# Pothole Detection using Accelerometer and Computer Vision with Automated Complaint Redressal

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***Abstract*—Road transport is the most widely used means of transportation around the world. With this high use of road transport, the safety of travellers' becomes the prime concern for any governing authority. While some safety concerns arise from driver errors and environmental factors, most cases are a result of poor maintenance of these roads. Potholes, specifically, are one of the leading causes of road accidents throughout the world and need to be taken care of immediately, by the authorities. This paper presents a solution that makes use of civilians' mobile sensors, along with image-based alternatives to detect potholes in real-time, using Machine Learning. The concerned authorities are then notified about the same through a web-based portal, to take the necessary action. The solution also incorporates pivoting existing complaints, location tagging and prioritization. Additionally, the solution provides a forecast of the likelihood of issues regarding potholes, constantly updating time series data of the locations.**

***Index Terms*—Road Safety, Pothole Detection, Sensors, Computer Vision, Machine Learning, Complaint Redressal, Predictive Maintenance**

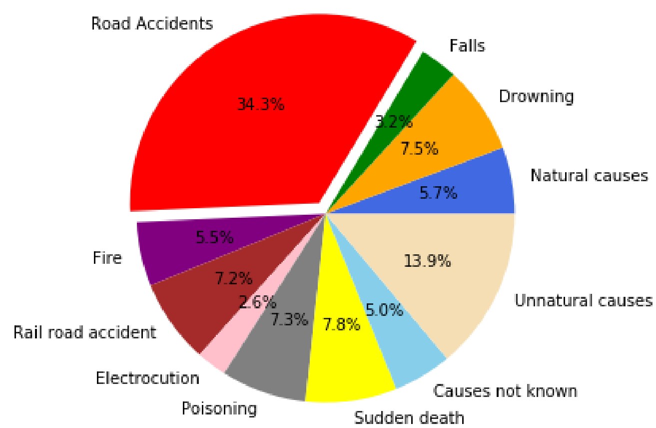



Fig. 1: Analysis of Death by Accidents

## I. Introduction

Road transport is the most common mode of transportation. Especially countries like India, which are highly populous, the number of vehicles are constantly increasing , causing several accidents on the streets. One of the main reasons being, uneven, road surface conditions. Moreover, people face difficulties on the roads be it walking or driving, especially during the monsoons when the roads are completely dilapidated. According to India's Ministry of Statistics and Program Implementation, majority of the accidental deaths in India take place because of mishaps on roads as shown in Figure 1. The research in [1] mentions that India has a total of two million kilometre roads, out of which, one million kilometre roads are poorly constructed. As per the data set obtained by the Ministry of Road Transport and Highways, approximately fifty thousand accidents take place because of the potholes every year. A large percentage ($\tilde{4}0\%$) of this often leads to death.

The main problem in addressing the road maintenance concerns is the lack of communication between the authorities and the civilians facing the issues, and poor tracking of locations where repairs are required. Involvement of civilians further enhances societal living and cooperation between the authorities and the citizens. Furthermore, a robust tracking system is also equally necessary to track the progress of repair and allowing citizens to be informed of such poor conditioned roads, thereby reducing the fatality caused by such situations.

Fortunately, using some of the latest technologies, we can avoid the loss of human lives due to road accidents. This paper aims to make the streets safe for everyone. We address this problem by bridging the gap of communication between the government and the civilians. We aim at crowd-sourcing the data so that every person is actively involved in the development and they have a platform to raise concerns.

We propose a solution that uses a real-time pothole detection system for automated detection of potholes using accelerometer and gyroscope sensors inbuilt in smartphones as well as through computer vision. The proposed system collects and analyses this data, which in turn can be used by the civic authorities responsible for maintaining the roads. The system keeps in check if the problems are being worked on to make it effective. The uniqueness of the proposed solution is that it predicts the localities susceptible to the problem using machine learning besides reporting the existing conditions of the road network.

## II. LITERATURE SURVEY

Artis Mednis et al. [2] and Fatjon Seraj et al. [3] used accelerometer sensors in smartphones to measure the acceleration values to detect potholes. They have described the use of different algorithms like Z-THRESH, X-DIFF, STDEV(Z), G-ZERO, SVM and compared those algorithms to accurately detect potholes on the road. By using different algorithms in optimal scenarios both were able to achieve accuracy up to 90%. Ghadge et al. [4] used K-means clustering algorithm for training and then was tested using Random forest algorithm. It was very feasible to implement because no external hardware components were required, and the accuracy was quite high for detecting potholes. The paper [5] proposed a method that uses Euler angle to normalize the data from the sensors and the combined Z-THRESH and G-ZERO methods to achieve better precision scores. The Real-time system accurately detected the pothole without false positives hence increasing the precision of the algorithm and then using GPS of the phone to mark the location of the detected anomaly. Thitaree et al. [6] proposed an algorithm that used unsupervised learning techniques with Neural Networks to develop a Real-Time system for the drivers. The training data showed that the system could identify the pothole within 7 seconds but during real-life training, they achieved an accuracy of 81% within 13 seconds which is independent of the speed and road traffic. The authors [7] used a different machine learning approach to identify potholes using data from accelerometer and gyroscope sensors built-in smartphones. They tested the results on different classification algorithms like Naive Bayes, C4.5, SVM and were able to achieve the best accuracy of 98.6% using the C4.5 decision tree.

The work proposed by S. Nienaber et al. [8] did not rely on machine learning to detect potholes. Instead, they used the Canny edge detection algorithm accompanied by dilation of the resultant edges to abort unwanted edges, and provided a precision of 81.8% and recall of 74.4% and used a dash-mounted GoPro camera for road surveillance. This approach, however, has to restrict the portion of the image to be observed as it depends on camera placement and distance from the car. Pothole detection approaches include various methods such as Vibration-based, 2D-Vision- Based, 3D Scene Reconstruction and Learning methods. Amita Dhiman and Reinhard Klette [9] presented the use of stereo-vision cameras that considerably enhanced the accuracy of the results. The four methods proposed in the paper included two based on stereo vision, while the other two being implemented with the help of Transfer Learning. Emir Buza et al [10] proposed a method that used normalized spectral clustering to extract non-linear shapes and regions on the road. Using segmented road data utilised the unsupervised learning approach for shape extraction. With a well-distributed set of seeds obtained from the clusters, the algorithm located the farthest points, vertically and horizontally, in the shape with the same pixel value as the seed point, which provided a nearly accurate shape of the pothole on the road. Rui Fan et al. [11] proposed their work which involved reproducing road surfaces as disparity maps, by extracting undamaged road surfaces as references and evaluating their difference with coarser potholes. It also used stereo vision for 3- dimensional perception. Conventional detection algorithms such as R-CNN and its variants make use of two-stage detectors as a part of detection. Recent works on YOLO and SSD show promising results that one-stage detectors might also yield an accuracy within the range of the two-stage detectors. However, these algorithms face the consequences of class imbalance. The work by Tsung-Yi Lin et.al. [12] introduced the Focal Loss function, implemented in their proposed RetinaNet detector for the dense sampling of input data. Our proposed methodology for Pothole detection makes use of this approach, owing to the promising accuracy over state-of-the-art algorithms.

Ayush Vora et. al [13] used a smartphone to report the road quality to maintenance authorities by facilitating the citizens' involvement for real-time data collection. Afify et al. [14] proposed the implementation of an electronic Customer Complaint Management System (e-CCMS) which dealt with all the complexities of a generic grievance system. The model helped them manage the various issues and solved the time-critical problems on time. The authors of the paper [15] proposed the use of a system linking the users and the government. The app kept track of all the complaints and increased the transparency between the two by enabling the users to know more information about their complaints and how the government was going to take action on the same. A smartphone-based solution is proposed in [16] to solve the problem of complaint redressal. Citizens could send a photo of the issue with the GPS location of it. The authorities could reject the complaint but only with a valid reason. The dashboard maintained a record of active, reported and resolved cases to help the users understand the steps taken by authorities to resolve their issue.

After reviewing the existing work, we found out that there are various methods to detect potholes but there is a lack of effective communication between the citizens and the government officials. The aim of the proposed solution is to develop an integrated system that detects, reports and addresses the grievances effectively. In the existing solutions, it was observed that even if the complaints were registered, some of them might be overlooked by the officials and they do not have a clear insight about the criticality of it. The proposed system resolves it by setting priority to the complaints and filtering them for the officials. Also, reports are generated for all the complaints which are displayed on the website and can be sent to higher authorities. The dashboard on the website provides the forecast of the roads which might need repair and hence dealing with pothole problems before they occur.

## III. METHODOLOGY

### A. Architecture Model Description

The core of this research involves detecting potholes through various methods on roads and its redressal. The aim is to implement a real-time pothole detection system that facilitates this. Therefore, a mobile application is used for interaction between the users and civic authorities about the queries put forward by the users and a web portal is developed for redressal of the queries. Smartphones sensors like accelerometer and GPS are used for the collection of the data. The system proposed uses two methods for detecting potholes; by using accelerometer sensors, and by using images uploaded by the users. Detection algorithms are applied to this data and coordinates of the potholes are obtained using Google Maps API. The complaints are displayed on the feed in the application for the users. Users can upvote any complaint to increase its priority. Several features are added in the system which allows the users to check the status of the complaints raised by them.

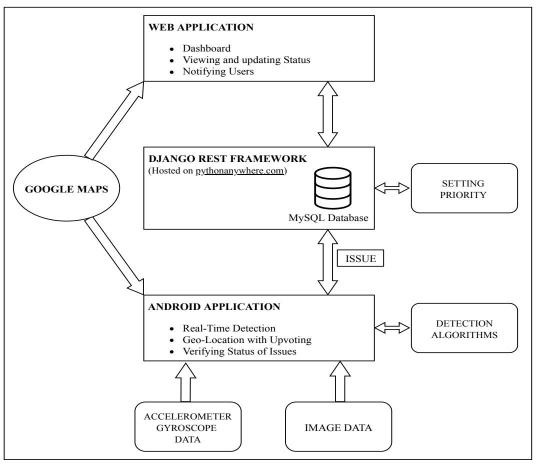



Fig. 2: Architecture

As illustrated in Figure 2, the complaints are sent to the Django server and stored in the MySQL database. An algorithm is developed to set a priority to each complaint which is displayed on the portal using Google Maps API, for the civic authorities to verify and facilitate the redressal of them. A status is added for each complaint which can be edited only by the civic authorities based on the actions taken for each complaint, which is displayed on mobile. Once the pothole is resolved, the complaint is removed from the database, which is thus reflected in the application.

*B. Mobile Application*

The solution deals with the detection of potholes using various methods which are done using Android OS based smartphones. The popularity of smartphones makes the system very user-friendly. It enables strong participation, and interaction of users to solve the problem. Several features have been added to make the system reliable. Some of the features are explained below.

*1) Using the Accelerometer sensor in mobiles:*

**Dataset:** The smartphone was mounted on the dashboard of the vehicle which recorded the time and accelerometer and gyroscope readings for training. The data was collected from the moment the driver started the application until the stop button was pressed. Once the driver stops the data acquisition, the data set is stored and used for training. For consistent results sampling rate of the accelerometer sensor in the system is set to 50Hz. To maintain uniformity in all cases, the cars were made to drive over the potholes for data collection at different speeds ranging from 20-40 km/hr simulating real-life road scenarios in urban cities. Four driving journeys of about 1 hour each were used for data collection. Twenty-five thousand samples of data having 7 features were obtained in the experimental study.

**Preprocessing:** To remove the irrelevant data, we filter out some of the factors. Different positions of smartphones cause changes in the magnitude of gravity. So, a low-pass filter is applied to isolate the force of gravity and filter out high-frequency signals by using a filter constant. Hence, the filtered accelerometer and gyroscope sensors give the resultant sample data.

**Labelling:** The features of the data are timestamp, 3-axes coordinates of accelerometer and gyroscope sensors. By taking into consideration the z-axis of the accelerometer, the threshold value was found which was used to identify potholes on the journeys recorded.

To detect potholes in real-time, consecutive samples are examined to find road anomalies by comparing with the threshold and the resultant down-sampled points are stored separately. When a pothole is detected, the z-axis of the accelerometer sensor has a pattern by which there is a sudden increase followed by a decrease in its value. Therefore, a vertical and a horizontal limit were set to create a window and were obtained by using the consecutive down sampling points. Since the z-axis of the accelerometer sensor was used for detection, the horizontal limit was used to find the "h-up" and "h-dn" values which created a window as shown in Figure 3. Here, the blue lines denote the sample data that was collected for training and the red marker denotes the downsampled data that was obtained after comparing with the threshold value. The X-axis denotes the time series data converted to integer for convenience and the Y-axis denotes the acceleration values in the z-direction for each sample. A window is also created whose upper limit is "h-up" and the lower limit is "h-dn".

Once these values are detected, the downsampled data is compared with the window and a label is assigned for each sample which gives the detail of the sample whether it is a pothole or not. The label '1' is assigned if it is a pothole, otherwise '0', For a continuous value of '1' in the sample data, it denotes one pothole. In Figure 4, the green marker denotes the label '1' that is, potholes are detected at those points and the other markers meaning the same as earlier.

**Training Classifier Model:** The dataset was divided into train and test data such that 30% of the data was used in test data in classification models to calculate accuracy. It is trained on the training data to detect potholes. Because

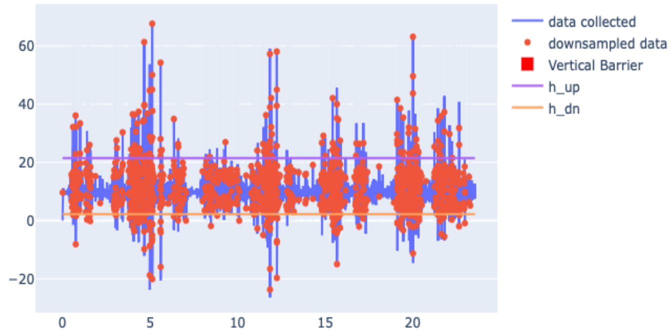



Fig. 3: Downsampled data

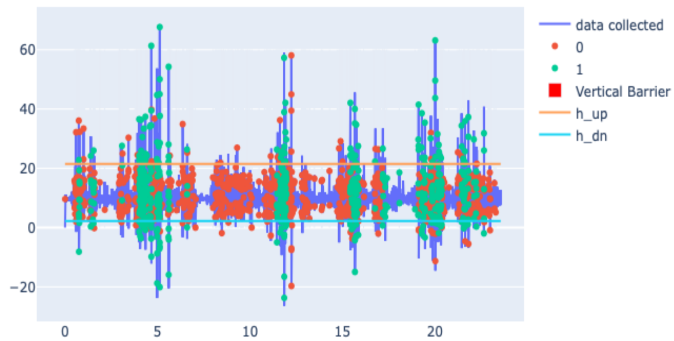



Fig. 4: Distinguishing between potholes and not potholes on downsampled data

the training data is a labelled data set, supervised machine learning algorithms are used to infer a model from the labelled sample data. Unlike the training data, the test data does not contain the label feature. Five classification algorithms were worked upon, on the testing data; Random Forest, Logistic Regression, Decision Tree, Naive Bayes and K-Nearest Neighbors and compared their accuracies. The model that gave the highest accuracy was used to detect potholes on roads.

**Prediction:** The system records the real-time data from the sensors and preprocesses it to remove the unnecessary high-frequency data for prediction. Afterwards, the prediction of potholes on this data is done based on the trained classifier model. Alerts of the locations of the predicted potholes are sent to the users on their smartphones. Finally, these locations are sent to the server which maintains the database of all recorded pothole locations.

*2) Image-based pothole identification:*
Using the accelerometer sensors to detect potholes provides automatic complaint redressal by the passengers of the vehicle. However, it requires driving into the pothole, which causes great inconvenience to the passengers. Hence, an image-based pothole detector is also considered, which can be utilized in two ways – as a dash-mounted phone camera setup or through pedestrian participation. Citizens can participate by drawing the authorities' attention to such problems. Generally, it is over social media platforms, which often gets overlooked in the heap of new information. This is where a dedicated complaint platform can come in handy.

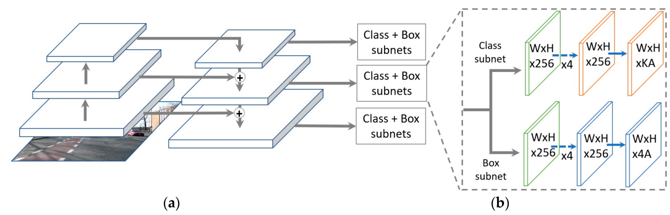



Fig. 5: **(a)** shows the feature extraction pyramid. Part **(b)** shows the two subnetworks - one for classification of the classes and the other for regression of the boundary boxes.

**RetinaNet:** In this manuscript, pothole detection is performed using RetinaNet, a one-stage detector. It is subject to class imbalance since the dataset only contains labelled data for the potholes and not the smooth roads. However, RetinaNet takes care of it by using Focal Loss allows biased learning towards the training samples [12]. The implemented RetinaNet architecture uses a ResNet backbone for feature extraction. A Feature Pyramid Network is used on top of ResNet to construct a rich multi-scale feature pyramid from one single resolution input image. This is accompanied by two subnetworks, one for the classification of classes and the other for bounding box regression. The classification subnet predicts the probability of object presence at each spatial position for each of the anchors and object classes. The subnet is a fully convolutional network (FCN) that applies four 3×3 convolution layers, each with 256 filters and followed by ReLU activation after each layer, followed by another 3×3 convolution layer. The box regression subnet is a similar FCN that regresses the offset from each anchor box to the nearest ground-truth object if it exists. Figure 5 shows the RetinaNet architecture.

**Dataset:** The dataset used for this work is obtained from Google Images of bad roads. It consists of 254 images and a total of 1757 samples of potholes. The potholes are manually annotated in the XML format, containing the vertices, $X_{min}$, $Y_{min}$, $X_{max}$ and $Y_{max}$ of the bounding boxes. The dataset is trained for 150 epochs with a batch size of 4 and 400 steps per epoch.

**Detection:** For detection, the input image is provided in the BGR format. It is normalized by subtracting the ImageNet mean of all three channels. It was found that a threshold of 0.4 detects the maximum true positive boundary boxes for the potholes, throughout multiple tests.

*3) Geotagging locations of the complaints:*
The complaints of the users are tagged with the GPS location.

For getting the GPS location, the fused location provider API is used. The API uses technologies like mobile GPS, Wi-Fi and cellular connection to accurately determine the exact position of the user. Hence, to achieve the best results in determining the location, the API is set to the highest accuracy. When the system detects a pothole or a user clicks a photo of it, the GPS coordinates of the last known location of the device are recorded. These values are sent to the server with the complaint, hence marking its location on the map.

*4) Complaint Feed and Upvoting similar complaints:*
The feed is added to the system to allow the users to view complaints raised by other users within their proximity. The default minimum range is 100 meter which can be increased using the slider by the users. This helps to display all the posts within that range for the user. The complaints recorded by the system are geofenced with a radius of fifty meters around each pothole location using Google Services API. Whenever a user passes over this region, a notification is sent to them which warns them about the nearby potholes beforehand.

In case a user finds any complaint critical, he can upvote that complaint to give it a higher priority, so that immediate action is taken on it. Similarly, upvoting is also used to consolidate repetitive complaints from the same location. The priority of complaints increases as the votes increase. Hence, a complaint with a higher number of votes is given the maximum priority which is considered as one of the important parameters for setting the priority of the complaints.

### *C. Web Portal*

The solution also deals with the redressal of pothole complaints by the users. This feature is solely handled by civic authorities using a web portal which helps them get information on the complaints and forecasts the expected number of complaints arising in the future. The portal is only accessible by the authorities who can perform several tasks for the resolution of the complaints. For making it a competent system, several novel functionalities have been added to the system which is explained below.

*1) Dashboard:*
The civic authorities have access to the web portal with a dashboard that serves the authorities to view and analyze all the complaints posted by the mobile users.

The dashboard helps in maintaining a count of active complaints, being worked on or those which are resolved. By using this data, we analyze and generate various insights which can be used by the Government authorities to plan better strategies for the resolution of the pothole problem. The data shows various wards which are facing the issue as shown in Figure 6. Information of the authority which was responsible for maintaining the roads in a particular ward can be found out. The statistics also show the time taken by the authorities to resolve the complaints and those areas where the problem kept on reappearing even after getting resolved by the authorities.

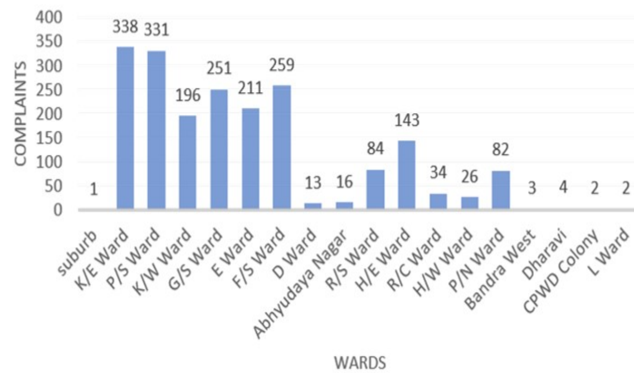



Fig. 6: Complaints per Ward

**Dataset:** During the testing of the application, the data reported potholes in Mumbai was collected. The data consists of the timestamp, latitudes and longitudes of various locations reported by the users, the number of people facing the problem and the date when the issue got resolved. The data is from the time period of 1st October 2019 to 28th February 2020 consisting of 1995 complaints in total.

**SARIMA Model:** As one of the important functionalities of the system is forecasting the number of potholes for the future on the dashboard, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model was used on our time series dataset which consisted of five months of data. To make the data stationary for efficient prediction, an Augmented Dickey-Fuller test was performed. While using univariate time data, some aspects like autoregression, differencing and moving average were considered. To smoothen the data, in the moving average model, three different window sizes 5 days, 30 days and 90 days were used to check for a trend in the curve. By increasing the window size, finding a trend was easier. While dealing with this model, seven important parameters need to be considered: trend autoregression order(p), trend difference order(d), the trend moving average order(q), seasonal autoregressive order(P), seasonal difference order(D), seasonal moving average order(Q) and the number of time steps for a single seasonal period(s). The equation for the SARIMA model is as follows:

$$SARIMA(p, d, q)(P, D, Q)s \tag{1}$$

The parameter values were set as follows: p = range(0, 5), d = 1, q = range(0, 5), P = range(0, 5), D = 1, Q = range(0, 5), s = 5. By fitting the model on the data, the duration of predictive maintenance of the predicted potholes prone roads is suggested to the authorities.

*2) Prioritization:*
Existing systems lack the insight the officials have over the complaints which are of utmost importance. It so happens

that the most important complaints are spammed by those which can be dealt with later. A unique way to deal with such a problem is by setting the priority to all the complaints reported by the users and sort them accordingly. Four key parameters significant to road conditions are identified and for setting the priority the sum of these parameters is considered.

**Upvotes By Users:** All the users can upvote any complaint they are facing. By these upvotes, the number of users facing a particular problem is derived and hence this is the most important parameter in the calculation of the priority.

It was found out that people tend to upvote complaints rather than uploading new ones. Priority will rapidly increase with each upvote and this can be a bias to this parameter. Therefore, a range for the number of upvotes is decided as mentioned in I to keep the value within a calculable range.

TABLE I: PRIORITY ACCORDING TO VOTES

| Number of Votes | Priority |
|---|---|
| <20 | 0.5 |
| 20-50 | 1 |
| >50 | 2 |

**Location of The Complaint:** A complaint's priority should be dependent on the type of people facing the issue. A pothole near a hospital, a school, an administrative building or highways are of more importance than any other place. The Locations API provided by the Google Cloud Platform provides all the nearby places of a location whose coordinates are provided to it. By setting The RADIUS to 50 metres and with the help of TYPE_SEARCH, if the nearby locations include the above-mentioned buildings, the priority is increased by a value of 1.

**Traffic In The Area:** Uneven roads filled with potholes is sure to restrict the movement of automobiles and cause hour-long traffic jams. The use of Roads API in conjunction with Directions API gives the traffic layer data. The authorities get to know the reason for these traffic jams which can be improved by fixing the road. The API provides us with the JSON value of traffic in the area. Heavy traffic areas increase the priority of that road by a value of 1.

**Repetitive Complaints:** It is meaningless if potholes are reported again even after the road has been reconstructed by the authorities. More attention is given to such complaints by the officials to get rid of the potholes altogether. The priority value of such complaints is increased by 1.

*3) Viewing all complaints:*
The proposed solution maintains and displays the records of all the complaints in a feasible manner. The complaints are fetched from the server and viewed by the civic authorities on the portal. They have the option of viewing a specific complaint, its address and location on the map.

Google Maps API has been used to view the location of the complaints and those can be consolidated together, ward wise to get a better view. A map view is also displayed on the portal which shows the number of complaints in different areas. The complaints are ordered according to their priority.

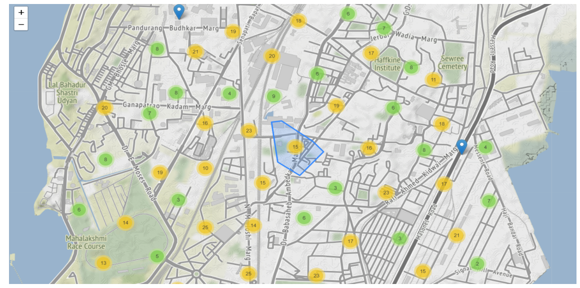


Fig. 7: Area Wise Complaints Clustered on Map

As shown in Figure 7, the complaints are clustered area wise such that all the complaints in a particular region are grouped with the count of those complaints printed above the marker. The blue region in the figure is one such identified location with 15 unresolved complaints in it. This gives a broader view to the officials which helps them resolve complaints according to a region.

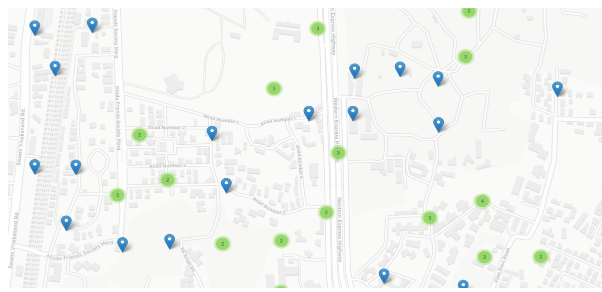


Fig. 8: Complaints Marked on Map

The government officials can view individual complaints marked on the map. The numbers on the marker in Figure 8 denotes the priority of the complaint. It can be clicked to get details like the coordinates, address, timestamp and the description of the complaints.

*4) Status Update on maintenance:*
There is a need for a system that facilitates the redressal of pothole complaints by the civic authorities. Hence, status is assigned to each complaint based on the activity performed on them. After the complaints are arranged in the order of priority, they are viewed by the authorities on the portal with a 'pending acknowledgement' status set as default.

Once the authority has reviewed the complaint, its status is changed to 'acknowledged'. This can be viewed on the user's feed. A resolution task is assigned for the complaint, which is viewed as 'work-in-progress' and finally, when the resolution is completed, the status of that complaint becomes 'resolved'. This lets the users know that the complaint has been resolved and after 7 days of the resolution, that complaint is deleted from the users' feed.

*5) Contacting higher authorities:*

The complaints can go unnoticed by the civic authorities due to which the complaint is not resolved which does not fulfil the purpose of the system.

Maintaining one portal for the different needs of the people is a challenging task for higher authority. Therefore, if any complaint registered by users is not acknowledged or is not worked upon by the concerned authority for a long period, then the system automatically makes a detailed report about the complaint to send to the higher officials of the state to maintain the functionality of the system. The report can also be published on Twitter or other social media platforms to increase awareness.

## IV. RESULTS

### *A. Pothole Detection Using Sensors*

Sample accelerometer and gyroscope sensor readings are divided into train and test data. Cross-validation is performed on the test data that has been scrutinized from the sample dataset. Several evaluation measures have been taken into consideration for choosing the most appropriate model.

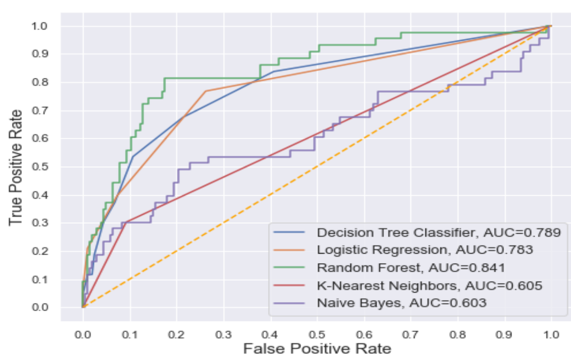



Fig. 9: ROC Curve

To evaluate the performance of the five models, accuracy was calculated. From table II, it was observed that the accuracy of the classifiers was very close, so it was more important to optimize precision and recall than to focus on a single factor.

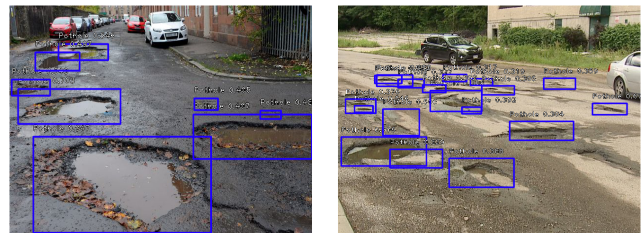
TABLE II: CLASSIFICATION REPORT

| Algorithm | Accuracy | Precision | Recall | f1-score |
|---|---|---|---|---|
| Random Forest | 89.63 | 0.71 | 0.45 | 0.55 |
| Decision Tree | 83.95 | 0.62 | 0.42 | 0.50 |
| Naive Bayes | 84.52 | 0.57 | 0.37 | 0.45 |
| Logistic Regression | 82.61 | 0.61 | 0.47 | 0.53 |
| KNN | 85.86 | 0.82 | 0.21 | 0.33 |

The ROC-AUC curve was plotted based on precision and recall to check how well a model fitted in the system. From Figure 9, it is observed that the AUC for Random Forest is **0.841**, which is the closest to 1 which means that this classifier was able to distinguish between the two classes quite well. Therefore, the performance of Random Forest works the best as compared to the other classifiers for the system and is best suited for our system to detect potholes.

### *B. Image-based Pothole Detection*

The manually-annotated dataset was trained with the RetinaNet model for 150 epochs. The model obtained was used to detect potholes of different texture and different angles, as shown in Figure 10, with some of the sample images that were tested.



(a) Potholes with patches of smooth road

(b) Dry-textured pothole without puddles

Fig. 10: Results of tested images

The progression of precision and recall over the epochs are given in Figure 11. After testing with around 25 images, the final model gives a precision of **0.83** and a recall of **0.72** which gives realistic performance for the model.

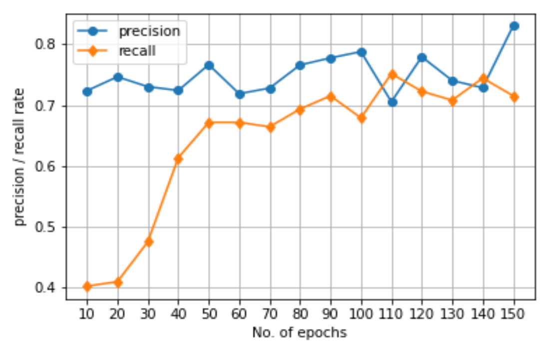



Fig. 11: Precision and Recall over training for 150 epochs

### *C. Predictive Analysis of Potholes*

Dickey-Fuller test was performed on the time series dataset to stabilize the data. It was found that the p-value was not less than 0.5, therefore, the data for forecasting was not stationary. The SARIMA model is a combination of several models which works well with non-stationary data, therefore, it fits well with our time series data.

After running the model for 625 epochs, the Mean Absolute Percentage Error (MAPE) was found to be 11%. By predicting the values of the last 25 days in the dataset, the predicted values were compared with the actual values for the month of February as shown in Figure 12 and the trend looks pretty close. The model gave an accuracy of 85.7% against the training data.


Fig. 12: Actual vs Predicted Number of Potholes

Figure 13 gives the prediction of the total number of potholes in the month March.

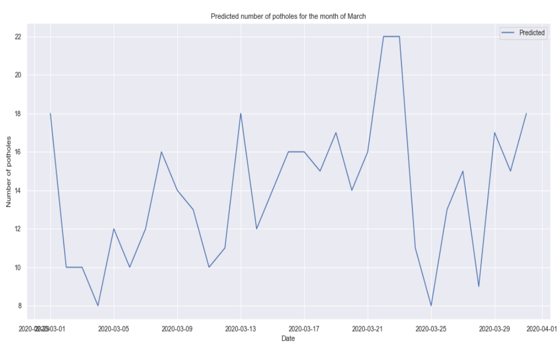



Fig. 13: Predicted Number of Potholes in March

## V. Conclusion

This paper identifies and addresses two important issues- the detection of potholes, and redressal of these complaints by the civic authorities. Using data from accelerometer and gyroscope sensors classification was performed and compared with five different algorithms: Naive Bayes, Decision Tree, Random Forest, Logistic Regression and K-Nearest Neighbor Classifier. Upon testing, it was revealed that the Random Forest algorithm performed the best out of the five, with an accuracy of **89.63%**. For image-based pothole detection, the RetinaNet model was able to record a precision rate of **83%**.

Secondly, to ensure timely redressal of the road safety grievances, a web portal is designed for the authorities to improve communication with the citizens. The dashboard maintains a list of all the complaints and prioritizes them based on the criticality. It also allows the authorities to update the status of complaints to help the users get information on the resolution of complaints. Prediction of the number of potholes is another important feature that helps the authorities, as well as the users, be aware of the areas populated by how many potholes. This is performed using the SARIMA model which gave an accuracy of **85.7%**.

Therefore, the combination of the two solutions provides an efficient and an effective system which takes care of all the detected potholes with the involvement of higher authorities. It provides a better knowledge of routes to be used by users to avoid road accidents and damages. Further, it helps the civic authorities keep a track of the number of potholes and improve the road conditions by the contribution of users.

In the future, the system can be scaled to report grievances like garbage, debris, graffiti, and so on. Furthermore, classification of roads into good and bad roads can also help in finding optimal routes for travel. A single integrated platform can be made for citizens to interact with the authorities, and express their issues with ease.

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