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IOT AND CLOUD BASED AUTOMATED POTHOLE DETECTION MODEL USING EXTREME GRADIENT BOOSTING WITH TEXTURE DESCRIPTORS

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Abstract. One of crucial activity related to road monitoring and maintenance is the occurrence of potholes. These potholes are also be major reason of road accidents, damaging of vehicles, discomfort of passenger journey and extensive in terms of time and cost. But, identification of potholes can significantly alleviate the aforementioned issues. Other side, the Internet of Things (IoT) plays a crucial role in different applications, and provides viable and state of art solutions for variety of problems. Hence, the aim of this work is to develop a real time automated pothole detection model to detect the potholes in asphalt roads based on IoT devices.The proposed model comprises of three main components such as collection of pothole data and labeling, image pre-processing and texture feature extraction, and extreme gradient boosting (XGBoost) algorithm. The potholes data on asphalt road is collected by three IoT sensors such as accelerometer, ultrasonic sensor, and GPS and further, the collected data is transmitted on cloud via Wi-Fi module. The texture features are extracted using Gaussian steerable and median filters. The extreme gradient boosting (XGBoost) classifier is adopted for prediction task. The simulation results showed that proposed XGBoost model obtains higher accuracy, recall, precision and F1-score rates as 94.56, 97.41, 96.40, and 96.90 respectively using 10-cross fold validation method.

Key words: Asphalt Road, Potholes, Detection Model, Extreme Gradient Boosting, Decision Tree

1. Introduction. The economic and development growth of a country is sustainably described through the road network. Several other sectors like health, education, social and employment are strongly connected with the road network and good road conditions provides an easy access to these sectors. But, it is seen that road infrastructures are damaged due improper maintenance, long duration of maintenance, continuous usage, and constant traffic loads etc. The adequate and timely maintenance planning significantly extends the life of road infrastructure and also helps to overcome the major repairs. The road network can be deeply damaged due to lack of improper maintenance and planning and these are irreversible damages. In turn, restore or rebuild cost of road infrastructure is increased. This increased cost can also have impact on the financial outlay and result in adverse effect on economy of country. It is advised that the planning and maintenance program should be examined the road condition on regular interval and timely maintenance of road should be done in order to avoid irreversible damages [16]. The pavement condition should be determined through structural adequacy, roughness, distress, and the extent of past maintenance activities, etc. It is also noticed that the safety and comfort of passengers are greatly affected through pavement distress. It also degrades the surface of the road and it can be one of the main reason for road accidents, damage of mechanical structure of vehicles and also increased the travelling cost in terms of time and wealth. Furthermore, the detection of pavement is also helpful for optimizing the road maintenance operations.Potholes can be described as one of most common and detestable road distresses. Moreover, the heavy traffic flow and presence of water in pothole can increased the affected area tremendously and it is also responsible for traffic accidents [25]. Potholes is a bowl-shaped holes on the asphalt road with cue texture and one of dominate parameter for road damages. Hence, potholes can be described as one of important activity of pavement maintenance. The rehabilitation process is also significantly affected due to potholes. The manual inspection of potholes makes it time consuming and cost extensive [19]. Recently, the automated detection of potholes can be considered as one of the significant issue regarding the pavement maintenance [5] - [17] - [22]. Several researches and practicing engineers have been developed variety of solutions to overcome the manual and tedious task of pothole detection. The rapid growth in computer hardware and digital image processing devices, the process of pavement assessment becomes easier

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and detects the pothole in asphalt road in significant manner [6] - [35]. The widely popular pothole detection methods are three dimensional reconstruction and three dimensional laser-based scanning methods [10]- [31]- [36] - [23], vibration-based systems [9] - [32] [33], and vision-based models [24]- [20]- [28]. The shortcomings of abovementioned techniques are described as increased cost (three dimensional laser approaches), reliability and accuracy are major concerns (vibration method), and image contrast (vision-based models). The number of accidents can also be significantly reduced with real time detection of potholes in asphalt roads and it is also an effective solution.

1.1. Motivation and Contribution of the Work. This subsection presents the motivation and contribution of the work. Several approaches have been presented for handling the pothole detection issue in asphalt road. But, cost, reliability, image contrasts and accuracy are major concerns. Hence, the objective of this paper is to develop an automated system for detection of potholes in asphalt roads using two dimensional vision. In this work, a real world road image dataset is constructed with the help of smart camera. The description of the roads that are utilized for constructing the road image dataset are mentioned in Figure 3.2. The identification of potholes is not an ease due to diversify shape, size, shadow, scale and even consists of complex background. Hence, the contributions of this work are summarized as

- To develop a pothole detection model for accurate identification of potholes in asphalt roads. The real time pothole data is collected through three sensor such as accelerometer, ultrasonic sensor, and GPS and further, the collected data is transmitted on cloud via Wi-Fi module for storage purpose and other activities
- The Gaussian steerable and median filters are adopted to determine the object features. The Gaussian filter is applied for computing the project integral, while the median filter is considered for object texture information.
- The K-Mean++ clustering algorithm is adopted to determine the more accurate segment of pothole in the road image dataset. Further, extreme gradient boosting classifier is utilized for prediction task.
- A total thirty two feature such as sixteen features through project integral (Gaussian steerable filter) and sixteen features through median filter and K-Mean++ segmentation are computed from road image dataset. The final dataset comprises of thirty two feature and one class label.
- The efficiency proposed model is examined over real world pothole image dataset. This dataset contains total eleven thousand one hundred fifty image, eight hundred sixty images having pothole and labeled as while rest of are related to not pothole class.
- The simulation results are evaluated using accuracy, precision, recall, F1-Score, ROC and AUC parameters. The accuracy rate behavior of training and validation sets along with loss function are also computed to investigate the overfitting issue of data.

The rest of the paper is structured as section 2 discusses the recent works on pothole detection and pavement of road network. Section 3 illustrates the proposed XGBoost based pothole detection model. The experimental results of the proposed model is presented into section 4. Section 5 concludes the entire work on the pothole detection.

2. Related Works. This section summarizes the recent works reported on pothole detection and pavement of asphalt roads.

Kamalesh et al. [18] presented an IoT based low-cost portable pothole detection model. Authors also claimed that proposed pothole detection system is economical for detecting of the potholes in road networks and also intimating the concerned authority regarding the potholes location. The proposed IoT based detection system is the combination of GPS, ThingsBoard server and mounted on AmazonWeb Service. The Raspberry Pi3 Single Board Computer (SBC) is used to implement the proposed detection model. The SBC is also responsible for capturing of the images, analyze images and communication. It is revealed that proposed model achieves 100% success rate for identification of damaged roads.

Lekshmipathy et al. [21] explored the applicability of smartphone accelerometers for detecting of the potholes. This work considers the two crucial components such as sensing component and reorientation of the smartphone-accelerometer with respect to vehicle axes for improving the accuracy rate. This work also focuses on significant threshold value for different pothole algorithm. Hence, different combination of threshold values are examined to determine the significant one. An external tri-axis accelerometer is also utilized for validating the accuracy of the smartphone accelerometers. The results showed that smartphone accelerometers based model obtains more than 93% of true positive rate.

Salaudeen and Celebi [29] presented the enhanced generative adversarial networks and object detection network for accurate and effective detection of potholes in road networks. The super resolution technique is integrated into generative adversarial networks, called enhanced generative adversarial networks (ESRGAN). The combination of YOLOv5 and EfficientDet networks is utilized for detecting of the potholes in road networks. The results are evaluated using mean precision and recall parameters and compared with LM1 and combination of ESRGAN and YOLOv5. It is seen that the combination of ESRGAN and EfficientDet Network obtains superior results in terms of mean precision (100%) and mean recall (63%) with PNW dataset.

Gayathri and Thangavelu [11] considered the deep learning based models for detection of potholes and vehicles through images. The proposed deep learning model consists of Faster R-CNN and IncpetionV3 architecture. The efficiency of proposed deep learning model is assessed through accuracy parameter and compared with YOLO and SSD. The results stated that proposed deep learning model obtains 86.41% accuracy rate than YOLO and SSD methods.

Ye at al. [34] explored the capability of convolutional neural network to detect the pothole using the digital images. This study considers the two CNN model such as conventional CNN and pre pooling CNN. In pre-pooling CNN, a pre-pooling layer is adopted for processing of the pavement images. The robustness of the CNN models are evaluated using precision parameters. The results showed that pre pooling CNN model having 98.95% of precision rate.

Anandhalli et al. [1] presented a vision based method for detecting of the potholes in different Indian traffic conditions. The proposed vision based method consists of sequential convolutional neural network (CNN), and anchor-based learning. The anchor based learning is described through YOLOV3 algorithm. The results are evaluated using the accuracy metric. It is revealed that proposed vision based method obtains more than 98% of accuracy rate.

Gupta et al. [13] developed a new approach on the basis of bounding box based pothole localization. It is noticed that proposed approach works with thermal images. The modified ResNet-34 model is integrated with bounding box based pothole localization. The modifications in ResNetare described in terms of cyclic learning rates, and discriminative layer learning Authors also claimed that proposed model works in different weather conditions such as rainy, foggy and night time. The efficacy of proposed approach is examined through precision rate. It is noticed that ResNet-50- RetinaNet obtains 91.5% of precision rate.

Cao et al. [4] presented an automatic detection model based on image processing technique for rutting of asphalt pavement road. The proposed detection model is the combination of image processing techniques (ITPs), least squares support vector classification (LSSVC), dynamic feature selection (FS) method, and forensic-based investigation (FBI). The texture computation of image are extracted through Gabor filter and discrete cosine transformation. The relevant features are determined using wrapper based feature selection method. LSSVC is utilized for predicting the data into rutting and non-rutting classes. Further, FBI is adopted for optimizing the hyper parameter of LSSVC. The well-known parameters like accuracy rate, precision, recall, and F1 score are considered for evaluating the efficacy of proposed automatic detection model. It is revealed that proposed model obtains 98.9% ofaccuracy rate, 0.994 of precision rate, 0.984 of recall rate, and 0.989 of F1 score rate than existing studies.

Hoang et al. [26] designed two approaches for automatic detection of crack in asphalt roads. The first approach comprises of sobel and canny algorithms as edge detection technique. It is also stated that threshold value have significant impact on the detection of edges. Hence, the differential flower pollination algorithm is utilized for computing the optimal value of parameters of first approach. In second approach, CNN model is implemented for detection of cracks in asphalt roads. It is noted that CNN model performs the feature extraction and prediction task in automatic manner. The results revealed that CNN model achieves better classification accuracy as 92.08%, while edge detection algorithm achieves 79.99% accuracy rate.

In continuation of their work, Hoang [14] presented an automated approach based on image texture analysis and hybrid machine learning algorithm potholes detection in asphalt roads. The statistical properties of color channel and grayscale matrix are adopted for extracting features based on texture analysis. Furthermore, LSSVM technique is utilized for detection of patch area from the non-patch area. For optimal parameter tuning, differential flower pollination algorithm is adopted in the training phase of the model. The robustness of the proposed automated model is evaluated using accuracy, positive prediction value (PPV) and negative prediction value (NPV). The results showed that proposed model achieves 95.30% of accuracy, 0.96 of PPV and 0.95 of NPV rates.

Hoang et al. [15]proposed a vision based approach for distinguish patched and unpatched potholes using two dimensional images. The texture information of asphalt roads is extracted using color channels, gray level co-occurrence matrix, and the local ternary pattern. Furthermore, the combination of support vector machine (SVC) and forensic based investigation (FBI) is utilized for prediction of potholes. In aforementioned combination, the hyper parameters of SVM is optimized through FBI algorithm. The results showed that proposed vision based approach obtains 94.83% of accuracy rate.

The automated detection of potholes in bad weather condition is tedious task. To address this issue, Sathya and Saleena [30] developed a novel method based on the thermal imaging for detecting the potholes. The proposed method comprises of convolutional neural network (CNN) and modified aquilla optimization (MAO) algorithm. Prior to prediction task, several image processing task like data acquisition, image preprocessing, and data augmentation. TheMOA algorithm is employed to tune the hyper parameters of CNN technique. The efficiency of proposed method is evaluated using accuracy, precision, recall and F1-score parameters and compared with CNN, CNN-TI, YOLO-NN, and DNN. It is seen that proposed method achieves superior results than CNN, CNN-TI, YOLO-NN, and DNN.

Smartphone based pothole detection methods are less expensive technique for detecting the potholes in asphalt roads, but, struggle for finding the optimal solutions. Firstly, Arya et al. [2] considered the smartphone based method to detect the potholes. Secondly, a heterogeneous road image dataset is constructed by collecting the image from different countries and this dataset consists of 26,620 images. The results showed that YOLO based ensemble method obtains 0.674 of F1-score rates.

Egaji et al. [8] considered the various machine learning model for detecting of the potholes. The data is collected through multiple android devices and cars. Furthermore, the relevant features are extracted using second level non-overlapping moving window. It is also noticed that the test data is entirely different from training and validation dataset. This work also considers the stratified k cross validation method is also adopted on training dataset. For the prediction task, random forest tree and KNN techniques are chosen and it is observed that both of techniques get similar results in terms of accuracy. But after tuning of hyper parameter of random forest tree, it obtains superior results than KNN as 0.9444 (random forest tree) and 0.8898 (KNN).

Guan et al. [12] designed an automatic pixel-level pavement detection framework based on stereo vision and deep learning. This work considers the multi-feature pavement image datasets including color images, depth images and color-depth overlapped images. A modified U-Net architecture is utilized for detecting of cracks and pothole segmentation. The depth wise separable convolution is integrated into U-Net architecture for reducing the computational cost. The results showed that proposed framework provides superior results in terms of accuracy and inference speed.

Several challenges are related to the highway infrastructure like increased traffic flow, insufficient budget and lack of resources. But, for smooth traffic flow and alleviate traffic accidents, the timely maintenance and detection of potholes in road network is significant task. Hence, Pandey et al. [27] presented an effective technique based on convolutional neural networks based on accelerometer datafor detection of potholes. Furthermore, ios based smartphone mounted on dashboard of the car is used for collected the data. The results showed that proposed CNN model with three hidden layers achieves 96.29% of accuracy rate. Table 2.1 depicts the existing works on the pothole detection in terms of issues, methods adopted for accurate detection of potholes and performance metrics for evaluating the performances of adopted methods.

3. Proposed Model for Pothole Detection. This section discusses the proposed model to detect the pothole on asphalt roads. The proposed model is the combination of the image processing technique, texture features and XGBOOST machine learning technique. The schematic description of the proposed model is illustrated into Figure 3.1. The working of proposed model is described as three fold- (i) Collection of images and labeling, (ii) Image Pre-processing and Texture Feature Extraction, and (iii) Extreme Gradient Boosting (XGBoost) algorithm.

Table 2.1: Depicts the existing works on the pothole detection in asphalt roads.

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Author	Issues	Method	Measure
Kamalesh et al. [18]	Low-cost portable and economically affordable device	Global Positioning System (GPS)	TimeStamp
Lekshmipathy et al. [21]	Accuracy rate	z peak algorithm and z sus algorithm	TPR and FPR
Salaudeen and Celebi [29]	Accurate and effective detection of potholes	Enhanced Generative Adversarial Networks	Mean Precision and Mean Recall
Gayathri and Thangavelu [11]	Accurate detection of Potholes	Faster R-CNN and IncpetionV3	Accuracy
Ye at al. [34]	Detect the pothole using the digital images	CNN	Precision and Efficiency
Anandhalli et al. [1]	Different indian traffic conditions	Sequential Convolutional Neural Network	Accuracy, Precision, Recall, and F-score
Cao et al. [4]	Identify rutting on asphalt pavement road	Least Squares Support Vector Technique	Accuracy, Precision, Recall, and F-score
Hoang et al. [26]	Automatic detection of cracks	Differential flower pollination algorithm	Classification Accuracy
Hoang et al [14]	Patch Detection in Asphalt Pavement	Least Squares Support Vector Machine and Differential flower pollination algorithm	Classification Accuracy Rate, positive Predictive Value,and the Negative Predictive value
Hoang et al [15]	Sealed crack and crack in asphalt pavement surface	Support Vector Machine and Forensic based Investigation	Accuracy, Precision, Recall, and F-score
Sathya and Saleena [30]	Thermal imaging for detecting the potholes	Convolutional Neural Network and Modified Aquilla Optimization	Accuracy, Precision, Recall, and F-score
Arya et al [2]	Smartphone based method and Heterogenous	YOLO based ensemble method	F1-Score
Egaji et al. [8]	Damage to the vehicle's Wheels tyres, and suspension system resulting in high repair bills	Random Forest Tree and KNN	Accuracy, Precision, Recall, and F-score
Guan et al [12]	Pixel-level pavement detection framework	Stereo Vision and Deep Learning	Accuracy and Inference speed.
Pandey et al [27]	Smooth traffic flow and alleviate traffic accidents	Convolutional Neural Networks	Accuracy Rate

3.1. Collection of Images and Labelling. The first step of the proposed pothole detection model corresponds to collection of road images and labelling of these images. The road image dataset contains of pothole and without pothole images of roads. In this study, two roads of the Delhi-NCR city are chosen for constructing the road image dataset. The information regarding these roads are mentioned in Figure 3.2. In this study, the smart camera is utilized for capturing the images of the asphalt road in day time. The altitude and longitude of road between Raj Nagar Extension to Meerutare (28.98668, 77.470516) and (28.70400, 77.43187) respectively, called Road1, while, the altitude and longitude of road between Raj Nagar Extension to Bhojpurare (28.70400, 77.43187) and (28.80516, 77.62447) respectively, called Road2. Furthermore, the selected roads are highlighted using blue color in Figures 3.2(a & b). To construct the road image dataset contains total one thousand one hundred fifty images with binary class- (i) pothole, and (ii) No pothole. Out of one thousand one hundred fifty images, eight hundred sixty images consist of potholes and rest of images are without pothole. Further, the image size is fixed to 64×64 to speed up the image pre processing and texture feature extraction. A committee of three members is utilized for labelling the images as pothole and without pothole.

3.2. Image Pre-processing and Texture Feature Extraction. The image pre-processing and texture feature extraction process is presented into Figure 3.3. The initial size of road images are512×512. Two filters are applied on the images for extracting the relevant features. These filters are Gaussian steerable and median filters. Gaussian filter is utilized to determine the projection integral, while the median filter is adopted for determining the object texture information. So, Gaussian steerable filter computes the VPI, HPI and diagonal PIs. Further, PI is described through four statistical measure such as maximum value, average value, standard deviation, and skewness. These measure are computed for every PI and it found that minimum value of PI is zero and it is neglected and cannot be used in computation. Hence, in total sixteen features are extracted on the basis of VPI, HPI and two diagonal. Apart for this, the object texture features are also computed, but to determine these features, firstly region of interest should be isolated. To achieve the same, several image pre-processing techniques are utilized such as median filter, morphological operation, edge detection and segmentation. The noise from the images are removed through median filter. For enhancing the quality of images, the morphological operations are utilized. Next, an edge detection technique is employed for detecting the edge of potholes. This work considers the gray scale images of road to detecting the potholes. So, four features such as mean, median, standard deviation and kurtosis is computed for each image. Finally, K-Mean++ segmentation technique is adopted for determine the pothole segment in the given road image and the texture features are extracted using histogram method as it describes the texture of the segmented image. In turn, mean, median, standard deviation and kurtosis is computed for each image as texture features.

3.3. Extreme Gradient Boosting (XGBoost) Algorithm. This subsection explains the XGBoost algorithm that are utilized for detection of potholes. XGBoost is the Extreme Gradient Boosting algorithm and can be described as ensemble tree methods which consider the gradient descent architecture for boosting the performance of weak learners. It is an extension of basic GB algorithm in terms of system optimization and algorithmic improvements. Chen and Guestrindeveloped XGBoost algorithm and further, improved by several other researchers [7]. It can be described as a package that related to Distributed Machine Learning Community (DMLC). The gradient boosting framework consists of several weak machine learning algorithm. Initially, a weak classifier is chosen and fit into data. In next step, another classifier is chosen for improving the performance of the current classifier and this process remains continue, until the current model not achieved better performance. So, the main component of the XGBoost algorithm is classification and regression tree (CART). The working procedure G algorithm is illustrated into Figure 3.4.

As illustrated in the Figure 3.3, initially feature (x_1) is estimated using the decision tree for fitting the data, the data in second tree is fitted using the residual of previous tree and it can be given as$(x - x_1)$. Second tree estimated the feature(x_2). The third tree is fitted using the residual of second tree and it can be given as$(x - x_1 - x_2)$. This process is continue until algorithmic error cannot be decreased. Now, the XGBoost algorithm is described as follows. Suppose the pothole detection dataset (D) consists of n number of data sample and d number of features. It can be summarized using equation 3.1.

$$D = a, b; |D| = n, a \in R^d, b \in R \tag{3.1}$$

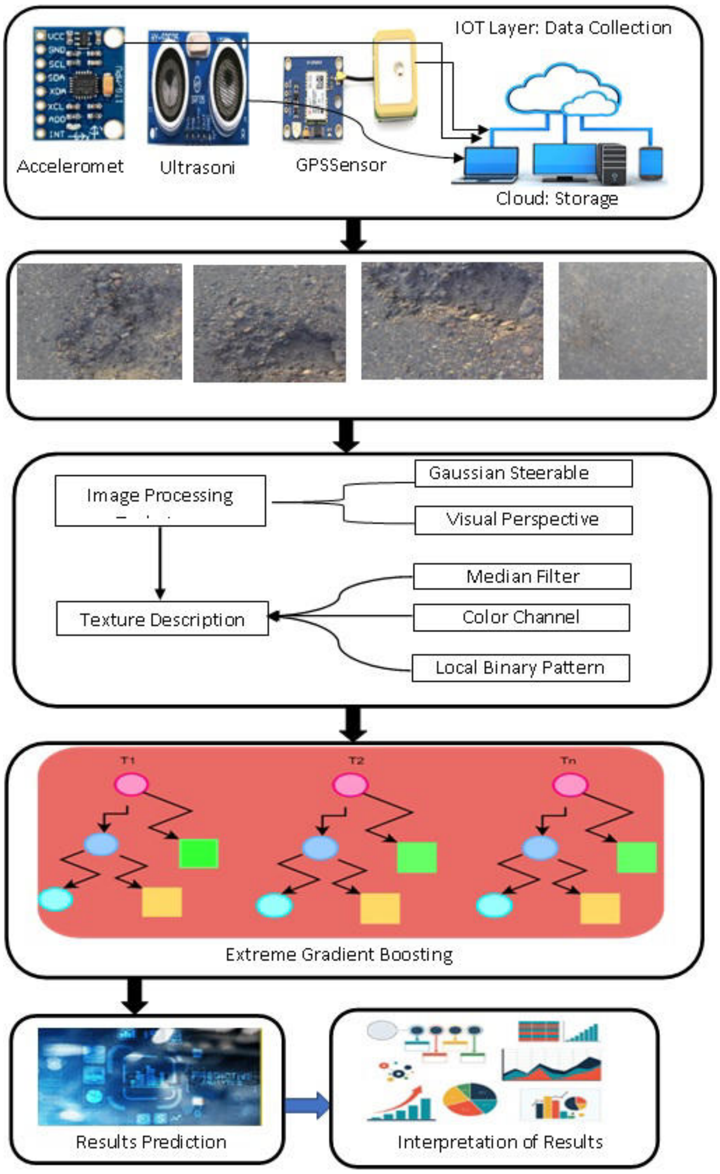

Fig. 3.1: Illustrates the proposed automated pothole detection model

In equation 3.1 D denotes the dataset, a represents the features of dataset, y represents the target variable of the dataset. In XGBoost, k-additive function is utilized for constructing the k trees and the prediction results can be given as sum of output of k-trees. The k-additive function is summarized into equation 3.2.

$$\hat{b}_i = \sum_{k=1}^{K} f_i(a_i), f_k \in F \tag{3.2}$$

In equation 3.2 $\hat{b_i}$ˆdenotes the ith instance prediction of the kth boost, (a_i) denotes the ith data sample, f_k (a_i) denotes the value of kth tree and function F denotes the sum of all values of decision tree. The main objective XGBOOST is to minimize the algorithmic error which is described in terms of loss function (LF) and

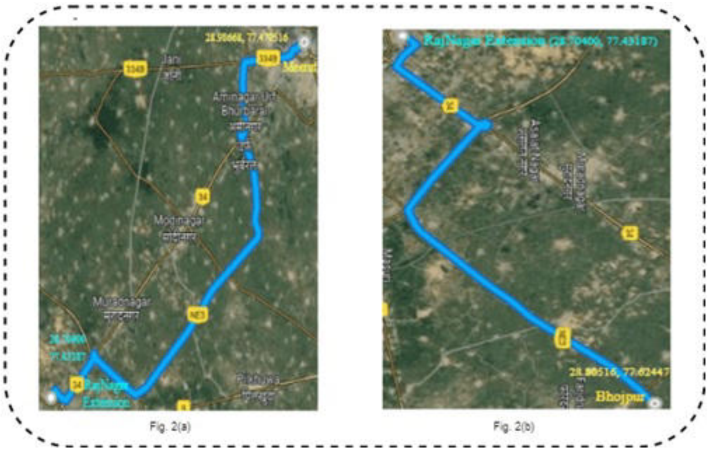

Fig. 3.2: Illustrates the proposed automated pothole detection model

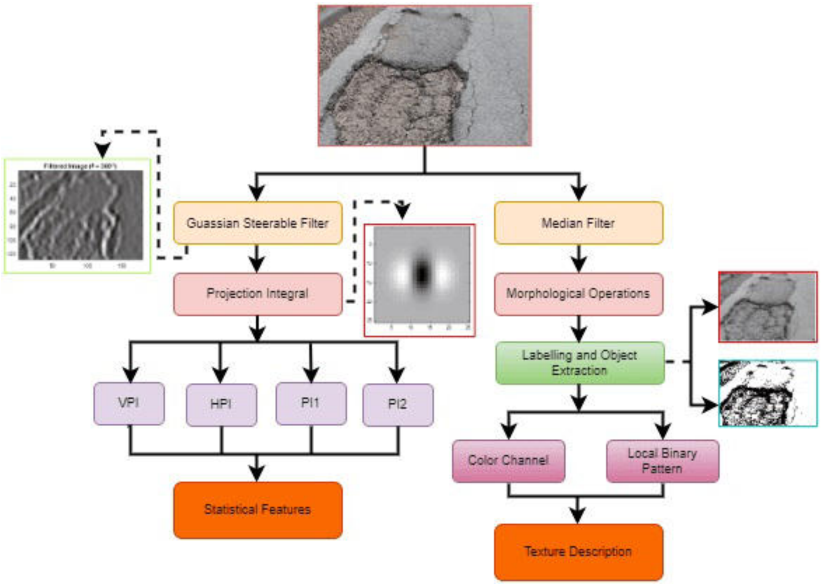

Fig. 3.3: Roads chosen for this study, (a) shows the description of the road between Raj Nagar Extension to Meerut, and (b): shows the description of the road between Raj Nagar Extension to Bhojpur

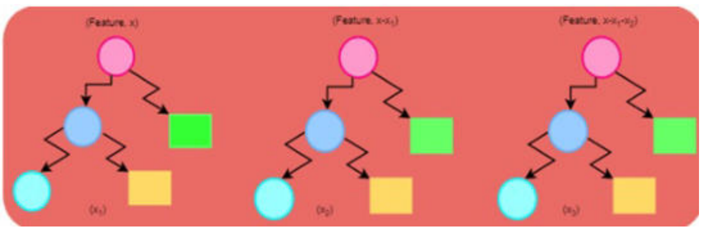

Fig. 3.4: Process of GD algorithm.

Table 4.1: Illustrates the user-defined parameters of XGBoost algorithm

Parameter	Default Value	Parameter	Default Value
learning_rate	0.3	gamma	0
n_estimators	100	subsample	1
booster	gbtree	colsample_bytree	1
min_child_weight	1	reg_lambda	1
max_depth	6	reg_alpha	0

it is mentioned in equation 3.3.

$$LF_k = \sum_{i=1}^{n} LF(\hat{b}_i, b_i) \tag{3.3}$$

It is already explained that XGBoost consists of several decision tree based algorithm. Hence, the overfitting issue is resolved through multiple hyper parameters related to decision tree such as subsample, learning rate, depth etc. and in turn optimization of these parameters are also improved the performance of the model. Furthermore, the weights of the tree that are included in the model, managed by learning rate parameter. This parameter significantly reduces the model adaptation rate with respect to training data. The hyper parameters of XGBoost are summarized into Table 1. The objective function of XGBoost is defined in terms ofregularization and loss function. The aim of the objective function is to select the predictive functions. The objective function of XGBoost is summarized into equation 3.4.

$$Obj_F un = \sum_{i=1}^{n} LF(\hat{b}_i, b_i) + \sum_{i=1}^{K} P(f_i) \tag{3.4}$$

In equation 3.4, LF denotes the loss function that computes the compatibility of model with training data; b_i denotes the predicted label of th data instance, b_i denotes the actual label of th data instance, $P(f_i)$is a penalty function related to training tree and also resolve the ove rfitting issue. Prior to defined the penalty function, a tree function T(a) is defined which is illustrated in equation 3.5.

$$T(a) = V_{u(a)}, V \in R^s; u : R^s \to \{1, 2, 3......., S\} \tag{3.5}$$

In equation 3.5, v denotes the leaves score, u is a mapping function for mapping the data instance to leaf, S denotes total number of leaf. Now, the penalty function is expressed using equation 3.6.

$$P(f_i) = \gamma^S + \alpha(||V||) + \frac{1}{2}\vartheta(||V||)^2 \tag{3.6}$$

In equation 5, γ and ϑ are two hyper parameters, S denotes the total leaves of tree and γ denotes the value of each leaf, ‖V‖ is described in terms of LP-1 and V^2 is described as LP-2 norm. LP-2 norm specified that weight should be small and it is controlled through hyper parameter ϑ. LP-1 favors the sparsity and it is controlled through parameter ϑ The loss reduction is computed through hyper parameter γ.

4. Simulation Setup and Results . This section presents the simulation results of the proposed model for detection of potholes in asphalt roads. A real world dataset is collected for evaluating the performance of the proposed model. In this work, two roads (mentioned in Figure 3.2 (a & b)) are chosen for collecting the real world dataset. Several well-known performance parameters such as accuracy, recall, precision, F1-Score and AUC are chosen to assess the efficacy of the proposed model. The proposed detection model is implemented in Python environment using window operating system, 16 GB RAM and corei7 processor. The different libraries used for conducting the experiment are as Keras, TensorFlow, sckitlearn, matplotlib, numpy and opencv. The parameter settings of the proposed XGBoost model is presented into Table 4.1.

Table 4.2: Simulation results of proposed XGBoost based detection model and other popular techniques

Technique	Accuracy	Recall	Precision	F1-Score
ANN	79.73	87.32	85.82	86.56
SVM	82.60	88.83	88.01	90.31
VGG16	84.43	90.58	88.82	90.99
VGG19	87.65	91.97	91.55	93.87
InceptionV3	90.06	92.55	94.87	95.69
Proposed Model	94.56	97.41	96.40	96.90

4.1. Experiment 1: Collected Dataset. This subsection discuss the simulation results of the proposed pothole detection model based on the collected dataset. The popular performance parameters like accuracy, precision, recall, and F1-score are considered for evaluating the results of proposed model. The several existing techniques (InceptionV3, VGG19, VGG16, SVM and ANN) are adopted for comparing the results of proposed model. The confusion matrix of proposed model and other techniques such as InceptionV3, VGG19, VGG16, SVM and ANN are depicted into Figure 4.1. On the analysis of confusion matrix, it is noticed that proposed model having more accurate confusion matrix than other technique. The other significance of computing the confusion matrix is to measure the values of accuracy, precision, recall and F1-score parameters. All these parameters are derived through confusion matrix. As confusion matrix consists of true positive, true negative, false positive and false negative. The true positive and true negative are correctly predicted data instances, while, false positive and false negative are incorrectly predicted data instance. False positive are those data instances that are predicted by classifier as positive data instance but in actual these data instances are negative. While false negative data instances are those data instance that are predicted by classifiers as negative data instance, but in actual these data instances are positive. The simulation results of proposed model and all other techniques using accuracy, precision, recall and F1-score parameters are reported into Table 4.2. It is observed that proposed model obtains 94.56% of accuracy rate than other techniques. Whereas, the accuracy rate of InceptionV3, VGG19, VGG16, SVM and ANN are 90.06%, 87.65%, 84.43%, 82.60%, and 79.73% respectively. It is observed that in neural network variants, InceptionV3 provides better results than VGG19, VGG16 and ANN. On the analysis of precision and recall parameters, it is also stated that proposed model obtains higher precision (96.40%) and recall (97.41%) rates. The precision rate of other techniques are 94.87%, 91.55%, 88.82%, 88.01%, and 85.82%. Similar, the recall rates of these techniques are 92.55%, 91.97%, 90.58%, 88.83%, and 87.32%. F1-score is significant parameter as like accuracy, to examine the performance of newly proposed model. This parameter considers the false positive and false negative data instances with respect to true positive data instance. While, accuracy parameter only considers the correctly classified data instances (true positive and true negative), so sometime accuracy can be questionable as true negative data instances may contribute higher in final results than true positive data instance. F1-score parameter of proposed model is 96.90% which is higher than all other techniques F1-score rates. The F1-score of other techniques like InceptionV3, VGG19, VGG16, SVM and ANN are 95.69%, 93.87%, 90.99%, 90.31%, and 86.56% respectively. It is also noticed that among neural network variants, InceptionV3 obtains at par results than VGG19, VGG16, and ANN using all performance parameters. SVM classifier obtains more accurate than ANN classifier for pothole detection in asphalt road, while ANN exhibits lower performance for detecting potholes among all techniques/model.

Figure 4.2 depicts the simulation results of proposed XGBoost model and other techniques such as ANN, SVM, VGG16, VGG19 and Inception V3 in graphical manner. It is clearly visible that proposed model achieves far better accuracy and recall rats for detection of potholes in asphalt road. The precision and F1-score rates of proposed model are also higher than other techniques and it is said that proposed model exhibits significant performance with these parameters. It is also highlighted that ANN technique gives less accurate results for potholes detection using all performance parameters.

The accuracy rate of the proposed XGBoost based pothole detection using training and validation sets are presented into Figure 4.3. The training set accuracy rate of the proposed model is described through green color curve, while the accuracy rate of validation set is represented through pink color curve. The training set accuracy of proposed model is 90.6%, whereas, validation set accuracy rate of the proposed model is 94.56%.

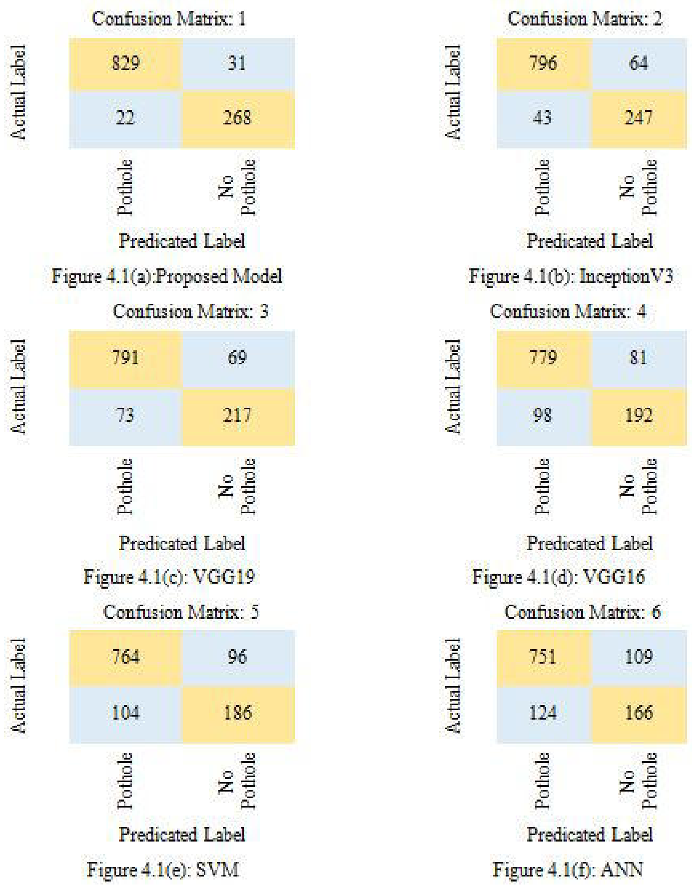

Fig. 4.1: Confusion matrix of proposed pothole detection model and other techniques like InceptionV3, VGG19, VGG16, SVM and ANN.

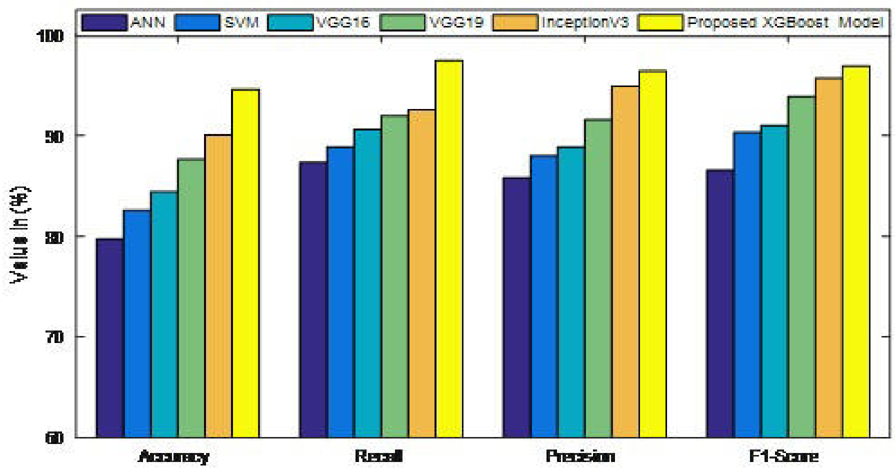

Fig. 4.2: Illustrates comparative analysis of proposed XGBoost model and other techniques using accuracy, recall, precision and F1-Score parameters

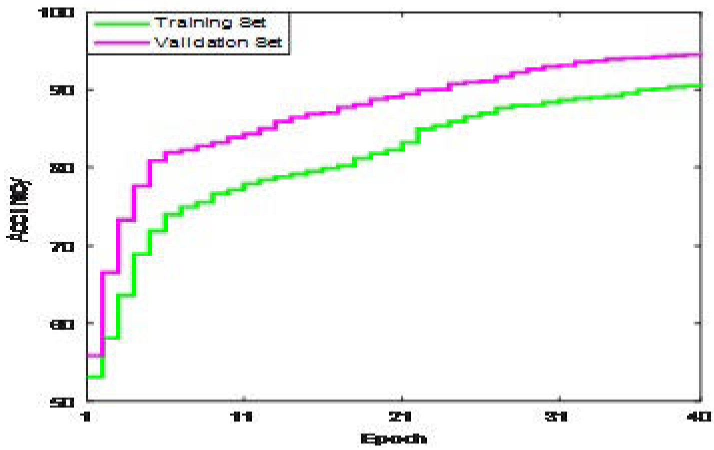

Fig. 4.3: Illustrates accuracy of the proposed Detection Model using the training and validation sets.

Along with accuracy rate, the loss function of proposed model is also plotted using training and validation set. The loss function curve is presented into Figure 4.4. It is analyzed that validation set having minimize loss function curve than training set. The significance of accuracy and loss function curves are to address the overfitting issue during the training and testing phase of the proposed model. Hence, it is stated that XGBoost based pothole detection model significantly handles the overfitting and under fitting issues of dataset. Furthermore, the simulation results of ROC and AUC parameters are reported into Figures4.5-4.6. The AUC measures the degree of separable between classes, while ROC denotes the probability curve. The higher value of AUC denotes better efficiency of the model. Whereas, ROC curve denotes the different threshold values and it is plotted by using TPR and FPR. The ROC curve of the proposed model is also compared with ROC curves of ANN, SVM, VGG16, VGG19 and InceptionV3 techniques which is depicted into Figure 4.5. This parameter illustrates the relationship among true positive rate and false positive rate. It is analyzed that proposed model obtains better ROC results than other techniques. It is observed that the proposed pothole detection model successfully handles the overfitting issue and the data are not over fitted the proposed pothole detection model. The results of the AUC parameter of proposed model is presented into the Figure 4.6. It is noted that proposed model achieves 0.974 as AUC value. Hence, it is stated that proposed XGBoost based pothole detection model is one of the effective and efficient model for accurate detection of potholes.

4.2. Experiment 2: Benchmark Pothole Dataset. This subsection presents the results of the proposed pothole detection model using the benchmark pothole dataset. This dataset is downloaded from the Github and comprised of 1243 pothole images with one class i.e. Pothole [3]. The simulation results of the proposed model and other techniques are depicted into Table 4.3. It is observed that proposed model obtains higher accuracy rate (96.21%) than other techniques being compared, while the accuracy rate of InceptionV3, VGG19, VGG16, SVM and ANN are 92.81%, 90.06%,88.99%,88.01%, and 87.29% respectively. It is observed that in neural network variants, InceptionV3 provides better results than VGG19, VGG16 and ANN. On the analysis of precision and recall parameters, it is also stated that proposed model obtains higher precision (99.02%) and recall (98.56%) rates. The precision rate of other techniques are 95.43%, 92.96%, 91.61%, 90.93%, and 88.89%. Similar, the recall rates of these techniques are 94.01%, 93.74%,92.16%,90.78%, and 88.24%. F1-score is also a significant parameter to examine the performance of newly proposed model. This parameter considers the false positive and false negative data instances with respect to true positive data instance. While, accuracy parameter only considers the correctly classified data instances (true positive and true negative), so sometime accuracy can be questionable as true negative data instances may contribute higher in final results than true positive data instance. F1-score parameter of proposed model is (97.14%) which is higher than all other techniques F1-score rates. The F1-score of other techniques like InceptionV3, VGG19, VGG16, SVM and ANN are 96.11%, 95.28%, 92.34%, 91.09%, and 89.34% respectively. It is also noticed that among neural network

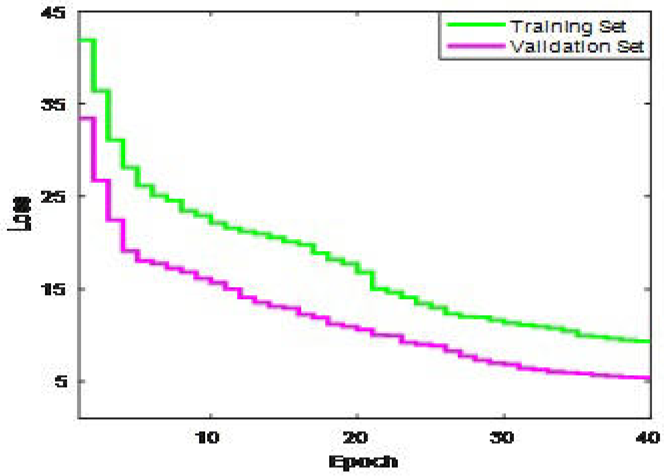

Fig. 4.4: Illustrates loss function of the proposed Detection Model the training and validation sets.s

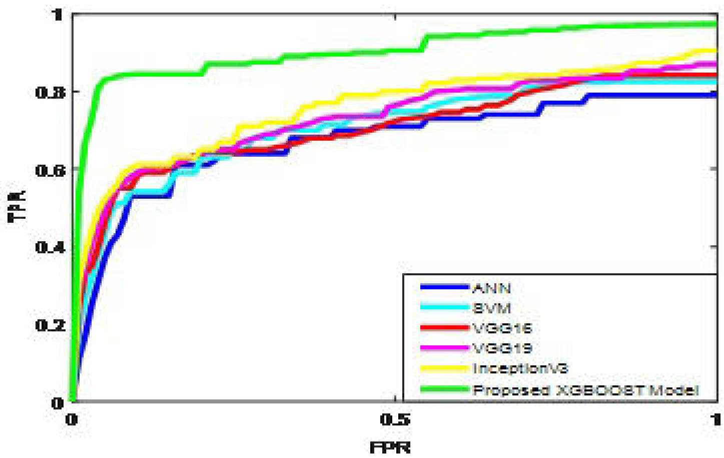

Fig. 4.5: Illustrates the ROC of proposed XGBoost based pothole detection model and other popular techniques.

variants, InceptionV3 obtains at par results than VGG19, VGG16, and ANN using all performance parameters. SVM classifier obtains more accurate than ANN classifier for pothole detection in asphalt road, while ANN exhibits lower performance for detecting potholes among all techniques/model.

Figure 4.7 depicts the simulation results of proposed XGBoost model and other techniques such as ANN, SVM, VGG16, VGG19 and Inception V3 in graphical manner using benchmark pothole dataset. It is clearly visible that proposed model achieves far better accuracy and recall rats for detection of potholes in asphalt road. The precision and F1-score rates of proposed model are also higher than other techniques and it is said that proposed model exhibits significant performance with these parameters. It is also highlighted that ANN technique gives less accurate results for potholes detection using all performance parameters.

5. Conclusion. In this work, an XGBoost based pothole detection model is proposed for effective identification of pothole in asphalt roads. The working of proposed model is three fold such as collection of images and labeling, image re-processing and texturefeature extraction, and extreme gradient boosting (XGBoost) algorithm. Furthermore in this work, a real world road image dataset is collected through smart camera. Two

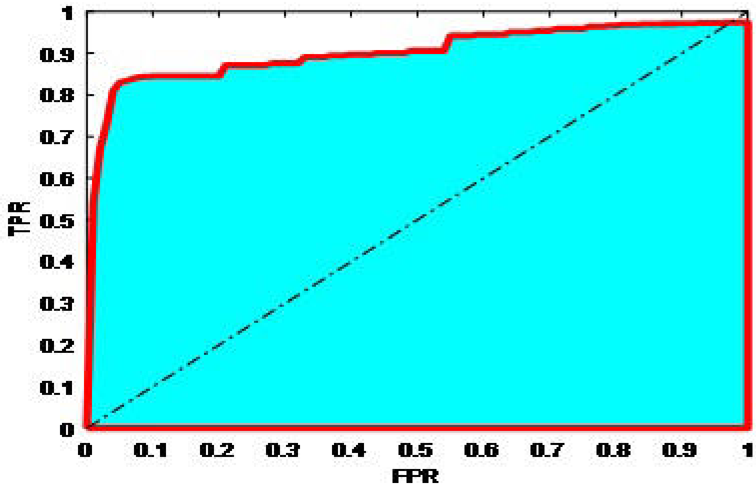

Fig. 4.6: Illustrates the AUC of proposed XGBoost based pothole detection model.

Table 4.3: Simulation results of proposed XGBoost based detection model and other popular techniques using benchmark pothole dataset

Technique	Accuracy	Recall	Precision	F1-Score
ANN	87.29	88.24	88.89	89.34
SVM	88.01	90.78	90.93	91.09
VGG16	88.99	92.16	91.61	92.34
VGG19	90.06	93.74	92.96	95.28
InceptionV3	92.81	94.01	95.43	96.11
Proposed Model	96.21	98.56	99.02	97.14

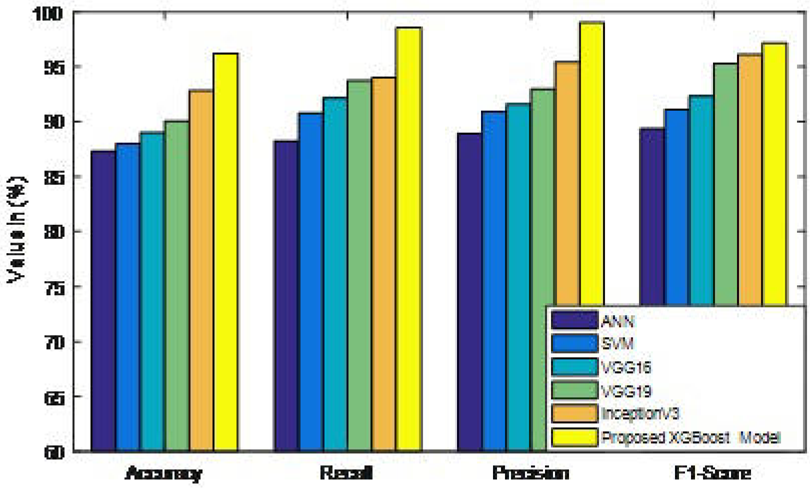

Fig. 4.7: Illustrates comparative analysis of proposed XGBoost model and other techniques using accuracy, recall, precision and F1-Score parameters based on benchmark pothole dataset.

asphalt roads of Delhi-NCR region are chosen for collecting the real world dataset and it contains eleven thousand one hundred fifty images with binary class. Moreover, the first phase of the proposed model is correspond to image collection and respective labels. In road image dataset, eight hundred sixty images are classified as pothole images and rest of images are without potholes. Second phase is responsible for image enhancement and texture feature extraction. The texture features are extracted using Gaussian and median filters, and later on K-Mean++ technique is adopted for segmentation task as well as features extraction. The prediction task is accomplished through XGBoost algorithm. A variety of parameters like accuracy, precision, recall, F1-score, AUC and ROC are considered for evaluating the proposed pothole detection model. The simulation results are also compared with several popular existing classifiers/models. The simulation results showed that proposed model achieves more than 94% of accuracy rate than other techniques. The proposed model also obtains better results with other parameters. The ROC results of proposed model is also better than other compared techniques. It is also noted that proposed model is significantly improve the prediction rate of potholes in roads. Hence, it is concluded that proposed XGBoost based pothole detection model is an effective model for detection of potholes in asphalt roads.

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