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Crack detection based on mel-frequency cepstral coefficients features using multiple classifiers

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ABSTRACT

Crack detection plays an essential role in evaluating the strength of structures. In recent years, the use of machine learning and deep learning techniques combined with computer vision has emerged to assess the strength of structures and detect cracks. This research aims to use machine learning (ML) to create a crack detection model based on a dataset consisting of 2432 images of different surfaces that were divided into two groups: 70% of the training dataset and 30% of the testing dataset. The Orange3 data mining tool was used to build a crack detection model, where the support vector machine (SVM), gradient boosting (GB), naive Bayes (NB), and artificial neural network (ANN) were trained and verified based on 3 sets of features, mel-frequency cepstral coefficients (MFCC), delta MFCC (DMFCC), and delta-delta MFCC (DDMFCC) were extracted using MATLAB. The experimental results showed the superiority of SVM with a classification accuracy of (100%), while for NB the accuracy reached (93.9%-99.9%), and (99.9%) for ANN, and finally in GB the accuracy reached (99.8%).

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1. INTRODUCTION

Every year, huge financial resources are allocated to purchase a variety of tools to assess and detect cracks in crucial infrastructure elements such as roads, bridges, buildings, dams [1]. Evaluating cracks, as a form of damage to infrastructure, is crucial as it contributes to the development of maintenance mechanisms. However, current methods for automatic crack detection mostly rely on expensive equipment with costly maintenance requirements [2]. In concrete construction, for example, crack is one of the most common damages and is detected through regular visual inspections, as it is limited to easily accessible locations in the concrete structure [3]–[5]. Recently, the use of image processing techniques and deep learning methods has emerged to detect cracks in various surfaces. Convolutional neural networks (CNNs) have high accuracy and effective learning capabilities for image classification. CNN-based automatic crack detection systems developed for pavements provide robust and reliable results for identifying damages such as cracks in concrete [6]–[8].

Hoang and Nguyen [9] adopted a model to train and validate machine learning algorithms such as support vector machine (SVM), artificial neural network (ANN), and random forest (RF). The study used datasets of pavement crack and according to the results, SVM had the highest classification accuracy rate (87.50%), followed by RF (70%), ANN (84.25%), and SVM (87.50%), the results may benefit inspectors and transportation authorities from this automated method. Athanasiou *et al.* [10] introduced a multiclass classification model that provides damage level estimations for cracked reinforced concrete elements and was trained using the parametric research findings as training data. Using well-defined and idealized two-dimensional pure shear stress loading conditions, experimental data of reinforced concrete shell components is used to train the classifier. For training, 119 images from reinforced concrete shell fracture patterns are included in the dataset. Achieving an overall test accuracy of 89.3%, the multifractal features successfully transform the geometry of the fracture patterns into useful information about the level of damage.

In another study using unmanned aerial vehicles, this research attempts to improve automation in infrastructure inspection by creating a machine learning-based model for identifying fractures on concrete surfaces. Using a deep learning convolutional neural network image categorization technique, the model considers several factors, including humidity, surface quality, and lightness. A transfer-learning approach was employed with a dataset including 3,500 images. When the accuracy of the model was assessed, the best result was an accuracy of 92.27%, demonstrating the ability of deep learning to identify concrete fractures [11]. The results of the research experiment presented by Silva and Lucena showed that the proposed CNN network is capable of classifying data with a high degree of accuracy. All proposed CNNs have an overall classification accuracy of more than 94%. The size of the receptive field has little effect on classification accuracy, according to our examination of the accuracy and training time of these neural networks. However, CNNs with smaller receptive field sizes need longer training time than others [12].

Hoang and Nguyen [13] presented work to increase the accuracy of pavement fracture classification by combining machine learning and image processing. It extracts characteristics from digital images using methods including median filter (MF), steerable filter (SF), and projective integral (PI). Six machine-learning techniques are applied to a dataset of 1,500 images with five class labels. The most competent models are the least squares support vector machine (LSSVM) and SVM, according to the results, with LSSVM performing somewhat better. LSSVM and SVM had overall classification accuracy rates of 92.62% and 91.91%, respectively. Ahmadi *et al.* [14] proposed an integrated model for feature extraction, crack classification, noise reduction, and picture segmentation. The hybrid model outperforms other models with an overall accuracy of 93.86% by utilizing heuristic algorithms, the Hough transform approach, and other classification models such as neural networks, SVM, decision trees, KNN, and bagged trees.

Praticò *et al.* [15] created a supervised machine learning (SML) based approach for determining and categorizing the structural health status (SHS) of various fractured road pavements, using vibroacoustic signature analysis. The proposed approach addresses the absence of existing methods for identifying surface defects and failures by successfully associating a distinct vibroacoustic signature to a differentially cracked road pavement. The accuracy was achieved using multiple machines learning classifiers, including MLP=91.8%, CNN=95.6%, RFC=91.0%, and SVC=99.1%. Müller *et al.* [16] demonstrated that linear classifiers are inadequate for surface crack detection that linear classifiers are inadequate, since non-linear, low-complex feed-forward network designs when paired with a considerable texture feature subset may attain classification accuracies of 99%. The difference and novelty in the work presented in our research paper lies in the use of new features to detect cracks in surfaces based on converting images into signals and then extracting mel-frequency cepstral coefficients (MFCC), features from them. This work is distinguished by the fact that it combines the use of Orange3 data mining techniques and the MATLAB program to build a model capable of detecting cracks in surfaces by training several machine learning classifiers, where the results demonstrated the superiority of the proposed model over its counterparts when comparing the results with what was reported in the literature.

2. METHOD

There are many studies in published literature that rely on image processing and deep learning to detect and evaluate cracks in surfaces. The current study aims to apply a new (ML) model to detect cracks in surfaces as shown in Figure 1. Initially, a registered dataset was obtained from Kaggle [17], which consists of 2,432 images of different surfaces. After that, the MATLAB program [18] was used to pre-process these images, and then the images were converted into signals from which the MFFC, DMFCC, and DDMFCC features were extracted, which are frequency-dependent features. These features were then fed to the Orange 3 data mining tool [19], after a classification model was built from four basic algorithms SVM, gradient boosting (GB), naive Bayes (NB), and ANN for crack detection.

In this work, the dataset was divided into two groups: 70% of the training dataset and 30% of the testing dataset, and due to the huge number of images (2,432) in the dataset, we were able to obtain a satisfactory result, taking into consideration, that 10-fold cross-validation was therefore used. Once the trained model was built, we assessed the dataset in terms of accuracy, sensitivity, precision, and F-measure. The performance of the trained classifiers in the proposed model was then evaluated using the confusion matrix. Additionally, the results were compared to determine which machine learning model had the highest performance metrics. Figure 2 shows the training model using Orange3.

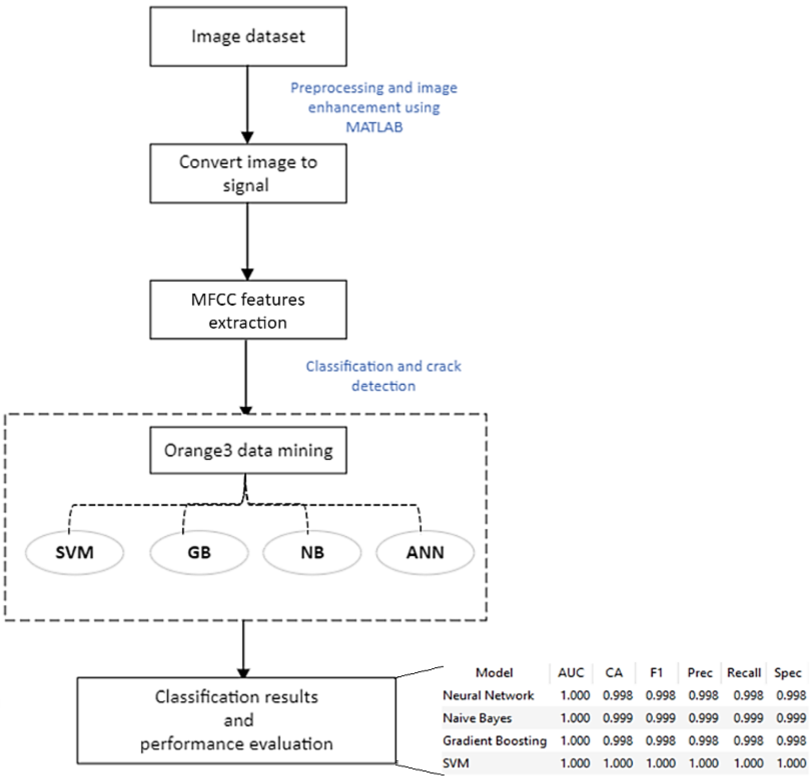


Figure 1. Crack detection model architecture

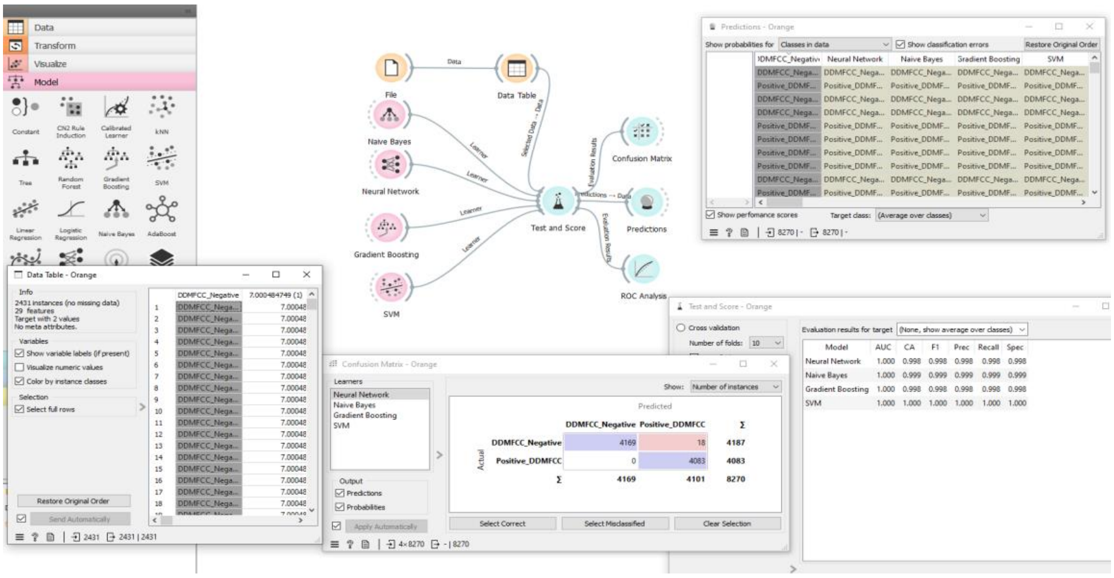
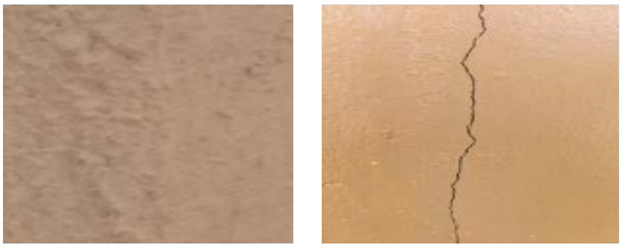


Figure 2. Classification model using Orange 3

2.1. Dataset

The dataset of 2,432 images was sourced from the Kaggle platform, where Omoebamiji Oluwaseun, a civil engineering student, selected images from the Nigerian Army University Biu in Borno State, Nigeria, for his senior thesis. A smartphone was used to capture images of subjects that were below the usual window height, and a DJI Mavic 2 Enterprise drone was used to capture the footage above. 227×227 pixels was the final size of the dataset in RGB and JPEG format [17]. A sample of these images is shown in Figure 3, where these images are divided into two groups: the first represents images of surfaces without cracks, as shown in Figure 3(a), and the other represents images of surfaces with cracks, as shown in Figure 3(b).

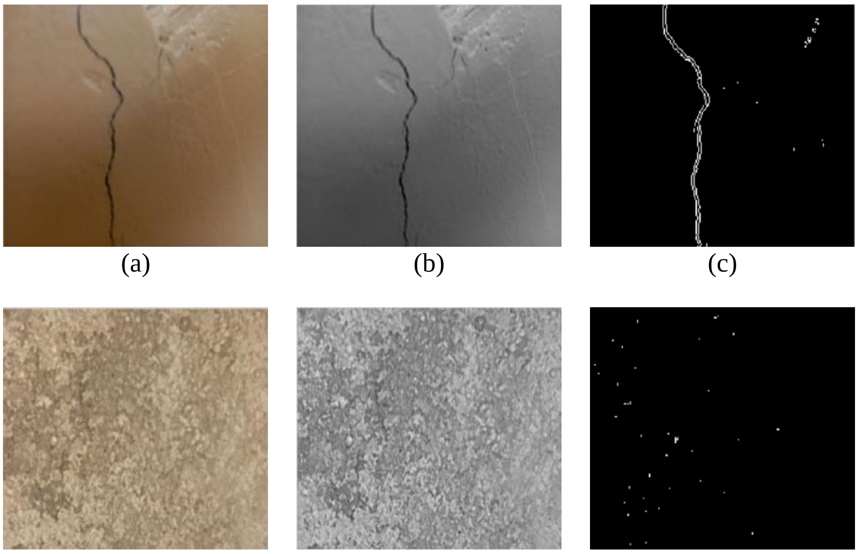


(a) (b)

Figure 3. Sample of Image dataset (a) surface without cracks and (b) cracked surface [17]

2.2. Features extraction

Many methods have been used in literature to extract features from images containing cracks to reduce the number of resources required. Feature extraction is the process of extracting the visual components of an image [20]–[23]. In other words, features are pieces of data needed to solve certain problems and convey important aspects of images. In computer vision, data mining, image retrieval, and image processing, feature extraction is a crucial step [24], [25]. This paper proposes a new method based on preprocessing techniques, such as normalization, thresholding, binarization, and application several filters were used, including the Median filter and Prewitt edge detection using MATLAB to prepare the images to extract MFCC, DMFCC, and DDMFC features after converting all images to signals. Figure 4 shows the image enhancement process done by MATLAB starting by loading the original image shown in Figures 4(a), and 4(d) then the enhancement process carried out by converting the image to grayscale as appeared in Figures 4(b) and 4(e) followed by several enhancement steps until reached the final stage, after which the image is converted into a signal in preparation for extracting MFCC features. Figures 4(c), and 4(f) show the final stage in the image enhancement process.



(a) (b) (c)

(d) (e) (f)

Figure 4. Image enhancement process (a) original image with crack, (b) grayscale version of the image, (c) the final version of the image is ready for feature extraction, (d) original image without crack, (e) grayscale version of the image, and (f) the final version of the image is ready for feature extraction

2.2.1. Mel-frequency cepstral coefficients

The MFCC technique for extracting features based on the frequency domain is considered one of the most effective techniques for signal processing, as the frequency bands are distributed based on the mel-scale [26], [27]. The proposed model is based on several steps as described in Figure 5 starting by converting the cracks images into signals and then segmenting them into a set of overlapping frames. The number of frames in this work is 40 of N=1500 samples, with consecutive frames separated by L=256 samples where the adjacent frames overlap with the N-L samples, which is about 65%.

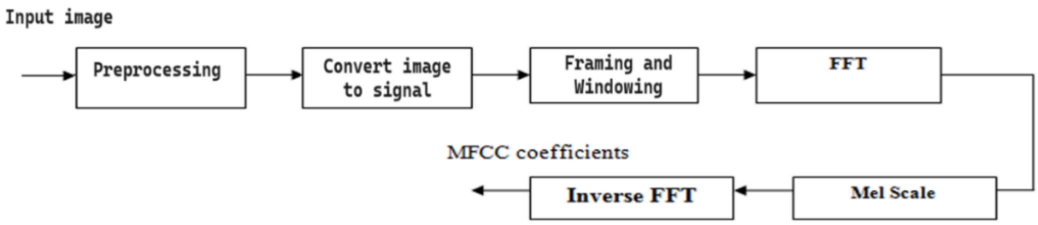


Figure 5. Steps of MFCC feature extraction

In the stage following framing, windowing is done by using a hamming window, then taking the discrete Fourier transformation (DFT), the resulting spectrum of the (DFT) is given as input to a mel-scale filter bank that consists of 20 filters. In the next step, as shown in Figure 6 the MATLAB code describes the process of multiplying the resulting coefficients of the Fourier transformation by the corresponding filter gain to produce a mel-spectrum using one of the most common formulas for converting (f) in hertz into (f_{mel}), as described in (1) [28], [29].

$$f_{mel} = 2595\ log_{10}\ (1 + \frac{f}{700}) \tag{1}$$

```
%--------------------------------------------------------
f=(Fs/2)*linspace(0,1,NFFT/2+1);
fmel=2595*log10(1+f./700); % CONVERTING TO MEL SCALE
fmelmax=max(fmel);
fmelmin=min(fmel);
filbandwidthsmel=linspace(fmelmin,fmelmax,No_Filter+2);
filbandwidthsf=700*(10.^(filbandwidthsmel/2595)-1);
fr_all=(abs(fft(y_framed',NFFT))).^2;
fa_all=fr_all(1:(NFFT/2)+1,:)';
filterbank=zeros((NFFT/2)+1,No_Filter);
```

Figure 6. Script of mel-spectrum coefficients computing using MATLAB

The inverse Fourier transformation (IFT) applied to the transformed mel-frequency coefficients produced a set of MFCC campestral coefficients which are referred to as static features, and to extract extra information about the dynamics features of the signal the first-order derivative (delta-MFCC), and the second order (delta–delta-MFCC) are computed [30]–[32].

2.3. Classification methods

In data mining and machine learning, classification is one of the critical functions of software engineering and pattern recognition, and researchers recommend using ensemble classification methods because of their more reliable and accurate results, which are essential for decision support systems. Machine learning is commonly used to classify crack images into specific categories. Classification methods are used to group input data into distinct categories for training and testing purposes. In this work, the classification model was made using the data mining tool Orange 3, which is a package of machine learning and data mining tools [33]. The classification process was carried out using four basic algorithms SVM, GB, NB, and ANN.

2.3.1. Gradient boosting

Gradient boosting is an advanced prediction method that solves infinite-dimensional convex optimization problems, creating linear combinations of elementary predictors, typically decision trees, to create a model [34]–[36]. As shown in Figure 7, by combining more trees and fixing errors in its prior base models, the gradient-boosting tree approach can increase prediction accuracy. Gradient boosting trees (GBT) models are described as (2):

$$Fm(x) = \sum_{m=1}^{M} \gamma_m \ h_m(x) \tag{2}$$

where $h_m(x)$ denotes weak learners and γ_m denotes the learning rate [37].

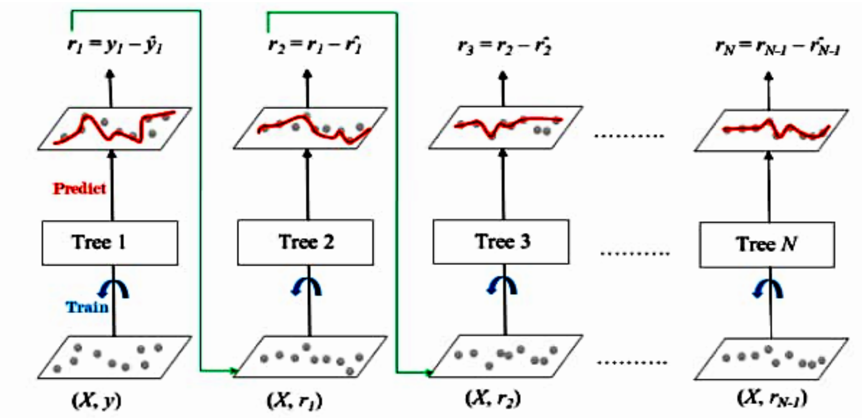


Figure 7. Architecture of gradient boosting [38]

2.3.2. Naive Bayes

A widely used data mining approach that assumes attribute independence is naïve Bayes, to reduce this, high-quality data that is newly collected is generated using feature transformation and attribute selection algorithms [39]. The goal of strong independence in features in Bayes (particularly in naïve Bayes) is that a feature in a data set is unrelated to the presence or absence of other characteristics in the same data set. The Bayes theorem, whose general formula is shown in (3), serves as the foundation for Bayes predictions. Whereas, if evidence is provided, $P(H|E)$ is the ultimate probability of a conditional probability that a hypothesis H s. E takes place. If evidence is not provided, $P(E|H)$ the likelihood that E evidence will materialize will influence the H. Hypothesis (H) The initial probability (priori) of hypothesis H holds in the absence of any supporting data, where $P(E)$: The likelihood that proof E happens first (priori), independent of any other evidence or hypothesis [40], [41].

$$P(H|E) = \frac{D(H|E) * P(H)}{P(E)} \tag{3}$$

2.3.3. Artificial neural network

Neural networks consist of building blocks that resemble neurons and are connected by connections that may be changed by algorithms or learning processes. To assess its level of activity, every unit separately integrates data from connections [42], [43]. A linear or nonlinear function of activation is the unit response. Eigenvectors and eigenvalues are fundamental ideas in linear algebra and are used to examine linear units. In a neural network, there are an arbitrary number of bias nodes, always one in each layer. However, it consists of three layers: The input layer, hidden layer, and output layer as demonstrated in Figure 8.

2.3.4. Support vector machine

SVM is a supervised machine learning technique that may be applied to regression or classification tasks and involves both linear and non-linear data [44]. On the other hand, it is a statistical learning approach with benefits like theoretical foundation, global optimization, sparsity, nonlinearity, and generalization. It assigns objects to two possible classes using the greatest distance between hyperplanes, dividing text into two classes (0,1). Figure 9 shows the SVM schematic model.

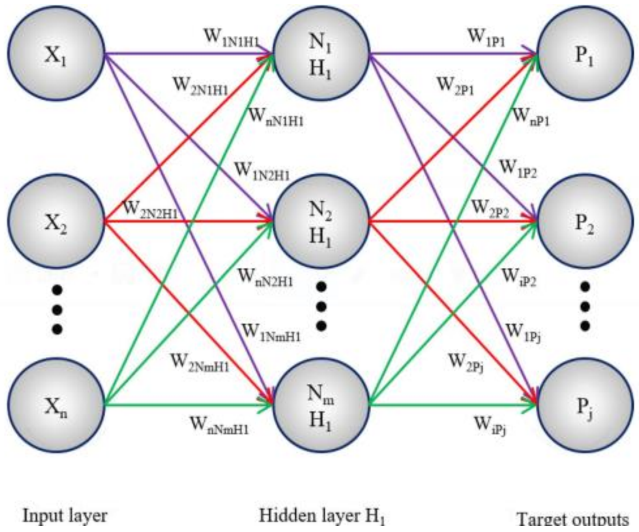


Figure 8. Architecture of neural network [45]

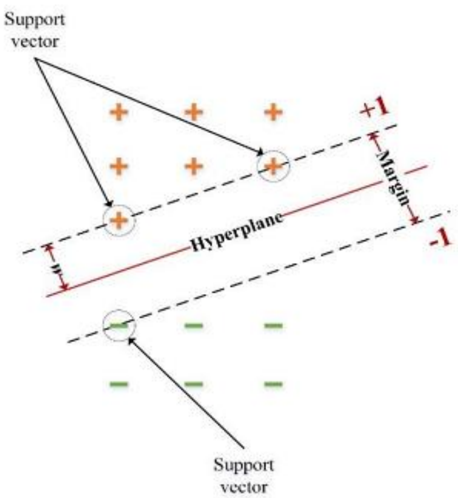


Figure 9. SVM schematic model [46]

3. RESULT AND PERFORMANCE EVALUATION

Analysis of the effectiveness and predictive power of the proposed model is important after verifying the main model assumptions. As a result, the evaluation metrics were applied to determine the relevance of the suggested models [47]. For this purpose, the confusion matrix is a helpful tool for determining how well the algorithm performed. It calculates the quantities of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) in the accuracy rate computations [48]. The efficiency of the proposed model was examined using F-measure, accuracy, precision, and sensitivity as described in Table 1.

Table 1. Classifier's performance evaluation [49]

Accuracy	Sensitivity	Precision	F-measure
$\frac{TP+TN}{TP+TN+FP+FN}$	$\frac{TP}{TP+FN}$	$\frac{TP}{TP+FP}$	$\frac{2*\text{Precision}*\text{Sensitivity}}{\text{Precision}+\text{Sensitivity}}$

Several methods were employed to classify the dataset, including GB, NB, SVM, and ANN. The classification results showed that SVM outperforms with an accuracy of 100% for all performance measurements. Accuracy, accuracy sensitivity, and F-measure according to DMFCC and DDMFC features. For GB, the classifier achieved (CA) of 99.8% for all performance measurements for all features. However, in NB the (CA) reached 99.0% for both DMFCC and DDMFCC but with MFCC features, NB achieved (CA) 93.9%. On the other hand, ANN had scores of (CA) 99.9%, 99.8%, and 99.8%, according to MFCC, DMFCC, and DDMFCC respectively. Table 2 depicts the classifier's performance of crack detection and classification using the Orange 3 tool, while Figure 10 shows a comparative analysis of different classifiers' performances. On the other hand, the result accuracy demonstrated in this paper is shown to be superior to previous research. As in research study [9], the accuracy rate was 87.50%, in research study [10], the accuracy rate was 89.3%, and in research study [11] the accuracy rate was 92.27%. However, in this study, the accuracy rate is around 100%.

Table 2. Comparison of ML performance classifiers on the training dataset

	SVM			Gradient Boosting		
	MFCC	DMFCC	DDMFCC	MFCC	DMFCC	DDMFCC
Accuracy	0.999	1.000	1.000	0.998	0.998	0.998
Sensitivity	0.999	1.000	1.000	0.998	0.998	0.998
Precision	0.999	1.000	1.000	0.998	0.998	0.998
F-measure	0.999	1.000	1.000	0.998	0.998	0.998
	Naive Bayes			Artificial Neural Networks		
	MFCC	DMFCC	DDMFCC	MFCC	DMFCC	DDMFCC
Accuracy	0.939	0.999	0.999	0.999	0.998	0.998
Sensitivity	0.939	0.999	0.999	0.999	0.998	0.998
Precision	0.945	0.999	0.999	0.999	0.998	0.998
F-measure	0.939	0.999	0.999	0.999	0.998	0.998
Accuracy	0.939	0.999	0.999	0.999	0.998	0.998

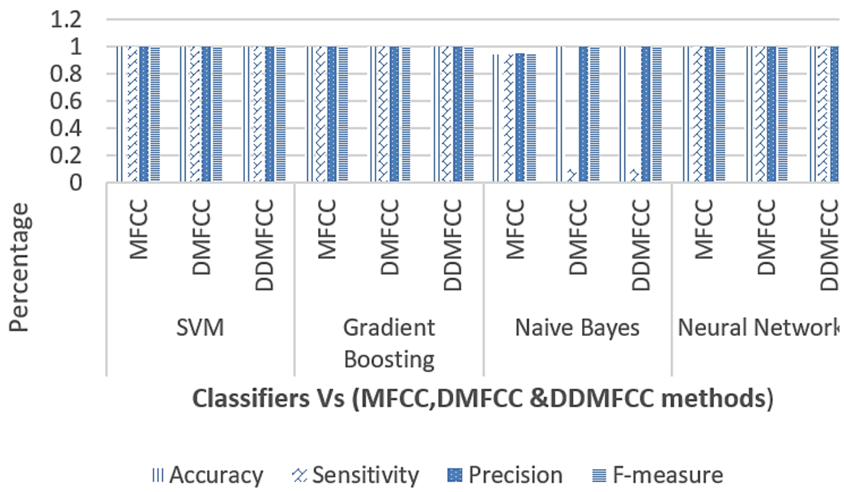


Figure 10. Comparative analysis of different classifiers' performances

4. CONCLUSION

This work explores and compares several classification methods to detect and classify cracks for different surfaces for a dataset of 2432 images obtained from Kaggle. This study relied on the use of pre-processing of surface images using MATLAB. Where the results demonstrated the effectiveness of the features extracted from the images in classifying surfaces that contain cracks from others. The results showed that cracks in a concrete or pavement structure could be found through MFCC, DMFCC, and DDMFCC feature extraction techniques used to feed the Orange 3 data mining tool. A comparative analysis was conducted to find the best classifier among four techniques NB, GB, SVM, and ANN for crack detection. Finally, an analysis was conducted of the results of the classifiers used in this work, where the performance comparison showed that the SVM classifier obtained the best accuracy of 100%.

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