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Tire Quality Inspection System Based on Deep Learning

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ABSTRACT
There have been many reports of accidents caused by the use of damaged and worn tires, and these accidents are more common on highways and during the rainy season. Although this is a common problem, many people cannot distinguish good tires from worn ones, increasing the risk of ending up with good tires on the road. A few years ago, the main technology for checking tire size was manual inspection. An important method is to determine the grade of the tread pattern bed by checking the depth and the shoulder pattern bed. Tires are one of the most important parts of a vehicle as they actively support driving. However, they often disagree when it comes to proper inspection and maintenance. Most of the time, the general public apparently does not care about their tires. Many will experience tooth wear and flank damage, and failure to follow up on these problems will cause long-term damage. However, this method is too expensive to use in a family car. This article presents a model used as a running image that can distinguish broken tires from rubbing tires. The model is based on the image displayed outside the user-supplied tire and determines its status after comparing it with the model data using the deep learning algorithm ResNet50. This model is made to remind you that it can be used in addition to equipment suitable for use in real life applications. With regulation by regulatory agencies, tire accidents can be reduced and damage to people and property on public roads can be prevented.
Keywords—Tires, Deep Learning, Image Processing, CNN, ResNet50, Cracked Tires, Friction Tires, Accident

1. Introduction

Around 2 billion tires were produced worldwide in 2016 and tire production is expected to increase steadily and demand is expected to be strong in many countries and developing countries for the coming year. Tires are an essential part of a large vehicle. Traction, braking and steering forces are produced by the road and tires and control the movement of the vehicle. However, the tire wears out, causing bad contamination of the wear parts and the disposal of environmentally damaging old tires. By knowing more about the causes of wear, it is possible to reduce tires, which is a good result both economically and ecologically. Friction occurs when two surfaces rub against each other. For example, when a car's tires move on the road, friction increases and racing tires appear to emit smoke. When the car slows down, the friction between the road and the tires helps stop the car when the wheels slow down. It is the friction between the wheel and the brake that slows the wheel down. Obviously, friction is a very important force when cycling. The dry and wet friction coefficients for tread tires are approximately 0.7 and 0.4, respectively. This value represents a compromise between the extreme values of approximately 0.9 (dry) and 0.1 (wet) achieved with slick tires. The tread follows the water under the tire, increasing the tire's friction with the road, providing firm grip even when driving in the rain. Cracks indicate that the rubber in the tire has begun to crack. This is because of exposure to ultraviolet (UV) light, oil, chemicals, and other substances that slowly break down the compound and reduce flexibility over time. The most important thing to understand is that tires have a shelf life. In other words, they can only be used for a limited period of time until the compound has deteriorated so much that it can no longer function properly. The good news is that under normal conditions, tires should last 5-7 years. As tires age, they begin to dry out and cracks form on the surface.

2. Literature Survey

CNN based Tire Life Prediction and Defect Identification System has been proposed in [1]. The tire life prediction system is designed to find the Bulges, Sidewall cracking, Air Inflation, Alignment issues, and Treadwear. This system is trained to identify common tire defects and they provide recommendations based on the predicted results to improve the tire 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 and this can be used from the user's mobile phone itself. They need not bring their vehicle for a garage place for their prediction. The model is trained for 10 iteration which yields a validation accuracy of around 76%. Accuracy can be increased by increasing the dataset.
A model Tire Wear Detection for Accident Avoidance Employing Convolutional Neural Networks, has been explained in [2]. This model for differentiating faulty tires had been implemented effectively, and the best algorithm for it was MobileNet. This model had higher accuracy and precision than both of the DenseNet models used in the paper while boasting a 100% accuracy in identifying bad tires in general. In the future, such classifications can be used to determine remaining tire life and compare the impact of different tread patterns in tires. This paper introduces a model that can differentiate between good and worn-out tires, which has been implemented using Image Processing. DenseNet121, DenseNet201, and MobileNet were compared, and a conclusion was reached that MobileNet surpasses all of them with an accuracy of 95.65%.
An Artificial Neural Network-Based Method for Identifying Under-Inflated Tire in Indirect TPMS has been proposed in [3]. In this paper an ANN based methodology is used to identify the deflated tire among properly inflated tries. And performance of this method can be further improved by employing a soft voting mechanism with 3 LSTM networks. In this paper, the optimum prediction accuracy of LSTM network is 0.83, and the performance of current ANN is mainly hindered by the decentralized distribution of data.
A Quality Inspection of Tire using Deep Learning based Computer Vision has been analyzed in [4]. This system measures the depth of tire treads using Lab View stereo vision and can determine the correct depth in the tread's region of interested (ROI) using image processing for edge detection. The proposed system will target to various tire making vendors, personal vehicle users i.e. drivers, fleet owners. Automatic quality inspection is strongly desired by tire industry to take the place of the manual inspection. Different from the existing tire defect detection algorithms that fail to work for tire tread images, the proposed detection algorithm works well not only for sidewall images but also for tread images. The Solutions indicated that the correct tire tread depth could be obtained from seven of the eight images of the same tire.
Tire Classification from Still Images and Video has been estimated and analyzed in [5]. This paper introduces a method for tire classification from still images and video frames. The proposed method provides an automated solution for determining the class to which a tire belongs and reduces the level of manual labor involvement for enforcing tire usage regulation. The features extracted from the frequency domain representation of edge maps of tire tread images was found to successfully ameliorate the interference from external factors such as illumination and positional variations in captured tire images. The majority vote strategy was used across 11 frames in each video. While the classification rate across individual frames was 80.99%, the algorithm classified 9 out of 11 tires correctly, for an overall classification rate of 81.81%.

3. Convolutional Neural Network

Convolutional neural networks, also known as CNNs or ConvNets, are a class of intermediate networks that specialize in processing data with a grid-like topology, such as images. A digital image

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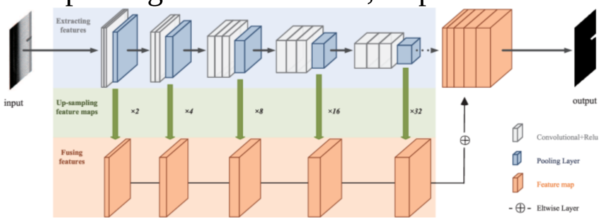
is a binary representation of visual information. It consists of a series of pixels arranged in a grid-like fashion, with pixel values to represent the brightness and color of each pixel. When we see a picture, the human brain processes a lot of information. Each neuron operates in its own receptive field and is interconnected with other neurons to cover the entire visual image. Layers are layered because they show simple patterns (lines, curves, etc.) first, and then more complex patterns (faces, objects, etc.). You can do computer vision using CNN. A. Design of Convolutional Neural Networks. In order to understand a lot of things, a convolutional neural network had been built. The convolutional neural network architecture is as follows:

[INPUT] → [CONV 1] → [BATCH NORM] → [ReLU] → [POOL 1] → [CONV 2] → [BATCH NORM] → [ReLU] → [POOL 2] → [FC LAYER] → [CONCLUSION]

For two convolutional layers, we will use a 5 x 5 spatial kernel with step 1 and padding 2. For both pooling layers we will use max pooling with ball size 2, step 2 and zero fill.

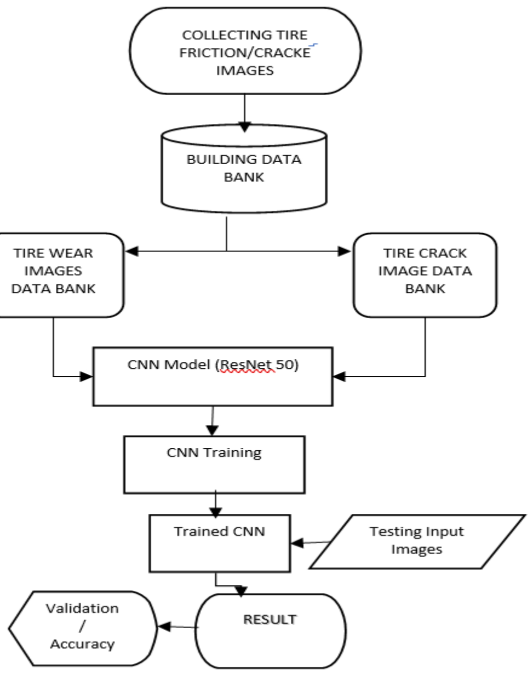


4. System Model

The one and only system model in a development project is just a conceptual idea, a way of thinking, an engineering vision. Current realizations of system models in practical approaches prove that this is the case.

Step 1: Collecting the images of tires.
Step 2: Building a data bank of tire images.
Step 3: From the data bank, we separated into two categories,
Step 4: Feed the databank into the CNN model of ResNet 50.
Step 5: Training the images in CNN.
Step 6: Testing input images into trained CNN and get the result.
Step 7: After getting the result, we found the accuracy.

A. Flow Chart



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B. Confusion Matrix

In Convolutional Neural Network (CNN), the confusion matrix shows where the model is confused, i.e. the classes predicted by the model are correct and the classes predicted by the model are incorrect. A confusion matrix is a summary of the predictions for a classification problem. The number of correct and incorrect predictions is calculated by counting the values and broken down by each category. This is the basis of the confusion matrix. He was confused when he made the guesses. From the confusion matrix, we can calculate five different matrices to evaluate the performance of our model.

Accuracy (all **correct** / all) = (TP + TN) / (TP + TN + FP + FN)

Error rate (all **incorrect** / all) = (FP + FN) / (TP + TN + FP + FN)

Precision (**true** positives / **predicted** positives) = TP / (TP + FP)

Recall **(true** positives / all **actual** positives) = TP / (TP + FN)

Specificity (**true** negatives / all **actual** negatives) =TN / (TN + FP)

Recall = TP/ (TP+FN)

F measure = 2(Precision * Recall)/ (Precision + Recall)

5. Result And Discussion

The results from the tire wear simulations are presented in this chapter. Images of Tires and categories into ten category of tire friction have been collected based on the km travelled by vehicles and its cracks. Train the data into CNN model and get the accuracy of 90%. In the future, to validate the complete model, more experiments are needed. The experimental data can be used to in daily life. The results are also compared with the reference results with figures to validate the conclusions drawn from the results. In just a few years deep learning almost subverts the thinking of image classification, speech recognition and many other fields are forming an end-to-end model in which most reprehensive deep features can be learnt and classified automatically. This model tends to make everything easier. In this system the aim is to develop a system using deep learning and algorithm approach firstly it is necessary to gather various images vendor and tire type wise then to classify that data set according to test dataset and training dataset approach. In this problem various deep learning algorithms which are based on CNN have been employed. From those various algorithmic approaches, the one which produces better results has been analyzed.

A. Accuracy

Accuracy is a very useful metric when all the classes are equally important. Accuracy is calculated as the total number of two correct predictions (TP+TN) divided by the total number of a dataset (P+N).

Accuracy = (TP+TN) / (TP+TN+FP+FN)

B. Error Rate

Error rate is calculated as the number of all incorrect predictions divided by the total number of the dataset. The best error rate is 0.0, whereas the worst is 1.0. Error rate is calculated as the total number of two incorrect prediction (FN+FP) divided by the total number of a dataset (P+N).

Error Rate = 1 – accuracy (or) (FP+FN) / (FP+FN+TP+TN)

C. Sensitivity

Sensitivity is calculated as the number of correct positive prediction divided by the total number of positives. It is also called recall (REC) or true positive rate (TPR). The best sensitivity is 1.0, whereas the worst is 0.0.

Sensitivity = TP / (TP+FN)

D. Specificity

Specificity is calculated as the number of correct negative prediction divided by the total number of negatives. It is also called true negative rate (TNR).

Specificity = TN / (TN+FP)

E. Precision

It is also called Positive predictive value. The ratio of the correct positive prediction to the total predicted positives.

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Precision = TP / (TP+FP)

F. Recall

It is also called sensitivity, Probability of detection, True Positive Rate (TPR). The ratio of correct positive predictions to the total positive examples.

Recall = TP / (TP+FN)

G.F measure

It is a measure of model's accuracy on a dataset. It is used to evaluate binary classification system, which classify example into positive or negative.

F measure = 2(precision x recall) / (precision + recall)

6. Comparison Of Results With Various Networks

As that of overall comparison with all the above four networks, Resnet_50 performances very well compared to others with accuracy of 91%. The second place of good performance is Resnet_18 which yields accuracy of 76.9 percentage of correct result. And then third performance is the Resnet_101 network which gives the accuracy of above 76 percentage but compared to other it is little bit back performance than others.

Coming to the category vice result effectiveness in F_1, Resnet50 performance 100% efficient result giving compared to others. In F_2, Resnet50 performances very good then others which yields 95% of accuracy. In F_3, Resnet50 performances very good which yields 90% of accuracy. In F_4, Resnet50 yield high accuracy performance then the others and has accuracy of 95%. In F_5, GoogleNet performance high then the other's and this network work gives full accurate result of this category. In F_6, Resnet18 performances good and has a accuracy performances of 98%. In F_7, Resnet50 performances high of 97% then the others. In C_1, Resnet_18 & Resnet_101 both performance the same of high resultant giving of accuracy of 100% of result. In C_2, ResNet101 performance 100% of resultant then the others. In C_3, Resnet_50 & resnet_101 both performances are same of 100& resultant of accuracy of this category identification correctly.

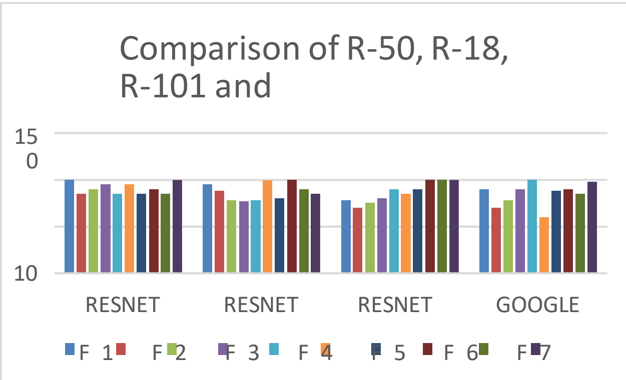

Fig. 1. Comparison of networks

7. Conclusion

This article analyzes the various methods for estimating the life of vehicles tires. An image database has been built on a CNN model and finally verify the model's accuracy using the appropriate metrics. The experiments show that the proposed method has accuracy, high performance and low cost in estimating tire life. However, this research still has some shortcomings. For example, factors such as road, tire size and tire quality should be taken into account. Also, this article only conducts prediction experiments based on small data, and this work should be extended to large-scale experiments.

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