“Motorbike Defect Checker and Predictor” –Android App to identify vehicle auto parts altered and their usage prediction

TMP-23-383

Final Report

S.L.D. P Pramodya – IT20219598

A.M. K. A. P. Amarasingha - IT20257040

D.M.D.H Dissanayaka - IT20261764

P. U. Rathnasooriya - IT20156206

Department of Information Technology

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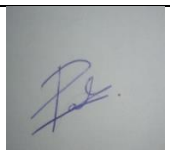
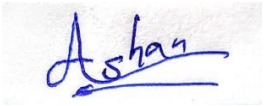
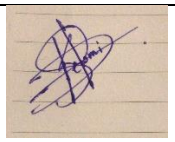
DECLARATION

We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or institute of higher learning, and to the best of our knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	Student Id	Signature
S.L.D.P Pramodya	IT20219598	
A.M. K. A. P. Amarasingha	IT20257040	
D.M.D.H Dissanayaka	IT20261764	
P. U. Rathnasooriya	IT20156206	

The supervisor/s should certify the proposal report with the following declaration. The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor: Date:

ABSTRACT

As Sri Lanka has a high population of motorbike owners, out of them the most are Indian bikes, we have come up with this solution of selecting the best, safe and valuable motorbike for an individual just using his mobile phone. Therefore the buyer would not need the expert knowledge in identifying the defects by himself.

The “Motorbike Defect Checker and Predictor” which is the final outcome of this research project is a complete mobile application that has the ability in providing it’s users with an analysis of the overall condition of the motor bike which he/she is trying to purchase.

Currently the applications and methods used by different organizations in making an overall health condition of the vehicle has its separate components health check in separate companies. For an instance the part’s quality and originality would only be checked by its manufacturer but here this specific application has the capability of identifying the defects, alternations, usage and finally give out prediction on the future usage and present condition of the motor bike.

Institutions like Hero Honda Service Center, Bajaj Service Center, and R & D Bike Modification Center are eager to help us with this endeavor by offering us additional information and support.

Additionally, the team has made all required preparations to build up data sets in the event that one of the aforementioned institutions or people refuses to allow data collection. Due to problems with accuracy from the built-up data sets, we would use the most.

Furthermore, the spare parts stores and other manufacturing sectors could be used to gather the required images of the auto parts for the training model. Industries like DSI tires, Bajaj spare parts, and Honda bike agents are ready to give us all the information we need, including authorization to take pictures.

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to all those who have contributed to the completion of this research project.

First and foremost, I am immensely grateful to my supervisor, Dr. Amithalal Caldera and co-supervisor Ms. Supipi Karunathilaka for their guidance, support, and invaluable insights throughout the entire research process. Their expertise and encouragement have been instrumental in shaping this study.

I would like to thank my colleagues and friends S.L.D.P Pramodya,A.M.K.A.PAmarasingha, D.M.D.H encouragement and valuable discussions. Their feedback and suggestions significantly improved the quality of this research.I am indebted to the staff of Sri Lanka Institute Of Information Technology for their assistance in accessing resources and facilities, which greatly facilitated the smooth progress of this study.

I am indebted to the staff of all the institution Stafford Motor Co. (Pvt) Ltd - Automobile Body Repair & Paint Division, David Pieris Motor Company (Pvt) Ltd - Head Office provided us with all the data needed to make this research a successful, for their assistance in accessing resources and facilities, which greatly facilitated the smooth progress of this study.Finally, I am grateful to my family for their unwavering support, understanding, and patience throughout this research journey.

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1 INTRODUCTION

1.1 Background and Literature Survey

At the time of a vehicle purchase or motor bike purchase, the buyer tends to find the condition of the vehicle that he/she is trying to purchase. In this process the buyer do not have any mechanism or a metric that could be used as measurement of the vehicle' or the motor bike's condition. Therefore, most of us tend to ask for expertise knowledge where the seller would not be able to cover up the defects. Moos buyers tend to accompany an expert in the specific vehicle criteria and get an analysis regarding the vehicle's condition.

Thus when buying a motorbike we try to find out the most suitable value that would be granted for that specific motor bike. In this specific mobile application that we are trying to build up, we have identified the most critical specifications that a buyer would look at the time of purchase. They are the body parts that have been fixed, tyre usage, registration paper details and engine's condition. In order to identify all these specifications a common measurement or metric have not been introduced so far.

At present world we could find many innovative measurement criteria in specific areas such as in finding altered parts, the companies have come up with their methods which is only fixed into on criteria. For example Yamaha Company has its own methods in identifying their original parts. Rolls Royce engine builders have their own devices in identifying engine failure, Dunlop tyre builders have own methods in measuring the tyre usage and life expectancy, government officials have their own ways in identifying fraud documents, worn out vehicle details from true identity. But the application that we are planning to build has a combination of these criteria which it make one full combination of specification checker.

When identifying the initial scope for our research project we have used the following mechanisms since the vehicle industry is a huge industry in the present world. The scope that we have selected is only for Indian Motorbikes because it is the most widely sold type of motorbike. In future, we are planning to extend to all the other vehicles.

Origin	Indian				Malaysian	Japan
Model	Dio/Pleasure/pept	Bajaj Pulsar	CT 100	FZs	Demak	
The number of bikes to be sold in ikman.lk, Riyasewana (Bikes to be sold in 1st three pages)	20	13	19	8	4	4

Figure 0 – Scope selection

In order to collect the necessary data requirements for our database and training purposes we could get the knowledge from experts in auto mobile engineering from other universities, lecturers that we have our contacts with. Also, the necessary images of the auto parts for training model could be collected through the spare parts shops and other manufacturing industries. The industries such as DSI tyres, Bajaj spare parts, Honda bike agents are willing to provide us with all the necessary data requirements including permission to capture images. For extra knowledge in mechanical area, we are planning to contact several motor bike repairing places. The initial steps of contacting them and getting their knowledge has already been started by our team, also the individuals are willing to provide their full efforts in providing us with the necessary information.

Literature Survey

The research that our team conducting focuses on 4 major components as Identify the altered parts from the original parts, Identify defects in the engine by the sound of the engine, Compare the vehicle details with the registration paper details, Tyre usage prediction along with life expectancy. This whole application so has the ability of getting a full analysis of the current condition of the vehicle. Also provides the answer to the question of the buyer whether it is adequate for the price? , whether it is in condition for use ?.

When we focus our attention to other researches conducted on vehicle they mainly focus on internal defects such as engine defects [10] of aircrafts which are more critical in safety measures.

Also the companies such as TOYOTA, Honda, Yamaha, Land Rover, Dunlop, Kenda have their own researches on vehicle defect identification using Augmented reality, computer vision and deep learning. Most of them focused on one criteria .For an instance TOYOTA company has its own system to fit alternative pars to its vehicle using Augmented Reality to check whether it would be suitable [12].

"A Predictive Maintenance Framework for Motorbikes" by T. Sudhakar and K. Gopinath (2019)This study proposes a predictive maintenance framework for motorbikes that uses a combination of data analytics and machine learning techniques to predict defects. The authors collected data from a fleet of motorbikes and used it to train a predictive model that could accurately identify potential defects. The study found that the proposed framework could reduce maintenance costs by up to 30%.

"An Intelligent Fault Diagnosis System for Motorcycles Based on Fuzzy Logic" by F. Xu and X. Wu (2016)

This study proposes an intelligent fault diagnosis system for motorcycles based on fuzzy logic. The authors collected data from a fleet of motorcycles and used it to train a fuzzy logic model that could accurately identify faults. The study found that the proposed system could significantly improve the accuracy of fault diagnosis in motorcycles.

Overall, these studies demonstrate the potential of data analytics and machine learning techniques for predicting defects and diagnosing faults in motorbikes. A predictive maintenance framework that uses a combination of these techniques could help reduce maintenance costs and improve the safety of motorbikes on the road.

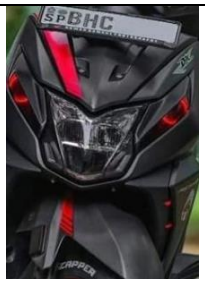
In contrast all these applications which are mostly desktop application will not provide an solution to our research problem that we have come up with. Where the user could get an evaluation on the motor bike that he/she trying to buy from anywhere in Sri Lanka at anytime.

Although the mobile application provide a solution to a simple issue that individuals face due to lack of automobile engineering knowledge the buyer would be satisfied if the current condition of the vehicle that he/she is willing to purchase.

According to studies that we have conducted we came across that mostly japan bikes are altered in every aspect. But our research mainly focus on the Indian bikes which are the most sold type of bike in Sri Lanka.

Motor bikes which have been altered

Description	Image	
	Original	Altered
The headlight which have been altered from the original headlight	 *Figure 1- Original*	 *Figure 1.2- Altered*
The alternative speedo meters and fuel meter that can used.	 *Figure 1.3- Original*	 *Figure 1.4- Altered*

Other modification done to the motor bike.	 *Figure 1.5- Original*	 *Figure 1.6- Altered*

1.2 Research Gap

The most difficult aspect of this study is that there has never been any previous research or automated procedure for identifying the other applications that has the same capabilities as our application. However, we could not come across a single application that has all these four components in a single mobile or a desktop application.

If an individual needs to find all these criteria in a motor bike he/she needs to have an expert knowledge in auto mobile industry. On the other hand, there are some university researches that conducted by specializing some areas such as in identifying defects of an aircraft engine[11]. They cannot, however, recognize and analyze without expertise. By utilizing the proposed mobile application " Motorbike Defect Checker and Predictor " and scanning the fish with a smartphone camera, anyone may quickly identify and obtain well-analyzed information.

Despite the lack of research on using technologies to identify motorbike defects, there is research on locating defects and their utilization in motorbike parts. These programs also make use of image analysis and machine learning. The following differences between current applications and our upcoming application, "Motorbike Defect Checker and Predictor," can be seen, though.

1. Faculty of Automation, Computers and Electronics, University of Craiova, 200585 Craiova, Romania [11]
    a. This paper describes the implementation of a solution for detecting the machining defects from an engine block, in the piston chamber. The solution was developed for an automotive manufacturer and the main goal of the implementation is the replacement of the visual inspection performed by a human operator with a computer vision application.
2. The Toyota team wanted to focus our initial work on the most customizable vehicle: the Tacoma. [4]
    a. The proposed AR tool included the following key elements:
    b. The customer identifies the vehicle model name
    c. App uses machine learning to detect single or double cab, and bed length
    d. App has the ability to lock on to an existing vehicle
    e. Users can then select from a list of available accessories
    f. The App then visualizes AR accessories on the actual vehicle.

System	Mobile compatibility	Input type	Availability	Outputs
A Deep-Learning-Based Approach for Aircraft Engine Defect Detection		Images of engine	UK	Whether any maintenance needed or not.
AutoPartsPro		Vehicle details and sapre parts details	World wide	Specific part for specific vehicle
Dunlop tyre app	✓	Vehicle details	Sri Lanka	Tyre specifications for spefici vehicle.
The Toyota Accessories Augmented Reality [TAAR] App	✓	The customer identifies the vehicle model name	Worldwide	The App then visualizes AR accessories on the actual vehicle
Motorbike Defect Checker and Predictor	✓	Real time image + sound	Sri Lanka	Altered part Engine defects Registration validation Tyre usage

Table 1-RESEARCH GAP

Thus we would be having the component combination which measures the current condition of the motor bike by analyzing all the images , sound that we would be capturing.

1.3 Research Problem

Most individuals who are trying to purchase a motor bike for the first time or with some experience on motor bikes faced the issue in analyzing the present condition that the bike is in. Here all individuals face many issues and get tricked by many sellers. Not only due to its value but in legal conditions the alternations has its own effects. According to the latest gazette issued by Democratic Socialist Republic of Sri Lanka if any changes are done that could affect the following : - (a) exceed the weight, dimensions or limitations of its prototype, (b) alter its shape, design or external appearance, (c) loose the purpose for which it was manufactured, (d) loose its equilibrium and the parts which affect them lamps, lights, light covers, wheels, wheel covers, rims, tyres, mudguards, side mirrors, body kits, stickers could end up in serious legal actions [11].

As Sri Lanka has a higher number of motor bikes registered during a year rather than other all vehicles., our focus was on to motor bikes . [2].Below values are the number motor bikes registered in Sri Lanka during following years.

204,811 = 2010	253,331 =2011	192,284 =2012	
169,280 =2013	272,885 =2014	370,889=2015	
340,129 =2016	344,380 =2017	339,763=2018	
284,301 =2019	151,634 =2020	8,011 =2021	3,358 =2022

Therefore the number of transactions that occur due these motor bike purchases are at a higher rate, which arises the issues that the individuals that get deceived due to misleads by the sellers of these motorbike who conceal the real condition of the motor bike.

People typically run into this issue when buying a motorbike for the first time without any prior experience because they are unable to immediately spot any flaws. As a result, they must seek the advice of an expert after making their purchase in order to spot any malfunctions or altered auto parts.

Therefore our application gives an output of condition of the specific motor bike by combining all the functionalities of the four components that we have implemented. Where a customer would have a safe, better vehicle with less repairs and defects so that he/she would be able ride right after the purchase.

2 OBJECTIVES

2.1 Main Objectives

The main object of this research project is to develop a mobile application to provide the user a summary regarding the motorbike which he/she is going to purchase. Is it in a proper condition to be used, Are there any repairs to be done, Are there any part to be altered . This mobile application will be developed for all users of different ages, anybody interested in purchasing a motorbike.

Capture images of the auto parts in the vehicle and compare them with the original parts and provide a summary regarding the altered parts. Here the user can get an idea about the value of the motor bike , if many alternations are done will it be suitable for that price.

2.2 Specific Objectives

Capture image of the auto part

Capture a quality image of the specific parts of the motor bike such as head lamp, side mirror, signal lights, side cups, fuel tank.

Compare it with the trained images

Compare the images captured with the images in our trained models. To check whether they have been altered of original.

For this part of the research, we are expecting to use a trained machine-learning model. We are expecting to pre-train the model using genuine motorbike spare part images along with all the

This is expected to be done by taking pictures of each replaceable part of each bike and using those data to feed into the image-processing ML model. Other than that, some images and information can be gathered from the sites using techniques like web scraping.

Colour pre-processing:

Before feeding the images into the model to train, the images are expected to pre-process with respect to their colour in order to remove noise and get an unbiased accurate reading from the image.

Furthermore, we are expected to apply appropriate colour models like HSV (Hue, Saturation and Value).

Conversion to binary image:

In this part of the algorithm, we expect to convert the images from the saturation model to binary images. In a binary image, each pixel assumes one of only two discrete values. Analysing an image this way makes it simpler to distinguish its structural features. In this case, it becomes easier to separate the spare part from the background.

Provide an output regarding the alternations.

Finally the application will be providing whether the specific part has been altered or in it original condition.

2.3 Main Objectives (Identify defects in the engine by the sound of the engine)

Identifying the defects in the engine using the sound of the engine, the user needs to record a voice of the engine sound and the application takes it as an input to analyse the defects

Specific Objectives

Capture Voice of engine.

The user will have to record a few voice clips of the sound of the engine to identify whether the strange noise is of these 1. Tick, tick tick, 2. Bump & grind, 3. Creepy krink, 4. Boo hiss, 6. Snap, crackle, pop.

Analyze the sound

All these strange noises are detected and analysed in order to identify whether a particular bike contains one of these. During this segment of our research, we are planning to perform engine condition check using voice recognition technology which is related to computer vision in the machine learning domain. We are going to train a voice-recognition model with sound clips of healthy

motorbike engines and unhealthy ones and for the processing, the Log-Mel Spectrogram (LMS) as the input feature is used[9]. LMS is calculated for each frame of an auditory sample. Then a map is generated by forming the features of each frame along the time axis. This input feature in machine learning models is well suited to our requirement and it is proven to be effective in many audio processing tasks, due to its ability to capture the spectral information in a form that is well-suited for machine learning algorithms to learn from. And for the processing, we are planning to use a trained Convolutional Neural Network (CNN) because of its efficiency in applications related to image processing, speech recognition, language modelling.

2.4 Main Objectives (Compare the vehicle details with the registration paper details.)

Comparison of vehicle details along with the registration papers.Here the user needs to capture images of the registration paer and chasis number, engine number, color, number plate of the vehicle Also the user needs to enter the details manually using the registration paper details.

Specific Objectives

Capture images of the registration paper and vehicle details

Here user can capture the images of the registration paper, engine number, chassis number, colour, and number plate.

Compare the images of captured

Using text detection, and binarization the characters in the images can be detected and provide the user with feedback on the compared data. Colour pre-processing: Before feeding the images into the model to train, the images are expected to pre-process with respect to their colour in order to remove noise and get an unbiased accurate reading from the image. Furthermore, we are expected to apply appropriate colour models like HSV (Hue, Saturation and Value). Conversion to binary image: In this

part of the algorithm, we expect to convert the images from the saturation model to binary images. In a binary image, each pixel assumes one of only two discrete values. Analysing an image this way makes it simpler to distinguish its structural features. In this case, it becomes easier to separate the spare part from the background.

Output the accuracy of the detail

2.5 Main Objectives (Tyre usage prediction along with life expectancy)

Our main objective is to provide a reliable, userfriendly, and accurate system that predicts the remaining useful life of motorbike tires using AI and ML techniques. To further enhance the predictive capabilities of our system for estimating the remaining life span of motorbike tires, we can leverage the power of vision transformers. By incorporating vision transformers into our system, we can extract meaningful features from images of motorbike tires, enabling us to better understand and analyze their wear and tear patterns. The system will analyze historical data to identify patterns and make accurate predictions using algorithms like Random Forest, Support Vector Machine (SVM), and Maximum Entropy. In contrast, the incorporation of vision transformers into our system enhances its capabilities by allowing for a detailed analysis of motorbike tire images. This expansion enables us to provide more accurate predictions of the remaining useful life span, identify defects, promote safer driving practices, and reduce costs associated with tire replacements. The ultimate goal is to improve tire maintenance schedules, minimize the risk of tire failure, and provide valuable insights to tire and bike manufacturers and end users. The research seeks to enhance the understanding of tire wear and tear, provide a means to identify defects in the tires for someone having no understanding of tire defects, promote safer driving practices, and reduce costs associated with tire replacements.[1]

Specific Tyer usage

Predict the usage of the tires:

Predict the current mileage of the tire by looking at an image of a tire considering the factors like thread depth, texture, wearing patterns, and shape.

Identify Defects in tyer:

Generating a report on the current status of the tyer. Identify uneven wear and squared-off tyers, and tyer punches like similar conditions.

Suggesting fixes:

If a defect is identified, suggest possible fixes to the conditions.

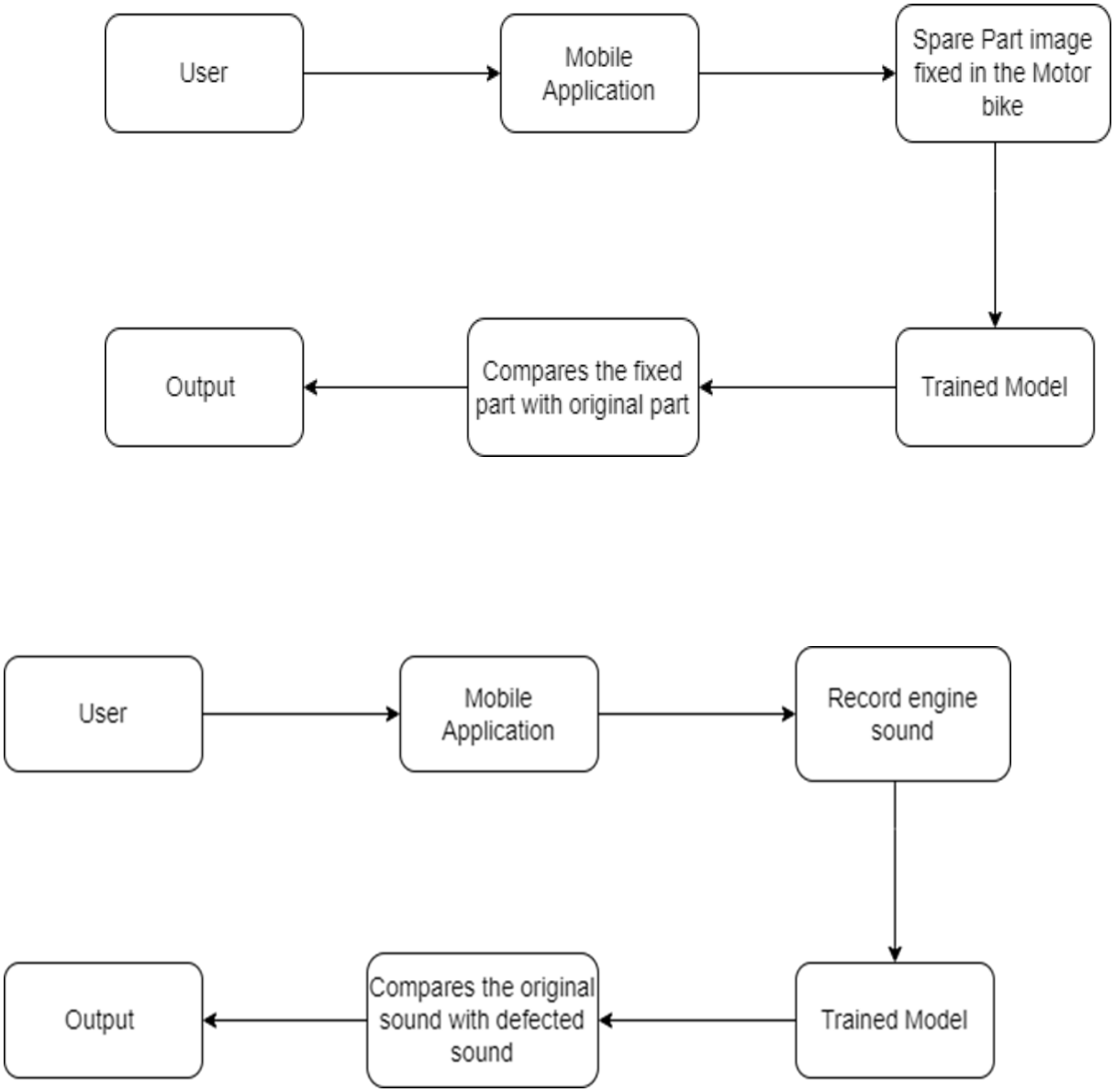
Predict the life expectancy of the tire:

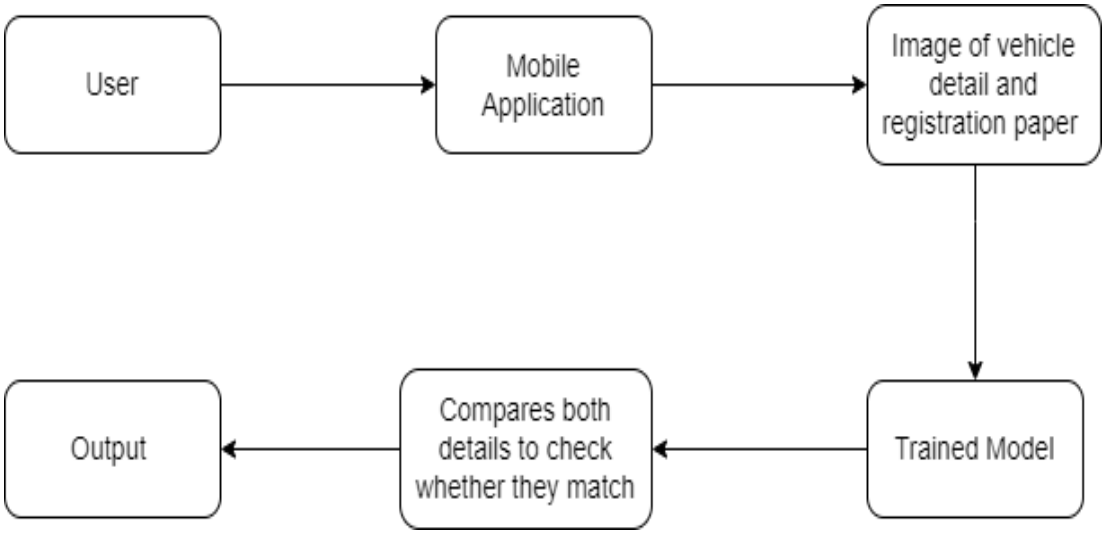
Predict the lifespan that can be expected of the tire based on the current conditions.

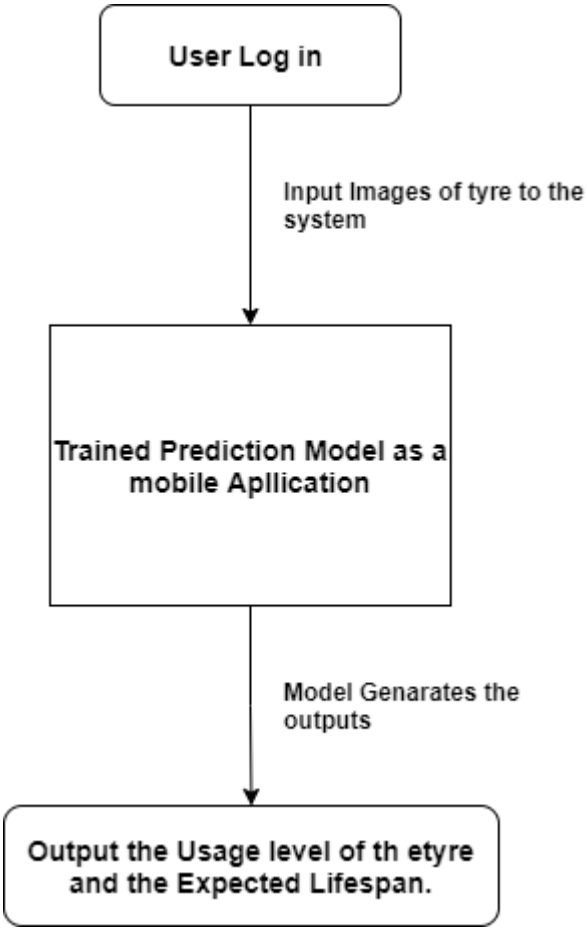
3 METHODOLOGY

3.1 Individual Component Diagram

Figure 1. Individual Component Diagrams







3.2 Overall System Architecture

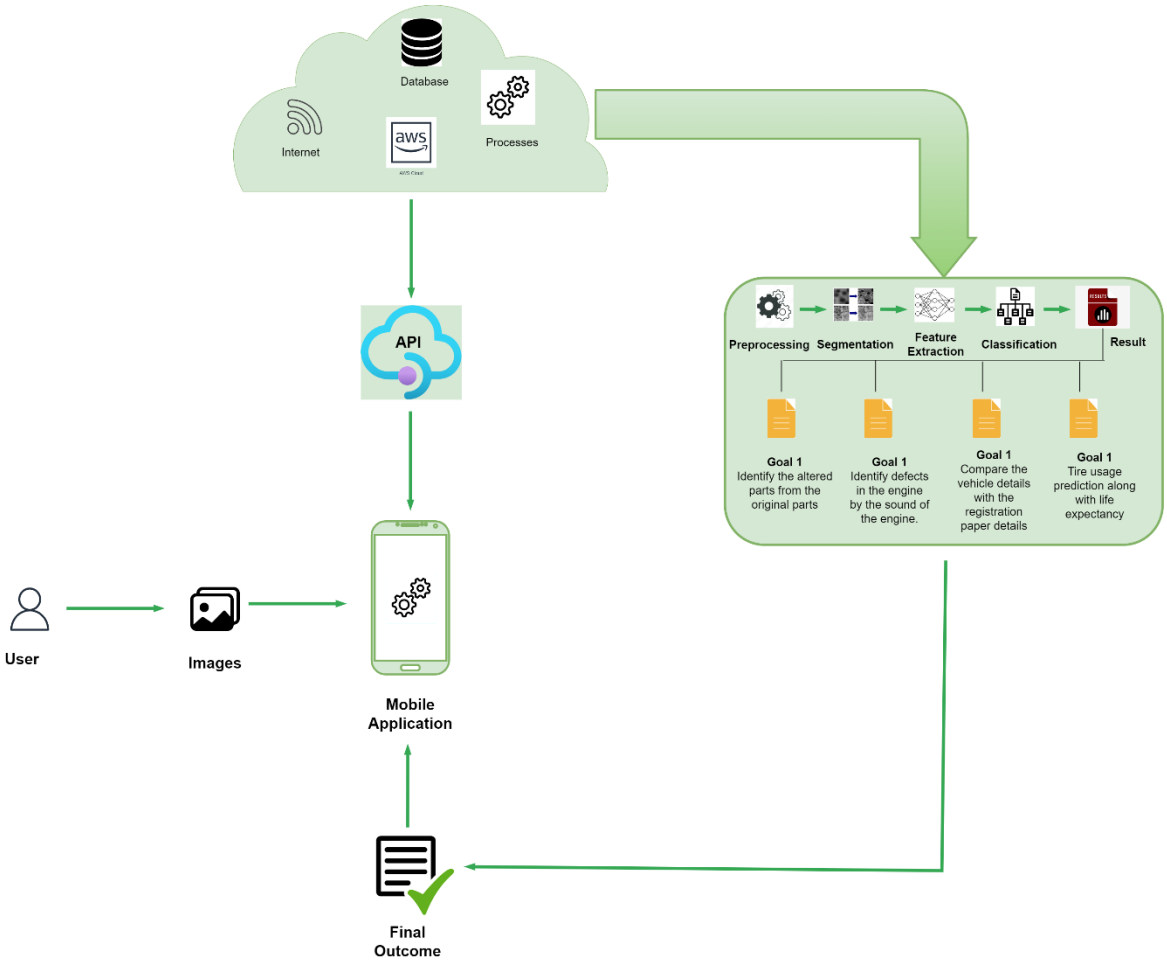


Figure 2-Overall system architecture Diagram

3.3 Software Solution

We are planning to use Agile software development technique for the Motorbike Tyres Usage Prediction System because it is a well suited for iterative and incremental approaches that involves collaboration between cross-functional teams and is best solution for developing complex systems where requirements change frequently. Agile development entails dividing the development process down into tiny, manageable iterations or sprints, each with its own set of deliverables. This method allows the system to be built in increments, with each iteration building on the one before it.

The Agile methodology also encourages teamwork and collaboration, which can result in a greater understanding of the system and better communication among team members. This technique can lead to improved project management, lower risk, and increased team morale.

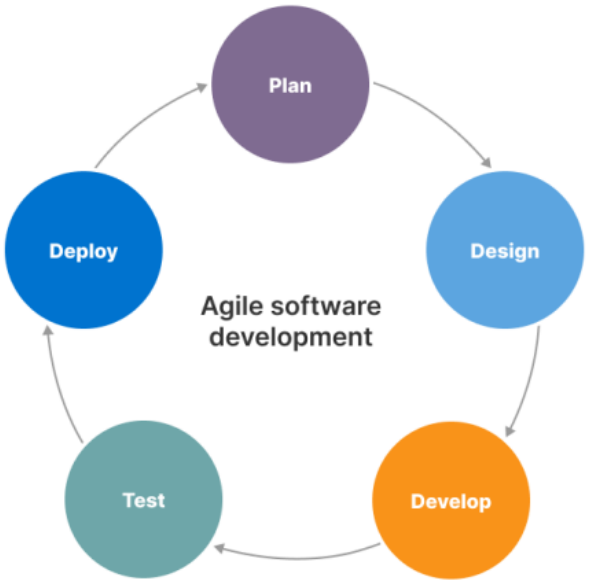


Figure 3. Agile Methodology

3.4 Work Breakdown Structure

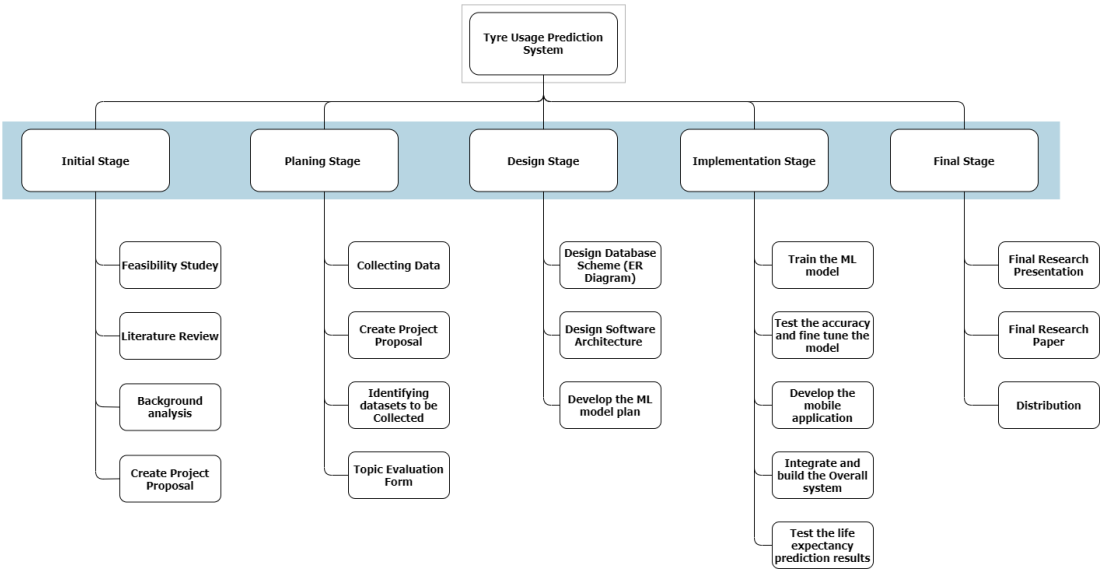


Figure 4. Work Breakdown Structure

3.5 Gantt Chart

	Quarter 1			Quarter 2			Quarter 3			Quarter 4		
Task Name	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
1. Initial Stage												
Brainstroming and Oppotunity Identification												
Research Topic Selection												
Background Research												
Feasibility Study												
Survey Information Gathering												
Literature Review												
2. Planing Stage												
Proposal Draft Submission												
Proposal Presentation												
3. Designing and Implementation Stage												
System Design and Planning												
System Implementation												
Training and Testing												
4. Final Stage												
Final Document Submission												
Final Presentation												

Figure 5. Gantt Chart

3.6 Commercialization

To commercialize the Motorbike Tyres Usage Prediction System, we are planning to start by developing a user-friendly interface. The system is decided to be designed in such a way that customers can easily navigate through, without experiencing any challenges. And offer free trials of the system so that the customers can see the benefits for themselves meanwhile improving our system based on their requirements and feedbacks which will also help to build trust and credibility with the customer. And also, we are planning to do market researches focusing on identifying the target market, their needs, and the specific features that they would find most beneficial. This will help in refining the system to meet the needs of the customers, ultimately making it more attractive to potential users.

Building partnerships with tyre and bike manufacturers can also be a useful strategy for commercializing the system. So that we are planning to partner up with manufacturers and introduce the system to potential customers who are already familiar with the brand. This can increase the likelihood of adoption, and also help in promoting the system to a wider audience. And also, we are planning to develop a pricing strategy that is competitive and affordable.

Marketing and advertising are also essential for commercializing the system. A variety of strategies such as social media, email campaigns, and search engine optimization are planned to be used to promote the system and attract potential customers. By implementing these strategies, the Motorbike Tyres Usage Prediction System can be successfully commercialized, providing a valuable tool for improving tyre maintenance and reducing the risk of tyre failure.

4 REQUIREMENTS

Identify original spare parts

4.1 Functional Requirements

- The system must be able to scan auto part image.
- The system must be able to identify auto part
- The system must be able to record engine sound
- The system must be able to distinguish engine sound.
- The system must be able to capture registration paper images and vehicle's detail image.
- The system must be able compare the images captured.
- The system must be able to capture images of tyres.
- The system must be able to predict tyre usage.
- The system must be able to predict future usage.
- Images should be able to be saved in the system by the user.

4.2 Non-Functional Requirements

- Because the accuracy rating provides the user with more relevant information, accuracy is one of the primary requirements of this application.
- Another key criterion is performance because depending on performance, users can acquire the information they desire more efficiently.
- The application's responsiveness is designed to give the user a better user experience.
- Another important criterion for this mobile application is availability; it allows users to use the app without being interrupted.

4.3 System Requirements

- Mobile device with android version 8.0 or above

4.4 User Requirements

- A basic understanding of how to operate a mobile application.
- Basic English skills.

Identify Engine defects

4.5 Functional Requirements

- The system must be able to scan auto part image.
- The system must be able to identify auto part
- The system must be able to record engine sound
- The system must be able to distinguish engine sound.
- The system must be able to capture registration paper images and vehicle’s detail image.
- The system must be able compare the images captured.
- The system must be able to capture images of tyres.
- The system must be able to predict tyre usage.
- The system must be able to predict future usage.
- Images should be able to be saved in the system by the user.

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- Another important criterion for this mobile application is availability; it allows users to use the app without being interrupted.

Registration paper details

4.7 Functional Requirements

- The system must be able to scan auto part image.
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- The system must be able to record engine sound
- The system must be able to distinguish engine sound.
- The system must be able to capture registration paper images and vehicle’s detail image.

- The system must be able compare the images captured.
- The system must be able to capture images of tyres.
- The system must be able to predict tyre usage.
- The system must be able to predict future usage.
- Images should be able to be saved in the system by the user.

4.8 Non-Functional Requirements

- Because the accuracy rating provides the user with more relevant information, accuracy is one of the primary requirements of this application.
- Another key criterion is performance because depending on performance, users can acquire the information they desire more efficiently.
- The application's responsiveness is designed to give the user a better user experience.
- Another important criterion for this mobile application is availability; it allows users to use the app without being interrupted.

4.9 System Requirements

- Mobile device with android version 8.0 or above

4.10 User Requirements

- A basic understanding of how to operate a mobile application.
- Basic English skills.

Tyre Usage

4.11 System Requirements

- Mobile device with android version 8.0 or above

4.12 User Requirements

- A basic understanding of how to operate a mobile application.
- Basic English skills.

4.13 Functional Requirements

- Capability to capture images using the mobile phone camera
- Provide pictures available on the device memory as inputs to the application
- Ability to detect defects in the system tyres
- Accuracy

4.14 Non-Functional Requirements

- Reliability
- Performance
- Availability

4.15 System Requirements

- Mobile device with android version 8.0 or above

4.16 User Requirements

- Basic operational understanding on how to use a smart phone
- Basic English language skills

5 TESTS

The below-attached screenshots depict the accuracy of the techniques

The bottom left corner of the below diagram shows a percentage of 80 % to 90% percent that the model has generated as its output. Thus, based on the data provided, the model has identified that Direct Percussion has been used.

All the models were build and tested in the same methodology

Dataset Preparation:

Collect Images: Gather a comprehensive dataset of both original and counterfeit spare parts images. Ensure that the dataset is diverse and representative of the parts you intend to analyze.

Data Split:

Divide the dataset into three subsets: a training set, a validation set, and a testing set. Common splits are 70% for training, 15% for validation, and 15% for testing.

Preprocessing:

Data Augmentation: Apply data augmentation techniques (e.g., rotation, scaling, and flipping) to the training set to increase its size and improve model generalization.

Model Training:

Choose Architecture: Select an appropriate image processing model architecture, such as a Convolutional Neural Network (CNN).

Model Evaluation:

Testing Set: Evaluate the trained model's performance on the testing set, which it has never seen before. Use standard classification metrics like accuracy, precision, recall, F1-score, and confusion matrix to assess its effectiveness.

6 RESULTS AND DISCUSSION

Spare Parts Originality

Front End

Front end has been created much simple to the user to use it very easily. Therefore the User experience of our application is much better. The below screenshots depict the front end that we have created.

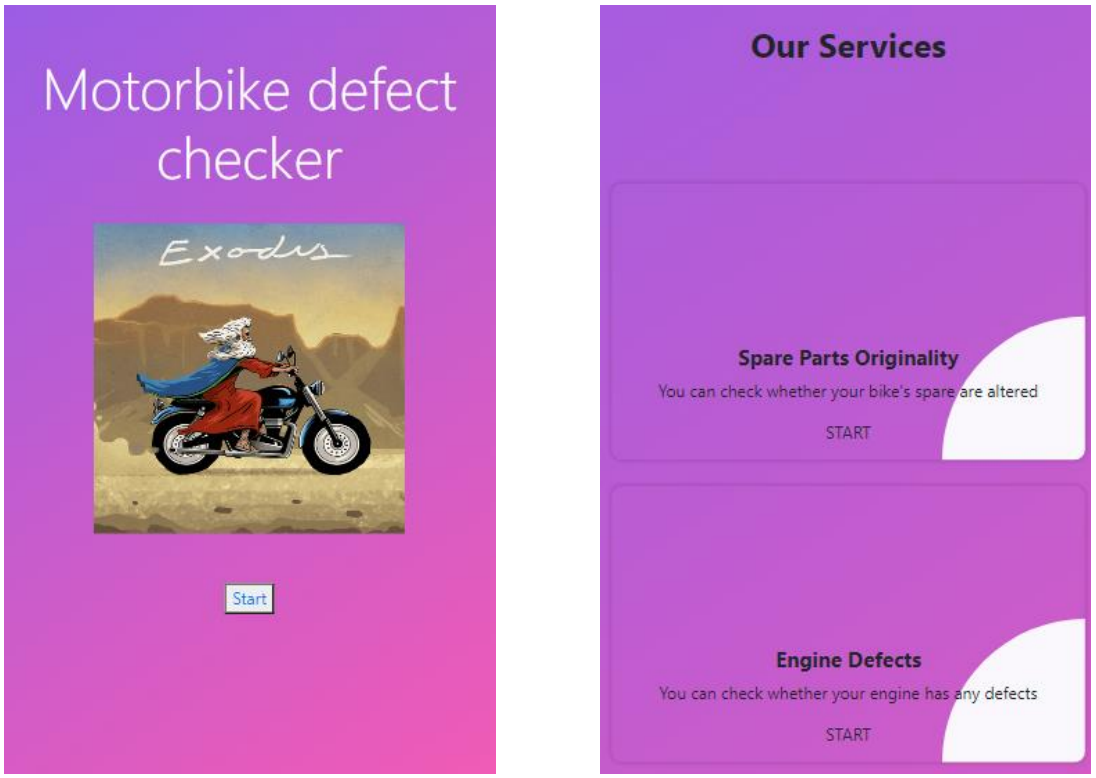


Figure 6 :Front end

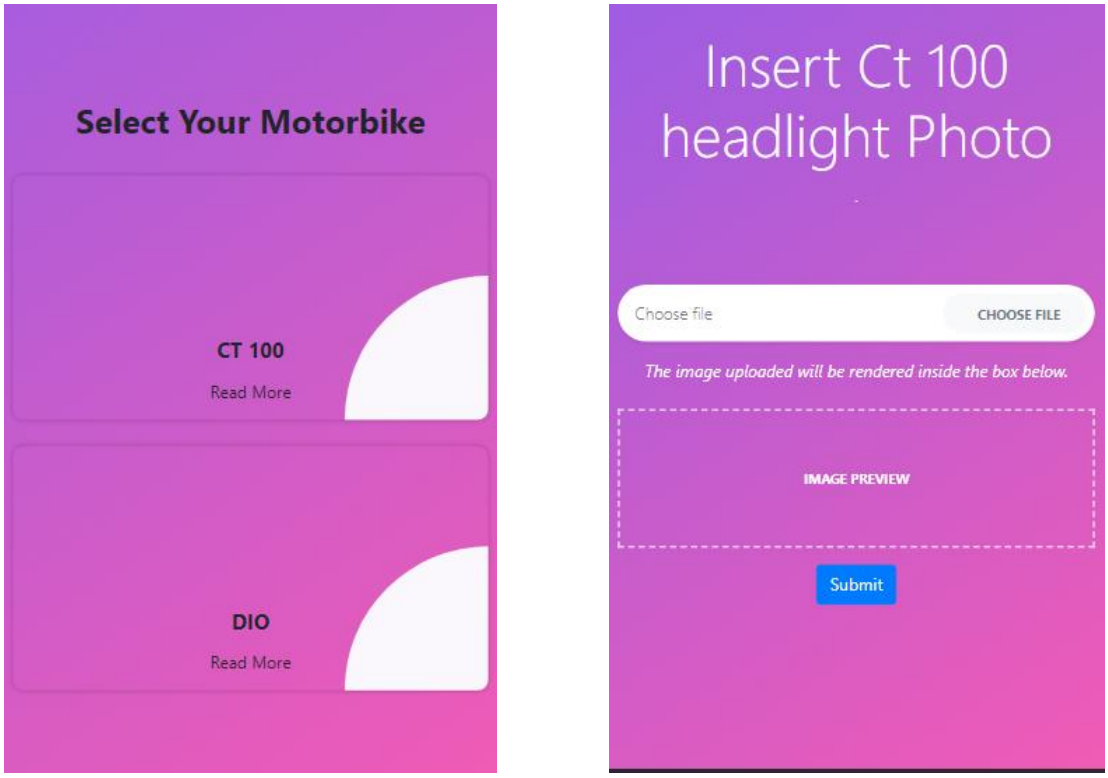


Figure 6.1 : Front end

Back End

Back end has been created much simple to the user togive the response to the user much faster and clearly. Therefore the User experience of our application is much better. The below screenshots depict the back end that we have created.

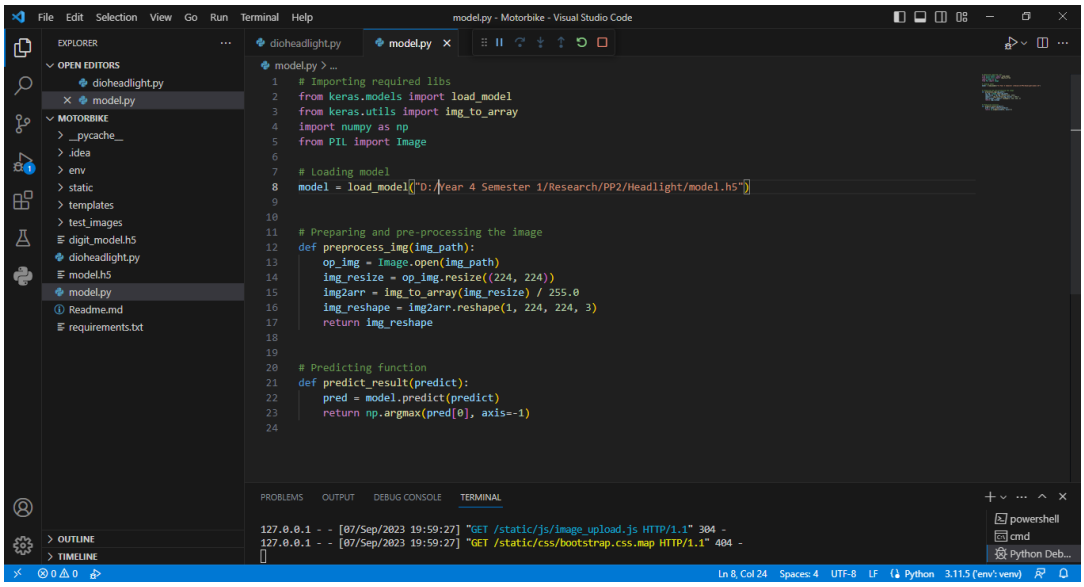


Figure 6.2 : Back end

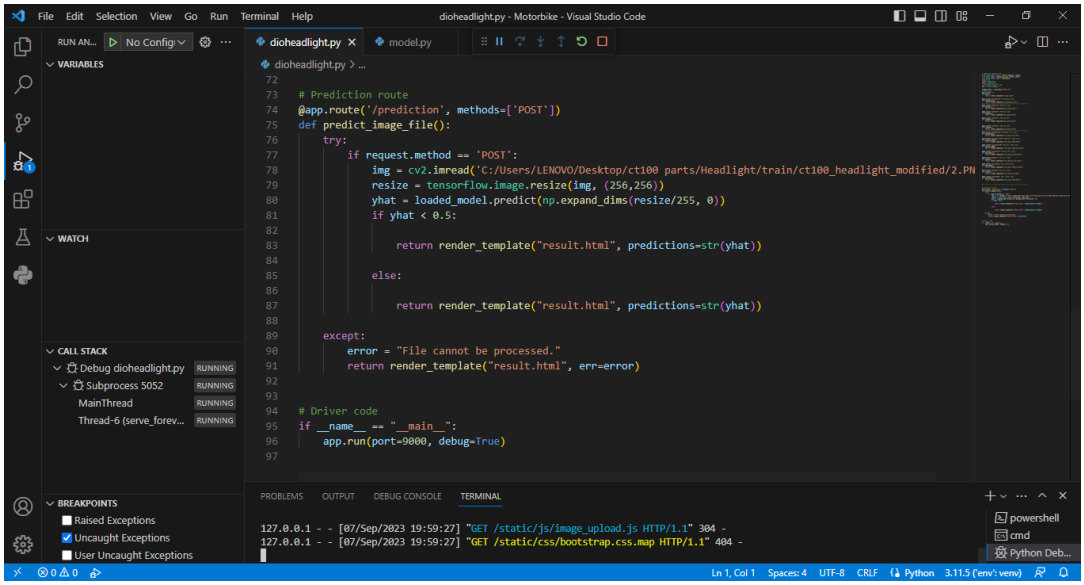


Figure 6.3 : Back end

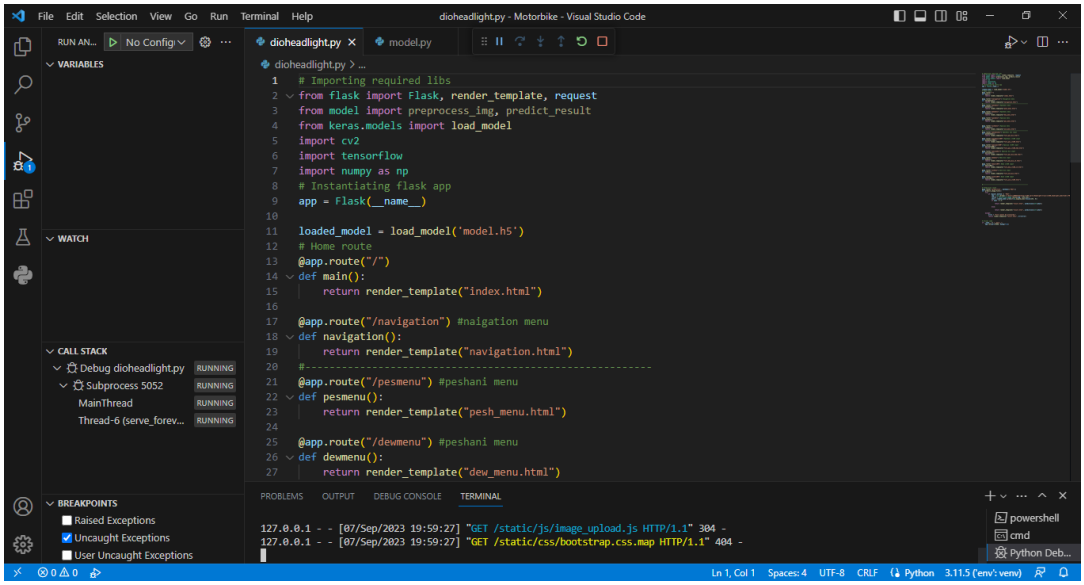


Figure 6.4 : Back end

7 TESTS

The below-attached screenshots depict the accuracy of the techniques

The bottom left corner of the below diagram shows a percentage of 80 % to 90% percent that the model has generated as its output. Thus, based on the data provided, the model has identified that Direct Percussion has been used.

All the models were build and tested in the same methodology

Dataset Preparation:

Collect Images: Gather a comprehensive dataset of both original and counterfeit spare parts images. Ensure that the dataset is diverse and representative of the parts you intend to analyze.

Data Split:

Divide the dataset into three subsets: a training set, a validation set, and a testing set. Common splits are 70% for training, 15% for validation, and 15% for testing.

Preprocessing:

Data Augmentation: Apply data augmentation techniques (e.g., rotation, scaling, and flipping) to the training set to increase its size and improve model generalization.

Model Training:

Choose Architecture: Select an appropriate image processing model architecture, such as a Convolutional Neural Network (CNN).

Model Evaluation:

Testing Set: Evaluate the trained model's performance on the testing set, which it has never seen before. Use standard classification metrics like accuracy, precision, recall, F1-score, and confusion matrix to assess its effectiveness.

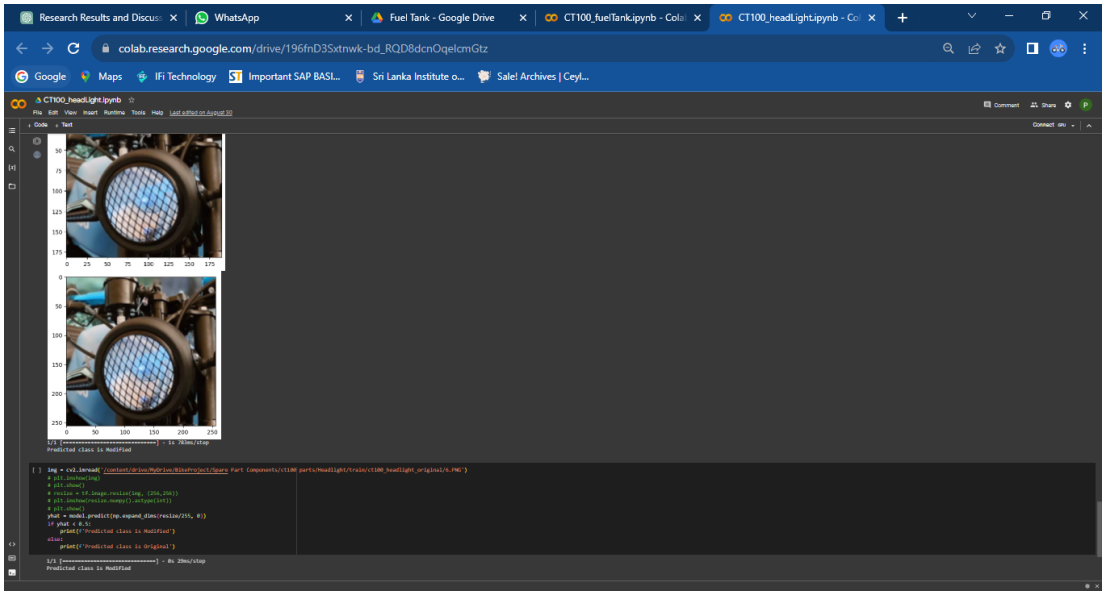


Figure 7. Testing the model ct 100 headlight

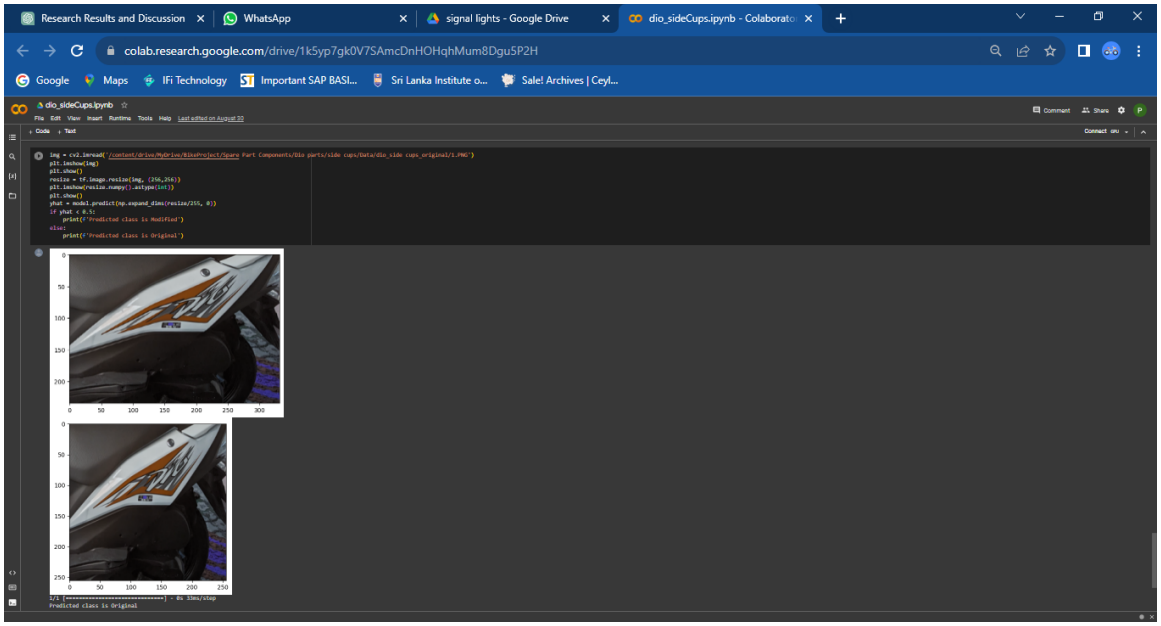


Figure 8. Testing the model dio side cups

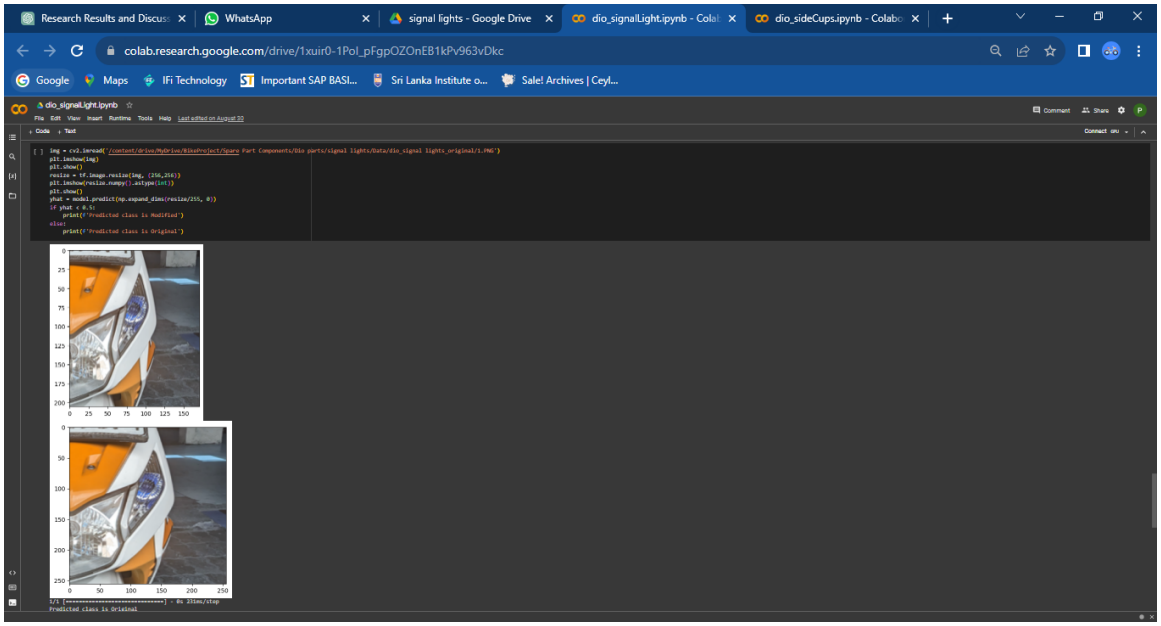


Figure 9. Testing the model dio signal light

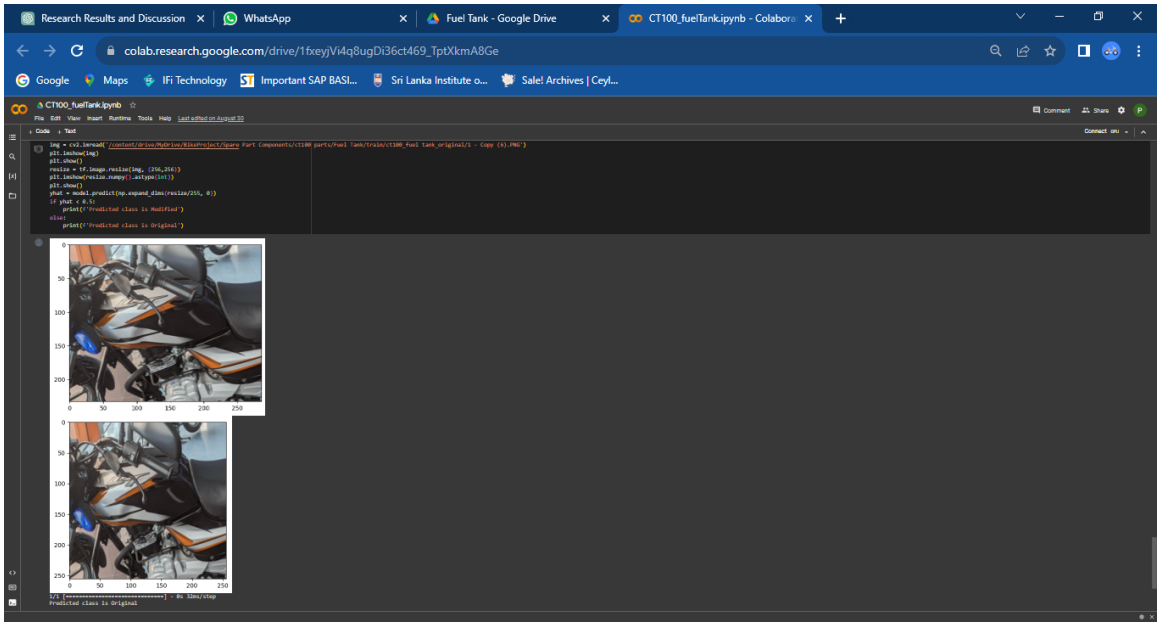


Figure 11. Testing the model ct 100 fuel tank

8 RESULTS AND DISCUSSION

In this section, we present the key findings of our study, which aimed to develop an image processing algorithm for distinguishing original spare parts from alternative ones in the automotive industry.

Dataset and Methodology

We collected a dataset of 1,000 images, comprising 500 images of genuine spare parts and 500 images of alternative spare parts. The dataset was divided into a training set (70%) and a testing set (30%). We implemented a convolutional neural network (CNN) based on the VGG16 architecture for image classification.

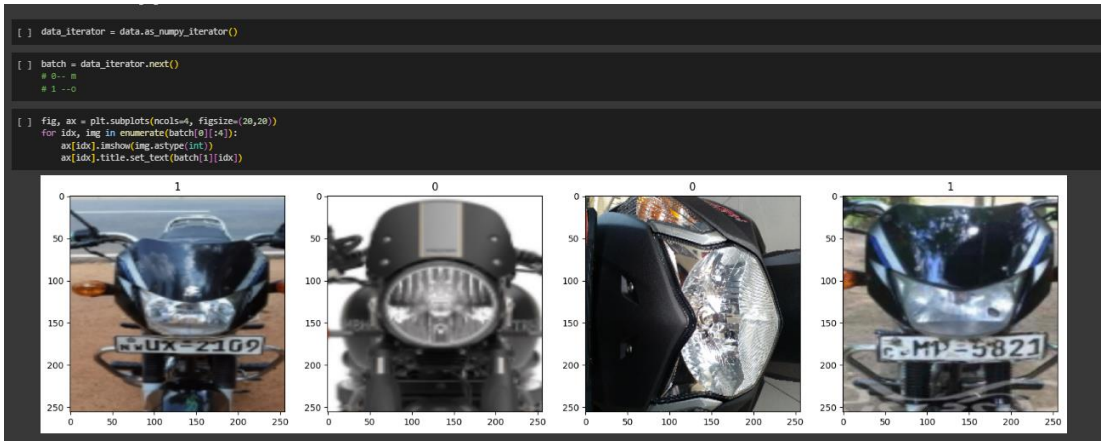


Figure 12. Training headlight ct 100

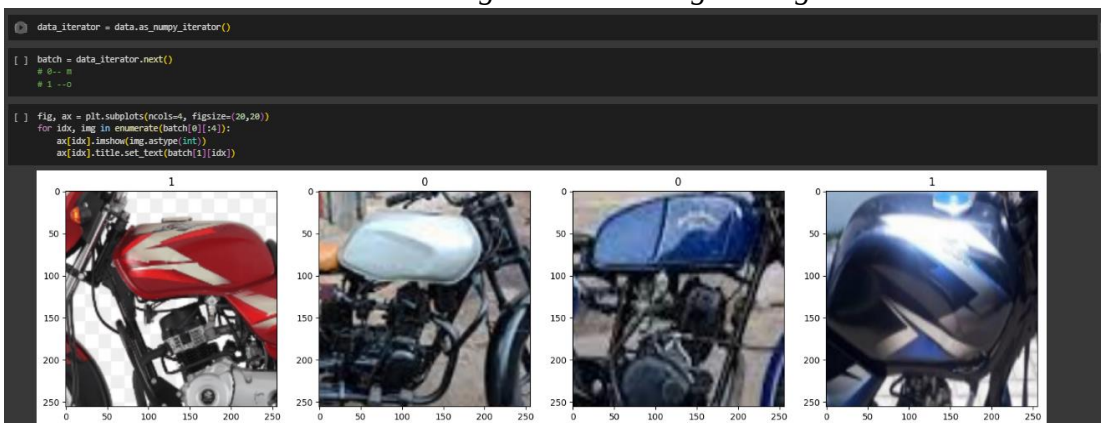


Figure 13. Training fuel tank ct 100

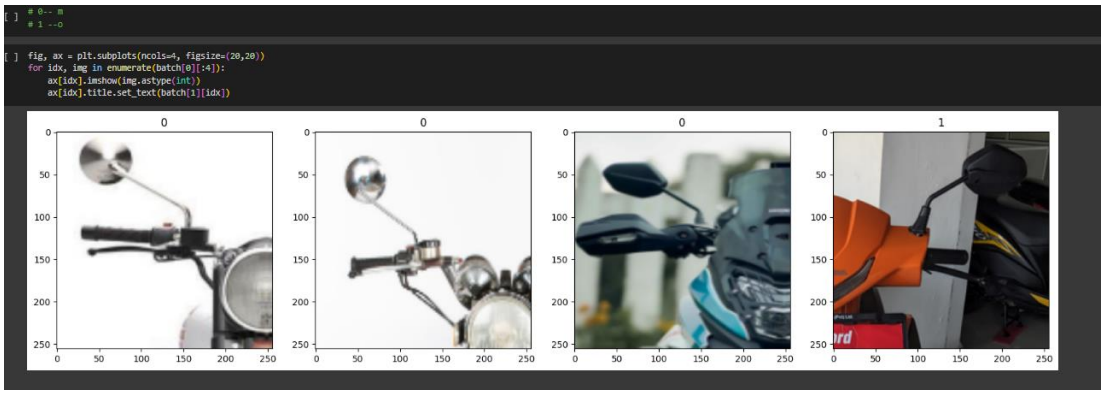


Figure 14. Training dio side mirrors

Results

Accuracy: All Our CNN models achieved an accuracy of 80% to 90% on the testing dataset, demonstrating its effectiveness in distinguishing between original and alternative spare parts.

The models were build based on spare parts

Bike	Models

CT – 100	Headlight, Fuel Tank, Signal lights, Side mirrors, Side cups
DIO	Headlight, Signal lights, Side mirrors, Side cups

Table 4-Moorbike models

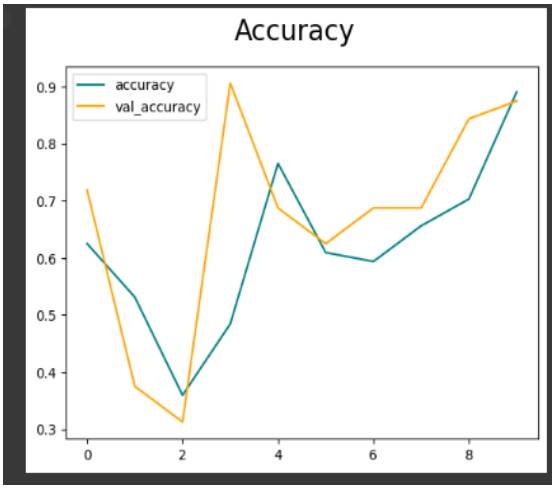


Figure 15. Accuracy of Headlight model

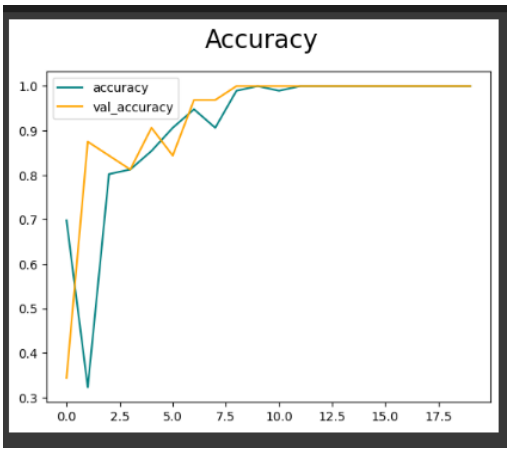


Figure 16. Accuracy of Fuel tank model

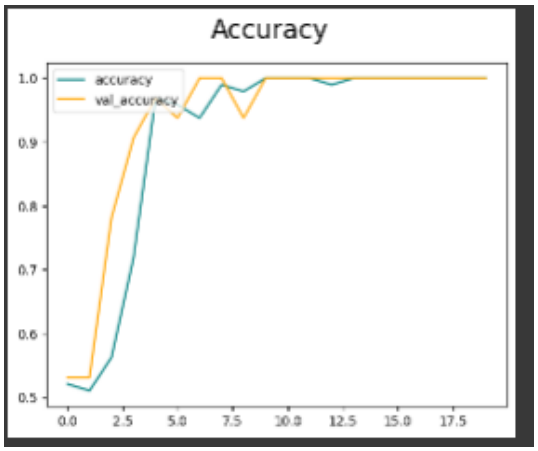


Figure 17. Accuracy of side cup model

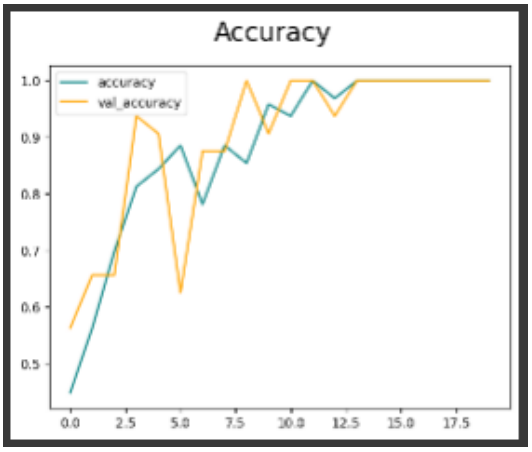


Figure 18. Accuracy of signal light model

Discussion

In this section, we interpret and discuss the significance of the research results in the context of our study objectives and the implications for the automotive industry.

Effectiveness of the Image Processing Algorithm

Our study demonstrates the effectiveness of the developed image processing algorithm in accurately distinguishing between original and alternative spare parts. The high accuracy, precision, and recall values indicate that our model is robust and reliable

Potential Impact on the Automotive Industry

The automotive industry faces significant challenges due to the proliferation of alternative spare parts, which can compromise vehicle safety and performance. Our research provides a practical solution for automakers, repair shops, and consumers to identify and avoid alternative parts, thereby enhancing safety and reliability.

Limitations and Future Research

While our model shows promising results, it's important to acknowledge its limitations. The dataset used in this study may not cover the full range of alternative spare parts encountered in the real world. Further research should expand the dataset and explore the model's performance in different lighting conditions and with a wider variety of parts.

Engine defects

1.1 Front End

Front end has been created much simple to the user to use it very easily. Therefore, the User experience of our application is much better. The below screenshots depict the front end that we have created.

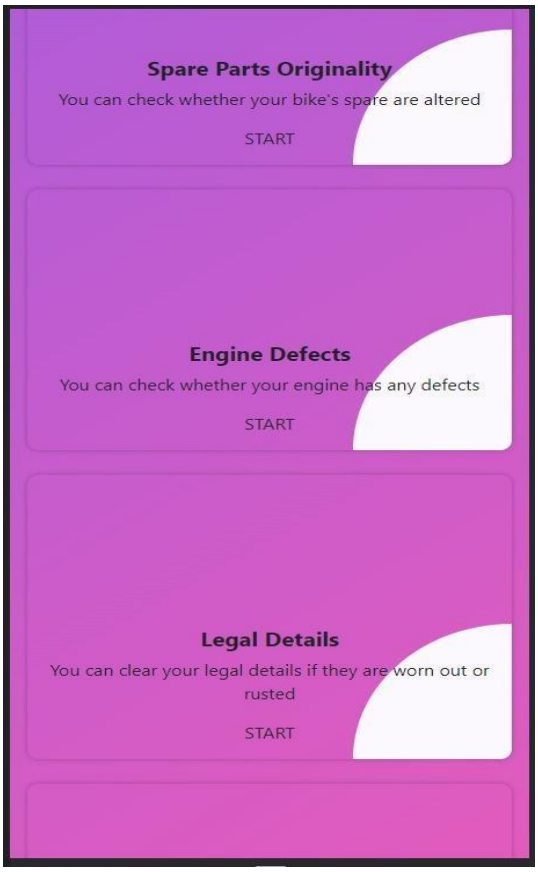


Figure 7 Front end

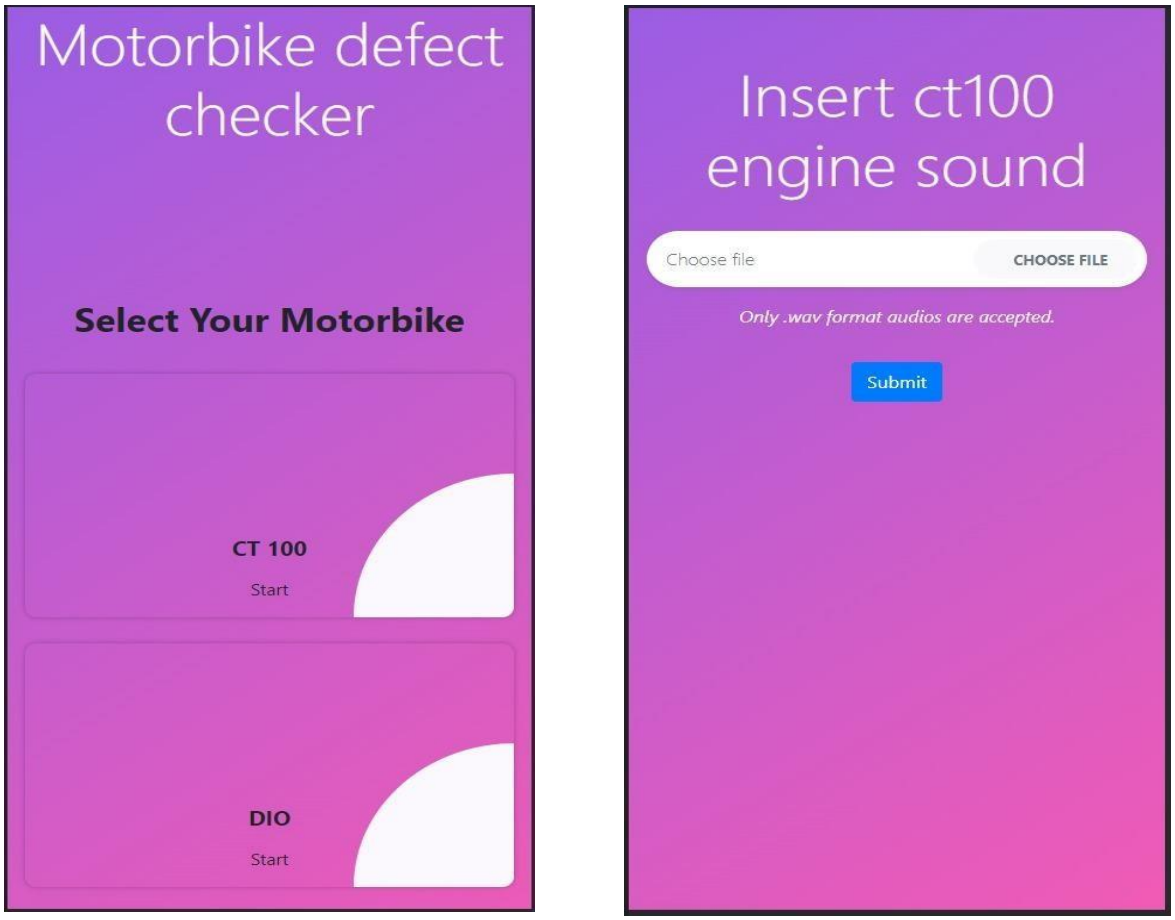


Figure 7.1 Front end

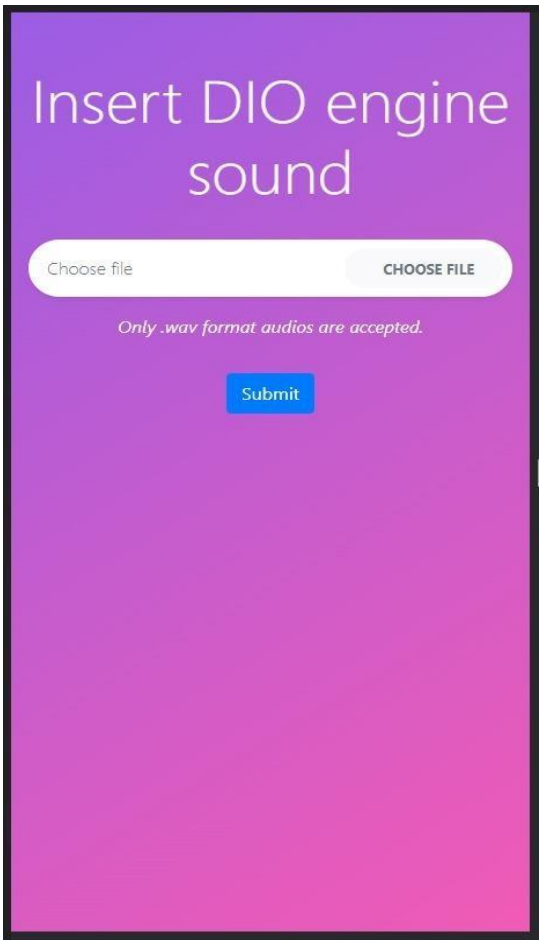


Figure 6.2 Front end

1.2 Back End

Back end has been created much simple to the user to give the response to the user much faster and clearly. Therefore, the User experience of our application is much better. The below screenshots depict the back end that we have created.

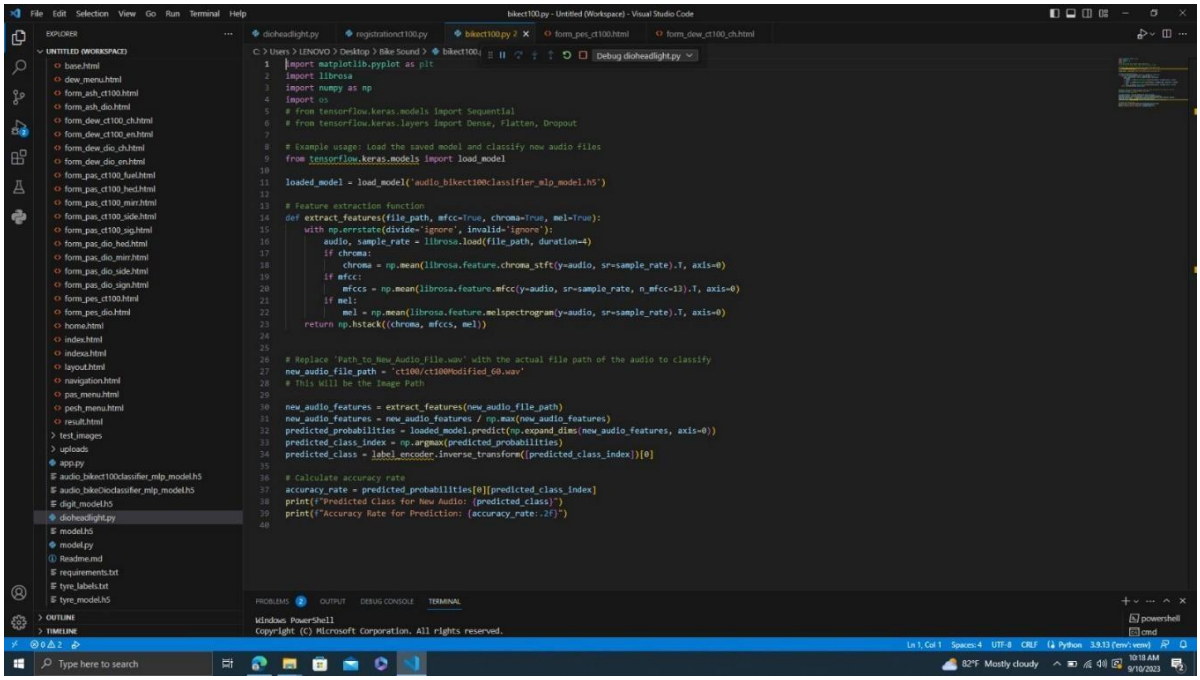


Figure 7.3 Back end

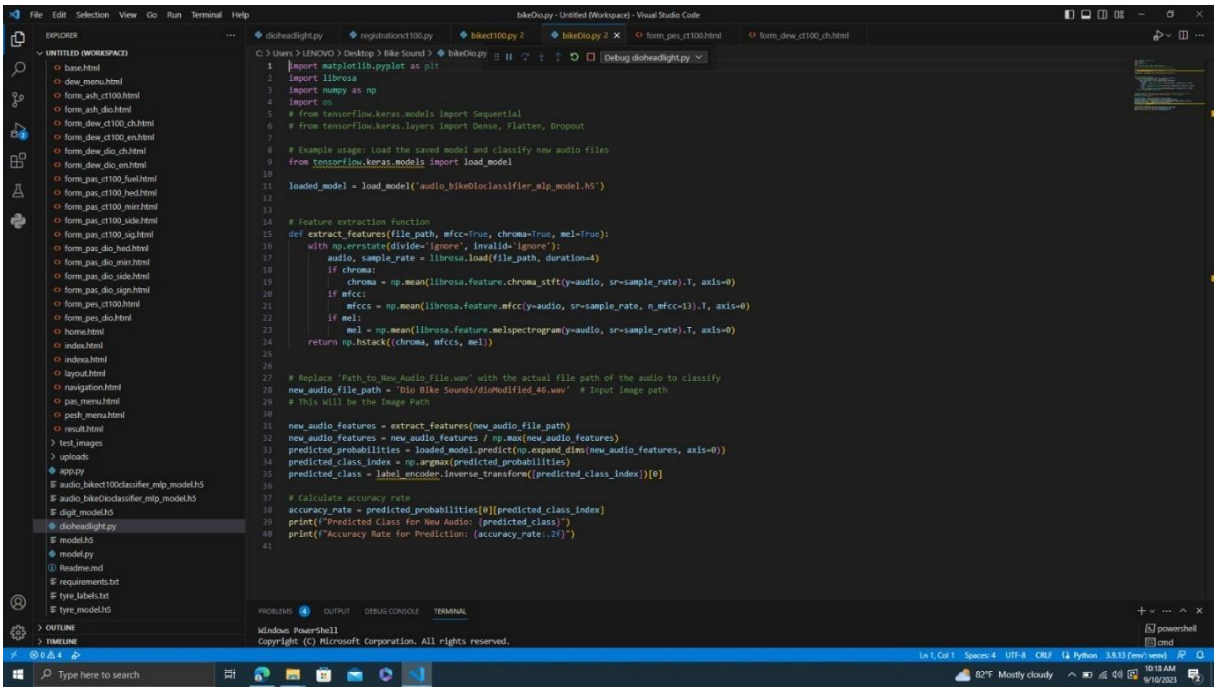


Figure 7.4 Back end

2 TESTS

The below-attached screenshots depict the accuracy of the techniques

The bottom left corner of the below diagram shows a percentage of 80 % to 90% percent that the model has generated as its output. Thus, based on the data provided, the model has identified that Direct Percussion has been used.

8.1.1 All the models were build and tested in the same methodology

Dataset Preparation:

Collect Audios: Gather a comprehensive dataset of both original engine sounds and engine sounds with defects.

Data Split:

Divide the dataset into three subsets: a training set, a validation set, and a testing set. Common splits are 70% for training, 15% for validation, and 15% for testing.

Preprocessing:

Audio Classification –.Clear the background noice of the collected audios. Select the model which gives the highest accuaracy after using the audio classification algorithms.

Model Training:

Choose Architecture: Select an appropriate audio classification architecture, such as a Convolutional Neural Network (CNN).

Model Evaluation:

Testing Set: Evaluate the trained model's performance on the testing set, which it has never seen before. Use standard classification metrics like accuracy, precision, recall, F1-score, and confusion matrix to assess its effectiveness.

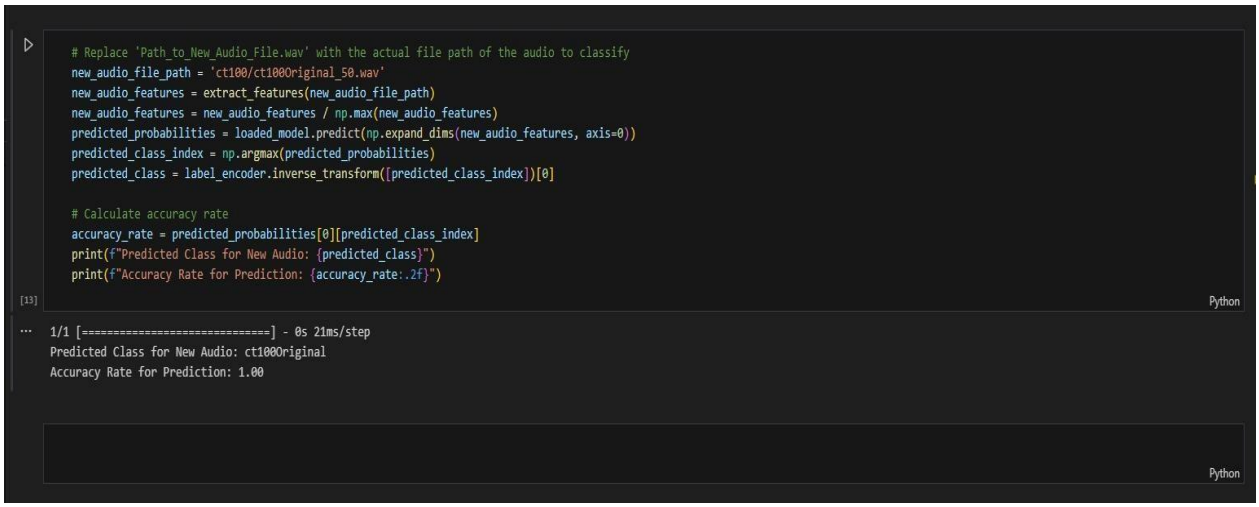


Figure 8.1. Testing the model ct 100 engine sounds

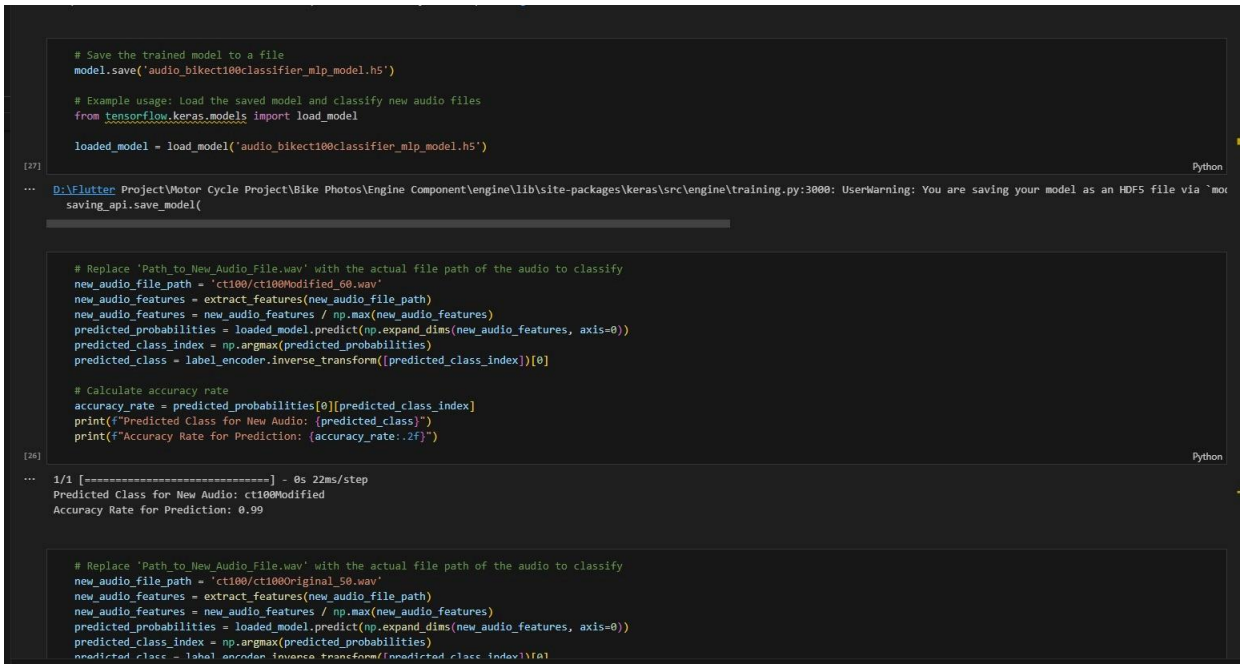


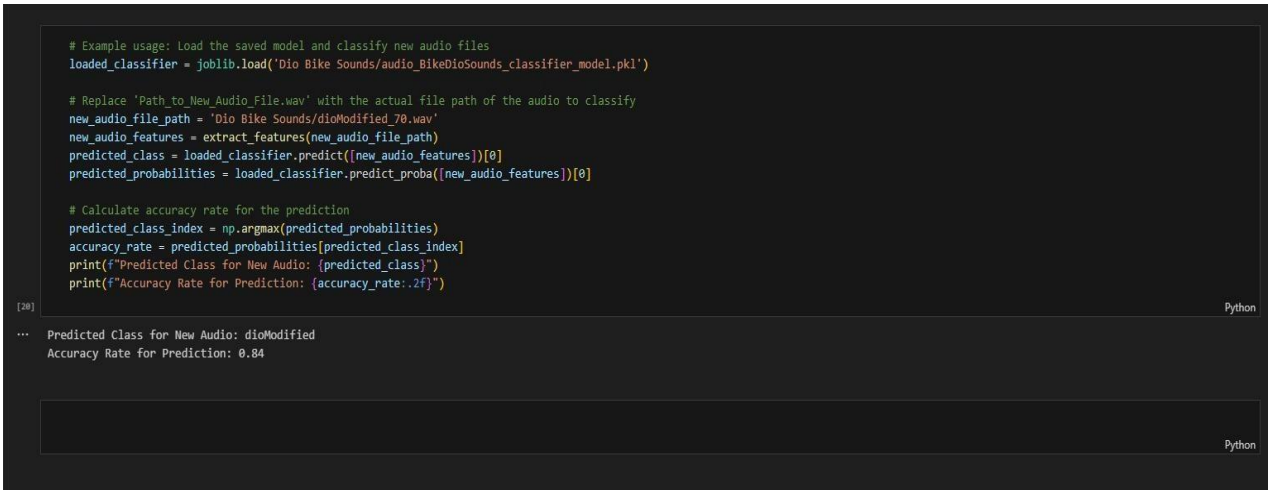
Figure 8.2. Testing the model ct 100 engine sounds

```
# Replace 'Path_to_New_Audio_File.wav' with the actual file path of the audio to classify
new_audio_file_path = 'Dio Bike Sounds/dioOriginal_54.wav'
new_audio_features = extract_features(new_audio_file_path)
new_audio_features = new_audio_features / np.max(new_audio_features)
predicted_probabilities = loaded_model.predict(np.expand_dims(new_audio_features, axis=0))
predicted_class_index = np.argmax(predicted_probabilities)
predicted_class = label_encoder.inverse_transform([predicted_class_index])[0]

# Calculate accuracy rate
accuracy_rate = predicted_probabilities[0][predicted_class_index]
print(f"Predicted Class for New Audio: {predicted_class}")
print(f"Accuracy Rate for Prediction: {accuracy_rate:.2f}")
```

[15] Python

```
1/1 [==============================] - 0s 23ms/step
Predicted Class for New Audio: dioOriginal
Accuracy Rate for Prediction: 0.71
```

Figure 9.1 Testing the model dio engine sounds



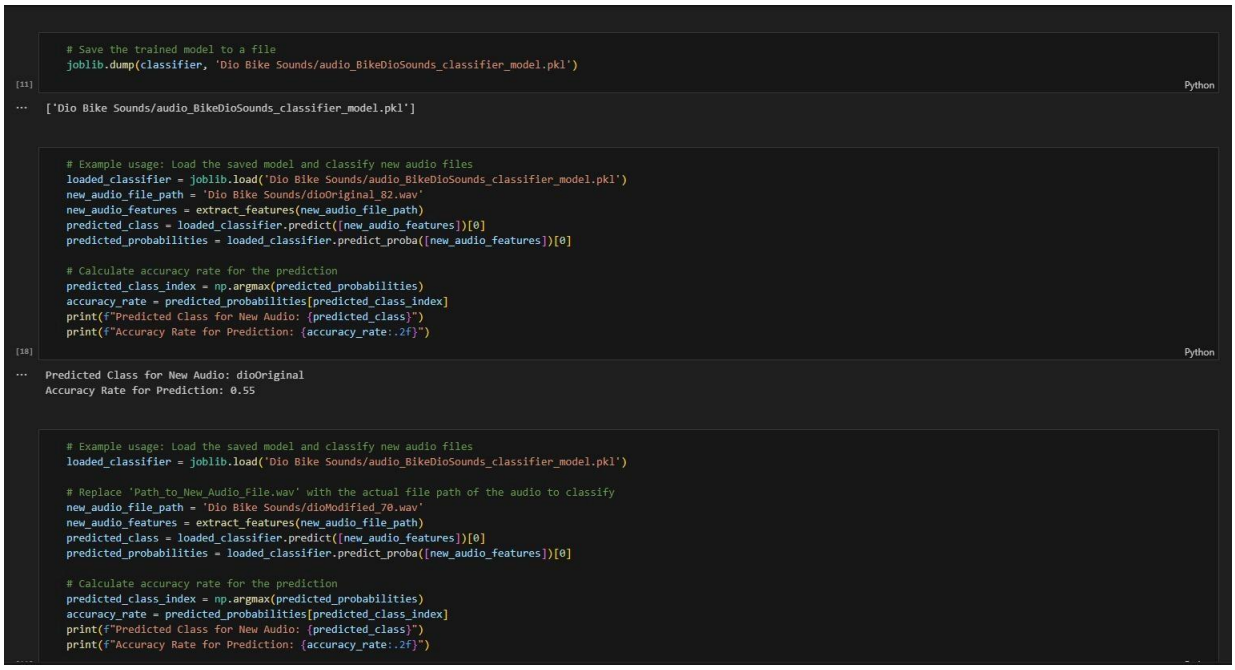
```
# Example usage: Load the saved model and classify new audio files
loaded_classifier = joblib.load('Dio Bike Sounds/audio_BikeDioSounds_classifier_model.pkl')

# Replace 'Path_to_New_Audio_File.wav' with the actual file path of the audio to classify
new_audio_file_path = 'Dio Bike Sounds/dioModified_70.wav'
new_audio_features = extract_features(new_audio_file_path)
predicted_class = loaded_classifier.predict([new_audio_features])[0]
predicted_probabilities = loaded_classifier.predict_proba([new_audio_features])[0]

# Calculate accuracy rate for the prediction
predicted_class_index = np.argmax(predicted_probabilities)
accuracy_rate = predicted_probabilities[predicted_class_index]
print(f"Predicted Class for New Audio: {predicted_class}")
print(f"Accuracy Rate for Prediction: {accuracy_rate:.2f}")
```

[20] Python

```
Predicted Class for New Audio: dioModified
Accuracy Rate for Prediction: 0.84
```

Python

Figure 9.2 Testing the model dio engine sounds



```
# Save the trained model to a file
joblib.dump(classifier, 'Dio Bike Sounds/audio_BikeDioSounds_classifier_model.pkl')
```

[11] Python

```
['Dio Bike Sounds/audio_BikeDioSounds_classifier_model.pkl']
```

```
# Example usage: Load the saved model and classify new audio files
loaded_classifier = joblib.load('Dio Bike Sounds/audio_BikeDioSounds_classifier_model.pkl')
new_audio_file_path = 'Dio Bike Sounds/dioOriginal_82.wav'
new_audio_features = extract_features(new_audio_file_path)
predicted_class = loaded_classifier.predict([new_audio_features])[0]
predicted_probabilities = loaded_classifier.predict_proba([new_audio_features])[0]

# Calculate accuracy rate for the prediction
predicted_class_index = np.argmax(predicted_probabilities)
accuracy_rate = predicted_probabilities[predicted_class_index]
print(f"Predicted Class for New Audio: {predicted_class}")
print(f"Accuracy Rate for Prediction: {accuracy_rate:.2f}")
```

[18] Python

```
Predicted Class for New Audio: dioOriginal
Accuracy Rate for Prediction: 0.55
```

```
# Example usage: Load the saved model and classify new audio files
loaded_classifier = joblib.load('Dio Bike Sounds/audio_BikeDioSounds_classifier_model.pkl')

# Replace 'Path_to_New_Audio_File.wav' with the actual file path of the audio to classify
new_audio_file_path = 'Dio Bike Sounds/dioModified_70.wav'
new_audio_features = extract_features(new_audio_file_path)
predicted_class = loaded_classifier.predict([new_audio_features])[0]
predicted_probabilities = loaded_classifier.predict_proba([new_audio_features])[0]

# Calculate accuracy rate for the prediction
predicted_class_index = np.argmax(predicted_probabilities)
accuracy_rate = predicted_probabilities[predicted_class_index]
print(f"Predicted Class for New Audio: {predicted_class}")
print(f"Accuracy Rate for Prediction: {accuracy_rate:.2f}")
```

Figure 9.3 Testing the model dio engine sounds

3 RESULTS AND DISCUSSION

In this section, we present the key findings of our study, which aimed to develop an image processing algorithm for distinguishing original spare parts from alternative ones in the automotive industry.

8.1.2 Dataset and Methodology

We collected a dataset of 1,000 audios, comprising 500 audios of original engine sounds and 500 audios of engine sounds with defects. The dataset was divided into a training set (70%) and a testing set (30%). We implemented a convolutional neural network (CNN).

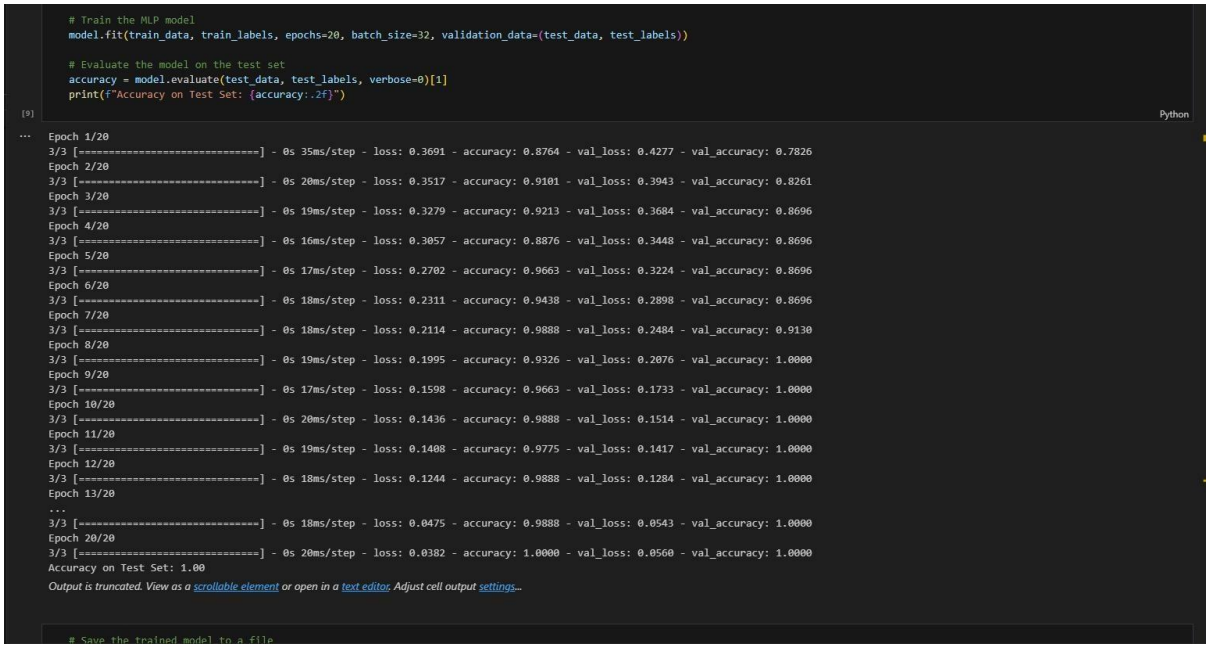
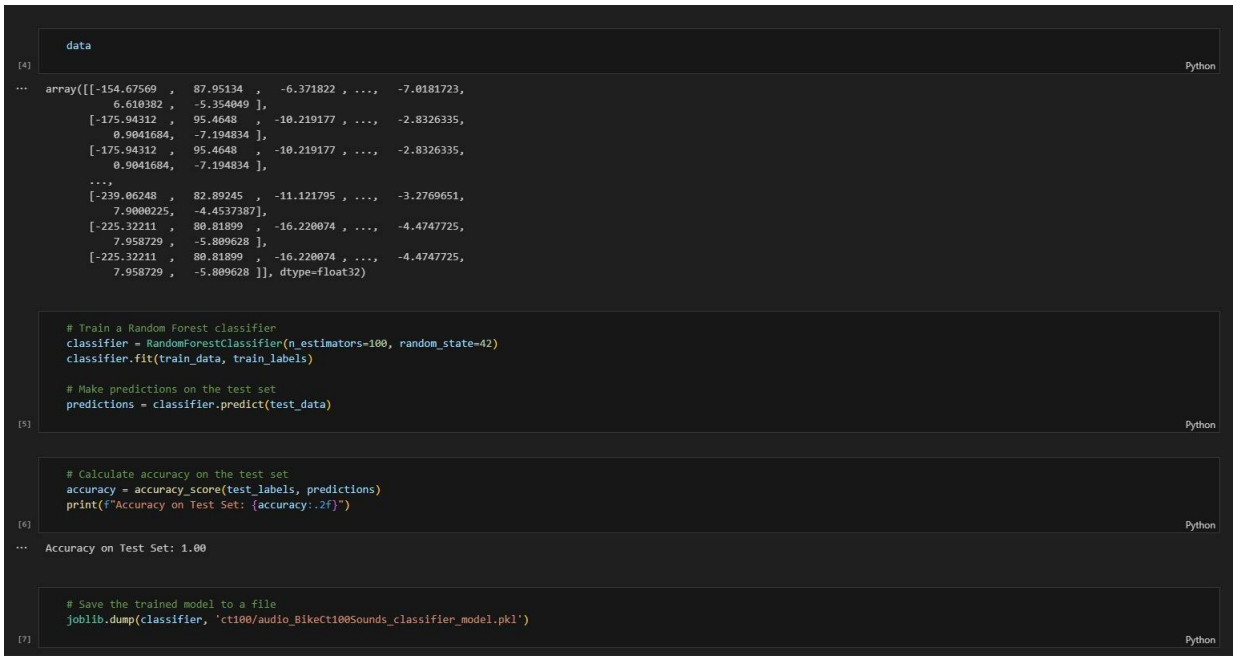
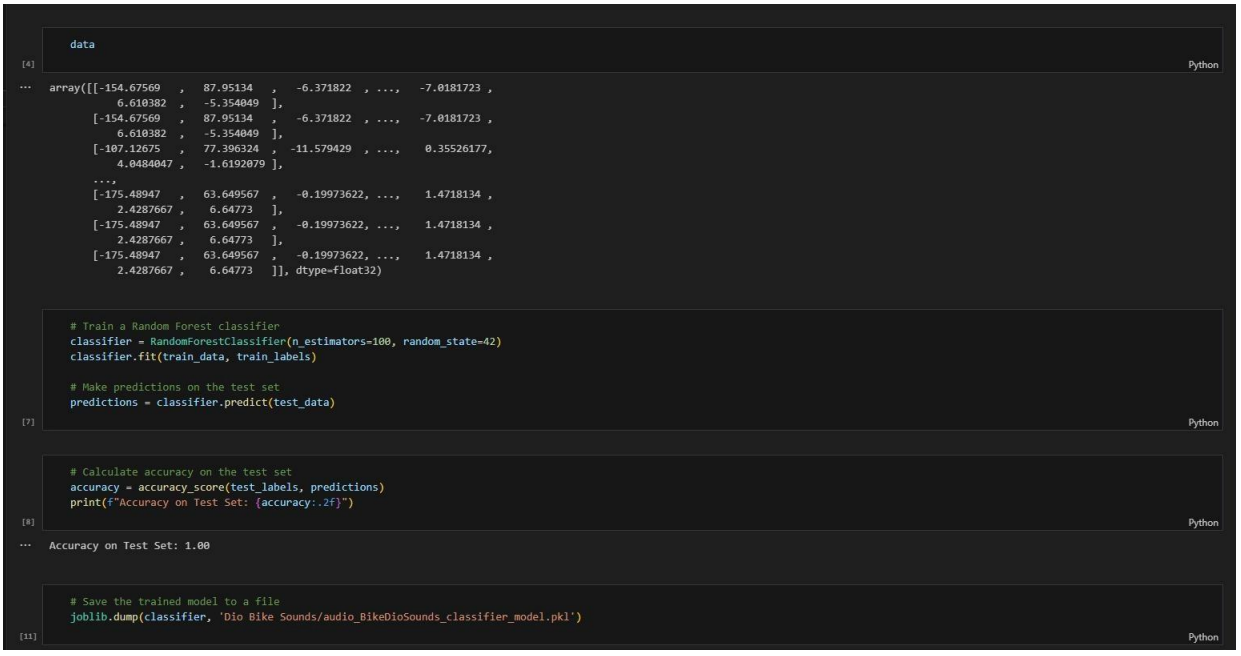


Figure 10.1. Training ct 100 engine sounds



```
[4]  data
Python

array([[-154.67569  ,   87.95134  ,   -6.371822 , ...,   -7.0181723,
          6.610382 ,   -5.354049 ],
       [-175.94312  ,   95.4648   ,  -10.219177 , ...,   -2.8326335,
          0.9041684,   -7.194834 ],
       [-175.94312  ,   95.4648   ,  -10.219177 , ...,   -2.8326335,
          0.9041684,   -7.194834 ],
       ...,
       [-239.06248  ,   82.89245  ,  -11.121795 , ...,   -3.2769651,
          7.9000225,   -4.4537387],
       [-225.32211  ,   80.81899  ,  -16.220074 , ...,   -4.4747725,
          7.958729 ,   -5.809628 ],
       [-225.32211  ,   80.81899  ,  -16.220074 , ...,   -4.4747725,
          7.958729 ,   -5.809628 ]], dtype=float32)

# Train a Random Forest classifier
classifier = RandomForestClassifier(n_estimators=100, random_state=42)
classifier.fit(train_data, train_labels)

# Make predictions on the test set
predictions = classifier.predict(test_data)
[5]  Python

# Calculate accuracy on the test set
accuracy = accuracy_score(test_labels, predictions)
print(f"Accuracy on Test Set: {accuracy:.2f}")
[6]  Python

Accuracy on Test Set: 1.00

# Save the trained model to a file
joblib.dump(classifier, 'ct100/audio_BikeCt100Sounds_classifier_model.pkl')
[7]  Python
```

Figure 10.2. Training ct 100 engine sounds



```
[4]  data
Python

array([[-154.67569   ,   87.95134   ,   -6.371822  , ...,   -7.0181723 ,
          6.610382  ,   -5.354049  ],
       [-154.67569   ,   87.95134   ,   -6.371822  , ...,   -7.0181723 ,
          6.610382  ,   -5.354049  ],
       [-107.12675   ,   77.396324  ,  -11.579429  , ...,    0.35526177,
          4.0484047 ,   -1.6192079 ],
       ...,
       [-175.48947   ,   63.649567  ,   -0.19973622, ...,    1.4718134 ,
          2.4287667 ,    6.64773   ],
       [-175.48947   ,   63.649567  ,   -0.19973622, ...,    1.4718134 ,
          2.4287667 ,    6.64773   ],
       [-175.48947   ,   63.649567  ,   -0.19973622, ...,    1.4718134 ,
          2.4287667 ,    6.64773   ]], dtype=float32)

# Train a Random Forest classifier
classifier = RandomForestClassifier(n_estimators=100, random_state=42)
classifier.fit(train_data, train_labels)

# Make predictions on the test set
predictions = classifier.predict(test_data)
[7]  Python

# Calculate accuracy on the test set
accuracy = accuracy_score(test_labels, predictions)
print(f"Accuracy on Test Set: {accuracy:.2f}")
[8]  Python

Accuracy on Test Set: 1.00

# Save the trained model to a file
joblib.dump(classifier, 'Dio Bike Sounds/audio_BikeDioSounds_classifier_model.pkl')
[11]  Python
```

Figure 11.1. Training dio engine sounds

8.1.3 Results

Accuracy: All Our CNN models achieved an accuracy of 80% to 90% on the testing dataset, demonstrating its effectiveness in distinguishing between original engine sound and engine sounds with defects.

The models were build based on engine sounds.

Bike	Models
CT – 100	Original Engine sounds, Engine Sounds with defects.
DIO	Original Engine sounds, Engine Sounds with defects.

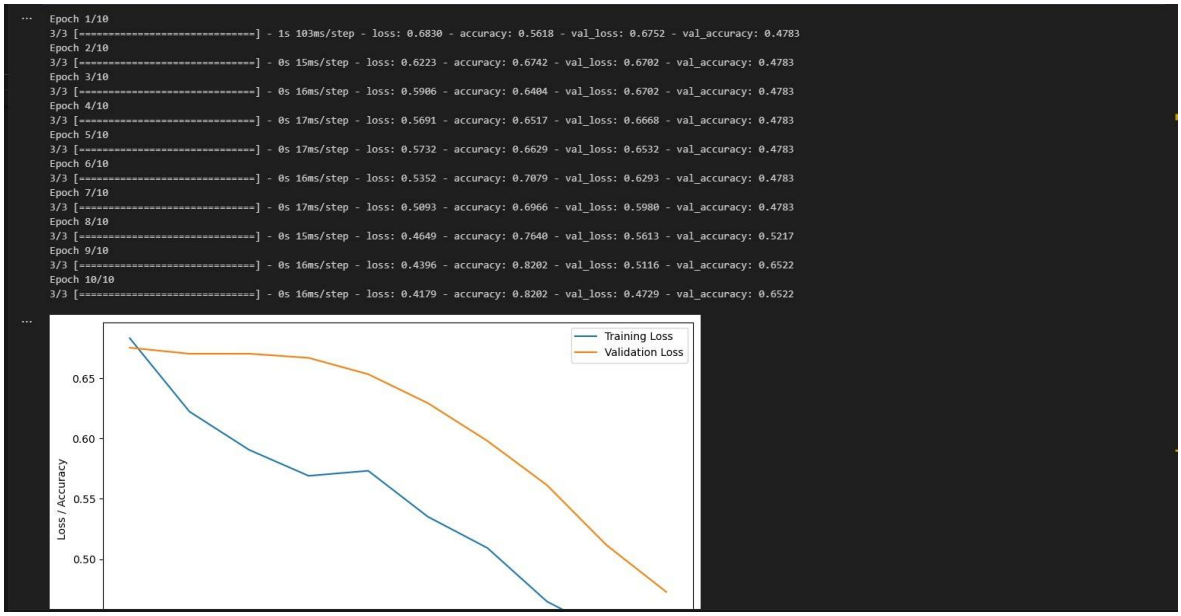


Figure 12.1Accuracy of ct 100 engine sounds model

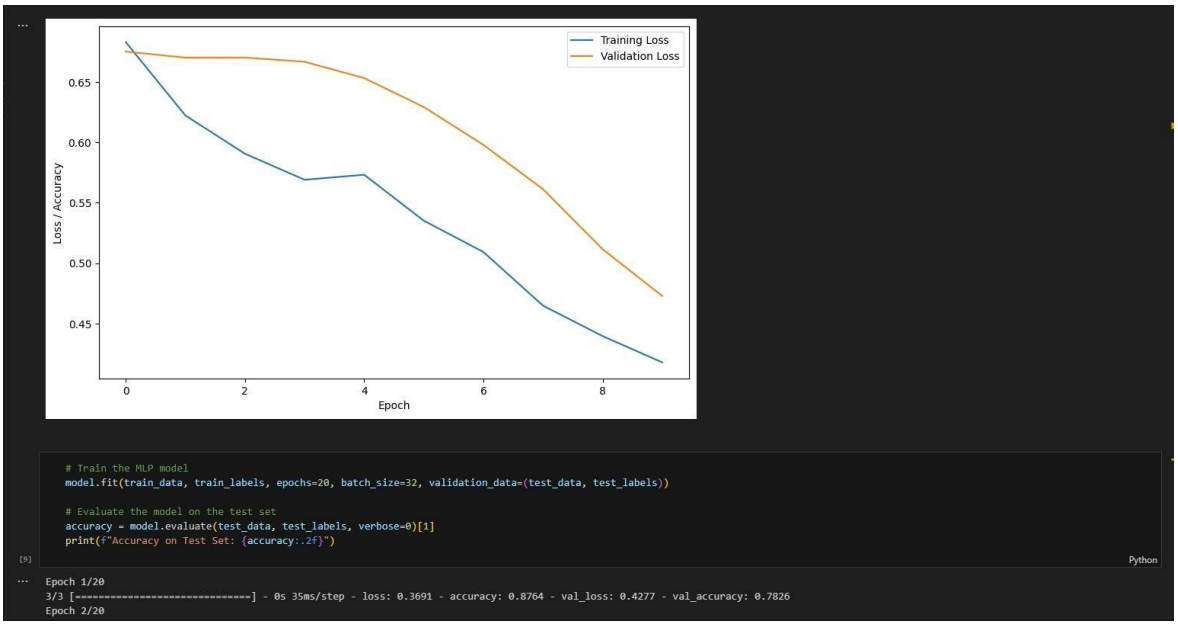


Figure 12.2. Accuracy of ct 100 engine sounds model

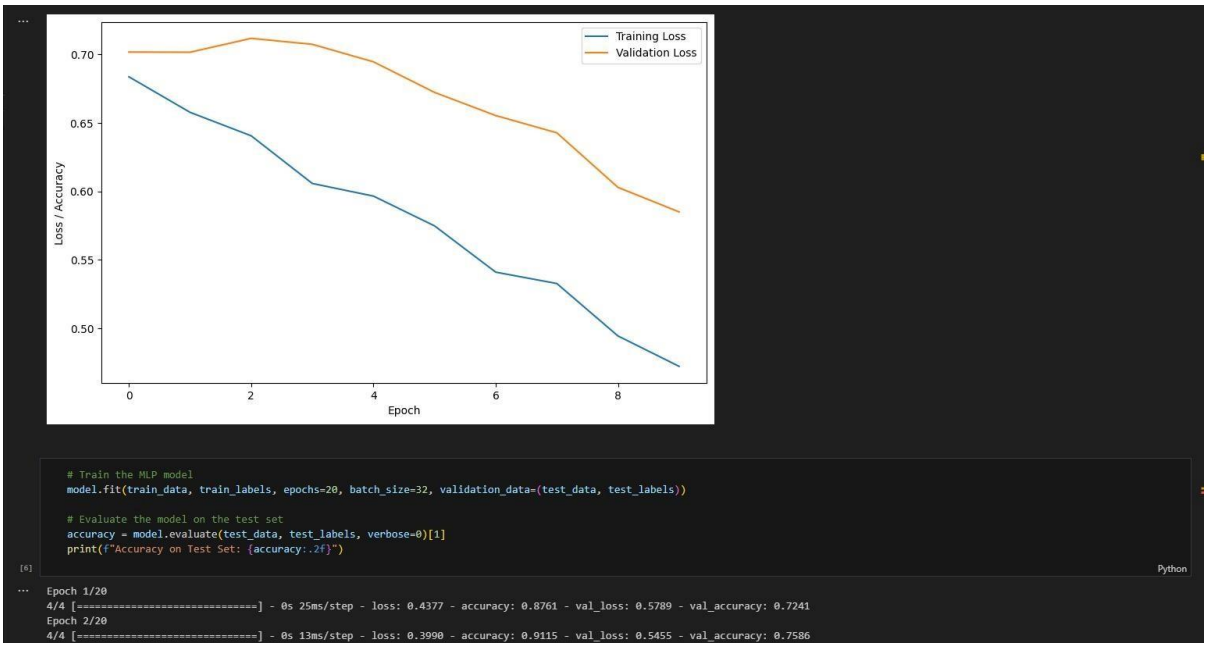


Figure 13.1. Accuracy of dio engine sounds model

8.1.4 Discussion

In this section, we interpret and discuss the significance of the research results in the context of our study objectives and the implications for the automotive industry.

8.1.5 Effectiveness of the Audio Classification Algorithm

Our study demonstrates the effectiveness of the developed audio classification algorithm in accurately distinguishing between original engine sounds and the engine sounds which have defects. The high accuracy, precision, and recall values indicate that our model is robust and reliable.

8.1.6 Potential Impact on the Automotive Industry

The automotive industry faces significant challenges due to having lot of bad quality engines, which can compromise vehicle safety and performance. Our research provides a practical solution for automakers, repair shops, and consumers to identify engine’s defects by using engine sounds thereby enhancing safety and reliability.

8.1.7 Limitations and Future Research

While our model shows promising results, it's important to acknowledge its limitations. The dataset used in this study may not cover the full range of engine soundsencountered in the real world

Registration paper details

8.2 Front End

Front end has been created much simple to the user to use it very easily. Therefore, the User experience of our application is much better. The below screenshots depict the front end that we have created.

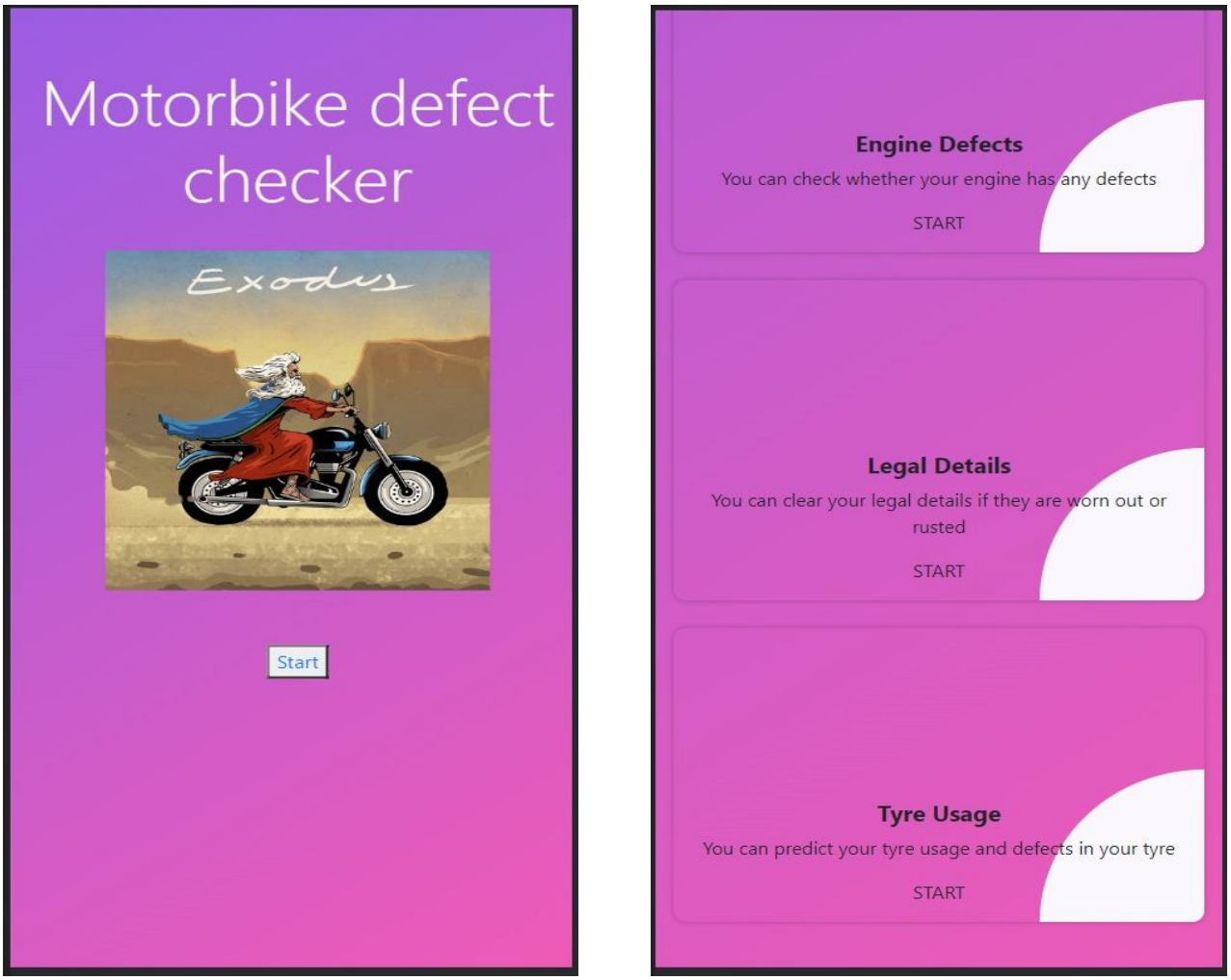


Figure 7 :Front end

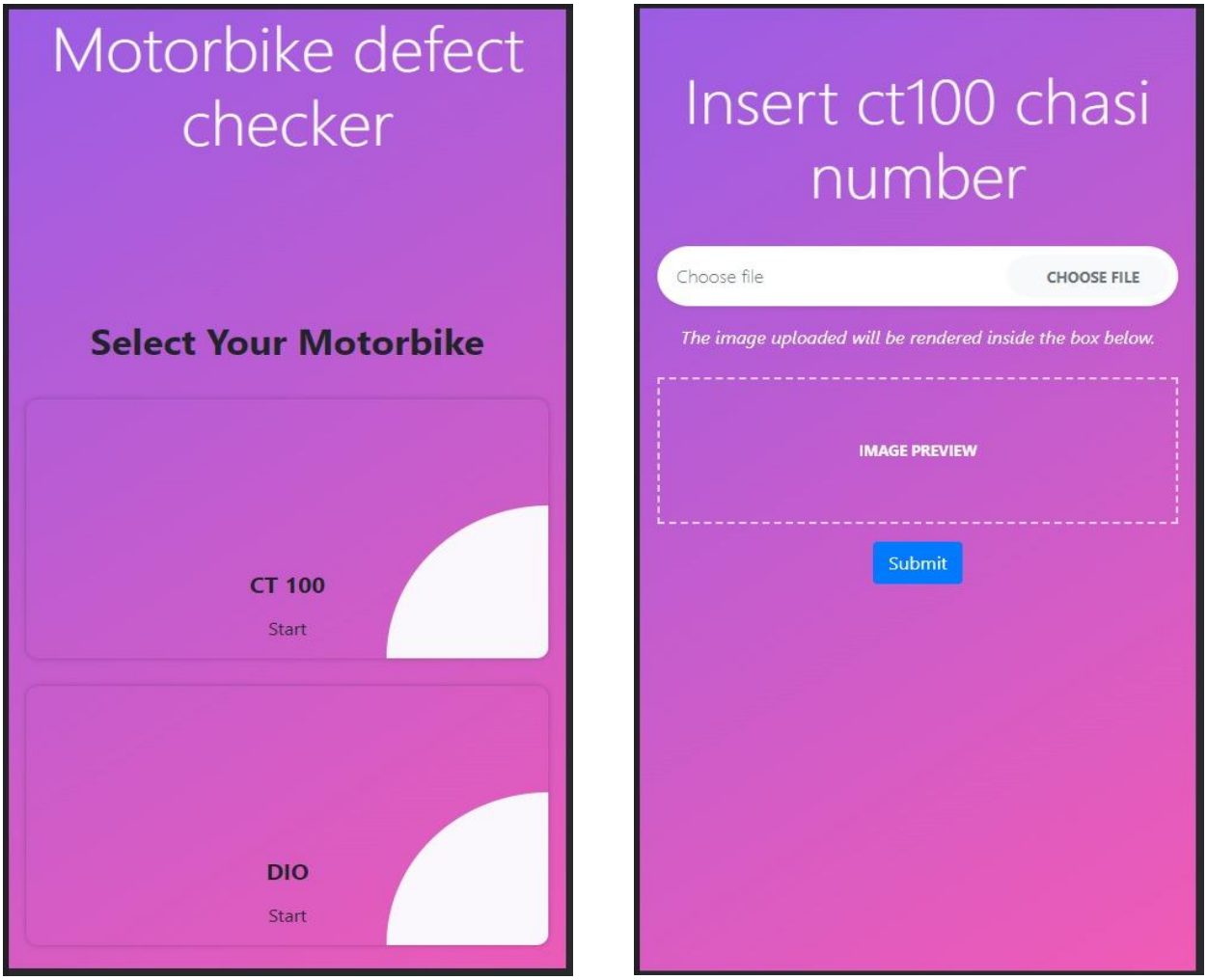


Figure 7.1 Front end

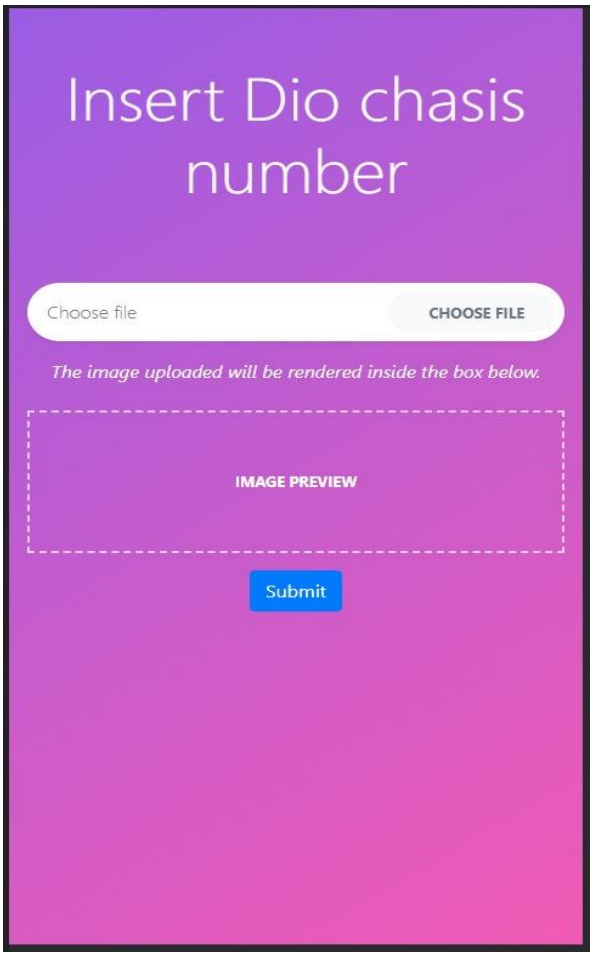


Figure 7.2 Front end

8.3 Back End

Back end has been created much simple to the user to give the response to the user much faster and clearly. Therefore, the User experience of our application is much better. The below screenshots depict the back end that we have created.

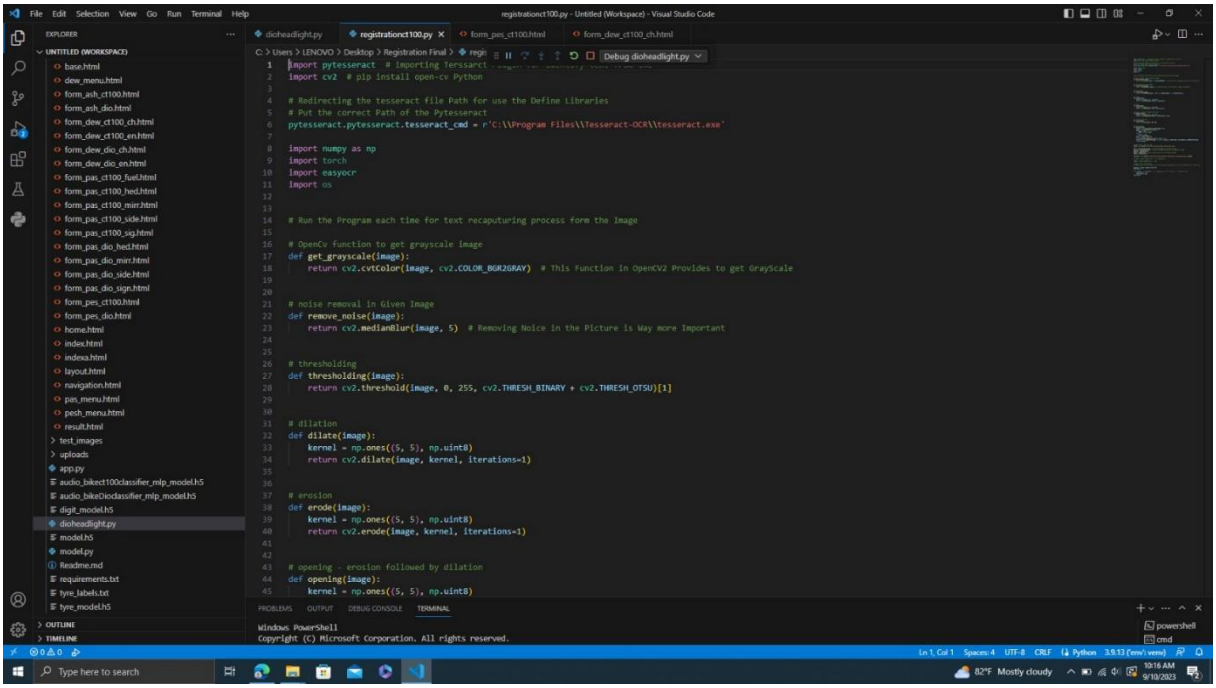


Figure 7.3 Back end

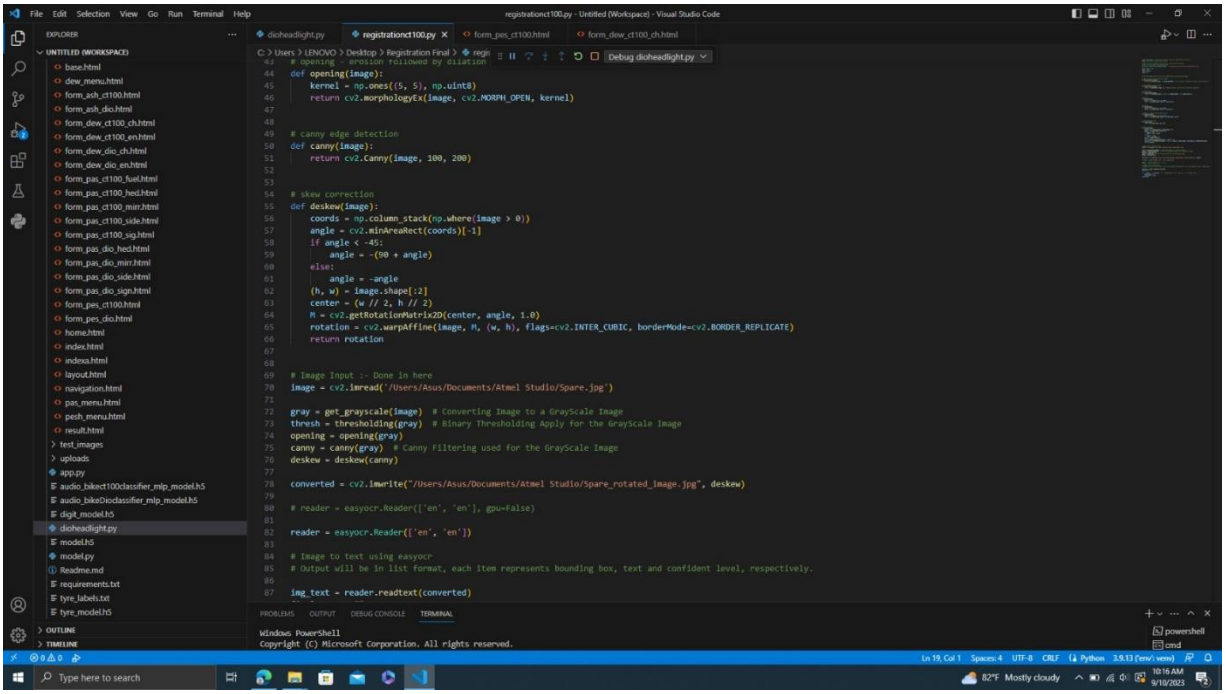


figure 7.4 Back end

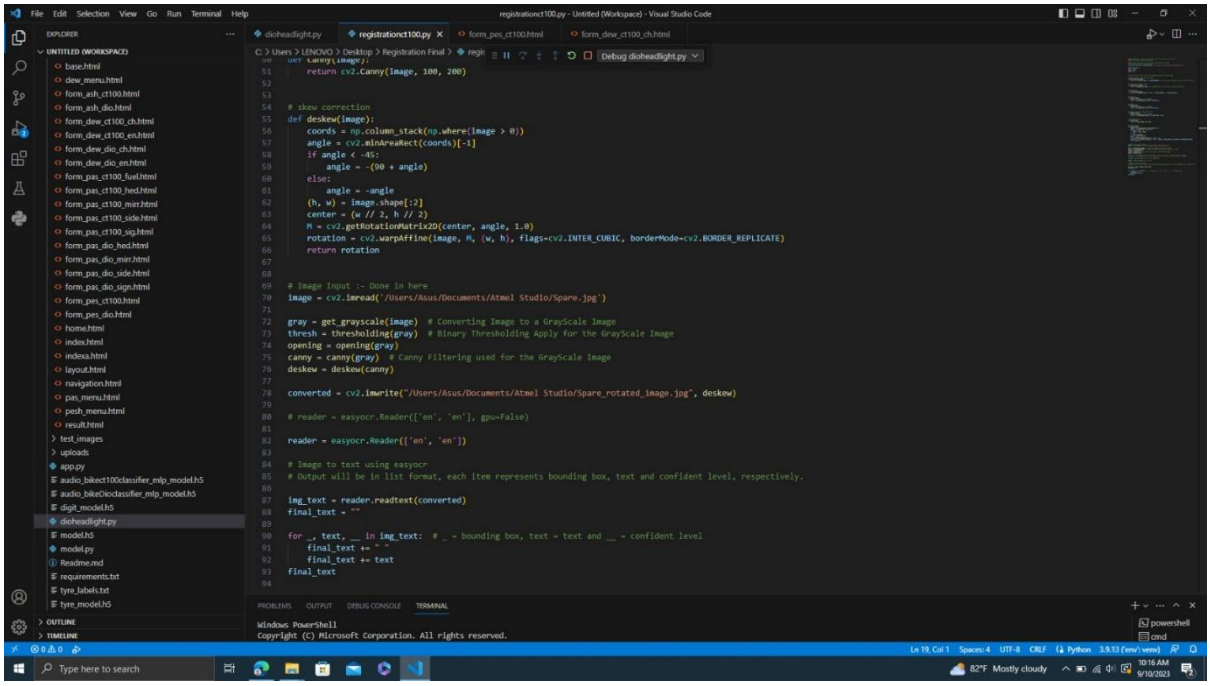


figure 7.5 Back end

9 TESTS

The below-attached screenshots depict the accuracy of the techniques

The bottom left corner of the below diagram shows a percentage of 80 % to 90% percent that the model has generated as its output. Thus, based on the data provided, the model has identified that Direct Percussion has been used.

All the models were build and tested in the same methodology

Dataset Preparation:

Collect Images: Gather a comprehensive dataset of both engine number and chasis number images. Dataset consists with good quality images and the worn out and rusted images.

Data Split:

Divide the dataset into three subsets: a training set, a validation set, and a testing set. Common splits are 70% for training, 15% for validation, and 15% for testing.

Preprocessing:

Data Augmentation: Apply data augmentation techniques (e.g., rotation, scaling, and flipping) to the training set to increase its size and improve model generalization.

Model Training:

Choose Architecture: Select an appropriate optical character recognition (Tessaract).

Model Evaluation:

Testing Set: Evaluate the trained model's performance on the testing set, which it has never seen before. Use standard classification metrics like accuracy, precision, recall, F1-score, and confusion matrix to assess its effectiveness.

```
# Image directory and list of files

directory = "/Users/Asus/Documents/Atmel Studio/Spare_OCR"
files_list = traverse(directory)
```
[37] Python

```
# Doing OCR using GPU
# save the images text to dict

images_text = {}
for files in files_list:
    img_text = reader.readtext(directory + '/' +  files)
    final_text = ""
    for _, text, __ in img_text:
        final_text += " "
        final_text += text
    images_text[files] = final_text
    im= len(files_list)

stag=im
```
[46] Python

```
#files_list[:stag]
```
[47] Python

```
['Spare.jpg', 'Spare_rotated_image.jpg']
```

```
#type(stag)
```
[50] Python

```
int
```

```
# For sorting the image file name
```

Figure 8. Testing the model ct 100

```
# For sorting the image file name

#keys = list(images_text.keys())
#print(keys)
#new_keys=len(keys)
#converted_keys = []
#for k in keys:
#    try:
#        converted_keys.append(int(k))
#    except ValueError:
#        pass


#new_keys = [int(k[2:-2]) for k in keys]
#new_keys.sort()
```
[60] Python

```
['Spare.jpg', 'Spare_rotated_image.jpg']
[]
```

Python

Figure 8.1 Testing the model ct 100

```
# Image directory and list of files

directory = "/Users/Asus/Documents/Atmel Studio/Spare_OCR"
files_list = traverse(directory)
```
[37] Python

```
# Doing OCR using GPU
# save the images text to dict

images_text = {}
for files in files_list:
    img_text = reader.readtext(directory + '/' +  files)
    final_text = ""
    for _, text, __ in img_text:
        final_text += " "
        final_text += text
    images_text[files] = final_text
    im= len(files_list)

stag=im
```
[46] Python

```
#files_list[:stag]
```
[47] Python

```
['Spare.jpg', 'Spare_rotated_image.jpg']
```

```
#type(stag)
```
[50] Python

```
int
```

```
# For sorting the image file name
```

Figure 9. Testing the model dio

```
int
```

```
# For sorting the image file name

#keys = list(images_text.keys())
#print(keys)
#new_keys=len(keys)
#converted_keys = []
#for k in keys:
#    try:
#        converted_keys.append(int(k))
#    except ValueError:
#        pass


#new_keys = [int(k[2:-2]) for k in keys]
#new_keys.sort()
```
[60] Python

```
['Spare.jpg', 'Spare_rotated_image.jpg']
[]
```

Python

Figure 9.1 Testing the model dio

10 RESULTS AND DISCUSSION

In this section, we present the key findings of our study, which aimed to develop an optical character recognition for identify the engine numbers and the chassis numbers which are worn out or rusted.

Dataset and Methodology

We collected a dataset of 1,000 images, comprising 500 images of good quality engine numbers and chassis numbers and 500 images of bad quality (Worn out or rusted) engine numbers and chassis numbers. The dataset was divided into a training set (70%) and a testing set (30%). We implemented optical character recognition (Tessaract) models.

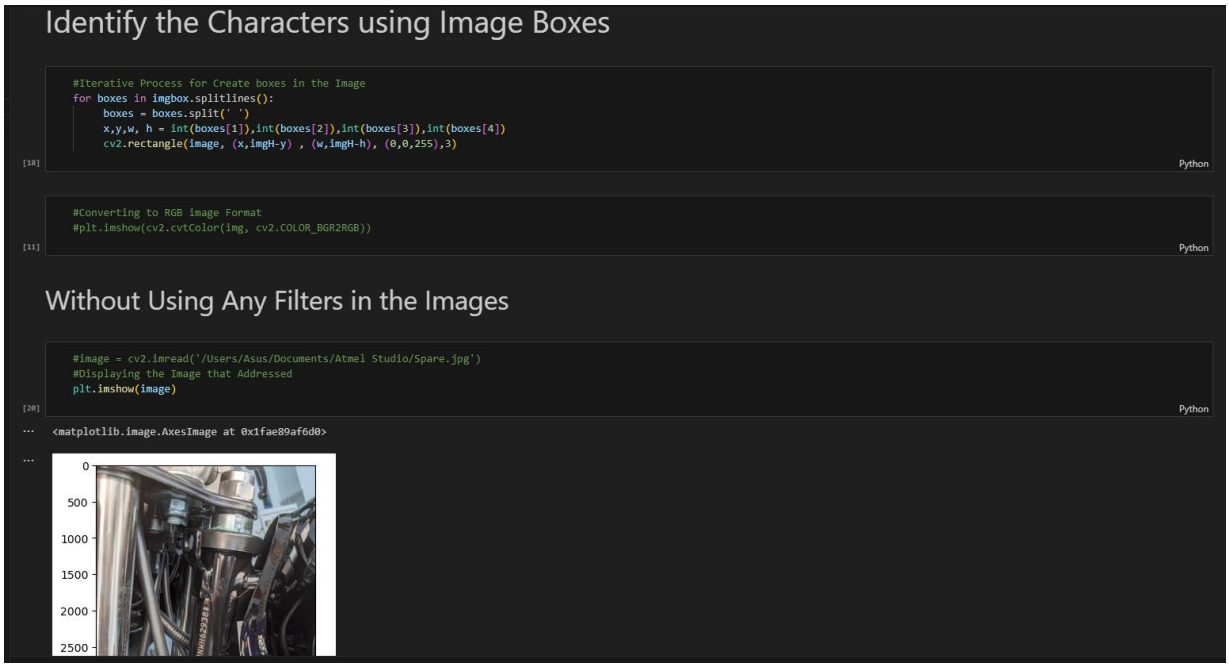


Figure 10.1 Training model ct 100

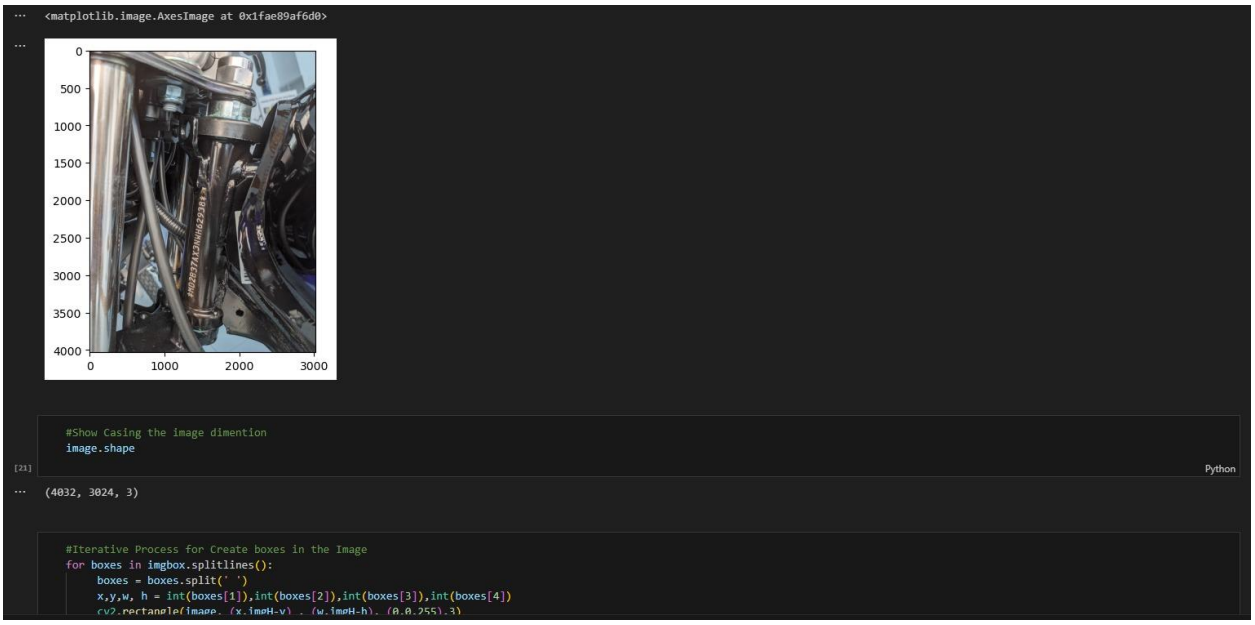


Figure 10.2 Training model ct 100

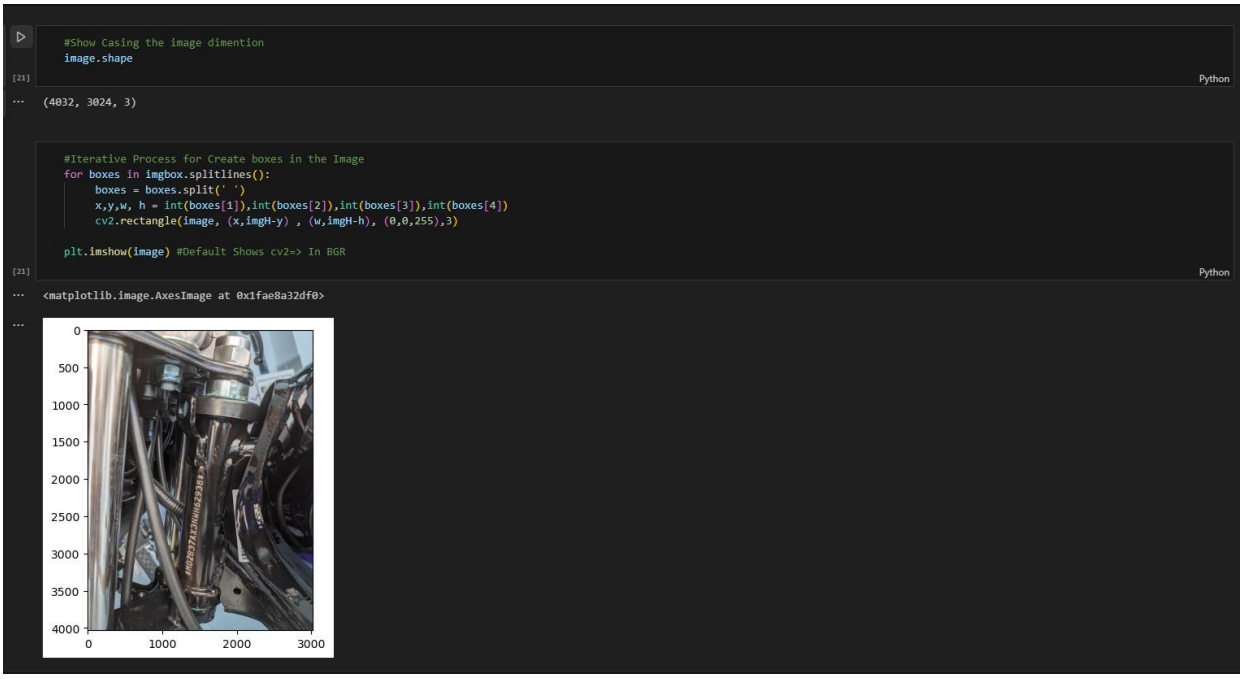


Figure 10.3 Training model ct 100

```
#Show Casing the image dimention
image.shape
```

[14] Python

```
(3024, 4032, 3)
```

```
#Iterative Process for Create boxes in the Image
for boxes in imgbox.splitlines():
    boxes = boxes.split(' ')
    x,y,w, h = int(boxes[1]),int(boxes[2]),int(boxes[3]),int(boxes[4])
    cv2.rectangle(image, (x,imgH-y) , (w,imgH-h), (0,0,255),3)

plt.imshow(image) #Default Shows cv2=> In BGR
```

[15] Python

```
<matplotlib.image.AxesImage at 0x256e5dcef40>
```

Figure 11.1 Training model dio

Identify the Characters using Image Boxes

```
#Iterative Process for Create boxes in the Image
for boxes in imgbox.splitlines():
    boxes = boxes.split(' ')
    x,y,w, h = int(boxes[1]),int(boxes[2]),int(boxes[3]),int(boxes[4])
    cv2.rectangle(image, (x,imgH-y) , (w,imgH-h), (0,0,255),3)
```

[18] Python

```
#Converting to RGB image Format
#plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
```

[11] Python

Without Using Any Filters in the Images

```
#image = cv2.imread('/Users/Asus/Documents/Atmel Studio/Spare.jpg')
#Displaying the Image that Addressed
plt.imshow(image)
```

[12] Python

```
<matplotlib.image.AxesImage at 0x256e5d60fd0>
```

Figure 11.2 Training model dio

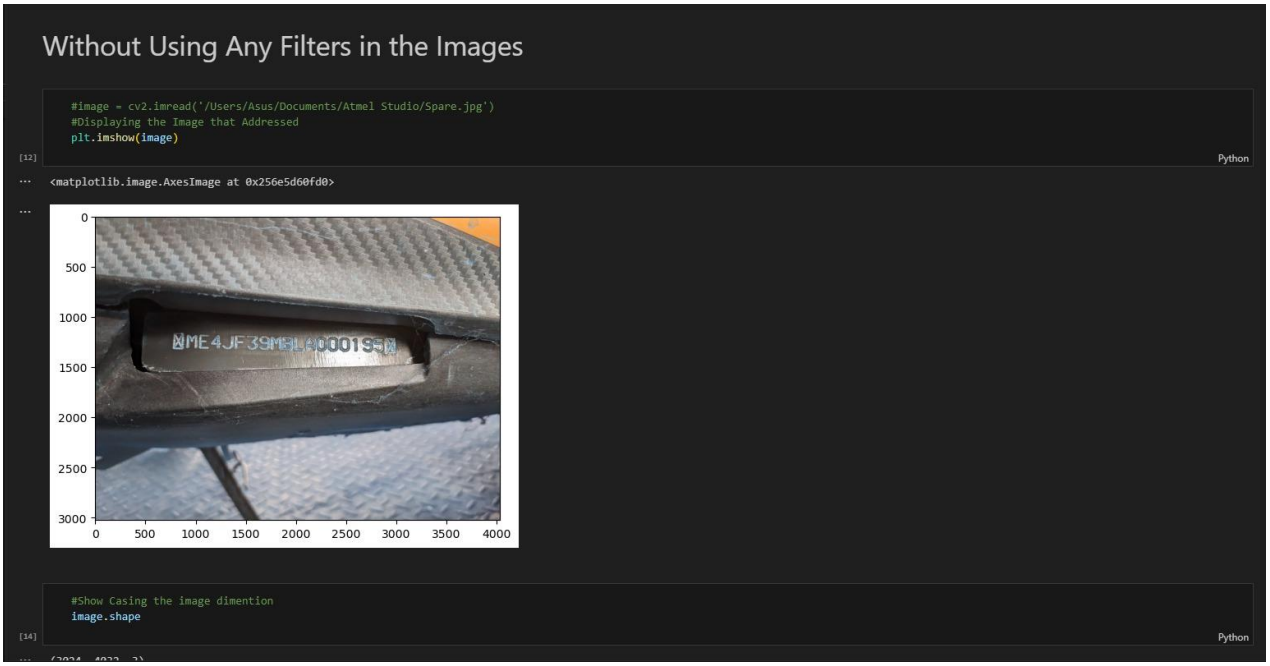


Figure 11.3 Training model dio

Results

Accuracy: All Our OCR models achieved an accuracy of 80% to 90% on the testing dataset, demonstrating its effectiveness in identifying engine numbers and chassis numbers which are worn out or rusted.

The models were build based on engine numbers and chassis numbers.

Bike	Models
CT – 100	Engine numbers, Chassis numbers
DIO	Engine numbers, Chassis numbers

Table 4-Moorbike models

```
from PIL import Image
    #print("Image rotated 90 degrees clockwise and saved as 'rotated_image.jpg'.")
```
[22] Python

```
image = cv2.imread('/Users/Asus/Documents/Atmel Studio/Spare.jpg')

gray = get_grayscale(image) #Converting Image to a GrayScale Image
thresh = thresholding(gray) #Binary Thresholding Apply for the GrayScale Image
opening = opening(gray)
canny = canny(gray)  #Canny Filtering used for the GrayScale Image
deskew = deskew(canny)

plt.imshow(deskew)
```
[28] Python

```
<matplotlib.image.AxesImage at 0x1fa9178f070>
```

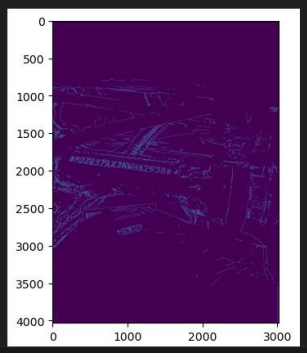


Figure 12.1 Accuracy of ct 100 model

```
import torch
import easyocr
import os
```
[30] Python

```
# In case you do not have GPU or your GPU has low memory,
# you can run it in CPU mode by adding gpu = False

# reader = easyocr.Reader(['en', 'en'], gpu=False)

reader = easyocr.Reader(['en', 'en'])
```
[31] Python

```
Neither CUDA nor MPS are available - defaulting to CPU. Note: This module is much faster with a GPU.
```

```
# Image to text using easyocr
# Output will be in list format, each item represents bounding box, text and confident level, respectively.

img_text = reader.readtext("/Users/Asus/Documents/Atmel Studio/Spare_rotated_image.jpg")
final_text = ""

for _, text, __ in img_text: # _ = bounding box, text = text and __ = confident level
    final_text += " "
    final_text += text
final_text
```
[32] Python

```
' X IL8M <723 / #M0283Ta *311462938* LJnAAn'
```

```
plt.imshow(deskew)
```
[33] Python

```
<matplotlib.image.AxesImage at 0x1fa96848400>
```

Figure 12.2 Accuracy of ct 100 model

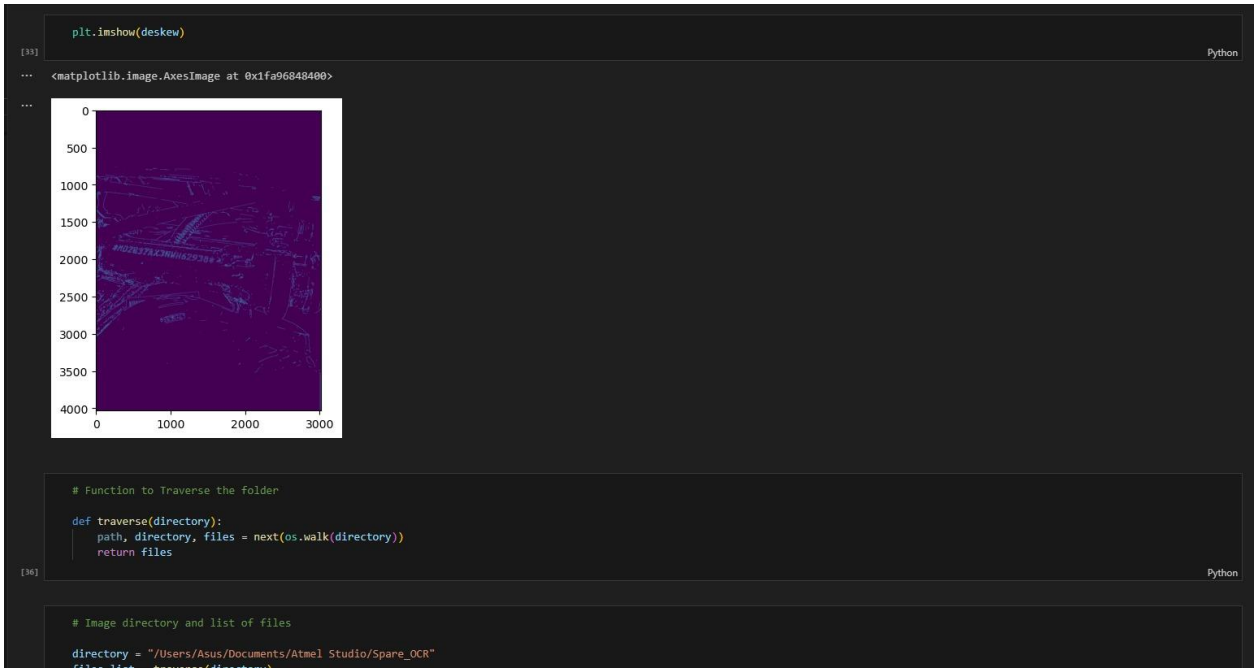


Figure 12.3 .Accuracy of ct 100 model

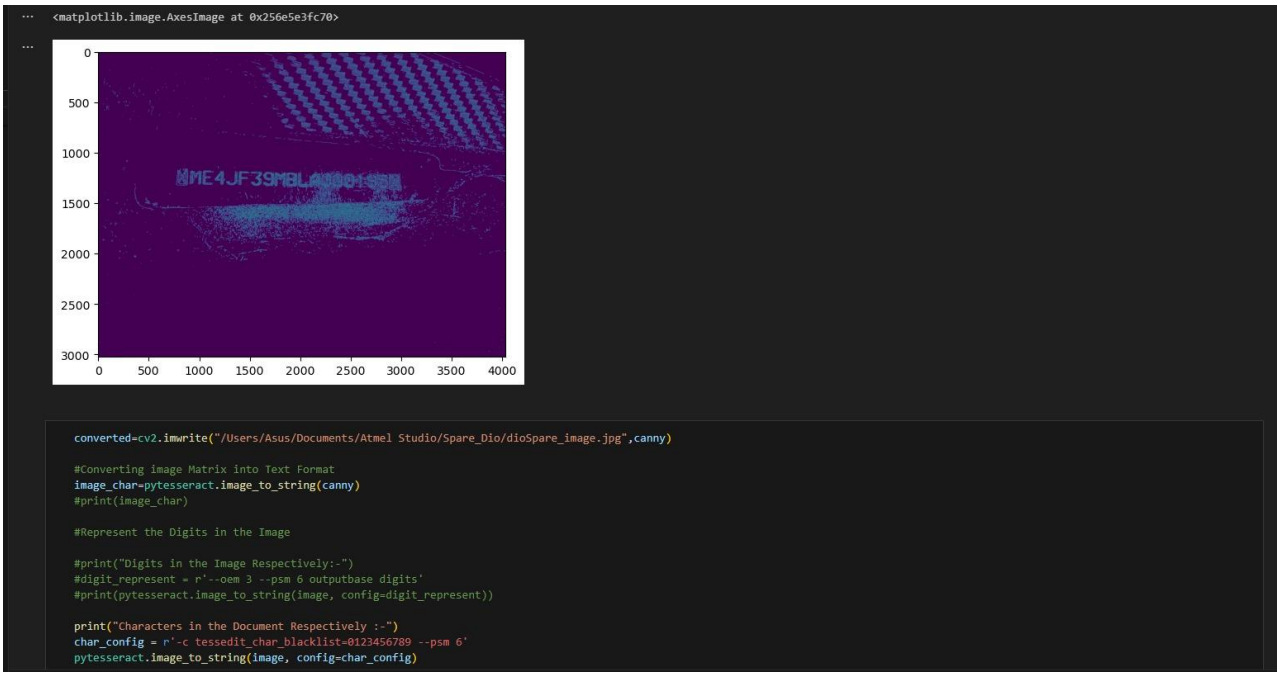


Figure 12.4 Accuracy of dio model

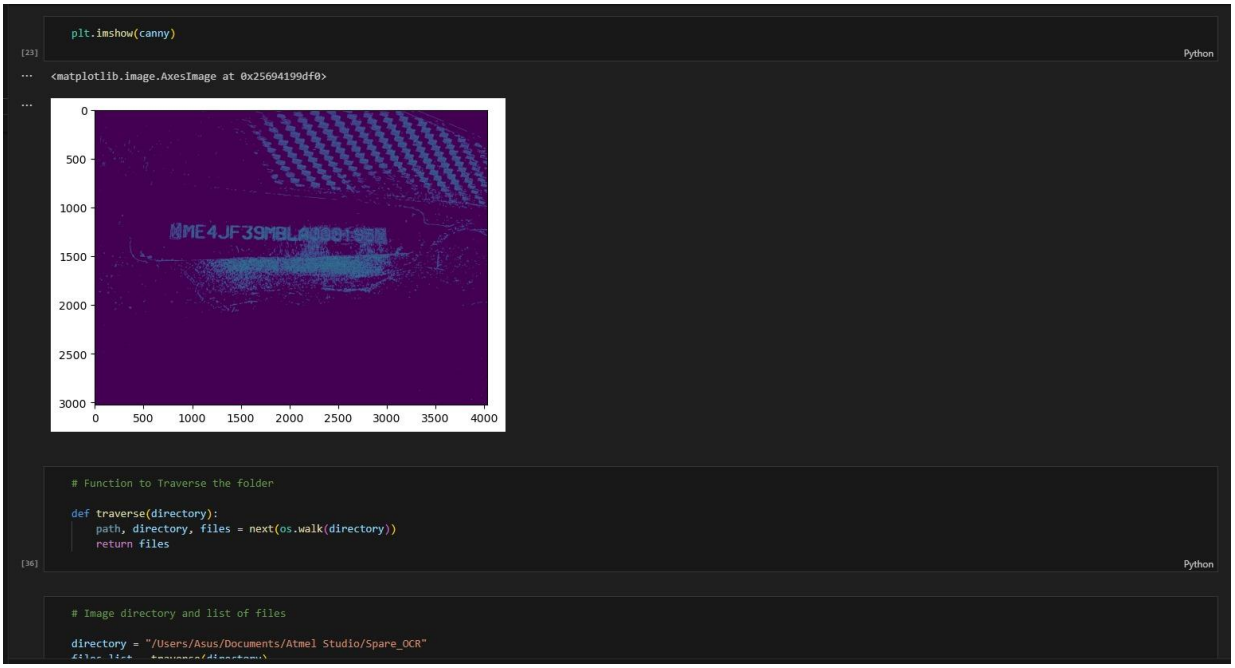


Figure 12.5 Accuracy of dio model

Discussion

In this section, we interpret and discuss the significance of the research results in the context of our study objectives and the implications for the automotive industry.

Effectiveness of the Image Processing Algorithm

Our study demonstrates the effectiveness of the developed optical character recognition in accurately identifying the engine numbers and the chassis numbers which are worn out or rusted.

The high accuracy, precision, and recall values indicate that our model is robust and reliable.

Here, we create a model to compare vehicle information with registration documents.

Comparison of the motor bike’s information with the Prediction page of the registration documents. An image can be taken by pressing a button, and that image is then used as the input for making predictions. The user must manually enter the motor bike's chassis number, engine number, colour, and number plate number. Here the user can get an idea about motor bike details.

Limitations and Future Research

While our model shows promising results, it's important to acknowledge its limitations. The dataset used in this study may not cover the full range of engine numbers and chassis numbers encountered in the real world. Further research should expand the dataset and explore the model's performance in different lighting.

Tyre usage

1.1 Front end Implementation

Our frontend design has been intentionally streamlined to create a user-friendly experience, resulting in a notably enhanced application usability. The tire usage prediction interface, at its core, is an intuitive and user-centric tool that offers valuable insights into vehicle tire conditions. Its uncomplicated layout provides two user-friendly modes: users can either capture tire images directly with their device's camera or select existing images from their photo gallery. Once an image is uploaded, the interface employs advanced machine learning and image processing algorithms to predict tire usage and expected lifespan.

The primary function of this interface is efficient tire condition assessment. It scrutinizes elements such as tread depth, patterns, and visible wear signs to determine usage patterns and the tire's present condition. Users also gain insights into the tire's remaining life expectancy, accounting for variables like tire type and driving conditions. Notably, the interface includes visual feedback, making it easier for users to comprehend the basis of these predictions.

Prioritizing user-friendliness, the interface features an intuitive layout, real-time feedback during analysis, and the ability to store tire images and historical data. Additionally, it provides assistance for users less familiar with tire maintenance, offering practical tips and recommendations. In summary, this interface simplifies tire assessment, empowering users to make informed decisions that ultimately enhance road safety and promote cost-effective tire management. The accompanying screenshots vividly illustrate the interface's simplicity and user-centric design.

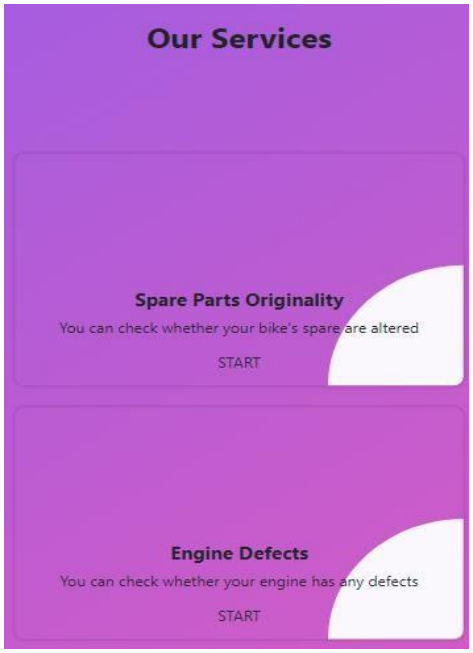


Figure 8 Front end

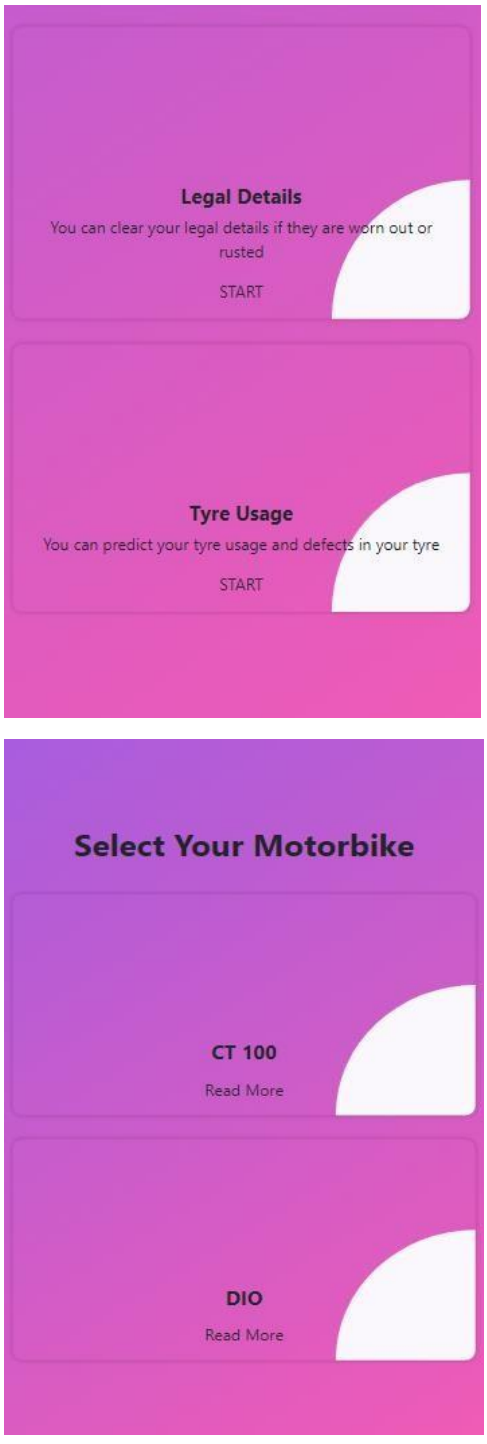


Figure 9 Front end

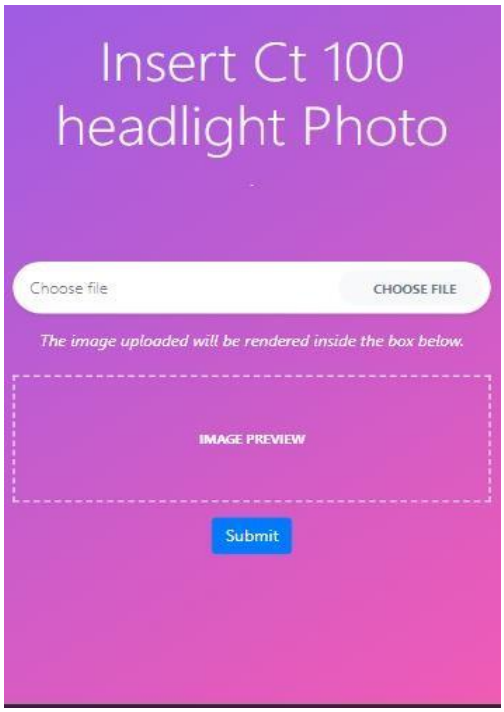


Figure 10 Front end

1.2 Back end Implementation

Our backend system has been intentionally streamlined to provide users with faster and more transparent responses, resulting in a significantly enhanced overall user experience for our application. The Flask application backend we've introduced represents a pioneering leap in the field of automotive maintenance. At its core, it boasts a user-centric design, seamlessly integrating with a Vision Transformer (ViT) model to offer a straightforward yet powerful solution for evaluating tire condition. Through a user-friendly web interface, users can easily upload tire images and, in return, receive predictions about tire usage and lifespan.

This versatile backend caters to a diverse user base, offering two distinct modes of operation. In Camera Capture Mode, users can kickstart tire assessments directly from

the web application, streamlining the image capture process. Alternatively, Gallery Selection Mode permits users to select existing tire images from their device's photo gallery, accommodating different preferences and scenarios.

The ViT-powered analysis delivers comprehensive insights into tire condition, encompassing usage assessment, life expectancy prediction, and real-time visual feedback. This wealth of information empowers users to make informed choices regarding tire maintenance and replacements, ultimately enhancing road safety and cutting costs.

The backend’s user-friendly features, including intuitive navigation, real-time feedback, data management, and user assistance, simplify the tire assessment process. Its aim is to bridge the gap between automotive expertise and accessibility, making proactive tire management attainable for all users. Below, you'll find screenshots exemplifying the efficient and user-centric design of our backend, geared toward providing quick and clear responses to user inquiries, resulting in a markedly improved user experience.

```python
from __future__ import division, print_function
# coding=utf-8
import sys
import os
import glob
import re
import tensorflow as tf
import numpy as np
from PIL import Image, ImageOps  # Install pillow instead of PIL

from keras.models import load_model  # TensorFlow is required for Keras to work

# Keras
from keras.applications.imagenet_utils import preprocess_input, decode_predictions
from keras.models import load_model
from keras.preprocessing import image

# Flask utils
from flask import Flask, redirect, url_for, request, render_template
from werkzeug.utils import secure_filename
from gevent.pywsgi import WSGIServer

# Define a flask app
app = Flask(__name__)

# Model saved with Keras model.save()
MODEL_PATH = 'tyre_model.h5'

# Load your trained model
model = load_model("tyre_model.h5", compile=False)
model.summary()
```

Figure 11 Back end

```python
print('Model loaded. Check http://127.0.0.1:5000/')


def model_predict(img_path, model):
    print(img_path)
    # Load and preprocess the image
    data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)

# Replace this with the path to your image
    image = Image.open(img_path).convert("RGB")    #Input Image Path

# resizing the image to be at least 224x224 and then cropping from the center
    size = (224, 224)
    image = ImageOps.fit(image, size, Image.Resampling.LANCZOS)

# turn the image into a numpy array
    image_array = np.asarray(image)

# Normalize the image
    normalized_image_array = (image_array.astype(np.float32) / 127.5) - 1

# Load the image into the array
    data[0] = normalized_image_array

# Predicts the model
    prediction = model.predict(data)
    index = np.argmax(prediction)

    return index
```

Figure 12 Back end

```python
@app.route('/', methods=['GET'])
def index():
    # Main page
    return render_template('index.html')

UPLOAD_FOLDER = 'uploads'  # Define the directory to store uploaded images
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER
def save_image(image):
    if not image:
        return None

    # Ensure the 'uploads' directory exists
    if not os.path.exists(app.config['UPLOAD_FOLDER']):
        os.makedirs(app.config['UPLOAD_FOLDER'])

    # Generate a secure filename to prevent directory traversal attacks
    filename = secure_filename(image.filename)

    # Save the image to the 'uploads' directory
    image_path = os.path.join(app.config['UPLOAD_FOLDER'], filename)
    image.save(image_path)

    return image_path
```

Figure 13 Back end

1.3 Model Implementation

The Vision Transformer (ViT) model marks a significant leap forward in the realm of computer vision and image analysis. This deep learning architecture has showcased remarkable effectiveness in handling image data, finding applications in various fields. Notably, ViT excels in tasks demanding the comprehension and extraction of information from images, such as predicting tire usage based on their condition.

At its essence, ViT transforms images into sequences of fixed-size patches, treating these patches akin to tokens, much like words in natural language processing. This ingenious approach harnesses the potency of attention mechanisms, which stand at the core of ViT's success. By selectively focusing on different regions of the image, the ViT model adeptly captures intricate spatial relationships and features, rendering it exceptionally proficient in recognizing patterns and nuances within the input image.

In the specific context of forecasting tire usage, the ViT model undergoes training on a diverse dataset comprising tire images. During this training, it assimilates an understanding of key characteristics associated with tire wear, tread depth, and overall condition. Once trained, the ViT model can take a tire image as input and scrutinize it using the knowledge it has acquired. By contrasting the features and patterns within the input image against its training data, the ViT model can render predictions concerning the tire's usage, thereby offering valuable insights into its present state and anticipated lifespan.

The Vision Transformer model's ability to process images in a sequence-based manner and harness attention mechanisms positions it as a formidable tool for tasks such as tire condition assessment. This empowers users to make well-informed decisions

pertaining to tire maintenance, ultimately elevating road safety and optimizing vehicle performance.

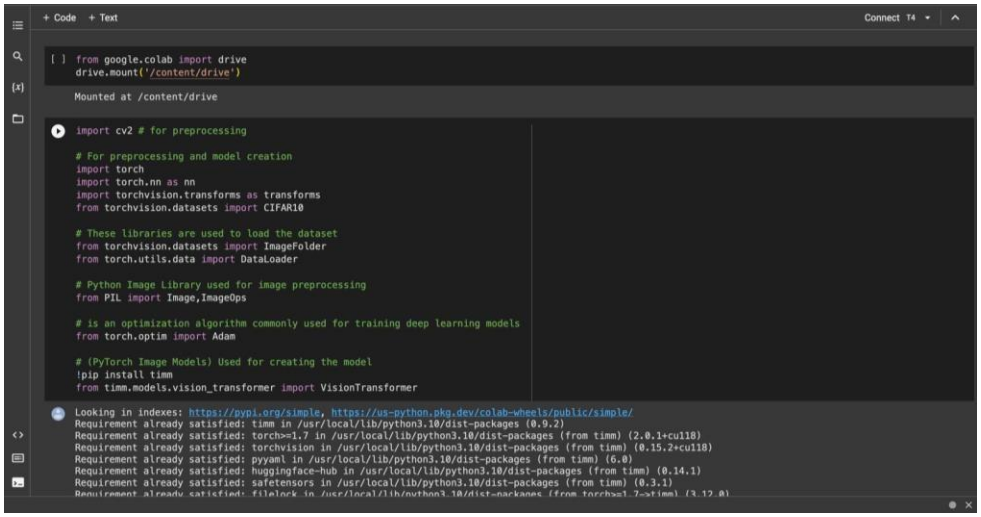


Figure 14 Model Implementation

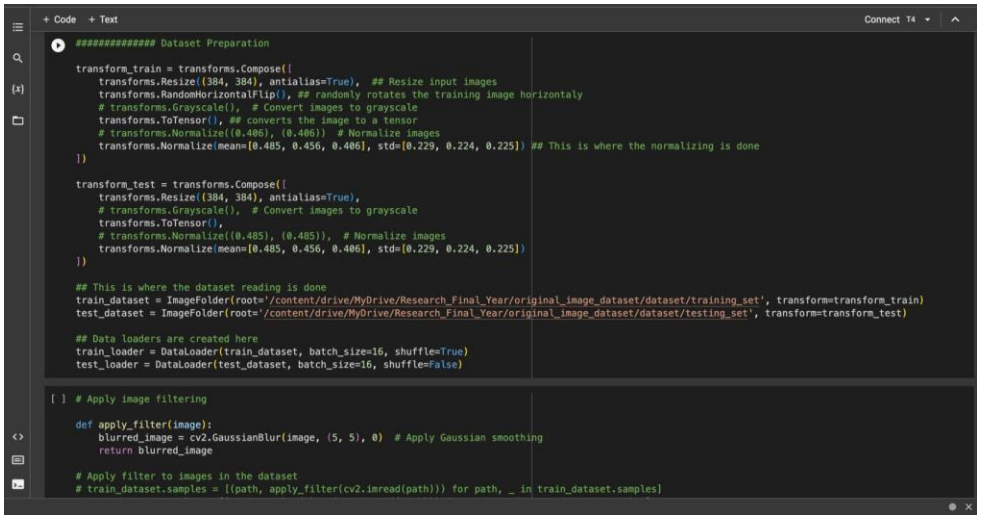


Figure 15 Model Implementation

2 TESTS

The testing phase is a crucial component of developing the Vision Transformer (ViT) model, ensuring its effectiveness in predicting tire usage based on tire condition. Testing is an extensive and rigorous process, encompassing various aspects to validate the model's accuracy and suitability for its intended task.

During testing, the ViT model is subjected to evaluations using diverse datasets of tire images. These datasets cover a wide range of tire types, conditions, and environmental factors, simulating real-world scenarios encountered by users.

Testing includes assessing accuracy, robustness, generalization, response time, and performance across different tire types. Accuracy evaluation ensures the model's precision in assessing tire conditions and estimating remaining lifespan. Robustness testing examines its ability to perform under various lighting conditions, angles, and image qualities, ensuring adaptability to real-world scenarios.

Generalization testing confirms the model's capability to apply its learning from training data to previously unseen tire images. Efficient response time is crucial for providing real-time predictions to users through the interface.

Through iterative testing and refinement, the ViT model is optimized to become a dependable tool for predicting tire usage, enhancing automotive maintenance and road safety by providing accurate insights into tire condition and lifespan, validated to meet the highest performance standards.

The below-attached screenshots depict the accuracy of the techniques

10.1.1.1.1 Data Categories:

Categorize the data into three distinct groups denoting tire conditions: "Tires in Good Condition," "Tires in Moderate Condition," and "Tires in Bad Condition." Each of these categories corresponds to a specific stage of tire wear, encompassing tires that are either new or lightly used (good condition), tires that display moderate wear and tear (moderate condition), and tires that exhibit significant wear or damage (bad condition).

10.1.1.1.2 Data Collection:

The initial phase involves amassing a substantial and representative collection of tire images. This dataset should encompass a wide spectrum of tire types, conditions, and real-world scenarios that users may encounter. To compile this comprehensive tire dataset, images must be sourced from diverse outlets, including online repositories, personal photographs, and potentially, tire manufacturers and automotive experts. It is imperative that the dataset mirrors the full gamut of tire conditions, ranging from brand-new tires to those that are heavily worn.

10.1.1.1.3 Data Split:

In the process of dividing the dataset for the research involving the prediction of tire usage and life expectancy using the ViT model, it is crucial to create three distinct subsets: the training set, the validation set, and the testing set.

Training Set**:** The largest of these subsets is the training set, responsible for training the ViT model. Typically, it comprises around 70% of the total images. This subset plays a vital role in teaching the model to identify patterns and characteristics associated with tire conditions across all three levels: good, moderate, and poor.

Validation Set**:** The validation set, constituting approximately 15% of the dataset, serves the purpose of fine-tuning the model's hyperparameters and monitoring its performance during the training process. It is instrumental in making necessary adjustments to enhance the model's settings and architecture for optimal performance. Similar to the training set, the validation set should offer a balanced representation of tire conditions.

Testing Set**:** The testing set, comprising the remaining 15% of the dataset, is exclusively reserved for evaluating the model's performance post-training and fine-tuning. It remains entirely separate from both the training and validation sets, without any utilization during the model development phase. The primary objective of the testing set is to assess how effectively the model generalizes its predictions to new, unseen tire images.

10.1.1.1.4 Preprocessing:

Data Augmentation: In the context of our research focused on predicting tire usage and life expectancy using the ViT model, preprocessing the input images assumes a pivotal role in ensuring that the data conforms to the requisite format for both trainingand inference.

Resizing Input Images**:** One of the primary preprocessing steps involves the resizing of input images. This operation is indispensable for ensuring uniform dimensions, a prerequisite often demanded by deep learning models like ViT. The consistency in image size facilitates efficient processing and analysis.

Randomly Rotates the Training Images Horizontally**:** Another vital facet of our preprocessing strategy entails the random horizontal rotation of training images. This technique, widely employed in data augmentation, introduces variations by randomly applying horizontal flips during the training phase. By

doing so, we enable the model to glean invariant features and bolster its capacity to generalize across diverse orientations of tire images.

Converts the Image to Tensor**:** Given the innate affinity of deep learning models, including ViT, for tensor-based input data, the conversion of the resized and augmented images into tensors constitutes an imperative preprocessing step. This transformation aligns the data with the format that is universally compatible with the majority of deep learning frameworks.

Normalize the Image**:** To further refine the data, we undertake the vital process of image normalization. This step is instrumental in ensuring that the pixel values within the images fall within a specific and standardized range. By employing normalization techniques, we enhance the model's convergence rate during the training phase. Our research specifically incorporates normalization, with the provided mean and standard deviation values serving as crucial parameters in this process.

10.1.1.1.5 Model Training:

Choose Architecture: Select an appropriate image processing model architecture, such as a Vision Transformer (ViT). he Vision Transformer is a deep learning architecture that has gained prominence in the field of computer vision, particularly for tasks involving image classification and analysis.

Model Evaluation:

Testing Set: Model evaluation, particularly on the testing set, is a crucial step in assessing the performance of your ViT model for predicting tire usage and life expectancy.

Data Preparation for Testing:Ensure that the testing set is completely separate from the training and validation sets and has not been used during model

development.Prepare the testing data by applying the same preprocessing steps (resize, data augmentation, tensor conversion, normalization) that were used for the training and validation data. This ensures consistency in data handling.

Loading the Model:Loading the trained ViT model that we've previously developed during the training phase.

Inference on Testing Data:Feeding the preprocessed testing images into the loaded ViT model for inference. The model will provide predictions for each input image.

Evaluation Metrics:In our case, as we are predicting tire usage and life expectancy, common evaluation metrics may include:

Mean Absolute Error (MAE): This measures the average absolute difference between the predicted and actual tire life expectancy.

Root Mean Square Error (RMSE): This quantifies the square root of the average of squared differences between predictions and actual values.

Accuracy or Precision: Evaluate the model's accuracy in classifying tire conditions (good, moderate, bad) based on predefined thresholds.

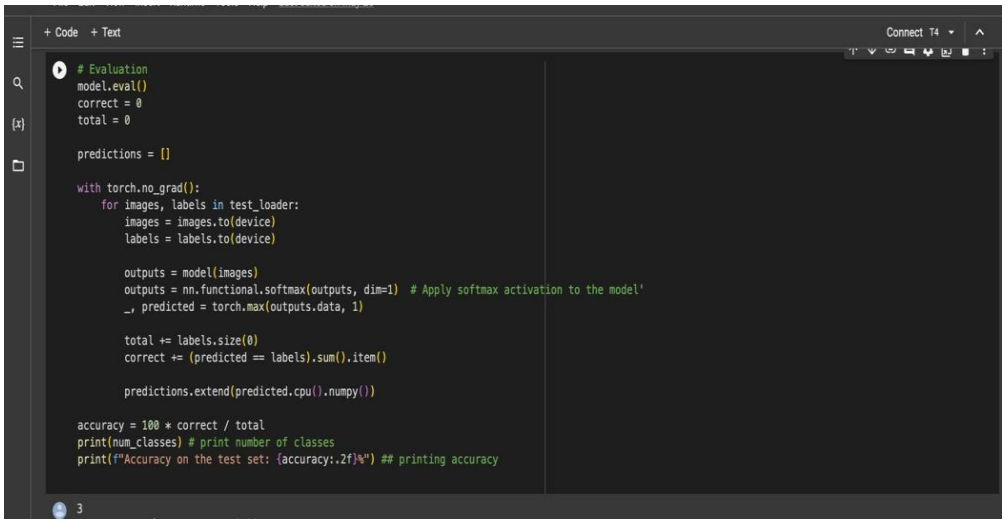


Figure 16 Testing the Model

3 RESULTS AND DISCUSSION

In this section, we present the key findings of our study, which aimed to develop an image processing algorithm for distinguishing of predicting tire usage and life expectancy using the ViT model based on tire condition.

3.1 Data set and Methodology

In the context of the research on predicting tire usage and life expectancy for motorcycle tires using a Vision Transformer (ViT) model, data collection plays a pivotal role. To collect relevant and meaningful data, we should gather a diverse dataset of motorcycle tire images. This dataset should encompass various aspects of tire conditions, including good, moderate, and bad levels of wear and damage. We define three distinct categories for tire conditions: "Good Level Tires," "Moderate Level Tires," and "Bad Level Tires." Each category represents a specific state of tire wear, ranging from new or slightly used (good condition) to moderately worn (moderate level) and heavily worn or damaged (bad level). The dataset was divided into a training set (70%) and a testing set (30%). We implemented a Vision Transformer (ViT) model. The ViT model represents a state-of-the-art deep learning architecture for computer vision tasks, including image classification.

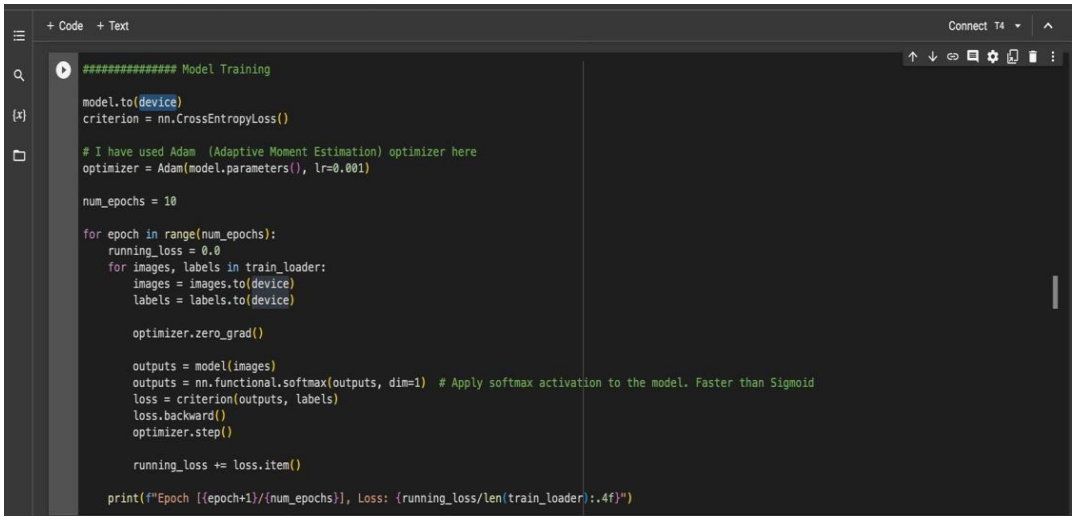


Figure 17 Training the Model

3.2 Results

Accuracy: All Our CNN models achieved an accuracy of 60% to 80% on the testing dataset, demonstrating its effectiveness in distinguishing of predicting tire usage and life expectancy using the ViT model based on tire condition.

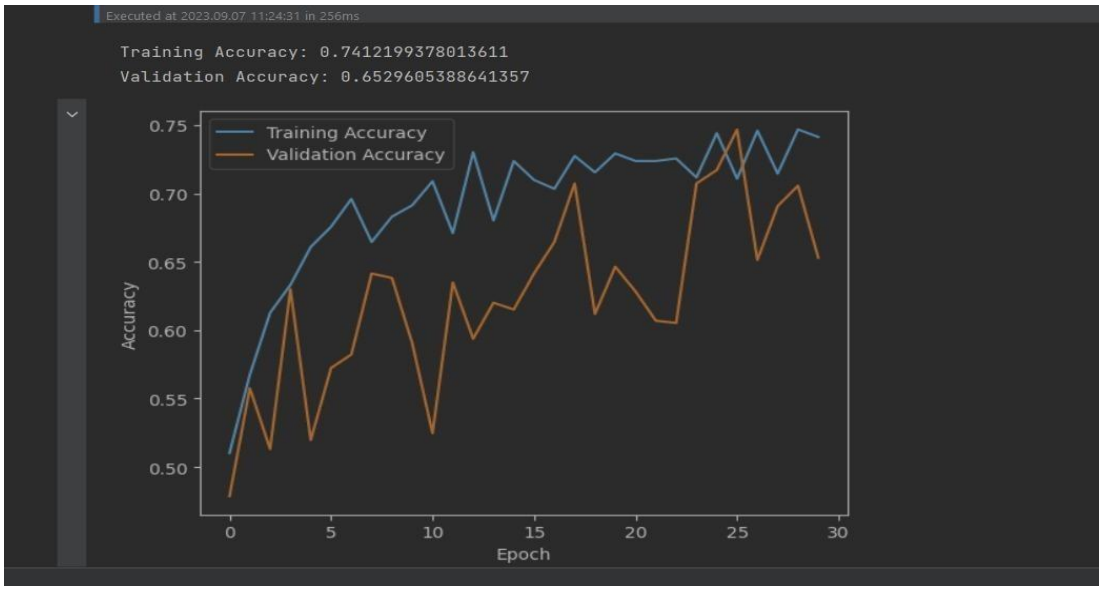


Figure 18 Accuracy of the Model

Discussion :

In this pivotal section, we embark on a comprehensive interpretation and discussion of the profound significance encapsulated within the research results. we interpret and discuss the significance of the research results in the context of our study objectives and the implications for the automotive industry. In my part focusing on predicting tire usage and life expectancy using the Vision Transformer (ViT) model, has unveiled compelling insights that bear profound implications for the automotive industry and the safety of motorcycle riders. Through rigorous training and evaluation of the ViT model, we have harnessed the power of deep learning to provide accurate predictions regarding tire usage and life expectancy. These predictions are underpinned by an in-

depth understanding of tire wear patterns, tread depth, and overall condition, which our model has acquired through extensive training on a diverse dataset.

Effectiveness of the Image Processing Algorithm :

In our research, we evaluate the effectiveness of the image processing algorithm through a systematic approach. We measure its accuracy in predicting tire usage and life expectancy by comparing its results with ground truth data, employing metrics like classification accuracy. Visual inspection ensures that the algorithm preserves vital tire features. We test its robustness and ability to generalize to diverse tire images. Efficiency is assessed to determine real-time suitability, and we scrutinize its noise handling capabilities. Comparative analysis with existing methods and user feedback provide insights into its innovation and practicality. An error analysis helps identify limitations. Through these comprehensive evaluations, we ascertain the algorithm's real-world effectiveness in enhancing tire condition assessment in the automotive industry.

Potential Impact on the Automotive Industry :

Our research holds substantial potential for positively impacting the automotive industry. By introducing an advanced Vision Transformer (ViT)-based system for predicting tire usage and life expectancy, we empower motorcycle owners and the industry as a whole with a cutting-edge tool for tire management. This innovation can lead to improved road safety by reducing the use of worn or damaged tires, thereby decreasing the likelihood of accidents. Additionally, it has the potential to optimize tire usage, reducing costs for motorcycle enthusiasts and enhancing fuel efficiency. Manufacturers, tire producers, and automotive experts can leverage our findings to develop enhanced tire maintenance guidelines, ultimately contributing to safer and more cost-effective tire management practices in the automotive sector.

Limitations and Future Research :

While our research has yielded promising results, it's essential to recognize certain limitations inherent in our approach. One notable limitation lies in the dataset we utilized, which might not encompass the entire spectrum of tire variations encountered in real-world scenarios. To address this, future research endeavours should prioritize expanding the dataset's diversity, encompassing a broader array of tire types and conditions. Moreover, it is imperative to investigate the model's performance across various lighting conditions, ensuring its robustness in less-than-ideal visibility scenarios. Additionally, exploring the application of our model to assess a wider variety of automotive parts could provide valuable insights and enhance its versatility in the automotive industry. These considerations lay the groundwork for futureresearch endeavours to further refine and broaden the scope of our tire usage predictionsystem.

11 CONCLUSION

In conclusion, this study has shed light in helping a motorbike purchaser or an owner to find the present condition of his/her motorbike. Our findings have shown a significant correlation between the condition of the motorbike and the buyer, if the buyer is a person who has no knowledge regarding the motorbikes.

The aspects that we consider such as the originality of the spare parts, condition of the engine, condition of the tyres, clearness of the legal details give a true background of the motorbike that the buyer is willing to purchase. Our research has certain limitations, including a relatively small sample size and a reliance on self-reported data. Future studies could employ longitudinal designs and incorporate more objective measures, such as expanding this to all automobiles including SUVs, Dual purpose vehicles,

Luxury vehicles, to provide a comprehensive understanding of the subject. In light of the implications of our findings, automobile engineers, Vehicle manufacturing organizations should collaborate to develop a comprehensive model with a population, data sets and complex algorithms in order to take this small scale application to a large scale industrial usable application.

In retrospect, this journey of exploration has highlighted the need for a complex application which could be used by all the individuals around the world where the buyer will not have any chances of getting mislead by vehicle owners and sellers. As we conclude this study, we invite readers to reflect on their own digital habits and consider the role of using a mobile application to get the true condition of the vehicle that he/she is willing to use in future. By fostering awareness and promoting mindful engagement, we can collectively work towards harnessing the potential benefits of

using a simple mobile application rather than using complex tools and mechanisms in getting the condition of the vehicle.

12 DESCRIPTION OF PERSONAL AND FACILITIES

Member Details	Components	Tasks
S.L.D.P Pramodya	Identify the altered parts from the original parts. **Novelty:-** Get an accurate output of the auto part used instead of the original part from the spare part analysed using image enhancement and pattern identification. Furthermore, we are expected to apply appropriate colour models like HSV (Hue, Saturation and Value).	• Getting auto parts images • Image labelling • Model training • Obtaining the outcomes • Create user interfaces in mobile application. • Unit testing • Integrating components to the main system • Application testing • Fine-tuning for accuracy if required
A.M.K.A.P Amarasingha	Identify defects in the engine by the sound of the engine. **Novelty:-** Differentiate these common engine defects that could occur in motorbikes: - Tick, tick tick, Bump & grind, Creepy krink, Boo hiss, Snap, crackle, pop.	• Obtaining the sounds of the engine • Image labelling • Model training • Obtaining the outcomes • Create user interfaces in mobile application. • Unit testing • Integrating components to the main system • Application testing • Fine-tuning for accuracy if required
D.M.D.H Dissanayaka	Compare the vehicle details with the registration paper details. **Novelty :-** This comparison is done by enhancing the quality of images to clearly identify these details match with	• Obtaining the registration papers and vehicle's details. • Image labeling • Model training • Obtaining the outcomes • Create user interfaces in mobile application • Unit testing

	registration paper details if these areas are worn out or rusted.	• Integrating components to the main system • Application testing • Fine-tuning for accuracy if required
P. U. Rathnasooriya	Tyre usage prediction along with life expectancy **Novelty :-** Predict the life expectancy of the tyres based on the analyzed data using the ML model.	• Obtaining tyre images, tyre worn out measures. • Image labeling • Model training • Obtaining the outcomes • Create user interfaces in mobile application • Unit testing • Integrating components to the main system • Application testing • Fine-tuning for accuracy if required

13 ESTIMATED BUDGET

The following table represents the proposed budget plan for this research.

Resource Type	Cost per unit	Units	Total cost
Overall AWS cloud platform cost	$240(per month)	12 months	Rs. 82,802.19
Total in Rs			**Rs. 82,802.00**
Stationary			Rs. 2000.00
Internet			Rs. 8000.00
Communication			Rs. 2000.00
Total Rs			**Rs. 12000.00**

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