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A Deep Learning Based Tire Quality Inspection System

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ABSTRACT: Tires are one of the most essential components of a vehicle, as they actively contribute to driving dynamics. However, they are often among the most overlooked when it comes to proper scrutiny and maintenance. More often than not, the general masses are found to be negligent of the condition of their tires. Tread wear and sidewall damage occur in abundance, and not tending to these problems can have devastating consequences in the long run. There is an innumerable number of road accident cases reported which were found to have been caused due to use of damaged and worn-out tires, and these occurrences are more prevalent in highways and during the rainy season. Despite being a widespread issue, many people are unable to identify good usable tires from worn-out ones, increasing their likelihood of using dangerous unsafe tires on roads. In the past few years, Manual Inspection has been the main technique used to detect the degree of tire wear. A mainstream method is to define the degree of tread pattern wear by detecting the tread depth and the pattern wear of the shoulder, which combines a mathematical model of the tire and local friction and determines the tire wear rule through experiments. However, this method are too expensive to use in a family car. This paper introduces a model that can differentiate between cracked and friction tires, which has been implemented using Image Processing. The model takes external pictures of tires provided by the user as input and provides a verdict on its condition after comparing them with the model's dataset using the deep learning algorithms ResNet50. This model has been made keeping in mind that it can be further used with appropriate hardware for implementing in real-life applications. By enforcing said implementation by the concerned regulatory bodies, tire-related accidents can be sharply reduced and damage to human life and property can be prevented on public roads.

Keywords: Tires, Deep Learning, Image Processing, CNN, ResNet50, Cracked Tires, Friction Tires, Accident.

I. INTRODUCTION

Approximately 2 billion tires were produced worldwide in 2016 and tire production is expected to increase steadily and demand is expected to be strong in most countries and in developing counties in particular over the next few years. The tire is an essential part of a road vehicle. Traction, braking and steering forces are generated between the road and the tires and control the vehicle's motion. Tires, however, wear down, causing dispersal of unhealthy wear particles as well as disposal of old tires, which is harmful to the environment. With more knowledge about what causes wear it might be possible to reduce tire wear, which would be beneficial from both an economic and an ecological point of view. The Regional Transport Office (RTO) or Regional Transport Authority (RTA) is the organisation of the Indian government responsible for maintaining a database of drivers and a database of vehicles for various states of India. 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. This whole process is not developed by this report. The aim of this thesis work is to develop a tyre images that can simulate tire wear by their friction and crackness.

- To recognize the tire friction by their km travelled by vehicles and categorize

- To recognize cracks in the tire and categorize.

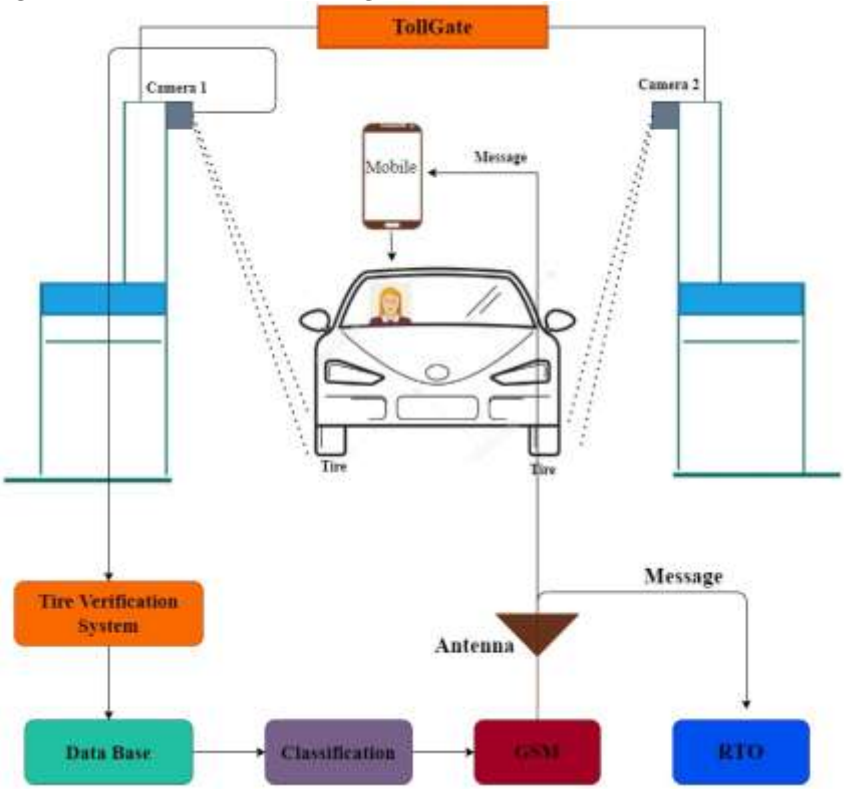

Figure 1 Tire inspection system at tollgate

II. LITERATURE SURVEY

[1] Dr .A Albert Raj.et.,al. in 2021[1] proposed the CNN based Tyre Life Prediction and Defect Identification System. The tyre life prediction system is designed to find the Bulges, Sidewall cracking, Air Inflation, Alignment issues, and Treadwear. This system is trained to identify common tyre defects and they 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 The model is trained for 10 iteration which yields a validation accuracy of around 76%. Accuracy can be increased by increasing the dataset.

[2] S.M. MynulKarim.et.,al. in 2021[2] proposed a model Tire Wear Detection for Accident Avoidance Employing Convolutional Neural Networks. 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%.

[3] Xiaoping Wang.et.,al. in 2020[3] proposed an Artificial Neural Network-Based Method for Identifying Under-Inflated Tire in Indirect TPMS. 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

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current ANN is mainly hindered by the decentralized distribution of data.

[4] HarshalBhanare.et,.al. in 2019[4] proposed a Quality Inspection of Tire using Deep Learning based Computer Vision . 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.

[5] Orhan Bulan.et.,al. in 2012[5] proposed Tire Classification from Still Images and Video. 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 involve ment 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%. They already published tire classification tire wear,tire tread in previous paper. In this paper, we add extra categories based on km travelled by vechicles and we add categories the cracked tires. Therefore, the detection of the quality can avoid the accidents and improve safety of vehicles.

III. 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.

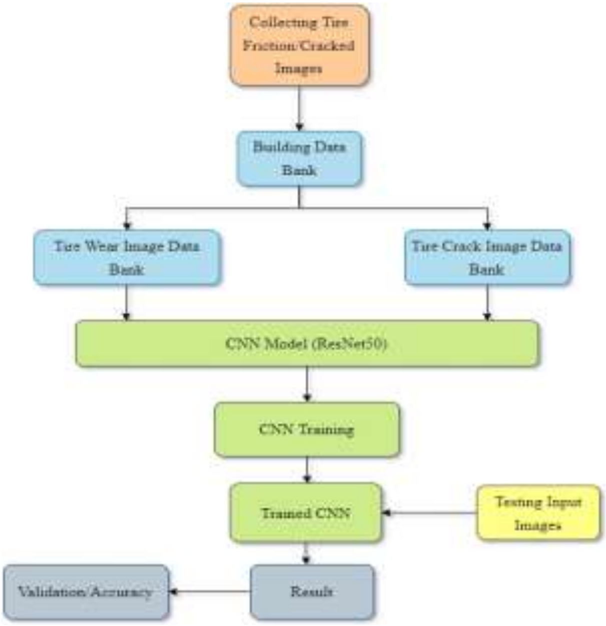

Figure: Representing system model of tire quality inspection system using CNN

Step by step process

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,

- Tire wear image data bank.
- 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.

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Friction Tire

Friction is created when two surfaces rub together. For example, when a car tire moves over the road surface, Friction can create heat and smoke can often be seen coming from the tires of racing cars.

Figure: Friction tyre wear

Category

- WEAR _1: The tire which travelled at the range of 0km to 10000km.
- WEAR _2: The tire which travelled at the range of 10000km to 20000km.
- WEAR_3: The tire which travelled at the range of 20000km to 30000km.
- WEAR _4: The tire which travelled at the range of 30000km to 40000km.
- WEAR _5: The tire which travelled at the range of 40000km to 50000km.
- WEAR _6: The tire which travelled at the range of 50000km to 60000km.
- WEAR_7: The tire which travelled at the range of 60000km to 70000km.
- CRACKED_1: The tire which are lightly cracked.
- CRACKED_2: The tire which are moderately cracked.
- CRACKED_3: The tire which are heavily cracked.

Figure: Lightly Cracked

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Moderately Cracked

Heavily Cracked

Convolution Layer

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.

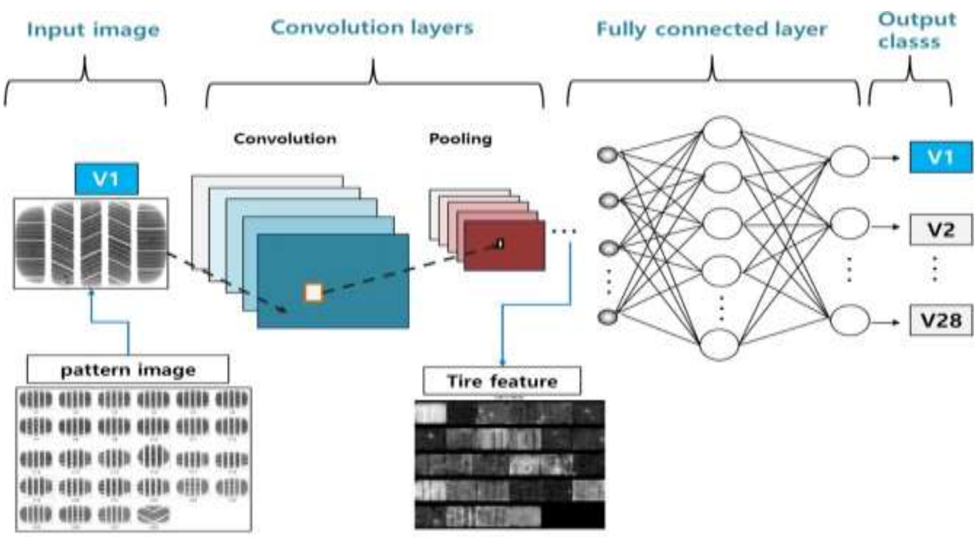

Figure 4.5. Tire wear prediction using CNN

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Why CNN for image classification?

Image classification involves the extraction of features from the images to observe some patterns in the dataset. Using an ANN for the purpose of image classification would end up being very costly in terms of computation since the trainable parameters become extremely large.

For example, if we have a 50*50 image of a cat, and we want to train our traditional ANN on that image to classify it into a dog or a cat, the trainable parameters become (50*50)*100 image pixels multiplied by hidden layer + 100 bias + 2 * 100 output neurons + 2 bias = 2,50,302.

Types of CNN models

Some of them have been listed below:

ResNet_50

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

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. Below is a zoomed-out image of the full GoogleNet architecture.

ResNet_101

ResNet-101 is a convolutional neural network that is 101 layers deep. You 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.

ResNet_18

ResNet18 is a 72-layer architecture with 18 deep layers. The architecture of 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.

PARAMETERS

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)

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)

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)

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

Specificity = TN / (TN+FP)

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

Precision = TP / (TP+FP)

Recall : It is also called sensitivity, Probability of Detection, True Positive Rate. The ratio of correct positive predictions to the total positive examples.

Recall = TP / (TP +FN)

F measure: It is a measure of a 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 × recall) / (precision + recall)

IV. RESULT AND DISCUSSION

The results from the tire wear simulations are presented in this chapter.We have collected images of Tires and categories into ten category oftire friction based on the km travelled by vehicles and its crackness. 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 every thing easier. In this system our

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aim is to develop a system using deep learning and algorithm approach firstly we need together various images vendor and tire type wise then we need classify that data set according to test dataset and training dataset approach. In this problem we will explore various deep learning algorithms which are based on CNN. From that various algorithmic approaches, we analyses which is better.

RESNET_50

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	C_1	C_2	C_3
F_1	100	0	0	0	0	0	0	0	0	0
F_2	2	99	2	1	0	0	0	0	0	0
F_3	0	0	90	10	0	0	0	0	0	0
F_4	0	0	0	95	5	0	0	0	0	0
F_5	0	0	0	0	100	0	5	0	0	0
F_6	0	0	0	2	1	95	0	2	0	0
F_7	0	0	0	0	0	3	90	0	0	0
C_1	0	0	0	0	0	5	0	100	0	5
C_2	0	0	0	0	0	0	0	2	95	2
C_3	0	0	0	0	0	0	0	0	0	100

Figure 7.1. Confusion Matrix table of ResNet50

The accuracy values for friction tires F_1, F_2, F_3, F_4, F_5, F_6, F_7 and cracked tires C_1, C_2, C_3 are shown above.

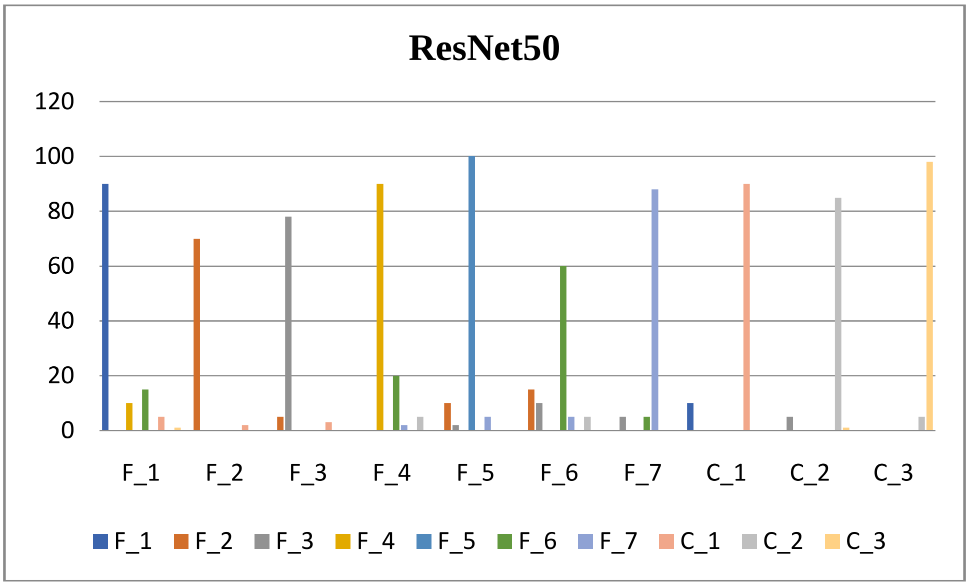

Figure : Graphical representation of Resnet50 resultant

From the ResNet50 Confusion Matrix, True positive = 953,True negative = 0, False positive= 47 and False negative = 47.

Multi Class Classification	Formula	Percentage
Accuracy	(TP+TN)/(TP+TN+FP+FN)	91%

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Error Rate	1 – accuracy (or) (FP+FN)/(FP +FN+TP+TN)	0.9%
Sensitivity	TP / (TP+FN)	95%
Specificity	TN/(TN+FP)	∞
Precision	TP/(TP+FP)	95%
Recall	TP/(TP +FN)	95%
F measure	2(precision×recall)/(precision+recall)	95%

Figure: Multiclass Classification of ResNet50

In ResNet_50, the overall percentage of the result gain is 91%. In this network all category resultant are above 85% correctly categoried are obtained accurately.

RESNET_18

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	C_1	C_2	C_3
F_1	96	0	3	0	0	0	0	2	0	0
F_2	0	90	2	0	10	0	0	0	0	0
F_3	0	0	78	2	0	15	5	0	0	0
F_4	0	8	0	89	5	5	5	0	0	0
F_5	12	0	0	0	90	0	10	0	0	0
F_6	0	0	0	1	0	89	0	0	0	0
F_7	4	0	0	9	6	0	88	0	0	1
C_1	0	0	0	0	0	0	0	93	0	0
C_2	0	5	0	0	0	0	0	5	89	0
C_3	0	0	0	10	0	5	0	0	0	92

Figure: Confusion Matrix table of ResNet 18

The accuracy values for friction tires F_1, F_2, F_3, F_4, F_5, F_6, F_7 and cracked tires C_1, C_2, C_3 are shown above.

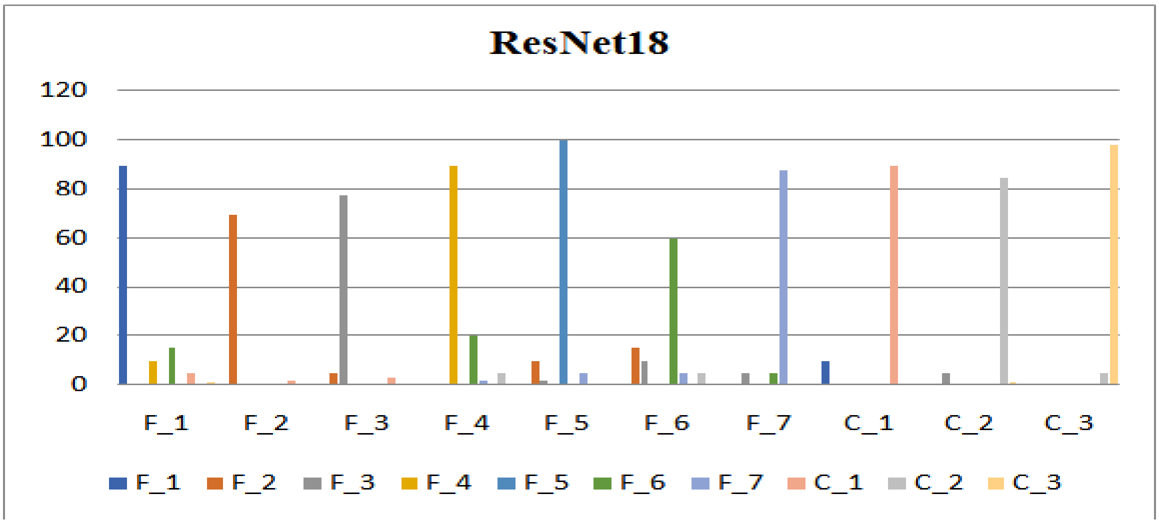

Figure : Graphical representation of Resnet -18 resultant.

From the ResNet50 Confusion Matrix, True positive = 870, True negative = 0,False positive =130 and False negative =130.

Multi Class Classification	**Formula**	**Percentage**
Accuracy	(TP+TN)/(TP+TN+FP+FN)	76.9%
Error Rate	1 – accuracy (or) (FP+FN)/(FP +FN+TP+TN)	23%
Sensitivity	TP / (TP+FN)	87%
Specificity	TN/(TN+FP)	∞
Precision	TP/(TP+FP)	87 %
Recall	TP/(TP +FN)	87%
F measure	2(precision×recall)/(precisio n+recall)	86.8 %

Figure : Multiclass Classification of ResNet18

In RESNET_18, the overall percentage of result gained is 77%. In this network resnet 18 the result accuracy obtained is 5% above than the resnet 50. Which performance much better than other networks.

RESNET_101

R_101	**F_1**	**F_2**	**F_3**	**F_4**	**F_5**	**F_6**	**F_7**	**C_1**	**C_2**	**C_3**
F_1	89	0	12	0	10	0	0	0	0	0
F_2	0	85	0	0	15	0	9	1	0	5
F_3	5	10	78	0	0	0	10	0	0	0
F_4	0	0	0	80	0	0	20	0	0	0
F_5	0	0	0	0	70	9	1	0	0	0
F_6	0	0	5	0	10	85	0	0	0	0
F_7	0	0	0	10	0	0	80	0	0	0
C_1	0	0	0	0	0	0	0	86	0	0
C_2	0	0	0	0	0	0	0	0	83	0
C_3	0	0	0	0	0	0	0	0	0	100

Figure7.7. Matrix representation of Resnet 101

The accuracy values for friction tires F_1, F_2, F_3, F_4, F_5, F_6, F_7 and cracked tires C_1, C_2, C_3 are shown above.

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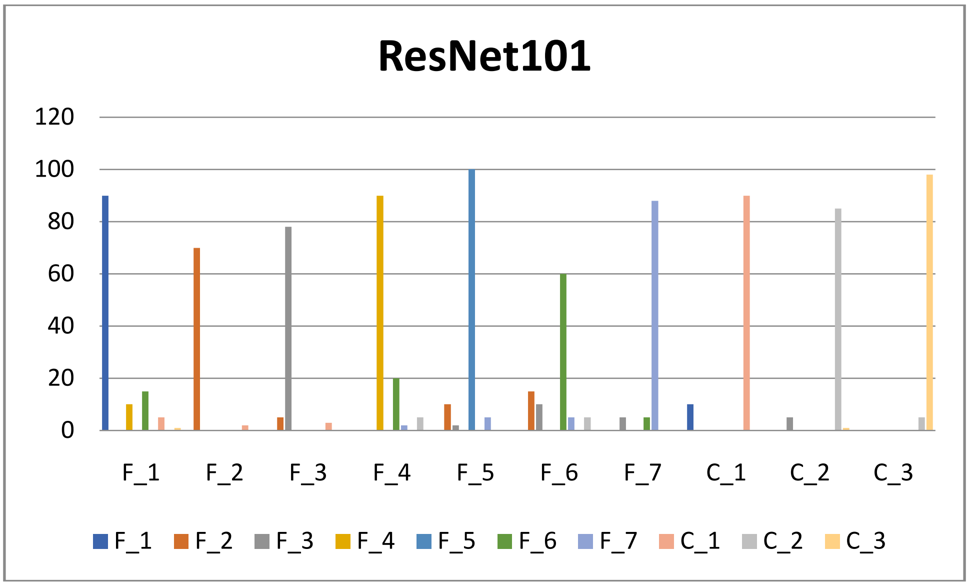

Figure 7.8. Graphical representation of Resnet 101 resultant

From the ResNet50 Confusion Matrix, True positive = 868, True negative = 0,False positive = 132 and False negative = 132.

Multi Class Classification	Formula	Percentage
Accuracy	(TP+TN)/(TP+TN+FP+FN)	76%
Error Rate	1 – accuracy (or) (FP+FN)/(FP +FN+TP+TN)	23%
Sensitivity	TP / (TP+FN)	86%
Specificity	TN/(TN+FP)	∞
Precision	TP/(TP+FP)	86%
Recall	TP/(TP +FN)	86.8%
F measure	2(precision×recall)/(precision+recall)	87%

Figure: Multiclass Classification of ResNet101

In RESNET_101, the overall result gain is 76%. This network works better than ResNet 50 which has gained the result two percent above then that ResNet 50 network.

Googlenet

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	C_1	C_2	C_3
F_1	70	0	0	0	0	0	0	10	0	0
F_2	0	65	5	0	10	15	0	0	0	0
F_3	0	0	75	0	2	10	5	0	5	0
F_4	10	0	0	77	0	0	0	0	0	0
F_5	0	0	0	0	75	0	0	0	0	0
F_6	15	0	0	20	0	70	5	0	0	0
F_7	0	0	0	2	5	5	70	0	0	0

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C_1	5	2	3	0	0	0	0	79	0	0
C_2	0	0	0	5	0	5	0	0	82	5
C_3	1	0	0	0	0	0	0	0	1	85

Figure : Confusion Matrix representation of Googlenet

The accuracy values for friction tires F_1, F_2, F_3, F_4, F_5, F_6, F_7 and cracked tires C_1, C_2, C_3 are shown above.

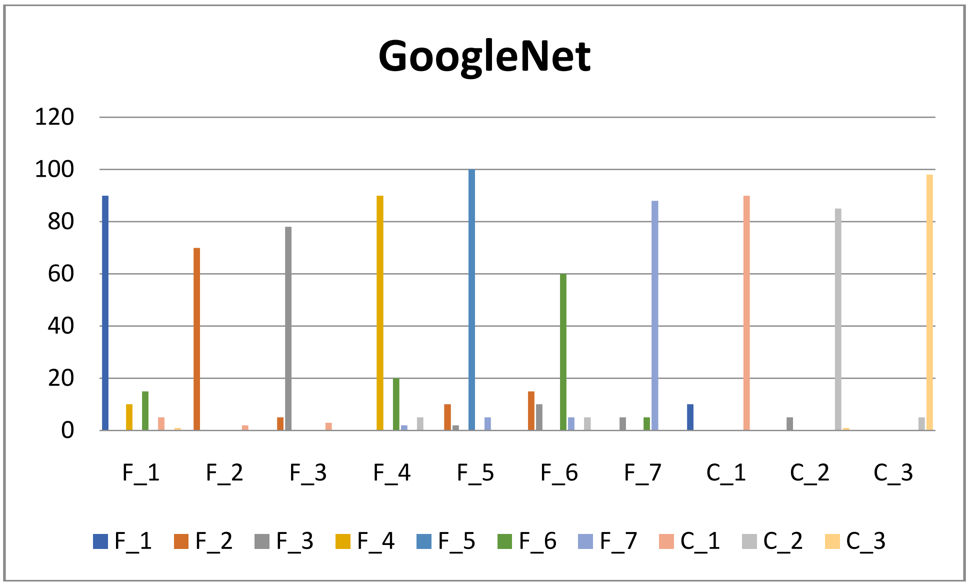

Figure 7.11. Graphical representation of Googlenet resultant

From the ResNet50 Confusion Matrix, True positive = 849, True negative=0,
False positive=148 and False negative =151.

Multi Class Classification	Formula	Percentage
Accuracy	(TP+TN)/(TP+TN+FP+FN)	73%
Error Rate	1 – accuracy (or) (FP+FN)/(FP +FN+TP+TN)	23%
Sensitivity	TP / (TP+FN)	84%
Specificity	TN/(TN+FP)	∞
Precision	TP/(TP+FP)	85%
Recall	TP/(TP +FN)	84%
F measure	2(precision×recall)/(precision+recall)	84%

Figure: Multiclass Classification of ResNet101

In Googlenet, the overall percentage of the gain is 73%. It works little bit slower and low accurate result giving than all other networks. In F_5 category the resultant is 100%. This network gives full efficient result in category 5 and it is also giving 90 and 98 percentage of result accuracy in C_1 & C_3. Overall its performs a good result but compared to other network its works little bit slower.

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Comparison result of ResNet_50, ResNet_18, ResNet_101 and Googlenet networks

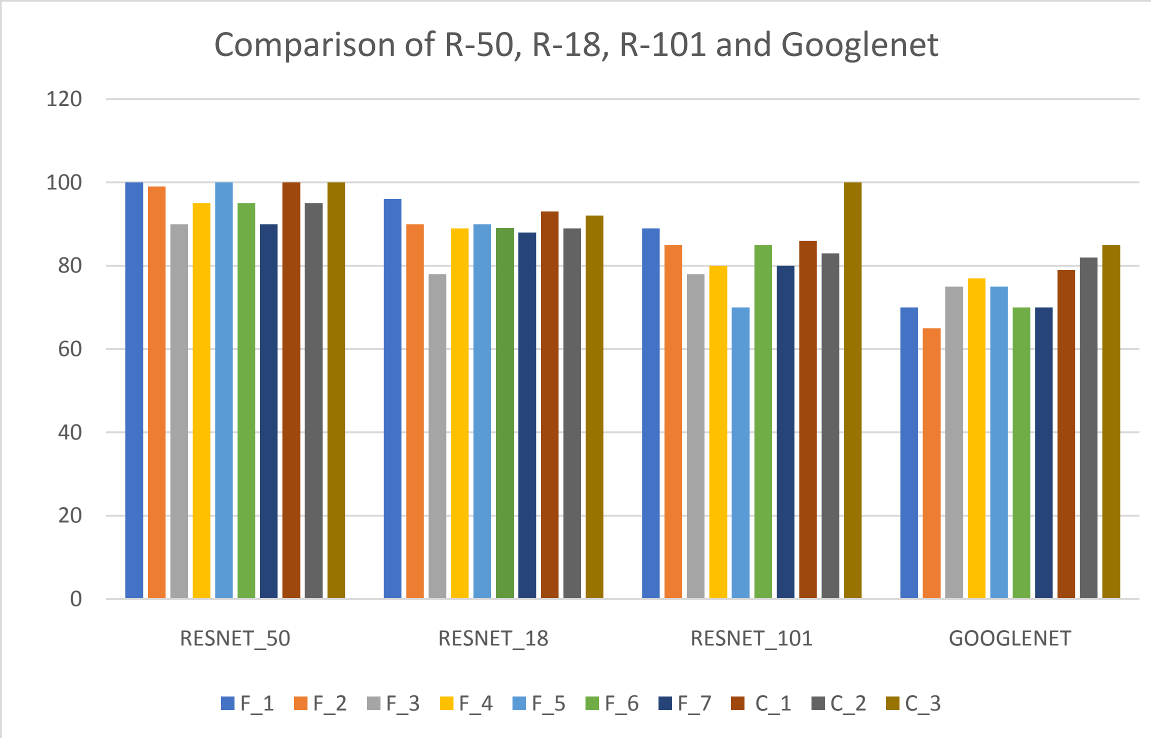

Figure: Comparison of ResNet_50, ResNet_18, ResNet_101 and Googlenet networks

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 he 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, Resnet50 performance high then the other's and this network work gives full accurate result of this category. In F_6, Resnet50 performances good and has a accuracy performances of 98%.In F_7, Resnet50 performances high of 97% then the others. In C_1, Resnet_50 performance the same of high resultant giving of accuracy of 100% of result. In C_2, ResNet 50 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.

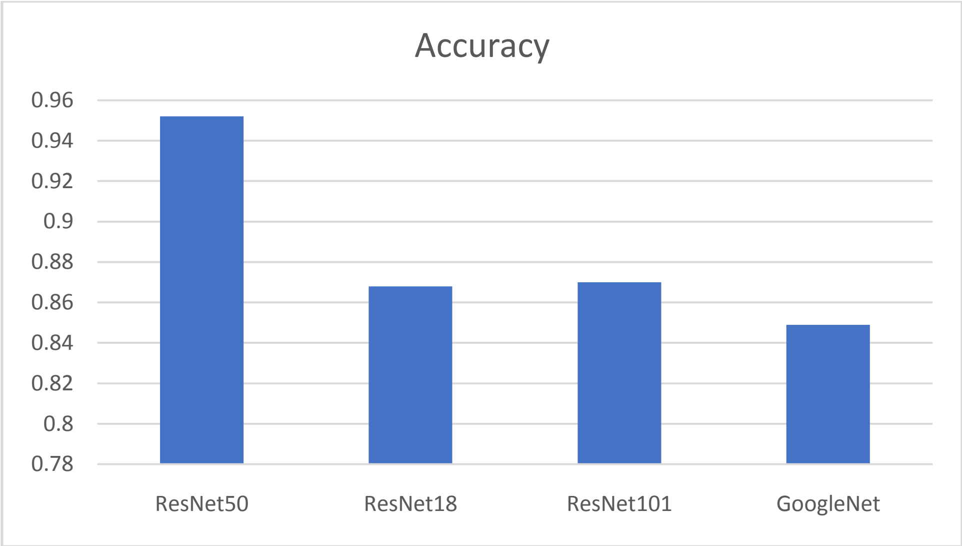

Figure :Accuracy of Four Networks

From the above model graph, we can see the accuracy of four network models showing which model has predicted the dataset the most accurately. Here, the model ResNet50 has the highest level of the accuracy.

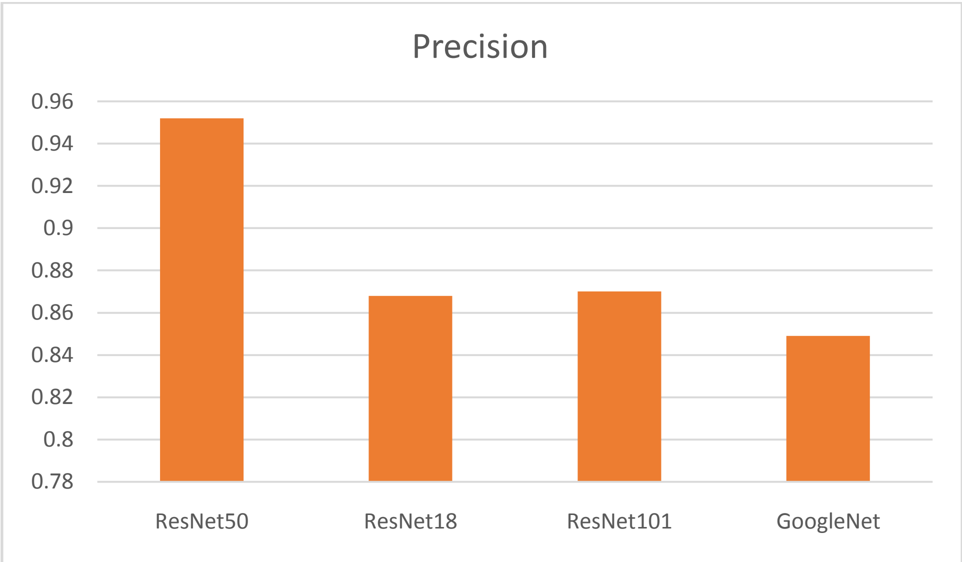

Figure :Precision of Four Networks

From the above model graph, we can see the precision of four network models showing which model has predicted the dataset the most accurately. Here, the model ResNet50 has the highest level of the precision.

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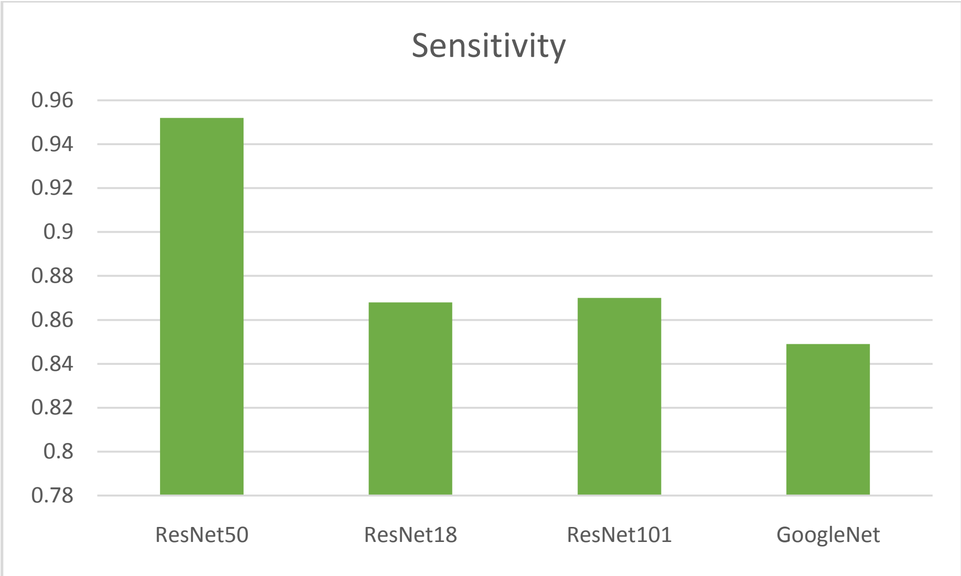

Figure : Sensitivity of Four Networks

From the above model graph, we can see the sensitivity of four network models showing which model has predicted the dataset the most accurately. Here, the model ResNet50 has the highest level of the sensitivity.

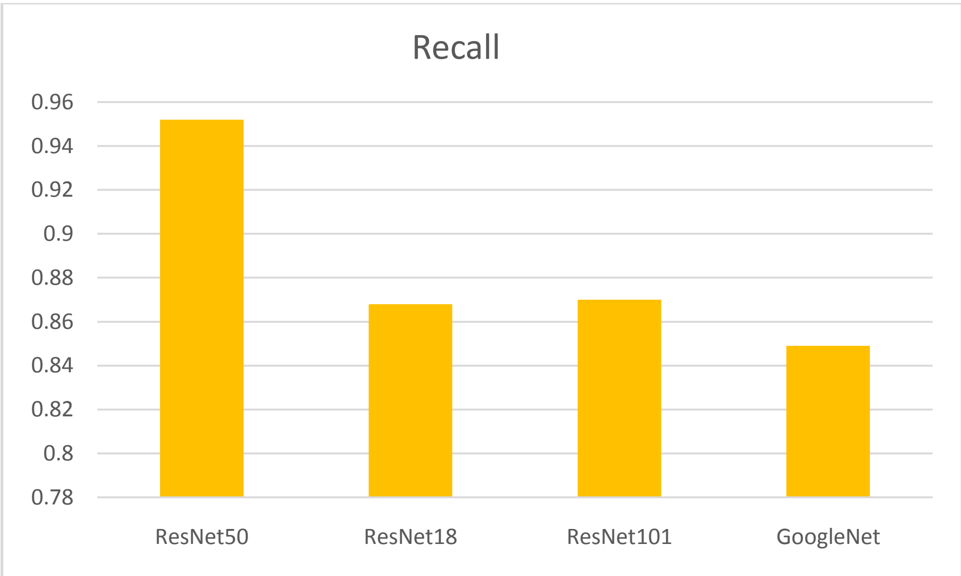

Figure :Recall of Four Networks

From the above model graph, we can see the recall of four network models showing which model has predicted the dataset the most accurately. Here, the model ResNet50 has the highest level of the recall.

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Figure Error Rate of Four Networks

From the above model graph, we can see the error rate of four network models showing which model has predicted the dataset the most accurately. Here, the model ResNet50 has the highest level of the error rate.

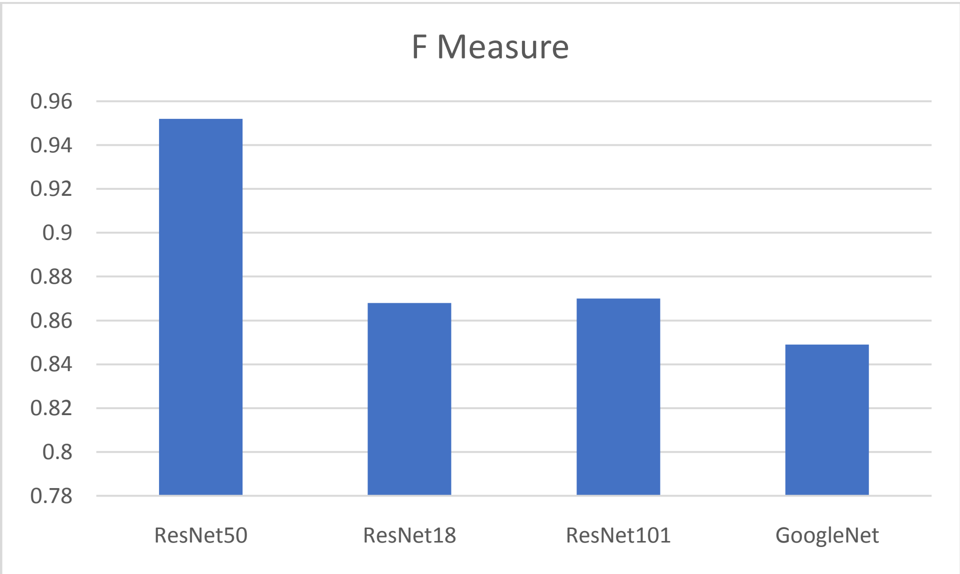

Figure F measure of Four Networks

From the above model graph, we can see the F measure of four network models showing which model has predicted the dataset the most accurately. Here, the model ResNet50 has the highest level of the F measure.

V. CONCLUSION

This paper presents a novel method for predicting the life of automobile tires. We establish an image database into CNN model and finally, we use appropriate evaluation indicators to analyze the accuracy of the model. Experiments demonstrate that the proposed method shows high accuracy, fast efficiency and low cost in predicting tire life. However, there are still some shortcomings in this study. For example, factors such as road conditions, tire size, and tire quality require further consideration. Moreover, this article only makes experimental predictions based on small sample data, and this work needs to be extended to large sample tests. We will report on these results in future publications.

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REFERENCE

[1]. Dr .A Albert Raj.et.,al. "CNN based Tyre Life Prediction and Defect Identification System" in 2021,6th International Conference on Communication and Electronics Systems (ICCES), 978-1-6654-3587.

[2]. S.M. MynulKarim.et.,al."Tire Wear Detection for Accident Avoidance Employing Convolutional Neural Networks" in 2021,8th NAFOSTED Conference on Information and Computer Science (NICS), 978-1-6654-1001-4.

[3]. Xiaoping Wang.et.,al. "Artificial Neural Network-Based Method for Identifying Under-Inflated Tire in Indirect TPMS" in 2020,IEEE Access,Volume B, 213799-213805.

[4]. HarshalBhanare.et.,al."Quality Inspection of Tire using Deep Learning based Computer Vision" in 2019, International Research Journal of Engineering and Technology(IRJET),Volume: 06 Issue: 11,3555-3559.

[5]. Orhan Bulan.et.,al. "Tire Classification from Still Images and Video" in 2012,15th International IEEE Conference, 485-490.