iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 Issue: VII Month of publication: July 2022

DOI: https://doi.org/10.22214/ijraset.2022.45968

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VII July 2022- Available at www.ijraset.com

Classification of Rail Track Defects Based on Computer VisionUsing DNN

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Abstract: Economic status of the country depends on the Trading which needs transportation. Railways is the most preferred road transportation as most of the profit oriented and movement of people in India is done by elevated railway. Hence it is required to monitor the track health condition frequently using an automated crack detection system. The proposed framework focuses on implementation of python to detect track defects based on Computer vision using image processing techniques. The proposed work uses CNN algorithm through yolov5 model. Yolov5 is one of the best model to achieve highest accuracy in object detection. Yolov5 has become industry standard for object detection due to its speed and accuracy. Here feeding of pre-processed image to CNN classifier to obtain the type of track. The proposed work also helps to identify the severity and non-severity of defects, also suggests the precautions. Automatic communication occur where the message is sentto authorized people of railway department. *The* ***Accuracyof the proposed work on the procured images is more than 95%.***
Keywords: Track defects, Computer vision, CNN, Yolov5, Automatic communication.

I. INTRODUCTION

Economic popularity of a country relies upon on road transportation such as railways. The railway is the biggest mode of transportation in India. Hence rail transportation has more significance in India. The modern framework used in Indian Railways interestingly lacks new technologies, consequently probabilities of human error is more. In the past days, rail inspection was manually done, which the exercise of analyzing railway tracks for faulty cracks that may lead to destructive breakdown. According to the US FRA workplace of security analysis track defects are the leading cause of accidents on Railways. The main motive of accidents in railways is accredited to human failure as humans need to go to a specific location and study the cracks and be aware down their location. If he finds negligible cracks, he will forget about which will develop with time and be regarded as most dangerous. Now the present device makes use of the signaling system. The track circuit consists of electrically isolated running rails and a relay, which is used to determine whether the railway track is occupied or unoccupied. This device is used to detect simple cracks such as broken rails. Even this existing system has drawbacks such as which will not be providing a distinct examination of track cracks such as corrosive track. At the same time the contemporary framework takes greater time for detection.

The proposed framework uses deep neural network approach, where the classification of defective and non-defective images of the rail track are done by neural network classifier. Also it identifies the condition of track and this information is automatically communicated to the authorized people in railway department.

The proposed work identifies five types of railway track defects and a non-defective railway track. The six types of classes are as shown below:

Fig 1 Broken railway

Fig 2 Head checks

Figure 1 shows the Broken track where a broken rail is a very small defect in the foot of the rail. Figure 2 shows the Head check on railway track. The Head check is one of the most famous cracks generated on the railway track. The head check is generated at the gauge corner of the rail floor.

Fig 3 Corrosion

Fig 4 Rolling fatigue

Figure 3 shows the Corrosion on Railway track where Corrosion is the loss of a material and its integral properties due to chemical, electrochemical and different reactions of the exposed material surface with the surrounding environment. Figure 4 shows the Rolling fatigue on Railway track where Rolling contact fatigue is a manner of gradual destruction due to the creation and development of a preliminary crack.

Fig 5 Squats

Fig 6 Non defective

Figure 5 shows the Squats on Railway track which Squats positioned specifically in the low leg of curves, the high leg of shallower curves and in tangent track. Figure 6 shows the Non defective Railway track which is suitable for railway transportation and will not cause any accidents.

The paper is organized as follows: Section II presents the related work with reference to the literature review by showing the previously published work of the railway track crack detection. Section III introduces the proposed work of the system. Section IV presents how the proposed work is implemented. Section V presents the experimental results and discussion. Section VI concludes the paper and discusses some perspective work.

II. LITERATURE SURVEY

R. Thendral et al. [1] proposal focuses on the detection of railway track cracks routinely using a computer vision- based technique. The device consists of a rolling digital camera attached beneath a self-moving automobile to seize the photographs and these images considered are the cracked and non-cracked images. The steps in this paper included pre-processing scheme and Gabor transform. In the pre-processing module, the step adaptive histogram adjustment manner is utilized to the pattern photos of railway track to improve contrast in the image, and then additional aspects are extracted from the Gabor magnitude image. These extracted facets are fed as source to deep learning algorithm getting to know neural community classifier to notice the cracks. The accuracy of this machine obtained is 94.9% and the error charge is ;1.5%. Scarlett Liu, [2] introduces the research and contribution of various students in the discipline of visual inspection, summarizes the utility and development of visual inspection technology in the railway industry, and ultimately forecasts the future lookup course of visual inspection technology. Less parameter to get the self assurance price may someday end result in false positive.

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Rahman Shafique, [3] ambitions at improving the ordinary railway crack device to tackle the issues with the aid of introducing an computerized railway track fault detection structures using Acoustic analysis. The speedy growth and miniaturization of sensors and electronics tools has made it ubiquitous and on hand on the market.
Mr. Mukul Pande et al. [4] This paper includes a railway track crack detection machine to forestall teach accidents the use of image processing technology. In this paper, Raspberry Pi four B is used to coordinate all the other units in the system. The work in this paper included a Raspberry Pi digital camera which takes the images of railway tracks and sends them to the Raspberry Pi to check for cracks. When the crack is detected region of the crack and area latitude and longitude coordinates are recognized by using the reader module. This paper consists of a Wheel encoder to send the statistics to the mobile about the vicinity of the crack detected.
Rijoy Paul et al. [5] The author of this paper developed an automatic railway track crack detection gadget using photo processing techniques.
This challenge also includes object detection using ultrasonic sensors and photos are captured by means of Raspberry Pi camera. In this paper, Raspberry Pi three is used to coordinate the undertaking of the devices and additionally consists of GPS and WIFI modules to ship the information and place latitude and longitude coordinates where the crack is detected. Erika Steyn [6] proposes Railway upkeep programs global uses rail grinding and rail milling to fight surface defects such as corrugations and rolling fatigue. However, rising applied sciences including of variations on rail grinding and rail milling are gaining pastime in the railway maintenance department. Limited academic literature is available on these alternative surface cure methods. This work includes supporting literature on rail grinding and milling technologies, and gives perception.
Lei Kou [7] discuss the opinions of contemporary lookup and investigation on the defect inspection of rail track in current years. In this paper, not only used regular ultrasonic and acceleration detection techniques but also includes the application of computer vision and deep learning for studying to discover defects on the rail track. Besides, the rising lookup on defect prediction to limit the inspection fees is attractive. Manikandan Rajagopal [8] proposes method that enhances the track photograph the use of adaptive histogram equalization technique and in addition aspects as Grey Level Co- prevalence Matrix (GLCM) and Local Binary Pattern (LBP) function are extracted from the enhanced rail track image. These extracted points are trained and labeled the usage of neural community classifier which classifies the rail song picture into either cracked track or non-cracked track image. S. Nandhini [9] focused on the faults or cracks in rail tracks is imperative in railway management, as it helps to avoid train accidents all through summer time and rainy times. During summer season due to the warmness cracks are fashioned in the tracks, which in the end leads to the slipping of the instruct wheel impacts rail tracks even in wet environments, causing cracks. This system makes use of CNN algorithm to pick out cracks on railway tune surfaces and gain their corresponding masks, which can then be used to extract other inspection applicable properties.

III.PROPOSED METHODOLOGY

A. Hardware Requirement

Fig 7 Node MCU

Fig 8 TTL

Wi-Fi module is connected to the LCD and Power supply which help to transfer the data to the cloud over internet as shown in Fig.7. The data will be directed to cloud by means of the Wi-Fi module and data can be viewed.A Transistor Transistor Logic is abbreviated as TTL which is used to interface between Hardware and Software as shown in fig 8. The Txd pin of TTL is connected to Rxd pin of node MCU.

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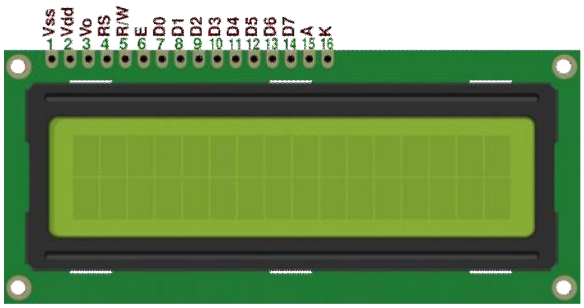

Fig 9 LCD Display

Fig 10 Power supply

It can show 16 characters per line and there are two such lines. In this LCD every character is displayed in 5*7 Pixel matrix as shown in Fig 9.A power supply is an electrical device that supplies electric power to an electrical load as shown in fig 10.

B. Software Requirement

S No	Software requirement	Version
1	Operating system	Windows 11
2	Software tool	Python 3.7.0
3	Flask library	2.1.2
4	Argparse library	1.6.3
5	Keras	2.7.0
6	Matplotlib	3.5.1
7	Numpy	1.21.6
8	Open CV	4.5.5
9	Pandas	1.1.5
10	Pip	22.0.4
11	Scikit-image	0.19.2
12	Tensorflow	2.7.0
13	tqdm	4.64.0
14	torch	1.11.0
15	Yolo V5	6.1.2
16	Torchvision	0.12.0
17	tflearn	0.5.0

Fig 11 Tabular column of Software requirement

IV. DESIGN AND IMPLEMENTATION

Figure 12 refers to the block diagram of the proposed device where the essential primary objective of the proposed work is to reduce labor work and time consumption in Railways Department while inspecting tracks. Yolov5 is the heart of the system where training of data is done in Yolov5 framework. Here CNN is used for detection of defected track and non defective track. NMS is used with Yolov5 to suppress the non-max output. Significantly the synchronization of Hardware and Software is done using nine single characters.

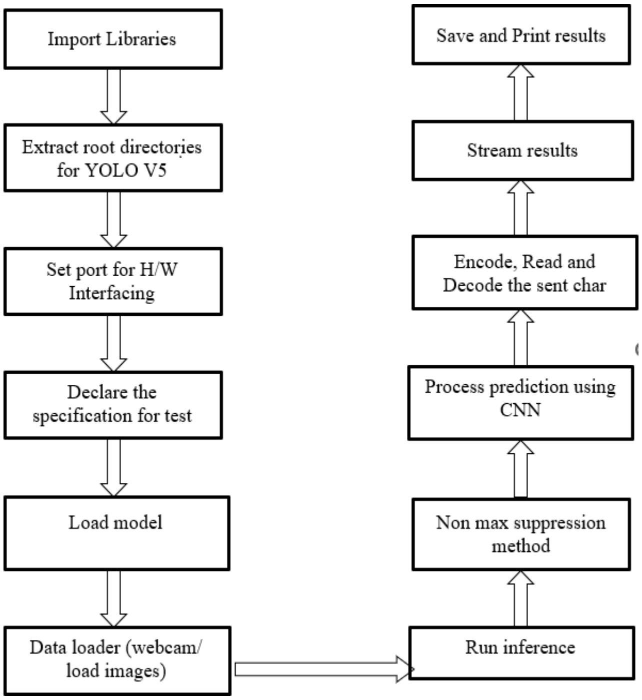

Fig 12 Block diagram of Proposed system

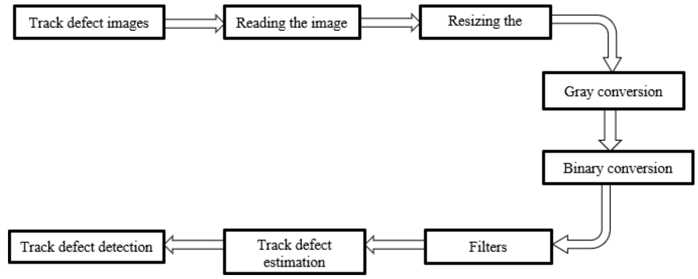

Fig 13 Block diagram of image processing

In the above figure which depicts the Block diagram of Image processing , where the Track defect images are fed as input to the python software, where images are read, Resizing of image takes place in order to get uniform sized images. Conversion of image from gray to binary occur to find the region of interest which is the portion of the image that needs to processed further. Keras filters are used to analyze the percentage of error. The simulated model provides a good accuracy and predictionscore.

A. Image processing and annotation

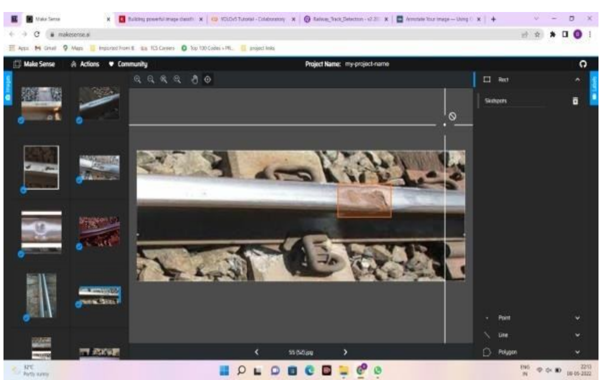

Fig 14 labelling using makesense

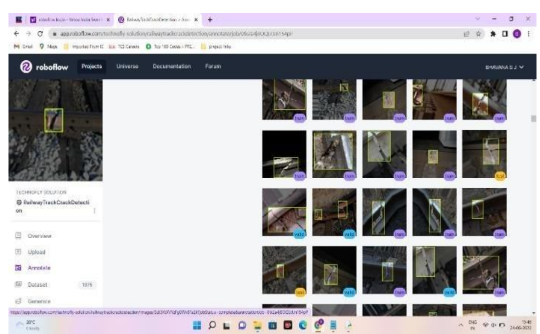

Fig 15 Classifying in roboflow

Figure 14 refers to the window where the user is labelling the track images in make sense. Referring to Figure 14 where left part of window displays the uploaded images, middle part of the window displays the image that needs to be labelled currently, Right part of the window displays the label name. Figure 15 refers to the robo flow window where 70% of dataset is classified as train, 20% of dataset is classified as valid, and 10% of dataset is classified as test.

B. Implementation of CNN and YOLOv5

The figure 16 shows the flowchart for pre-processing of datasets. The acquired data is converted from Gray to Binary to extract the required region of the image which need to undergo processing. Median filtering technique is used to remove the noise in the image. Global thresholding is used to replace the negative values by 0. The output from previous step is passed through the high pass filter where the image sharpening occurs. In this module emphasis on fine parts of image.

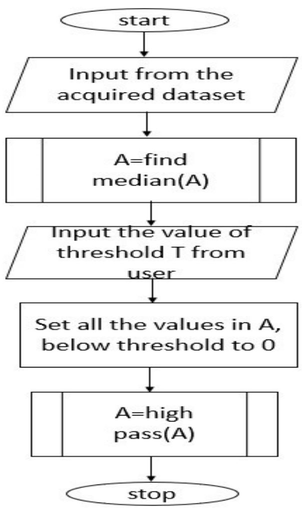

Fig 16 Flowchart for pre-processing

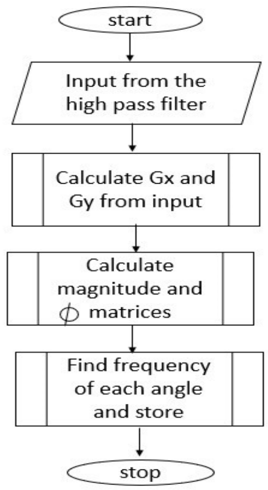

Fig 17 Flowchart for feature extraction

Conversion from RGB to Grayscale can be carried out by using the use of formula:

$$\boxed{0.2989*R+0.5870*G+0.1140*B}$$

The figure 17 shows the flowchart for the feature extraction. we use a method called Histogram Orientation Gradient (HOG). It involves multiple steps like finding Gx and Gy, which are gradients about each pixel in the x and y axes. Then Gx and Gy are calculated. After finding the Gradiant x and Gradient y it is required to find the magnitude of angle and find frequency of each angle and plot in histogram.

Gx = value on right –value on left
Gy=value on top-value on left

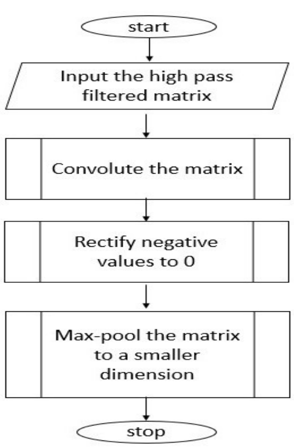

Fig 18 Flowchart for classification using CNN

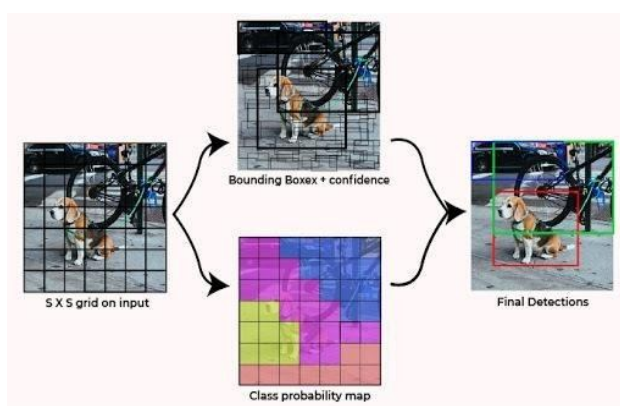

Fig 19 Yolov5 detection process

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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The figure 18 depicts the classification of image. Convolving the matrix mean the output from the high pass filter is processed by convolution layer to extract the features and it also retains the relationship between pixels of the input image. It is basically the multiplication of two inputs, followed by rectifying the negative values and replace it by 0. The output from previous step is sent to relu layer to reduce the noise and maxpooling layer is used to reduce the matrix size. Finally fully connected layer is used to classify the output.

The figure 19 depicts The architecture of Yolo divides the image into a grid of S*S size. If the center of the box bounded around the object is in that grid, then this grid is responsible for the detection of object.

If the confidence score = 0, then there is no object exists in the grid.

If the confidence score = IOU, then there exists object present in the grid.

Each bounding box contains five parameters such as(x, y, w, h, confidence score) where (x, y) coordinates represent the center of the bounding box. (h, w) coordinates represent the height and width of bounding box. The confidence score represents the presence of an object in the bounding box. Here we multiply conditional class PROand the individual box confidence predictions which gives the class specific confidence score for each box. These scores encode both probability of that class appearing in the box and how wellthe predicted box fits the object. After applying the non maximal suppression, the final predictions are generated.

$$P_r\left(Class_i|Object\right) * P_r\left(Object\right) * IOU_{pred}^{truth} = P_r\left(Class_i\right) * IOU_{pred}^{truth}$$

C. Hardware Implementation

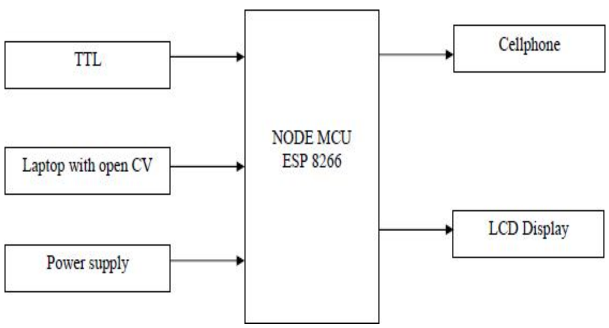

Fig 20 Hardware block diagram

Fig 21 Proposed System Model

As shown in figure 20, ESP 8266 is a self sufficient MCU which has inbuilt WIFI in it, it has the ability for data processing read and control the GPIO pins. The proposed work uses ESP8266 to send character and message received from software to hardware. The Txd pin of TTL is connected to Rxd pin of ESP8266.TTL(Transistor Transistor Logic is a UART convert module which creates a virtual com port using USB to interface between hardware and software. LCD is a liquid crystal display which has 16x2 dimensions used to display message. Power supply is used to supply power to ESP and Lcd, Cell phone is used to input the video clip and display the received message.

Figure 21 depicts proposed system model .The proposed system model works in such a way that the TTL is connected to the laptop to interface the hardware and software. Power supply is turned on to activate the hardware components . Open project folder in laptop, in the path type cmd in order to open the command window with project folder path address. Type "flask run" command and execute, the IP addressof "AI PROCTORING IN INDIAN RAILWAYS" webpage is

obtained which needs to be opened in web browser. Once the web page is opened, more importantly it will allow only the authenticated users. If the user has permission then the user canuse the proposed system.

The type of track defect is detected which is displayed on the laptop screen and the same is displayed on the LCD display. Hardware and Software synchronization is done by sending single character for each detected class such as 'H', 'G', 'S', 'T', 'R', 'Q', 'B', 'C', and 'N' for Head check severity, Head check non-severity, Squats severity, Squats non-severity, Rolling fatigue severity, Rolling fatigue non-severity, broken severity, corrosion non-severity, and non-defective respectively. .The detected track defect, condition of track and precautions are sent to the authorized people in Railway department through telegram. Based on the type and condition of track defect the authorized people in Railway department can take action.

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D. Flowchart and Working

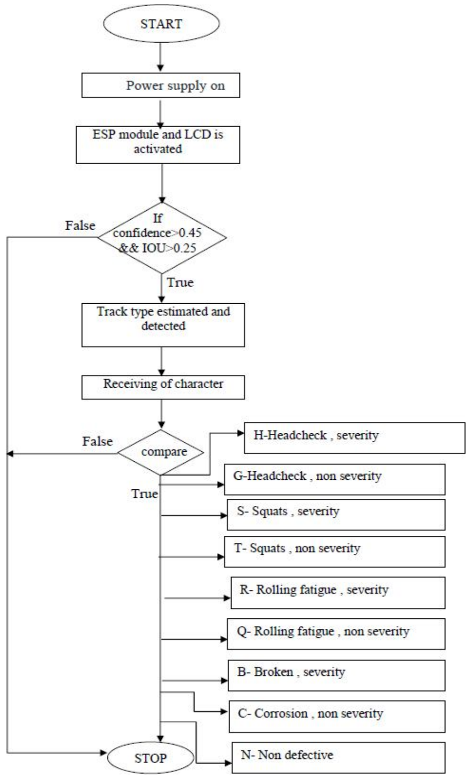
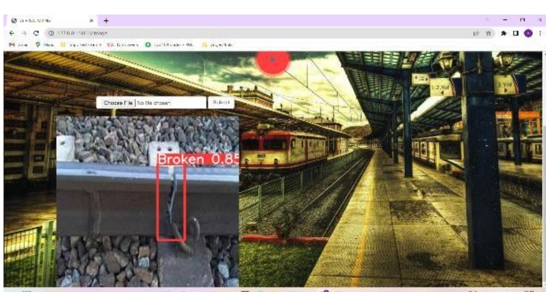


Fig 22 Flowchart of proposed system

When the power supply is ON, Lcd and ESP module gets activated. TTL is to be connected to laptop, and Lcd displays the message "Railway crack monitoring system". Once the system is turned on, there are two possibilities of inputting the image either by selecting the image within the laptop or by showing the video to the PC's camera. As shown in flowchart if the confidence score is greater than 0.45 and IOU is greater than 0.25 then the type of crack is detected and is shown on lcd screen. The detected type of crack is compared against the character which is to be sent to hardware such as 'H', 'G', 'S', 'T', 'R', 'Q', 'B', 'C', and 'N' for Head check severity, Head check non-severity, Squats severity, Squats non-severity, Rolling fatigue severity, Rolling fatigue non-severity, brokenseverity, corrosion non-severity, and non-defectiverespectively. These characters synchronize hardware and software.

V. RESULTS AND OBSERVATIONS

Figures shows the detection of defective rails and is also displayed on LCD display. Simultaneously data such as type of defect with the precautions and condition of defect is sentthrough telegram.



a) b)

Fig 23 Detection of Broken track

Figure 23 a) and b) shows that broken rail is detected and the same message is displayed on LCD and sent through telegram.

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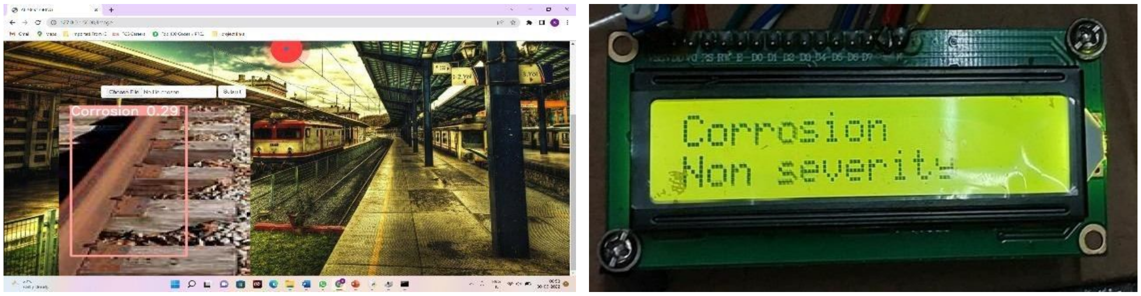
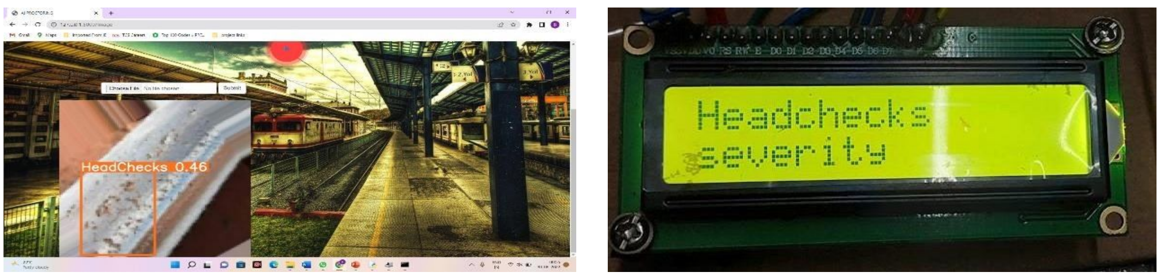


a) b)

Fig 24 Detection of Corrosive track

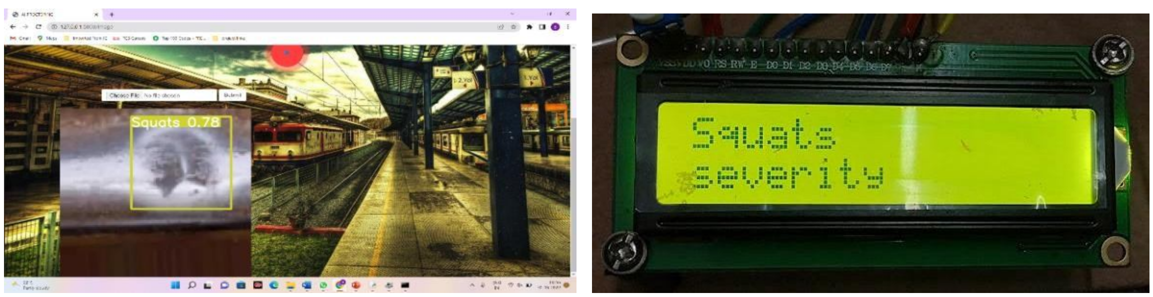
Figure 24 a) and b) shows that corrosion on rail is detected andthe same message is displayed on LCD and sent through telegram.



a) b)

Fig 25 Detection of head checks on track

Figure 25 a) and b) shows that head checks on rail is detected and the same message is displayed on LCD and sent through telegram.



a) b)

Fig 26 Detection of Squats on track

Figure 26.a) and b) shows that squats on rail is detected and the samemessage is displayed on LCD and sent through telegram

a) b)

Fig 27 Detection of Rilling fatigue on track

Figure 27 a) and b) shows that head Rolling Fatigue on rail is detected and the same message is displayed on LCD and sent through telegram.

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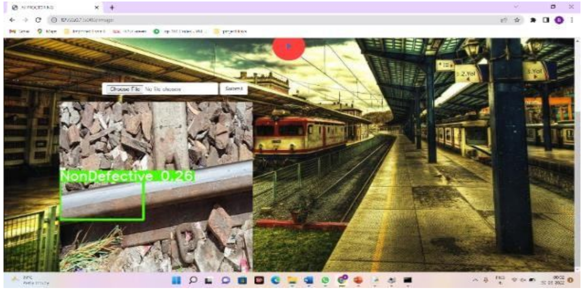

a) b)

Fig 28 Detection of Non defective on track

Figure 28 a) and b) shows that head Non defective on rail is detected and the same message is displayed on LCD and sent through telegram.

A. *Evaluation Metrics*

The performance of our proposed approach is measured using confidence metrics. These confidence metrics are defined using the following parameters.

True Positive (TP): The number of correctly predicted track defects

False Positive (FP): The number of wrongly predicted track defect

True Negative (TN): The number of corrected predicted Non defective track

False Negative (FN): The number of wrongly predicted Non defective track

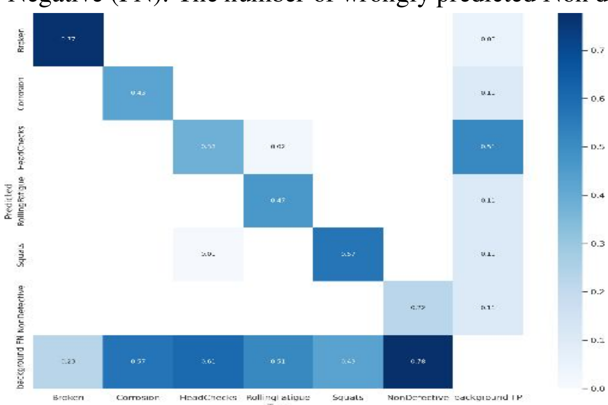

Fig 29 Confusion matrix

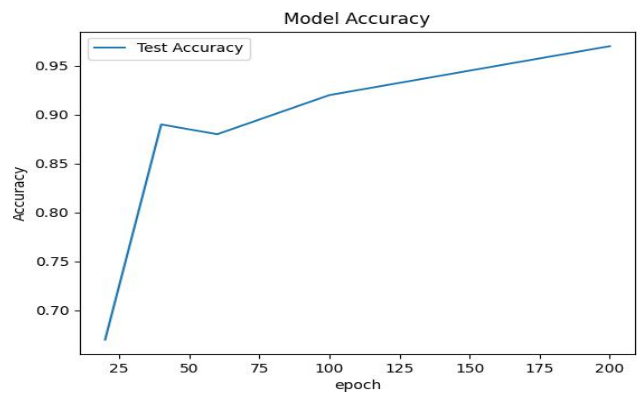

Fig 30 Graph of model accuracy

Figure 29 depicts the confusion matrix for the proposed work Then, the following notations used in computing the performance metrics of the proposed approach.

Accuracy: Accuracy is calculated for the entire model, It defines how efficiently the model works. Figure 30 depicts the Accuracy graph which is more than 95%.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FN+TN+FP)}$$

Recall: Recall defines how many predictions are correct from the predicted positives and negatives.

$$\text{Recall} = \frac{TP}{TP+FN}$$

Precision: Precision defines how many predictions are correct from the predicted positives.

$$\text{Precision} = \frac{TP}{TP+FP}$$

F1-score: F1 score defines the individual performance of each class. F1 score is calculated using Precision and Recall. Figure 31 depicts the F1 score graph.

$$F1 = \frac{Precision*Recall}{Precision + Recall}$$

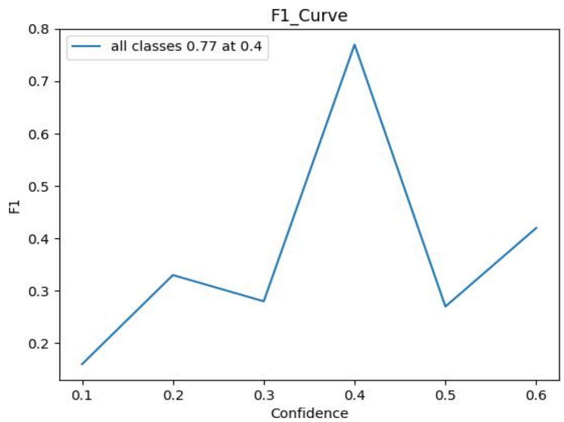

Fig 31 Graph of F1-Score of different types of cracks

CLASSES	PRECISION	RECALL	F1 SCORE
Non-Defective	0.85	0.22	0.1653
Squats	0.83	0.57	0.3392
Rolling Fatigue	0.81	0.43	0.2830
Head checks	0.78	0.38	0.7774
Corrosion	0.79	0.43	0.2791
Broken	0.93	0.77	0.4230

Fig 32 Tabular column of results

Figure 32 depicts the tabular column which describes the Precision, Recall, F1 score of different types of railway tracks, is calculated from the above mentioned formulas usingconfusion matrix.

The important aspect of the proposed work is that, it is not required to install any application or software as the user can use and get results in web browser. Besides the user-friendly environment, we also care about the users confidential data hence only the authenticated person is allowed to use. Here In the proposed system the message is sent to through the telegram to the authenticated user as shown in Figure 33.

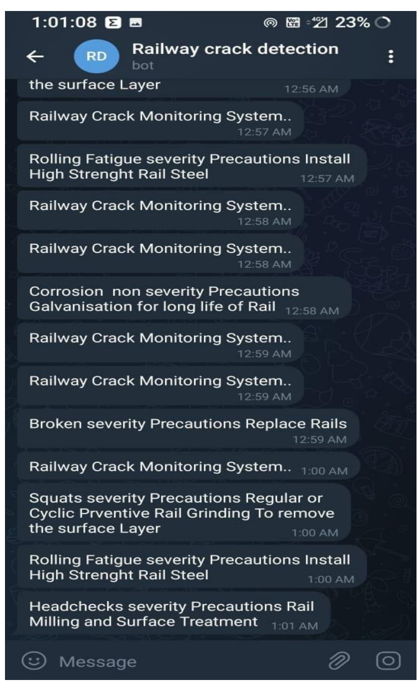

Fig 33 message in telegram

VI. CONCLUSION AND FUTURE SCOPE

Through this method of using Deep Learning forthe detection of cracks in railway we are able to eliminate the cost of using expensive audio based or physical method of finding cracks. We have achieve an accuracy of more than 95% after testing it with the validation dataset. If this system is brought in railways, the accident could be controlled and the same message is sent automatically to the control room and since it's a completely automated system it can be used in village areas by which man power is reduced and time is saved. Moreover the system minimize the train accidents caused by train track cracks . There by possible to save precious lives of passengers and loss of economy. It also saves the time and money for identification of track defects.

The future of railway inspection include neural network analysis to improve defect detection. So the proposed system can be implemented along with self driving vehicle with a high resolution camera where the camera takes the images of rails and fed them automatically to the deep learning neural networkalgorithm for the detection of cracks. Simultaneously an alert message is sent to the Control room through hardware attachedto the proposed system and in future GPS can be added to findthe location of the cracks.

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