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Pavement Crack Classifiers: A Comparative Study

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Abstract: Non Destructive Testing (NDT) is an analysis technique used to inspect metal sheets and components without harming the product. NDT do not cause any change after inspection; this technique saves money and time in product evaluation, research and troubleshooting. In this study the objective is to perform NDT using soft computing techniques. Digital images are taken; Gray Level Co-occurrence Matrix (GLCM) extracts features from these images. Extracted features are then fed into the classifiers which classifies them into images with and without cracks. Three major classifiers: Neural networks, Support Vector Machine (SVM) and Linear classifiers are taken for the classification purpose. Performances of these classifiers are assessed and the best classifier for the given data is chosen.

Keywords: Gray Level Co-occurrence Matrix (GLCM), linear classifier, neural networks, Support Vector Machine (SVM)

INTRODUCTION

Non destructive testing is presently the most efficient and cost effective technique used to identify the existence of damage without causing a minute harm to the testing product. Huge growth in the field of automated crack detection, where the digital image of the test material is sufficient to detect the exact location of the crack in the material. [automated] Abundance of images may affect the efficiency of the method as the images may contain both positive and negative results for the occurrence of cracks. Hence soft computing techniques are used to classify images with and without cracks; positive outcomes are fed into to the detector to accurately detect the miniature cracks present. Santhi *et al*. (2012) Classifiers are analysied based on the performance; best suited classifier for the required application is chosen to classify pavement images for the occurrence of cracks. This study provides a comparison between several important classifiers for classifying pavement images. A range of well-known performance metrics were used for this comparison, thus helping in identifying the paramount classifier.

LITERATURE REVIEW

In this section, a brief description about various methods for crack classification and detection is presented. Until now, various studies and researches have been done in this field with varying degree of success.

Yong *et al*. (2010) proposed a similar method in classification of cracks using six GLCM features and classifying them by SVM.

Mohamed and Stephen (1993) used parameters of gray level histograms and classified them into cracks and non-cracks using Multi Linear Feed forward neural network. Mustaffar *et al*. (2008) proposed a different approach in classification of cracks by using 3D-Digital Elevation Model (DEM) parameters.

Many other methods have been proposed such as wavelet transform by Zhou *et al*. (2005) and fuzzy set theory (Cheng *et al*., 2001).

In this study, we use GLCM features for classification purpose. And these results are compared using different performance metrics.

MATERIALS AND METHODS

Pavement crack and non-crack images were collected from different online resources in which 70% of images were used for training and remaining 30% for testing purposes. The proposed model is validated and results are discussed.

Figure 1 represents the flow diagram which describes the method of work flow in this study.

Image acquisition: Images which are used in the study are acquired from various search engines randomly, depending on the requirements of the classifiers. Images are obtained such that it can be used to train the classifiers in an efficient manner.

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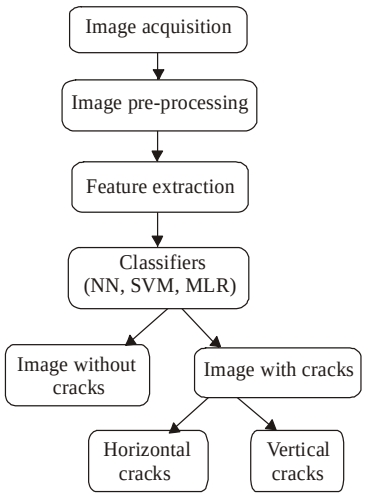

Fig. 1: Proposed work flow

Image pre-processing: The obtained images are pre-processed and made feasible such that it can be provided as input to the classifiers. In this phase, images are processed to get rid of noise and other unnecessary information and then fed into the feature extractor.

Feature extraction: Gray Level Co-Occurrence matrix technique is based on manipulating the gray levels of the images. More number of gray levels provide accurate analysis but at the cost of computational speed. GLCM is a square matrix to which the given image is reduced. It can be defined as: "a two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship." Renzetti and Zortea (2011). Using this GLCM matrix, 22 features are calculated. And these features are as follows:

- Autocorrelation
- Contrast
- Correlation Matlab
- Correlation
- Cluster prominence
- Cluster shade
- Dissimilarity
- Energy
- Entropy
- Homogeneity Matlab
- Homogeneity
- Maximum probability
- Sum of squares variance
- Sum average
- Sum variance
- Sum entropy
- Difference variance
- Difference entropy
- Information measure of correlation1
- Information measure of correlation2
- Inverse difference normalized
- Inverse difference moment normalized

Classifiers:

Neural networks: Neural network comprises of elements working in parallel.Learning process can be majorly classified into three categories: Supervised learning, Unsupervised learning and Reinforcement learning. Supervised learning technique is used for pattern recognition and for regression. In Unsupervised learning, the weights are learned and the biases are changed based on the response to network inputs only, as no target outputs are available. Reinforcement learning technique is a process in which the data is not provided and it is obtained due to the interaction with the environment. In this study supervised learning is used and its training algorithm is BPN (Back Propagation Neural Network).

Linear classifier: The Multiple Regression Analysis (MRA), analyzes the relationship between metric dependent variables and metric independent variable. Information obtained from the relationship improves the accuracy in predicting values for the dependent variable. There are three types of multiple regression analyzers, Standard multiple, hierarchical and statistical. Standard regression evaluates the relationships between a particular set of dependent variables and independent variables. Hierarchical regression performs the same function of standard regression, but by controlling the effects of some other independent variables on the dependent variable. Statistical regression identifies the subset of independent variables that has the strongest relationship to a dependent variable. $Y = \alpha+\beta_1 X_1+\beta_2 X_2+\beta_n X_n+e$ where, Y is the dependent variable; α is the Y-intercept; β_1, β_2 and β_n, are the slopes associated with X_1, X_2 and X_n, respectively; X_1, X_2 . . . , X_n are the values of independent variables; e is the error (Yildirim and Gunaydin, 2010).

Support vector machines: Support vector machine concept is used to analyse and recognise datasets for classification and pattern matching. Dataset is provided as input to the SVM, these data are then classified into a certain group which have similar characteristic features. SVM comes under the category of kernel method, in this method data are taken as dot products. The dot product can be replaced by a kernel function which computes a dot product in some possibly high dimensional feature space. SVM has certain advantages namely, generates non-linear decision boundaries using methods designed for linear classifiers. The use of kernel functions allows to apply a classifier to datasets which have no fixed-dimensional vector space representation. SVM has to be properly trained, as the decision it has to make relies completely on the training. Training includes how to pre-

process the data, what kernel to use and also setting the parameters of the SVM and the kernel. Improper choices may lead to severely reduced performance. Gaussian kernel, with a single parameter γ is opted. Combinations of parameter choices are checked using cross validation, the ones with highest accuracy are chosen. Finally, the parameters with highest accuracy are used for training purpose. The trained model is used for testing and classification of the data set (Ben-Hur and Jason, 2007).

EXPERIMENT AND RESULTS

In this algorithm, data sets collected from various web resources are fed into the classifier and its results are obtained.

This is followed with detection of cracks from the classified crack images. Confusion matrix, which is a specific table layout, tabulated for a supervised learning method provides visualization of the performance of an algorithm. Using this matrix, the performance metrics like accuracy, specificity and sensitivity of the different classifiers are calculated using the following formulas:

Accuracy = (TP+TN)/ (TP+FP+FN+TN)
Specificity = TN/ (TN+FP)
Sensitivity = TP/ (TP+FN)

where,
TP : Number of true positives
TN : Number of true negatives
FP : Number of false positives
FN : Number of false negatives

Here, Table 1-3 represents the Confusion Matrix of BPN, SVM and MLR classifiers, respectively. And Table 4 represents the consolidated result. Figure 2

Table 1: Confusion matrix: BPN

	Crack	Non-crack
Crack	5 (TP)	1 (FN)
Non-crack	0 (FP)	3 (TN)

Table 2: Confusion matrix: SVM

	Crack	Non-crack
Crack	6 (TP)	0 (FN)
Non-crack	0 (FP)	3 (TN)

Table 3: Confusion matrix: MLR

	Crack	Non-crack
Crack	4 (TP)	2 (FN)
Non-crack	0 (FP)	3 (TN)

Table 4: Consolidated result

	BPN	SVM	MLR
Accuracy	88.9	100	77.8
Specificity	100.0	100	100.0
Sensitivity	83.3	100	66.7

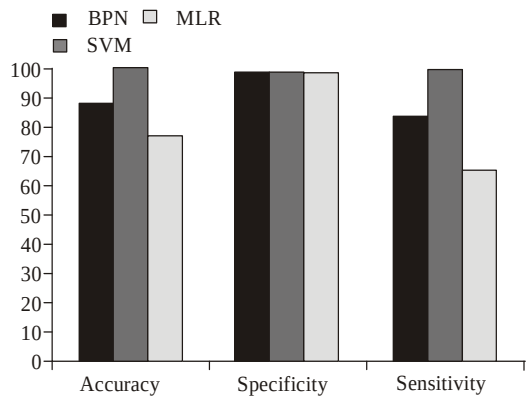

Fig. 2: Comparison graph

represents a comparison graph of the output of the three classifiers with respect to performance metrics.

CONCLUSION

The Sample images are fed into the classifiers which classify the samples into crack and non crack images. Now the non crack images need not be fed to the detectors for detection of cracks. These detectors precisely detect the location of cracks (Santhi *et al*., 2012). By doing so, the process time of the detector is fairly reduced. The performance metrics indicate that the sensitivity and the accuracy of SVM and BPN are higher than that of MLR. SVM and BPN perform far better in classification of cracks when compared to MLR for the given data set.

SVM classified 100% of the images precisely and BPN classified 90% of the images precisely. But, MLR managed to classify only 78% of the images precisely. This makes SVM and BPN more suitable for crack classification.

In future, this study can be further improved for classifying random multiline cracks. Classification of images and detection of the precise location of cracks in the image can be clubbed, making it highly useful for industrial applications (leather, metal sheets, etc…). These can be used for distress detection in pavements and buildings also.

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