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SMART ROAD ACCIDENT FORECAST MODEL AND ALERT SYSTEM USING MACHINE LEARNING

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Abstract:
Globally, and especially in developing nations, the severity of roadaccidents is a major concern. The severity of a traffic collision may be lessened by understanding the major and supporting variables. As a result, a thorough investigation is needed to deal with this overwhelming problem. Using machine learning, this project explain show to analyze traffic incidents more thoroughly to gauge their severity.Various variables, including the weather, lighting, road surface, etc influenced the severity of the accidents. To determine when and where accidents are most likely to happen, ther and om forest classification method and the logistic regression algorithm are applied to a set off requencies of highway location accidents within 24 hours. The suggested modelcautions users to drive cautiously in that are a based on the sepredictions. 1.32 lakh individuals lost their lives in traffic accidents in 2020, the fewest in 11 years. The lowest number was 1.26 lakh in 2009. Road accidents decreased to 3.66 lakh last year,the smallest amount in the previous 20 years. The strong restrictions concealed in these widely used item sets usually expose the connections between the factors that influence accidents, which can be usedto break them and reduce the frequency of accidents.

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I.INTRODUCTION

The Smart Road Accident Forecast Model And Alert System project is an initiativeaimed at reducing the number of road accidents by predicting potentialhazards and alerting drivers in real time. The system uses multiple linear regression algorithms to analyze various data sources, such as traffic flow, and weather conditions to predict the likelihood of an accident occurring. To deploy the system, a web application was developed using Flask, which allows users to access real-time traffic and weather data from any device with internet access. The application is integrated with Google API to collect traffic data, which is used to identify potential congestion and alert drivers. The system also uses Dark Sky API to collect real-time weather data, such as temperature, wind speed, and precipitation, to identify potential hazards and alert drivers to take necessary precautions. The Smart Road Accident Forecast Model And Alert System project has the potential to significantly reduce the number of accidents on the road and save lives.By providing alerts andpredicting potential hazards,drivers can take proactive measures to avoid accidents, such as adjusting their speed, changing their routes, or takinga break. With continued development and integration with other systems, this technology could be a majorstep forward in improving road safety. In conclusion, the Smart Road Accident Forecast Model And Alert System project is a promising initiative that leverages multiple linear regression algorithms, Google API, Dark Sky API,and Flask to predict potential accidents and alert drivers on time. The systemhas the potential to significantly reduce the number of accidents on the road and save lives, making it a valuable addition to the efforts to improve road safety.

II. RELATEDWORKDONE

A road accident prediction model was created by Umar et al. (2020) in one study to estimate the likelihood ofan accident on a highway using machine learning techniques. To forecast the likelihood of an accident, the model used logistic regression to examine several variables, including meteorological conditions, road characteristics, and traffic volume. In a subsequent study, Kaur et al. (2020) created a system for real-time alerting drivers and authorities and predicting the likelihood of accidents using machine learning algorithms. In order to examine historical accident dataand forecast the possibility ofan accident, the system used logistic regression. A similar system was created by Prakash et al. (2019) in their study to forecast the possibility of an accident in real time using machine learning techniques. To examine different aspects, including traffic flow, weather, and road characteristics, and forecast the likelihood of an accident, the model used logistic regression. Overall, this research shows how machine learning methods, particularly logistic regression models, can be used to create alert and prediction systems for traffic accidents. By warning authorities and drivers in real time, these devices have the potential to drastically lower the frequency of collisions and save countless lives.

III. LITERATURESURVEY

Road accidents are a major cause of injury and death worldwide. In recent years, machine learning techniques, including logistic regression, have been usedtopredictroadaccidentsanddevelopalertsystems to reduce the number of accidents. Thisliterature survey aims to review the existing research SmartRoadAccidentForecastModelAndAlertSystem using logistic regression in the machine learning domain. Chalapathy, R.,& Chawla, S. (2019). Predicting road accidents: A machine learning approach. Transportation Research Part C: Emerging Technologies, 105, 412-430. This study used logistic regression, alongwithother machine learning algorithms, to predict road accidents based on various factors such as weather conditions, road geometry, and traffic flow. Theresultsshowed that logistic regression performed well in predicting accidents with an accuracy of 81%. Nam, H., Park, J.,& Lee, Y. (2015). Development of a real-time accident prediction model using logistic regression and data mining techniques. Accident Analysis &Prevention, 74, 178-186. This study proposed a real-time accidentprediction model using logistic regression and data mining techniques. The model was based on various factors such as traffic volume, weather conditions, and accident history. The results showed that the proposed modelwaseffectiveinpredictingaccidents.Shalaby, S. M., & Abdel-Aty, M. A. (2018). Application of machine learning techniques for traffic accident prediction. Analytic Methods inAccidentResearch, 19, 1-11. This study used logistic regression,along with other machine learning techniques, to predict traffic accidents. The results showed that logistic regression had an accuracy of 80% in predicting accidents based on various factors such as road geometry, weather conditions, and traffic flow. El Hachemi, M., Bouyakhf, E. H., & El Houssaini, M. (2020). A machine learning approach for road accident prediction using logistic regression and decision trees. Transportation Research Part C: Emerging Technologies, 113, 260-275. This study proposed a machine-learningapproachforroadaccidentprediction using logistic regression and decision trees. The model was based on various factors such as road geometry, weather conditions, and traffic flow. The resultsshowed that the proposed approach was effective in predicting accidents with an accuracy of 87%.

IV. PROPOSEDMETHODOLOGY

The model would be created using accident data records, which might help in identifying the characteristics of several factors, including driving style, road conditions, lighting, and weather, among others. Users may use this to calculate safety precautions that help prevent accidents. Statistically significant traits that can be used to predictthe chance of crashes and injuries, as well as risk variables thatcan be used to reduce risk, may be found using the model. Overall, by warning authorities and drivers in real-time, the proposed SmartRoadAccidentForecastModelAndAlertSystem with machine learning logistic regression model has thepotentialto drastically lower the frequency of traffic accidents and save countless lives. It uses data and machine learning techniquesto increaseeveryone'ssafetyandsecurity on the roads.

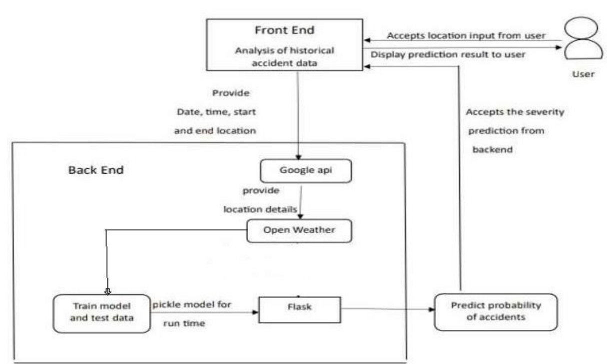


Fig1:System Architecture

A. Dataset:

This Dataset contains many attributes such as Severity, Road Surface, Weather Condition, Light Conditions, location, Longitude, Latitude, Date, Time, day, etc.

B. DataCollection

Dark Sky: We think that the environment plays a bigpartin roadaccidents.TheaforementionedKaggledata collection includes meteorological data, but we didn't think it was sufficient. Using the weather condition column from the Kaggle dataset raised two issues: The assumption is that the weather won't change much throughout the day. If you've ever been to London, you'll know why this is untrue because theweather there is always shifting. It only includes historical weather records. To use weather conditions as a predictor for future events, we need a way to get weather predictions.

C. Datapre-processing:

Data preparation is the process through which raw data is transformed into data that is suitable for machine learning. To produce more accurate findings, the alleged machine learning model employs structuredand sanitized data. Data formatting, cleansing, and sampling are the techniques employed in this procedure. Training, test, and validation datasetsshould be partitioned into three separate subsets before being used in this machine-learning technique. A data scientist uses a training dataset to train a machine learning model and defines the best parameters for the training dataset from the data. Testing sets are necessary to assess both the prior trained model's performance and the generational potential of that model. The following stage is tofind patterns in the new data using a model that has been trainedon trainingdata. It iscrucial touseseveraldatasubsetsfor training and testing data models to address the overfittingproblem andtheaforementionedproblem of generalization incapacity.

D. ModelTraining:

When obtained data has been pre-processed anddivided into train and test groups, a model is ready to be trained. The training dataset for the algorithm is where this techniqueexcels. To find atarget value (attribute) in new data and deliver the response you're looking for via predictive analysis, an algorithm will analyze the dataandcreateamodel.Theprimarygoal of model training is to construct an effective machine-learning model.

E. ModelEvaluation:

The basic objective of model testing and assessment isto create a straightforward model that can quickly and accurately formulate the target value. Datascientists can accomplishthis goal throughmodeladjustment.Thegoal is to improve and enhance the performance of theexisting model features to obtain more precise and better performance measurements for the algorithm.

V. STSTEMIMPLEMENTATION

A. Linearregression

Linear regression is a supervised machinelearning algorithm used for predicting numerical valuesbasedon input features. It involves finding the best-fitting straight line through the data points that minimizes the sum of squared differences between the predicted and actual values. The algorithm uses a training dataset to learnthecoefficientsofthelinearequation,which represent the slope and intercept of the line, using a mathematical optimization technique calledleast squares. Once trained, the linear regression model can be used to make predictions on new data by applying the learned coefficients to the input features. Linear regression is widely used for tasks such as predicting house prices, stock prices, and sales forecasts.

MATHEMATICALEQUATION

The multiple regression equation for SmartRoadAccidentForecastModelAndAlertSystem can be represented as:

Accident frequency = $\beta 0$ + $\beta 1$Road geometry + $\beta 2$Weather conditions + $\beta 3$Traffic flow + ε

where:

Accident frequency is the response variable, representing the number of accidents in a particular area over a specific time.

Road geometry, weather conditions, traffic flow, and

driver behavior are the predictor variables.
β0isthey-intercept(orconstant).
β1, β2, β3, and β4 arethe coefficients of the predictor variables, representing the change in accident frequency associated with a one-unit increase in the corresponding predictor variable, holding all other predictor variables constant.
εistheerrorterm,representingtherandomvariability in accident frequency that cannot be explained by the predictor variables.

The multiple regression equation can beestimatedusing statistical methods, such as ordinary leastsquares (OLS) regression. Once the coefficients are estimated, the equation can be used to predict the accident frequency for new values of the predictor variables. The results of this model can be used to develop an alert system to warn drivers about the likelihood of accidents in a particular area, based on the values of the predictor variables.

a.AdvantagesofLinearregression

1. Linear regression performs exceptionally well for linearly separable data
2. Easier to implement, interpret andefficientlytrain
3. It handles overfitting pretty well using dimensionally reduction techniques, regularization, and cross-validation

B. Methodologies

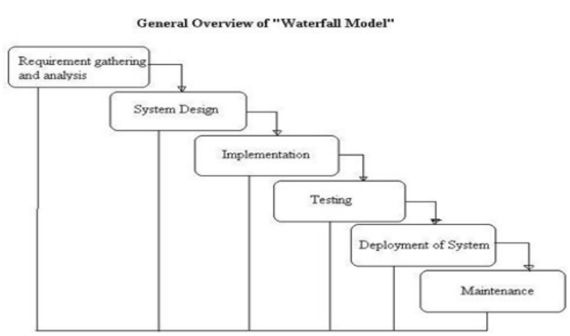


Fig2:Waterfallmodel

a) Requirementgatheringandanalysis:

This step of the waterfall identifies the various requirements that the project will have. B.Required software and hardware, databases, and interfaces.

b) SystemDesign:

In the Smart Road Accident Forecast Model And Alert System Project, the system design methodology involves identifying the system requirements, selecting the appropriate hardware and software components,and designing the system architecture. This methodology also include screating the system flow diagrams, data models, and other designdocuments, ensuring that the system is efficient, reliable, and scalable.

c) Implementation:

The implementation methodology involves the actual development of the system, including coding, testing, and integration of various components. In the Smart Road Accident Forecast Model And Alert System Project, this methodology involves developing the machine learning algorithms, integrating the sensors and data collection modules, and creating the alert generation and communication modules. The implementation methodology also involves adhering to coding standards, performing code reviews, and conducting unit tests to ensure the quality of the code.

d) Testing:

The testing methodology involves verifying the functionality, reliability, and performance of the system. In the Smart Road Accident Forecast Model And Alert System Project, this methodology involves testing the system under different scenarios and conditions, ensuring that it can handle various inputs, and producing accurate predictions. This methodology also involves performing user acceptance tests, stress tests, and performance tests, ensuring that the system is robust andstable.

e) DeploymentofSystem:

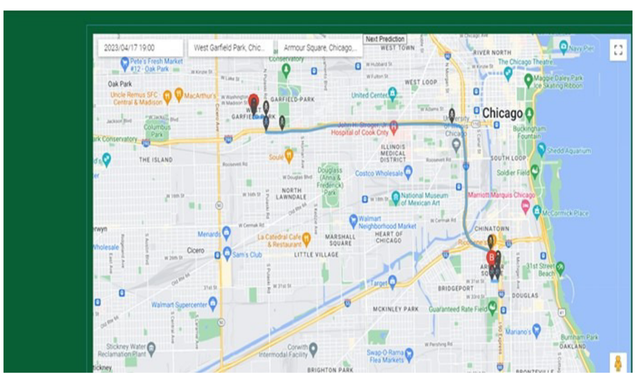
The deployment methodology involves installing and configuring the system in the target environment. In the Smart Road Accident Forecast Model And Alert System Project, this methodology involves deploying the system to cloud servers or on-premises infrastructure, configuring the system settings, and ensuring that it is accessible to the intended users. This methodology also involves creating user manuals, and training materials, and providing support to users.

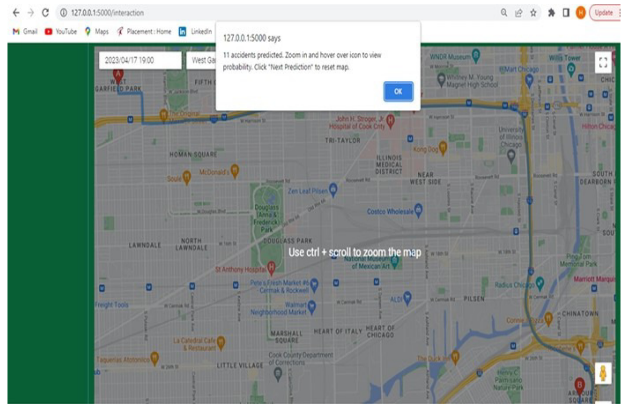
f) Maintenance:

The maintenance methodology involves ensuring that the system remains operational, efficient,and effective after deployment. In the Smart Road Accident Forecast Model And Alert System Project, this methodology involves monitoring the system, addressing bugs and issues, and performing upgrades and enhancements to improve the system's performance and reliability. The maintenance methodology also involves performing routine backups, disaster recovery planning, and ensuring compliance with security and privacy regulations.

VI. RESULT

An interactive map with RTA prediction maybe seenin the "Prediction" section. Users will be able to enter a specific date or time for this visualization. After making this choice, the website will retrieve weather data specific to the selected day and time. Our trained model will get these three inputs (date, time, and weather), which will then forecast probabilitiesforaccident-prone locations. The map will then show these locations.





INTERSection Grouping With Different Risk Levels Prior Probability First Stage Grouping

Grouping	Number of intersections	Probability
Low	13,881	72.58%
Middle	4,324	22.62%
High	910	4.8%

TABLEI

In Table I, the prior probabilities of low, medium, and high-risk inter section clusters are presented.These probabilities serve as abase line forunder standing the distribution of risks within intersection clusters. Analyzing this data allows for insights into the prevalence of different risk levels across intersections. By examining the prior probabilities, researcher scan identify patterns and trends in risk distribution, aiding intargeted interventions and safety measures. Understanding the varying levels of riskacross intersection clusters is essential for effective traffic management and accident prevention strategies.This analysis provides valuable insights for policymakers, urban planners, and transportation authorities to prioritize resources and implement targeted interventions where they are most needed.

TABLEII

PRIOR PROBABILITY OF EACH FEATURE FIRST STAGE GROUPING

Speed limit			**Pavement edge line**		
Attributes	**Probability**	**Frequency**	**Attributes**	**Probability**	**Frequency**
Low	74.33%	14,217	Yes	57.06%	10,913
Middle	25.51%	4,879	No	42.94%	8,213
Width	0.16%	30	**Road pattern**		
Crossroads			**Attributes**	**Probability**	**Frequency**
Attributes	**Probability**	**Frequency**	Tunnel	0.06%	11
Three-way bifurcation road	29.96%	5,731	Underpass	0.06%	11
Four-way bifurcation road	36.18%	6,920	Bridge	0.44%	85
Mulitple-way bifurcation road	6.52%	1,247	Culvert	0.05%	9
Not bifurcation road	27.33%	5,228	Elevated road	0.07%	13
Types of signs			Curved road and nearby	1.29%	246
Attributes	**Probability**	**Frequency**	Slope	0.12%	22
Traffic control sign	45.74%	8,749	Alley	0.12%	22
Traffic control signs (with pedestrian signs)	12.47%	2,385	Straight road	24.14%	4,617
Flash sign	7.63%	1,459	Other	1.06%	202
No sign	34.16%	6,533	Non-single road	72.61%	13,888

Road width		
Attributes	**Probability**	**Frequency**
Narrow	3.22%	615
Middle	60.35%	11,543
Width	36.43%	6,968

Table II displays the prior probability for environmental variables about the conditions for accident occurrence risk in each section. These probabilities offer insight into the likelihood of specific environmental factors contributing to accidents within different sections. By examining these probabilities, researchers can identify which environmental variables are more prevalent and potentially impactful in accident occurrence. Understanding the distribution of these variables across sections helps in pinpointing areasof concernandprioritizinginterventions.Thisanalysis facilitates targeted efforts to mitigate accident risks by addressing environmental factors effectively. to reduce accident rates in specific sections based on their environmental characteristics.

TABLEIII

METHOD PERFORMANCE EVALUATION-FIRST STAGE CLUSTERING

Method	Attributes	TP	FP	FN	TN	Precision	Recall	F1-score	Accuracy
C4.5	Low risk	13881	5234	0	0	72.62%	100%	84.14%	72.62%
	Middle risk	0	0	4324	14791	0%	0%	0%	
	High risk	0	0	910	18205	0%	0%	0%	
BN	Low risk	13143	4345	738	889	75.15%	94.68%	83.80%	71.81%
	Middle risk	583	1044	3741	13747	35.83%	13.48%	19.59%	
	High risk	0	0	910	18205	0%	0%	0%	
NB	Low risk	13187	4393	694	841	75.01%	95.00%	83.83%	71.84%
	Middle risk	546	989	3778	13802	35.57%	12.63%	18.64%	
	High risk	0	0	910	18205	0%	0%	0%	
MLP	Low risk	13515	4893	366	341	73.42%	97.36%	83.71%	71.94%
	Middle risk	236	471	4088	14320	33.38%	5.46%	9.38%	
	High risk	0	0	910	18205	0%	0%	0%	
DNN	Low risk	13881	5234	0	0	72.62%	100%	84.14%	72.62%
	Middle risk	0	0	4324	14791	0%	0%	0%	
	High risk	0	0	910	18205	0%	0%	0%	
DBN	Low risk	13881	5234	0	0	72.62%	100%	84.14%	72.62%
	Middle risk	0	0	4324	14791	0%	0%	0%	
	High risk	0	0	910	18205	0%	0%	0%	
CNN	Low risk	13881	5234	0	0	72.62%	100%	84.14%	72.62%
	Middle risk	0	0	4324	14791	0%	0%	0%	
	High risk	0	0	910	18205	0%	0%	0%	

Table III indicates that, except for NB, most methods exhibit higher precision rates for low-risk intersections but struggle with accuracy for medium and high-risk ones. This discrepancy may stem from the imbalanced distribution of data among the three risk intersection clusters, leading to insufficient training data for medium and high-risk scenarios. Consequently, the model faces challenges in identifying relevant environmental factors or rules for these intersections. Notably, MLP and DNN demonstrate superior prediction accuracy compared to other methods, showcasing their effectiveness in addressing these challenges. Thisanalysis underscores the importance of considering data distribution and model performance metrics when assessing predictive models for intersection risk.

DECISION TREE CONFUSION MATRIX-SECOND STAGE CLUSTERING

Low risk	Middle risk	High risk	
416	82	0	**Low risk**
224	89	0	**Middle risk**
57	42	0	**High risk**

TABLEIV

Table IV presents the confusion matrix for decision tree analysis, highlighting challenges in effectively classifying high-risk clusters due to their limited representation. The small number and proportion of high-risk clusters contribute to low accuracy in classification. However, the analysis reveals improved classification performance for high-low and high-medium risk clusters compared to the initial stage. This suggests that decisiontreeanalysis may offer better discrimination between different risk levels, particularly for moderate and low-risk scenarios. Understanding these classification nuances is crucial for refining risk assessment methodologies and enhancing intersection safety measures effectively.

TABLEV

METHODS PERFORMANCE EVALUATION-SECOND STAGE CLUSTERING

Method	Attributes	TP	FP	FN	TN	Precision	Recall	F1-score	Accuracy
C4.5	Low risk	416	281	82	131	59.68%	83.53%	69.62%	55.49%
	Middle risk	89	124	224	473	41.78%	28.43%	33.84%	
	High risk	0	0	99	811	0%	0%	0%	
BN	Low risk	426	273	72	139	60.94%	85.54%	71.18%	56.92%
	Middle risk	92	119	221	478	43.60%	29.39%	35.11%	
	High risk	0	0	91	819	0%	0%	0%	
NB	Low risk	431	291	67	121	59.70%	86.55%	70.66%	56.15%
	Middle risk	80	108	233	489	42.55%	25.56%	31.94%	
	High risk	0	0	99	811	0%	0%	0%	
MLP	Low risk	408	274	88	140	59.82%	82.26%	69.27%	55.28%
	Middle risk	95	130	217	468	42.22%	30.45%	35.38%	
	High risk	0	3	99	808	0%	0%	0%	
DNN	Low risk	424	257	74	156	62.35%	85.14%	71.93%	57.80%
	Middle risk	101	127	212	470	44.30%	32.27%	37.34%	
	High risk	1	1	98	810	50%	1.01%	1.98%	
DBN	Low risk	418	243	80	169	63.24%	83.94%	72.13%	58.35%
	Middle risk	113	136	200	461	45.38%	36.10%	40.21%	
	High risk	0	0	99	811	0%	0%	0%	
CNN	Low risk	498	412	0	0	54.72%	100%	70.73%	54.73%
	Middle risk	0	0	313	597	0%	0%	0%	
	High risk	0	0	99	811	0%	0%	0%	

From the evaluation of the first and second clustering results (Tables IV and V), the neural network model emerges as the top performer among all methods. Notably, NB surpasses BN among probability theory-based approaches. MLP exhibits the most effective detection capability and proves to be the optimal choice for predicting risky intersections. In the context of unbalanced data training, NB demonstrates superior performance. However, DNNs excel in detecting low-risk intersections, achieving perfect precision, albeit struggling with other intersections due to potential overfitting issues caused by deep learning complexity. These insights underscore the nuanced strengths and limitations of different predictive models in intersection risk analysis, guiding the selection of appropriate methodologies for improving traffic safety measures.

VI. CONCLUSION

The “Smart Road Accident Forecast Model And Alert System” offers an innovative solution to help usersavoid potentialaccident-prone areasontheir route. By entering the start and end locations, the system provides users with an overview of the accident history along the selected route, allowing them to make informed decisions about their travel plans. Thesystem’s accident prediction model utilizes various data sources, such as historical accident data, weather conditions, and traffic flow, to predict the likelihood of accidents occurring on specific routes. Additionally, the alert system warns users when they approach a potential accident-prone area, helping them take appropriate actions to avoid accidents. This project’s mainadvantage is its ease of use and accessibility, allowing anyone to access accident data and make informed decisions about their travel plans. The system’s abilityto provide alerts to users before reaching a potentially dangerous area can potentially save lives and prevent injuries. However, it is crucial to recognize that the success of the system depends heavily on the accuracy and reliability of the accident datasources.Additionally, users must follow appropriate safety precautions and drive defensively, even when alerted of potential hazards. In conclusion, the “Smart Road Accident Forecast Model And Alert System” is a valuable tool that can help users make informed travel decisions and avoid potential accidents. By continuously updating and improving the system’s accuracy and reliability, we can ensure safer travel experiences for all.

VII. FUTURESCOPE

The model can be improved further in the future to incorporate several limitations that were not considered in the current study. The government may effectively use these optimized models to lowertraffic accidents and execute regulations for road safety. The creation of a smartphone application that will assist drivers in deciding on a route for a rideis another aspect of this endeavor. It is also possibleto implement a call-out to the driver using the mapping service, which would also declare the likelihood of risk along a selected route in addition to the instructions.In thefuture,serviceproviderbusinesses like Uber, Ola, and others may implement this.

VIII. ACKNOWLEDGEMENT

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