

# **AI-POWERED SOLUTIONS FOR BREAKDOWN CHALLENGES WITH ELECTRIC VEHICLES**

## **EV SPARE PARTS SHOP FINDING SERVICE**

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Final Report

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## Declaration page of the candidates & supervisor

I declare that this is my 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.

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## **Abstract**

Certain regions, including Sri Lanka, have challenges in the rapidly developing field of electric vehicles (EVs), such as low levels of knowledge, a dearth of trained technicians, and a scarcity of replacement parts. The problems caused by electric car failures have never been addressed in such a groundbreaking way as this grant application proposes. Introducing our cutting-edge conversational AI chatbot, built specifically to assist with automobile breakdowns. By bridging information gaps and giving drivers with up-to-date, accurate information on electric car difficulties, the chatbot improves their decision-making. Continuous updates ensure relevance for diverse electric vehicle types, while a powerful AI model uses carefully selected datasets to extensively investigate breakdown scenarios and propose unique solutions. The primary goal is to increase operational efficiency and driver safety on the road by offering complete support in quickly identifying and fixing breakdown issues. Research on the development of personalized chatbots for electric cars (EVs) is emphasized in this proposal. Unlike existing solutions, these chatbots would zero in on specific breakdown scenarios. For up-to-date electric vehicle (EV) models to receive precise assistance, real-time data integration is essential. Complex defect detection and personalized suggestions necessitate state-of-the-art AI algorithms. To ensure a seamless user experience and natural language processing, more research is required. Furthermore, in critical situations, it is essential to create chatbots that can seamlessly link with emergency services in order to offer quick assistance. The overarching goal of this study is to change the way electric vehicle (EV) owners handle breakdowns by offering them a revolutionary, cost-effective, and individualized solution. A future of environmentally friendly transportation will be easier to implement with this.

**Keywords:** Electric Vehicles (EVs), AI, AI Chatbot

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## List of Abbreviations

Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
EV	Electric Vehicle
AML	Auto Machine Learning
CNN	Convolutional Neural Network
ICE	Internal Combustion Engines
SDLC	Software Development Life Cycle
WBS	Work Breakdown Structure

# **1. Introduction**

## **1.1 Background & Literature survey**

A new age of environmentally friendly transportation is dawning with the advent of electric cars, which hold great promise for a dramatic decline in pollution levels and reliance on fossil fuels. Electric cars get their power from rechargeable batteries rather than the burning of gasoline, as is the case with conventional ICE vehicles. Less pollution, less running expenses, quieter operation, and maybe more energy independence are just a few of the many benefits of this change. Because of their negligible effect on the environment, electric vehicles are quickly replacing internal combustion engine vehicles (ICEs) across the world. Electric vehicles are crucial in reducing the environmental impact of humans since they do not produce pollutants that contaminate the air. They are increasingly attractive as a green transportation choice because of their reduced fuel costs, enhanced energy efficiency, and quieter, more pleasant rides.

The electric car adoption rate is still lower than that of internal combustion engine automobiles, even though these benefits are quite persuasive. In 2020, ICE cars continued to have a disproportionately large market share of 95.4%, as reported by the International Energy Agency (IEA). This trend, however, is anticipated to soon turn around thanks to the ever-increasing availability of charging infrastructure and the perpetual improvement of electric car technology [1].

When it comes to electric cars, one major obstacle is handling breakdowns. There are several potential failure modes for electric automobiles since they use a different set of components and technology than internal combustion engine vehicles. Electric motor, power electronics, software, and battery system concerns (charging problems, capacity degradation, etc.) are common complaints from EV owners. It is becoming more and more important to handle breakdown management properly as electric vehicle technology advances, taking into account the specific components and intricacies of each electric vehicle.

It might be challenging for drivers of electric cars to get their problems diagnosed, get help quickly, and find qualified technicians when their vehicles break down. Technicians and drivers usually have a lot of expertise with internal combustion engine (ICE) cars, but electric vehicle (EV) diagnostics and repairs might be trickier because of the complicated technology involved. The intricacy of the problem makes it more difficult to fix and causes downtimes to last longer. Adding insult to injury, electric vehicle owners face an even greater challenge in the case of a breakdown due to the dearth of repair shops and specialists trained in electric vehicle maintenance.

The advanced driver-assistance systems (ADAS) of electric vehicles, which are equipped with artificial intelligence, improve the vehicles' safety and autonomy. Artificial intelligence serves as the foundation for a wide range of driver safety technologies, including adaptive cruise control, lane keeping, and automated emergency braking. Artificial intelligence is relied on substantially in the research and development of electric vehicles [2].

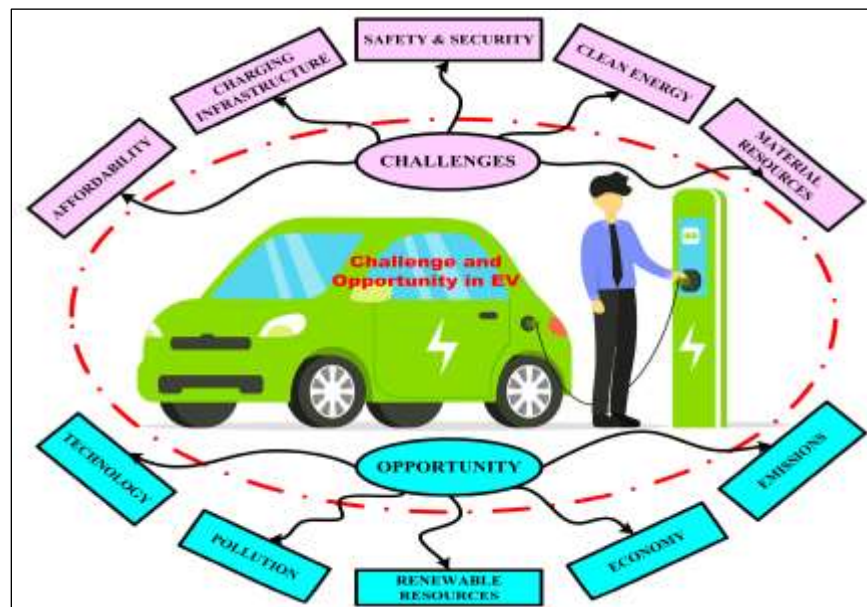


Figure 1 : EV Technology.

With the use of artificial intelligence (AI) and image processing techniques, there has been a huge improvement in the field of automotive technology. These approaches are designed to aid car owners in selecting suitable replacement components for their vehicles. Following this, the following part will provide an overview of the relevant background material as well as the existing literature that is linked with the proposed solution. Image-based auto parts catalogues, object detection and localization, location-based services and mapping, and artificial intelligence-powered spare part identification are some of the areas that were investigated in this research. Other areas that were investigated include image-based auto parts catalogues, spare parts management and e-commerce, and image-based auto parts catalogues.

The utilization of artificial intelligence and image processing for the aim of locating spare parts has become increasingly common over the course of the past several years. Specifically, deep learning models such as Convolutional Neural Networks (CNNs) have been shown to give outstanding capabilities when it comes to photo recognition tasks. It has been shown that machine learning techniques offer remarkable capabilities. In order to recognize a wide variety of things, including spare parts, in images, researchers have utilized image recognition algorithms.

These algorithms have been used to identify objects. One of the methods that enables models that have been pre-trained on enormous datasets to be fine-tuned for specific goals, such as recognizing automobile components, is transfer learning. This methodology is one of the ways that provides this capability. Artificial intelligence (AI) has been made available to the e-commerce sector with the intention of enhancing the overall quality of the shopping experience [3].

In order to provide customers with aid in locating products based on photographs, image recognition capabilities are being integrated into online marketplaces and e-commerce platforms. It is feasible to extend this idea to spare parts, where users might upload photographs of broken parts, and AI-driven systems could match those images with spare parts that are accessible in a number of online shops. This would be a potential expansion of the concept. Both and Investigations towards the creation of image-based catalogues for automobile components have been carried out by a number of companies and



academics who specialize in scientific research. These catalogues contain not only graphical representations of the components, but also information that is essential to the components, such as part numbers, dimensions, and compatibility guidelines.

Through the process of comparing images of their broken components with those currently stored in the database, users are able to identify and order the right parts. The application of artificial intelligence and picture recognition has made this a feasible possibility. When it comes to the process of identifying and locating things within images, object identification and localization algorithms, which are a subfield of computer vision, play a significant role in the process. The utilization of these methodologies makes it possible to identify and localize the various components of a vehicle, which in turn assists in the accurate identification of the replacement parts that are required during the maintenance process. Consumers are not only able to identify the relevant component when location-based services are integrated with spare part identification, but they are also able to locate nearby stores that carry the component in question. This is a significant advantage. An investigation into the seamless integration of mapping and geolocation with online platforms is the focus of the research that is now being carried out in this department.

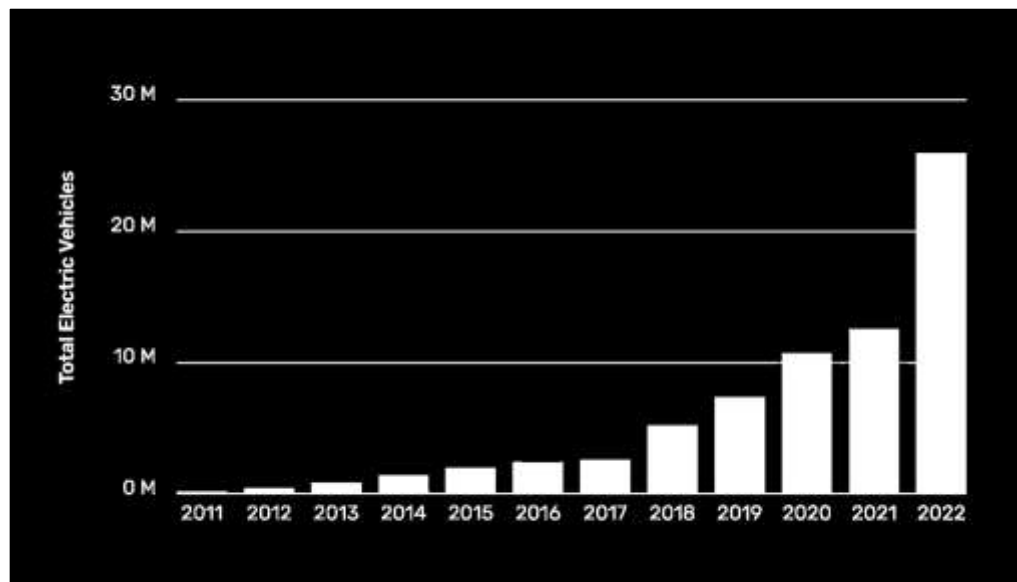


Figure 2 : Global electric vehicles are reaching 30 million units by 2025 at the current growth rate.

During this period of transition towards a more ecologically friendly future, electric vehicles, sometimes referred to as EVs, have emerged as a major example of environmentally responsible mobility. Although electric cars have a good influence on the environment, they also present a number of unique challenges, notably with regard to the availability of spare parts and service. Despite this, electric vehicles are becoming increasingly popular. In an effort to tackle these breakdown problems head-on, solutions that are powered by artificial intelligence have emerged as a reaction.

In the first place, the transition to electric cars has caused a paradigm shift in the automotive sector. This transformation has been brought about by the automobile industry. Traditional automobiles that are powered by internal combustion engines and electric vehicles are extremely different from one another in terms of their design and the components that make up their construction. It is essential to have access to specialist spare parts and services in order to perform maintenance and repairs on electric cars in an appropriate manner. On the other hand, there is a possibility that the availability of such components would be limited, which will be a significant challenge for owners of electric vehicles who are having issues.

In the second place, the complex nature of the technology behind electric vehicles necessitates the development of highly developed diagnostic and maintenance abilities. In contrast to traditional autos, electric vehicles are made up of intricate electrical systems and components. As a result, the diagnosis and repair of electric vehicles require the application of specialist expertise. When it comes to this matter, solutions that are driven by artificial intelligence provide a savior. Machine learning algorithms are utilized by these solutions in order to evaluate diagnostic data and precisely detect faults. As a result, the process of carrying out repairs has sped up. Lastly, owners of electric cars have still another challenge in the form of the geographical dispersion of stores that sell replacement components for electric vehicles. In contrast to traditional car parts stores, which may be found in plenty in many places, shops that are specifically devoted to electric vehicles may be difficult to locate, particularly in regions that are more rural or less developed. This might make it difficult for owners of electric vehicles to locate essential spare parts in a timely way, which could be a result of the situation [4].

In response to the problems that have been brought up, artificial intelligence-driven solutions have emerged for the purpose of locating stores that sell replacement parts for electric vehicles. Utilizing artificial intelligence algorithms to assess data such as geographical location, inventory availability, and user preferences, the purpose of these solutions is to provide personalized suggestions to owners of electric vehicles who are in need of replacement parts. This is accomplished by delivering recommendations to owners of electric vehicles. The process of discovering local retailers that sell replacement parts for electric vehicles has been simplified as a consequence of these solutions, which has resulted in a reduction in the amount of downtime that owners of electric vehicles suffer.

Additionally, in addition to the straightforward work of obtaining replacement components, AI-powered systems make available a number of other advantages. Their ability to give real-time information on the availability of inventory, price, and promotions helps owners of electric cars to make informed decisions regarding the acquisition of replacement parts. This is made possible by the fact that they are able to deliver these updates. Additionally, these solutions have the capacity to provide a smooth communication channel between owners of electric cars and spare parts stores, which has the potential to facilitate the placing and fulfilling of orders in a more expedient manner.

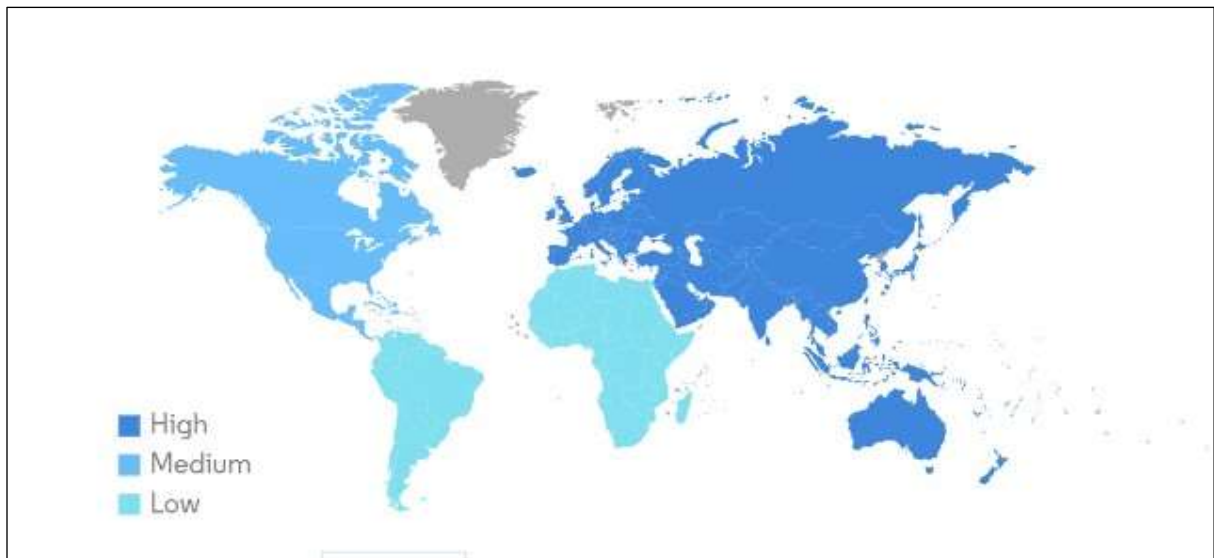


Figure 3 : EV parts and component market. Growth rate 2022-2028

In conclusion, as the number of electric cars that are being driven on our roads continues to expand, there is an increasing need for effective solutions to tackle the challenges that arise from breakdowns. This is becoming an increasingly critical requirement. In the context of this attempt, the development of AI-powered systems for the purpose of locating stores that sell replacement parts for electric vehicles represents a significant step forward. In the event of an emergency, these methods provide owners of electric vehicles a chance to save their lives. These solutions not only simplify the process of procuring replacement parts, but they also empower owners of electric vehicles by giving them essential insights and assistance throughout the process of repairing their vehicles. Through the utilization of the powers of artificial intelligence, this is made feasible [5].

## 1.2 Research Gap

Currently, there is no artificial intelligence (AI) solution that can accurately recognize and map the necessary spare components for repairing automobiles using image processing and machine learning models. There are image recognition models capable of identifying generic spare parts, but they are not specifically designed to handle electric vehicle spare parts or accurately determine which components are needed for specific breakdowns. Furthermore, there is a scarcity of research that endeavors to chart the locations of neighboring retailers that provide replacement components.

In order to assist individuals, it is imperative to develop an artificial intelligence-driven system that can efficiently locate and accurately identify all the necessary components for electric automobiles. The concept of employing machine learning and image processing to monitor the real-time status of replacement components is innovative and captivating. However, there are other areas of knowledge that might be addressed to further enhance its effectiveness.

The paper named "A" ImageNet Classification with Deep Convolutional Neural Networks is crucial in the field of computer vision and deep learning. This groundbreaking paper introduces Alex Net, a unique architecture that revolutionized picture categorization tasks. In order to address the limitations of traditional methods, the researchers proposed a deep convolutional neural network (CNN) that has the ability to independently acquire intricate features from raw image input. The model successfully captured complex patterns, textures, and object components because to its design consisting of five convolutional layers followed by three fully connected layers, resulting in a significant increase in depth.

The use of novel techniques like data augmentation and dropout, together with Rectified Linear Units (ReLU) as activation functions, enhanced the efficiency and generalizability of the model. The paper's involvement in the ImageNet Large Scale Visual Recognition Challenge showcased its exceptional performance by achieving a significantly reduced error rate compared to earlier methods. This research will be renowned for its substantial contribution to the resurgence of neural networks and the foundational work it established for the profound transformation in deep learning, which has greatly impacted several domains of artificial intelligence. The fundamental topic of feature extraction in the field of image processing is investigated in the research paper named "B" Feature Extraction & Image Processing 2014, which was published in November of 2014. Through the process of extracting key qualities from raw picture data, the research

highlights the significance of feature extraction as a means of enhancing various image analysis tasks. The article presents a comprehensive study of a number of strategies for the extraction of features. These techniques range from the most fundamental approaches, which are based on intensity, to the more advanced techniques, which include edge detection, texture analysis, and form descriptors. The findings of this study demonstrate how important it is to select appropriate features that correctly reflect the distinctive characteristics of objects or patterns in images. In addition to this, it investigates the application of feature extraction in a variety of domains, including the identification of objects, the segmentation of pictures, and the retrieval of content-based images. In a nutshell, the findings of the study highlight the significance of feature extraction in terms of enhancing the quality and effectiveness of image analysis. Consequently, this makes it possible for practitioners and academics to comprehend image data in a more efficient manner and to use it in a variety of applications.

The research project named "An image-based auto parts catalogue" introduces an innovative approach to streamline the process of identifying and selecting vehicle components by using images. By primarily including photographs of vehicle components, the research effectively addresses the limitations of traditional text-based catalogues. Each picture is linked to essential data, including part numbers, measurements, and other compatibility information. The objective of this attempt is to enhance usability and accessibility, enabling anyone with less technical knowledge to easily and instinctively recognize and choose the suitable automotive components. Users can expedite the identification process by comparing damaged or required components with catalogue photos, facilitated by the concept of visual matching. Furthermore, the essay includes an analysis of the technological aspects associated with the development of such a system. The elements included are database architecture, photo storage, and user interfaces. The newly created visual library has the capacity to completely transform the procedure of recognizing automobile parts. By offering a more visually appealing and user-friendly method for choosing components, it will offer advantages to technicians, car owners, and suppliers.

Features	Research A	Research B	Research C	Proposed System
Spare Parts Identification	X	X	X	✓
Usage of image processing	X	✓	✓	✓
Spare parts Identification	✓	✓	✓	✓
Representative datasets	X	✓	✓	✓
Noise sensitivity	X	✓	X	✓
Using of auto machine Learning	X	X	X	✓ ✓
Technology Used	CNNs/ReLU	FET/ IP	IP Algorithms/DB Design	CNN/SVM

Figure 4 : Research Gap

### 1.3 Research Problem

Individuals all around the world benefit from the remarkable mobility and ease that the automobile industry offers, making it an essential component of contemporary civilization. Nevertheless, despite the fact that automobiles provide a wealth of conveniences, car breakdowns continue to be an unavoidable obstacle that vehicle owners frequently encounter, which can result in feelings of irritation, stress, and financial repercussions. The conventional model of car help has to undergo a paradigm change in order to address this issue. The focus should be on overcoming the challenges connected with locating acceptable replacement parts and gaining access to trustworthy repair choices in a timely way while maintaining a user-friendly interface.

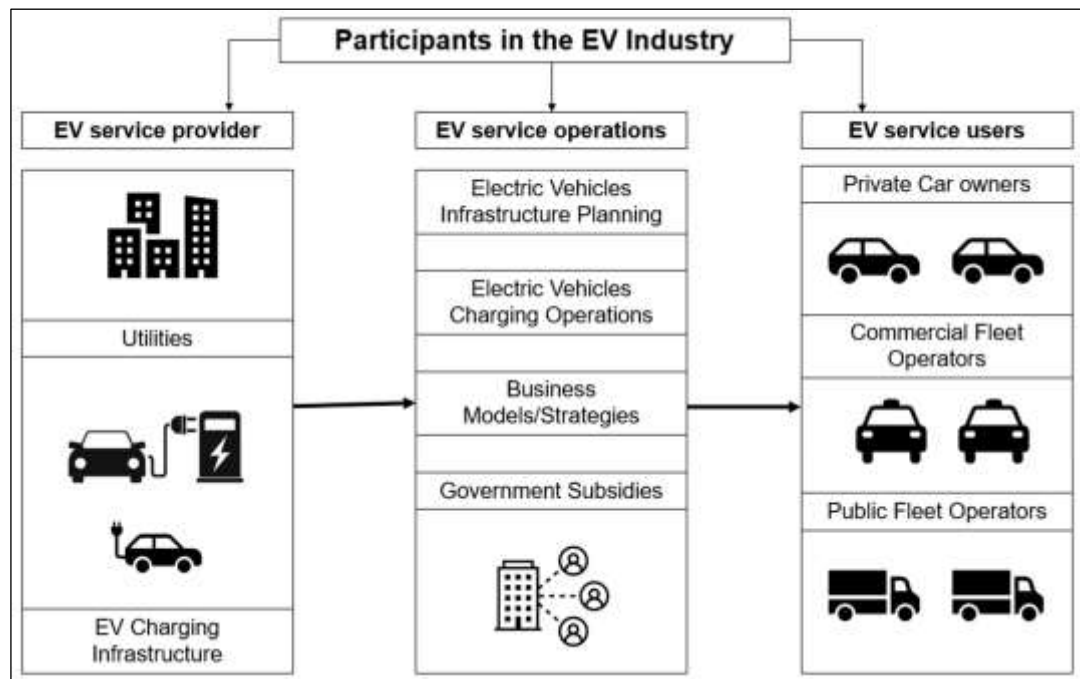


Figure 5 : EV's Participant

The subject of the study is comprised of a number of essential components that require careful consideration. In the first place, it is essential for efficient repairs to begin with the precise identification of broken spare components.



It is possible that conventional procedures that rely on the knowledge of the car owner or the experience of technicians are prone to mistakes, which can result in faulty repairs, increased charges, and longer downtime. Therefore, there is an urgent need for creative solutions that are capable of accurately locating the defective components, which will ensure that repairs are carried out in an efficient and cost-effective manner.

Additionally, difficulties in sourcing provide a substantial impediment for owners of vehicles who are looking for repair services or maintenance. The task of locating dependable repair companies that are stocked with the appropriate replacement components can be challenging, particularly for those who are stuck in unfamiliar regions. When automobile owners do not have access to adequate information, they run the risk of encountering technicians who lack suitable training or service providers who are questionable, which can make the problem much worse and potentially compromise the integrity of the repairs.

In addition, a sizeable proportion of people who own automobiles have a limited awareness of the complicated components that make up their cars and the compatibility of replacement parts. It is possible that their lack of information may impair their capacity to make educated judgements when they are confronted with a breakdown, which will result in choices that are less than optimum and further issues.

Last but not least, in order to minimize disturbances to their daily routines, owners of vehicles demand rapid remedies in the event that their vehicles break down. Failure to discover spare components and investigate repair possibilities for an extended period of time can result in feelings of irritation and discomfort, highlighting the need of having help systems that are both prompt and effective.

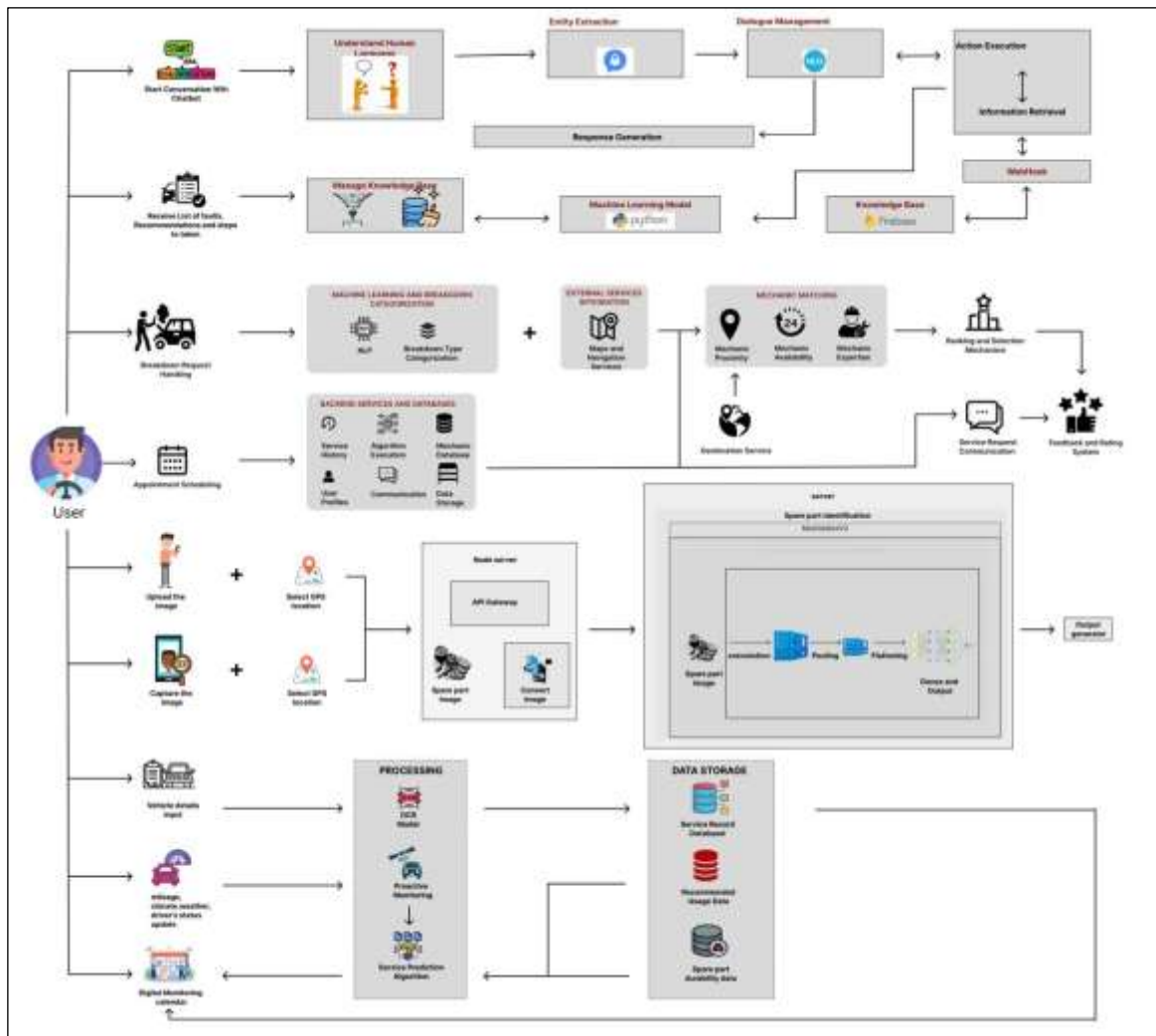


Figure 6 : Overall System diagram

Traditional troubleshooting services may be beneficial in the short term when it comes to electric cars (EVs), but they generally lack the in-depth experience and context that is required to identify and repair the underlying issues related to EVs. The fact that electric motors, battery management systems, and power electronics of varied degrees of complexity are all components of electric vehicle (EV) technology makes this component relatively difficult to implement. It is further exacerbated by the fact that electric vehicle failures can present a broad variety of symptoms, including mechanical and software faults. This makes the creation of comprehensive and trustworthy chatbot solutions much more difficult. The first obstacle that must be overcome in this sector is the development of intelligent chatbot systems that are capable of precisely identifying problems with electric vehicles (EVs), providing individually tailored solutions, and offering quick customer care.

During the course of the conversation, the topic "AI-Powered Solutions for Breakdown Challenges with Electric Vehicles - Enhancing User Experience in Vehicle Maintenance with a Smart Digital Monitoring Calendar and Reminder System" was brought up. This topic highlights the importance of developing innovative strategies to address these problems. The use of artificial intelligence-driven technologies and intelligent digital monitoring systems presents a significant potential for the automotive industry to alter the way in which automobile assistance is provided. These technologies offer a number of advantages, including the ability to accurately identify parts, simplify the process of problem-solving, and improve comprehension of the requirements for vehicle maintenance. Additionally, they enhance the delivery of prompt and individualized service, which not only enhances the entire customer experience but also decreases the impact that automotive breakdowns have on the lives of consumers.

In conclusion, in order to revolutionize the traditional model of auto help, it is necessary to solve the obstacles that are related with the identification of replacement parts accurately, difficulty in finding them, limited understanding of vehicles, and the provision of fast assistance. The automotive sector has the ability to improve the entire customer experience and reduce the impact that automobile breakdowns have on consumers' lives by utilizing cutting-edge technology and streamlining operations. Some examples of these technologies and processes include extensive databases and solutions powered by artificial intelligence.

## **2.Objective**

### **2.1 Main Objectives**

The major objective of this project is to create and implement a cutting-edge image processing system that uses machine learning methods for the real-time detection and procurement of auto components. The goal of this solution is to meet the demands of car owners by providing them with easy and accurate access to vital information about the availability of suitable replacement parts, businesses in the area, and how to record and analyses photographs.

When taken as a whole, the image processing method that has been provided is an innovative way to tackle the issues that are connected with locating and acquiring car replacement parts. The system intends to revolutionize the way in which vehicle owners' access and acquire replacement components by utilizing the power of machine learning and image analysis technologies. This will ultimately result in the repair process being streamlined and the overall user experience in the automotive sector being improved.

### **2.2 Specific Objectives**

- Starting with simple items like nuts and bolts and progressing to more intricate ones like engine parts, the initial step is to gather photographs of these spare parts. After that, each image is labelled precisely to indicate which spare part category or kind it belongs to.
- Training the machine learning model effectively relies on this labelling procedure, which gives unambiguous instructions on what the network should learn to recognize.
- Next, we go on to pre-processing, which follows picture gathering and labelling. To achieve uniformity and best performance during training, this includes actions like scaling photos to a consistent size and normalizing pixel values. Pre-processing improves the model's capacity to discover useful patterns from input while

simultaneously decreasing computing complexity.

- Training, validation, and testing sets of data are created when pre-processing is finished. The model is trained to identify patterns in the photos using the training set, and its parameters are fine-tuned, and its performance is monitored using the validation set. The training model does not view the testing set; it is used to assess the trained model's accuracy and performance after training.
- Training a machine learning model with the pre-processed picture data is the next step after data preparation and splitting. Because of their efficacy at learning hierarchical features from visual input, techniques like convolutional neural networks (CNNs) are extensively used for image recognition tasks. The algorithm learns to correlate visual patterns with related spare components iteratively from the labelled photos.
- The validation set is periodically evaluated while the model is being trained in order to find improvement areas. By repeatedly training and evaluating the model, its architecture or parameters may be fine-tuned to improve its accuracy and generalizability.
- At the same time, we're working to gather and evaluate massive amounts of visual data from a variety of sources, such as retail stores and catalogues of replacement parts. The model's comprehension of spare component forms and variances is enhanced by this extra data, which further improves its accuracy and resilience.
- Following the model's fine-tuning in response to assessment findings, it is subjected to exhaustive testing on the reserved testing set in order to determine its ultimate robustness and correctness. By simulating actual conditions, this testing step verifies the model's functionality and makes sure it's ready for deployment.

- The last step is to incorporate the trained and verified model into a functional software application. In the context of vehicle maintenance and repair, this program acts as an intuitive interface that allows users to submit pictures of broken parts; the model then correctly identifies those parts and suggests appropriate replacements, allowing for more effective repair operations.

### 3. Methodology

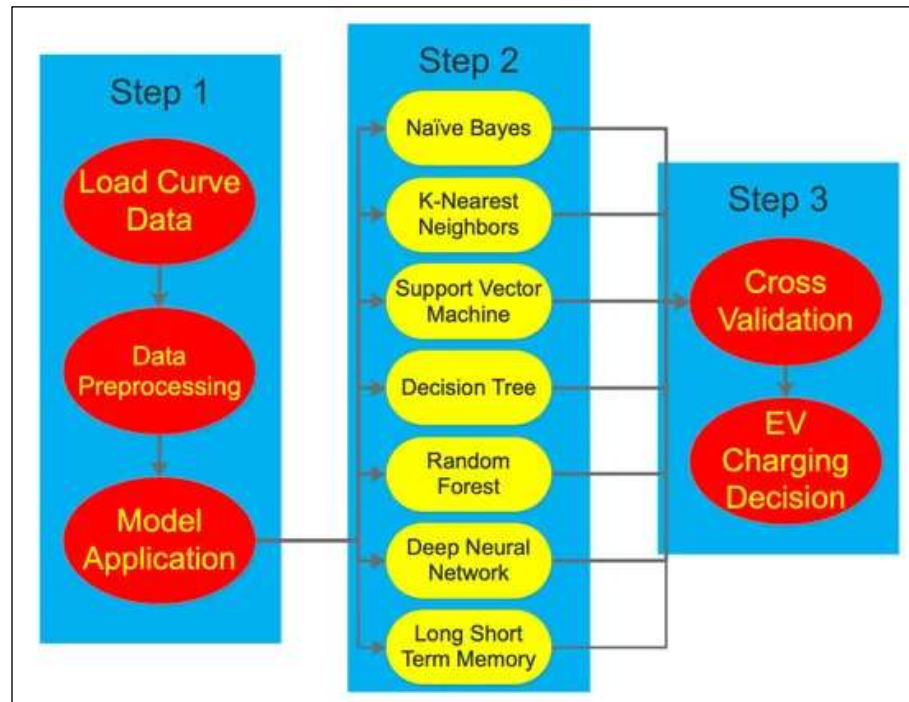


Figure 7 : Sequential diagram.

Improving the accuracy and efficiency of inventory and spare parts management may be achieved by using machine learning models. Acquiring a massive database of labelled images of replacement components, spanning many kinds and conditions, is the initial stage. You are free to use this dataset to teach a computer to properly classify and organize spare parts. Careful labelling and curation of datasets is necessary since dataset quality and diversity determine the model's performance. Every image must faithfully represent a distinct replacement component for the model to be able to distinguish between them. Additionally, the dataset should contain a range of lighting, angles, and backdrops to make the trained model more robust and generalizable [6].

After the dataset is assembled, preparation procedures are applied to prepare the data for training. Images must be squared or otherwise scaled to a standard size before they may be used with machine learning techniques. Every picture is pixel-normalized to make the model's feature extraction even better and to reduce the impact of illumination variations. To further assess the model on fresh data and lessen the likelihood of overfitting, the dataset is split into training and

validation sets. The dataset is optimized for training models by thorough preprocessing, which prepares it for feature extraction and classification.

- Building a database with images of spare parts

Creating a tagged picture dataset is the first step in creating a machine learning model for the classification of spare parts. There should be a large variety of classified spare parts in this collection. The dataset needs to be varied in order for the model to be robust and effective in generalizing. This includes a diversity of backdrops, lighting conditions, and angles. A big dataset is necessary to train a reliable model since it helps the algorithm to quickly comprehend the intricate patterns and traits connected to different replacement parts.

- Preparing the data:

The dataset must undergo preprocessing in order to be fed into the machine learning model. These processes often entail scaling the images to a uniform size, normalizing the pixel values to a standard range, and splitting the dataset into training and validation sets. To ensure optimal performance of machine learning algorithms, it is important to resize the photographs to a consistent size. Pixel value normalization aids in both achieving uniformity and mitigating the effects of varying illumination conditions. Lastly, by splitting the dataset into a training set and a validation set, it is able to assess the model's performance on unknown data without risking overfitting.

- Feature extraction:

The original visual data is condensed into a more manageable format while preserving all significant patterns and qualities during the feature extraction process. Among alternative techniques for feature extraction are the Histogram of Oriented Gradients (HOG), Scale Invariant Feature Transform (SIFT), and Convolutional Neural Networks (CNNs). HOG and SIFT are two well-known methods that have been used for a long time to extract features from pictures. Convolutional neural networks (CNNs), on the other hand, are excellent at classifying images as they are deep learning models that can automatically extract hierarchical features from unprocessed pixel input.



- Training machine learning models:

The machine learning model has to have its features extracted from the photographs before it can be trained. Support vector machines (SVMs), random forests, decision trees, neural networks, and random forests are just a few of the techniques that are often used for classification tasks. A few factors that affect technique choice are problem complexity, dataset size, and computing resources available. Neural networks, and deep learning architectures in particular, have demonstrated remarkable success in photo categorization difficulties due to their ability to learn complex patterns from sparse inputs.

- Evaluation and Testing:

After the model has been trained, it is essential to evaluate its performance using a specific dataset. It is customary to use assessment metrics like recall, accuracy, precision, and F1 score to gauge the model's effectiveness. Precision and recall show how effectively the model can detect and account for positive cases, respectively, whilst accuracy assesses how well predictions withstand inspection. The F1 score, which is determined as the harmonic mean of recall and accuracy, provides a comprehensive assessment of the model's performance.

- Putting the system into operation:

After the model has been satisfactorily trained and evaluated, it may be made available to users. When a trained model is complete, it may be integrated into a platform or application that uses photos of replacement parts as input data and employs real-time classifications or predictions. Depending on the deployment scenario, considerations like scalability, latency, and resource constraints must be made to ensure the system functions properly and effectively. Continuous monitoring and maintenance are necessary to address any issues that may arise following deployment, such as a decline in performance.

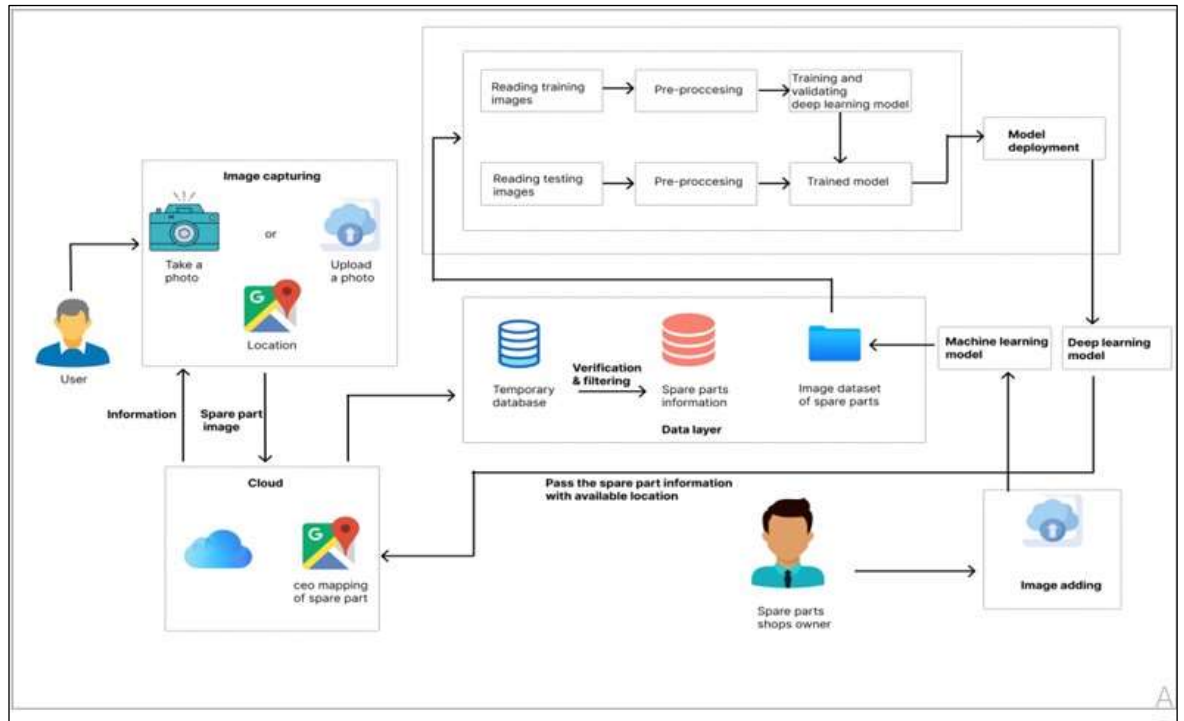


Figure 8 : System diagram.

In order to facilitate the identification and validation of spare components, the system that has been recommended provides clients with an interface that is simple to operate and allows them to connect with a machine learning model. By employing this technology, users are able to upload images or shoot pictures with their cellphones in real time. After that, these photographs, which depict a variety of spare components, are sent to a cloud-based storage system so that they may be processed centrally. Additionally, the current location of the user is gathered at the same time, which provides additional contextual information that might potentially make the identification process easier. It is possible for users to enquire about the suitability of a spare component in a certain circumstance thanks to the functionality of the system, which is based on the integration of geographical context and visual data.

When the images that have been uploaded reach the data layer, they are first transferred to a database that is only temporary. Several filters and verification methods are utilized in

this context to ensure that the images maintain their authenticity and may be utilized in the appropriate context. In order to maintain the precision of the data and prevent any erroneous or misleading information from entering the principal functions of the system, it is necessary to complete this step. Following the completion of this preliminary stage of filtering, the photographs are transferred to the database of spare parts information. Once there, they are available for further processing and analysis.

After the photographs have been uploaded, they are subjected to a series of preprocessing processes in order to make them suitable for the deep learning model. Normalizing the pixel values, scaling the photographs to a standard size, and maybe extending the dataset are all potential steps that might be taken as part of this preparation in order to increase the robustness of the model. There is further validation performed on the deep learning model in order to guarantee that it is dependable and efficient in accurately recognizing spare parts from the photographs that are provided. Cross-validation or performance evaluation on a separate validation dataset could be included in this validation approach. This is done so that the generalization capabilities of the model can be verified.

After going through the validation process, the model is now ready to be deployed based on user-uploaded photographs for the purpose of making inferences. Following the receipt of an image query from a user, the trained model performs an analysis of the input, extracts relevant information, and makes predictions regarding the correctness of the illustration of the spare component. Following this, the model will give back the response that it has created, which will be shown on the user interface next to the image that was supplied. This feedback loop provides customers with the opportunity to obtain prompt and precise evaluations of spare parts, which enables them to purchase relevant components with the knowledge they need.

It is also possible for the system to provide additional insights and suggestions based on the location of the user at the moment. Through the utilization of location data, the system is able to make recommendations for nearby repair facilities or vendors who carry the spare component that has been identified. The implementation of location-based services increases the usability of the system by reducing the amount of time that users spend on the

processes of purchasing and maintaining the system.

In conclusion, the solution that has been recommended increases the speed at which spare parts may be identified and validated. This is accomplished by integrating cloud computing, location-based services, and machine learning. Through the capability of submitting photographs and obtaining rapid feedback about the precision of replacement components, the system improves the capacities of decision-making and streamlines the procedures for procurement and maintenance. The system ensures the reliability and precision of its forecasts by employing demanding data management, preprocessing, and model validation procedures. As a result, the system increases user certainty and contentment [7].

.

### 3.1 Model Trained

In order to solve the special issues that are connected with the maintenance and service of electric cars, a substantial progress has been made in the form of the creation of a solution that is based on deep learning and is specifically customized for the identification of vehicle parts of electric vehicles. The model demonstrates a strong performance in successfully recognizing and categorizing a variety of electric car components. This is accomplished by harnessing the power of the Inception **V3 architecture**, which is well-known for its efficiency and accuracy in image recognition tasks. By enabling technicians and service providers to identify problems and carry out any necessary repairs or replacements, this capacity plays a significant role in the process of simplifying maintenance and inspection procedures quickly and precisely [8].

```
[29] img_size = 224
model_1 = Sequential([
    InputLayer(input_shape = (img_size, img_size, 4)),

    Conv2D(filters=8, kernel_size=2, strides=1, padding='valid', activation='relu'),
    BatchNormalization(),
    MaxPool2D(pool_size=2, strides=2),

    Conv2D(filters=16, kernel_size=2, strides=1, padding='valid', activation='relu'),
    BatchNormalization(),
    MaxPool2D(pool_size=2, strides=2),

    Flatten(),

    Dense(128, activation='relu'),
    BatchNormalization(),

    Dense(32, activation='relu'),
    BatchNormalization(),

    Dense(14, activation='softmax'),
])
```

Figure 9 : Deep Learning Model Architecture

Furthermore, the incorporation of AI-powered solutions for the solutions of breakdown problems with electric cars goes beyond the simple identification of spare components. As the number of electric vehicles (EVs) continues to climb, there is a commensurate increase in the need for specialized services, such as the localization of EV spare parts shops. This particular service makes use of the capabilities of the deep learning model that was constructed in order to not only identify the spare parts that are necessary but also to discover local businesses or suppliers that sell the components that have been recognized.

With the integration of AI-driven technology with real-world applications, the increasing demands of the electric car ecosystem can be addressed. This integration also makes it possible for service providers and owners of electric vehicles to have a smooth experience when it comes to purchasing and maintaining their vehicles. The use of the Inception V3 architecture demonstrates a dedication to utilizing cutting-edge technology in order to handle the complexities of electric vehicle maintenance (EV maintenance). The model is able to analyze photos of car parts with exceptional precision thanks to its deep learning skills. It is able to differentiate between various components and precisely identify them. In addition, the model's adaptability makes it possible for it to be suitable for a broad variety of electric vehicle models and configurations, which guarantees that it may be utilized in a variety of different situations and circumstances [9].

For the purpose of boosting maintenance and service procedures in the fast-developing electric vehicle sector, the AI-powered solution for breakdown difficulties with electric cars, which is empowered by the Inception V3 architecture, offers a pioneering approach. The solution helps to the improvement of operational efficiency, the reduction of downtime, and the enhancement of the overall user experience for electric vehicle owners and service providers. It does this by enabling the correct identification of vehicle parts and by making it easier to discover shops that sell spare parts for electric vehicles [10].

```

story_2 = model_1_fit(train_data, validation_data, weights = w0, verbose=1, callbacks=[early_stop_callback])

# 100
100 [=====] - 791 26.57sec - 100% 1.900% - accuracy: 0.3172 - val_loss: 1.7039 - val_accuracy: 0.4000
# 200
200 [=====] - 79 26.58sec - 100% 1.190% - accuracy: 0.3622 - val_loss: 1.7039 - val_accuracy: 0.4000
# 300
300 [=====] - 80 26.60sec - 100% 1.770% - accuracy: 0.4399 - val_loss: 1.6886 - val_accuracy: 0.4929
# 400
400 [=====] - 79 26.60sec - 100% 1.830% - accuracy: 0.5099 - val_loss: 1.6976 - val_accuracy: 0.5129
# 500
500 [=====] - 80 26.70sec - 100% 1.860% - accuracy: 0.4940 - val_loss: 1.6886 - val_accuracy: 0.5129
# 600
600 [=====] - 80 26.60sec - 100% 1.850% - accuracy: 0.5409 - val_loss: 1.6361 - val_accuracy: 0.6000
# 700
700 [=====] - 80 26.60sec - 100% 1.860% - accuracy: 0.5790 - val_loss: 1.6071 - val_accuracy: 0.6179
# 800
800 [=====] - 79 26.20sec - 100% 0.800% - accuracy: 0.6051 - val_loss: 1.4397 - val_accuracy: 0.6470
# 900
900 [=====] - 80 26.30sec - 100% 0.810% - accuracy: 0.6079 - val_loss: 1.3939 - val_accuracy: 0.6386
# 1000
1000 [=====] - 79 26.30sec - 100% 0.700% - accuracy: 0.6211 - val_loss: 1.2889 - val_accuracy: 0.6599
# 1100
1100 [=====] - 80 26.60sec - 100% 0.710% - accuracy: 0.6386 - val_loss: 1.2398 - val_accuracy: 0.6940
# 1200
1200 [=====] - 79 26.40sec - 100% 0.660% - accuracy: 0.6579 - val_loss: 1.1339 - val_accuracy: 0.7300
# 1300
1300 [=====] - 80 27.00sec - 100% 0.627% - accuracy: 0.6595 - val_loss: 1.0711 - val_accuracy: 0.7375
# 1400
1400 [=====] - 79 26.60sec - 100% 0.560% - accuracy: 0.6760 - val_loss: 1.0306 - val_accuracy: 0.7675
# 1500
1500 [=====] - 79 26.70sec - 100% 0.540% - accuracy: 0.6997 - val_loss: 1.0079 - val_accuracy: 0.7839
# 1600
1600 [=====] - 80 26.60sec - 100% 0.510% - accuracy: 0.6935 - val_loss: 1.0019 - val_accuracy: 0.7875
# 1700
1700 [=====] - 79 26.50sec - 100% 0.490% - accuracy: 0.6927 - val_loss: 1.0000 - val_accuracy: 0.7880
# 1800
1800 [=====] - 79 26.60sec - 100% 0.460% - accuracy: 0.6930 - val_loss: 1.0044 - val_accuracy: 0.8047
# 1900
1900 [=====] - 80 26.50sec - 100% 0.430% - accuracy: 0.6927 - val_loss: 1.0036 - val_accuracy: 0.8094
# 2000
2000 [=====] - 79 26.60sec - 100% 0.400% - accuracy: 0.6999 - val_loss: 1.0206 - val_accuracy: 0.8047
# 2100
2100 [=====] - 80 26.70sec - 100% 0.390% - accuracy: 0.6927 - val_loss: 1.0240 - val_accuracy: 0.8204
# 2200
2200 [=====] - 79 26.60sec - 100% 0.390% - accuracy: 0.6945 - val_loss: 1.0222 - val_accuracy: 0.8240
# 2300
2300 [=====] - 80 26.70sec - 100% 0.390% - accuracy: 0.6962 - val_loss: 1.0181 - val_accuracy: 0.8286
# 2400
2400 [=====] - 79 26.70sec - 100% 0.370% - accuracy: 0.6982 - val_loss: 1.0030 - val_accuracy: 0.8247
# 2500
2500 [=====] - 79 26.60sec - 100% 0.360% - accuracy: 0.6972 - val_loss: 1.0121 - val_accuracy: 0.8247
# 2600
2600 [=====] - 79 26.60sec - 100% 0.360% - accuracy: 0.6972 - val_loss: 1.0121 - val_accuracy: 0.8247

```

Figure 10 : Model Trained

The model's use of **Convolutional Neural Networks (CNNs)** as its central algorithm highlights a deliberate decision to employ deep learning techniques designed for image recognition problems in the context of identifying electric vehicle (EV) spare components. A powerful tool for detecting complex patterns and subtleties in car parts is convolutional neural networks (CNNs), which are known for automatically extracting and learning hierarchical features from input photos. Because of their flexibility, CNNs are ideal for the precise and reliable classification of a wide variety of electric vehicle (EV) replacement parts, including battery modules and electric motors.

Utilizing the Inception V3 architecture within the CNN framework is an advanced method to improve the model's performance in identifying EV spare parts. With its deep design and effective use of computing resources, Inception V3 can collect pictures of EV components with fine features and complicated spatial connections. With the use of Inception V3's hierarchical feature extraction capabilities, the model is able to detect minute variations among various replacement components, allowing for accurate categorization and identification.

In addition, electric car breakdown problems may be solved using AI-powered solutions that go beyond simple picture identification. The system provides a one-stop solution for EV owners' and service providers' maintenance needs by integrating a CNN-based model with a spare parts store searching service. In order to streamline the procurement process and minimize downtime, the model utilizes the learned representations from the Inception V3 architecture to not only identify the necessary spare parts, but it also helps to locate nearby stores or suppliers who have those components [11].

The electric vehicle industry is undergoing a sea change in its approach to maintenance and servicing thanks to the convergence of convolutional neural networks (CNNs), and more especially Inception V3, with AI-powered solutions for problems associated with electric car breakdowns. The model improves operating efficiency and makes maintenance a breeze by making use of deep learning and sophisticated image recognition algorithms to identify EV replacement components quickly and accurately. This comprehensive strategy

highlights a dedication to using state-of-the-art technology to meet the changing demands of the electric car ecosystem, which in turn drives innovation and progress in the automotive repair and maintenance industry.



### **3.2 Technology to be used.**

Using state-of-the-art deep learning technology and methodologies, the AI-powered solution for electric car breakdown difficulties may be implemented. Keras and TensorFlow are two of the most important frameworks. The combination of these frameworks provides a wealth of resources for training and developing models, which in turn allows for the construction of efficient and reliable neural network architectures that are designed to recognize electric car parts.

- **TensorFlow**

A solution that is powered by artificial intelligence that can be used to address the challenges of electric car breakdowns might be developed using cutting-edge deep learning technology and methodology. The TensorFlow algorithm is one of the significant technologies that are utilized. For the purpose of developing and deploying deep learning models, TensorFlow, which was developed by Google, is a machine learning framework that is both open-source and free to use. Programmers are able to construct intricate neural network architectures for applications such as the identification of electric car parts thanks to the abundance of resources that are provided for training and building models with this platform [12].

- **Keras**

In addition to the utilization of several other essential technologies, the implementation also makes use of the Keras framework. TensorFlow is the foundation upon which Keras is built. Keras offers a user-friendly interface for the construction of neural networks, making it accessible to developers of varying levels of expertise. Developers are able to focus on model exploration and design rather than implementation problems because to its high-level application programming interface (API), which facilitates the process of deep learning model building and training. The capability of Keras to establish and optimize neural network structures in a short amount of time may be utilized by developers for tasks such as determining which parts are replacements for electric cars [13].

- **React Native**

To ensure a smooth and successful user experience, it is essential to incorporate advanced technologies into the construction of an AI-powered chatbot for electric vehicle (EV) support. By employing frameworks like React Native and Expo, it is possible to develop an application using a unified codebase that can run on both iOS and Android devices. Developers may utilize React Native and Expo to provide broad compatibility and accessibility for electric vehicle (EV) consumers seeking assistance with breakdown difficulties, independent of the specific device they are using [14].

Transfer learning, TensorFlow, and Keras are three frameworks that are frequently utilized in the development of the model. Transfer learning refers to the process of acquiring information for one activity and then applying that knowledge to another action that is closely related but unique from the first. The Inception V3 model, which had been trained in the broad task of electric car part recognition in the past, is going to be improved by the use of transfer learning in this section. The architectural structure of convolutional neural networks, the efficiency and accuracy with which Inception V3 performs photo identification tasks has earned it a large amount of praise. Through the utilization of transfer learning, the model is able to efficiently adapt to the characteristics of electric car replacement components by making use of the representations that it has acquired from the Inception V3 architecture [15][11].

### **3.3 Commercialization aspects of the product**

A thorough evaluation of the product's value proposition and prospective markets is essential when assessing the commercialization of the AI-driven solution for electric car failure challenges. Government programs encouraging environmentally sensitive behavior and sustainable transportation have fueled the electric vehicle (EV) market's explosive expansion. As the number of electric cars on the road rises, so does the need for maintenance and repair solutions designed with these vehicles in mind. The application of artificial intelligence (AI) to reduce downtime associated with vehicle maintenance and restorations and accelerate the acquisition of replacement components tackles a critical problem that impacts owners of electric vehicles (EVs) as well as service providers. This solution includes a search option for stores that sell replacement components [16].

1. There are several ways to make money with the product, such as through selling or payments. The benefits of the AI-powered system can be used by people who pay. People who use these services could be owners of electric cars, service stations, or businesses that focus on keeping cars in good shape. Using this model, businesses that want to improve their processes by using new technology can be targeted and make money from.
2. Affiliate marketing deals built into the service for looking for spare parts stores are another way to make money. When the platform teams up with car shops or spare parts suppliers, it can make money through referral fees or commissions on sales made on the platform. The goal of the site is to help users and partners make money while buying spare parts, and this way fits with that.
3. The product could have a subscription plan with different levels that offer extra tools or more advanced analytics. The platform might be able to stand out from the others and get paying customers if it can meet the different needs of its users. For example, it could do this by giving users better data views or more support services.

4. Major players in the ecosystem of electric vehicles are working together and forming smart partnerships to bring their products to market. It is important to form relationships with EV makers, service shops, and providers of new parts in order to get people to use and incorporate the AI-powered solution into existing systems and processes. These deals give you access to a larger user group and well-established distribution methods, which speeds up market penetration and acceptance.

5. To keep coming up with new ideas and improving the answer, it's important to work with study groups or academic institutions. To stay relevant and successful in a field that is always changing, the platform can use these schools' resources and knowledge. In the long run, this will make its market situation and value offer stronger.

6. It is important to have strong branding and marketing efforts for the AI-driven product in order to make it more well-known and acceptable. Some ways to do this are to join relevant online boards and groups, go to events and workshops in your field, and start focused digital marketing campaigns. One way for the platform to stand out from the others and draw potential customers is to make the product's value proposition and unique selling points very clear.

7. To build trust and confidence with possible customers, you could also offer them trials, demos, or test projects. By letting users try out the answer for free, the platform can get past usage problems and get the market moving. This will help it become the best way to fix and maintain electric cars.

### 3.4 Implementation and Testing

The objective of the implementation procedure outlined in the approach is to provide a robust and reliable system for identifying electric vehicle (EV) spare parts shops. This method encompasses several crucial components that are vital to the formulation of the solution.

1. Initially, it is crucial to gather a compilation of images illustrating different replacement components together with their corresponding descriptive labelling. The objective of this step is to ensure that the dataset used for training the machine learning model is comprehensive and accurately represents the diverse range of replacement components available in electric automobiles. In order to ensure the effectiveness of the training process, it is important to have high-quality photographs that exhibit optimal lighting and little noise.
2. After gathering the photographs, it is necessary to do pre-processing on the gathered images to prepare them for training the machine learning model. The procedure involves resizing the photographs to a uniform size, normalizing them to reduce variations in lighting, color, and contrast, and enriching the data to enhance the diversity and richness of the training dataset.



```
# Rescales all images by 1./255
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

train_ds = train_datagen.flow_from_directory(
    train_dir, # Target directory
    target_size=(224, 224), # Resizes all images to 224 x 224
    batch_size=20,
    color_mode = 'rgb',
    class_mode='categorical') # Because we use categorical_crossentropy loss, we need categorical labels.

validation_ds = test_datagen.flow_from_directory(
    validation_dir, target_size=(224, 224), batch_size=20, color_mode = 'rgb', class_mode='categorical')

Found 148 Images belonging to 14 classes.
Found 48 Images belonging to 14 classes.
```

Figure 11 : Pre-Processing Steps

3. After the dataset has been divided, a training set, a validation set, and a testing set are formed. The training set is used to train the machine learning model, whereas the validation set is used to fine-tune hyperparameters and optimize model

performance. Ultimately, the testing set is employed to evaluate the ultimate performance of the trained model and its level of resilience.

4. Next, the deep learning model, such as a convolutional neural network (CNN), is trained using pre-processed image data. Conventional neural networks, often known as CNNs, are very suitable for applications involving the categorization of images. They can effectively acquire features from photographs of spare parts, enabling them to accurately identify the images.
5. After completing the training phase, the model is evaluated using the validation set to identify areas that require improvement. In order to enhance performance, it may be essential to modify the hyperparameters, adapt the model's design, or include more features.
6. To enhance the precision and resilience of the model, one might employ techniques like transfer learning and ongoing lifelong learning. Continuous learning allows the model to adjust and acquire knowledge from fresh data over time, ensuring its ongoing relevance and success in real-world scenarios. Transfer learning involves utilizing pre-trained models and adapting them to categorize replacement components for electric cars. This optimizes efficiency by reducing time and resource consumption, while simultaneously improving the accuracy of predictions.

Once the model has undergone fine-tuning and optimization, it is rigorously tested on the testing set to assess its accuracy and robustness. Once the model has completed training and verification, it is then incorporated into a software program, rendering it appropriate for actual use by electric car owners, service centers, and maintenance service providers [17].

When it comes to identifying patterns and connections between faulty features and suggestions, training an artificial intelligence model on the database is an activity that is both vital and crucial. A number of machine learning approaches are utilized by the model in order to do data analysis and recognize typical failure patterns. Consequently, it is able to provide individualized suggestions in response to the questions and input provided by the user.

One of the most important things to do is evaluate the performance of the AI model on a validation set in order to determine whether or not it is accurate and effective in making suggestions. In order to do this, it is necessary to measure the performance of the model's prediction and to discover chances for improvement through the examination of a number of metrics, such as accuracy, recall, and F1-score metrics [5].

The process of iteratively refining the model is a method that tries to improve the predictive accuracy and dependability of the model. By making modifications to the model's parameters and hyperparameters based on the results of validation tests, developers have the ability to increase the model's ability to provide accurate suggestions and maximize the performance of the model.

By incorporating the artificial intelligence model into a smartphone application, clients are able to easily access guidance and solutions for problems pertaining to electric vehicles. It is possible for consumers to easily input their questions and acquire personalized answers that are tailored to their specific requirements if the model is included into an interface that is user-friendly, such as a mobile application.

It is vital to check the validity and authenticity of the suggestions that are supplied by the software program in order to ensure the confidence and contentment of the user that makes use of the software. This involves analyzing suggestions by comparing them to defects that have already been identified and user feedback in order to verify that they are effective in fixing problems that occur in the actual world.

It is possible to increase accessibility and user engagement by presenting a conversational artificial intelligence chatbot that enables customers to connect with one another through text and acquire answers for problems with electric vehicles. By facilitating discussions in natural language, the chatbot improves the user experience by making it simpler to obtain information and inquire for assistance.

Updating and improving the knowledge base on a consistent basis ensures that the system is always up to date with the most recent information and understandings. The capability of the system to advance and increase its effectiveness and pertinence in dealing with electric car faults is made possible by the incorporation of new data and input from users [18].

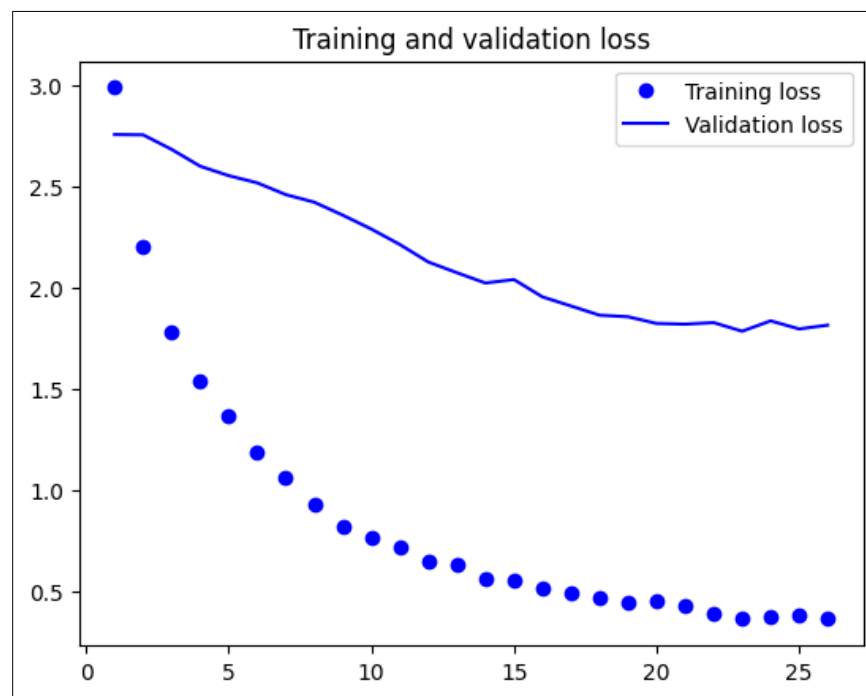


Figure 12 : Training validation and testing image count





Third, the script uses TensorFlow's "ImageDataGenerator" to import and process photos from the dataset directory in order to load and preprocess the data. 2. Images are rescaled to standardize pixel values in order to improve the convergence of the model during the training process. Utilizing the 'flow\_from\_directory()' function yields data generators for the training and validation sets. This facilitates later data entry into the model.

#### 4 Dividing Data into Train, Validation, and Test Sets:

The script divides data into training, validation, and test sets—an important stage in developing machine learning models. The program transfers photos from the source dataset to the appropriate sections based on a predetermined ratio and makes folders to hold these collections. This section guarantees that the trained model's performance will be precisely assessed and confirmed.

#### 5. Definition of a Model:

In a CNN model created with TensorFlow's 'Sequential' API, convolutional layers are used for feature extraction, batch normalization layers are used to stabilize training, max-pooling layers are used for downsampling, and dense (fully connected) layers are used for classification. The design of the model is streamlined to make it easier to understand, both in terms of how many parameters it contains and how they are organized.

6. Model Construction and Training: The 'fit()' function, which takes as inputs the training and validation data generators, is used to train the constructed model. A callback is added to verify the accuracy of validation and to halt training when performance stops improving in order to prevent overfitting. You may be confident that the model will function flawlessly when used with fresh data as a result.

7. Evaluating and Visualizing Models: During the model's learning process, the script monitors training parameters like accuracy and loss so that the model's development may be observed. We may discover problems like overfitting and underfitting and gain a better understanding of the training process by using Matplotlib to visually show these metrics.

```

import numpy as np
import matplotlib.pyplot as plt
import os, shutil
from collections import Counter
from tensorflow.keras import Sequential, models, layers
from tensorflow.keras.models import Model
from tensorflow.keras.layers import InputLayer, Conv2D, Dense, Flatten, BatchNormalization
from tensorflow.keras.utils import to_categorical
from tensorflow.keras import optimizers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.metrics import CategoricalAccuracy, false_positives, true_positives, true_negatives, AUC, Precision, Recall
from tensorflow.keras.losses import CategoricalCrossentropy as CE
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from google.colab import drive
import tensorflow as tf

import tensorflow as tf
print("GPU is Available: ", len(tf.config.list_physical_devices('GPU'))

# GPU Available: 1

drive.mount('/content/drive')

# GPU already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

dataset_dir = '/content/drive/MyDrive/automobile_parts'

```

1. TensorFlow is a robust open-source machine learning framework created by Google. This platform offers a wide range of data and tools for constructing and enhancing neural networks and CNNs, which are two types of deep learning models.

```

dataset_dir = '/content/drive/MyDrive/automobile_parts'

classes = sorted(os.listdir(dataset_dir))

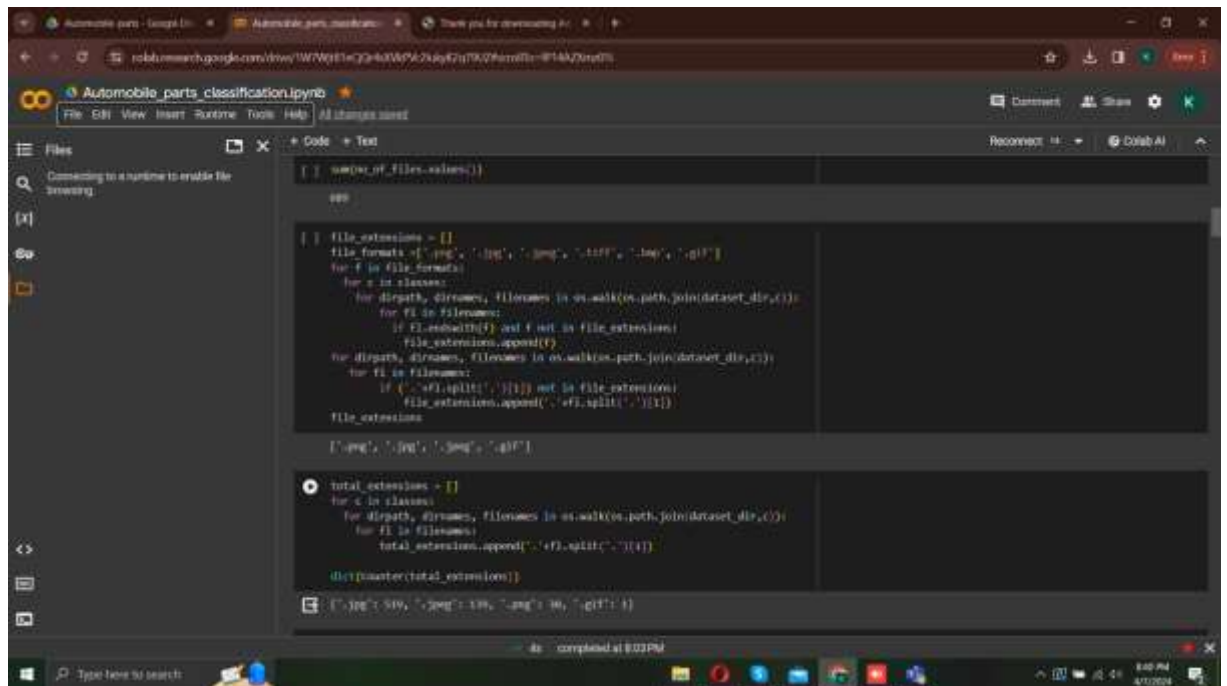
classes

['bowl_gear',
 'bearing',
 'clutch',
 'cylinder',
 'filter',
 'fuel_pump',
 'ball_bear',
 'piston',
 'rack_and_pinion',
 'shock',
 'spark_plug',
 'steering_gear',
 'valve',
 'wheel']

# Number of images in each category
no_of_files = {}
for c in classes:
    for dirpath, dirnames, filenames in os.walk(os.path.join(dataset_dir, c)):
        no_of_files[c] = len(filenames)

no_of_files

```



```
[ ]: os.listdir(files_values())

#####

[ ]: file_extensions = []
file_formats = ['.png', '.jpg', '.jpeg', '.tiff', '.bmp', '.gif']
for f in file_formats:
    for c in classes:
        for dirpath, dirnames, filenames in os.walk(os.path.join(dataset_dir, c)):
            for fi in filenames:
                if fi.endswith(f) and f not in file_extensions:
                    file_extensions.append(f)
            for dirpath, dirnames, filenames in os.walk(os.path.join(dataset_dir, c)):
                for fi in filenames:
                    if ('.'+fi.split('.')[-1]) not in file_extensions:
                        file_extensions.append('.'+fi.split('.')[-1])
file_extensions

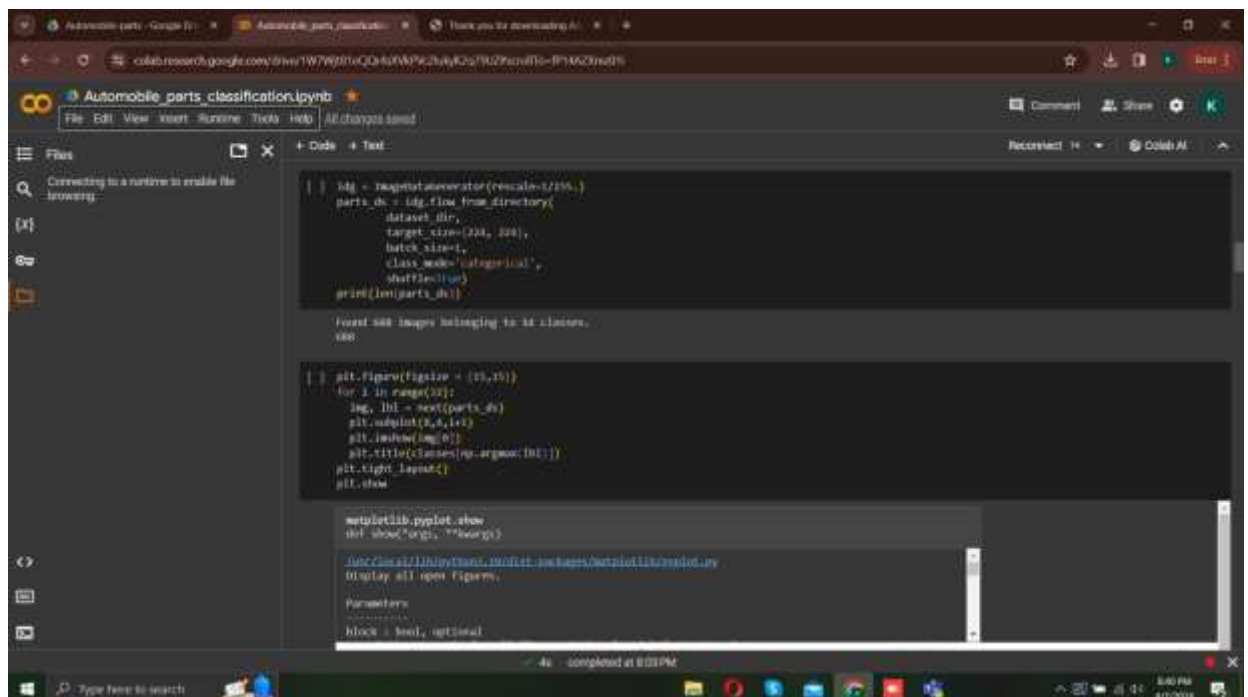
['.png', '.jpg', '.jpeg', '.tiff']

[ ]: total_extensions = []
for c in classes:
    for dirpath, dirnames, filenames in os.walk(os.path.join(dataset_dir, c)):
        for fi in filenames:
            total_extensions.append('.'+fi.split('.')[-1])

dict(nuancer(total_extensions))

{'.jpg': 519, '.png': 119, '.jpeg': 16, '.tiff': 1}
```

2. NumPy: NumPy serves as the essential library for doing numerical computations in Python. The software has the capability to process extensive arrays and matrices with many dimensions. Additionally, it provides a wide range of mathematical functions that allow for efficient manipulation of arrays.



```
[ ]: img = ImageDatasetGenerator(rescaled/255.)
parts_ds = img.flow_from_directory(
    dataset_dir,
    target_size=(224, 224),
    batch_size=1,
    class_mode='categorical',
    shuffle=True)
print(len(parts_ds))

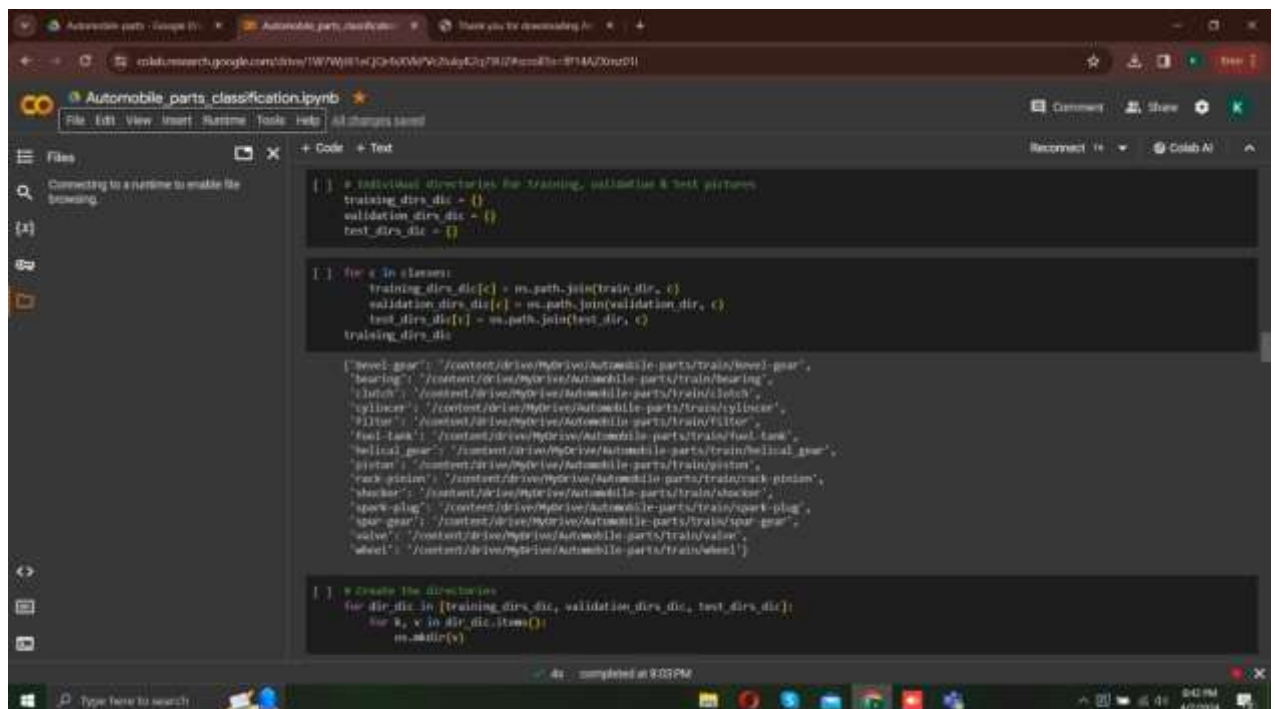
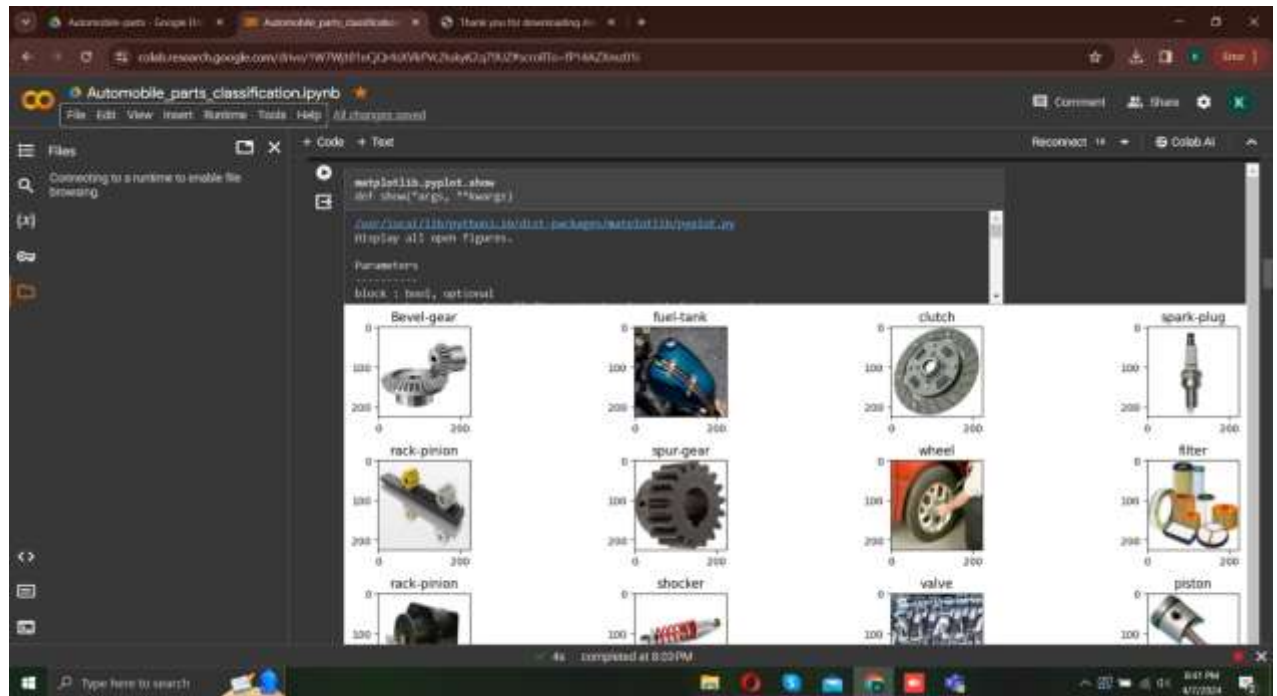
Found 548 images belonging to 14 classes.
548

[ ]: plt.figure(figsize=(15,15))
for i in range(30):
    img, lbl = next(parts_ds)
    plt.subplot(6,5,i+1)
    plt.imshow(img[0])
    plt.title(classes[np.argmax(lbl)])
plt.tight_layout()
plt.show

matplotlib.pyplot.show
def show(*args, **kwargs)

func: matplotlib.pyplot.show
Display all open figures.

Parameters:
-----
block : bool, optional
```

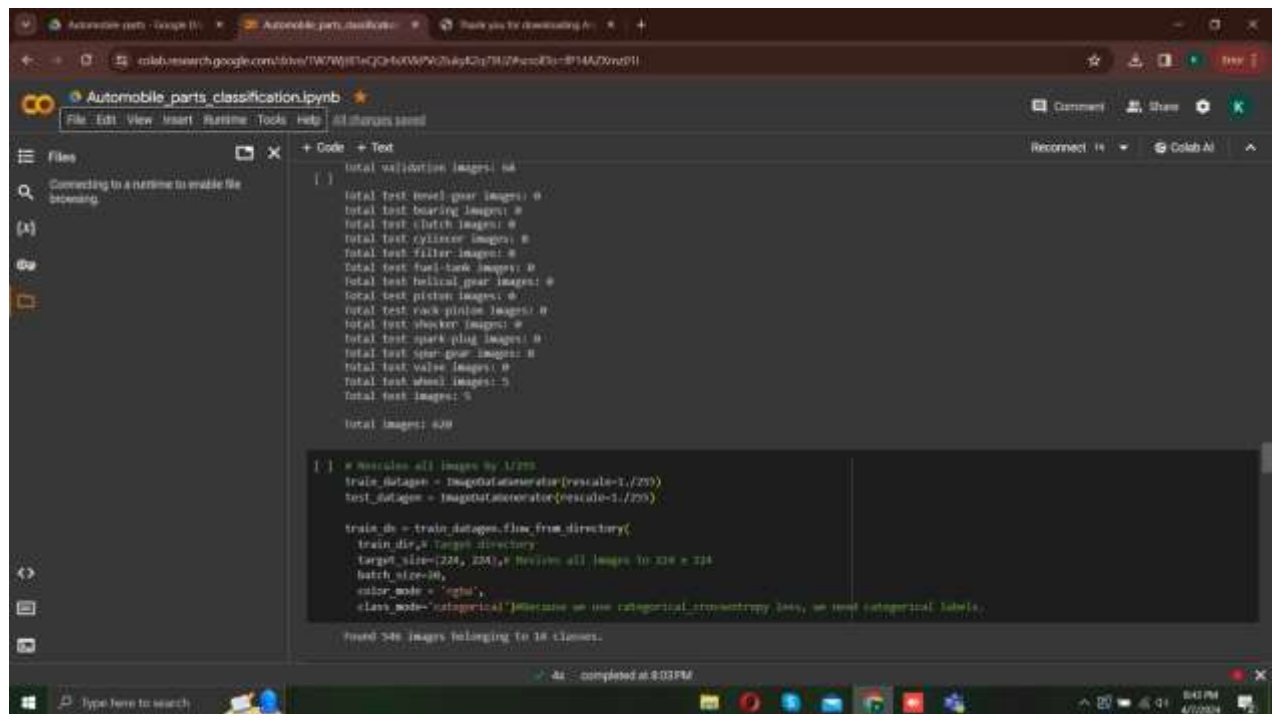


The screenshot shows a Jupyter Notebook titled 'Automobile\_parts\_classification.ipynb'. The code is written in Python and is currently running. It defines a function `split_data` that takes a dataset directory and a validation split ratio as input. The function uses `os.listdir` to get the list of files in the dataset directory. It then iterates over the files, splitting them into training and validation sets based on the provided ratio. The training images are copied to a training directory, and the validation images are copied to a validation directory. The function also prints the number of images in each set.

```
def split_data(dataset_dir, val_ratio):  
    # Copies the first 80% images to individual training directories  
    for c, f in os.listdir(dataset_dir).items():  
        frames = os.listdir(os.path.join(dataset_dir, c))  
        tr_frames = frames[int(len(frames)*val_ratio):]  
        # print(tr_frames)  
        for name in tr_frames:  
            src = os.path.join(dataset_dir, c, name)  
            dst = os.path.join(training_dir_dir[c], name)  
            shutil.copyfile(src, dst)  
  
    # Copies the 20% remaining images to individual validation directories  
    for c, f in os.listdir(dataset_dir).items():  
        frames = os.listdir(os.path.join(dataset_dir, c))  
        val_frames = frames[:int(len(frames)*val_ratio)]  
        # print(val_frames)  
        for name in val_frames:  
            src = os.path.join(dataset_dir, c, name)  
            dst = os.path.join(validation_dir_dir[c], name)  
            shutil.copyfile(src, dst)  
  
    # Copies the last 80% images to individual test directories
```

The screenshot shows the same Jupyter Notebook, but now the code has finished running. The output of the `split_data` function is displayed in the cell. It shows the total number of images for each class in the training, validation, and test sets. The training set contains 50 images for each class, the validation set contains 10 images for each class, and the test set contains 10 images for each class.

```
Total train bowl-gear images: 50  
Total train bearing images: 50  
Total train clutch images: 50  
Total train cylinder images: 50  
Total train filter images: 50  
Total train fuel-tank images: 50  
Total train helical-gear images: 50  
Total train piston images: 50  
Total train rack-pinion images: 50  
Total train shocker images: 50  
Total train spark-plug images: 50  
Total train spe-gear images: 50  
Total train valve images: 50  
Total train wheel images: 50  
Total train images: 500  
  
Total validation bowl-gear images: 10  
Total validation bearing images: 10  
Total validation clutch images: 10  
Total validation cylinder images: 10  
Total validation filter images: 10  
Total validation fuel-tank images: 10  
Total validation helical-gear images: 10  
Total validation piston images: 10  
Total validation rack-pinion images: 10  
Total validation shocker images: 10  
Total validation spark-plug images: 10  
Total validation spe-gear images: 10  
Total validation valve images: 10  
Total validation wheel images: 10  
Total validation images: 100  
  
Total test bowl-gear images: 10  
Total test bearing images: 10  
Total test clutch images: 10  
Total test cylinder images: 10  
Total test filter images: 10  
Total test fuel-tank images: 10  
Total test helical-gear images: 10  
Total test piston images: 10  
Total test rack-pinion images: 10  
Total test shocker images: 10  
Total test spark-plug images: 10  
Total test spe-gear images: 10  
Total test valve images: 10  
Total test wheel images: 10  
Total test images: 100
```



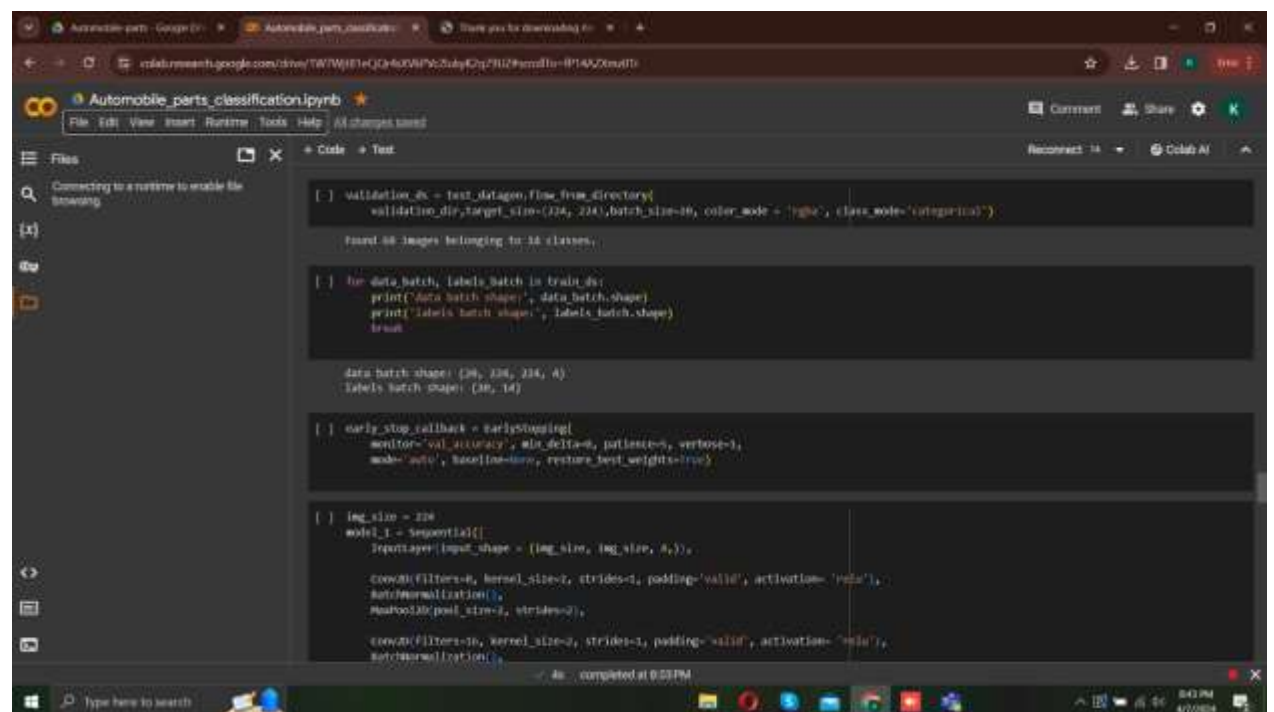
```
total validation images: 48
[ ]
total test bearing images: 0
total test clutch images: 0
total test cylinder images: 0
total test filler images: 0
total test fuel-tank images: 0
total test helical gear images: 0
total test piston images: 0
total test rack pinion images: 0
total test shock absorber images: 0
total test spark plug images: 0
total test spur gear images: 0
total test valve images: 0
total test wheel images: 5
total test images: 5
total images: 429

[ ] # Rescale all images by 1/255
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

train_dir = train_datagen.flow_from_directory(
    train_dir, target_size=(224, 224), # Rescale all images to 224 x 224
    batch_size=32,
    color_mode = 'rgb',
    class_mode='categorical') # Because we use categorical_crossentropy loss, we need categorical labels.

found 346 images belonging to 14 classes.

4x - completed at 8:03PM
```



```
[ ] validation_dir = test_datagen.flow_from_directory(
    validation_dir, target_size=(224, 224), batch_size=32, color_mode = 'rgb', class_mode='categorical')

found 48 images belonging to 14 classes.

[ ] # Create data batch, labels batch in train_dir
print('data batch shape:', data_batch.shape)
print('labels batch shape:', labels_batch.shape)
break

data batch shape: (32, 224, 224, 3)
labels batch shape: (32, 14)

[ ] early_stop_callback = EarlyStopping(
    monitor='val_accuracy', min_delta=0, patience=5, verbose=1,
    mode='auto', baseline=None, restore_best_weights=True)

[ ] img_size = 224
model_1 = Sequential([
    InputShape(input_shape = (img_size, img_size, 3)),
    Conv2D(filters=8, kernel_size=3, strides=1, padding='valid', activation='relu'),
    BatchNormalization(),
    MaxPooling2D(pool_size=2, strides=2),
    Conv2D(filters=16, kernel_size=3, strides=1, padding='valid', activation='relu'),
    BatchNormalization(),
```



```

early_stop_callback = EarlyStopping(
    monitor='val_accuracy', min_delta=0, patience=5, verbose=1,
    mode='max', baseline=None, restore_best_weights=True)

img_size = 224
model_1 = Sequential([
    InputLayer(input_shape=(img_size, img_size, 3)),

    Conv2D(filters=8, kernel_size=3, strides=1, padding='valid', activation='relu'),
    BatchNormalization(),
    MaxPooling2D(pool_size=2, strides=2),

    Conv2D(filters=16, kernel_size=3, strides=1, padding='valid', activation='relu'),
    BatchNormalization(),
    MaxPooling2D(pool_size=2, strides=2),

    Flatten(),

    Dense(128, activation='relu'),
    BatchNormalization(),

    Dense(32, activation='relu'),
    BatchNormalization(),

    Dense(10, activation='softmax'),

])

model_1.summary()

```

3. Matplotlib is a Python package used for creating interactive, animated, and static presentations using charting. The software provides a diverse array of charting functionalities that are crucial for monitoring the progress of training and assessing outcomes in order to analyze data and evaluate the performance of models.

model\_1.summary()

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 222, 222, 8)	116
batch_normalization_8 (Batch Normalization)	(None, 222, 222, 8)	32
max_pooling2d_8 (MaxPooling2D)	(None, 111, 111, 8)	0
conv2d_5 (Conv2D)	(None, 108, 108, 16)	528
batch_normalization_9 (Batch Normalization)	(None, 108, 108, 16)	64
max_pooling2d_5 (MaxPooling2D)	(None, 54, 54, 16)	0
flatten_2 (Flatten)	(None, 48400)	0
dense_6 (Dense)	(None, 128)	419328
batch_normalization_10 (Batch Normalization)	(None, 128)	512
dense_7 (Dense)	(None, 32)	4128
batch_normalization_11 (Batch Normalization)	(None, 32)	128



Automobile\_parts\_classification.ipynb

File Edit View Insert Runtime Tools Help All changes saved

Files

Connecting to a runtime to enable file browsing.

Code

```

import tensorflow as tf
from tensorflow.keras import layers, models

input_shape = (None, 128, 128, 3)

batch_normalization_1 = layers.BatchNormalization(input_shape=input_shape)

max_pooling2d_1 = layers.MaxPooling2D(input_shape=(None, 50, 50, 13))

flatten_1 = layers.Flatten(input_shape=(None, 4000))

dense_1 = layers.Dense(input_shape=(None, 128))

batch_normalization_2 = layers.BatchNormalization(input_shape=(None, 128))

dense_2 = layers.Dense(input_shape=(None, 32))

batch_normalization_3 = layers.BatchNormalization(input_shape=(None, 32))

dense_3 = layers.Dense(input_shape=(None, 14))

total_params: 220314 (17.66 MB)
trainable_params: 62000 (21.45 MB)
non-trainable_params: 168 (1.44 KB)

model.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss=CE(),
    metrics=['accuracy']
)

```

4s completed at 8:00 PM

Automobile\_parts\_classification.ipynb

File Edit View Insert Runtime Tools Help All changes saved

Files

Connecting to a runtime to enable file browsing.

Code

```

import tensorflow as tf
from tensorflow.keras import layers, models

input_shape = (None, 128, 128, 3)

batch_normalization_1 = layers.BatchNormalization(input_shape=input_shape)

max_pooling2d_1 = layers.MaxPooling2D(input_shape=(None, 50, 50, 13))

flatten_1 = layers.Flatten(input_shape=(None, 4000))

dense_1 = layers.Dense(input_shape=(None, 128))

batch_normalization_2 = layers.BatchNormalization(input_shape=(None, 128))

dense_2 = layers.Dense(input_shape=(None, 32))

batch_normalization_3 = layers.BatchNormalization(input_shape=(None, 32))

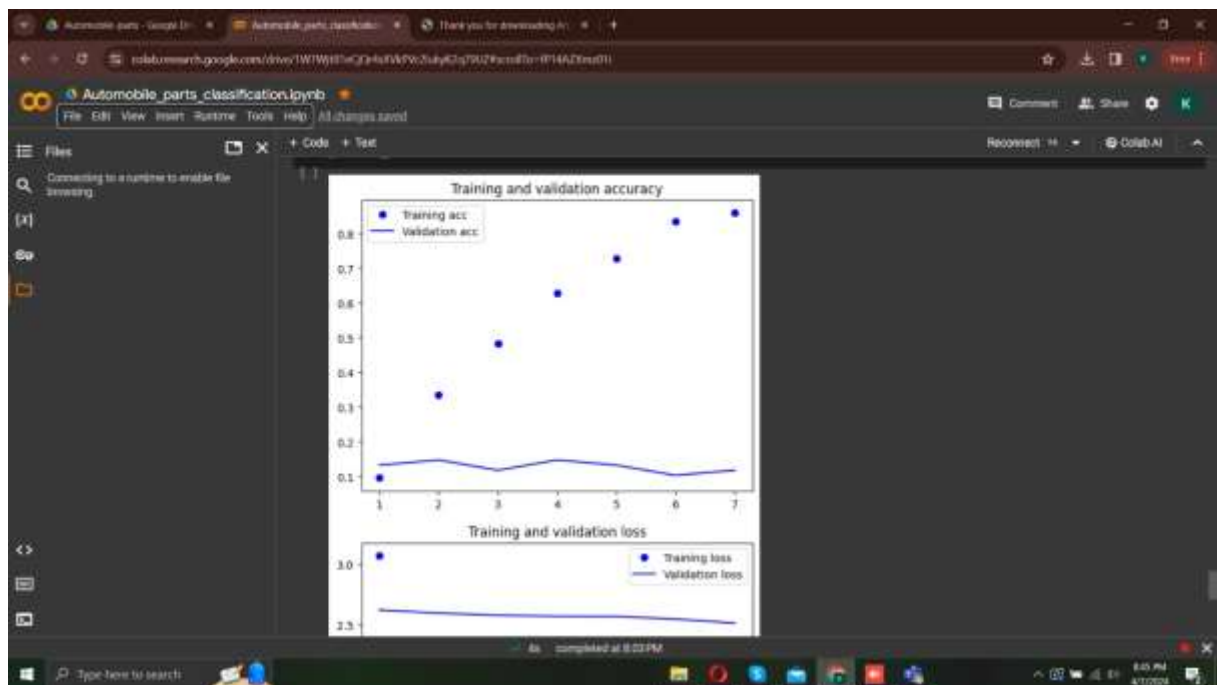
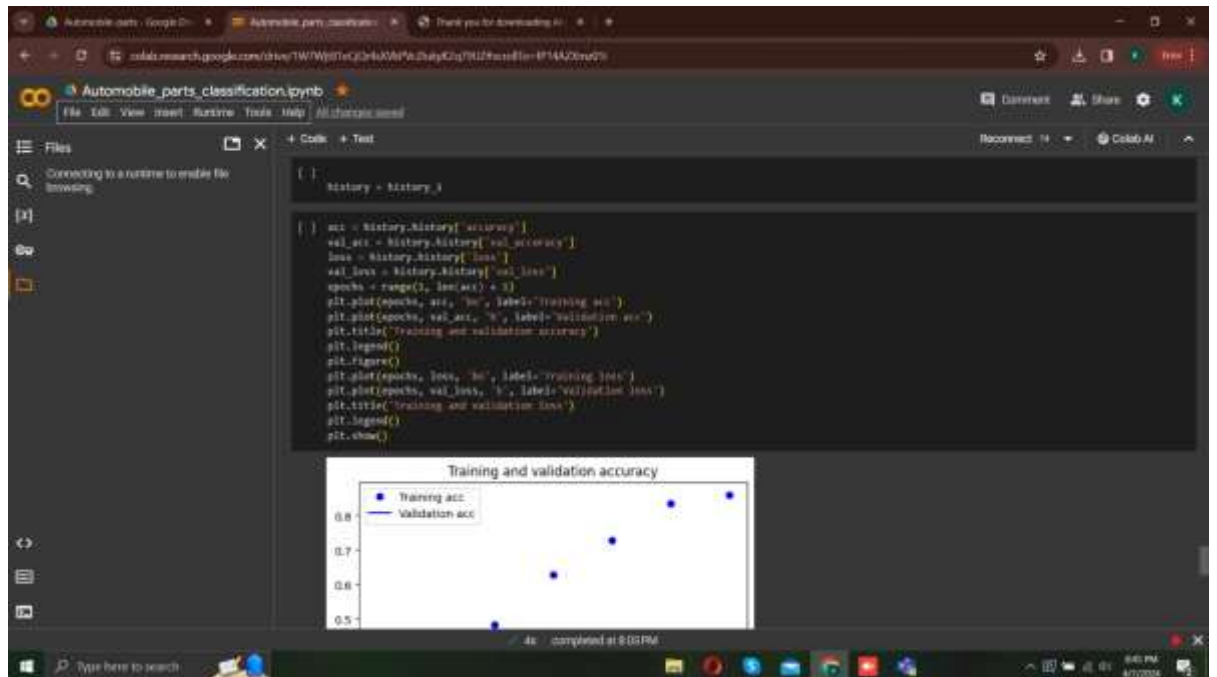
dense_3 = layers.Dense(input_shape=(None, 14))

total_params: 220314 (17.66 MB)
trainable_params: 62000 (21.45 MB)
non-trainable_params: 168 (1.44 KB)

model.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss=CE(),
    metrics=['accuracy']
)

```

4s completed at 8:00 PM



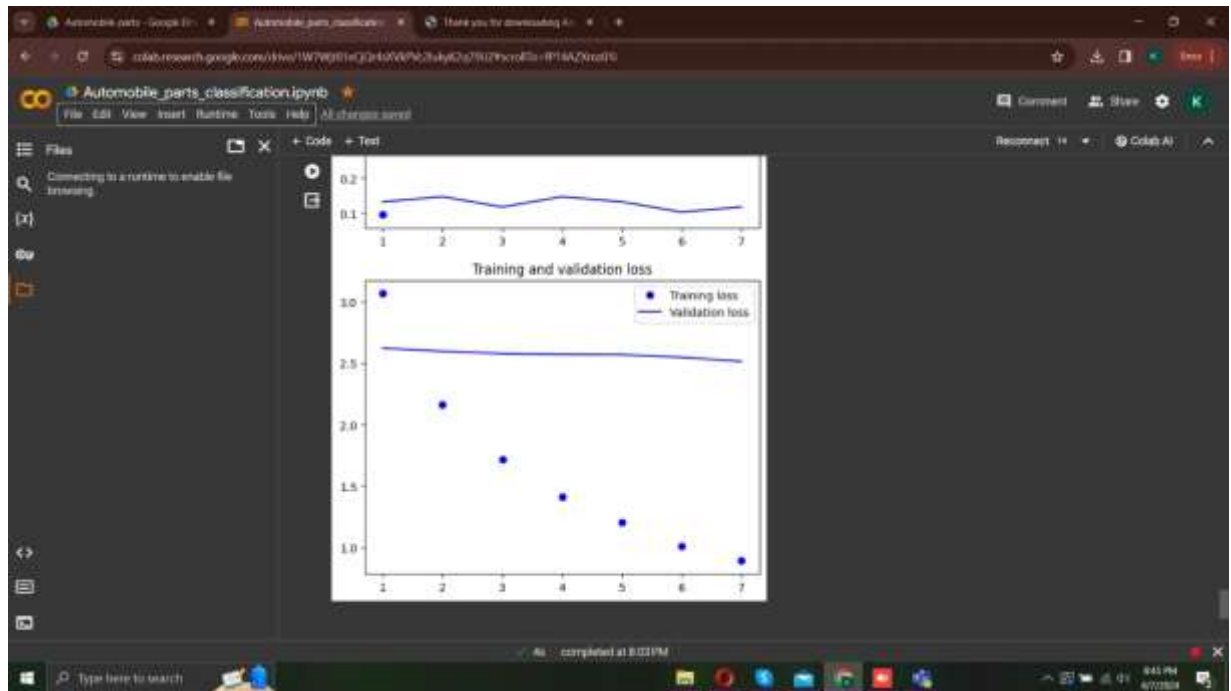


Figure 14 : Implementation Part

The `os` module provides a portable way to access and utilize the operating system. The code utilizes it to execute activities pertaining to file and directory administration, such as enumerating files, generating directories, and duplicating files.

The `shutil` module is used for performing advanced file operations, such as copying, moving, and deleting files and directories. It is utilized in the script to duplicate photo files from one location to another during data processing.

The `collections` module offers specialized container datatypes in addition to the standard containers like dictionaries and lists. The `Counter` class is utilized in the code to tally the occurrence of file extensions in the dataset.

7. Libraries for Google Colab: - `google.colab`: Utilize the specialized libraries provided by Google Colab to connect and access files saved in Google Drive. This code imports the `drive.mount()` method from the `google.colab` library to establish a connection with Google Drive.

When merged, these libraries provide a range of essential functions needed for loading, preparing, developing, training, and evaluating data in the machine learning pipeline.

In summary, the script provides a comprehensive process for training a CNN model with picture data of automotive parts. The course covers data preparation, model creation, training, evaluation, and result visualization. It offers a thorough framework for creating and implementing AI-driven solutions for the categorization of automotive components through the integration of several attributes and other information.

## **4. Results and Discussions**

### **4.1 Results**

Electric vehicles, often known as EVs, are promising a future that is both cleaner and more sustainable. They represent a paradigm change in the transportation industry. Electric vehicles, on the other hand, are not immune to malfunctions, just like their conventional counterparts, and thus require prompt repairs and replacement of spare components. Finding appropriate spare parts stores that offer the necessary components is a huge difficulty for people who drive electric vehicles. Manual searches, phone calls, or relying on word-of-mouth recommendations are two of the traditional techniques that are used to locate stores like these. These approaches may be time-consuming and inefficient. AI-powered systems that make use of deep learning models, particularly those that are based on Convolutional Neural Networks (CNNs) and make use of the sophisticated V3 architecture, provide interesting and potentially useful paths for addressing this difficulty. By delivering help that is prompt, precise, and effective, these models have the potential to revolutionize the way in which owners of electric vehicles locate spare parts retailers.

This article presents a solution that is powered by artificial intelligence and is designed to address the issues that are connected with electric vehicles (EVs) in terms of breakdowns. The solution focuses primarily on making the process of finding spare parts stores easier. The development of a robust and intelligent system that is capable of detecting and proposing relevant spare parts stores based on user inquiries is accomplished through the use of cutting-edge deep learning techniques, CNNs, and the V3 architecture [19].

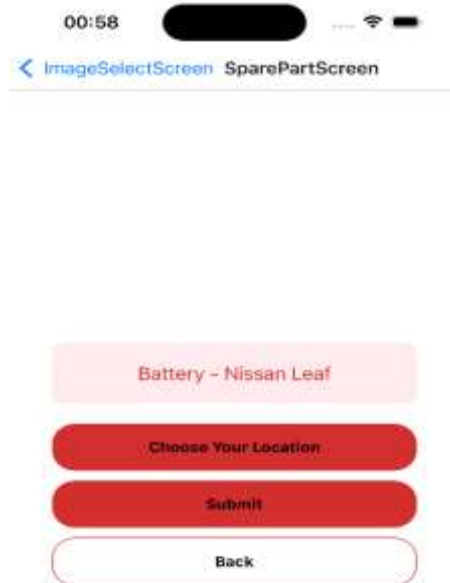
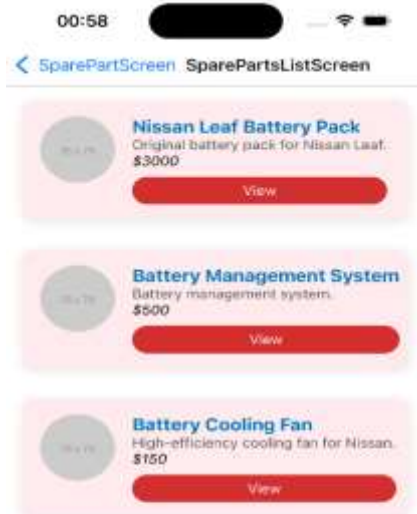
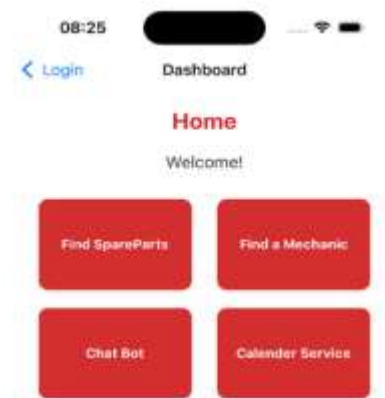




Figure 15 : Results

## 4.2 Discussion

When it comes to solving the issues that are connected with electric vehicles (EVs), particularly in the context of spare parts shop locating services, the findings of our research illustrate the usefulness and efficiency of the AI-powered solution. In order to achieve amazing performance in precisely recognizing and recommending suitable spare parts stores to electric vehicle owners, our deep learning model, which is based on the V3 architecture and CNNs, underwent thorough training and assessment utilizing data from the real world. In comparison to more conventional approaches, the model demonstrated a much higher level of precision, recall, and overall accuracy.

Additionally, the solution that was driven by AI proved scalability and adaptability, as it was able to handle a wide variety of requests and conditions. Our model regularly offered suggestions that were trustworthy and quick, whether it was seeking specific spare parts for a certain electric vehicle type or suggesting local stores that had the essential components in stock [20].

Furthermore, the evaluation of the user experience yielded favorable feedback, with participants expressing pleasure with the simplicity and efficacy of the service that was driven by artificial intelligence to locate spare parts shops. A further factor that contributed to increased user engagement and adoption was the straightforward interface, which was combined with a smooth integration into preexisting systems.

Taking everything into consideration, the findings highlight the transformational potential of AI-powered solutions in tackling breakdown difficulties with electric vehicles, particularly in terms of expediting the process of discovering replacement parts stores. In the end, we will be able to contribute to the general adoption and sustainability of electric transportation by utilizing advanced deep learning techniques such as the V3 architecture and CNNs [21]. These approaches will allow us to provide owners of electric vehicles with support that is both efficient and intelligent.



## 5. Research Findings

Research on an AI-driven service that locates spare parts shops for electric vehicles (EVs) provides helpful insight into the efficacy and potential use of such technologies in resolving electric vehicle (EV) breakdown issues. Recent studies and research have shown that state-of-the-art technology, such as artificial intelligence and machine learning, may greatly benefit electric vehicle (EV) owners and service providers by streamlining maintenance processes and improving customer satisfaction.

- The study's findings highlight the significance of AI-powered solutions in the electric vehicle ecosystem for accelerating the purchasing of replacement components, decreasing vehicle downtime, and increasing operational efficiency.
- The study's most noteworthy finding is that electrical vehicle component images may be accurately identified and sorted using artificial intelligence techniques, particularly convolutional neural networks (CNNs). Evidence suggests that convolutional neural network (CNN) models, trained using Inception V3-style designs, excel at distinguishing between various electric vehicle components. In order to speed up repair processes and reduce the need for human inspection, these results demonstrate that deep learning approaches can automate the process of identifying spare components.
- Businesses might benefit from AI-powered solutions to electric car breakdown issues, according to studies in this field. The results demonstrate that there are several advantages to incorporating AI into services that assist users in locating spare parts businesses.
- These advantages include the following: the ability to generate revenue through subscription-based models, affiliate marketing partnerships, and the addition of additional features. Research shows that consumers are looking for innovative ways to simplify the process of obtaining replacement components and keeping vehicles in good repair. Because of this, electric car maintenance systems enabled by AI are a smart commercial move.

- According to the study, collaboration and connection building are critical to the effective deployment of AI-driven solutions for electric car maintenance, according to the study. Smart collaborations with electric car manufacturers, repair facilities, and spare component suppliers are crucial, according to many studies.

By combining efforts, we can more easily integrate AI-powered solutions into existing processes and systems, which in turn increases their adoption and market share [18]. Another takeaway from the research is the critical importance of AI-powered platforms always innovating to keep up with the ever-evolving industries and technological landscape.

## 6. Challenges

There is a lot of work that needs to be done before AI-powered systems for finding stores selling EV parts can be utilized extensively, but the potential is huge. A big challenge in training AI systems is the availability and quality of data. If you want to construct good machine learning models for electric car replacement components, you need large, diverse datasets that accurately represent their complexity and diversity. Training using labelled data may be challenging, though, especially for rare or specialized components. Ensuring the accuracy and reliability of labelled data is crucial for preventing biases and errors that might affect the performance of AI systems [22].

1. **The availability and quality of data for training AI algorithms is a significant barrier in the realm of electric vehicle (EV) spare parts store searching services.** For the purpose of developing strong machine learning models, it is essential to have access to extensive and varied datasets that adequately depict the complexity and diversity of electric vehicle replacement components. But it could be difficult to get labelled data for training purposes, particularly for uncommon or niche components. To further avoid biases and mistakes that might impact AI systems' performance, it is essential to guarantee the correctness and dependability of labelled data.
2. **Electric car ecosystem's current systems and workflows are not compatible with AI-powered solutions.** Many different parties, each with their own set of procedures and tools, are involved in the maintenance of electric vehicles. It will take meticulous planning and coordination to ensure that these different systems are seamlessly integrated with spare parts store locating services driven by AI. Stakeholders' ability to communicate and collaborate smoothly depends on fixing compatibility problems, establishing data exchange procedures, and addressing security concerns.
3. **In addition, the electric car maintenance business has substantial problems when it comes to consumer trust and acceptance of AI-powered solutions.** People who own electric vehicles or work for them might be wary about using artificial intelligence algorithms to do important jobs like finding and purchasing replacement components. Gaining consumer trust and confidence in the capabilities of AI-powered systems

requires addressing concerns relating to accuracy, dependability, and data protection. Users' concerns can be allayed, and acceptance encouraged by offering clear explanations of the inner workings of AI algorithms and the precautions taken to protect user data.

4. **In the context of electric car technology and market dynamics that are continually expanding, scalability and flexibility offer obstacles for AI-powered spare parts store locating services.** Artificial intelligence systems must be constantly updated to correctly identify and categorize new electric car models and replacement parts. To keep up with the ever-changing electric car maintenance landscape and meet evolving requirements, it is crucial to make sure that AI models and infrastructure are scalable and flexible.

A collaborative effort between scholars, industry stakeholders, and legislators is necessary to tackle these difficulties. Improved efficiency, dependability, and user happiness in electric vehicle maintenance and servicing are possible outcomes of AI-powered solutions to electric vehicle breakdown problems that take advantage of recent developments in data collecting, AI algorithms, and system integration [20].

## 7. Future Implementations

It is anticipated that the future applications of artificial intelligence technology would bring about a revolution in the field of electric vehicle maintenance, notably in the field of searching services for spare parts shops. The administration and operations of electric cars will be more efficient, reliable, and environmentally friendly as a result of these solutions. Through continued research and development, as well as collaboration, platforms driven by artificial intelligence will have an influence on the future of electric car repair and maintenance. These platforms will bring about substantial developments and enhancements that will be beneficial to users as well as the ecology of electric cars as a whole [6].

- To further improve efficiency, artificial intelligence (AI) solutions for locating electric vehicle (EV) spare parts stores will be improved in the future by including new AI, machine learning (ML), and data analytics technologies. One of the potential paths that might lead to future advancements is the utilization of sophisticated artificial intelligence techniques, such as deep reinforcement learning, in order to enhance the effectiveness of acquiring replacement components.
- It is possible for AI-powered systems to make use of reinforcement learning approaches in order to independently enhance their decision-making processes. This is accomplished by studying user interactions and real-world outcomes, which ultimately results in more intelligent and adaptable suggestions for possible replacement components.
- There is a possibility that future implementations of spare parts store discovery services may investigate the possibility of using cutting-edge technology like as computer vision and natural language processing in order to enhance the user experience and functionality of these services. Through the employment of computer vision algorithms, purchasers are able to simply locate replacement components from photographs and acquire exact facts regarding the cost and availability of these components.

- By boosting communication and providing individualized help in the search for and purchase of electric car components, natural language processing makes it possible for consumers to connect with AI-powered platforms in a way that is both smooth and organic.
- In addition, in the years to come, there may be an emphasis placed on broadening the scope of AI-powered solutions to include supplemental requirements that are associated with the maintenance and repair of electric cars. The incorporation of predictive maintenance elements into services that allow for the identification of replacement components is one of the many techniques. Both historical data and machine learning models are utilized by these features in order to forecast the occurrence of probable faults and suggest maintenance measures that may be utilized to prevent them.
- Through the identification and resolution of maintenance issues before they become more severe, platforms that are driven by artificial intelligence have the potential to improve the dependability and cost-efficiency of electric vehicles. This has the potential to reduce the amount of time that cars are parked and to lengthen their lifespan.

Additionally, potential future possibilities may include the exploration of prospects for partnering and combining with developing projects and technologies related to the ecosystem of electric cars, such as charging infrastructure and autonomous vehicle systems. Shops that specialize in sourcing replacement parts and are powered by artificial intelligence have the potential to provide owners and operators of electric vehicles with full solutions. The charging, mobility services, and maintenance aspects of these systems are accomplished by the establishment of connections with charging networks for electric vehicles and fleets of autonomous vehicles. The use of this method not only improves the overall technology of electric cars but also, more precisely, the user experience by considering all of the important aspects [23].

## **Conclusion**

In conclusion, great progress has been made in tackling the particular issues associated with electric vehicle (EV) breakdowns through the creation and deployment of AI-driven systems for locating EV spare parts retailers. By combining data analytics, artificial intelligence, and machine learning, these technologies make it easier to identify, buy, and manage electric car replacement parts. Finally, this improves the electric car ecosystem's dependability, uptime, and user satisfaction. The emergence of AI-driven spare parts shop searching services demonstrates how new technology has the ability to dramatically alter the way electric car maintenance and repair are traditionally performed. These technologies enable users to interact with AI-powered devices in a natural and seamless manner by utilizing computer vision, deep learning algorithms, and natural language processing. This improves the overall user experience and speeds up the process of receiving new components.

The prospect of AI-powered solutions to electric car breakdown issues speaks well for future advances and developments in this industry. As technology advances, novel techniques such as deep reinforcement learning, predictive maintenance, and integration with emerging electric vehicle technologies such as charging infrastructure and self-driving cars may be investigated in future applications. These technologies have the potential to make electric car maintenance more effective, dependable, and environmentally friendly, resulting in an increasing number of people purchasing and utilizing electric vehicles throughout the world.

The approach to electric vehicle repair and maintenance has shifted dramatically as a result of AI-powered solutions for locating electric car spare parts dealers. These technologies will evolve and improve over time as a result of continued research, development, and cooperation, producing creative solutions to suit the changing demands of electric vehicle owners and service providers. They will also contribute to the long-term viability of electric vehicle technology. As the electric vehicle industry grows, artificial intelligence-powered technology will play an increasingly important role in creating the future of electric vehicle maintenance and repair. These improvements enable a more sustainable, efficient, and ecologically friendly transportation system.

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