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Automatic Bridge Crack Detection Model based on Convolutional Neural Network and Support Vector Machine

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Abstract: The structural integrity and dependability of bridges must be checked on a regular basis if they are to last. An essential part of bridge maintenance is the identification of bridge cracks, one of the most common forms of structural deterioration. In the literature, visual and image processing-based inspection methods are available for bridge crack detection. Out of these methods, image processing-based inspection method is superior over visual inspection method. In the image processing-based inspection method, image processing and machine learning algorithms are hybrid. In this paper, we have designed an automatic bridge crack detection model. In the pre-processing step, the image noise is removed and enhanced by deploying the wiener filter and adaptive histogram equalization algorithm. After that, two machine learning algorithms such as convolutional neural network and support vector machine are trained by pre-processing images. The machine learning algorithm is tested by inputting the random images. In the last, the predicted values of both machine learning algorithms are hybrid. The performance analysis of the proposed model is done on the standard dataset images and various performance metrics are measured for it. The simulation evaluation shows that the proposed method shows superior results over VGG19, VGG16, Resnet50, Resnet34, and CNN.

Keywords: Adaptive Histogram Equalization, Convolutional Neural Network, Crack Detection, Support Vector Machine, Wiener Filter

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1. Introduction

There are several examples of cracking in various constructions, including buildings, pavements, and bridges. Cracking is a crucial signal that maintenance is needed since it speeds up the deteriorating process. It is thus essential to conduct crack evaluations in order to protect public security [1].

There are two types of inspection methods are available for bridge crack detection. The first method is visual inspection method. When evaluating the present condition of a bridge, visual inspection is a frequent approach utilised [2]. Inspectors must be experienced and knowledgeable in order to accurately evaluate the structural integrity of a building based just on its appearance. In addition, the technique is time-consuming and prone to human error, and the locations are typically inaccessible, making it difficult to undertake regular inspections. On the other side, the second method is image processing-based method. In the image processing method, image processing and machine learning algorithms are hybrid to detect the crack. This method is superior over visual inspection method in terms of accuracy, labor cost. In the literature, convolutional neural network [3], support vector machine [4], random forest [5], and neural network [6] is successfully applied machine learning algorithms in the image processing-based methods. Out of these, convolutional neural network (CNN) and support vector machine is most preferred.

The main contribution of this paper is to design an automatic bridge crack detection model. To achieve this goal, two machine learning algorithms are taken under consideration and their output predicted values are hybrid to enhance the accuracy. Besides that, pre-processing of the crack images is done using wiener filter and adaptive histogram equalization algorithm to reduce noise and enhance the images. The simulation evaluation result shows that the proposed method achieves high values of accuracy, precision, sensitivity, and specificity, and F-score over the existing models [3] such as VGG19, VGG16, Resnet50, Resnet34, and CNN.

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The paper is organised as follows. Section 2 shows the related work in which we have explained the different algorithms deployed for the proposed method. Section 3 explains the proposed methodology is designed for crack detection. Chapter 4 shows the simulation evaluation using qualitative and quantitative analysis. Conclusion and future scope are drawn in Section 5.

2. Related Work

The proposed method has different phases in which we have deployed wiener filter, adaptive histogram equalization algorithm, and two different classifiers such as convolutional neural network and support vector machine. In this section, the detailed description of these algorithms is given.

2.1 Wiener Filter

It is based on Norbert Wiener's Wiener theory that linear least square error filters are built [7]. Linear prediction, signal restoration, echo cancellation, system identification, and channel equalisation are all examples of applications where Wiener filters play a significant role. If there is a minimum average squared distance between the output side and a desired signal, then the Wiener filter coefficients are optimized. Because of this, it is assumed that all signals in a signal chain are stationary processes in the original Wiener formulation. But if the filter coefficients are regenerated on a regular basis for each block of N signal samples, the filter becomes block-adaptive and adjusts to the average features of signals inside those blocks. Block-adaptive (or segment-adaptive) filters may be employed for signals like voice and picture that are nearly steady across a limited block of samples. As seen in Figure 1, the coefficient vector w represents a Wiener filter.

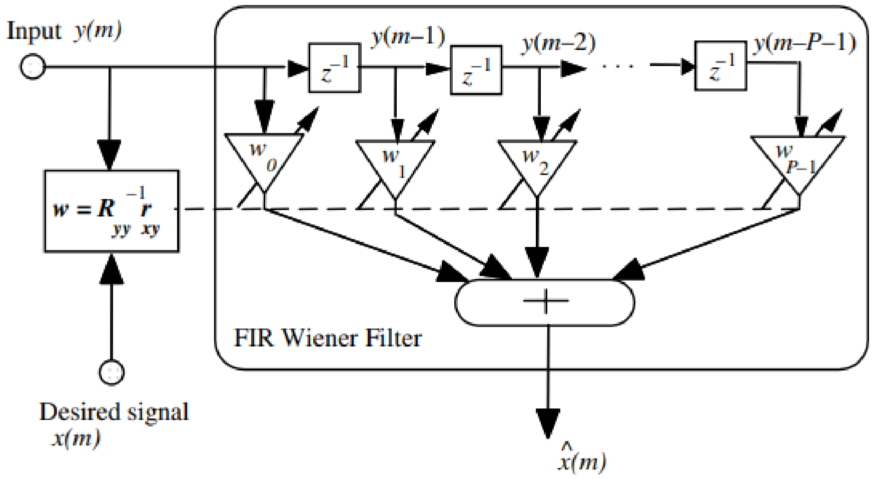

Figure 1 Wiener Filter [7]

As an input, the filter receives a signal y(m), and as an output, it generates a waveform with an estimated least mean square error (LMSE) of the intended or target waveform x. (m). Given the filter input-output connection below:

$$\hat{x}(m) = \sum_{k=0}^{P-1} w_k\, y(m-k) = \boldsymbol{w}^{\mathrm{T}} \boldsymbol{y} \qquad (1)$$

In Eq. (1), m denotes the discrete time index, y is the filter input signal, and W^T is the wiener filter coefficient vector. Equivalent forms of a convolutional sum and an internal vector product are used in Equation (1) to express the filtering operation. Error signal, e(m), is the difference between desired signal x(m) and the filter output signal $\hat{x}$ (m)

$$e(m) = x(m) - \hat{x}(m) = x(m) - \boldsymbol{w}^{\mathrm{T}} \boldsymbol{y} \qquad (2)$$

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2.2 Adaptive Histogram Equalization Algorithm

To improve the contrast of images, adaptive histogram equalization (AHE) is employed in digital image processing [8]. There are a few key differences between adaptive histogram equalisation and traditional histogram equalization. The image is divided into sections and the histogram equalisation is calculated for each segment. There are a number of histograms generated by AHE for different parts of the image. It improves the contrast and clarity of the image's borders in all distinguishable areas. Listed below are some of the algorithm's benefits.

- It calculates the HE of individual image parts.
- It keeps the image's edges sharp in certain areas.
- It improves the contrast in the immediate area.

2.3 Convolutional Neural Network

CNN (also known as ConvNet) is a deep learning architecture that does not need human feature extraction [9-11]. The number of layers in a convolutional neural network may reach the tens or hundreds, with each layer learning to recognise distinct aspects of an image. As depicted in Figure 2, a CNN has an input layer, an output layer, and several hidden layers in between.

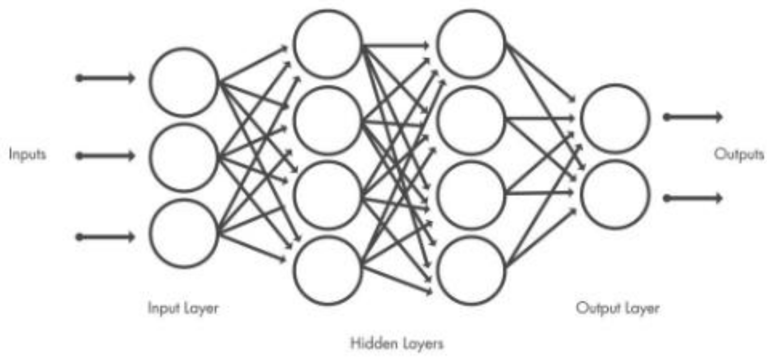

Figure 2 CNN [9]

These layers carry out actions that have the effect of changing the data in order to learn characteristics that are unique to the data. Convolution, activation or ReLU, and pooling are three of the most popular layers.

- On activate certain aspects of the input images, convolution applies a series of convolutional filters to them.
- Negative values are mapped to zero while positive values are maintained via the Rectified linear unit (ReLU), allowing for faster and more efficient training results. A term for this is activation, since only those characteristics that have been activated are carried over to the next layer.
- Pooling helps to simplify the output by conducting nonlinear downsampling, which in turn reduces the number of parameters that the network has to learn.

As these actions are done over and over again, each successive layer has a better understanding of the characteristics of the data it's processing.

2.4 Support Vector Machine

SVM, or Support Vector Machine, is a widely used Supervised Learning technique for both classification and regression [12]. However, it is mostly utilised in Machine Learning to solve Classification difficulties. A key objective of the SVM method is to find the optimal decision boundary or line that can divide n-dimensional area into categories, allowing us to quickly classify fresh data points in the future. A hyperplane is a boundary around which the optimal decisions may be made. To create the hyperplane, the SVM uses the most extreme

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points and vectors. So-called “support vectors” refer to these extreme circumstances, and the process is known as a Support Vector Machine.

3. Proposed Method

This section explains a technique for crack detection that has been suggested. The suggested technique combines the predictions of CNN and SVM algorithms in order to improve its performance. Figure 3 depicts the suggested method's flowchart. When using the suggested approach, the standard dataset of crack images is first read [13]. In order to smooth and eliminate the noise from crack photos, pre-processing utilizing the wiener filter is carried out. The image is then enhanced using an adaptive histogram equalisation method. There are other SVM techniques and a convolutional neural network for crack identification. Unlike SVM, which has a single phase of training, CNN and SVM have two. The improved images are used to train the CNN and SVM during the training phase. On the other hand, in the testing step, the created crack detection model is put to the test by entering random photos. For the final findings, a combination of CNN and SVM prediction algorithms is used. Finally, the suggested technique is subjected to a thorough qualitative and quantitative evaluation. Crack images are evaluated in a qualitative study based on their visual quality. Quantitative analysis, on the other hand, looks at numerous performance indicators including precision, accuracy, sensitivity, F-score, and specificity.

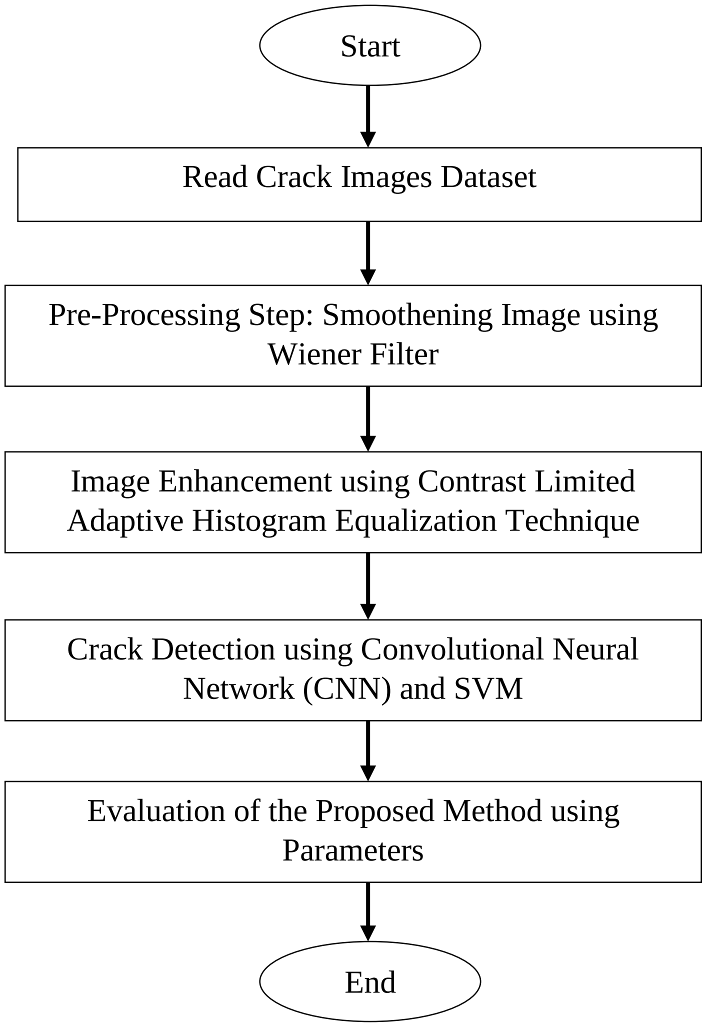

Figure 3 Proposed Methodology

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4. Simulation Evaluation

In this section, the simulation evaluation of the proposed model is given to shows its effectiveness over the existing models.

4.1 Simulation Setup Configuration

In this section, simulation setup configuration is given that are taken for the proposed model.

Table 1 Simulation Setup Configuration for the Proposed Model

Parameters	**Value**
Max Epochs	30
Initial Learn Rate	0.001
Learn Rate Drop Factor	0.1
Learn Rate Drop Period	20
No of Layer	18
Min. Batch Size	2
Input Layer	28 x 28
Conv. Filter Window size	3 x 3
No of stride	2 x 2
No of Pool Size	2 x 2
Dropout Layer Probability	0.2

4.2 Evaluation

The proposed method evaluation is done using qualitative and quantitative analysis.

4.2.1 Qualitative Analysis

In the qualitative analysis, based on the visual quality, the input and output images are compared. In the proposed model, crack images are taken as input. After that, pre-processing is done using filter and enhancement algorithms. Therefore, in the qualitative analysis, these images are compared.

4.2.2 Quantitative Analysis

In this section, various performance parameters are explained that calculated in the quantitative analysis. Table 2 shows the performance parameters [14-15].

Table 2 Performance Parameters

Parameter	Value
Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$
Precision	$Precision = \frac{TP}{TP + FP}$
Sensitivity or Recall	$Sensitivity = \frac{TP}{TP + FN}$
Specificity	$Specificity = \frac{TN}{FP + TN}$
F1-Score	$F1 - Score = 2 * \frac{Precision.Recall}{Precision + Recall}$

Note: TN = true negative, FP = false positive, FN = false negative, TP = true positive

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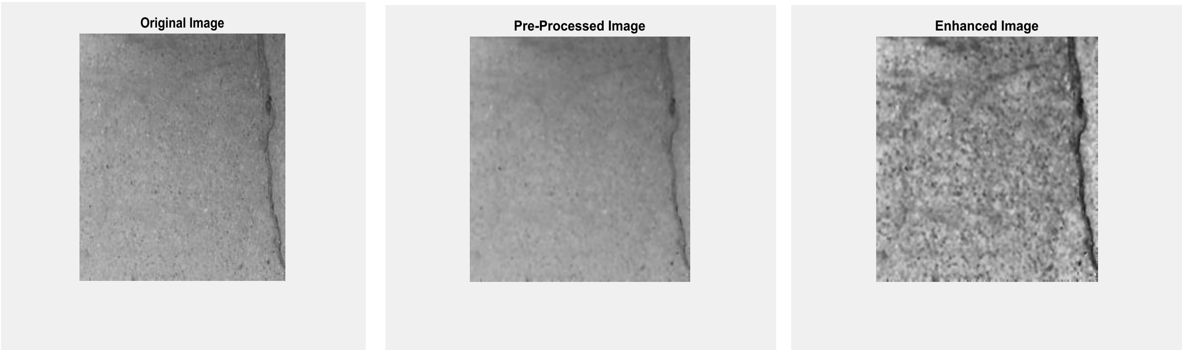
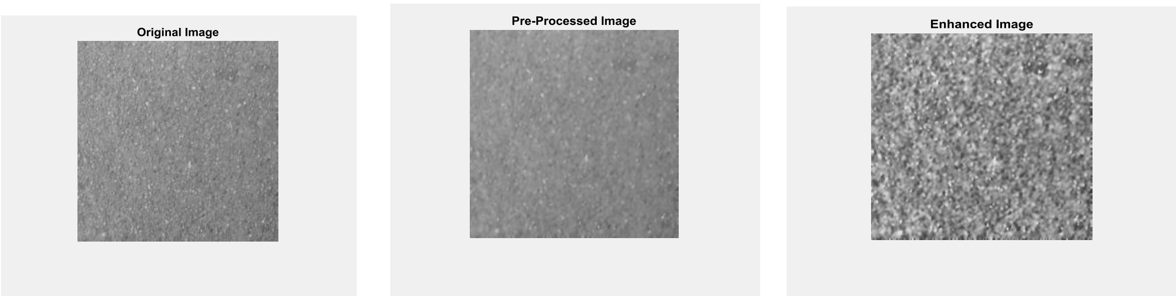
4.3 Simulation Results

In this section, simulation results of the proposed method are shown. Figure 1-2 the qualitative analysis in which original image, pre-processed image, and enhanced images are shown.



(a) (b) (c)

Figure 1 Original Image (a) Pre-Processed Image (b) Enhanced Image (c)



(a) (b) (c)

Figure 2 Original Image (a) Pre-Processed Image (b) Enhanced Image (c)

Table 2 shows the quantitative analysis of the proposed method using various parameters. The result shows that the proposed method achieves high value of accuracy, precision, sensitivity, specificity, and F1-score.

Table 5.2 Quantitative Analysis of the Proposed Method

Parameters	Values
Accuracy	0.992
Precision	1
Sensitivity	0.984
Specificity	1
F1-Score	0.9919

4.3.1 Comparative Analysis

In this section, the proposed model is compared with the existing models [3] based on various performance metrics, as explained below.

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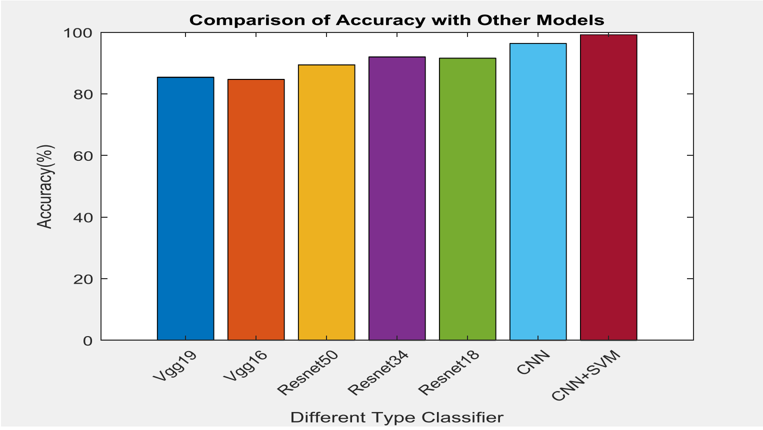

Figure 3 Comparative Analysis of Various Classifiers based on Accuracy Parameter

Figure 3 shows that the proposed method achieves highest accuracy over the existing different type of classifiers such as VGG19, VGG16, Resnet50, Resnet34, and CNN.

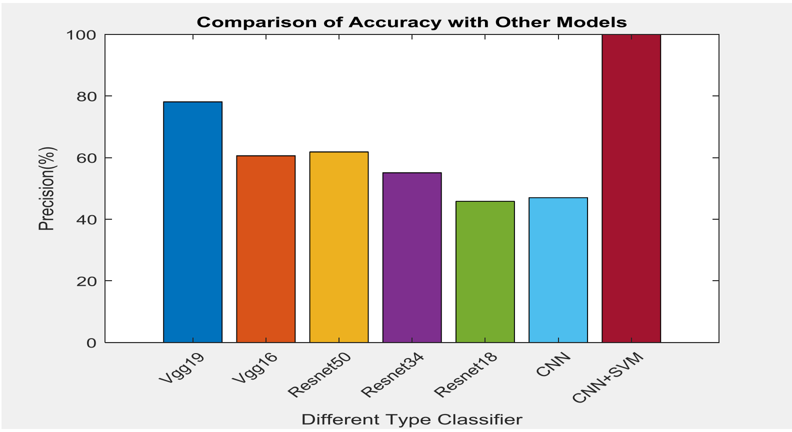

Figure 4 Comparative Analysis of Various Classifier based on Precision Parameter

Figure 4 shows that the proposed method achieves highest precision over the existing different type of classifiers such as VGG19, VGG16, Resnet50, Resnet34, and CNN.

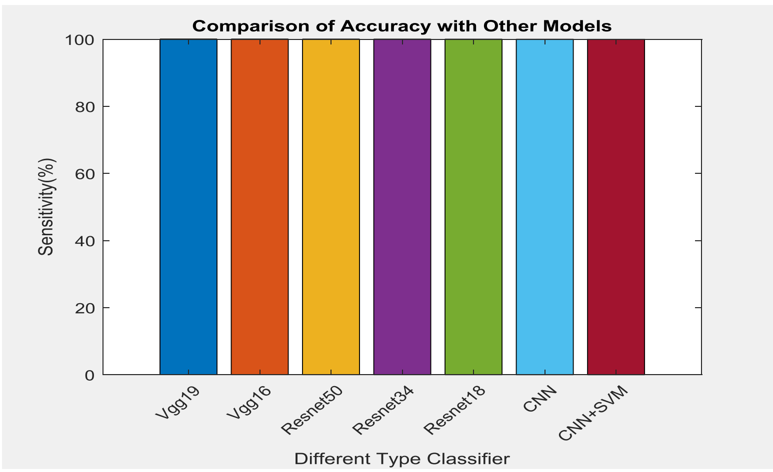

Figure 5 Comparative Analysis of Different Classifiers based on Sensitivity Parameter

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Figure 5 shows that the proposed method achieves highest sensitivity over the existing different type of classifiers such as VGG19, VGG16, Resnet50, Resnet34, and CNN.

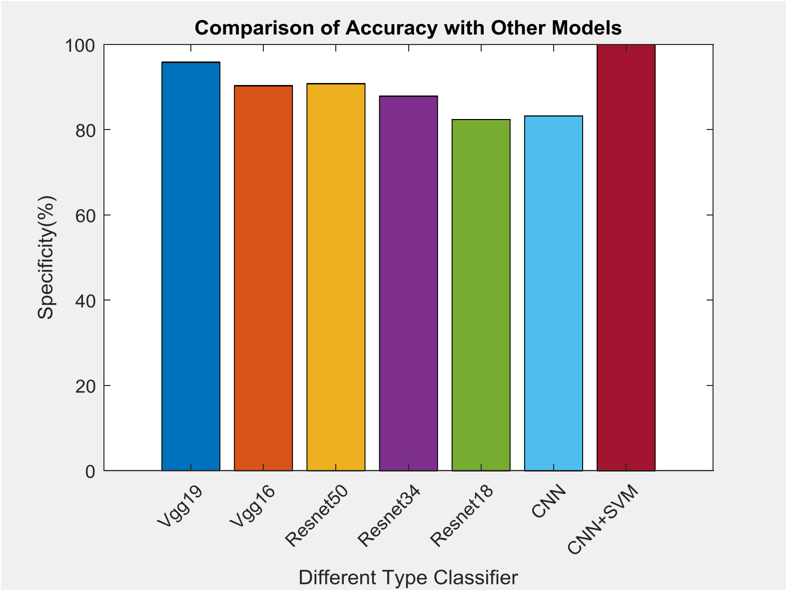

Figure 6 Comparative Analysis of Various Classifiers based on Specificity Parameter

Figure 6 shows that the proposed method achieves highest specificity over the existing different type of classifiers such as VGG19, VGG16, Resnet50, Resnet34, and CNN.

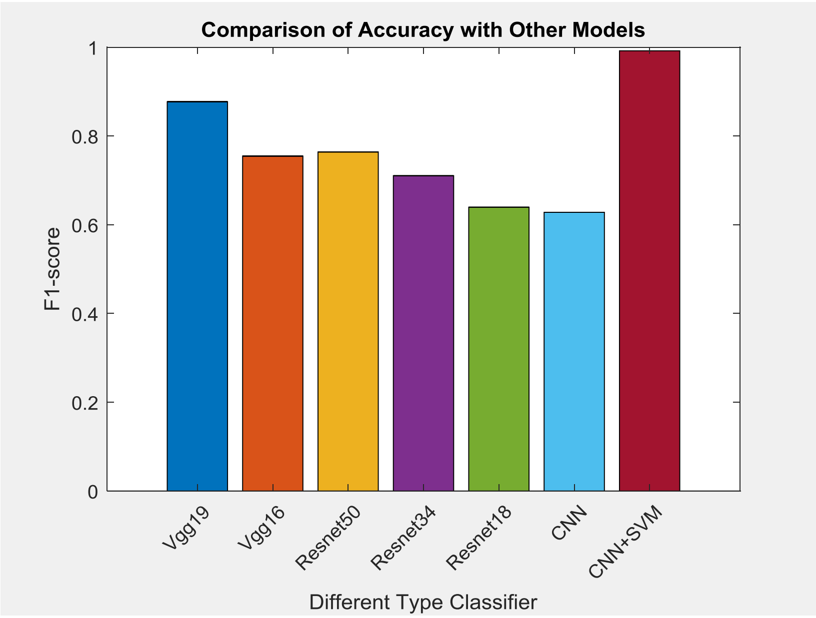

Figure 7 Comparative Analysis of Various Classifiers based on F1-Score Parameter

Figure 7 shows that the proposed method achieves highest F1-score over the existing different type of classifiers such as VGG19, VGG16, Resnet50, Resnet34, and CNN.

5. Conclusion and Future Scope

In this paper, we have designed an automatic crack detection model using image processing-based method. In this model, the pre-processing of the images are done using wiener filter and adaptive histogram equalization. After that, two machine learning models such as convolutional neural network and support vector machine are

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taken under consideration. The prediction of both machine learning algorithms is hybrid for enhance the accuracy of the model. The performance analysis show that the proposed method achieves high accuracy, precision, specificity, sensitivity, and F-score. On the other side, the hybridization of machine learning algorithm increases the complexity of the proposed method. In the future, we will explore other machine learning algorithm and determine the optimal hyper tuning parameters of it using bio-inspired algorithms.

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