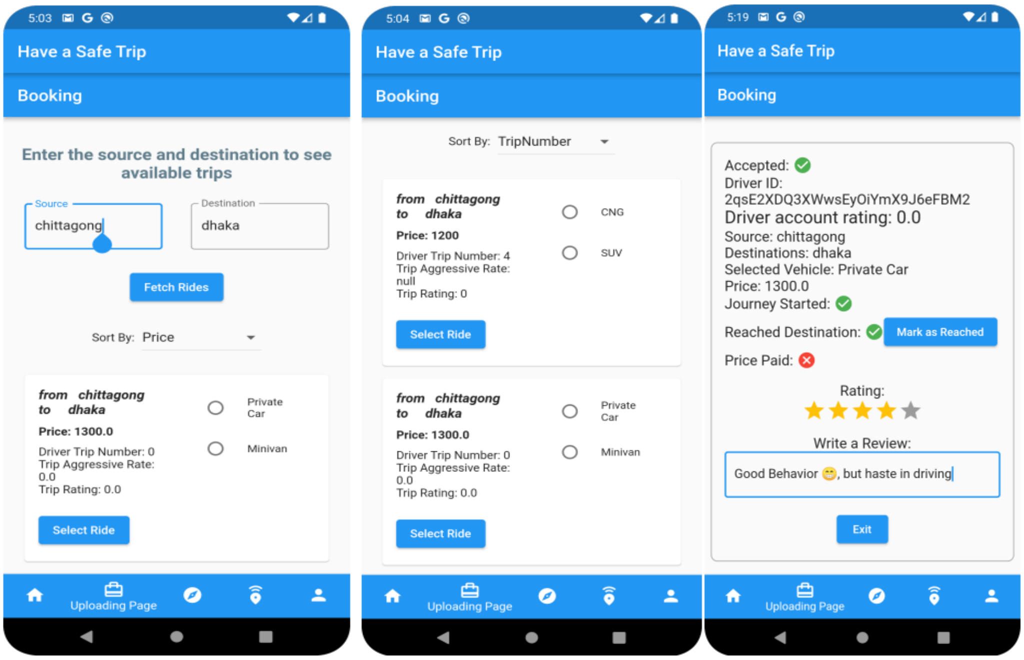
(a) (b)

Fig. 18. (a) Watching current weather and (b) Security Suggestions

3.5. Model selection and hyper parameter tuning

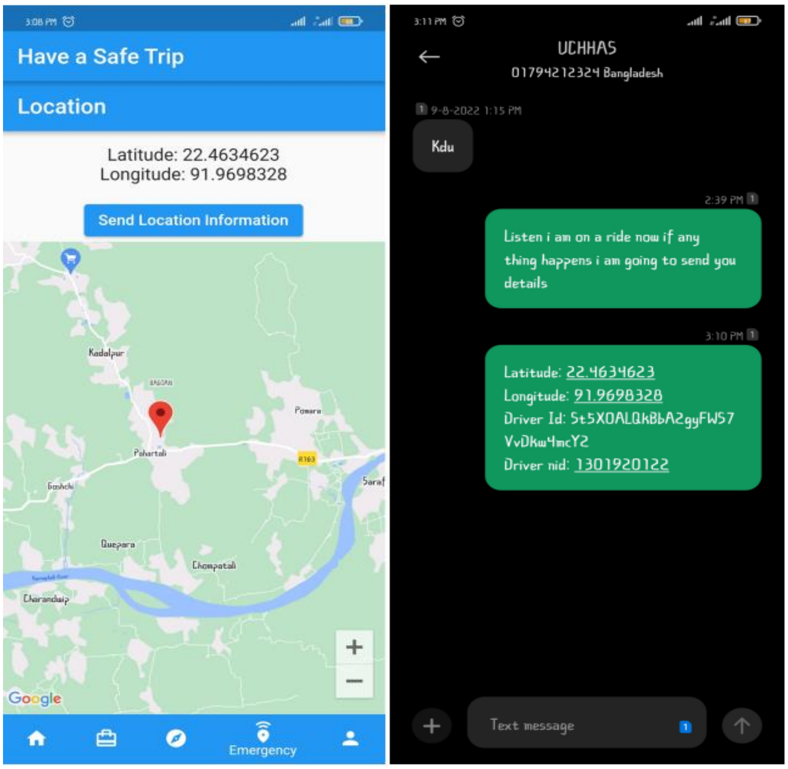
Our dataset was divided into a training set (80%) and a testing set (20%). Then, to train and fit the data, we used several machine learning algorithms, including the K Neighbors Classifier, SVC, Decision Tree Classifier, Random Forest Classifier, MLP Classifier, Gaussian NB, and Linear SVC. The models were then adjusted, and their performance was enhanced, using cross-validation and hyper parameter tuning. The accuracy evaluation metric was employed to gauge the models' efficacy. This methodical approach helped us identify the best algorithm for our particular binary classification problem. The next step is Pre-processing the raw data of the accelerometer and the gyroscope. We turned them into time windows to increase precise prediction. The time window ranged from 2 to 22.

The best time window with the best algorithm will be selected. We have performed two different machinelearning operations. One for the detection of suspicious activity and another for the detection of aggressive riding or driving. After performing different ML algorithms we found that the best algorithm for the aggressive driving detection is the Random Forest Classifier and the best time window is from 16 to 20. And as for Suspicious Activity Detection, the best algorithm is the SVC algorithm.



(a) (b) (c)

Fig. 19. Booking, Sorting Trips, and Rating a Driver's Ride Performance



(a) (b)

Fig. 20. (a) The Current Location Map and (b) Button to Send Current Location With Message to Friend

Fig. 21. Aggressive and safe driving detection

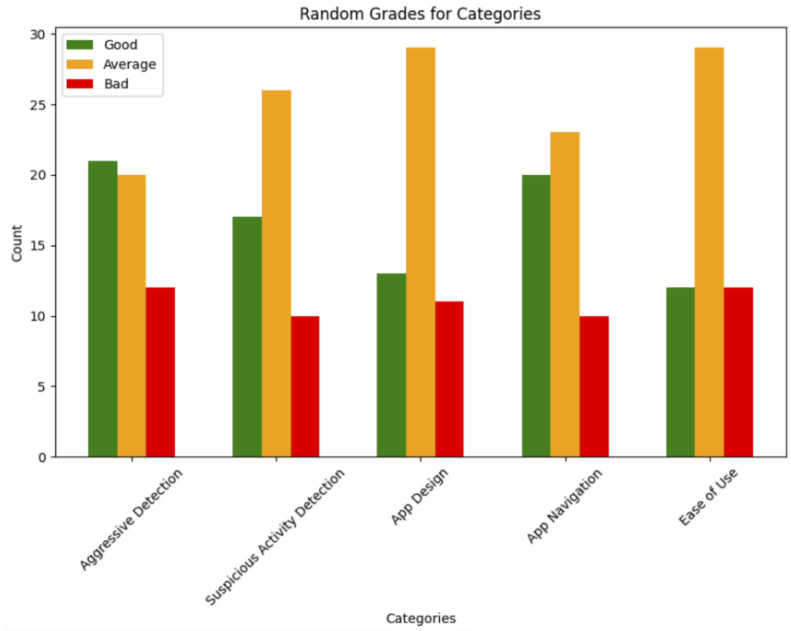


Fig. 22. Application evaluation by users

3.6. *Performance Evaluation using F1-score and accuracy*

Evaluating a machine learning model is important to understand how well it performs. We compare its predictions with the actual values to see how accurate it is. This helps us know the model's strengths and weaknesses, and where it can be improved. There are different ways to measure a model's performance, such as R squared, RMSE, MAPE, F1 score, specificity, ROCAUC curve, confusion matrix, and precision, recall, and accuracy. In a multi-class classification problem related to Suspicious Activity Detection, the terms True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are important. True Positives represent the number of cases correctly identified as positive for each class. True Negatives represent the number of cases correctly identified as negative for each class. False Positives are cases that were mistakenly classified as positive for each class, while False Negatives are instances that were mistakenly classified as negative for each class. The F1 score is a statistic that evaluates a classification model's performance by combining accuracy and recall to create a single number. From Figure 5, we get a detailed representation of the F1 Score for the different algorithms that we used. Here we can see the best-performing algorithms are SVC, Gaussian NB, and Logistic Regression. The least performing algorithms are KNeighbors and Decision Tree

Classifier. Accuracy is a commonly used evaluation metric in classification tasks that measures the overall correctness of the predictions made by a model. A perfect classifier would have an accuracy of 1, while an accuracy of 0 represents a completely incorrect classifier. It is clear from Figure 6 that the highest accuracy-giving algorithm is again the SVC classifier. And the lowest-performing Classifier is the K Neighbors and Decision Tree Classifier.

Table 1. Comparison results (suspicious activity prediction during transport riding)

Classifier	Accuracy	Precision	Recall	F1 score
Compared scheme [28]	.94	.95	.86	.90
Compared scheme [29]	.85	.86	.84	.86
Our proposed scheme (SVC)	.97	.98	.975	.97

Table 2. User feedback analysis regarding application suitability and effectiveness in different aspects

question	Proper	Not proper	No comment
Useful for suspicious activity prediction during riding	65%	25%	10%
Usable and effective for emergency help	55%	25%	20%
Application is secure	60%	30%	10%
Application is economically and practically sound	70%	20%	10%

3.7. Performance evaluation of ML models using different approaches

Figure 7 contains the confusion matrix of KNN and Decision Tree. The KNN had 42 true positives and 49 true negatives but it also had a disappointing 15 and 17 false positives and negatives. Likewise, the performance of the Decision Tree is also not satisfactory. The Confusion Matrix of the Gaussian NB, Logistic Regression, and Linear SVC can be found in Figure 8. Here, among these three algorithms, the best-performing algorithm is Gaussian NB, It has only 4 false positives and negatives in total. However, from Figure 9, it can be seen that the best-performing algorithm is once again SVC as it accumulates only a total of 3 false positives and false positives. The rest of the models also did good performance in comparison to K Neighbors and Decision Tree algorithms. The rows of the matrix correspond to the true classes, while the columns represent the predicted classes. Each cell in the matrix displays the count of observations falling into a specific combination of true and predicted classes.

Precision is particularly useful when the focus is on minimizing false positive errors. It provides insights into the model's ability to correctly identify positive instances without falsely labeling negative instances as positive Figure 10 highlights the performance of each classification by precision and the formula it uses. Time and again the best model is clearly SVC and the next model is the Gaussian NB Classifier. The chart represents both of the classes: Safe and Suspicious. Recall, also known as sensitivity or true positive rate, is a performance metric used in binary classification tasks. From Figure 11, it is shown that the SVC offers a better recall value than other classifiers. Specificity, also known as true negative rate, is a performance metric used in binary classification tasks. Figure 12 illustrates the performance of each classifier in light of specificity. From Figure 12, it is seen that SVC, logistic regression, and Gaussian naive Bayes (NB) offer better specificity performance than other classifiers. MAPE (Mean Absolute Percentage Error) is frequently used to assess the precision of prediction algorithms (i.e., the average percentage difference between expected and actual values). RMSE (Root Mean Square Error) is frequently used to assess the size of prediction mistakes in a model (i.e., The average squared difference between anticipated and actual values). The coefficient of determination, abbreviated Rsquared, measures how much of the variation in the dependent variable is accounted for by the independent variables in a regression model. From Figure 13, we can see a clear distinction between the tried models and the performance of those models in these last matrices can determine the best option that is to be chosen for the needed classification. From Figure 13 it can be shown that SVC is the best option in terms of MAPE, RMSE, and R-squared. The ROC curve is created by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds. The AUC is the numerical measure of the ROC curve's performance. It represents the overall ability of the model to distinguish between positive and negative classes across all possible thresholds. Figure 14 shows the ROC-AUC Curve of the chosen SVC Model and according to that graph, SVC is a suitable model for the Classification of Suspicious Activity. Table 1 compares the result of our proposed scheme with existing prediction schemes. For comparison, we have used our collected dataset for all compared scheme. It can be visualized from table 1 that that the proposed scheme outperforms existing scheme ([28, 29, 30]) by providing more accuracy, precision, recall, and F1-score. Thus, the proposed scheme is more suitable regarding suspicious activity detection during transport riding.

4. Mobile Application Development for Transport Riding Assistance

Before using the app you of course have to register with your name, email, phone number, nid, password, and some necessary information. If you are a driver you will have to add additional information like vehicle type and also driving license. Figure 15(a) is a snapshot of registering as a passenger account only after an authenticated login or registration. If the user doesn't have an account he/she cannot access the functions of the application. The account information screen shows the current information. There is some read-only information and there is some information that can be changed. For example, the Rating, trip history, ride counts, and aggressive rates cannot be changed. And as for a passenger account, there will lesser information naturally. Figure 15(b) shows the information of a current passenger. We can see the account is new and the user has not been in any trip yet.

The Home Screen Contains a total of 6 cards with different functionalities. Figure 16(a) displays the first Home Screen. The second picture shows the main focus of this entire work. The questionnaire is needed to be answered (see Figure 16(b)). After answering the questionnaire if it is safe then nothing happens except the screen shows it is safe. But if it is suspicious then the app provides some steps to follow and to stay alert all the time (see Figure 16(c)). To detect suspicious activities, users are prompted to answer a set of carefully curetted questions, aimed at identifying potential risks and ensuring proactive measures. These questions and their possible answers play a vital role in assessing the situation and recommending appropriate actions. The asked questions (see figure 16(b)) are Is the Driver known to you?, Is the Driver verified?, How is the behavior of other passengers?, What is the quality of the driving?, Is the driver taking alternative routes?, Does the driver make unplanned stops?, Does the driver frequently talk on the mobile phone?, Is the route known to the passenger?, Are there any incidents during the ride?, What is the gender of the passenger?, What kind of baggage is the passenger carrying?, Was the passenger pressurized to do something?, Has the passenger been teased? Is the route prone to dangerous activity? Does the driver intentionally prolong the ride?, Does the driver frequently look through the mirror?, What is the condition of the road?, Is there any coordinated activity observed? What is the condition of the vehicle?, How would you describe the driver's behavior?, Did the driver follow traffic rules?, Did the driver ask any inappropriate or personal questions?, Is the driver taking detours?, and Has the driver created an uneasy or threatening environment?. Figure 17 displays 3 more screens that are accessed by pressing the cards on the home screen. The first Screen shows the Driver Verification. The second Screen shows the verification of any Passenger Id. The last Screen is a display of the rating and review given to the application as a whole by any type of user. Figure 18(a) shares a view of weather information with temperature and humidity too. The last picture (Figure 18(b)) shows some preventive measures that can be taken before any trip whether on the system built by this app or elsewhere. Whatever the case, if the users are verified, they can use the application. The booking page is a page from the perspective of the passenger. The driver uploads trips. From Figure 19(a), we find in the first image that after writing the source and destination of the trip some suggestion pops up. In the second Screen (Figure 19(b)), we can find that there is an option to sort. There are 4 options to sort by: Price, Trip Number, Aggressive Rate, and Driver Rating. The last image (figure 19(c)) shows the passenger has reached the destination and now he/she has to rate the driver and also pay the price. Only the driver can set the price paid section to true. The map page is an additional feature. It allows the user to locate the current position or the current location by allowing GPS permission to the application. There is also a section that shows the latitude and longitude of the current position. Figure 20(a) has a screen on the left side that shows the map and also a button can be seen upon pressing which the right screen is popped that sends information (see Figure 20(b)) about the current location and some authenticated information about the riders or drivers. The aggressive rate screen shows how much aggressive the driver was during the whole trip. But it should be noted that the smart phone device has to be set on a stationary and non-moving space to have an accurate prediction on aggressive detection. Figure 21 shows the aggressive and safe driving notification via our application interface.

5. Evaluation Results

Evaluation of the application system is important to have a clear view of the actual performance of the app and how the users are feeling during the real-time use of the application. We have provided the application to 53 individuals to run and test, and we took their feedback on some categories and rated those categories as good, average, and bad (not satisfied). Figure 22 shows the visualization of their opinions. Among 53 individuals, 21 expressed that the aggressive detection was good, 20 expressed that it was average, and a minority (12) said it was not good enough. In the case of suspicious activity detection, 17 individuals said it was good, 26 individuals said it was average, and 10 individuals voted it to be not good enough. Likewise, we can see the other classifications of app evaluation. From the figure, it can be seen that more than 80 percent of users are satisfied (good and average) regarding the different features of our mobile application. Table 2 visualizes the user survey results regarding the suitability and effectiveness of the proposed application. We have collected user survey comments from 100 users. For this survey, we have asked questions about whether the app can be effective for transport riding, whether it is secure, and whether it is economically and practically sound or not. The survey results clearly indicate that more than 55 percent of users delivered positive remarks about the proposed transport riding safety assistance mobile application.

5.1. Challenges and scalability issues

Currently, we have tested our mobile application with 10,000 users. We have noticed that with our locally managed server and storage (e.g., Intel core i7 processor with 10 GB storage), the system works well with this limited number of customers. To support a diverse range of customers, both cloud server and storage capabilities must be improved. For this, we can purchase a faster CPU-based server as well as private cloud resources (such as Google

Cloud). Another major concern is security. To increase security, we will use federated learning and block chain technology.

6. Conclusion

This paper presents the development and implementation of a unique application designed to enhance passenger safety. The application utilizes advanced algorithms to identify suspicious behavior. This mobile application offers several features for passengers' safety, such as passenger verification, driver verification, application rating, suggestions regarding security and safety, and suspicious activity detection, among others. Through the utilization of machine learning techniques, the application demonstrates promising results in accurately detecting suspicious activities, enabling prompt intervention when necessary. This feature enhances the overall security of passengers and contributes to a safer transportation environment. For efficient machine learning model selection, we have evaluated several algorithms, such as K Neighbors Classifier, SVC, Decision Tree Classifier, Random Forest Classifier, MLP Classifier, Gaussian NB, and Linear SVC. For suspicious activity detection, this paper shows that the best ML algorithm is the SVC algorithm due to its higher accuracy results (97 percent). The mobile application evaluation results (via user feedback and comments) indicated that more than 80 percent of users are satisfied with the application features. Furthermore, the incorporation of sensors such as accelerometers and gyroscopes enables the detection of aggressive driving behaviors. This aspect adds a layer of safety by monitoring and alerting drivers to potentially dangerous driving patterns, ultimately reducing the risk of accidents and improving road safety. The combination of machine learning algorithms, questionnaires, and sensor technologies showcased in this work presents a holistic approach to passenger safety. The application's ability to accurately detect suspicious activities and aggressive driving behaviors highlights its potential for real-world implementation and its contribution to enhancing transportation safety.

6.1. Future research issues

Future research and development can focus on further refining the algorithms and expanding the application's capabilities. This includes exploring additional safety features, such as detecting other types of hazardous behaviors and incorporating real-time notifications and alerts to passengers and authorities. Overall, this work lays the foundation for a comprehensive passenger safety application that utilizes advanced technologies to proactively address security concerns and improve the overall safety and well-being of passengers. One of the future research scopes is the exploration of additional data sources, such as social media feeds, GPS data, or external sensors. It can provide a more comprehensive understanding of passenger behavior and driving patterns. This can lead to more accurate detection and prevention of potential risks. While the current focus is on passenger safety in a specific context, such as ridesharing or public transportation, future work can involve expanding the application's scope to other transportation modes, such as aviation or maritime modes, to cater to a wider range of safety concerns. In the future, this suspicious activity prediction work can be extended to other geographic regions by using IoT-based systems and artificial intelligence technologies, health status monitoring using wearable technologies, inaccurate driving activity detection by taking into account diverse transport types, and location-specific issues.

References

[1] I. T. Forum, "Road safety annual report 2022," *https://www.itf-oecd.org/road-safety-annual-report2022*, last accessed on July, 2023.

[2] R. Chun, "Rough ride-share: Why drivers are also at risk of violence, " *https://www.theguardian.com/usnews/2020/feb/06/uber-rideshare-lyft-safety-crime*, last accessed on december, 2020.

[3] S. Tasnim Cynthia et al., "Security concerns of ridesharing services in bangladesh, " *in 2019 2nd International Conference on Applied Information Technology and Innovation (ICAITI)*, Denpasar, Indonesia, pp. 44-50, 2019.

[4] I. Cojocaru and P.-S. Popescu, Building a driving behaviour dataset, in RoCHI, 2022, pp. 101–107.

[5] M. E. Hossain et al., "Manifesting a mobile application on safety which ascertains women salus in bangladesh, "*International Journal of Electrical and Computer Engineering*, vol. 9, no. 5, pp. 4355-4363, 2019.

[6] H. Aghayari et al., "Mobile applications for road traffic health and safety in the mirror of the haddon's matrix, " *BMC medical informatics and decision making*, vol. 21, no. 1, pp. 1–12, 2021.

[7] T. Wang et al., "Walksafe: A pedestrian safety app for mobile phone users who walk and talk while crossing roads, " *in Proceedings of the twelfth workshop on mobile computing systems and applications*, 2012, pp. 1–6.

[8] J. Trager et al., "Warning apps for road safety: A technological and economical perspective for autonomous driving– the warning task in the transition from human driver to automated driving,"*International Journal of Human–Computer Interaction*, vol. 37, no. 4, pp. 363–377, 2021.

[9] S. Group, "Sitata travel safe(3.5.3), "*https://www.sitata.app/en/*, last accessed on July 2023.

[10] I. Hitch Technologies, "Hitch — City-toCity Rideshare App for Long-distance Rides, " *https://www.ridehitch.com/*, last accessed on July 2023.

[11] Bridj company, "BRIDJ – Demand Responsive Transport Solutions, " *https://www.bridj.com/*, last accessed on July 2023.

[12] J.-L. Martin et al., " Cannabis, alcohol and fatal road accidents, " *PLoS one*, vol. 12, no. 11, pp. 1-10, 2017.

[13] R. Khan et al., "Security-aware passwords and services usage in developing countries: A case study of bangladesh, " *in International Conference on Services Computing*, Springer, pp. 67–84, 2018.

[14] P. Wawage et al., “Smartphone sensor dataset for driver behavior analysis, ” *Data in Brief*, vol. 41, no. xx, pp. 1-10, 2022.
[15] A. Carballo et al., “Libre: The multiple 3d lidar dataset, ” *2020 IEEE Intelligent Vehicles Symposium (IV)*, las vegas, USA, pp. 1094-1101, 2020.
[16] E. Romera et al., “Need data for driver behaviour analysis? presenting the public uah-driveset, ” *in 2016 IEEE 19th international conference on intelligent transportation systems (ITSC)*, Rio de Janeiro, Brazil, 2016, pp. 387-392
[17] H. Wang et al., “A recognition method of aggressive driving behavior based on ensemble learning, ” *Sensors*, vol. 22, no. 2, pp. 1-24, 2022.
[18] A. B. Ellison et al., “Driver behaviour profiles for road safety analysis, ” *Accident Analysis and Prevention*, vol. 76, pp. 118-132, 2015.
[19] V. Ramanishka et al., “Toward driving scene understanding: A dataset for learning driver behavior and causal reasoning, ” *in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 7699–7707, 2018.
[20] U. of Michigan, “Division of Public Safety and Security, Report a crime or concern suspicious behavior, ”*http://dpss.umich.edu/content/services/report-acrime/suspicious-behavior/*, pp. 1-10, 2023.
[21] SecuriGroup, “Understanding the challenges of cctv monitoring, ” *https://www.securigroup.co.uk/news/understandingthe-challenges-of-cctv-monitoring*, last accessed on july 2023.
[22] Tennessee govt., “Tennessee Suspicious Activity Reporting, ” *https://www.tn.gov/safety/homelandsecurity/report-suspicious-activity.html*, last accessed on july 2023.
[23] N. Tilley and G. Farrell, “The crime drop and the security hypothesis, ” Journal of Crime Science, vol. 4, no. 1, pp. 1–17, 2015.
[24] L. Goel et al., “Transfer Learning-based Driver Distraction Detection,” *ICSCDS conferenc*e, India, 2023, pp. 58-63.
[25] M. Almoqbel and E. Alyami, “Am I Safe? Understanding Saudi Women Rideshare Drivers Safety Perspectives,” *3rd ICCIT,* Saudi Arabia, 2023, pp. 618-621.
[26] S. S. Jacob et al., “IoT based Driver Assist System with Application of OpenCV and Python,” *3rd ICESC*, India, 2022, pp. 481-488.
[27] S. Shilaskar et al., "Driver Safety System using Microcontroller and Image Processing," *2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*, Bengaluru, India, 2023, pp. 340-344.
[28] M. V. P. R. Meneses et al., "Driver Drowsiness Classification using Machine Learning and Heart Rate Variability," *2023 11th International Symposium on Digital Forensics and Security (ISDFS),* USA, 2023, pp. 1-6.
[29] M. Guria et al., "IoT-Enabled Driver Drowsiness Detection Using Machine Learning," *Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC),* India, 2022, pp. 519-524.
[30] S. Rathod et al., "RealD3: A Real-time Driver Drowsiness Detection Scheme Using Machine Learning," *IEEE Wireless Antenna and Microwave Symposium (WAMS),* India, 2023, pp. 1-5.

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