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A Deep Learning based Tire Quality Inspection System

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Abstract-- 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. 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. 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.

I. INTRODUCTION

Around two 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.

Cracks are a sign that the rubber in tires is starting to break down. This happens naturally due to exposure to Ultra Violet (UV) Light, Oils, chemicals, and other elements that slowly breakdown compound and reduce the rubber's flexibility over time. 7 Figure 1.4. Cracked tire A key thing to understand is that tires do have a shelf life. In other words, they're only good for a set period of time until the compounds break down to the point where they fail to function properly. The good news is that tires should last around 5-7 years under normal circumstances. As tires age, they will begin to dry rot, and cracks will appear across the surface. It's only a matter of time before they begin to appear on tires. Whether it should be concerned depends on the severity of the cracks. If the tires are relatively young and the cracks are shallow and fairly limited on the surface of the tire, there really isn't much call for alarm. However, this does tell us that the tires are aging, but it's still more cosmetic than anything. If, however, the cracks are deep and widespread, it should be replacing the tires as it means the entirety of the tire has become brittle. A tell-tale sign that aging is of concern is also when tread blocks begin breaking apart as well.

II. REVIEW OF LITERATURE

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. A new artificial neural network (ANN) based method was also proposed to identify deflated tire based on speed data point collected through antilock brake system (ABS) sensors in tests. A long short-term memory (LSTM) network was developed to locate the deflated tire with an accuracy of 0.83 after training for individual data points. 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%.

III. BACKGROUND OF STUDY

A. General Architecture

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 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. Just as each neuron in the biological visual system only responds to stimuli in a limited area of the visual field called the receptive field, each neuron in a CNN processes information only in its receptive field. 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.

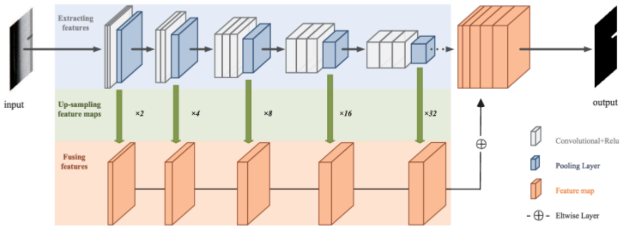


Fig.1 General Architecture

B. Existing System

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.

C. Proposed System

They already published tire classification, tire wear, tire tread in previous paper. In this paper, we add extra categories based on km travelled by vehicles and we add categories for cracked tires and friction tires. Therefore, the detection of tire quality can avoid the accidents and improve safety of vehicles.

Convolution leverages three important ideas that motivated computer vision researchers: sparse interaction, parameter sharing, and equivariant representation. Trivial neural network layers use matrix multiplication by a matrix of parameters describing the interaction between the input and output unit. This means that every output unit interacts with every input unit. However, 22 convolution neural networks have sparse interaction. This is achieved by making kernel smaller than the input e.g., an image can have millions or thousands of pixels, but while processing it using kernel they can detect meaningful information that is of tens or hundreds of pixels. This means that need to store fewer parameters that not only reduces the memory requirement of the model but also improves the statistical efficiency of the model. If computing one feature at a spatial point (x1, y1) is useful then it should also be useful at some other spatial point say (x2, y2). It means that for a single two-dimensional slice i.e., for creating one activation map, neurons are constrained to use the same set of weights. In a traditional neural network, each element of the weight matrix is used once and then never revisited, while convolution network has shared parameters i.e., for getting output, weights applied to one input are the same as the weight applied elsewhere. Due to parameter sharing, the layers of convolution neural network will have a property of equivariance to translation. It says that by changing the input in a way, the output will also get changed in the same way.

The convolution layer is the core building block of the CNN. It carries the main portion of the network's computational load. This layer performs a dot product between two matrices, where one matrix is the set of learnable parameters otherwise known as a kernel, and the other matrix is the restricted portion of the receptive field. The kernel is spatially smaller than an image but is more in-depth. This means that, if the image is composed of three (RGB) channels, the kernel height and width will be spatially small, but the depth extends up to all three channels. Figure 4.4. Illustration of Convolution Operation During the forward pass, the kernel slides across the height and width of the image-producing the image representation of that receptive region. This produces a two-dimensional representation of the image known as an activation map that gives the response of the kernel at each spatial position of the image. The sliding size of the kernel is called a stride.

Neurons in this layer have full connectivity with all neurons in the preceding and succeeding layer as seen in regular Fully CNN. This is why it can be computed as usual by a matrix multiplication followed by a bias effect. The Fully Connected layer helps to map the representation between the input and the output.

IV. SYSTEM DESIGN

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,
    i. Tire wear image data bank.
    ii. Tire cracked image data bank.
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.

By following these steps we can get the confusion matrix and progress the input images.

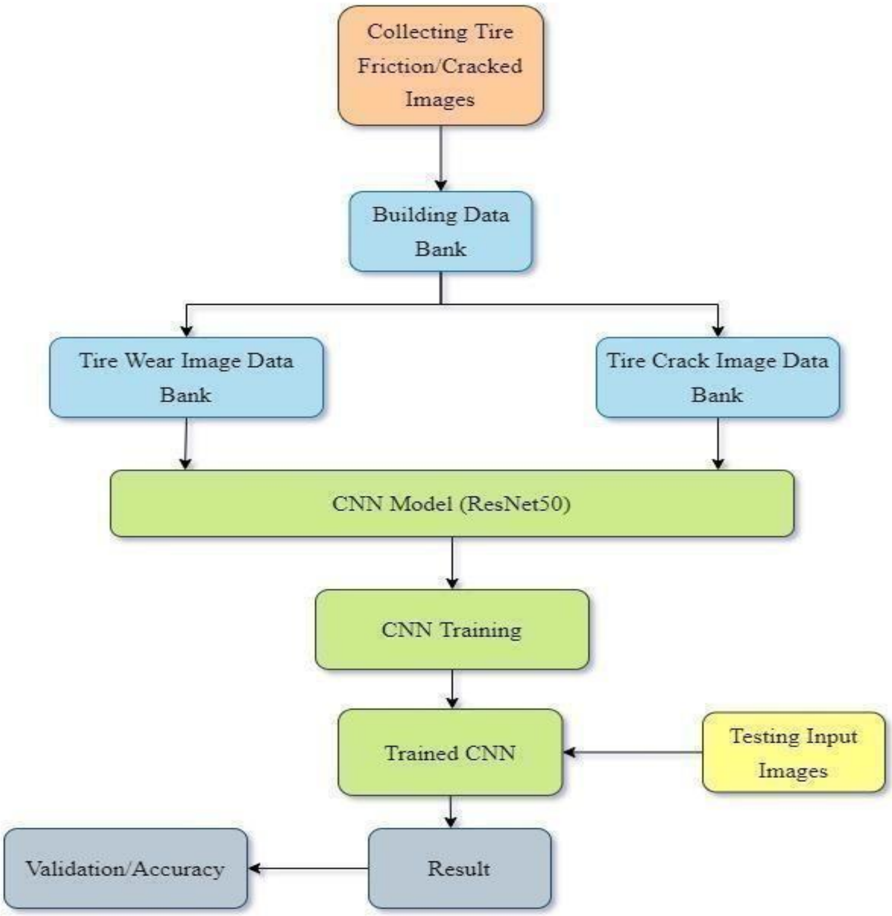


Fig.2. Flow Chart For Tire Quality Inspection System Using CNN

V. Methodology

1. 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)

2***. Types of errors:***

Type I - The first way is to re-write False Negative and False Positive. False Positive is Type I error because False Positive = **F**alse True and that only has one F. False Negative is a Type II error because False Negative = **F**alse so thus there are two F's making it a Type II.

Type II. - The second way is to consider the meanings of these words. False Positive contains one negative word (False) so it's a Type I error. False Negative has two negative words (False + Negative) so it's a Type II error.

3.***ResNet50***

4.RestNet18.

5.RestNet 101

6.Convolution

7.Pooling

8.Flattening

9.Full connection

10.Types of layers:

i. Input layer

ii. Hidden layer

iii. Output layer

These are the various different terminologies involved in this deep learning based tire prediction system.
These terminologies has a major effect and important usage around the prediction system.

VI. SYSTEM DESIGN AND REALIZATION

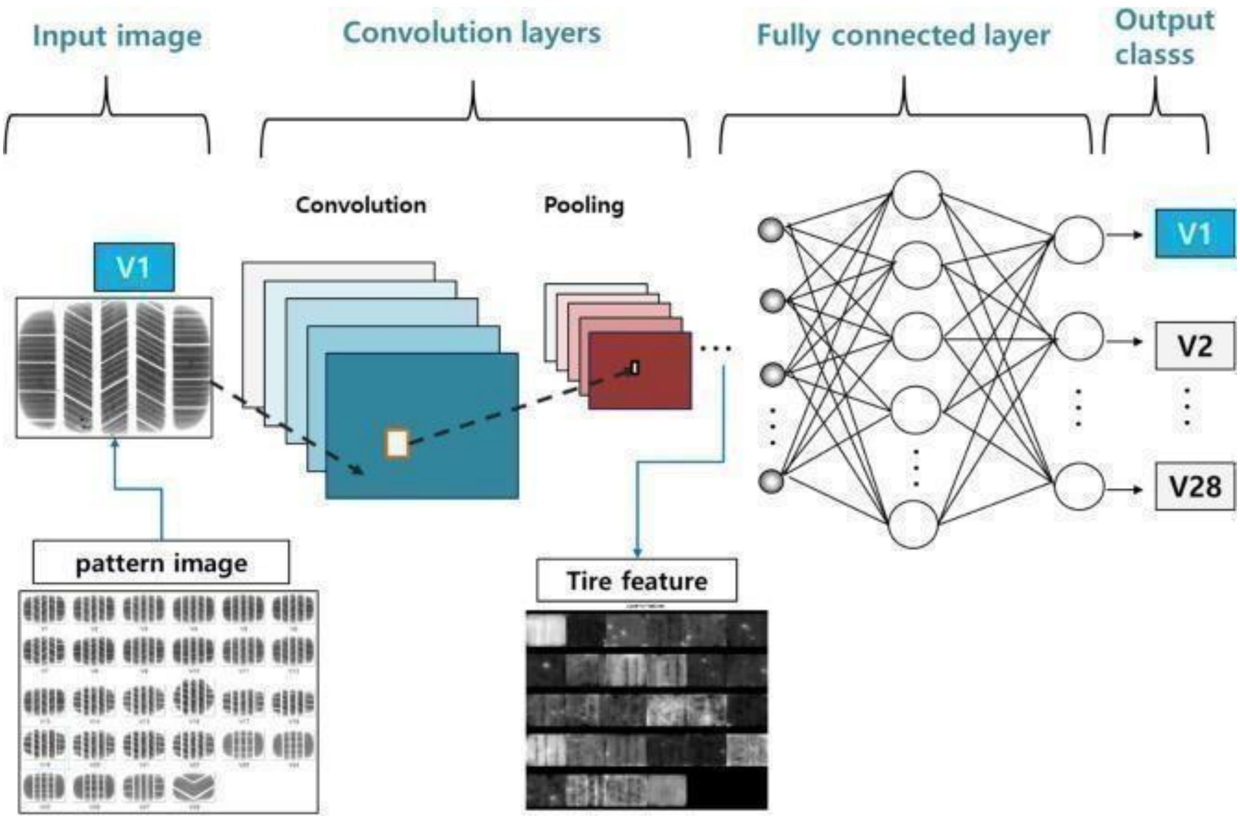


FIGURE 3.Tire Wear prediction using CNN

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

1.ResNet50:

It is a convolutional neural network that is 50 layers deep. Can loadpre-trained version of the network trained on more than a million image from the ImageNet database. The pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

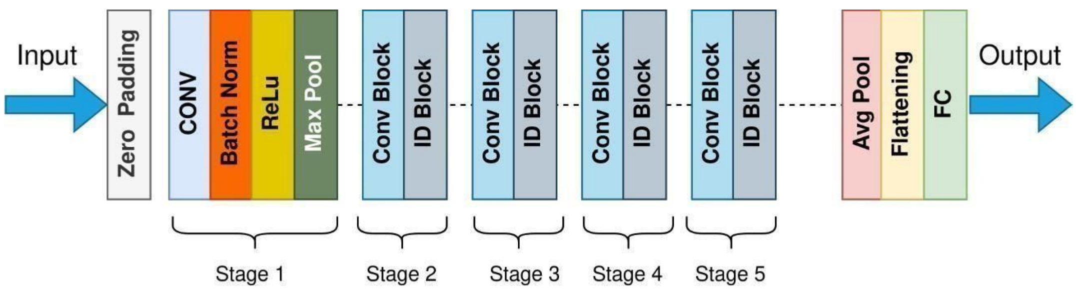


FIGURE 4. ResNet_50 model Architecture

2.RestNet18:

ResNet18 is a 72-layer architecture with 18 deep layers. The architectureof this network aimed at enabling large amounts of convolutional layers to function efficiently. However, the addition of multiple deep layers to a network often results in a degradation of the output.

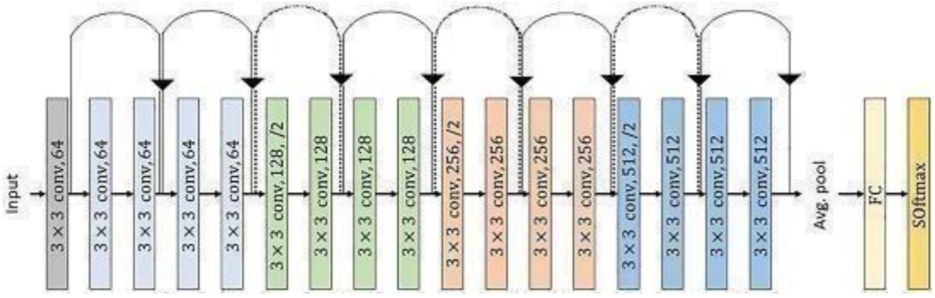


FIGURE 5. ResNet_18 model Architecture

3.*ResNet101:*

ResNet-101 is a convolutional neural network that is 101 layers deep. can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

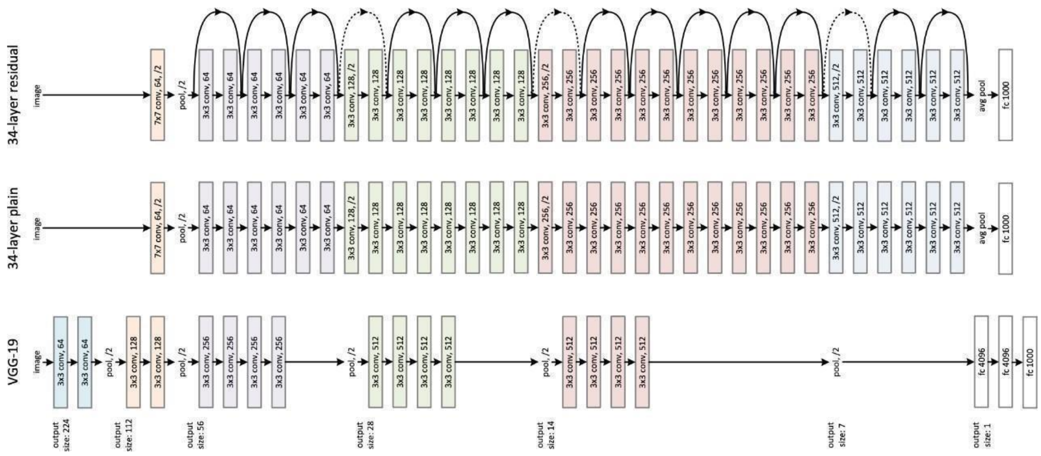
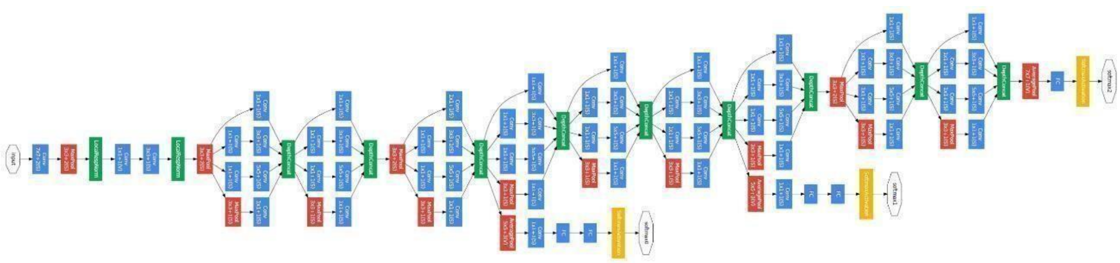


FIGURE 5. ResNet_101 model Architecture

4.GoogleNet:

The GoogleNet Architecture is 22 layers deep, with 27 pooling layers included. There are 9 inception modules stacked linearly in total. The ends of the inception modules are connected to the global average pooling



layer.

FIGURE 6. GoogleNet model Architecture

VII. RESULT AND ANALYSIS

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 isthe 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.

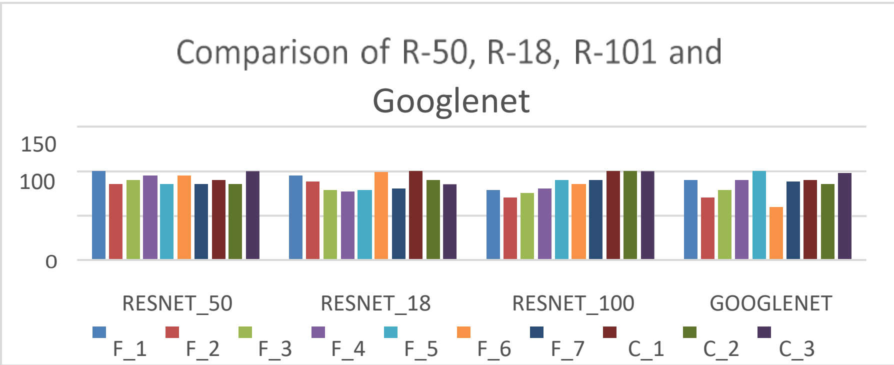


FIGURE 7. Comparison of ResNet_50, ResNet_18, ResNet_101 and GoogleNet networks

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VIII. CONCLUSION

This project 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.

IX. FUTURE SCOPE

Tollgate methodology helps to make the team and the organization aware of the importance of investing time and resources in good and completed planning. A Global System for Mobile (GSM) antenna is a type of antenna commonly used in mobile phones and cell towers. GSM is the most common type of cellular network worldwide. When the vehicles came in the Tollgate, the camera which is placed in the tollgate to capture the image of the vehicle’s tire, focused on the tire and capture the image. The image database is collected and classified. After classification, it check the tire in which category. Suppose the tire is in the danger category, the message is send to the owner of the vehicle and RTO through the GSM Antenna.

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