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Performance Analysis of Various Image Feature Extractor Filters for Pothole Anomaly Classification

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Abstract: Machine learning (ML) classifiers have lately gained traction in the realm of intelligent transportation systems as a means of enhancing road navigation while also assisting and increasing automotive user safety and comfort. The feature extraction stage, which defines the performance accuracy of the ML classifier, is critical to the success of any ML classifiers used. Nonetheless, the efficacy of various ML feature extractor filters on image data of road surface conditions obtained in a variety of illumination settings is uncertain. Thus, an examination of eight different feature extractor filters, namely Auto colour, Binary filter, Edge Detection, Fuzzy Color Texture Histogram Filter (FCTH), J-PEG Color, Gabor filter, Pyramid of Gradients (PHOG), and Simple Color, for extracting pothole anomalies feature from road surface conditions image data acquired under three environmental scenarios, namely bright, hazy, and dim conditions, prior classification using J48, JRip, and Random Forest ML models. According to the results of the experiments, the auto colour image filter is better suitable for extracting features for categorizing road surface conditions image data in bright light circumstances, with an average classification accuracy of roughly 96%. However, with a classification accuracy of around 74%, the edge detection filter is best suited for extracting features for the classification of road surface conditions image data captured in hazy light circumstances. The autocolor filter, on the other hand, has an accuracy of roughly 87% when it comes to classifying potholes in low-light conditions. These findings are crucial in the selection of feature extraction filters for use by ML classifiers in the development of a robust autonomous pothole detection and classification system for improved navigation on anomalous roads and possible integration into self-driving cars.

Index Terms: Classifier, Feature, Image, Machine-Learning, Potholes

1. Introduction

Road transportation is a prominent means of transportation in most developing countries, including Nigeria, and is used for the vehicular movement of goods and services. This form of transportation's effectiveness has a significant impact on the nation's economic growth and development[1, 2]. As a result, it is vital to ensure that the road is in good condition, ensuring the safety of people and property. Initiatives such as road repair with anomalies, assuring compliance with appropriate road construction standards, and compliance with acceptable speed restrictions have been implemented in this regard [3–5] . However, considerable numbers of anomalies can still be found on roads in developing countries such as Nigeria. According to statistics obtained from the Nigeria Federal Roads Maintenance Agency (FERMA), the total road network across the country is approximately 200,000 km, consisting of both state and 35,000 km of federal roads, of which approximately 10,000 km are in good condition, 13,300 km are in fair condition, and 11,700 km are in poor condition [6]. As a result, a paradigm shift in approach is required to equip cars with the ability to sense, detect, and notify drivers of the presence of road anomalies.

We note that the vibrational and image processing/computer vision-based approaches have been the two most widely used and documented approaches for anomalies sensing and detection on roads, particularly potholes, which are observed as hollow bowl shapes of about 150mm diameter and above and pose the greatest danger to road users [7]. Nonetheless, image processing/computer vision has the advantage of real-time sensing and detection, as proven by various suggested approaches published in the literature [3, 8] and, more recently, the application of Machine Learning (ML) classifiers [9, 10] . The type of image feature extractor used during the pre-processing step has a considerable impact on the performance of the ML model when used for classification. Furthermore, the lighting used to sense road image data influences the effectiveness of the ML classifiers [9, 11] . As a result, in this paper, we investigate the performance of eight different image feature extractor filters, namely, Auto Color, Binary filter, Edge Detection, Fuzzy Color Texture Histogram Filter (FCTH), J-PEG Color, Gabor filter, Pyramid of Gradients (PHOG), and Simple Color, for extracting pothole anomalies features from road surface conditions image data acquired under three different environmental scenarios, namely, bright, hazy, and dim conditions, prior classification using J48, random forest, and JRIP classifiers. The ML classifier was chosen because of its indicated performance in these various lighting settings [9,11,12].

We note that the computer vision-based approaches have the advantages of real time detection prior to a vehicle encounter the pothole anomaly, algorithm for realtime onboard processing, less physical setup infrastructure among others [13,14]. Nevertheless, a major limitation lies in the performance dependency of the approach on the atmospheric weather conditions and time of the day at which the road surface conditions data are being sensed as well as the type of feature extractor utilized by the machine learning model prior classification. Thus, leading oftentimes to misclassification of the system. Similarly, the vibrational based approaches such as that reported in [15,16] have the advantage of quick response, long term monitoring capabilities with minimal setup infrastructure cost, providing good qualitative data for potholes anomaly detection and characterization [17]. However, a major drawback lies in the need for the vehicle to encounter the pothole prior to detection. Thus, may lead to loss of lives and properties as a result of induced road traffic accident. Therefore, this study adopts the computer vision approach by assessing the performance of different feature extractors such as autocolor, FCTH, PHOG, Gabor filter among others for potholes anomalous feature extraction. The choice of this feature extractors was based on their reported performance and potentials for extracting features prior to classification by traditional machine learning models such as the random forest, J48 and so on [18,19] .

The main contribution of this study is the performance examination of the effect of these distinct feature extractor filters on the categorization of road surface conditions image data by different ML classifiers under various environmental settings. The study sought to determine the highest-performing feature extractor filter for use by ML classifiers for road anomaly classification, with the ultimate goal of constructing a robust autonomous pothole detection and classification system. The rest of the paper is organised as follows: A review of relevant work is included in Section 2. Section 3 discusses the suggested method as well as the analysis technique. Section 4 summarises and analyses the findings. Section 5 concludes the paper.

2. Related Works

To establish the technique used for our inquiry, an analysis of previous works on road surface condition monitoring and anomaly classification is required. Several studies have been conducted using vibrational-based approaches and accelerometers to identify and monitor road anomalies [20, 22] . Vision-based systems, in which cameras are mounted on vehicles to capture and distribute images for proper processing, were also investigated [7, 23–26] . However, real-time monitoring under varying environmental lighting conditions, as well as building an accurate pre-processing filter in such scenarios, remain key challenges for vision-based approaches. This drawback necessitates a careful assessment of the best-suited filter under a variety of environmental conditions. We examine the effects of image classification filters in several application domains in order to gain insight into their use and effects on road anomalies classification.

In [27] , for example, a new descriptor for object and scene image categorization based on the Gabor wavelet transformation was developed. The Gabor descriptor was concatenated with the Pyramid of Histogram of Oriented Gradients for all of the filtered images with different orientations (PHOG). Six diverse colour spaces were used to evaluate the performance of the proposed novel Gabor-Pyramid of Histogram of Oriented Gradients (GPHOG) on some of the colour spaces discovered. To minimise dimensionality in the six colour spaces, Principal Component Analysis (PCA) was performed, yielding a unique Fused Color Gabor-Pyramid of Histogram of Oriented Gradients (FC-GPHOG) descriptor. To extract features, the Enhanced Fisher model and Nearest Neighbor were utilised. The CALTECH 256 and MIT scene datasets demonstrated that the proposed FC-GPHOG image descriptor provides promising results in the realm of object and scene image categorization. When an inappropriate PCA space is used, the model overfits. Similarly, for image segmentation and grouping, [28] employed Fuzzy C-means, as well as the Gabor Filter, Gray Low Covariance Matrix (GLCM), and Color histogram. To learn and identify satellite images, the Support Vector Machine (SVM) was utilised. The researchers classified components acquired from satellite images as desert, mountain, residential, river, and woodlands in their method. The GLCM and Gabor filter were particularly well suited for feature extraction because to their inherent invariance qualities. The researchers, however, did not look into the findings and methods of implementation of these feature extractors and classifiers that can demonstrate their performance.

A method for detecting multi-class disease classification as well as the presence of anomalies in patients' gastrointestinal tracts was developed in [29] . The centre symmetric local binary pattern (CS-LBP), the auto colour correlogram (ACC), and the visual bag of features were all used in the proposed method (VBOF). The combination of these feature extraction techniques has been shown to be useful in removing noise and other components that impair the background of an image. A dataset of 3500 images was considered, which was divided into an 80:20 ratio for training and testing images, and then classified into seven (7) classes using a 5-fold validation strategy with the Support Vector Machine (SVM) as a classifier. In terms of accuracy, specificity, and sensitivity, the proposed strategy (CS-LBP+SIFT+ACC) outperforms existing methods. Other criteria, such as F-Measures, that could further validate system performance and behaviour, were not considered.

In order to reliably identify the human ear, [30] used a Pyramid Histogram of Gradient (PHoG) as a local descriptor for feature extraction. The operational principle of the PHoG requires increasing the number of levels and bin sizes, resulting in a dimensionality problem. To avoid overfitting and reduce computing time and storage requirements, a Linear Discriminant Analysis (LDA) was utilised to address this issue. As a result, two PHoG image feature extraction descriptors are created (i.e., normal PHoG and the reduce PHoG LDA-based approach). The similarities between images were analysed using histogram intersection and the Chi-squared statistics to determine the distance obtained from the histograms of the two PHoG descriptors. The experimental design required the use of two ear datasets: the IIT Delhi ear database and the University of Notre Dame database (Collections E). The images were taken on several days with different poses and lighting conditions. The obtained data demonstrated the effectiveness of the Chi-squared approach for determining distance. Similarly, the reduced PHoG based on LDA surpassed the normal PHoG in terms of speed and accuracy. However, it was revealed that selecting the appropriate parameter settings and lighting fluctuations had a substantial impact on the system's performance.

An autonomous real-time detection approach for cracks and potholes that may be easily deployed on any Graphical Processing Unit (GPU) was proposed in [31] . Their method used a CNN-based architecture to detect potholes and cracks in the backdrop. This classification was based on a texture-based feature learned in the encoding layer and paired with spatial data. To accomplish the pre-processing, video frames with a high probability of potholes and cracks were prepared using traditional image processing techniques. The video frames were first run through a customised Segmentation Network (Seg Net) to separate the section of the road with the abnormality from the other sequences using two masks. The second stage involved creating a basic edge identification algorithm based on differentiation (canny edge). The edge detector produces a two-channel image with lighter pixels representing edges and dark pixels representing backgrounds. When shadows and strong light illumination appeared in the input images, however, their technique still produced certain undesired borders and boundaries. Similarly, false positives occurred during patch restoration due to problems in distinguishing potholes from cracks.

Similarly, [32] built a pothole detection system that allows drivers to take necessary precautions when they encounter water-filled potholes by utilising edge detection filters, Gabor, and a Random Forest classifier for feature extraction and classification. A dataset was created and used for the research that included images of potholes that had been resized and tagged to a 400X300 pixel range. The feature extraction procedure was carried out by converting RGB images to greyscale to decrease computing costs. Edge filters such as Canny, Roberts, Sobel, Scharr, and Prewitt were utilised for the edge-based features. Noise and blur were removed using the Gaussian, median, and variance filters. The Gabor filter was created primarily to extract texture-based information. Based on the computation conducted during the Random Forest Classifier (RFC) model training, these returned characteristics were ranked in order of relevance. According to the obtained data, the RFC training models produced encouraging results ranging from 0.94 to 0.99, with a testing accuracy of 0.877. However, there was the issue of high computing costs, particularly when dealing with a huge dataset.

A machine learning-based approach for detecting flaws in machinery parts using Autocorelogram (Auto Color) as a feature extraction tool was developed in [33]. The researchers aimed to detect and classify flaws on the surface of a metallic object, particularly rust, in order to reduce manual inspection and save time. The acquired images contained noise and distortions generated by the acquisition and transmission of metallic images. The employment of pre-processing filters aids in the removal of noise from acquired images. The autocolor feature extraction method was utilised to reduce dimensionality while maintaining image accuracy. The results revealed that the models' accuracy, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were compared (RMSE). Ensemble approaches such as Random Forest and Decision Stump obtained 95% accuracy for a 10-fold cross-validation strategy among the strategies used. The Bagging and Logit Boost algorithms were 95-97 percent accurate. Similarly, the J48 technique achieved the lowest error rate when compared to other classification models. The method, however, was only suitable for detecting and classifying rust. Other issues that could improve system performance were not investigated.

A solution to the problem of plant recognition difficulty caused by damaged leaves, environmental, and biological factors was proposed in [34]. The authors combined a bag-of-features, fuzzy colour, and edge-texture descriptor with a multi-layer perceptron to recognise fragmented plant leaves. Normalizing the direction and size of these fragmented leaf images proved difficult until a contracting method was used to keep images within the confines of the rectangle. A combination of fuzzy colour and edge-texture histogram-based features were used throughout the feature extraction process. The multi-layer perceptron classifier classified fragmented images using a probability function known as back-propagation. According to the results, the accuracy of the fragmented images using multi-layer perceptron for classification required fragmentation percentages ranging from 80% to 20% at a 10% separation. When the recognition rate was high, the results demonstrated poor fragmentation and a higher categorization rate when the leaf's core was fragmented. The analysis indicated that the proposed method was the first of its kind to take a fragmented leaf into account. As a result, images that only considered centre fragmented (20%) test images performed 20.9 percent better than Hierarchical clustering and 17 percent better than Pyramid of Gradients (PHoG). The study's drawback was that no publicly available fragmented leaf dataset was available because the testing stage required such images.

[35] described a flood management technique using an optimal Fuzzy Wavelet Neural Network based Road Damage Detection (OFWNN-RDD). The system classifies different types of roads images including potholes obtained through remote sensing. The Gabor filter was used to aid noise removal from images obtained. DenseNet 121 was applied to OFWNN-RDD for the generation of feature vectors that considers hyperparameter tuning using Modified Barnacles Mating Optimization (MBMO) algorithm. A fuzzy based image classification approach employed for the road damage detection. The proposed system had a good performance of 98.56% accuracy outperforming other existing models. Ensemble learning can be considered towards improving performance in future works.

[36] presented a study of road damage detection that applies machine learning and CNN. The experimental study showed that other road damage detection means such as Sobel algorithm, Gabor filtering and local binary descriptors where these methods were very sensitive to noise and performed poorly in distinguishing damage or anomalies from image background. Therefore, the use of CNN portrays a solution to this challenge. The data classification model was built on the idea of data augmentation techniques and transfer learning with an initial dataset size of 333 samples that was augmented to 700 in grayscale images. The results obtained of the proposed approach achieved good results at 80% accuracy. However, the model developed still had some difficulty in distinguishing the various categories of cracks i.e., longitudinal, crocodile, and transverse cracks.

[37] worked on a road pavement anomaly specifically crack detection using spectral clustering. The authors highlighted a previous approach which applied Gabor-filter to minimize noise. Though, the approach created a scenario of having crack images detected to be larger in size than their true image size (shape). This necessitated the new proposed approach that considers crack detection without pre-processing aimed at reducing noise using a clustering algorithm. Images were categorized to classes with little noise components having two classes. While, those with higher noise components with three classes. The experiments were made using images in grayscale at 80x80 pixel resolution. The results showed better accuracy than previous methods. However, the proposed approach still resulted to the presence of noise components in the output images obtained.

It is clear that a lack of dataset for some application areas, the type of image, the classifier used and its application domain, environmental lighting conditions, and the type of feature extractor used all have a significant impact on the type of feature extractor used. As a result, this paper presents an investigation of the efficacy of various machine learning-based visual feature extractors for road anomalies classification.

3. Methodology

This section summarises the phases of the investigation into the effect of several image feature extractors on the classification accuracy of road anomalies, notably potholes.

3.1. Creating the Dataset

A database from the Cranfield repository was used to train and monitor the performance of the several image feature extractors used in this study. This collection of pothole image datasets (PotDataset) can be accessed at: https://doi.org/10.17862/cranfield.rd.5999699. These images, in particular, comprise manually annotated pothole and non-pothole images that were scaled to 300 by 300-pixel size and recorded in bright light. In addition, the second dataset used images captured with a Nikon D40 digital camera from specific local Nigeria road networks. Bright light, dull light, and hazy conditions were the three main environmental variables studied. These are the most likely scenarios in which image-based road anomaly detection and classification systems will be used. It's worth mentioning that 100 different images were gathered into a single dataset for each condition resulting to a total of 300 images. To reduce the system's computing requirements in carrying out this investigative activity, the collected images were shrunk to 2000 x 2000-pixel resolutions. Other augmentation techniques that can be used, such as random zoom in/out within a range of 0.7 to 1.3, horizontal image flipping, and random shearing, to increase the number of potholes images that could be harnessed for further research, will be investigated in the second phase of this research to improve the diversity and representativeness of the dataset.

3.2. Summary of the Machine Learning Filters used

Image processing is an important step in image feature extraction since it improves image quality by resizing, augmentation, colour, smoothness, rotation, cropping, and so on. Image filtering techniques aid in the reduction of noise, blur, and, most importantly, the precise identification of pothole edges. Typically, this is accomplished by utilising specific machine learning image filtering algorithms based on artificial intelligence. These algorithms typically extract features from input images (road surface conditions), which are then segmented and classified as pothole road anomaly (PRA) or smooth road anomaly (SRA). We evaluated eight different machine learning feature extractors (filters) in this work: Auto colour, Binary, Edge Detection, Fuzzy Color Texture Histogram Filter (FCTH), J-PEG Color, Gabor, Pyramid of Gradients (PHOG), and Simple Color. For additional information on how these algorithms function, we recommend that interested readers check [38–40] . These algorithms were selected because they have demonstrated potential in a number of machine learning-based applications.

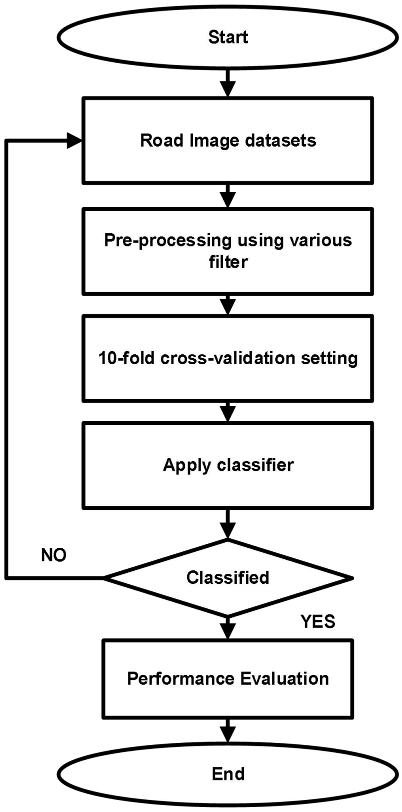

Fig. 1. Implementation process for the Method of Performance Comparison of the Filters and Classifiers

3.3. Method of Comparison

This section details the process used in the implementation of each machine-learning image extractor and associated unique best-suited classifier for the classification of road potholes under three different environmental circumstances. Pothole images that had been resized were included in the dataset retrieved from the Cranfield database. Furthermore, the obtained real-time images were linked with those from the Cranfield database to provide a basis for comparison. The 10-fold cross-validation technique was adopted because it reduces the amount of bias induced by the variable sizes of the training/testing datasets employed. The 10-fold cross-validation process is implemented by randomly shuffling the dataset, followed by partitioning the dataset into ten (10) separate groups. Each group served as test data, while the remaining groups served as training data. Fig. 1 depicts the implementation process flow and method of comparison.

3.4. Metrics of Analysis

When comparing the performance of accurately recognised potholes to smooth roads, this section discusses criteria such as true positive (TP), false positive (FP), precision, recall, and F-measure. Fig. 2 shows how these measures were produced in respect to the road surface images used. When there is an anomaly in the input image, this is referred to as a positive (P). A TP is proclaimed when a classifier accurately segments and classifies an image as a pothole road abnormality (PRA). If such a PRA is discovered to be a smooth road (SR), a false negative (FN) is declared. Similarly, if the input image is an SR, it is referred to as a negative image (N). When a classifier correctly recognises an SR image as an SR, a true negative (TN) is declared; conversely, a false positive (FP) is declared if an SR is correctly classified as a PRA. The recall is the number of positives recognised and correctly categorised among all positive classes and is reported appropriately. The precision is defined as the number of positives identified and correctly classified as actual positives. The F-Measure is computed using the model's precision and recall harmonic means. It is worth mentioning that an F-measure of 1 is frequently obtained for a flawless model. This metric is expressed as follows:

$$Accuracy = \frac{TP+TN}{P+N} \tag{1}$$

$$\Pr ecision = \frac{TP}{TP+FP} \tag{2}$$

$$\mathrm{Re}\,call\,(TPR) = \frac{TP}{TP+FN} \tag{3}$$

$$FPR = \frac{FP}{FP+TN} \tag{4}$$

$$F-Measure = \frac{2\times \Pr ecision \times \mathrm{Re}\,call}{\Pr ecision + \mathrm{Re}\,call} \tag{5}$$

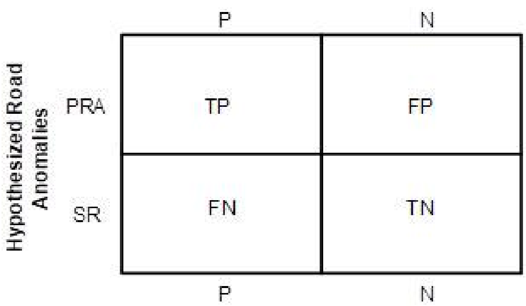

Fig. 2. Confusion Matrix.

4. Experimental Results

When performing preprocessing of the image, the performance of eight different machine learning image feature extractors such as Auto colour, Binary filter, Edge Detection, Fuzzy Color Texture Histogram Filter (FCTH), J-PEG

Color, Gabor filter, Pyramid of Gradients (PHOG), and Simple Color filter is investigated. Using pothole images obtained from multiple sources, the analysis examined three different environmental conditions, including bright light, dim light, and hazy conditions.

4.1 Under Bright Light Condition (Cranfield database)

Tables 1, 2, and 3 show the results of an experiment that used a dataset from the Cranfield database to show how multiple image extractor filters were applied to the bright light illumination condition. Some machine learning classifiers that have been demonstrated to be suitable for classification, such as the J48, Random Forest, and JRip, were used in conjunction with distinct image extractor filters. According on the Cranfield database, the J48 classifier proved to be the best suitable in bright light ambient settings, confirming the findings of the previous research in [9]. As a result, the performance of these various image extractors under bright light conditions was examined, as shown in Table 1.

Table 1. Summary of Bright Light Condition from Cranfield database for J48 Classifier

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	0.980	0.040	0.961	0.980	0.970
2	Binary	0.970	0.010	0.990	0.970	0.980
3	Edge Detection	0.870	0.150	0.853	0.870	0.861
4	FCTH	1.000	0.020	0.980	1.000	0.990
5	Gabor	1.000	0.040	0.962	1.000	0.980
6	J-PEG Color	0.960	0.040	0.960	0.960	0.960
7	PHOG	0.920	0.100	0.902	0.920	0.911
8	Simple Color	1.000	0.020	0.980	1.000	0.990

Table 1 shows that when the J48 classifier was used, the FCTH and Simple Color both achieved approximately 100% TPR, 2% FPR, 98% precision, and 0.99 F-measure. This could be due to the inherent benefit of filtering out high-noise components while refining the edges of the pothole's anomaly for classification. This is closely followed by the binary filter, which achieved 97%, 1%, 99%, and 97%, respectively. TPR, FPR, precision, and recall, with an F-measure of 0.98. (see table 1). We find that edge detection filters perform poorly, with 87% TPR, 15% FPR, 85.3% precision, 87% recall, and 86.1% F-measure. This poor performance could be attributed to inconsistencies in the shape and edges of the input pothole datasets utilized in the studies.

Similarly, the top-performing feature extractor filter for the Random Forest classifier is the auto colour, with 100% TPR, 0% FPR, 100% precision, 100% recall, and 1 f-measure, signaling a perfect model and best suited for the classification of pothole anomalies under bright lighting settings. The PHOG is the worst feature extractor filter, with 92%, 6%, 94%, 92%, 0.93 TPR, FPR, precision, recall, and f-measure, respectively (see table 2). However, when employing a Random Forest classifier, the low-performing PHOG outperformed the edge detection filter, which had the lowest performance when using a J48 classifier under the same bright light conditions.

Table 2. Summary of Bright Light Condition from Cranfield database for Random Forest Classifier

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	1.000	0.000	1.000	1.000	1.000
2	Binary	0.960	0.030	0.970	0.960	0.965
3	Edge Detection	0.980	0.040	0.961	0.980	0.970
4	FCTH	1.000	0.030	0.971	1.000	0.985
5	Gabor	1.000	0.040	0.962	1.000	0.980
6	J-PEG Color	0.980	0.030	0.970	0.980	0.975
7	PHOG	0.920	0.060	0.939	0.920	0.929
8	Simple Color	1.000	0.010	0.990	1.000	0.995

Furthermore, similar performance was seen for the JRIP classifier, with autocolor recording the best performance with around 98% TPR, 1% FPR, 99% precision, 98% recall, and around 0.99 F-measure (See Table 3). Thus, whether using either the random forest or the JRIP classifier, the autocolor is an excellent feature extractor for extracting features of potholes to increase classification accuracy under bright light settings, however, the FCTH or Simple Colors are more suitable when using a J48 classifier.

Table 3. Summary of Bright Light Condition from Cranfield database for JRIP

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	0.980	0.010	0.990	0.980	0.985
2	Binary	0.980	0.050	0.951	0.980	0.966
3	Edge Detection	0.950	0.030	0.969	0.950	0.960
4	FCTH	0.950	0.030	0.969	0.950	0.960
5	Gabor	0.980	0.050	0.951	0.980	0.966
6	J-PEG Color	0.990	0.030	0.971	0.990	0.980
7	PHOG	0.870	0.080	0.916	0.870	0.892
8	Simple Color	0.960	0.050	0.950	0.960	0.955

4.2. Bright Light Condition Using Acquired Images

Further experiments and analysis were performed to confirm some of the deductions made from applying different feature extractor filters on the three classifiers documented to have performed best for potholes classification in [9] by extending these different feature extractors to acquired datasets under the bright light conditions used for the experiment in [9] using the best-reported classifiers for such scenario. When considering the J48 classifiers utilising acquired data in bright light conditions, similar performance was observed when other feature extractors were applied, with the FCTH recording the greatest performance with approximately 96% TPR, 4% FPR, 92% precision, 96% recall, and 0.94 F-measures (See Table 4). As shown in Table 4, the Simple colour had the same 0.94 F-Measure, a little lower TPR of 94% compared to the FCTH's 96%, and superior FPR of around 3% and 94% for precision and recall, respectively. As a result, earlier findings indicating either the FCTH or simple colour is more suited for improving pothole classification accuracy in bright light circumstances are verified.

Table 4. Summary of Bright Light Condition from Acquired Images for J48

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	0.920	0.056	0.902	0.920	0.911
2	Binary	0.900	0.136	0.882	0.900	0.891
3	Edge Detection	0.740	0.078	0.841	0.740	0.787
4	FCTH	0.960	0.044	0.923	0.960	0.941
5	Gabor	0.860	0.067	0.878	0.860	0.869
6	J-PEG Color	0.960	0.022	0.960	0.960	0.960
7	PHOG	0.780	0.089	0.830	0.780	0.804
8	Simple Color	0.940	0.033	0.940	0.940	0.940

When random forest and JRIP classifiers were used on pothole datasets acquired in the same bright light conditions, a similar trend was observed, with the auto colour classifier recording the best performance with 98% TPR, about 2% FPR, 96% precision, 98% recall, and 0.97 F-measure for the random forest classifier, as shown in Table 5. When the JRIP classifier was applied to the acquired pothole images in bright light, the simple colour performed best with 96% TPR, about 3% FPR, 94% precision, 96% recall, and 0.95 F-measure, closely followed by the autocolor with about 0.9 F-measure and about 5% FPR, and 90% each for TPR, precision, and recall (See Table 6). As a result, it is inferred that either the Auto colour or the simple colour is more suitable for classifying potholes in bright light environments using the JRIP classifier.

Table 5. Summary of Bright Light Condition from Acquired Images for Random Forest Classifier

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	0.980	0.022	0.961	0.980	0.970
2	Binary	0.980	0.114	0.907	0.980	0.942
3	Edge Detection	0.920	0.044	0.920	0.920	0.920
4	FCTH	0.840	0.111	0.808	0.840	0.824
5	Gabor	0.880	0.033	0.936	0.880	0.907
6	J-PEG Color	0.960	0.033	0.941	0.960	0.950
7	PHOG	0.900	0.078	0.865	0.900	0.882
8	Simple Color	0.960	0.033	0.941	0.960	0.950

Table 6. Summary of Bright Light Condition from Acquired Images for JRip Classifier

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	0.900	0.056	0.900	0.900	0.900
2	Binary	0.960	0.386	0.738	0.960	0.835
3	Edge	0.700	0.178	0.686	0.700	0.693
4	FCTH	0.900	0.156	0.763	0.900	0.826
5	Gabor	0.920	0.133	0.793	0.920	0.852
6	J-PEG Color	0.920	0.067	0.885	0.920	0.902
7	PHOG	0.820	0.133	0.774	0.820	0.796
8	Simple Color	0.960	0.033	0.941	0.960	0.950

4.3. Hazy Light Condition Using Acquired Images using One-Rules (One R) Classifier

This section investigates the efficacy of various feature extractor filters using a one-R classifier that has been demonstrated to be the most effective for classifying pothole anomalies under Hazy conditions [9]. When using the one-R classifier, the performance accuracy of all of the tested filters decreased significantly, as shown in Table 7. This is due to the low visibility (poor lighting) at the time such images were captured. Table 7 shows that the J-PEG colour filter performed the best, with roughly 90% sensitivity, 17% FPR, 75% precision, 90% recall, and 0.82 F-measure. As a result, its applicability in pothole classification under hazy light conditions is inferred. Furthermore, we discovered that the performance of the simple colour and edge detection filters, which generated comparable results in almost all case scenarios, was closely followed. TPR and recall of 74%, FPR of about 28%, Precision of 60%, and F-Measure of 0.66 (see Table 7), implying their possible application for pothole assessment in foggy illumination situations.

Table 7. Summary of Hazy Light Condition from Acquired Images for One R Classifier

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	0.480	0.022	0.923	0.480	0.632
2	Binary	0.773	0.208	0.531	0.773	0.630
3	Edge Detection	0.740	0.278	0.597	0.740	0.661
4	FCTH	0.740	0.289	0.587	0.740	0.655
5	Gabor	0.700	0.144	0.729	0.700	0.714
6	J-PEG Color	0.900	0.167	0.750	0.900	0.818
7	PHOG	0.540	0.367	0.450	0.540	0.491
8	Simple Color	0.740	0.278	0.597	0.740	0.661

4.4. Dim Light Condition Using Acquired Images using Random Forest Classifier

The Random Forest classifier has been shown to be the most effective in classifying collected images in dim light conditions [9]. As a result, the classifier's performance was assessed using several feature extraction filters. With around 88% TPR, 60% FPR, 85% precision, 88% recall, and 0.86 F-measure, while using the autocolor filter that fared the best in terms of TPR, FPR, precision, recall, and F-measure. This performance is closely followed by the FCTH filter, which has about 83% TPR, 5% FPR, about 87% precision, 80% recall, and 0.83 F- Measure. This observed performance could be attributed to its distinct computational strategy, which aids in detecting image boundaries (borders) even in low-light environments with shadows. As a result, in dim-light settings, either the auto colour or the FCTH filter is preferred as a feature extractor for pothole classification using a random forest classifier. Throughout the majority of the studies, the Pyramid Histogram of Gradients performs the worst. This is because the algorithm's operational procedures require that the distance between two PHOG image descriptors describe the amount to which the images include comparable forms and correspond spatially.

Table 8. Summary of Dim Light Condition from Acquired Images for Random Forest Classifier

S/N	Filters	TPR	FPR	Precision	Recall	F-Measure
1	Auto Color	0.875	0.060	0.854	0.875	0.864
2	Binary	0.545	0.125	0.571	0.545	0.558
3	Edge Detection	0.550	0.110	0.667	0.550	0.603
4	FCTH	0.825	0.050	0.868	0.825	0.846
5	Gabor	0.825	0.070	0.825	0.825	0.825
6	J-PEG Color	0.725	0.090	0.763	0.725	0.744
7	PHOG	0.500	0.140	0.588	0.500	0.541
8	Simple Color	0.800	0.050	0.865	0.800	0.831

5. Conclusion

This research investigates the use of several feature extractor filters for pothole classification by different machine learning classifiers under bright, hazy, and dim light circumstances. The purpose of this investigation was to find the best-performing image feature extractor for pre-processing raw pothole images under varying environmental circumstances. This is part of a larger effort to create a comprehensive real-time road anomaly detection and classification system for use in both manned and autonomous vehicles. According to our findings, the camera resolution employed during data gathering has a substantial impact on the overall performance of the classifier because it directly affects the feature extraction stages prior to classification, particularly in bright light settings. It was revealed that FCTH or simple colour is better suited for improving pothole classification accuracy using J48 classifier, and that Auto colour or simple colour is better suited for classifying potholes using random forest or JRIP classifier. Furthermore, the JPEG filter is better suited for usage with a one-R classifier for pothole classification in Hazy light. In addition, under dim-light settings, the auto colour filter outperforms competing filters that use the Random Forest classifier. As a result, feature extraction and pothole classification are influenced by the time of day, external weather conditions, and image data capture equipment. In the future, the use of affine data augmentation and Generative Adversarial Networks to improve class-imbalance, avoid overfitting, and build scenarios for varied angles of obtained images will be investigated. Furthermore, unmarked bumps, fractures, and rutting will be identified, and the research will serve as a template for the development of a strong real-time road surface condition monitoring and anomaly detection system.

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