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Railway Track Fault Analysis using Dynamic ROI Detection in Cluttered Environment using Deep Learning

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Abstract

The safety of the railway track can be accomplished by the regular inspection of the track by detecting the faults which occur due to several parameters. The fault analysis is very necessary, if they are not timely monitored then the train can face severe accidents which may result in the loss of several lives. The condition monitoring of the track is taken manually these days and the world is moving towards automation to avoid human error and acquire high accuracy. The inspection of faults can be carried out by either using sensors or image processing techniques in which Deep Learning can play a vital role to have efficient systems. This research is carried out using the Deep Learning techniques, the rail surface faults such as squats and corrugation are monitored by the Deep Learning techniques with an addition of IOT (Internet of Things) feature for real time fault alerts with GPS locations on Desktop Systems using the Web Portal.

Keywords: *Railway Fault Analysis, Dynamic ROI, Cluttered Environment, Deep Learning, IOT.*

1. Introduction

The condition monitoring of the railway track is very necessary for the accident avoidance. If the track health monitoring is not carried out timely then the train can face severe accidents which results in the loss of several lives and damages to the trains and tracks which costs high maintenance cost. Currently track inspection is

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carried out manually which is time consuming and requires too much labor work. The manual inspection is replaced by automated Track Recording Vehicles (TRVs), but they are very expensive. The irresponsible and unsatisfactory manual inspection results in many errors in the track health status report which is conducted by railway higher authorities. So, to replace the manual inspection, an automated track condition monitoring system with an IOT feature is proposed which is not only cost effective but indigenous too. The proposed system comprises railway track's rail surface faults such as squats and corrugation with real-time fault alerts having GPS location for easy tracking of the faults on the user-friendly web portal in order to reduce the train accidents.

As the time passes the things are being converted from manual to automated and this is the common fact of this modern era. We know that no technology can provide 100% ideal systems so everywhere we have some technology gaps, and this gap is the major reason behind the development of innovative products by the technologist to enhance the performance of the systems as much as they can do. Nevertheless, the errors exist, and the systems are vulnerable to error and disparity. The railway track condition monitoring systems also have some gaps and due to it trains face major accidents. To enhance the performance of those systems with the latest trends of the technology of this modern era, we have decided to work on the following railway track surface faults as represented in Figure 1.

Squat Corrugation

Figure 1: Railway Track Surface Faults.

As we know that Deep Learning is playing an enormous role nowadays due its robust features, so this research is purely based on using the power of deep learning to ensure the timely detection of railway track surface faults such as squats and corrugation to avoid such miserable train accidents in the future.

2. Related Work

The condition monitoring of the railway track is very necessary to avoid the endless train accidents. The track geometric inspection is accomplished by Track Geometric Vehicle (TGV) or Track Recorded Vehicle (TRV). The accurate results are received by TRV's, but they are very expensive, and they use optical sensors which are highly sensitive to the dirt which is commonly found on railway track [1]. Now-a-days the sensors are being used in automation of devices because of their lower costs, which enables their usage in railway geometry detection and its fault analysis [2]. Machine Learning based techniques are proposed in [3] by which the track components such as rail, clip and bolt detection is performed using object detection algorithms. A comparative study using pre trained networks such as VGG-16, CNN and R-CNN using deep learning techniques are proposed in [4] for railway track fastener detection. Semantic-Segmentation-Based rail fastener state recognition is proposed in [5] and the missing fastener detection is proposed in [6]. By using the histogram of oriented gradients features and a combination of linear SVM classifiers for fastener detection is proposed in [7]. To address the limitations of traditional algorithms many detection algorithms of vision and image processing are given in [8], [9], [10]. The rail surface fault monitoring is highly challenging because there are many surface faults such as cracks, squats, spalling, flacking, corrugation, and shelling occur on the rail as time passes, some of them looks similar making it nearly difficult to identify the exact fault. Many researchers proposed different methods for fault analysis using the sensors and as well as image vision techniques. The IR and ultrasonic sensors-based crack detection is performed in [11], [12], [13]. GPS (Global Positioning System) is used for the recording of crack location. The Machine Learning techniques are also used for the track health monitoring such as track normal and abnormal status detection is proposed in [14]. Railway track corrugation, spalling and fastener detection is performed in [15] using YOLO v3. By using the deep convolutional neural network, the squats were detected in [16] but real time implementation is not performed. By using Canny edge detector and 2D discrete wavelet transform, the squat detection is performed in [17]. In [18] a machine vision-based system for real time detection of defects by using an inspection system is proposed, in which cracks were analyzed.

A lot of research is being carried out by various researchers around the globe, but detection of exact faults accurately is still a challenging and unsolved problem. This paper tries to solve two of the surface faults of railway tracks with high accuracy. This

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paper is organized in such a manner that section 3 describes the design methodology. Section 4 represents the results and evaluation of the proposed system whereas the paper is concluded in section 5.

3. Methodology

The research as discussed earlier is based on rail surface faults such as squats and corrugation. As most of the techniques lodged in previous works were not efficient enough to provide productive results as some were not giving real time results, some were not suitable to be adopted in real (prototypes or those with bulky hardware). The methodology of the proposed system is split into multiple sections to make it easier for readers to understand.

3.1 Hardware Design

The hardware of the proposed system comprises the Jetson Nano (2GB) Developer Kit, EKEN H9R cameras and ublox NEO-6M-V2 GPS module. Jetson Nano is a little bit expensive but has better performance than other traditional controllers such as raspberry pi due to a better Graphic Processing Unit (GPU) [19]. The GPUs are basically used to accelerate the geometric calculations in Machine Learning (ML), and they are valued because of their parallel processing ability in ML model training and evaluation [20], [21]. The Jetson Nano (2GB) Developer Kit is represented in Figure 2.

Figure 2: Jetson Nano (2GB) Developer Kit.

The EKEN H9R cameras were selected due to its high FPS (Frame per Second) which is up to 120 and it also has battery backup and IP connectivity and waterproof features with 2" display [22], [23]. The EKEN H9R camera is represented in Figure 3.

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Figure 3: EKEN H9R Camera module.

The ublox NEO-6M-V2 GPS module is selected for the real time fault alerts of the damaged track with its coordinates (Latitude and Longitude) [24]. The GPS module ublox NEO-6M-V2 is represented in Figure 4.

Figure 4: GPS Module Neo 6m.

For the designing of the hardware of the proposed system NVIDIA Jetson Nano is interfaced with the two cameras of EKEN H9R for rail surface faults detection such as squats and corrugation which are major cause of rail derailment and GPS Module NEO-6M-V2 for the location detection of detected faults. Figure 5 represents the hardware of the proposed system.

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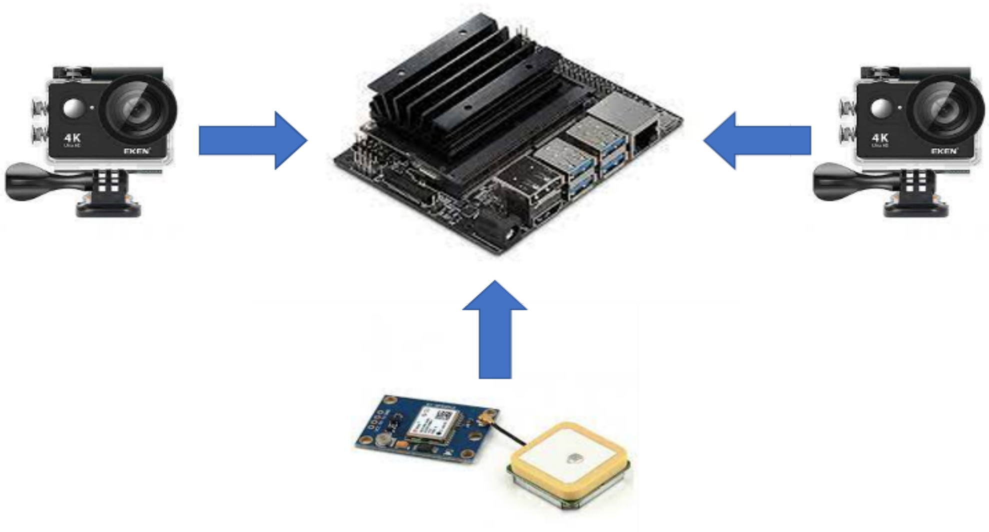

Figure.5. Hardware of the proposed system.

The hardware of the proposed system will be responsible for the monitoring of surface faults on Railway track.

3.1.1 Railway Track's Rail Surface Faults Detection

For the detection of rail surface faults, a dataset was collected from railway track by interfacing EKEN H9R camera modules in the motorized railway track recording vehicle at Kotri Junction Sindh, Pakistan as represented in Figure 6.

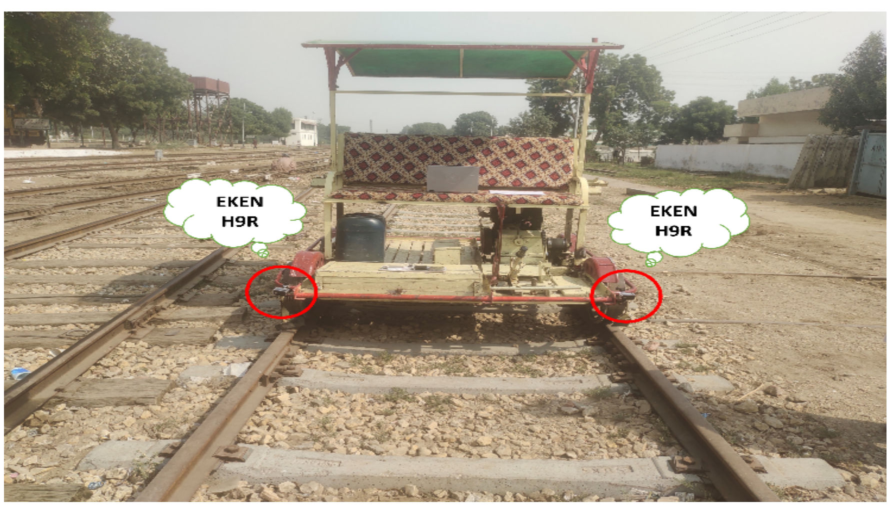

Figure 6: EKEN H9R Interfacing with Motorized Manual Track Recording Vehicle (TRV).

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From the data acquisition, following number of samples of squat and corrugation were found in the collected raw data as represented in Table 1.

Table 1: Collected Dataset.

S. No	Detections	No. of Samples
1	Squat	3500
2	Corrugation	5000

The labeling of acquired faults into their classes is carried out for the detection of squats and corrugation. To train the deep learning model, the dataset containing squats and corrugation samples was divided into train, test and valid sets, as represented in Figure 7.

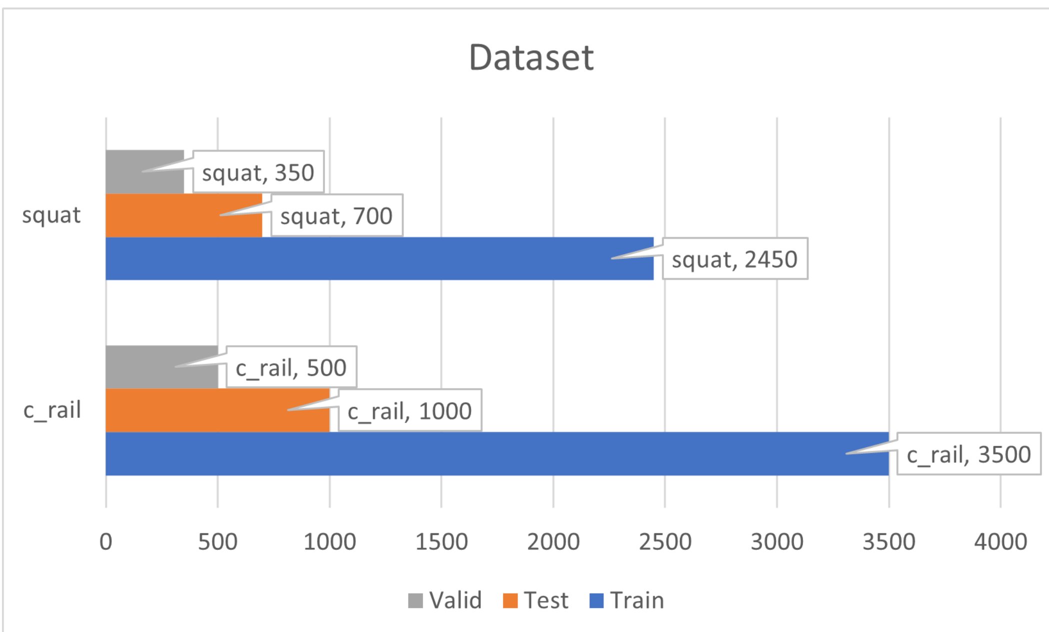

Figure 7: Squat and Corrugation Dataset.

For model training, the fastest keras pretrained models were used having accuracy greater than 93% and FPS greater than 120 [25]. The FPS of the model can be calculated from the Time per inference step using equation 1.

$$FPS = \frac{1}{Time\ per\ Infernece\ Step}$$

(1)

As per the analysis of keras pre trained models, Table 2 represents the models which were found having accuracy greater than 93% and FPS greater than 120 on GPU:

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Table 2: Keras Pre-trained Models.

S. No	Model	Top-5 Accuracy	FPS (CPU)	FPS (GPU)
1	Xception	94.5%	9.13	124.06
2	Inception V3	93.7%	23.66	145.77

As we know the mentioned models can perform at fps (124.06≤fps≤145.77) on GPU which is quite reasonable and compatible to EKEN H9R camera fps but on a CPU based controller, they can perform at FPS (9.13≤fps≤23.66) which is not reasonable for high-speed trains. The squats and corrugation dataset were feed to the mentioned models for the training of the desired model for real time prediction of the railway track faults such as squat and corrugation.

After the training of the model, an input image will be passed from the camera module to predict whether there is squat, corrugation.

3.2 Software Design

The web interface of the proposed system is designed using PHP and HTML languages with MySQL Database. The Developed web interface is named as “Intelligent Instrumentation and Condition Monitoring Systems (IICMS)” which is responsible for the for data storing and visualization as shown in Figure 7.

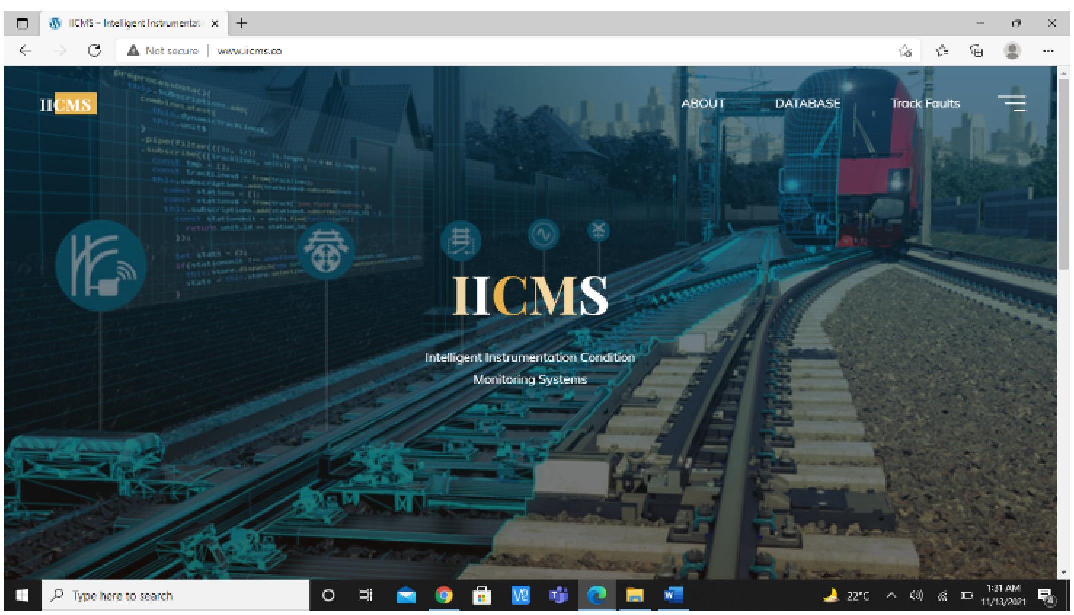

Figure 7: Web Portal of the developed system.

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3.3 System Integration

After the development of hardware and software, they are integrated together to form a compact system. The system integration is shown in Figure 8, it shows that the device sends railway track faults record to server, the server is managed online, and information is accessible using Web Portal for Desktop Systems.

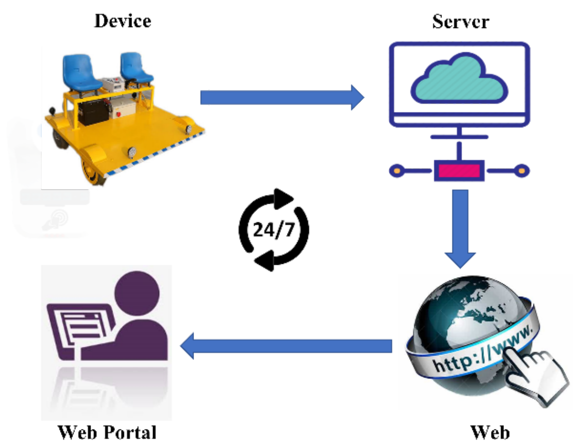

Figure 8: System Integration.

4. Results and Discussion

In this paper, different supervised deep learning networks are utilized for developing the proposed system for the classification of squats and corrugation. By considering the high accuracy and FPS, two supervised networks are presented here based on their high accuracy acquired and one of the best will be concluded in this research work.

4.1 Squat and Corrugation Classification

The squats and corrugation detection are carried out using deep learning models such as Xception and Inception V3.

4.1.1 Xception

The Xception can be defined as a deep convolutional neural network architecture which involves Depth wise Separable Convolutions having top-5 accuracy of 94.5. The labelled dataset of squats and corrugation was feed to the model and trained for 200 epochs. After the training of the model, a reasonable training loss, training accuracy, validation loss and validation accuracy are acquired as shown in Table 3.

Table 3: Xception Performance Parameters.

S. No	Parameters	Value
1	Training Loss	1.0830e-05

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2	Training Accuracy	0.98
3	Validation Loss	1.2456e-04
4	Validation Accuracy	0.96

For the validation of the trained model, the confusion matrix and classification report were generated on the validation dataset, and it is found that the correct predictions of squats are 91% and false predictions are 9%. Similarly, 98% correct predictions are made of corrugation with 2% false predictions as shown in Figure 9. In the classification report, it is shown that the model has an average accuracy of 95% which is represented in Figure 10.

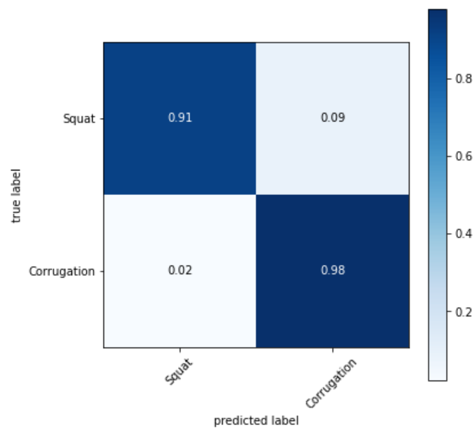

Figure 9: Xception Confusion Matrix.

```
In [16]:  print(classification_report(truth, prediction, target_names = classes))

                 precision    recall  f1-score   support

       Squat          0.97      0.91      0.94       350
  Corrugation         0.94      0.98      0.96       500

      accuracy                            0.95       850
     macro avg        0.95      0.94      0.95       850
  weighted avg        0.95      0.95      0.95       850
```

Figure 10: Xception Classification Report.

4.1.2 Inception V3

Inception-v3 is a convolutional neural network architecture from the Inception family which makes several improvements in the older inception networks with top 5 accuracy of 93.7. The labelled dataset of squats and corrugation was feed to the model and trained for 200 epochs. After the training of the model, a reasonable training loss, training accuracy, validation loss and validation accuracy are acquired as shown in Table 4.

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Table 4: Inception V3 Performance Parameters.

S. No	Parameters	Value
1	Training Loss	1.6892e-06
2	Training Accuracy	0.99
3	Validation Loss	1.6892e-06
4	Validation Accuracy	0.97

For the validation of the trained model the confusion matrix and classification report were generated on the validation dataset, and it is found that the correct predictions of squats are 96% and false predictions are 4%. Similarly, 98% correct predictions are made of corrugation with 2% false predictions as shown in Figure 11. In the classification report it is shown that the model has an average accuracy of 97% as represented in Figure 12.

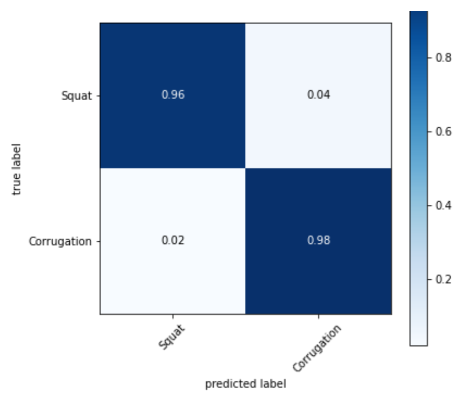

Figure 11: Inception V3 Confusion Matrix.

```
In [35]:  print(classification_report(truth, prediction, target_names = classes))

              precision    recall  f1-score   support

       Squat       0.97      0.96      0.96       350
  Corrugation      0.97      0.98      0.98       500

    accuracy                           0.97       850
   macro avg       0.97      0.97      0.97       850
weighted avg       0.97      0.97      0.97       850
```

Figure 12: Inception V3 Classification Report.

For the comparative analysis of the proposed models, a comparative classification report of the models is generated as shown in Figure 13. It is evaluated that both the models have better accuracy, but Inception V3 performed outclass with an average accuracy of 97% in the classification of squats and corrugation.

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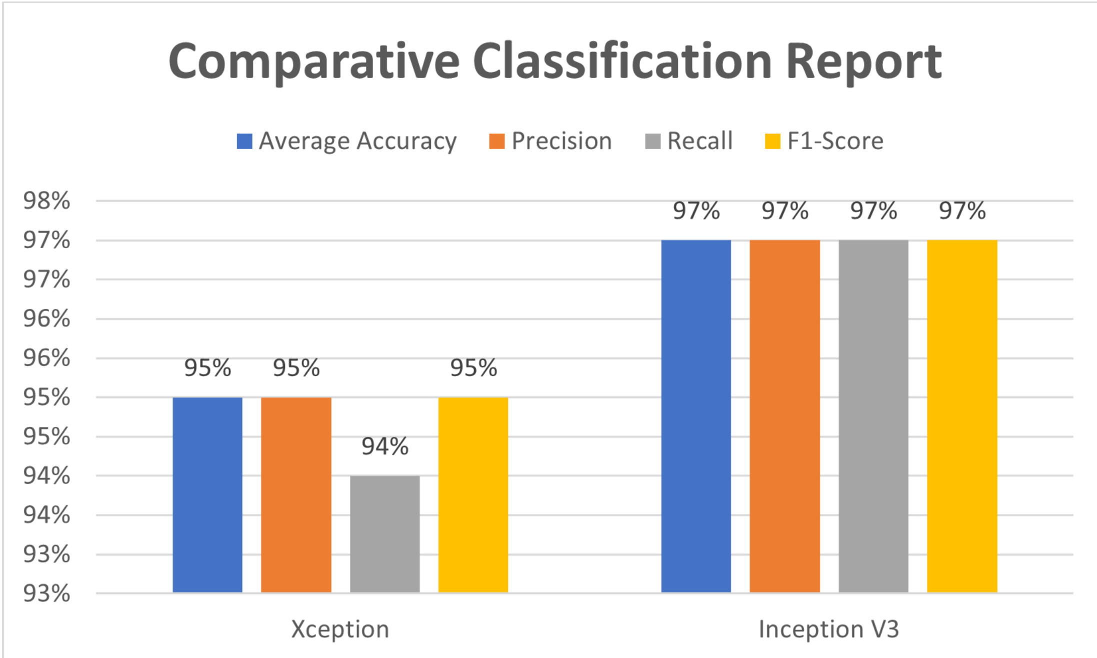

Figure 13: Comparative Classification Report.

Finally, the concluded best model Inception V3 is used for the detection of squats and corrugation with the designed hardware as shown in Figure 14. The corrugation detection is represented in Figure 15 and squat detection is represented in Figure 16.

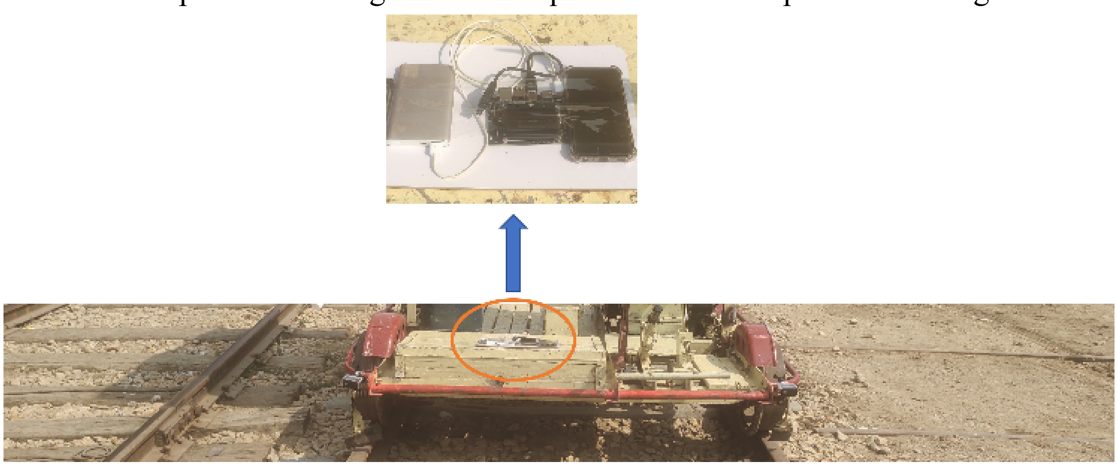

Figure 14: Final developed System.

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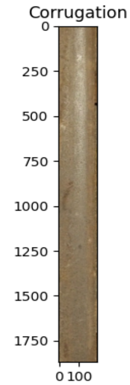


Figure 15: Corrugation Detection.

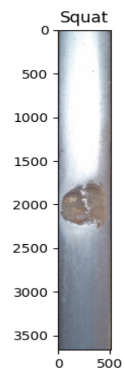
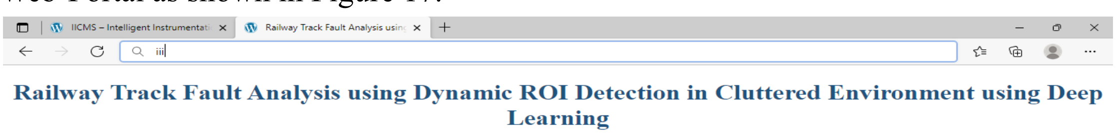


Figure 16: Squat Detection.

The Detected Faults such as Squat and Corrugations are displayed on the designed Web-Portal as shown in Figure 17.



No	Date	Time	Latitude	Longitude	Corrugation	Squat
1	2021-10-12	11:14:38	25.505112	68.2824115	Detected	Not-Detected
2	2021-10-12	11:14:39	25.5052386666667	68.28247	Detected	Not-Detected
3	2021-10-12	11:14:39	25.5053643333333	68.2825291666667	Detected	Not-Detected
4	2021-10-12	11:15:33	25.5061141666667	68.2829033333333	Detected	Not-Detected
5	2021-10-12	11:15:45	25.5066123333333	68.2831575	Detected	Not-Detected
6	2021-10-12	11:15:48	25.5067383333333	68.2832218333333	Detected	Not Detected
7	2021-10-12	11:15:52	25.5068653333333	68.283286	Detected	Not-Detected
8	2021-10-12	11:20:12	25.5084026666667	68.2840608333333	Not-Detected	Detected
9	2021-10-12	11:22:19	25.5087953333333	68.284258	Detected	Not-Detected
10	2021-10-12	11:22:19	25.5089235	68.2843245	Detected	Not-Detected
11	2021-10-12	11:23:39	25.5106286666667	68.2853821666667	Not-Detected	Not-Detected
12	2021-10-12	11:24:34	25.5142045	68.2883643333333	Not-Detected	Detected
13	2021-10-12	11:24:35	25.5143103333333	68.2884513333333	Not-Detected	Detected
14	2021-10-12	11:25:15	25.5147371666667	68.2888131666667	Detected	Not-Detected
15	2021-10-12	11:25:15	25.514846	68.2889041666667	Detected	Not-Detected
16	2021-10-12	11:25:16	25.5149545	68.288997	Detected	Not-Detected

Figure 17: Web-Portal of the Proposed System.

5. Conclusion

The device is specifically designed to address Pakistan Railway immediate needs such as railway track faults including squats and corrugation. The comparative analysis of different convolution neural networks is carried out for squat and corrugation classification in which Inception V3 is found the best model having an accuracy of 97% which is reasonable for practical implementation of the system in Pakistan Railways.

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