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AI Enabled Accident Black Spot Alerting Mobile System to Enhance Road Safety Using GMM-SVM

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Abstract: Andhra Pradesh consistently ranked in the top 10 Indian states with the highest number of traffic accidents over the past ten years, according to statistics made public by the National Crime Record Bureau. Andhra Pradesh saw a 20 percent rise in road accidents in the year 2021, totaling 21,556 accidents, of which 8,186 resulted in fatalities. Future accidents can be decreased by comprehending the causes affecting road accidents and using the insights gained from them. When analyzing the causes of traffic accidents, driver's behavior is a crucial component to take into account. Inappropriate driving behaviors can lead to abnormal circumstances that may result in traffic accidents. The proposed methodology uses an integration of Gaussian Mixture Modelling and Machine Learning classification algorithms on the data of road crashes in the Vijayawada region to predict accidents in the future and notify drivers of impending danger. The Road Transportation Authority (RTA), Vijayawada, provided data on road accidents, including three accident classifications and variables influencing accidents. Firstly, the data has been preprocessed and then the proposed methodology is applied to classify the black spots. The developed model can potentially classify accidents based on severity into three classes: fatal, severely injured, and generally injured. Then the developed models are integrated with an Android mobile application through the Google Cloud platform. The mobile application keeps a database of all the crucial user information, including the user's age, gender, vehicle type, and age, and it uses GPS to monitor the user's location. The driver inputs his source and destination addresses to check for any susceptible blackspots before beginning the drive. He is also given the option of real-time safety support, which, when activated, warns the user when he is approaching a blackspot that would have serious repercussions.

Keywords: *Android Mobile Application, Blackspots, Gaussian Mixture Modelling, Machine Learning, Road accidents.*

1. Introduction

Around the world, traffic accidents are a serious problem. The fundamental cause of road accidents which is often neglected is irresponsible driving, which is innately influenced by infrastructure and traffic conditions, among other factors [1,2]. In India, the number of traffic accidents is increasing rapidly. A total of almost 4.37 lakh traffic accidents were reported on Indian roadways in 2019, of which 1.54 lakh resulted in fatalities and 4.39 lakh in nonfatal but significant injuries. As per the reports of the National Crime Record Bureau(NCRB), from 3,68,828 in 2020 to 4,22,659 in 2021, India's number of traffic accidents has increased. About 3,73,884 people were injured and 1,73,860 people died as a result of the incidents in 2021. The statistics of Andhra Pradesh showcase a total of 22,131 accidents that have occurred which resulted in 8,946 fatalities [3,4]. Eight zones of the Vijayawada region are considered in this research. The dataset consists of observations that were taken from the RTA of Vijayawada. The dataset is classified into 8 zones namely Ibrahimpatnam, Bhavanipuram, Gandhinagar, Poranki, Patamata, Vidyadarapuram, Mylavaram, and Penamaluru. The main objectives are to predict blackspots, display the blackspots in mobile application using Google Maps API, and notify the user whenever he is entering the blackspot zone while he is traveling. The first objective is achieved by using Gaussian mixture modeling and machine learning classification algorithms. The second objective which is displaying the blackspots is implemented by developing a mobile application making use of Android Studio. The final objective which is notifying the user, when he approaches the blackspot is achieved using the Google Maps API.

1.1. Literature review

Athiappan et al. [5] making use of Getis-Ord GI found out the most influential factors in a road accident. The most influential factors are the human factors including the driver's age, drinking alcohol before driving, and distracted driving caused by roadside advertisements. Comi et al. [6] used clustering and data mining techniques to determine whether data mining techniques are better suited for analyzing accidents and determining the key contributing factors.

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Wang et al. [7] found that decision-makers and incident management organizations could utilize a BPNN model to predict the time interval between primary and secondary collisions to avoid or lessen secondary collisions. Li et al. [8] performed the statistical analysis and data mining tools on the fatal accident dataset. The Apriori algorithm developed association rules to locate critical attributes like location, weather, time, etc. The classification model was built using the Naive Bayes classifier, and the clusters were built using the K-means clustering method. Sanchez et al. [9] used big data and a Poisson model with fixed effects to determine how traffic congestion causes accidents on the roads.

Zhang et al. [10] used segment-based identification to identify secondary events and continuously analyze them. Zhan et al. [11] used logistic regression to identify factors associated with accidents and performed k-means clustering to identify groups of secondary crashes. They also used survival analysis to predict when subsequent crashes would happen after the initial crash. Siddiqui et al. [12] discovered that different road safety measures affect death rates differently, with seat belts and speed limits having the most effects.

Devaraj et al. [13] used a decision tree algorithm and devised a location-based level categorization of the accident severity model. The classifiers used are support vector machines as classifier (SVC) and Naive Bayes. In SVC, the decision plane known as the hyperplane separates objects into many classifications. Kashevnik et al. [14] built a mobile application that gathers user data using sensors like the GPS, accelerometer, and gyroscope. The data is then analyzed using machine learning methodologies to analyze patterns of unsafe conduct and give the driver feedback in real time.

Faiz et al. [15] developed a mobile application that uses GPS to track the driver, classifies sudden deceleration as an accident, and alerts neighboring medical institutions when it occurs. Fan et al. [16] proposed a novel approach for locating black spots or places where accidents happen frequently. The Support Vector Machine method is used to train the complex model, maximizing the classification interval for the best learning of accident black spots. The results of the investigation show that the proposed approach successfully identifies black spots with high accuracy.

Zhang et al. [17] built a black spot recognition model using a Bayesian network and then applied logistic regression, ID3 decision tree, and support vector machine for comparison. Montero-Salgado et al. [18] devised a method in which the database was examined using a Pareto chart with a quadratic trend. The Pareto chart helps sort the few critical aspects from the numerous un-important ones, identifying the most significant sources of issues, and aiding in the assignment of resources and setting priorities. Time series analysis is also performed on the dataset to find hidden patterns.

Bokaba et al. [19] examined the performance of five different classifiers, the k-nearest neighbor, decision tree, random forest, support vector machine, and artificial neural network. Results indicate that, in comparison to other classifiers, the random forest technique performed effectively. Labib et al. [20] proposed models to predict the severity of accidents at specific locations and found that their predictions were relatively accurate. According to the study's findings, machine learning approaches can help determine how serious an accident will be, and decision tree-based models are particularly effective.

Santos et al. [21] utilized both supervised techniques like decision trees, and naive Bayes and unsupervised machine learning techniques such as hierarchical clustering and DBSCAN using which based on past data, a model for predicting future traffic accidents is derived. The findings suggest that a rule-based model using the C5.0 algorithm is capable of correctly anticipating the crucial signs of how serious a traffic incident is. Adanu et al. [22] adopted a binary logistic regression model to estimate the probability that accidents will result in serious injuries or fatalities. Large truck collisions are more likely than collisions involving passenger vehicles to cause serious injury or death.

Shen et al. [23] assessed bicycle-involved collision data in the UK by applying the partial proportional odds (PPO) and generalized ordered logit (GOL) models. A wide range of factors that might have an impact on injury severity were taken into account, including rider characteristics, junction features, environmental factors, and the movement and position of cyclists before the event. Wang et al. [24] created a Long Short Term Memory network (LSTM) with a gating mechanism in which two layers of LSTM make up bi-directional LSTM. The two layers of inputs are identical, but the direction of data transmission is different.

Zhang et al. [25] used the Gini diversity index, and the relative contribution of attributes to crash frequency was assessed. An ensemble of learners is created by applying the weighting factor to each learner and the dataset separately. The results demonstrate that in the crash frequency analysis, the two averaging Ensemble Machine Learning (EML) models outperformed the two boosting EML models in terms of prediction accuracy, generalization potential, and stability. Tao et al. [26] developed a Bayesian neural network model with three hidden neuron layers, sixteen hidden nodes in the first layer, eight hidden nodes in each of the second and third layers, and three hidden neuron layers. This model's performance was contrasted with that of a few other machine learning methods, such as random forest modeling, and conventional neural networks out of which the Bayesian network works efficiently.

Cho et al. [27] developed a framework for multi-task learning that can predict different levels of accident severity. The findings demonstrate that, for all severity classes, the multi-task learning model beats single-task models in terms of accuracy. Yang et al. [28] provided a multi-task Deep Neural Network for determining the level of severity of the injury, death, and property loss. The deep learning design enables a thorough and precise analysis of the significance of traffic accidents. The proposed model works better than state-of-the-art techniques and anticipates the likelihood of serious traffic accidents with better accuracy.

Classifiers such as support vector classifier, naïve Bayes, K nearest neighbors, decision trees, and random forest can be used to predict whether a situation leads to an accident or not. The proposed system is embedded into a mobile application and it takes the user's data that is the condition or the state the user is in at the beginning of the ride and then the application shows the route from the given source to the destination and highlights all the predicted black-spots. The mobile application takes the Global Positioning System (GPS) of the user and when the user approaches the blackspot an alert message is sent to the user to take extra care in that route. The alert is given to the user in the form of an SMS message.

The remaining part of the paper is structured as follows. The study area was described in Section 1.2. The proposed methodology describing the data pre-processing, application of Gaussian mixture modeling, classification of accidents, predictive model markup language (PMML), and mobile application were described in Section 2. Results and discussions of the model performance were described in Section 3. The conclusion of the model is described in Section 4.

1.2. Study Area

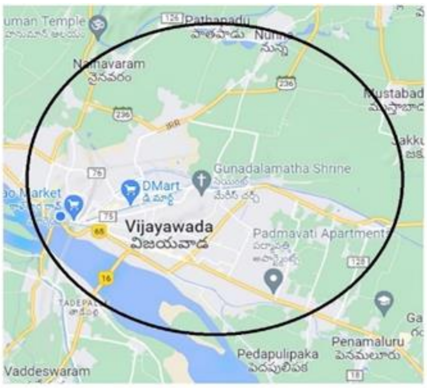

Fig. 1. Vijayawada Region

The circular area shown in Fig. 1 is the region of study which consists of 8 zones namely, Penamaluru, Bhavanipuram, Ibrahimpatnam, Gandhinagar, Krishnalanka, Patamata, Vidyadarapuram, Mylavaram in Vijayawada, Andhra Pradesh, India. The accident data is obtained from the RTA Vijayawada.

Fig. 2. Month-wise accidents in Vijayawada in the years 2019-2021

Fig. 2 shows the detailed month-wise statistics about how the accident rate has increased in the years 2019-2022. Every year there is a rise of 2-5% in the total number of accidents in Vijayawada. The rise in the number of fatal accidents is also on par with the increase in the number of accidents.

2. Method

Preprocessing the raw data is the first phase of the procedure. This entails several stages, including cleansing the data, reducing noise, encoding it, choosing important features, oversampling data, and other related processes. A Gaussian Mixture Model is created using the preprocessed data, consisting of three Gaussians, each of which represents a different class of accident. A new dataset that serves as an ideal representation of the original data is created using the vector of means and vector of variances. The new data is used to train a variety of machine learning classification algorithms, which then classify the incidents according to severity. Following training, the accuracy of all the machine learning classification models is evaluated. The model's accuracy may be improved by changing its hyperparameters and retraining it. The most appropriate model for each zone is chosen, exported into PMML format, and then embedded into a mobile application. Fig. 3 depicts the proposed methodology, which consists of multiple stages.

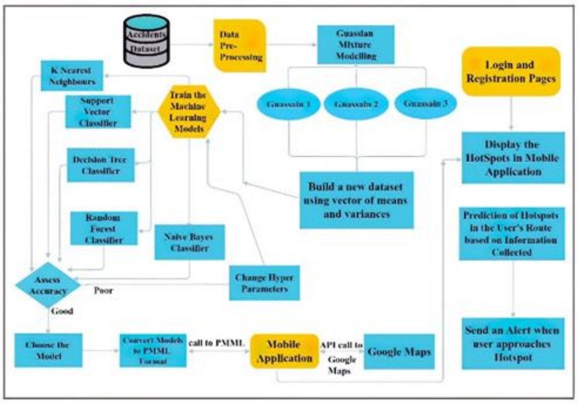

Fig. 3. Proposed Methodology

The various modules involved are explained as follows:

1)Data-Preprocessing

2)Application of Gaussian Mixture Modelling

3)Training Machine Learning Models for the classification of accidents using the Vector of Means

4)Exporting trained model from Python (PMML format).

5)Embedding the Model in the Android Application.

2.1. Data Preprocessing

2.1.1. Data Cleaning and Data Encoding

The data is cleaned and preprocessed, then statistical modeling and machine learning techniques are used to learn more about the data and make predictions about future accidents. A lot of inconsistency, missing values, and noise are present in the raw accident dataset. In this stage, data cleaning is done to transform the data into a useful format. The attributes in the transformed data which are not in numeric format are encoded into numeric data.

2.1.2. Important Feature Selection

The raw data contains many attributes as it was extracted from the First Information Record (FIR). By selecting the most relevant and informative features from a dataset, its dimensionality reduces and hence improves the performance of a machine learning model. In this study, the important attribute selection is done by assessing the information gain of every attribute. The basic idea behind information gain is to quantify the amount of information gained about the target variable when a particular feature is used to split the data. Entropy is a measure of the randomness or uncertainty in a dataset.

By splitting the data based on a feature, we can reduce the entropy of the resulting subsets, which means we have gained information about the target variable. The formula for information gain

$$F(a) = -\sum_{q=1}^{l} f(z_q)\log f(z_q)$$
$$+f(a)\sum_{q=1}^{l} f(z_q \mid a)\log f(z_q \mid a) + f(\bar{a})\sum_{q=1}^{l} f(z_q \mid \bar{a})\log f(z_q \mid \bar{a})$$

Where z_q represents q^{th} category, $f(z_q)$ is the probability of the q^{th} category. f(a) and f(ā) are the probabilities that the term a appears or not. $f(z_q/a)$ represents the conditional probability of the q^{th} category given that the term z appears. $f(z_q/\bar{a})$ represents the conditional probability of the q^{th} category given that the term z does not appear.

After performing important feature selection the results are shown in Fig. 4

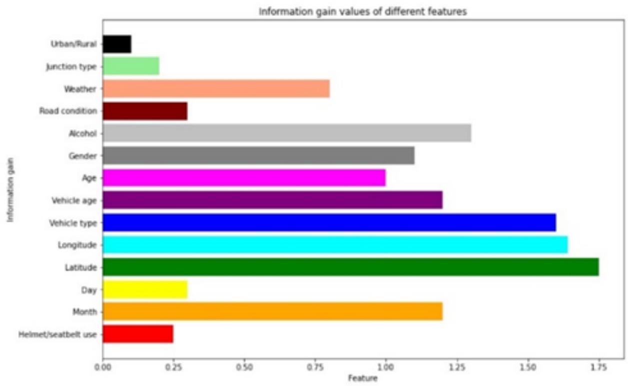

Fig. 4. Importance of attributes measured using information gain

Attributes such as wearing a helmet/seatbelt, day of the accident, road condition, junction, and whether the accident spot is urban or rural have less information gain compared to others. The attributes that have high information gain are latitude, longitude, and vehicle type. However, the month of the accident, latitude, longitude, vehicle age, age of rider, gender of rider, alcohol consumption status, and weather are taken into consideration in training models.

2.1.3. Oversampling of Data

An imbalance of data in the severity of the accidents is observed. An imbalance in a dataset occurs when one class has significantly fewer observations than another class. This can be a problem for machine learning models because they tend to learn to predict the majority class more accurately while ignoring the minority class. This can result in biased predictions and reduced performance of the minority class. To solve this problem, the Synthetic Minority Oversampling Method (SMOTE) is used, SMOTE generates synthetic data points for the minority class by interpolating between existing minority class instances. By choosing one or more minority class examples and building new instances along the line segments connecting them, the new synthetic instances are produced.

A new sample is generated using SMOTE according to the below equation.

$$q_{new} = q_p + \lambda(q_{kp} - q_p)$$

Here q_{new} is the new sample generated. q_p is the minority class instance, q_{kp} is one of the nearest neighbors to the minority class, and lambda which ranges from 0 to 1 is a random number that determines the amount of interpolation between q_p and q_{kp}.

Table 1. Total data points corresponding to each class before and after SMOTE

Class	Before SMOTE	After SMOTE
Fatal	2044	9433
Serious Injury	6753	9405
General Injury	9457	9457

2.2. Application of Gaussian Mixture Modeling

A probabilistic model called Gaussian Mixture Modeling (GMM) is utilized in machine learning for density estimation and grouping. GMM works well for soft clustering, which divides data points across clusters with different membership levels rather than grouping them all together in one cluster.

The parameters of the model (the means and covariances of the Gaussians) are estimated from the data using the Expectation-Maximization (EM) process. Each Gaussian distribution represents a cluster in the data. A Gaussian distribution's probability density function is given by:

$$p(a \mid \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{M}{2}} |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(a-\mu)^T \Sigma^{-1} (a-\mu)}$$

Here a is the data point, N is the total data points, μ is the mean, Σ is the standard deviation

The probability density function of the GMM is then given by:

$$p(b \mid \{\mu_w\}, \{\Sigma_w\}, \{\phi_w\}) = \sum_{w=1}^{m} \phi_w \cdot p(b \mid \mu_w, \Sigma_w)$$

Here b_w is the wth datapoint in a dataset with M datapoints. μ_w is the mean vector of the wth Gaussian component, where w in [1, m]. m is the number of Gaussian components in the mixture model. Σ_w is the covariance matrix of the w^{th} Gaussian component. ϕ_w is the mixing coefficient of the w^{th} Gaussian component, which represents the probability of choosing the j^{th} component. M is the dimensionality of the data. The goal of the EM algorithm is to estimate the parameters μ_w, Σ_w, and ϕ_w, that maximize the log-likelihood of the data. The algorithm consists of two steps: the E-step and the M-step. In the E-step, we compute the posterior probability of each data point b_w belonging to each of the m Gaussian components. This is given by:

$$v_{ef} = \frac{\phi_f \cdot p(x_e \mid \mu_f, \Sigma_f)}{\sum_{l=1}^{k} \phi_l \cdot p(x_e \mid \mu_l, \Sigma_l)}$$

where v_{ef} is the posterior probability of data point x_e belonging to the f^{th} Gaussian component.

In the M-step, we update the parameters μ_f, Σ_f, ϕ_f using the posterior probabilities v_{ef}. The updates are given by:

$$\phi_f = \frac{1}{K} \sum_{e=1}^{K} v_{ef}$$

$$\mu_f = \frac{\sum_{e=1}^{K} v_{ef} x_e}{\sum_{e=1}^{K} v_{ef}}$$

$$\Sigma_f = \frac{\sum_{e=1}^{K} v_{ef} (x_e - \mu_f)(x_e - \mu_f)^T}{\sum_{e=1}^{K} v_{ef}}$$

We can initialize the parameters randomly or using other methods such as k-means clustering. We then alternate between the E-step and M-step until convergence. Once the parameters are estimated, we can use the GMM to cluster new data points by assigning them to the Gaussian component with the highest posterior probability. After performing GMM the accuracy of GMM is assessed and only if the accuracy is not less than seventy percent the model is considered, else hyperparameter tuning is done by adjusting the covariance type, initialization method, regularization parameter, convergence threshold, and maximum number of iterations.

2.3. Classification of Accidents

The GMM consists of three Gaussians each acting as an indication of the severity of the accident. Making use of the vector of means and variances associated with each Gaussian a new training dataset is developed to train classification models on it. The new dataset is an ideal representation of the original data, this is now split for testing and training purposes. The machine learning classification models used here are support vector classifiers, KNN classifier, Decision Tree classifier, Random Forest Classifier, and Naïve Bayes Classifier. The accuracy of the classifiers is assessed using the test data. If the accuracy is not up to the mark then to increase the accuracy of each model, hypertuning of parameters is done and training is again done using the new model. Finally, the classifier with the highest efficiency is chosen for the prediction of accidents.

2.4. Predictive Model Markup Language

PMML (Predictive Model Markup Language) is a widely used standard for representing predictive models as XML-based files. It is used to represent machine learning models in a portable format that can be easily deployed across different platforms and programming languages. Using Python packages, the trained models are converted to PMML format and are exported to embed in an Android application. Making use of PMML- Android library the models are loaded into the application. The user gets registered with all the details required during his initial sign-up and these details are stored in an SQLite database. Data like day, time, weather conditions, latitude, and longitude are fetched using APIs in real time. When the user is on a ride all his data gets encoded and is fed as input to PMML. The model determines which coordinates (latitude and longitude) are user-vulnerable blackspots, which indicates an accident might result in death or serious harm. When the user is traveling the application gives him notifications while entering, dwelling, and exiting a black spot.

2.5. Mobile Application

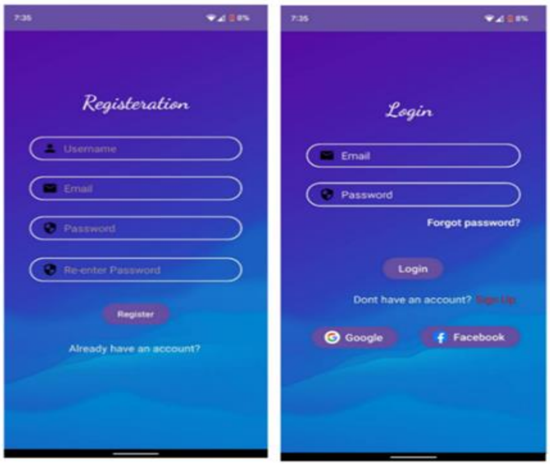

Fig. 5. Registration and Login Screens

The registration screen in Fig. 5 shows how the user can create a new account in the application. The details of the users are managed by the SQLite database. It is a lightweight and efficient database engine that can be easily embedded into mobile applications. After registration, the user is redirected to the login page. Upon login, if the user is logging first time into the application then some additional details are requested from the user which are shown as follows.

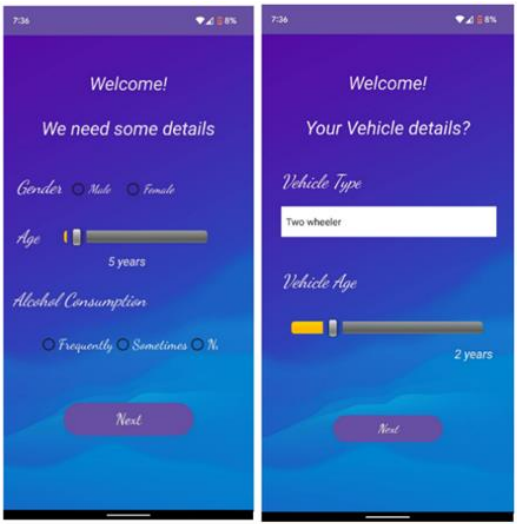

Fig. 6. Data Collection from User

These additional details shown in Fig. 6 are required from the user to know the driver's behavior and to predict which places are potential danger areas (blackspots) for that particular user.

3. Results and Discussion

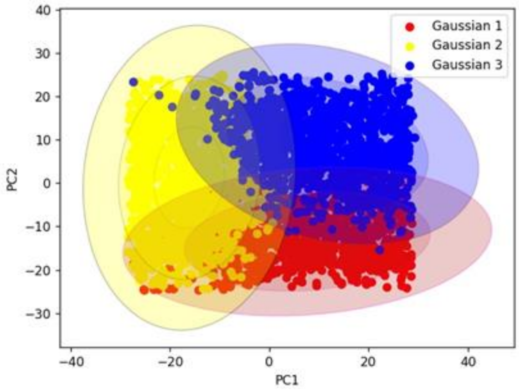

Fig. 7. Gaussian Mixture of Penamaluru Zone

Fig. 7 shows how the data is separated into 3 classes. This figure illustrates the Gaussians of the penamaluru zone (one of the 8 zones in Vijayawada). Here Gaussian 1 represents the fatal cases, Gaussian 2 represents General Injury (GI) cases and Gaussian 3 represents Serious Injury (SI) cases [29].

Table 2. Performance Analysis of all classifiers using Accuracy

Random Forest	Decision Tree	SVM	K-Nearest Neighbor	Naive Bayes
68.93	94.95	96.66	81.12	88.98

Table 2 shows how efficient the classifiers are in classifying the data. As the Support Vector Classifier is giving the highest accuracy it is chosen as the classifier for the prediction model.

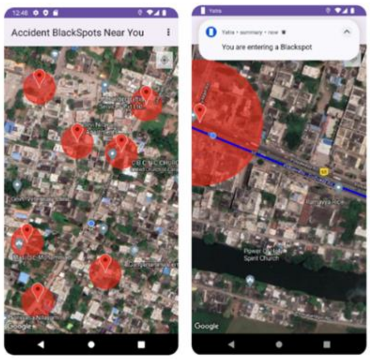

Fig. 8. Blackspots located near the user and how the alert is sent to the user

Fig. 8 shows all the blackspots near the user location and also an alert that he is entering a blackspot with text as "You are entering a Blackspot".

As the accident dataset of Vijayawada city is limited to the eight zones, the blackspots can only be shown in those specific regions but the routes can be shown in the other regions as well which makes it easy for the user to navigate from one place to any other place.

4. Conclusion

Gaussian Mixture Modeling is used to perform soft clustering on all the data points over five classifiers: K-Nearest Neighbours, Decision Tree Classifier, Random Forest Classifier, Support Vector Classifier, and Naïve Bayes Classifier. In the accident dataset, each region has good accuracies but the Support Vector Classifier is giving the highest accuracy which is why it is chosen for the prediction model. Determining where the blackspots are, it is easy to show the locations in the application. As a result, the mobile application can be used by the police department to accurately see the places where most accidents are occurring and it also provides real-time assistance to the users by not only providing the route from the source to the destination but also showing the places where there is a high chance of accident occurrence and sends an alert to the user so that the user can be more cautious on that route.

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Author contributions

Sobhana M: Contributed to conceptualization, methodology, software development, and conducting field research. **Krishna Rohith V**: Played a role in data curation, initial draft writing, software development, validation, and participation in the field study. **Avinash T**: Involved in data visualization, and investigation, and contributed to the reviewing and editing of the document. **Malathi N**: Contributed to data visualization, and investigation, and also participated in the reviewing and editing process. **Smitha Chowdary Ch**: Contributed to data visualization, and investigation, and also participated in the reviewing and editing process.

Conflicts of interest

The authors declare no conflicts of interest.

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