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Rail Surface Faults Identification from Low Quality Image Data Using Machine Learning Algorithms

Asfar Arain, Tanweer Hussain, Sanaullah Mehran Ujjan, Bhawani Shankar Chowdhry, Tariq Rafique Memon

NCRA- Condition Monitoring Systems Lab, Mehran University of Engineering and Technology, Jamshoro.

Bhawani.chowdhry@faculty.muet.edu.pk

Abstract

Rail surface faults or deformities that form on railhead of the track, owe their existence to various operational and environmental factors. To ensure comfortable and safe operation of railway vehicles, on-time detection of these surface faults is necessary. It is also of paramount importance that fault types are identified because it can lead to the identification of causes. This eventually leads to development of better maintenance strategies. Automation of the rail inspection is highly desirable because it results in accurate, robust, and cost-effective condition monitoring of the railway track. Automated systems of track monitoring currently in use are highly sophisticated instrumentation systems, with high-speed cameras and equipped with state-of-the-art level hardware. In this research, a preliminary work towards developing a low-cost rail condition monitoring system is presented. A suitable action camera EKEN-H9R is used to acquire videos of track surface. This data is preprocessed and later used to train data-driven models for fault identification. A comparative analysis of multiple data-driven classification algorithms is conducted on the acquired data and research is concluded with support vector machine algorithm which was able to achieve about 96% accuracy on the fault classification task.

Keywords: Rail Surface faults, Fault identification, Condition monitoring, Machine learning, Data-driven models, Classification, Noisy data.

1. Introduction

Deformities on rail surface occur due to various causes such as fatigue, repetitive passing of rolling stock over welds, joints, switches, or impact of a damaged wheel. These deformities need to be detected and treated on time to avoid the chance of a critical failure or further degradation of the rail. Either of which can result in delay of the train, high maintenance cost, and higher risk to the safety of passengers [1]. The existence and severity of surface faults depend upon various operational and environmental factors. These deformities develop in many forms and shapes.

However, this research targets four surface fault types abundantly sighted in Pakistan's railroad infrastructure. Faults targeted in this research are shown in Figure 1: Flaking is commonly found near the gauge corner of rail, identified with scaling or chipping of small slivers on the running surface. Shelling on the other hand usually forms on the gauge side of the railhead and is identified as progressive horizontal separations. Subsequently, spalling is identified as displacement of parent metal from the railhead because of high contact stresses whereas, squats form in an oval-like shape and result in widening of the rail running band [2].

Flaking Shelling Spalling Squat

Figure 1: Prominent Rail Surface Deformities

Automation of the railway track monitoring is desirable due to manual inspection's obvious limitations. Manual/detailed inspection of the rail track is difficult and time-consuming. It requires trained individuals to ensure the exclusion of errors during the inspection [3]. Therefore, automatic detection of faults is important to improve performance and safety. In the past few years, various methods have been employed for automated railway track condition monitoring. New advancements in the field of machine vision and pattern recognition have fueled the development of visual inspection systems (VIS) [4]. However, the majority of these VIS's are highly sophisticated instrumentation systems and also very expensive. These VIS's incorporate high-speed cameras, capable of grabbing 5000 frames per second (FPS), state of the art processing hardware to deal with enormous data flowing into the system, and illumination schemes to ensure quality data acquisition. The emergence of data-driven models in the field of pattern recognition and their deployment to solve domain-specific problems has achieved promising results [3]. These models have the ability to work with raw data and provide good end to end prediction capability. Therefore, in this research with the intent of developing a cost-effective VIS solution we try to take advantage of the prediction power of data-driven models to compensate for high-quality data and sophisticated hardware. We test various data-driven algorithms on fault classification/identification task from raw image data. Rail surface defect data is collected from Kotri Junction and its vicinity. Different algorithm's generalization capability is compared by subjecting them with unseen data.

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2. Related work

In [5] Alnaimi and Qidwai et al., proposed an automated system that uses convolutional neural network to classify captured images into normal and abnormal classes. The proposed system also marks the location details of abnormal images for a detailed inspection by human experts. In [6] Wei et al., Used deep learning and image processing techniques for detection and classification of rail fasteners into classes (normal, broken, and missing), spalling, and corrugation. Data augmentation techniques are used to balance the classes due to small number of defect images. In [7] Niu et al., developed a system based on global low rank and non-negative reconstruction (GLRNNR). The system can obtain precise stereoscopic images along with profile information for building a data set of defects. Experimental results of the proposed method show good accuracy. In [8] Gan et al., proposed a novel BODI (background-oriented defect inspector) for the detection of rail surface faults. The proposed method uses a random strategy to generate background information and perform several statistics operations on samples to validate that the pixels under observation belong to a specific background class or not, during experimental study the method performed well. In [9] Wang et al., proposed an entity sparsity pursuit method that extracts features from input images to detect surface fault, the proposed method can detect faults from various data sets in an unsupervised manner. Experimental results show that the method performed well on all datasets. In [11] Yu et al., proposed a novel coarse-to-fine method to detect faults by considering pixel consistency. Performance of the proposed method was tested on the rail line by installing line scan cameras with led lights under the test train. In [12] Min et al., proposed a system based on machine vision for detection of defects using plane array CCD cameras along with light sources installed on inspection vehicles. The proposed system performs various image enhancement techniques to improve the quality of data. In [13] Zhuang et al., developed a system based on extended haar-like features and cascading classifiers (logitboost algorithm) for crack registration and boundary identification, the method is validated on image data set provided by Hong Kong mass transit railway and china railway corporation. According to experimental results, the data-driven method proposed in this study performed well for crack registration and boundary detection. In [14] Li et al., proposed a cyber-enabled visual inspection system based on rail locating algorithm, weighted projection profile (RLWP), and SVM classifier for detection of rail corrugation. The proposed system is based on an image acquisition system and a corrugation identification system, acquired images are segmented according to the algorithm based on weighted projection profile which detects only rail from the input image. Images are detected as corrugated or not by a binary SVM classifier. In [15] Gan et al., proposed an automatic visual inspection system based on a novel hierarchical extractor (coarse and fine extractor), which capture images through a camera then feed them to an inspection framework which is based on several extractors to find background modes, reduce the effect of noise, and remove irregularities. The proposed method showed good accuracy on the defect dataset. In [1] Jamshidi et al., developed an image processing technique that relies on

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deep convolutional neural network, for detection and classification of squats and their severity by measuring their length and estimates the probability of failure, estimations are done on samples taken from the track of Dutch railway system. In [16] Ma et al., proposed a method based on generalized hough transform and SVM classifiers for automatic detection and classification of severity levels of defects from images collected by high-resolution cameras installed with laser light source for illumination. In [3] Faghih-Roohi et al., compared training time and classification performance of three DCNN structures for classification of images from six classes (normal, joint, weld, severe squat, moderate squat, and light squat). The large DCNN proposed in this study achieved classification accuracy of 92%. However, the majority of the above-mentioned methods focus on detection of the surface faults [7, 9-15, 17]. Fault type identification is not the focus of these studies which is crucial for a variety of reasons. Fault classification leads to the identification of the cause and helps determine more appropriate action in order to remove or minimize the cause. Few of the above-mentioned studies do employ methods to identify types of faults but focus either on different types of faults as targeted in this study [6][18][3][1] or simply avoid defining the types of faults being classified [5][16]. Moreover, bulk of the research employs highly sophisticated instrumentation systems with components such as illumination schemes to ensure high-quality data acquisition. Contrary to that, this research works with noisy and raw data as acquired on-site with a low-cost image acquisition device and aims at harvesting the end-to-end prediction capability of data-driven models.

3. Methodology

In Figure 2: step by step methodology followed during this research is shown. Video acquisition is done through two EKEN-H9R cameras mounted on both sides of the inspection vehicle as shown in Figure.2. Cameras are capable of recording videos at 120 FPS and have a FOV (field of view) of approximately 14 inches. Unnecessary parts of the collected videos were later removed in the second step. Frames needed to ensure the inclusion of every useful information possible were calculated as shown in Equation 1.

Table 1: Details of gathered data after labeling

Cracks	51
Flaking	2850
Joint	9
Shelling	231
Spalling	296
Squat	2163
Groove	8
Miscellaneous	79860
Total	85468

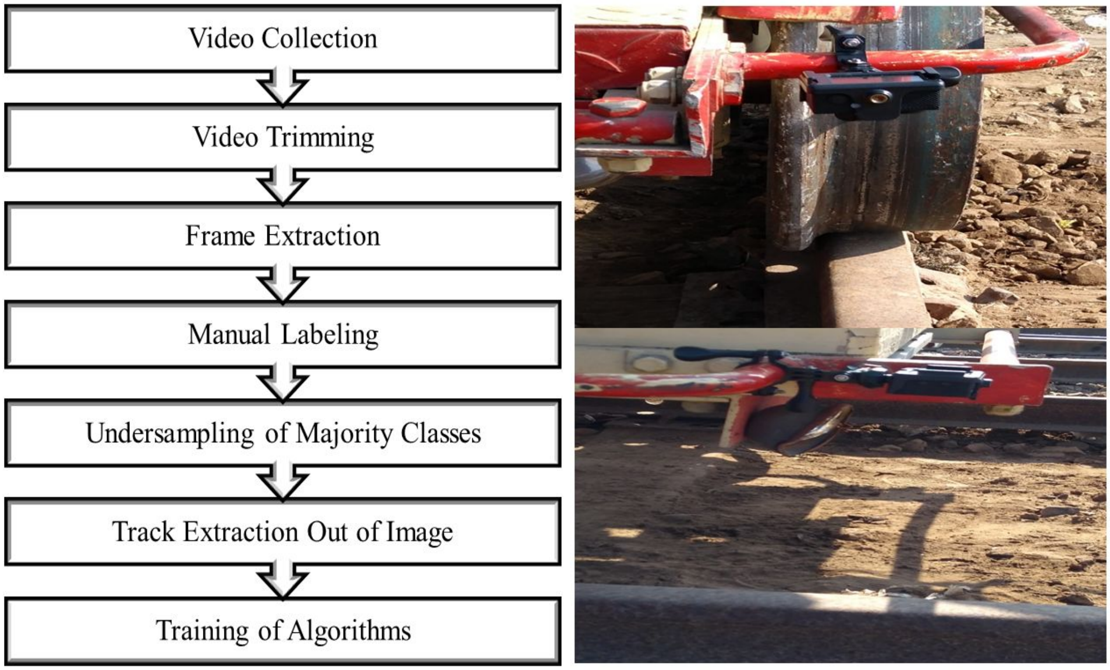

Figure 2: Research Methodology and Video Capturing Setup

$$Frames\ Required = 2 \times \frac{Assumed\ Maximum\ Speed\ of\ Vehicle\ (\frac{meter}{sec})}{Field\ of\ View\ (meter)} \quad \ldots..\text{(Equation 1)}$$

After extracting required frames out of videos manual labeling of the images was done. Table 1 shows the details of the data gathered. Data gathered on-site and manually labeling resulted in a class imbalance problem. Grooves, Joints, and Cracks were barely represented and other types of faults also had a large difference of samples. Therefore, under-sampling of the majority classes (Flaking, Squat) was done and 230 images from four classes (Flaking, Shelling, Spalling, Squat) were selected. Out of total 920 images 70% are used for training the data-driven models and 30% are used for validation. Later, the region of interest (railhead image) was cropped out of full image. Various machine learning algorithms were implemented in this study, which have comparatively less computational cost than deep learning models. Machine learning models implemented include; Decision tree, K-nearest-neighbors, Logistic regression, Random forest, Naïve bayes, and also two variances of Support vector machines. Models were fed with RGB rail images of 700x200 cropped out of the recorded video. To test the learning capability of these models, no image enhancement or de-noising of the images was done.

4. Results and discussion

Classification algorithms of machine learning were one by one trained and evaluated on the dataset. Their performance was compared, details of this comparative analysis is given below; Decision tree which is one of the fundamental models used for classification purposes was implemented first. Decision tree keeps splitting the

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features of a dataset into nodes and subnodes until feature space runs out. These nodes or branches represent different possible outcomes. An optimized version of the CART [19] based decision tree was implemented in this study. Figure 3: shows the confusion matrix of the decision tree obtained on the validation data. Promising accuracy is achieved on predicting shelling but struggles to predict other three classes. This is probably due to the fact that shelling in appearance is quite different from other classes and has different points of appearance in the images. Decision tree achieved 81% average accuracy. However, it has 76.45 % accuracy if shelling is excluded.

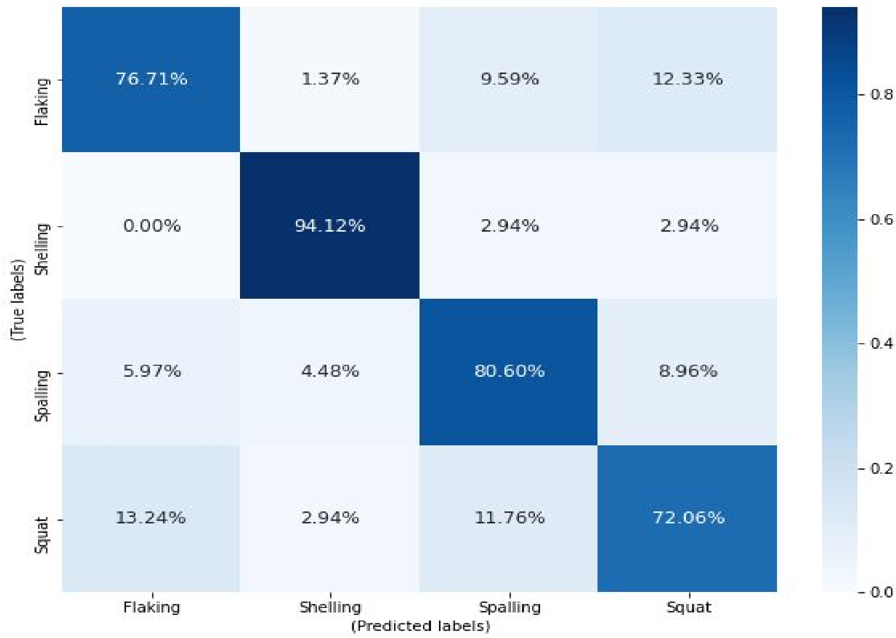

Figure 3: Confusion Matrix of Decision Tree

K-nearest-neighbors were tried next. KNN works on multi-dimensional geometrical properties and Euclidian distance calculation for optimization of the results. Different points are initialized in the feature space and based on their Euclidian distance from the individual feature they are moved towards or away from features till the optimum position is obtained. K-nearest-neighbors achieve slight improvement in predicting flaking as shown in Figure 4: But, performs rather poorly on squats and spalling. KNN was able to achieve 74% average accuracy on predicting individual classes which falls mostly on the shoulders of shelling on which 100% is accurately predicted. However, performance on the other three classes has an average accuracy of 67.11% only and approximately 60% on spalling and squats.A multiple logistic regression unit's model was implemented next. It achieved 79% average accuracy on individual classes. Figure 5: shows the performance of logistic regression model on individual class prediction. It is apparent that the model has a certain degree of bias towards squat class on which it achieves good accuracy however performs poorly on other classes. A different approach based on probabilistic calculations Naïve Bayes was implemented next. Naive Bayes is a combination of Bayes theorem [20] and maximum a posteriori. It was able to achieve 81% accuracy in predicting faults.

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Figure 6: show the performance of Naïve Bayes. It seemed to have achieved a good generalization capability and good balance in prediction accuracy among different classes. However, overall performance was average.

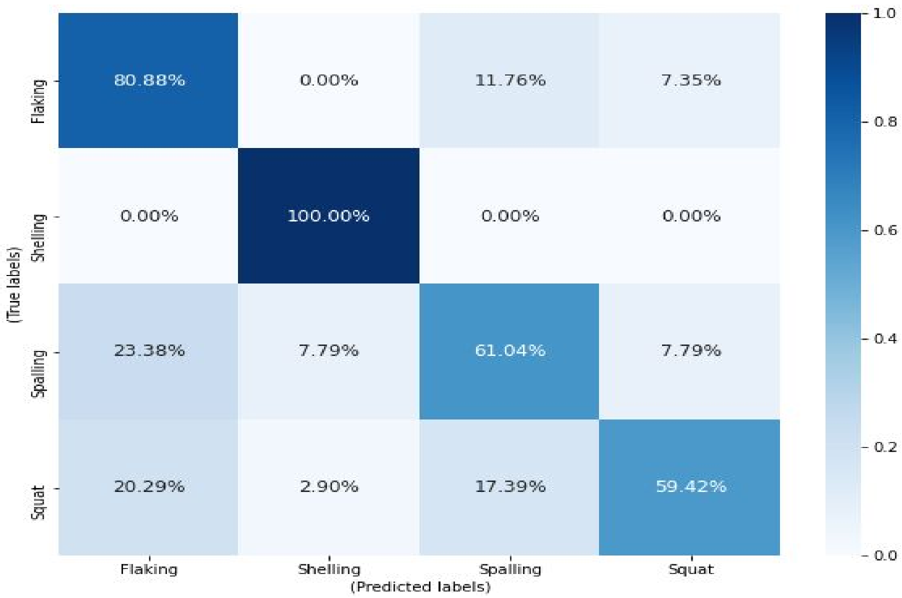

Figure 4: Confusion Matrix of K-Nearest-Neighbors

A random forest classifier model was also implemented which achieved 92% average accuracy on the prediction task. Random forest proved to be by far the best model without any bias towards a certain class and performed effectively on all the classes as shown in Figure 7.

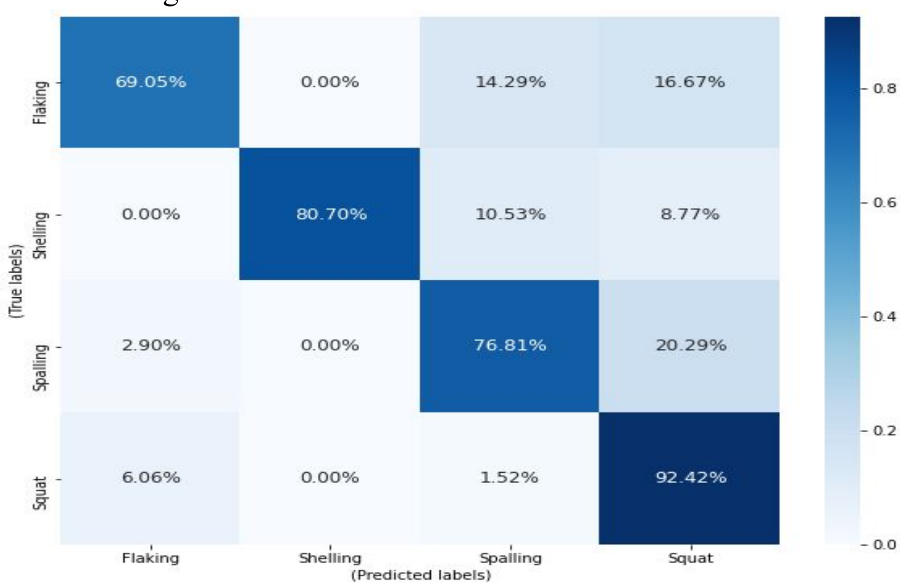

Figure 5: Confusion Matrix of Logistic regression

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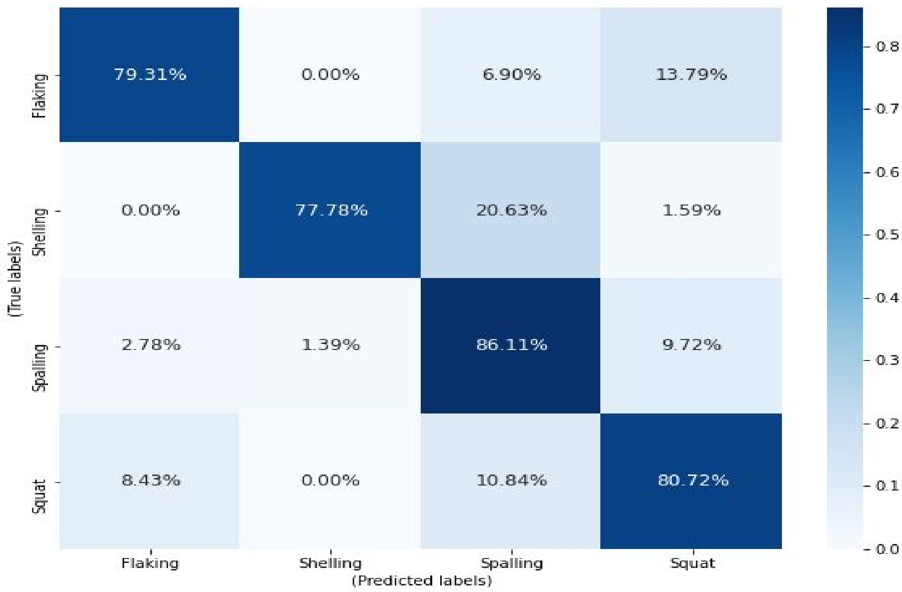

Figure 6: Confusion Matrix of Naïve Bayes

However, did perform poorly on predicting spalling. This is probably because spalling is the most unnoticeable faults in our prediction classes. Two variances of Support vector machine based classification were tried next, these algorithms try to find the equation of optimum position of the hyperplane which separates different classes in a multi-dimensional space. SVM Gaussian was able to achieve about 91% accuracy and surpassed every model tried in our study as shown in Figure 8.

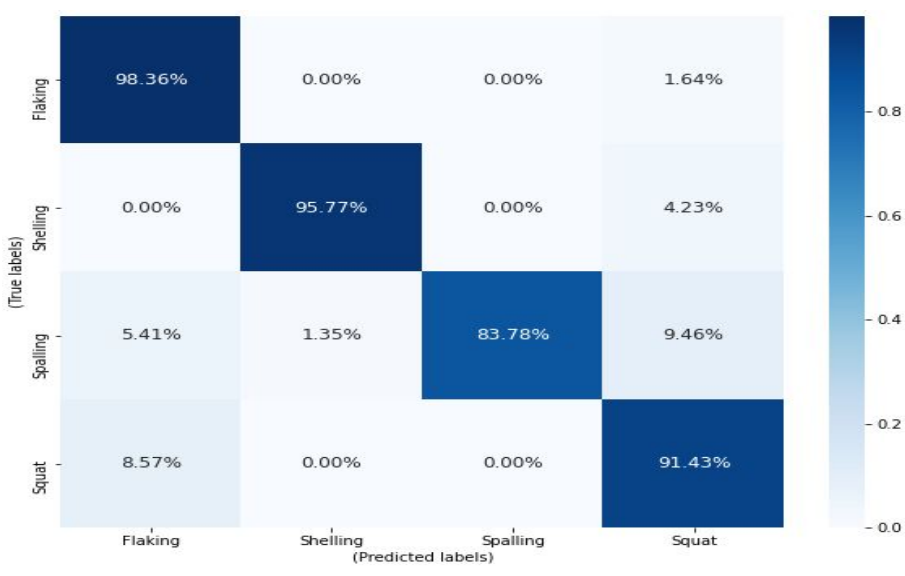

Figure 7: Confusion Matrix of Random Forest

The polynomial version of the support vector machine resulted in even better performance which achieved 96%. And performed equally well on all the classes as

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shown in Figure 9. The overall performance summary of all the data-driven models tried in this study is shown in Figure 10: in the form of bar graph. The bar graph shows the score of each model on different evaluation matrices such as Precision, Average Accuracy, F1-Score, and Recall. These evaluation matrices are one of the most used methods of evaluating the performance of classification models.

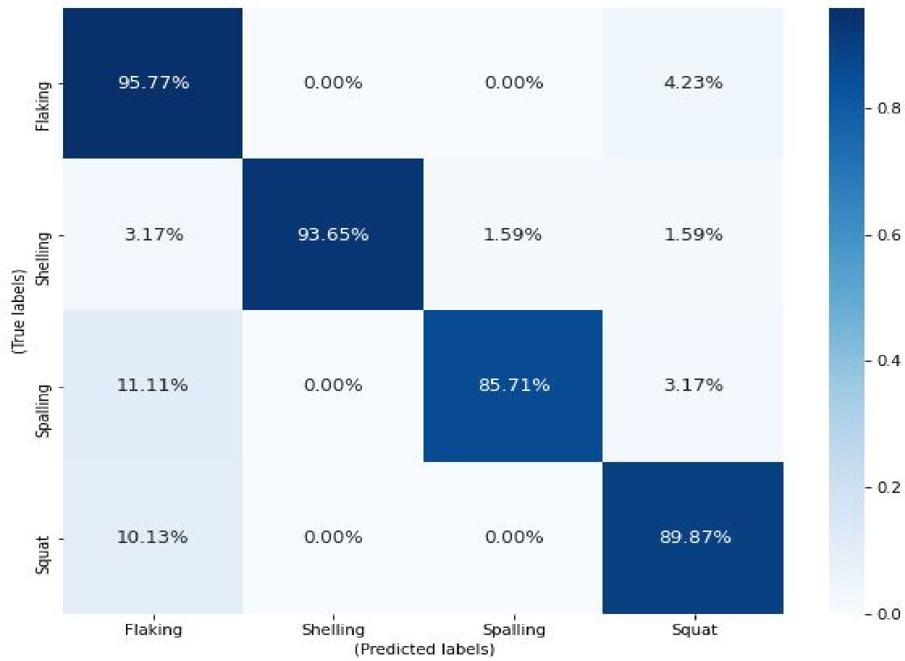

Figure 8: Confusion Matrix of SVM Gaussian

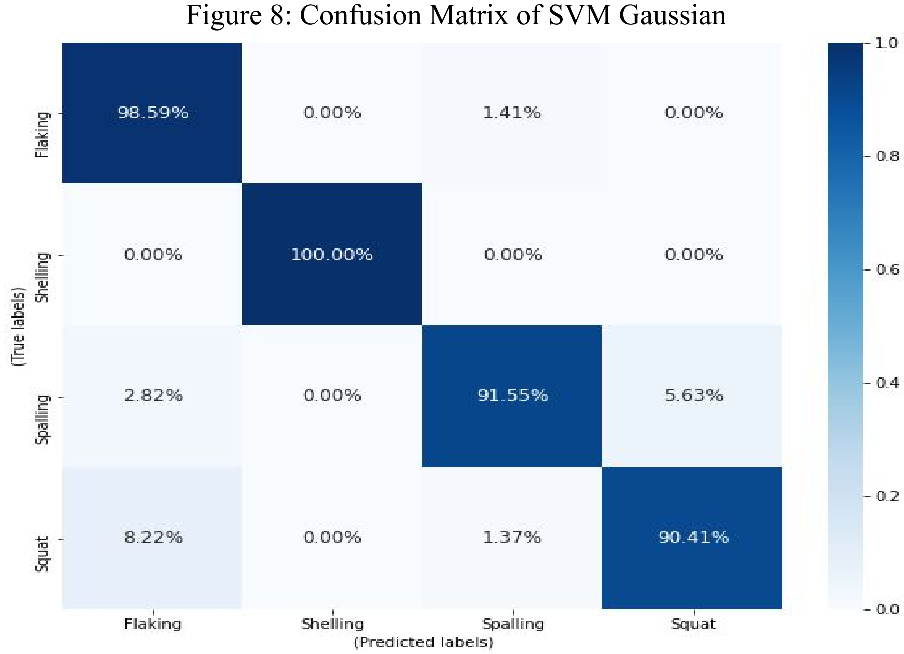

Figure 9: Confusion Matrix of SVM Polynomial

It is evident from Figure 10: that all of our models have acquired consistent scores on different performance evaluation matrices. But support vector machine variances outperform all the other models in the classification task.

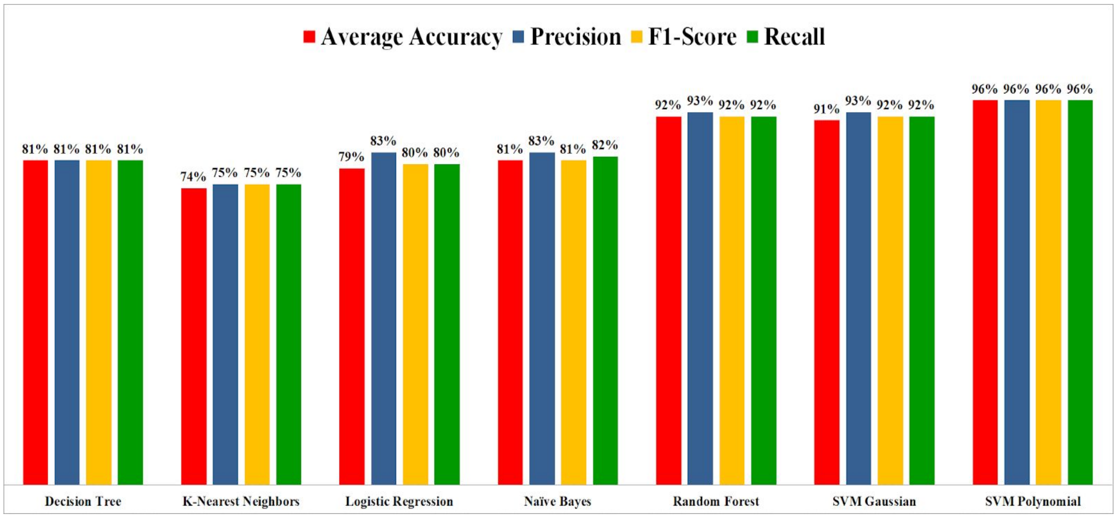

Figure 10: Performance summary of data-driven models

5. Conclusion and future recommendation

In this research, preliminary work towards developing a low-cost rail condition monitoring system is presented. The distinct feature of this study is that it works with low-quality images acquired from EKEN-H9R cameras on-site without adding any illumination, feature extraction, or image enhancement techniques. We input raw RGB image to our models and obtain end to end prediction. This approach has proved to be successful and shows the potential of data-driven models to work with low-quality data and their deployment in fault identification scenarios. Our final model support vector machine polynomial achieves greater than 95% accuracy on identifying different surface faults without any bias towards a certain class. This study can be further extended by acquiring more data because some of the faults are rarely represented in our study and were ignored due to very reason. The class imbalance problem was solved with under-sampling of the majority classes. Data augmentation or oversampling techniques remains to be explored. Moreover, for this study we went through a trying process of manually labeling data, unsupervised approaches could also be explored.

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