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# EFFICIENT CONCRETE CRACK DETECTION SYSTEM USING SURF AND RNN ALGORITHM

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**Abstract:** *Crack Detection (CD) is significant for the calculation and reviewing during the maintenance of Concrete Structure (CS). In CS, surface (Roads, building and Bridges) cracks are the main signs of structure serviceability, and durability. Manual Vision Inspection (MVI) is normally adopted, but given measures ineffective in the form of accuracy, safety, reliability and cost. This research method proposes an image based CD method using Recurrent Neural Network (RNN) classification. RNN classification is designed through the varying RNN network and then trained and validated using a collected dataset with 200 images. For the image acquisition process, it resizes the image with 128*128 pixel resolutions. It identifies the unwanted salt & pepper noise in surface crack and non-crack images. Applied the 3D-Box filtration and Gaussian Filtration method to remove the unwanted noise and calculate the smooth image. It converts the smooth image to a binary image. It detects the crack in the surface image regions. It developed the feature extraction method to extract the features in the concrete crack surface image. The classification models are implemented based on Speedup robust features (SURF) and Recurrent Neural Network (RNN). This model is easy to detect the concrete crack of the surface images and improve the detection rate and overall performance has achieved the parameter values such as accuracy is 98.7%, the precision is 98.5% recall is 99.5 % and Computation time 0.467 seconds as compared with existing methods.*

***Keywords: Concrete Crack Detection System, Recurrent Neural Network, Speedup Robust Feature Extraction and Filtration Approach.***

## 1. INTRODUCTION

Technology encourages the growth of detection methods to the age of computerization, intelligent crack detection automobiles arise in significant periods. Generally, cracks are partially or wholly division of the concrete into more than two parts, formed by a break or fracture. Diverse areas in which crack may take place are Building, Toll road, Railway Tracks, Tunnel and so forth shown in fig 1.Cracks are categorized as dynamic and dormant [1]. It is longitude, oblique, and a mirror image crack. In dynamic crack, the alteration in the way, thickness or intensity that takes place over a considered amount of time [2]. On the other hand, dormant cracks present a way for moisture dispersion that may cause further destruction [3]. An essential sub-group of intelligent crack detection methods may be divided into two parts on the basis of the entity features [4]. Generally, H/W is the detection scheme that receives the road region picture data at a definite speed using car, vehicle processor and other sensors. In contrast, the s/w part of the detection system may detect the cracks to acquired pictures. Thus, the detection scheme is the key approach of elegant, smart crack detection tools [5] [6]. However, the detection of the cracked areas is the main approach at the time of assessment, diagnosis, maintenance, and lifespan prediction for the security of the concrete structure because cracks are the earliest signs of the degradation of the concrete structures (CS). The crack data is acquired to adapt the suitable analysis technique to secure the cracked structure and avoid any disastrous breakdown. Hence, crack detection on concrete pictures is the complex approach due to traditional techniques involving manual approach.

(i) (ii)

(iii)

**Fig.1** (i) Building (ii) Road Cracks and (iii) Railway Cracks

Cracks are computed by social users [7] [8]. Practically, the knowledge, talent of the user, attentiveness and consistency of the image quality has mainly influenced the accuracy of identification of the cracks, deficiency or breakdown of concrete structures [9]. In the earlier period, various techniques for automated crack detection have been developed. Conversely, the irregularities of the shape, size, blemishes and irregular illuminated situations makes the segmentation of cracks of concrete picture hard [10]. It often leads to fake identification. Therefore, crack identification is required mainly for different cracks in complicated background or irregular illuminated situations [11] [12]. Crack detection must be done in an accurate way by considering the size of the cracks for consistent nature. However, automated crack detection methods are acquired for gradual human assessment by reducing the time usage [13]. Normally, the crack detection is analyzed using an image analysis model that considers an accurate outcome as compared to traditional manual techniques. The major issue during the detection occurs due to the size of the picture [14]. Current digitized cameras have the picture resolution of more than 10 megapixels. The increased resolution enabled the acquisition of the comprehensive pictures of concrete areas [15]. Using the recent digital cameras, the crack area pictures are captured [16].

In the image processing, the detection is done in various phases which are [17] shown in fig 2.

1. Collecting the pictures through some resource and input through the image acquisition process.
2. Then, the pre-processing occurs for segmentation of pictures.
3. Afterwards, a few of the models are engaged to proceed with the picture sample.
4. Crack detection may be analyzed on the design using the output of a processed picture.
5. Then, detecting the cracks through a feature extraction process that is based on the breath, thickness of the propagation of the break or crack.

However, various algorithms are used for detection of the concrete crack pictures using feature extraction and classification models [18]. Deep learning algorithms like CNN (Convolution Neural Network), RNN recurrent suggest a way to prevent the previous restrictions in crack detection [19]. Mainly, CNN has profitably been useful to picture classification and high rate of generalized features. Such features are the key approach to identify devastation like a concrete crack in a healthy and consistent way; contemporary neural network based crack detection schemes. In addition, an application of the neural network is an automated analysis of the buildings. It focused on the automatic identification and localization of the key defect, occurring due to humidity from building pictures. The main motivation of the research approach is to enhance the process of detection and classification of building cracks. For this a new feature extraction process is added into the proposed model and SURF and RNN classifier is used to improve the recognition accuracy. Secondly, performance analysis is on the basis of different parameters that are precision, recall and computational time and Accuracy rate. Detection of concrete crack classification involves some fundamental image processing, measures for detection and classification of building crack image data sets. Moreover, these steps also include image acquisition, image pre-processing, image segmentation, feature extraction, and classification.

The above Section I described the introduction of the crack detection, normal detection model, existing work and proposed work. Section II defined the related work using various deep learning and machine learning methods. III and IV sections expressed the proposed work and result analysis with comparison. Section V shows the conclusion of the crack detection system.

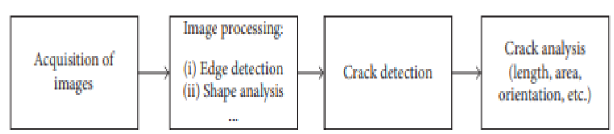



**Fig.2.** Basic Crack Detection Model

## 2. LITERATURE REVIEW

Crack Detection (CD) is a vital suggestion of the poverty of models. The detection of cracks is given necessaries in the phase of building, road and railway maintenance. Examinations of model integrity depend on crack analysis becoming substantial for the service life classification of models. Because the manual procedure for crack size is carefully timed consumption for large- scale models. Various researchers have implemented structures dependent on image processing, which allow a faster speed and more effective path for computing the cracks in concrete surfaces.

**Guo, L. et al., 2019 [20]** proposed research on the method for the identification of the concrete cracks using machine learning. This technique helped in the presence and position of the cracks from the area pictures. The planned model was designed for the classification of the cracks and noise crack designs, which were not easy to differentiate the data using image-processing methods. In planned method, the training phase has the picture linearization that was used for the extraction of the crack and candidate user areas, later; the classification methods were built that depends on the speedup robust feature and CNN. The desired crack detection techniques were basically comparable using the novel concrete area pictures comprising cracks and non cracks.

**Kim, H. et al., 2019 [21]** implemented a technique for the classification of the cracks and noise, cracks designs which were not simple to differentiate using the current image processing methods. During the training phase, the planned method used the picture binary data for the extraction of the crack candidate areas, and classification models that depend on the speedup robust features and CNN. The obtained crack detection techniques were quantitatively and qualitatively comparable used novel concrete region pictures consisting of cracks and non cracks. The main goal of the research was a categorization model that depends on the crack identification with the availability of the non-crack objects, which share the same picture features. The concrete area pictures in the training phase along with the cracks and non-cracks were performed from the picture linearization during the automated extraction of the data. When the creation of the crack detection, the SURF and CNN based model was achieved to the crack detection for the extraction of the essential characteristics of the cracks and non-cracks that was relatively used for building the classified methods. The achieved crack detection method was identified through the concrete area pictures, which was a portion of the training set.

**Li, S. et al., 2019 [22]** developed a picture based crack detection technique using deep-CNN. The CNN was considered by the modification of the Alexnet and after that training and validating through the construction of the dataset along with 6000 pictures. The validated accuracy below various learning data sets were selected in the top learning stage along with maximum validation accuracy up to 99.06% and the trained outcome was used for the accurate learning value with maximum accuracy up to 99.06% and the training output was used in subsequent testing procedure. The trained CNN was tested on the 205 pictures along with 3120x4160 pixel resolution that was not utilized for the training and the identification stage for the detection of the cracks. The resulting value confirmed that the planned model identified the cracks in pictures from actual concrete areas. The planned method determined that CNN was more influential in classifying the automated learning definite features from a large set of the pictures. The proposed method in this research was achieved in another kind of destruction identification like scaling of the concrete area.

**Mohan, A. et al., 2018 [23]** presented a comprehensive survey of various picture processing methods used for the identification of the cracks in business designs. The main goal of the research was to investigate and study the review of the crack detection scheme that depends on picture processing models. Hence, crack detection based research papers were analyzed. It has been reviewed that depends on the various characteristics. The initial stage of the selective data, such as the dimension of crack propagation was measured. On the other hand, the database used for the different models was estimated where a large amount of the network used a real time database for efficient expediency. In the next procedure the accuracy rate and error rate were based on the picture processing method in every scheme. They presented the investigated problems that were essential for the future investigation on picture processing which depends on crack detection schemes. They conclude that large investigators had used the digital camera kind picture for analyzing the suitable segmentation approach such as threshold technique and constructed features extraction method for the complete destruction analysis of the data.

**Chatterjee, A. et al., 2018 [24]** presented an exact crack detection method. The method contains the subsequent stages, which include picture pre- processing, preface crack segmentation for reducing the false negative, crack object creation, and connection to eliminate the false positives, improvement of the crack segmentation by shortest path find method. The planned model acquired the complete scoring of about 80 in the crack detection approach performance execution scheme (CDAPES). The main goal of the research was obtaining automated input points for the fast marching method that has been searched on the correct way for searching the crack route between two desired points on crack. The planned algorithm given in this research offered a robust, correct and fast crack detection method that has a tough valuable impact on the extensive achievement of automatic road situation investigations, and making more secure and efficient roads. Explained table I with various methods, performance metrics, and drawbacks of the detection system.

**Lin, M. et al., 2019 [27]** developed a crack detection algorithm by linking an adaptive line identifier and HMRF-EM approach. They presented an effective and exact crack detection technique. The two major goals of the research were; initially, the linking of the Adaptive Line Identifier (AL) And Hidden Markov Random field (HMRF) method and its estimated maximize (EM) algorithm improved the precision rate. After that, detailed study of the cracked areas reliability and situation link improved the integrity and regularity of the crack. Experimental outcome represented that the proposed model was more reliable and correct. Also, the cracks acquired by the proposed algorithm have maximum integrity and regularity along with other current crack detection techniques. The planned method has maximum recall value which narrows the identified cracks and compared to previous methods. The precision rate was having better performance that was caused because of the inappropriate amount of the iterations of HMRF-EM approach. However, the planned model achieved major enhancement in accuracy and effectiveness.

**Quan, Y. et al., 2019[28]** developed an Otsu threshold crack detection technique that depends on the gray histogram. The planned model enhanced the accuracy rate of target extraction that prevents the issue of projecting peaks, resolves the issue of road IP of different of different crack kinds. Experimental outcome showed that planned model has received the reliability in identifying cracks on various pavements also computation speed. In this research, novel otsu crack identification technique dependent on gray histogram was planned road cracks identification. The planned technique has maximum effectiveness and accuracy of identification has acquired. The Otsu segmentation approach, the recall improves up to 94%, the precision rate up to 85%, F-measure up to 88%. Moreover, average picture dimension of 1046x798 was 543.65 have the planned model presented high operation velocity. It was appropriate for pavement crack identification scheme that required maximum effectiveness and accuracy.

**Kang, S. M et al., 2019 [29]** implemented image processing approach and movable scheme for identifying the crack in region of the structure. There were different methods of cracking and digital camera dependent technique that was utilized in this research. In addition, the digital camera based techniques have some benefits like as humble, reasonable and prevailing. The planned crack detection scheme comprises of the digital camera and small fixed board. In addition, it may simply be stored on any sensors or the vehicles. This research develops a network and, experienced the outcomes of the real situations of the road. In addition, this research developed a crack detection approach and it was developed using small digital camera and embedded-board. The planned approach was simply stored on mobility vehicle. Experimental outcome estimated that the processing time interval was 20fps and accuracy of the crack detection was maximum up to 89.34%.

**Qu, Z et al., 2019 [30]** settled a genetic algorithm (GA) depends on genetic programming and percolation method. This technique includes three stages: cracks were previously extracted by the IP method of genetic programming. In next procedure, the crack gradient was computed after the extraction of the crack region. Simultaneously, the crack unit zones were filtered for the association. At last, the pre-extricated breaks are associated with the splits identified by the permeation, and the mass obstruction region was expelled to acquire the genuine splits on the solid surface. The reproduction results showed that the solid surface split location calculation depends on the GP and permeation model can adequately consolidate both of their focal points. The algorithm developed in this research identified the genuine solid area cracks precisely and successfully with solid strength. The trial results showed that the calculation not exclusively can rapidly and precisely distinguish the solid surface breaks, yet additionally can adequately dispose of the obstruction factors, for example, the stain, the square, water spillage, and so on. So as to improve the location exactness, the inner capacity of the improved tree model can be measured in upcoming research.

**TABLE- 1:** Comparative Analysis

| Author Name | Year | Parameters | Method | Dataset Images | Images/ Pixel |
|---|---|---|---|---|---|
| Li Guo et al., [20] | 2019 | Accuracy Rate Time | SAE DBN CNN | 2000 | 227*227*3 |
| Kim et al., [21] | 2019 | Precisio n Recall F1- Score Accurac y Computation Time | CNN SURF | 487 | 333*333*3 |
| Li, S et al.,[22] | 2019 | False Negative False Positive | CNN | 6000 0 | 256*256 |
| Mohan, A et al.,[23] | 2018 | Accuracy Rate Error Level | Image Processing Methods | - | - |
| Chatterjee et al., [24] | 2018 | Speed and Accuracy | CDA-PES | 68 | - |

**Fu, S. et al., 2019 [40]** presented a visualized detection and identification method for the region crack of the steel rail. This research mainly described in accordance to the configuration and main standard of machine visualization inspection scheme, associated along with digital camera imaging and railway display environment. The acquisition sensor was selected that depends on the inspection needs of the trace inspection picture. Various major approaches for the image filtration were compared and that enhanced the weigh medium filtration approach and filtering the detection picture. Moreover, the association of the customized and selective techniques was utilized to compute the threshold value and extract the cracked region. Lastly, GUI in MATLAB created the significant s/w model and the interrelated amount of the variable of every stage to display, store and along with other users. The recognition and the detection model include the picture display boundary, model regulated interaction and metric memory. Experimental outcome showed that the detection technology of rail-cracks in the track inspection picture that may quickly position the rail region and correctly extract the cracked picture, that have an improved accuracy and speed needs of the track inspection.

## 3. RESEARCH PROPOSAL

The detection of concrete crack classification involves some fundamental image processing, measures for detection and classification of building crack image data sets. Moreover, these steps also include image acquisition, image pre-processing, image segmentation, feature extraction, and classification. The process mainly includes the following modules:

1. Image Acquisition
2. Image pre-processing
3. Image enhancement
4. Feature extraction
5. Classification

**A. Image Acquisition:** The first step of any vision system is image acquisition. Image acquisition includes the step of obtaining the building cracks and capturing images of high quality through the camera. Images will be obtained from the internet field. The concept's effectiveness relies on the image quality of the database. This image is in the form of RGB (Red, Green, and Blue).

**B. Image Pre-processing:** Image pre-processing involves the second steps of image enhancement, converting RGB to Greyscale, filtering, etc. to increase the contrast, image enhancement is performed here. Filtering techniques are used to smooth the image. In image processing, there are various types of filtering methods available such as median filter, average filter, Gaussian filter etc.

**C. Image Segmentation:** Image segmentation implies partitioning or getting some resemblance of the image into different parts of the same characteristics. Different parts of the same features or having some similarity. Segmentation can be performed using different methods such as the Otsu method, K-means clustering is used, converting RGB image into HIS model, etc. The clustering of K-mean is used to cluster an object based on a set of features into a K-number of classes. The classification of objects is done by minimizing the sum of the squares of the distance between the object and the corresponding cluster.

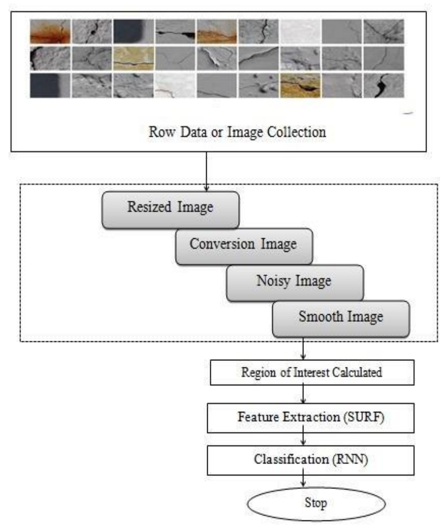



**Fig.3.** Research Proposed Methodology Flow Chart

**D. Feature Extraction using SURF:** The SURF method (Speeded up Robust Features) is a fast and robust algorithm for local, similarity invariant representation and comparison of images. The main interest in the SURF approach lies in its fast computation of operators using box filters, thus enabling real-time applications such as tracking and object recognition.

SURF algorithm comprises the major portions:

1. Essential Image Creation: Create the significant picture in the required dataset.
2. Intersect Point Recognition: After the creation of the picture, the intersect point points are created for the demonstration of the picture.
3. Orientation Descriptor Assignment: In this stage, there is the assignment of the oriented descriptor that arranged in the required format value.
4. Creating of the descriptor: After the intersection of the desired point, there may be generation of the feature description.
5. Feature Mapping: This process is done after generating the features that create the descriptor value.
6. Detect the object: After the complete procedure, there is the detection of the object.

***Pseudo code of Proposed Classification Model : RNN***

**Step 1:** Initialization of the weights,
**While** if the criteria is not satisfied
**Step 2:** Compute $e^{p.1}$ (w) for the every structure;
$e^{p.1} = \sum_{p=1}^{P} e^{p.1} (w)^{p} . e^{p.1} (w)$ ;
**Step 3:** Compute the value $j^{p}$ (w) for every design;
Repeating the value;
**Step 4:** Computing the Δ w;
$e_2 = \sum_{p=1}^{P} e^{p.1}_{} (w + \Delta w)^{t} e^{t} (w + \Delta w)$;
If ($e_1 \leq e_2$) then,
$\mu := \mu * \beta$ ;
End if;
**Step 5:** Unless ($e_2 < e_1$);
$\mu := \mu / \beta$ ;
**Step 5:** w + Δ w
Endfor
End

**E. Classification using RNN algorithm:** RNN is a type of NN, where the outputs from the existing steps are fed as input to the recent phase. In traditional NNs, all the input values and the outputs are independent of each other, still in some cases like when it is needed to detect the next crack of the surface image, the existing images are needed and hence, there is a need to remember the existing surface images. Thus, the RNN classification came into existence, which solved this problem with the help of HL (Hidden Layer). The major characteristic of RNN methods is hidden state, which recollects some valuation or information about the surface images. Recurrent Neural Network (RNN) is the sub-group of ANN in which the inter-connections among the hops from the direct graph towards the temporal series. It used the internal memory for process variable length series of the inputs. RNN is utilized generally that referred the set of the grouped network with same structural designs in which definite and indefinite impulse is required. RNN is a kind of the NN in which the output of the last stage is inserted as the input to the present stage.
Advantages of RNN:

1. RNN is used with ConvLayers to extend the effective image pixel regions.
2. Faster prediction as compared with other NN.
3. Each and every information save according to the time.

***Pseudo code of Feature Extraction algorithm:***

**Input:** A group of the key-point k for every single selected set of the pictures.
**Output:** Array of m and n are mapped pairs
**Step 1:** n←0
**Step 2:** For every C in picture $C_1$ and $C_2$ do,
**Step 3:** For every key point p in $k^{c}_{1}$ do,
**Step 4:** j←0
**Step 5:** For every key point q in $k^{c}_{1}$ do,
**Step 6:** D[j] ← $d_{eucledian\ dis}$ {p,q}
**End for**
**Step 7:** Array with distance d
**Step 8:** Selecting the nearest k points **Step 9:** Matching the p and q← m [n] Endif
Endfor
**Step 10:** Eliminate the value repeated in [m, n]

## 4. RESULT AND DISCUSSIONS

In this result discussion section, demonstrates the research process, proposed algorithm, and performance graphs and comparative analysis are done to existing methods. In addition, the comparison between planned and previous methods along with parameters difference is given in the table.

**Dataset:** The dataset comprised about 40000 concrete pictures with the positive crack and negative crack for the classification of the image. Every class of the dataset contains 20000 pictures along with 227x227x3RGB data pixels. The complete pictures cropped in to 128 x128 pixels and unique illuminance acquired for improving the calculated efficiency rate. About 38000 pictures are used for training and last are 2000 pictures for testing. This dataset is gathered from the METU institutional campus building [25].

This proposed model is executed in MATRIX Lab. (MATLAB 2018a) and a GUI has developed a project desktop application. In this experiment result, total 40000 ~ 200 categories images of Concrete sample images were taken under digital camera and almost 2000 ~100 samples from each road image were taken for the training model. The testing system performance of the research classification algorithm, long-term data set images of road were chosen for the testing module. Applied defines experimental methodology of research work, concrete crack images (Road) were stored in .jpeg format. The Computer system for detection of road crack and non-crack images are generally based on features such as region, edges, and area, etc. The final research proposal is usually concerned with various angles of regions, a high crack area with segmentation and filtration is playing a main role in proposing this novel system.

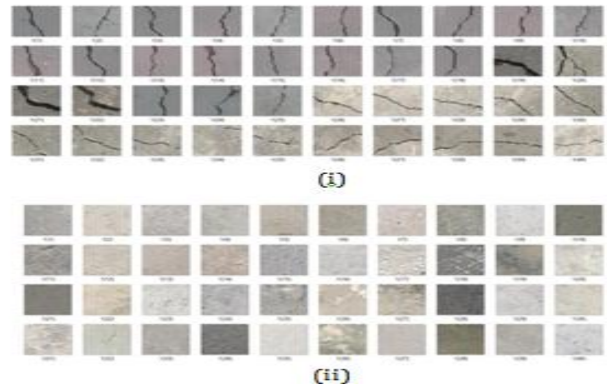



**Fig.4.** (i) Positive and (ii) Negative Road Images

This research model has enhanced the performance compared with different types of feature extraction and classification methods, which can be seen in various types of features such as accuracy rate, precision, recall, F1-Score and Computation time of the RNN classification Model.

**Formulas:**

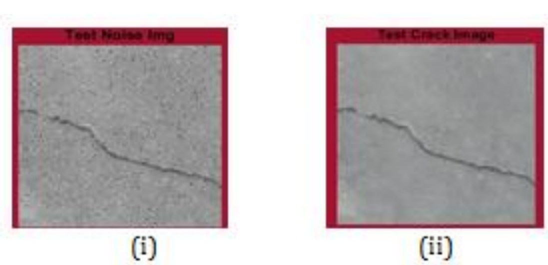
**Accuracy Rate:** It is the ratio between the amounts of the predicted value took place to the total amount of the data.

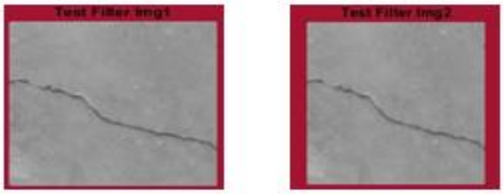
**Precision:** It is the ratio of the amount of the true positive to the sum of the true and false positive.

**Recall:** It is the ratio of the true positive to the sum of the true positive and false negative.

**Computation Time:** It is defined as the time consumption means extract the time, meaning the time required for obtaining the feature extraction and total time for complete computation taken.

**F-Score:** It is defined as a weigh average value of Precision and Recall.






(ii) (iv)

**Fig.5.** Upload Test Crack Image, Noisy Image, Filter Image 1 and 2


(i) (ii)

**Fig. 6** Test Road image segmentation

Fig. 5 defines the crack road test image uploaded; it calculates the size of the image and reset the size o an uploaded image in rectangle shape. After that, it converts the 3D image into 2D gray image. It reduces the dimensionality of the road crack uploaded image. It verifies the noise information in the image. Then applied the two types of filtration methods first one is median filter and the second one is the Gaussian filter method. This method is used to remove the noise in the uploaded image. Firstly, applies the median filtration method to remove the noise in the input image. After that median filter output as an input of Gaussian filter. It means a hybrid filtration method applied to remove the unwanted noises in the uploaded images.

Fig 6 shows the edge detection output, smooth edge detected image and highlights the cracked image. The research work has developed the canny edge detection method to extract the edges in the filtered image. K-Means clustering method is used to calculate the smooth edges or region in the crack image. After that calculates the crack image with a highlight area in the filtered image.

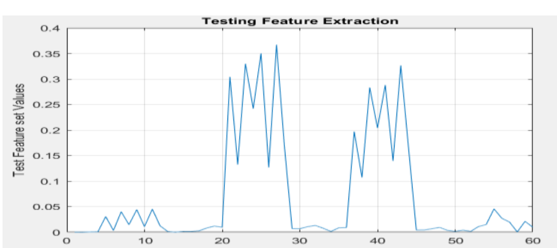



**Fig. 7** Feature Extraction

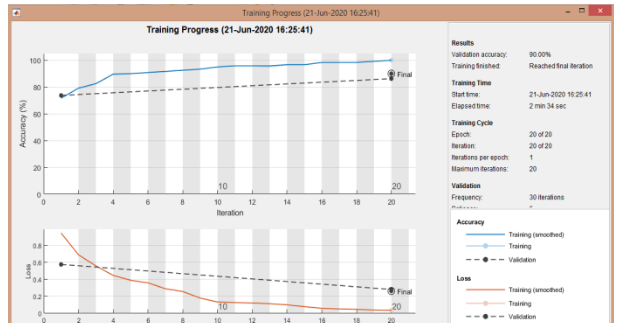



**Fig. 8** Training Section

Fig. 7 shows the feature extraction output. In this graph shows the extracted feature in the form of numeric data values. It extracts the unique feature key points using the SURF algorithm. This figure defines the region values have increased then the extracted features have varied.The concrete sample of uploaded images of the road is detected using the recurrent neural network algorithm. It detects the concrete crack image with category accordingly and computes the mathematical expression like accuracy rate, precision, recall, F1-Score and Computation Time.

The RNN classification model creates the layers, options, validation of the train model, and model design. Above figure 8, shows the 'Training Process' in RNN model. It represents the Train accuracy 100 percent and validation accuracy 91 percent. In this model evaluates accuracy with respect to the number of epochs/iterations.

Initial Parameters: Epochs, Start Time, Elapsed Time, Maximum Iterations Loss and Validation Accuracy, etc.

**Comparison Graphs: Proposed Method and Existing Methods:**

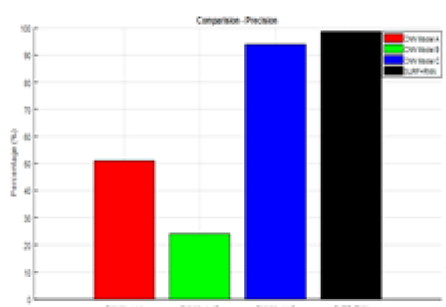


**Fig. 9** Comparison Graphs with proposed Model using SURF+RNN and Existing CNN classifier in three Modules (A, B and C): Precision

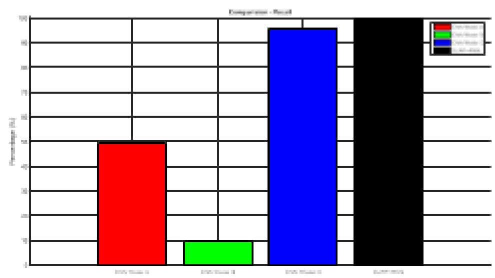


**Fig. 10** Comparison Graphs with the proposed Model using SURF+RNN and Existing CNN classifier in three Modules (A, B and C): Recall

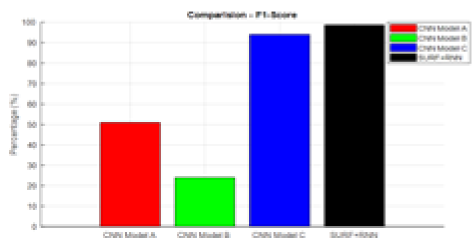



**Fig. 11** Comparison Graphs with the proposed Model using SURF+RNN and Existing CNN classifier in three Modules (A, B and C): F1-Score

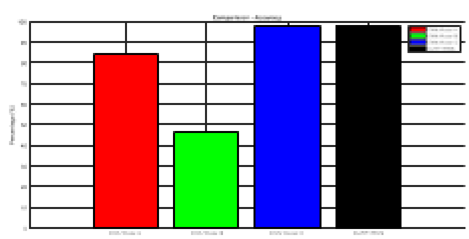


**Fig. 12** Comparison Graphs with the proposed Model using SURF+RNN and Existing CNN classifier in three Modules (A, B and C): Accuracy Rate

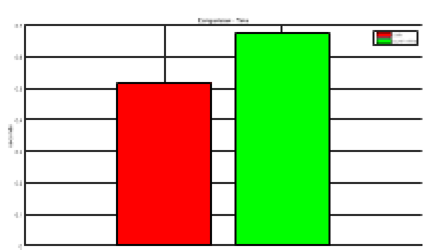


**Fig. 13** Comparison Graphs with the proposed Model using SURF+RNN and Existing CNN classifier in three Modules (A, B and C): Consumption Time

Above fig. 9, 10, 11, 12 and 13 shows the two types of bar graph plotting with a comparison between proposed and existing methods such as Accuracy Rate (%), precision, recall, F1-Score and Time Consuming in seconds. The proposed algorithm has enhanced the accuracy rate compared to different types of algorithms such as CNN-Model1, CNN-Model2, CNN-Model3 and SURF+RNN classifier.

**Table- 2:** Performance Metrics: Proposed RNN System

| Parameters | Values |
| --- | --- |
| Accuracy (%) | 98.7 |
| Recall (%) | 99.5 |
| Precision (%) | 98.5 |
| F1-Score (%) | 99.0 |
| Time (Second) | 0.467 |

Table IV shows the research model's performance, accuracy rate value is 98.7%, recall value is 99.5%, precision rate value is 98.5, F1-Score value is 99%, and time value is 0.467. In research, the model has improved the precise values and reduces the time complexity with the RNN classification method. RNN algorithm performs better than other classifiers.

## 5. CONCLUSION

In the proposed research concluded, it is essential to improve the procedure of detection and classification for constructing the cracks. The features are extracted using surf technique that is a fast and robust technique for same invariant demonstration and comparison of pictures. The main goal of SURF algorithm is based on the fast computation of operators using box filters and thus capable of real time services like tracking and object detection. In addition, RNN is a simple method for detection of the concrete crack of the area pictures. RNN is the kind of the NN where the output creates the previous stage as input to the current stage. In conventional NN, complete input and output are not dependent on each other, but in some cases it is required to detect the nearest crack of the region, and current pictures are required for remembering area pictures. Therefore, RNN classification resolved the issue through a hidden layer. The main feature of RNN technique is the hidden stage, which again collects any value or data about the area pictures. The method is simple for detection for the detection of the area pictures and improves the detection value in terms of accuracy, precision, recall and computation time. The proposed system has improved 1%

accuracy rate as compared with the existing three CNN Model. The existing CNN model achieved 98% accuracy, but the research system achieved the 98.7 percent accuracy rate.

## 6. FUTURE SCOPE

Future scope will emphasize on the fitting outcome and decrease the required calculation time during the detection procedure. The maximum picture of concrete destruction below different situations is presented to the previous dataset to improve the adoption and robustness of the detection technique. It will develop the novel ROI detection model to calculate the crack region with value bases.

## CONFLICT OF INTEREST

Authors have no any conflict of interest.

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