CNN based Tyre Life Prediction and Defect Identification System

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Abstract— **The only part of the vehicle in contact with the road is the tyre. The tyre tread depth has a significant impact on the vehicle's braking ability and should be checked on a regular basis for driving protection. Slippage, a longer stopping time, and even flat tyres are all symptoms of worn tyres, which can lead to a car accident. If there is an automated inspection method that will allow the vehicle users to monitor their tyre life with their own hands instead of getting the vehicle to the garage spending time to diagnose it, resolving such types of the defect will boost the confidence while drive and saves significant money by extracting the maximum out of the tyres without compromising on safety. The prediction involves capturing the image of the thread section and sidewall of the tyre to be predicted. Then, the image will be processed to extract the thread and wall condition from an image for defect identification and to further improve the result and life predictions the vital information inputs are taken from the user through a mobile app. The proposed research work utilizes the CNN based prediction algorithm in order to leverage the best prediction result and recommendations to improve the tyre life.**

Keyword: Convolutional Neural Network, tyre defects, tyre tread depth, neural network, tyre life

I.INTRODUCTION

The tyres are the most crucial part of every vehicle the worn-out tyres have many risk factors involved. Tread alone is not the one deciding the life of the tyre but also, the new tyres could be defective sometimes

due to the manufacturing process and tyres could also get damaged due to bad roads like sidewall damage that could lead to tyre change. Another thing is tyre wear this could happen two ways Normal wear and Uneven wear, Normal wear is due to normal vehicle wear and tear the Uneven wear is due to improper alignment, worn out suspension, and also due to over-inflation or under-inflation. The tyre will deteriorate once it is exposed to the atmosphere tyre due to this age is also one deciding the tyre life other than that the high-speed operation and overloading also causes of irregular tyre wear. Currently, there is no automated system to identify the defects in a vehicle tyre and also to predict the tyre life. At present life prediction of tyres involves penny test for tread depth and other defects by naked eye judgment. With our method, automated testing has been proposed for analyzing defects and also predict tyre life. For automated defect identification, we use Convolutional Neural Network (CNN).

II. DESCRIPTION

A. Overview

The tyre life prediction system uses the Convolutional Neural Network (**CNN**)[3] defect identification and life prediction. Our System is trained to identify common tyre defects and we provide recommendations based on the predicted results to improve the tyre life so that the user will be able to ensure safety at the same time they can save the money investing in a new tire. The system is designed simply to use this can be used from the user's mobile phone itself. They need not bring their vehicle for a garage place for their prediction

B. Defect Classification

The system is designed with taking the major defect parameters which degrade the tyre life are clubbed into three classification groups to improve accuracy.

2.2.1 Good:
The tyres classified under the good category are the ones without any defects like alignment problems, inflation issues and new tyres, deep thread.

2.2.2 Normal:
The tyres under this category are the tyres that have half the tread life and one without any major defects.

2.2.3 Bad:

The tyres under this category are the ones with major defects like sidewall bulge sidewall crack tread cracks and are legally unfit to use.

C. Prediction Algorithm

The tyre defect detection is done with the pre-trained CNN model and life prediction is done with getting the critical parameters that cannot be extracted from tyre image are acquired as field input from the user. And we created an algorithm to predict remaining tyre life by our extensive research on wear and tear factors and by precise percentage deduction of remaining life. We can predict the remaining life meanwhile the recommendations are given based upon the defect detected and life predicted to get maximum out of tyre.

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Rem Life = [Manufacture claimed life of current tyre] – [Kms cover with current tyre]
Remaining life = Rem life -(Air pressure + alignment check + usage area + average speed) %

III. RELATED WORKS

Shih-Yen et al [1]. presented a system which is used to determine the tyre tread depth using machine vision backed by image triangulation. He developed an Android app which will be used to record the result in the user's smartphone. To measure the tread depth user's, need to bring their vehicle to the tyre shops with these facilities and tyres needed to be unmounted and placed on the camera base for the tread measurement. This system does not have any additional features and only gives tread depth details.
Xi-Bowang et al. [2] developed a system which uses machine vision to determine the tyre tread depth accurately. In this method, the tyre to be measured is being over a measuring device that captures the tyre tread section with the help of the laser plane. After that, an algorithm was used to identify the tread grooves on the profile curve and decide their locations. Finally, the depth of each groove was determined one by one. This system also measures the tyre tread depth alone but with the help of laser involved to provides results with greater accuracy. The vehicle with tyre to be measured for tread depth should be bought to the garage with this system installed and to be moved over the test platform to perform the measurement. In Detection of Tyre wear Out Using OpenCV and Convolution Neural Networks paper [3] the authors have considered various parameters which determine the lifetime of the tyre. Considering the parameters, the image of the tyre to be predicted is given to the model that uses a convolutional neural network to find the contours in the image. Yuanyuan Xiang et al. [4] presented a Dictionary-based Method for Tire Defect Detection. In which the distribution coefficient of defect-free images is stored in the dictionary. So, when it is compared with the faulty images the defect is identified. However, this method can reveal the defects of the tyre only. The survey on fabric defect detection techniques is presented in [5, 7, 13] which is useful in evaluating the characteristic of specific features. A wavelet band selection procedure is developed in [6] which is used here to figure out defects in a variety of real textures. Based on texture, background and defect various studies [8-12] presented their research. Also, Kumar et al [15] explained "a data mining-based decision support system using decision tree and artificial neural network as a hybrid approach to estimate the marketing strategies for an organization". But they did not mention the lifetime of the tyre.

IV. PROPOSED MODEL

The Proposed model will be implemented on a mobile app. The system will use CNN Classification for defect detection. For this, the user needs to Capture the image of the tread section and sidewall of the tyre for
Classification and form data for life prediction. The flow diagram and the block diagram are given in fig (1,2).

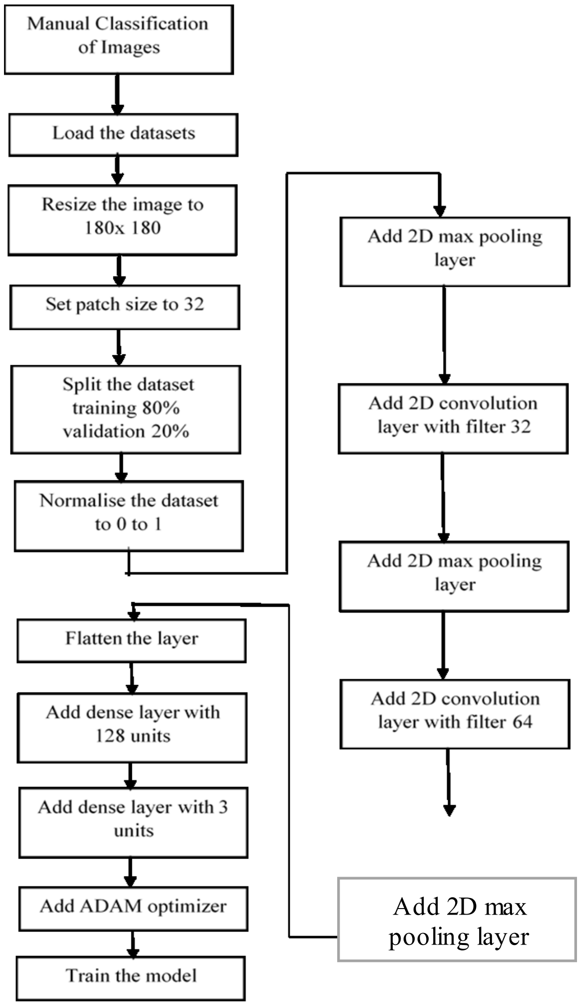

Figure.1 *Flow Diagram*

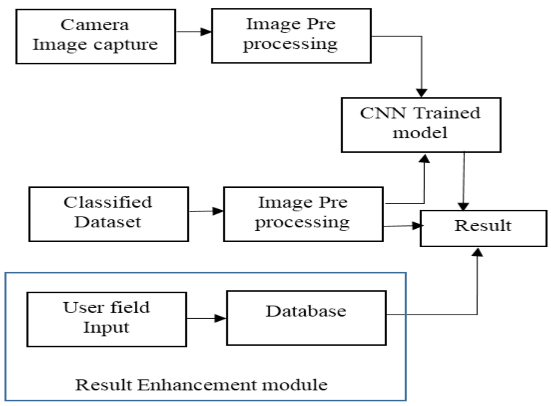

Figure 2. *Block Diagram*

A. Convolution Neural Network

Convolution Neural Network is a deep learning algorithm that takes an image as input and assigns weights and biases to different aspects of the image to classify it. Convolution neural networks were first used to identify handwritten zip codes, and then they were applied to image recognition and classification.

CNN can only work with massive datasets, but it can also work with small datasets. It does, however, operate on small datasets, but with poor accuracy. Object recognition, object detection, and motion detection in the video have all been successfully implemented with CNN. The CNN layers are the building blocks that help to structure and link the data. The layers are well-structured, allowing CNN to train and execute the model more quickly.

B. Types of layers in Neural Network

4.2.1 Input Layers:

This is the layer where our model input is sent. The number of neurons in this layer equals the total number of features in our results (number of pixels in case of an image).

4.2.2 Hidden Layer:

The data is received by the secret layer from the input layer. Depending on our model and data size, there may be a lot of hidden layers. The number of neurons in each secret layer may vary, but they are usually more than the number of features. The output from each layer is computed by matrix multiplication of the previous layer's output with that layer's learnable weights, then the addition of learnable biases, and finally activation function, which makes the network nonlinear.

4.2.3 Output Layer:

The output of the hidden layer is then fed into a logistic function like sigmoid or SoftMax, which converts the output of each class into a probability ranking.

C. CNN Algorithm

CNN model is constructed by adding three 2D convolution layers with filters 16,32,64 respectively. For each convolution layer, a 2D Maxpooling layer is added for reducing redundant values present in the input feature. The activation function rectified linear unit gives higher accuracy than other activation functions like sigmoid. Adam optimizer is used to minimize the cost function. The model is trained for 10 iteration which yields a validation accuracy of around 76%. Accuracy can be increased by increasing the dataset.

V. RESULTS

In this project, the model is trained using CNN (fig 3) for the used tyre fig(4). This algorithm pre-processed the image by taking a model which took the inputs of width and height (fig 5). And the predicted models are given from figure 6 to 8.

A. CNN Trained Model

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling_4 (Rescaling)      (None, 180, 180, 3)       0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 180, 180, 16)      448
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 90, 90, 16)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 90, 90, 32)        4640
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 45, 45, 32)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 45, 45, 64)        18496
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 22, 22, 64)        0
_________________________________________________________________
flatten_2 (Flatten)          (None, 30976)             0
_________________________________________________________________
dense_4 (Dense)              (None, 128)               3965056
_________________________________________________________________
dense_5 (Dense)              (None, 3)                 387
=================================================================
Total params: 3,989,027
Trainable params: 3,989,027
Non-trainable params: 0
_________________________________________________________________
```

Figure 3. *CNN Model*

B. Defect Detection

```
TestImg_path = "gdrive/My Drive/TyreLifePrediction/Tes

img = keras.preprocessing.image.load_img(
    TestImg_path, target_size=(img_height, img_width)
)
img_array = keras.preprocessing.image.img_to_array(img
img_array = tf.expand_dims(img_array, 0) # Create a ba

predictions = model.predict(img_array)
score = tf.nn.softmax(predictions[0])

print(
    "This image most likely belongs to {} with a {:.2f
    .format(class_names[np.argmax(score)], 100 * np.ma
)

This image most likely belongs to Normal with a 52.97
```

Figure.4 *Defect Detection*

A. Life Prediction:

```
Enter Tyre Details :
 Total KM: 40000
KM covered: 20000
Air Pressure Checking Frequency: '1'
 for <=15 days , '0' for >15 days : 0
Alignement Checking Frequency: '1'
 for <=5000 kms , '0' for >5000kms : 0

Usage Area: '2' for 'Highway' , '1'
for 'Mixed Roadways','0' for 'Broken Roads': 1
'0' for >70km/hr : 0
Average Speed: '1' for <= 70km/hr ,
Remaining Life : 13122.0Km
```

Figure.5 *Life Prediction*

A. Mobile App

With the mobile app, the users enter the data through the input page and capture the image of the tyre and the result along with the recommendations will be displayed on-page. The input and the result page snapshots are given in fig (6,7).

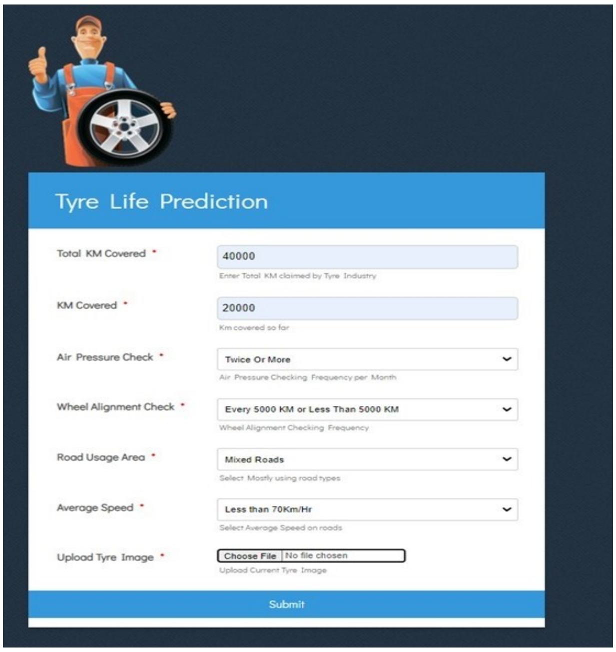

Figure.6 *Mobile App Input Page*

Figure.7 *Mobile App Prediction Output*

VI. CONCLUSION

The tyre life prediction system can find the Bulges, Sidewall cracking, Air Inflation, Alignment issues, and Treadwear. Pretrained model is used in our system to save computation time and resources. The automated inspection method will allow the vehicle users to monitor their tyre life with their own hands instead of getting the vehicle to the garage spending time to diagnose it. With the image of the thread section of the tyre, the real-time condition of a tyre is predicted. Then, the image will be processed to extract the thread profile and tread depth from the image. The depth calculation method to be improved. The future prediction system would include a lot more parameters and also result would be more informative by including analysis-based ratings and recommendations to improve the current tyres life to get the maximum out of the tyre. A lot more types of tyre models to be included and also a more precise algorithm to be developed for the rethreaded tyres and commercial vehicle tyres by taking their route of operation and load conditions into account. Another image of the sidewall of the same tyre will be captured, which gives details such as tyre brand, model, and size. The depth will be calculated and information will be processed to provide the prediction output in Kilometres. Tyre plays a key role in vehicle safety, resolving such types of issues we need such tools and techniques end of the day such systems will boost the confidence while drive and saves significant money by extracting the maximum out of the tyres.

REFERENCES

[1] Shih-Yen Huang, Yen-Cheng Chen, Jih-Kai Wang 2016 ”Review Based On Measurement Of Tire Tread Depth With Image Triangulation” International Symposium on Computer.

[2] Xi-Bowang, Ai-Juan Li, Qin-Peng C 2019 “The Study on Tire Tread Depth Measurement Method Based on Machine Vision Advances in Mechanical Engineering Vol. 11(4) 1–12.

[3] Allipilli Harshitha And Samyuktha Samala 2020 “Detection Of Tyrewear Out Using Opencv And Convolution Neural Networks” Communication Software and Networks Springer

[4] Yuanyuan Xiang, Caiming Zhang, and Qiang Guo; 2014 “A Dictionary-based Method for Tire Defect Detection” School of Computer Science and Technology.

[5] A. Kumar, “Computer-vision-based fabric defect detection: a survey,”IEEE Trans. Industrial Electronics , vol. 55, no.1, pp.348–363, 2008.

[6] D. Tsai and C. Chiang, “Automatic band selection for wavelet reconstruction in the application of defect detection,” Image and Vision Computing, vol. 21, no. 5, pp.413–431, 2003.

[7] F. Tajeripour, E. Kabir, and A. Sheikhi, “Fabric defect detection using modified local binary patterns,” EURASIP Journal on Advances in Signal Processing, vol. 2008, 783898, 2008.

[8] Q. Guo and Z. Wei, “Tire defect detection using image component decomposition,” Research Journal of Applied Sciences, Engineering and Technology, vol. 4, no. 1, pp.41–44, 2012.

[9] J.Vijila ,A.Albert Raj 2020 “Ameliorate Security by Introducing Security Server in Software Defined Network” Journal of Computers,Materials & Continua Vol 62 No3 pp 1077-1096.

[10] A.Albert Raj,T.Latha 2020 "VLSI Implementation of Multicarrier Complementary coded CDMA downlink system" Material Science proceeding - Volume 33, Part 7, 2020, Pages 3288-3291.

[11] A. Albert raj and J. Vijila, "Design of Indoor Air Quality Monitoring System to Ensure a Healthy Universe," 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2020, pp. 1123-1127, doi: 10.1109/ICOSEC49089. 2020. 9215297.

[12] P.Maria Jessi, A.Albert Raj 2019 “A neoteric approach for preserving infrastructure and nodes mobility through weight based clustering and distributed scheduling” Journal of Intelligent & Fuzzy Systems 36 (4), 3345-3356

[13] H. Y. Ngan, G. K. Pang, and N. H. Yung, ‘‘Automated fabric defect detection—A review,’’ Image Vis. Comput., vol. 29, no. 7, pp. 442–458, Jun. 2011.

[14] Vijayakumar, T. "Posed Inverse Problem Rectification Using Novel Deep Convolutional Neural Network." Journal of Innovative Image Processing (JIIP) 2, no. 03 (2020): 121-127.

[15] Kumar, T. Senthil. "Data Mining Based Marketing Decision Support System Using Hybrid Machine Learning Algorithm." Journal of Artificial Intelligence 2, no. 03 (2020): 185-193.