Condition Monitoring of Brake Disc Images using Convolutional Neural Network

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***Abstract*—Predictive health maintenance in automobiles is soon a necessity fueled by the evolution of autonomous vehicles. Data driven approaches are popularly being used for vehicle maintenance to discover anomalies and predict malfunctions. Health monitoring systems in an automobile can be employed for brakes, suspension elements, tyres, and components of an engine. Brake system is one of the critical components of an automobile which must be supervised regularly to avoid serious consequences during driving. Brake disc is one of the contributing factors to complaints about faulty brake systems. Brake disc are damaged due to cracks formed either as a result of thermal stresses which arise because of sudden braking or due to high braking cycles. An intelligent system which can monitor the condition of brake system using CNN with the help of images of brake disc is discussed. A dataset of disc images is prepared from the videos of brake disc captured at varying accelerations in a test reg in addition to static images captured with varying scale, rotation and background. Performance of pre-trained CNN models is tested on the dataset of disc images in order to identify a healthy or a unhealthy disc.**

Keywords—Brake Disc, Images, Health Monitoring

I. INTRODUCTION

Automobile industry is a rapidly growing industry with ad- vancements in smart technology being utilised across produc- tion, supply chain, customer experience, and mobility services in addition to autonomous vehicles. Applications of AI in automobiles include detection of defects of failed assembly on the production line, voice enabled customer interaction using virtual digital assistants in the car, driver monitoring with in- car sensing etc. When it comes to vehicle maintenance, data can be used to discover anomalies and predict malfunctions before they occur, avoiding costly repairs and services. An intelligent system for health monitoring of the vehicle can lead to better safety, comfort of the user and an improved service life of the vehicle.

The brake system of an automobile is the most important control component which ensures the safety of passengers and vehicles. A brake system failure occurs due to continuous application of the brakes depending on various reasons. These failures need to be monitored to avoid incidents that may lead to accidents. Thus, monitoring the braking system is imperative for the safety of the passenger and vehicle. So, an experimental investigation is performed for monitoring the wear and tear of the brake disc, which is one of the critical components of a braking system. Machine learning based data driven health monitoring systems (HMS) are popularly being adopted in several systems. Compared to conventional data- driven health monitoring (HMS), Deep learning based health monitoring does not require extensive human knowledge for feature design and therefore can be applied to HMS in a very general manner [1]. Use of sensor data such as pressure, temperature, vibration etc. are most common in automobile HMS. Success of Deep learning architectures such as CNNs across several vision based applications has motivated us to explore the use of images in brake disc condition monitoring.

Convolutional Neural Networks (CNN), have enabled a learned representation of images and are proved to be effective to classify a wide range of image categories. The parameters of CNN's such as Alexnet, are trained using large datasets with millions of photos for each category. However, for applications where significant number of images of each class are not always available, transfer learning, which involves fine tuning a pre-trained CNN has shown excellent results. CNN features are proved to be generalized enough to be used as image features when compared to several hand crafted features such as SIFT for image matching [2]. Performance of pre-trained CNNs for monitoring the wear and tear of a disc brake is experimentally evaluated and presented in this paper. Major contributions are as follows:

- Establish the feasibility of use of image data in healthmonitoring of an automobile.
- Use of transfer learning approach and posing condition monitoring as an image classification problem

- Create a dataset of brake disc images using a test rig to simulate the operating conditions of hydtraulic brake ofa 2 wheeler automobile.

Paper is structured as follows: In Section II, Survey, referring to research on automated health monitoring of auto- mobiles is presented. In Section III details regarding brake disc dataset creation and the pre-trained CNN architectures employed are discussed. In Section IV experimental results are discussed and Conclusion is given in Section V.

II. LITERATURE SURVEY

Objective of a Prognostic and Health Management (PHM) system is to use intelligent approaches and monitor the status of the mechanical system, with the help of data collected using sensors [3]. Automated health monitoring systems can broadly classified into model based, signal based and data driven approaches [4]. With the advent of machine and deep learning approaches, data driven health monitoring is commonly being adopted to address the challenges of detecting and diagnosing faults in non linear, noisy systems. Data driven machine learning approaches have evolved in predictive maintenance of automobile industry [5]. Brake health monitoring has been the topic of a number of research and review articles. Manghai et al. [6] carried out an experiment for monitoring the brake system using vibration signals. Using a variety of classifiers from the tree family, including random forest, random tree, LMT, and decision trees were used to categorize the statis- tical data. In another study, Manghai et al. [7] demonstrated the use-case of wavelets in fault diagnosis of the hydraulic braking system by taking vibrational signals from a test setup. Wavelets have received a lot of attention in defect diagnosis studies in recent years because they efficiently and accurately break down complex data into simpler forms for additional analysis. In the above-mentioned research studies, only one form of input was considered for the brake fault diagnosis i.e. vibrational data extracted from the testing rig.

Although vibrational analysis of hydraulic braking systems is accurate for fault diagnosis, it fails to elaborately analyze the wear and tear of the metal brake disc. For instance, vibrational data cannot detect the slight air fissures or scratches that develop as a result of the frequent use of vehicles. Deep learning approaches like CNN are more efficient for monitoring the brake disc and assessing the damage done to it. There are very few to no use-case instances of deep learning in the field of data-driven health management in automobiles even though there is so much undiscovered potential in deep- learning.

Although CNNs have not been used for brake health monitoring, there are several instances of using CNNs for automobile HMS, some of which are listed here. Signals com- ing from sensors, such as accelerometers , vibration sensors are commonly used as input to Neural Networks. Signal to Image approach is popularly adopted when using CNNs for automobile health monitoring. Authors in [1] converted signals into two-dimensional (2-D) images, and tested CNN on three datasets, motor bearing dataset, self-priming centrifugal pump dataset, and axial piston hydraulic pump dataset. Performance of CNN is tested for diagnosis of automotive damper defects using signals of a classic Electronic Stability Control (ESC) system, such as wheel speeds, longitudinal and lateral vehicle acceleration, and yaw rate [8]. CNN is used for detecting faults in bearing, by converting vibration signals to images in [9]. CNNs are employed on transformed time series data such as Wavelet Transform, Fourier Transform etc [11]. Authors in [11] use images to detect oil leakage aftermarket motorcycle damping system with CNN. Other areas of CNN application include scratch detection in cars from experimentally collected images, with results between 95% and 98.5% accuracy in the classification, as presented by Suescún et al. in [13]

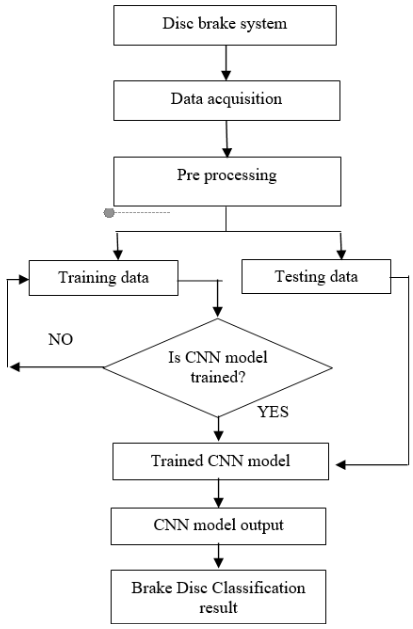

Fig. 1. Brake disc classification using CNN model

III. PROPOSED APPROACH

In the current work, the construction of a system for classifying brake discs on the basis of their wear is revealed. Transfer learning was used to train the CNN, and divisions of the global picture were utilized to conduct in-depth searches for any type of damage, such as scratches or wear on the brake disc’s surface. The process began with using pre-trained CNN architecture, for the training of a new CNN focused on the identification of wear and tear of the brake disc. Figure 1 shows the major steps involved in the approach.

The main purpose of the research is to monitor the condition of the brake disc system. This research paper mainly focuses on the use of convolutional neural networks for the classifi- cation of healthy and damaged discs of the brake setup. A training and validation dataset of disc images is essential to train a CNN model. The following section describes the data collection process.

Fig. 2. Capturing of Images using Experimental Setup containing SampleDisc Brake

Fig. 3. Disc Images processed using Experimental Setup

A. Data Acquisition

As shown in Figure 2, the testing rig for the disc brake was setup. The experimental setup used for brake testing and monitoring is a real-time vehicle that runs upon a 330 cc Briggs and Stratton I.C Engine, of 10 BHP power at 7100 RPM.

Frames of the videos captured from the test rig are saved as images, as shown in 3. To improve the generalization of CNN model, additional disc images are captured from various angles and orientations. The images are then divided into parts. Dataset consisted of up to 1500 disc images divided into four classes: New disc front, New disc rear, Old disc front, and Old disc rear. Sample images are shown in 4, details of class distribution is shown in I

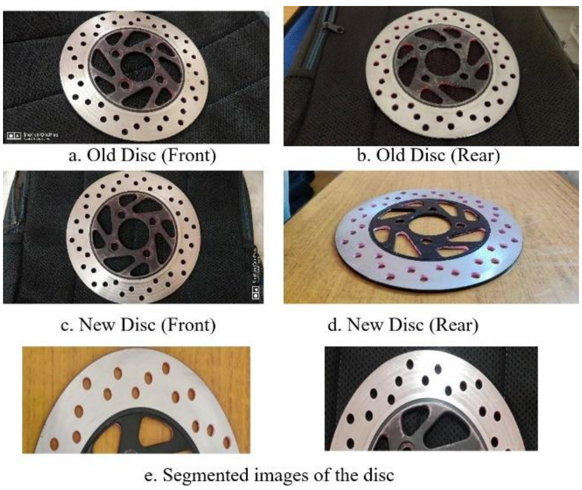

Fig. 4. Disc Images captured using camera

TABLE I. CLASS DISTRIBUTION OF DISC IMAGES

SNo.	Class	No. of images
1	Old Disc (Front)	286
2	Old Disc (Rear)	482
3	New Disc (Front)	321
4	New Disc (Rear)	374

B. CNN Model Architecture

The dataset of brake disc images was trained on three different Neural Network Architectures namely MobileNetV2, Res-Net, and Inception net, which are some of the most used architectures in transfer learning. MobilenetV2 is a 53-layer deep neural network that is capable of classifying images into 1000 object categories. But in this research, there are only 4 classes to classify i.e. New disc front, New disc rear, Old disc front, and Old disc rear. By retaining only the convolution layers and primary architecture of the these layers, fully connected layers (dense) are separately added to the pre- trained model to meet the requirements of the study. Table II the architecture, the training parameters of the network are carefully chosen in order to make the neural network model more suitable for the current study. 80% of the dataset, i.e. 1171 images are used as training dataset and 20% of the dataset for testing. Batch size is taken as 32 images and the models are compared by restricting the number of epochs to 10. Loss function used is sparse categorical cross entropy and the optimizer is Adam.

TABLE II. CNN ARCHITECTURE

Layer	Details
Input channels	3 channels [RGB format]
Inception-like module	MobileNetV2,ResNet,Inceptionnet
AveragePooling	Kernel of size (7,7)
Dense	4096 nodes with Relu Activation
Dropout	Dropout rate 0.5
Dense	4096 nodes with Relu Activation
Dropout	Dropout rate 0.5
Dense	900 nodes with Relu Activation
Dropout	Dropout rate 0.5
Dense	4 nodes with Softmax Activation

IV. RESULTS

The dataset of brake disc images divided into 4 classes obtained from the testing rig of the hydraulic braking system as shown in figure 4, was first trained on the Alexnet CNN model. Although the training accuracy obtained was optimal, the model failed to predict the classes accurately. Alexnet architecture was being overfitted to the dataset. Therefore the dataset was reclassified into two classes namely New and Old and three different CNN architectures MobileNetV2, InceptionNet and ResNet were employed. Figure 5 shows the results of training different CNN's as the base models, on the dataset of disc images. From the results, it is clear that among the three architectures employed, InceptionNet has given the best training accuracy and validation accuracy compared to the other two models. Although the training accuracy of MobileNetV2 was good, the validation accuracy was not as good as other networks. Results obtained from the ResNet were low compared to the InceptionNet. The advantages of using InceptionNet are its efficiency, better computation, and less load on the GPU. Figure 6 shows the change in loss and accuracy values as the model is trained with disc images with 80% as training and 20% as validation data.

Figure 7 shows the prediction result of InceptionNet model when 2 parts of a disc image are given as input.

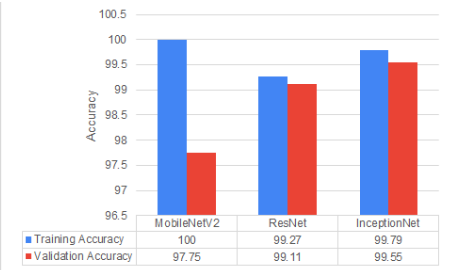

Fig. 5. Comparison of classification accuracy of three different CNNs

V. Conclusion

Challenges in the area of intelligent health management of automobiles are addressed with the help of advances in machine learning and deep learning. In this research, convolu- tional neural networks were used on the images of brake disc, for classifying them into healthy and unhealthy. Four different pre-trained CNN models were fine tuned on the disc dataset. From the results obtained, it can be concluded that the use of images and deep learning is a sensible approach in detecting the damage as the model achieved an accuracy of 99.5 %. The research can be further explored by finding and detecting the brake disc's broken sections. Real time detection of cracks and assessing the amount of damage on the disc forms our future work.

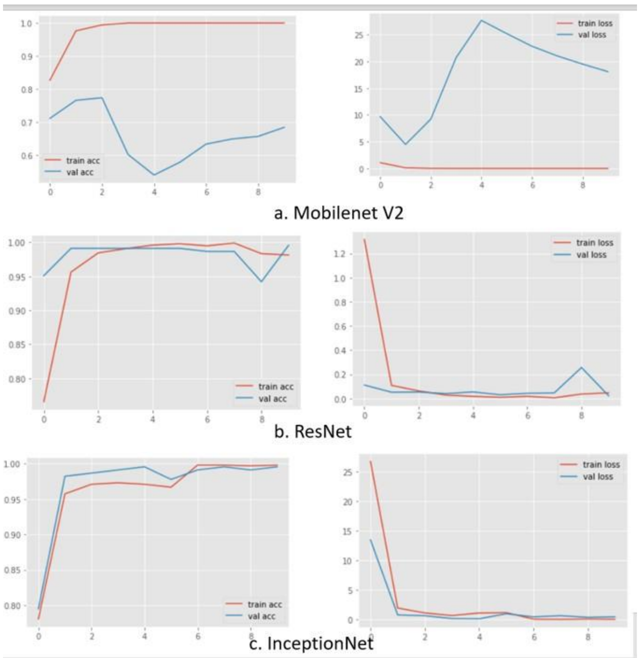

Fig. 6. Accuacy and Loss function values for 10 epochs on three CNNs

Fig. 7. Prediction result for two parts of a disc

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