Assessing Wear Out of Tyre using Opencv & Convolutional Neural Networks

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Abstract. This work proposes a process to detect the wear and tear of car tires. Tire is the only part of the road that does not interact with the road. The condition of the wheel should therefore be monitored in a timely manner for safe driving. Tired fatigue occurs due to limitations such as that the tread limit is less than 1.6 cm, the damage to the rubber, where there are pipes around 4 to 5, the affected tire. We look at some of the above limitations of tire wear testing using computer viewing techniques such as opencv and convolutional neural networks. Opencv and convolutional neural networks are widely used for object detection and image classification. We used these methods and obtained 90.90% accuracy, with which we can predict tire wear to avoid dangerous accidents.

Keywords. Accuracy, OpenCV, Convolutional neural networks (CNN), Tyre wear out

1. Introduction

With Tyre is the only part of the vehicle which is in contact with the road. The tyre performance should be monitored timely in order to maintain safety. A layman might not know when a tyre is going to wear out. If the tyre is not replaced in time then there might be chances of fire, heavy damage and might cause accidents. To avoid such fatal situations, a device or a mobile application is to be developed with which it can be known when a tyre is weared [11].

The limit of tread is to be checked in order to detect the wear of tyre. If the tread limit is less than 1.6 cm, then the tyre cannot be used further. A 4 digit number is present on the tyre which is the month and year when the tyre is manufactured, tyre should be replaced within 6 years from the date of manufacture or else the rubber degrades and results in accidents. If the tyre is punctured for 4 or 5 times, then it is considered as weared and should be replaced. Tyre should be properly fitted, inflated and balanced on to the car. If the tyre is not parked properly or if rubber degrades then cracks or bulges occur which causes tyre burst and leads to fatal accidents [1-14].

What if we does not change the tyre after wear out
There are various disadvantages that occur if the tyre is not changed on time after wear out. They are as follows [15]:

- Brakes may fail.
- The control over the vehicle is lost.
- Cannot handle the vehicle
- Tyres might lose grip and friction on certain road conditions like wet and icy roads.
- Vehicle loses grip even on the dry roads.
- Causes the car to skid during sudden stops.
• Mileage of car reduces.
• Cannot go for long drives, if so then it leads to burst of tyre causing fatal accidents.

2. Relevant Work
Praful Darekar et.al (2018) [1] researched on detection of tyre wear out using color coding technique with the use of sensors. Different colors of color coding are added to tyre. Those colors can be visualized by humans with which the change of color of tyre can be detected easily to ensure that the tyre is weared out. Manfred Klueppel (2014) [2] conducted an experiment on the parameters that causes wear of tyre. Certain parameters like tyre design, model, material used, pressure applied, temperature and surface of road that results in the wear of tyre. Tyre pressure monitoring system (TPMS) device is developed by Sivaraos et.al (2019) [3] that monitors the temperature and pressure of tyre. Tyre pressure and temperature plays an important role in safety of tyres which should be monitored properly.

2.1 Convolutional Neural Networks
Convolutional neural network is a deep learning technique which is used to classify the images. CNN takes an image and applies weight and bias to it so as to classify the images properly. CNN was introduced to recognize hand written zip and later it was used to classify the MNIST images which are the handwritten. Now-a-days CNN is used to classify objects, detect, objects motion detection in video streaming. CNN contains 4 layers which are used to train the model effectively so as to classify the images properly. The functionality of each layer is detailed below [4-8].

2.1.1 Convolution Layer
It is the top most layer in the architecture of CNN. It contains certain filters such as sobel and scharr filters. These filters size must be less than the input image. A dot product is computed in between filter and the input image at each every position by sliding around the input image. At last all the products are summed up to get a single number. These values are then sent to the next layer.

2.1.2 Activation Layer
Activation functions are used in this layer which decides whether a neuron should be active or to be dropped in the neural network. Activation functions that are broadly used are: sigmoid, tanh, relu, leaky relu.

2.1.3 Pooling Layer
Pooling layer down samples the features that are obtained from previous layers. Hence it is also known as down sampling layer. It reduces the noise and distortion by selecting only the important features from the previous layers that is it selects only the maximum value to retain maximum information. There are 2 types of pooling layers. Average pooling which takes the average of all the pixel values from each window. Max pooling is used to find maximum value from each window so as to retain maximum information of the image.

2.1.4 Fully Connected Layer
Fully connected layers takes neurons from previous layers and connects to every activation unit of next layers. This layer is used to compile the values obtained from previous layers to give the final result. In this layer we use activation functions such as sigmoid and softmax to classify the images into classes.

2.2 OpenCV
Open computer vision is open source computer vision library. OpenCV library has more than 2500 algorithms which are related to computer vision and machine learning algorithms. These algorithms
are used to detect, recognize and classify the objects. OpenCV is also used to increase the quality of image.

Meghna Raj Saxena et.al (2019) [16] conducted an experiment on object detection using machine learning and OpenCV. Object detection is identifying objects in images and in video streaming. Matlab tool is used to detect behaviour of humans so as to implement CC TV surveillance systems. Zainab Nazar Khalil Wafi et.al (2010) [17] developed a CC TV surveillance system to place at the side ways of the road to capture the images and video solve the traffic and accident related issues. Nilesh J Uke et.al (2013) [18] conducted an experiment to monitor the vehicles and traffic on the highways. The author used visual c++ with intel OpenCV video streaming system in order to capture the images and video to detect and monitor the movements of vehicles. Rahul R Palekar et.al (2017) [19] conducted a research to detect license plate number from video or images. The image is converted into text using OpenCV libraries and tesseract to recognize character patterns from the image.

3. Dataset description
Many kinds of tyre images in different resolutions, noise characteristics and with variety of camera types are collected. The types of tyres that were collected are cracked, blast, punctured, new and old images. Images are taken from different angles, distances, different lighting conditions, some are blurred and covered with dirt. Some of the images are collected from internet and some are collected by going to the shops manually which is a time-consuming process [9-10]. All these images were segregated as weared and not weared in separate folders to determine the classes to be classified by the CNN. The weared tyre images are around 150 and not weared tyre images are around 240 representing a total train images of 390. The test images are separated same as weared and not weared images considering 11 images for testing.

Fig.1. These images are weared images of tyre such as blast, cracked and punctured images.

Fig.2. These images are not weared images of tyre such as old, new and in different light conditions.

4. Proposed methodology
The main purpose of this research is to detect and classify the tyre whether it is weared or not so as to reduce the effect of accidents. Considering all the parameters that were discussed in the Introduction section such as how to identify the wear and what are the causes if tyre is not changed on time. Hence we have implemented the model using OpenCV and CNN to classify the wear effectively. The methodology that was followed is discussed below.
The graphical representation of process of methodology proposed is efficient and appropriate for the detection of wear of tyre through images. The first step is collection of data of various kinds of tyres like punctured, blast, bulged, cracked, new and old tyres. These data is collected with different noise and distortion and at different lighting conditions and from different angles and distance. The second step is pre-processing with opencv techniques such as converting the BGR image to RGB image and applied bilateral filter which is used to blur the side ways to reduce the noise and distortion in order to make the image look clear without much disturbance. The third step of pre-processing is data augmentation. We applied techniques such as rotation, rescaling, width shift, height shift, shear range, zoom range, and horizontal flip so as to make the image to be viewed in every angle and from any distance on training and testing data sets.

After augmenting the data we create our model in a sequential manner. Then the layers such as convolution layer which is used to apply a filter so as to get a single pixel value and the value is then forwarded to pooling layer to get the average or maximum information from the image. A dropout function is used in the model in order to make sure that our model over fits and drops certain neurons from the network. Then finally dense layer is used to sum up all the neurons from previous layers and gives a final result. A single layer of Conv2D and Max pooling layers are applied. Two dense layers are added in which one dense layer is with 256 neurons and the other is the final dense layer which is used to obtain the output. The implementation of convolutional neural networks is done with keras and the tensorflow is used as backend.

After all the layers are created for the model, we compile the model. Compiling the model is necessary in order to optimize the algorithm and increase the accuracy and reducing the loss. The main aim of compilation is to minimize the loss. A detailed summary of layers applied in the model are explained in the figure below.
Fig. 4. The summary of the model is detailed

After model creation and compilation, we train the model with training dataset and validation set. Early stopping monitor function is used in order not to overfit or underfit the data. Next a new set of images are given for predicting the classes, with which we ensured that our model is able to classify the tyres effectively.

5. Mobile Implementation

After designing the process in order to make CNN model effective we have come up with an idea of implementing on mobile devices. Users with the help of their tire pictures can actually find condition of their tires. Deploying CNN model require an environment that supports tensorflow runtime. Many cloud services like AWS and IBM can be used. We have opted Flask for deploying model, which is a Web Framework that is used to build web applications. The connection between server and application is obtained with WSGI and jinja2 template that is used for dynamic web pages. After design process we save the model in the .h5 file.

![Device Working Architecture](image)

**Fig. 5. Device Working Architecture**

Figure 5 shows the working of the device. A user sends image of tyre to know the state of it by sending a request. Then the server loads the model and the server contains a classifier which runs on the uploaded image file and an HTTP web page is generated to the user as a result.

For mobile application we initially need to load .h5 model, after initialization of app we need to specify route in order to redirect into different web pages based on the application. Html pages are included using render template in flask. In this application we have created html page with CSS and JavaScript. While html page is saved in template folder, style sheets and scripts are to be saved in static folder. Input is given to the server from html page. Using request object we will be able to access incoming data, this data can be of any format, these images are decoded into raw format and the model is used for prediction of output. Different functions are created based on the functionalities to store and load model. We need to check whether the method is GET or POST. If it is a get request we
simply open same web page. If it is Post request then we need to process the data. Based on the result the flask server we provide one among two html pages. In this application we have created safe and unsafe web pages if the condition is true it then redirects to safe web page indicating user that this tyre is in safe condition, if the condition is false then it redirects to unsafe web page which indicates that his tyre is unsafe and he need to replace the tyre. Debug mode is used to reload server continuously whenever changes are made this also acts as debugger whenever there is error. Flask implementations are best and easiest way as they can easily render to any webpage based on the result and can provide a simple and better interface to users.

6. Results & Discussion
The experimental results are presented here. The experiment was conducted with 390 training images and 11 test images. These training images are computed along several layers as discussed in the above with several epochs, where epoch is defined as the ratio of product of number of iterations and batch size to the total number of training images. Here we have given batch size as 40 per epoch and number of iterations are 30 in which it takes 390 training images. Precisely one epoch is all data processed one time. Each epoch is validated with the validation data set so as to make sure that it does not over fit and the assumptions are correct. Validation data set is used to cross check whether the trained model is correctly predicting the value or not for the new data without being over fitting or under fitting. With this training and validating we have obtained 90.90% of accuracy with 0.26% of loss for 30 epochs.

| Predicted not weared | Actual not Weared | Actual Weared |
|----------------------|------------------|--------------|
|                      | 6                | 0            |
| Predicted weared     | 1                | 4            |

Table 1. Confusion matrix for test data with n=11.

Table 1. shows the confusion matrix for the test data with 1 images. Confusion matrix is used to check error and accuracy percentage. Confusion matrix determines true positive, false positive, true negative and false negative rates. Where true positive rate is determined if actual and predicted values are same and are positive, true negative rate is determined if actual and predicted are same and negative, false positive and false negative are determined if actual and predicted values are different and from the above table, we saw that the true positive rate i.e., the actual and predicted values for not weared is 6, the true negative rate i.e., the actual weared and predicted weared is 4, false positive rate i.e., the actual not weared but predicted weared is 1, false negative rate is 0.

|               | Precision | Recall | F1-Score |
|---------------|-----------|--------|----------|
| Not weared     | 0.86      | 1.00   | 0.92     |
| weared         | 1.00      | 0.80   | 0.89     |
| Total/average  | 0.92      | 0.91   | 0.91     |

Table 2. Classification report for the test data
Table 2. details the classification report for the test data with 11 images. A classification report is used to measure the quality of predictions i.e., how many predictions are true and how many are false.

Precision allows not to label an instance positive when it is actually negative. Precision is defined as ratio of true positive to the sum of true positive and false positive i.e., when it predicts correct classes, how often it is correct? From the Table 2. the precision for not weared is 86% and weared is 100% correct. Recall allows to find all positive instances. Recall is defined as ratio of true positive to the sum of true positive and false negatives i.e., for all instances that were actually positive, what percent was classified correctly? From Table 2. The recall for not weared is 100% and weared is
80% correct. The model has obtained an accuracy of 90.90% for the test data. With which the model assures that it can be able to classify the images as weared or not weared. Hence the tyre can be replaced on time avoiding the dangers and ensures safety to the vehicles.

7. Conclusions
Tyre is the only part of vehicle which is in contact with road. Hence it is to be primarily considered. Since a layman does not know when the tyre wears out. To implement a model which can be able to detect and classify the weared tyre images require tools like opencv and cnn. This paper presents a model that has used these two tools and techniques to classify the images and has given an accuracy of 90.90%, with which we can be able to classify it in order to play an important role in safety of vehicle users.

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