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Automatic Charging System Using Image Processing For Electric Vehicle With UPI Payment System

Abhinev Ram [a], Sulagna Maji [a], Ritwik Tripathy [a], Samiappan Dhanalakshmi [a]
[a] Department of Electronics and Communication Engineering, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, India

Abstract— In recent years, electric cars (EVs) have gained popularity across the globe as a more environmentally friendly substitute for conventional gasoline-powered automobiles.
In addition to the fact that most of the population still cannot afford EVs, they also face other difficulties including an inefficient charging system.
The many methods for correctly determining which category an image of an electric socket belongs to are covered in this paper. The classification of images makes use of deep learning, a subset of machine learning. CNN-style algorithms have mostly been used for picture classification and recognition applications. Image processing uses edge detection methods to locate and emphasize an image's edges and boundaries.

I.INTRODUCTION

The electrification of the automotive industry is on the rise, and electric vehicle charging stations are becoming more common in public spaces. Different electric vehicles require different types of charging connectors, and it is essential to identify the correct connector to ensure a safe and efficient charging process. In this context, the problem of identifying different types of electric sockets becomes critical.
This problem statement involves classifying images of three types of electric sockets: CCS1, CCS2, and Tesla. The objective here is to develop a machine learning model that accurately predicts the class of test images from the dataset and is divided into separate folders for training and testing images, which enables the model to learn from the training data and evaluate its performance on unseen test data.
The solution to this problem can have practical applications in the electric vehicle industry, such as identifying the correct charging station for different electric vehicles.
This problem can be solved using various machine learning algorithms, such as CNN, SVM, KNN, and Decision Trees. By developing a robust and accurate classification model we can standardize the identification of electric sockets and enhance the efficiency and safety of electric vehicle charging.
This paper talks about using data augmentation to increase the size of the dataset to 1000 images. The Edge detection algorithm is used in image processing to identify and highlight edges and boundaries of an image. Finally, the dataset is trained in the CNN model to do image classification.
The fundamental principle of CNN is learning hierarchical representations of the input data, where lower-level features are merged to create high level features.
As a result, the network can recognize intricate patterns in the data and make precise predictions.

II.OBJECTIVE

The main goal behind this project is to develop a machine learning model that can accurately classify images of electric sockets into three categories: CCS1, CCS2, and Tesla.

The model is trained using the training dataset and is evaluated on the testing dataset to ensure its accuracy and robustness.

The goal is to create a model that can identify the correct electric socket type from an image, which can have various real-life applications in the electric vehicle industry.

By accurately identifying the type of electric socket, the proposed solution can contribute to the standardization of electric sockets and improve the efficiency and safety of electric vehicle charging.

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III. DATASET

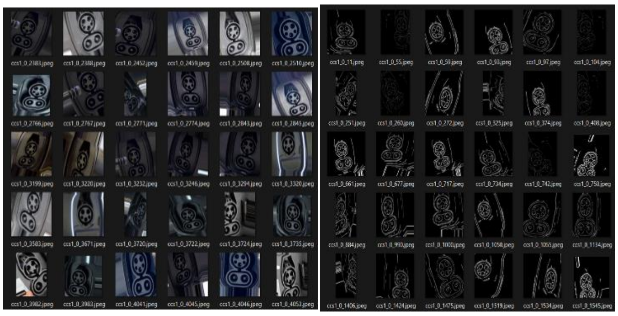

Fig1: Dataset Collection Normal and edge detected dataset

In this project three different types of sockets have been used namely CCS1, CCS2,Tesla.

CCS1: The CCS1 connector is an improved Type 1 AC plug that has two extra power connections for DC rapid charging. Aside from Tesla's Supercharger technology, which has its own socket and can charge at up to 350 kW, it is among the most popular fast-charging outlet in North America.

CCS2: It is an advanced Type 2 AC plug that has two extra power connections to provide DC rapid charging. DC power output ranges from 50 kW to 350 kW for CCS connectors. For CCS1 or CCS2, the upper part of the connector may be plugged into a conventional Type 1 or Type 2 socket to facilitate AC charging while keeping the bottom DC power contacts unplugged.

Tesla: The Tesla charging connector is a modified version of the Type 2 charging connector, also known as the Mennekes connector, which is commonly used in Europe for charging electric vehicles. The Tesla charging connector is larger than the Type 2 connector and has additional pins to support higher charging rates.

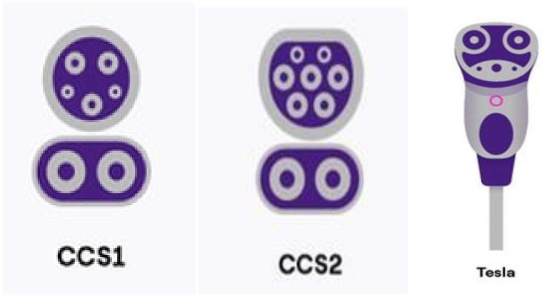

Fig2: Different types of Sockets

IV.RELATED WORK

In this problem statement, deep learning is used for image classification of electric sockets. Specifically, Convolutional Neural Networks (CNN) are a popular deep learning approach for image classification tasks. CNNs are designed to extract features from images through convolutional layers and pooling layers, which helps to identify patterns and objects within the image. In the paper Development of Next Generation Image Processing vehicle detector [7], the authors Hidenori Yamamoto proposes an innovative image detector that is compatible with the next generation system. Mingqiang Pan[8]studies the process of detection of electric vehicle charging ports. The detection is done through various image processing algorithms like CNN. This process is done in three phases namely: through the recognition of charging ports, location of the charging ports and robotic arm insertion. In this paper, an Integrated Processing System has been designed to improve the efficiency of Electric Vehicle supporting products [9] which the authors Jianyun Xu and Hui Wan talks about in detail method to do the various parts of the vehicle. Various image processing methods like grabcut algorithm is briefly studied and the implementation of this algorithm is understood from this paper.
Hui Zhang and Xiating Jin in 2016 published a paper that stated the all the methods for detecting new energy electric vehicle charging hole detection and location based on machine vision [10].

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It studies how the detection of holes can be quickly and precisely and extract important information about the holes based on a new technique called Machine Vision.
Justinas Miseikis proposed a concept on shape based matching technique [1]. However, there is a drawback in the approach that the charging port is assumed that it is already open.
Finally in Automated robot-based charging system for Electric vehicle it talks about the previously proposed models in the market [5].

V.CHALLENGES

Although the electric vehicle industry has advanced significantly in recent years, there are still many obstacles to overcome. Among the difficulties the electric vehicle sector faces are:

(i)Range anxiety: It is the inability of an electric vehicle to make it to the destination before it runs out of power. The concerning short range of electric vehicles and the lack of charging infrastructure has proven to be a significant barrier for many prospective electric vehicle buyers.
(ii)Lack of charging infrastructure is yet another key issue the electric vehicle sector must deal with. Owners of electric vehicles need access to charging stations, yet many locations currently lack a public charging infrastructure.
(iii)Battery technology: The success of electric vehicles depends on battery technology. There is still a long way to go before electric vehicles can equal the range and performance of gasoline-powered vehicles, despite substantial advancements in battery technology over time.
(iv)Cost: The high price of electric vehicles continues to be a major obstacle to their widespread adoption. The expense of batteries continues to be a major issue in why electric vehicles are more expensive than gasoline-powered vehicles.
(v)Consumer education: There is a dearth of information on the technology, and many consumers are still unaware of the advantages of electric automobiles. Increasing consumer awareness and educating people about the benefits of electric vehicles are important.

VI. METHODOLOGY

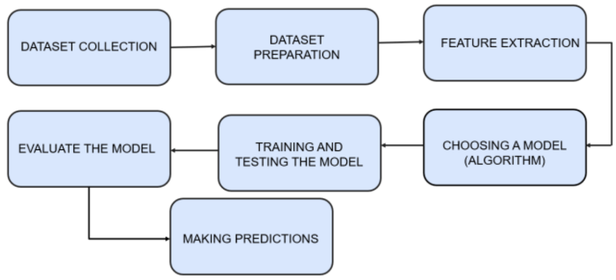

Fig 3: Methodology of the project

A. Image data Augmentation

Our database needed photos of numerous socket types from throughout the globe, including the CCS1, CCS2, TESLA types, but the data was limited. Therefore, we utilized image augmentation techniques to increase the size of our dataset. By applying various methods like cropping, flipping, rotating, and adding noise, we generated new images with the same underlying information as the original ones, but with slight variations. This allowed us to increase our dataset to 1000 images of sockets, crucial for accurate machine learning model training. With a larger dataset, our models can better adapt to new and unseen images, leading to enhanced accuracy and robustness.

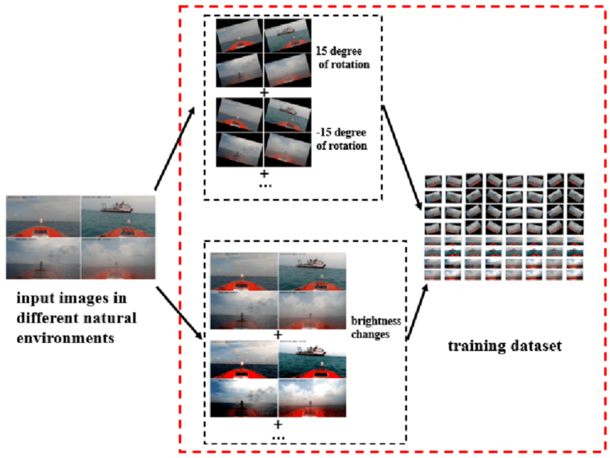

Fig 4: Image Data Augmentation

B. Pre-processing

Data splitting is one of the most important phases in preparing a dataset for machine learning model training. Data splitting's main objective is to prevent the model from overfitting the training set and to make sure it can generalise well to new data.

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The dataset is split into two subsets—training data and testing data—to accomplish this objective. The model is trained using the training data, and its effectiveness is assessed using the testing data. For the model to be properly trained and tested, there must be enough data in both subsets.

The quality of the input data is one of the most important elements that might impact the accuracy and resilience of machine learning models. The dimensions of the photographs are an important consideration when dealing with image datasets. The model's capacity to generalise adequately to fresh data can be hampered by the inconsistent findings that can result from images of various sizes and aspect ratios.

To solve this problem, we pre-processed our dataset by standardising the dimensions of the input photos. All of the photos were downsized to 224 by 224 pixels, a typical size that is frequently employed in computer vision applications. By lowering the chance of the model being over-fit to certain image sizes or aspect ratios, this step not only helped to ensure that all input photos had the same dimensions but also helped to increase the model's accuracy and resilience.

In conclusion, preparing and standardising the input data is an essential stage in the training of machine learning models. We can enhance the model's performance and its capacity to generalise well to new data by ensuring that the input data is of high quality and uniformity.

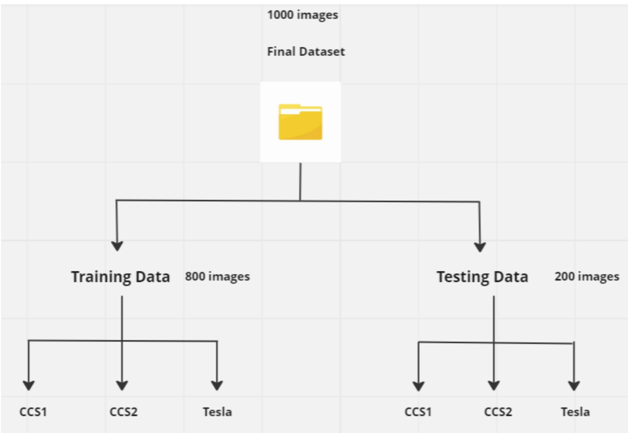

Fig 5: Pre Processing dataset

C. Edge Detection

To identify the edges on the socket, we employed OpenCV's Canny edge detection algorithm. Before executing the Canny algorithm, we transformed the image into black and white and incorporated supplementary layers like gray threshing.

We implemented this process on our complete database to maintain uniformity in image processing. Essentially, the pre-processing layers enhanced the image's clarity and emphasized the edges, thereby facilitating better edge detection using the Canny algorithm.

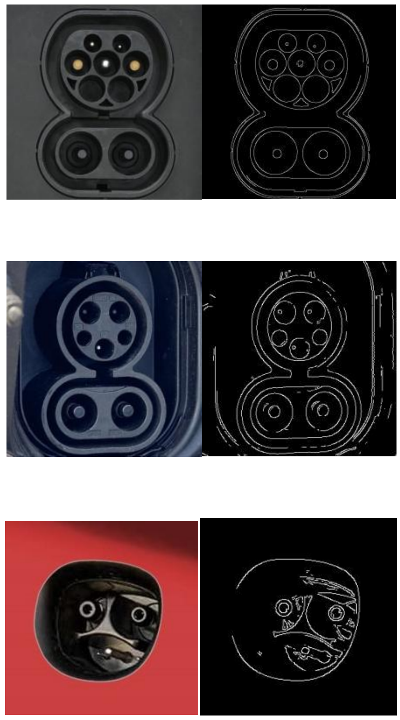

Fig 6: Original image and its edge detected image

D. API integration

The project has incorporated an API to simulate the UPI functionality, as the original UPI integration would entail numerous prerequisites that were not suitable for the project. To integrate the UPI system, the project would require securing necessary licenses and permissions, setting up a safe network infrastructure, and complying with regulations. Moreover, the costs of integrating the UPI system may not be justifiable for the project's scale and scope. To overcome these obstacles, the developers have implemented an API that replicates the UPI system's critical features. APIs enable various software applications to communicate with each other using protocols and tools. By using an API to replicate the UPI functionality, the developers can provide users with a seamless payment experience without requiring complex integration criteria. Overall, implementing an

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API to mimic the UPI functionality is a practical and cost-effective approach that allows the project to achieve its objectives while working within its constraints.

E. *Algorithm*

The CNN algorithm has been employed to classify sockets into 3 distinct categories, using a model comprising of a convolution layer and a max pooling layer. However, it is worth noting that the accuracy of the CNN model was not particularly high when the raw socket images were used.

To address this issue, the edge detection algorithm was applied to the dataset, resulting in a significant improvement in the accuracy of the CNN model. This indicates that pre-processing the images by enhancing the edges can greatly improve the performance of the classification model.

In essence, the use of pre-processing techniques such as edge detection can help to enhance the quality of the input images and make them more suitable for classification purposes. By extracting important features from the images, the CNN model is able to better differentiate between the different categories of sockets, resulting in a higher accuracy rate.

In summary, the CNN model used for socket classification showed low accuracy when raw socket images were used. However, the accuracy improved significantly when pre-processing techniques such as edge detection were applied to the dataset, highlighting the importance of image pre-processing in achieving accurate classification results.

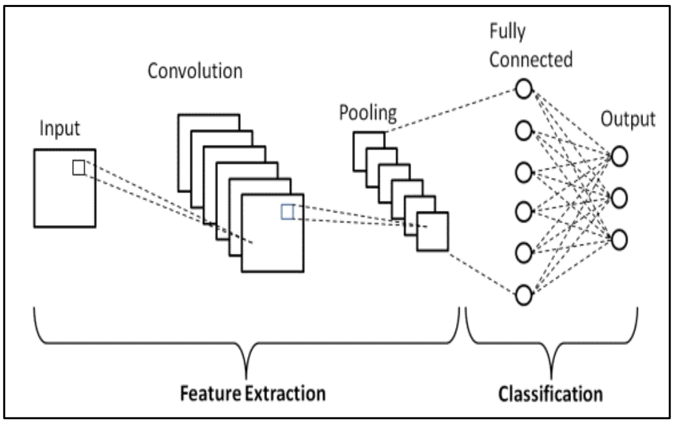

Fig 7: The convolution Layer Architecture:

Convolution Layer: The convolution layer (CONV) makes use of filters that perform convolution operations as it scans the input with regard to its dimensions. Stride and filter size are its hyperparameters. A feature map or activation map is what is created as the output O.

Pooling Layer: Following a convolution layer, which performs some spatial invariance, the pooling layer (POOL) is a down- sampling operation. The special types of pooling known as max and average pooling, respectively, take the maximum and average value.

Fully Connected (FC)- Each input is coupled to every neuron in the fully connected layer of a CNN, which operates on a flattened input. The FC layers, which are typically located at the conclusion of the CNN architecture, can be utilised to optimise goals like class rankings.

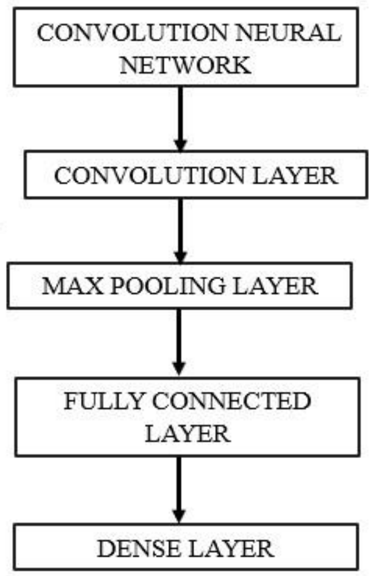

Fig8: CNN architecture

Convolutional layer formula: Output height/width = ((Input height/width - Filter size + 2 * Padding)/Stride) + 1

Pooling layer formula: Output height/width = ((Input height/width - Pooling size)/Stride) + 1

Number of parameters in a convolutional layer: Number of filters * (Filter height * Filter width * Number of channels in input + 1 bias term)

Number of parameters in a fully connected layer: Number of neurons in previous layer * Number of neurons in current layer + 1 bias term

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Output size of a convolutional layer: Output height * Output width * Number of filters

VII FLOWCHART

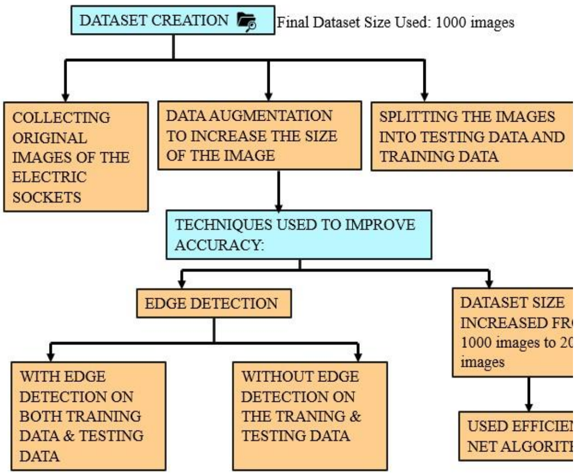

Fig 9: Project Flowchart

VIII. RESULTS

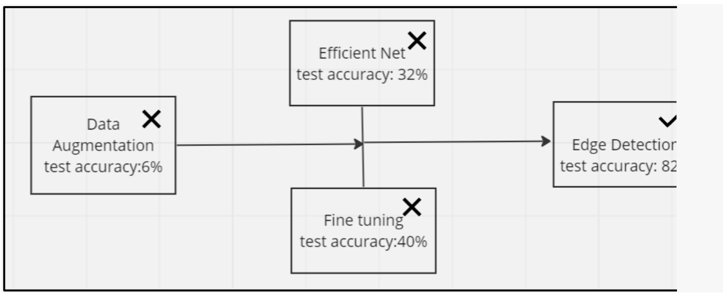

Fig 10: Project observation

(1). Original dataset (1000 images) is used to train the model in the CNN architecture

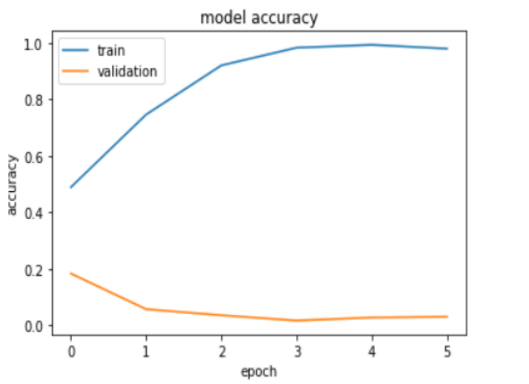

Fig 11: Test accuracy is around 29% and training accuracy is 95%

(2). To improve the accuracy of the model dataset is increased from 1000 images to 2000 images using Data Augmentation

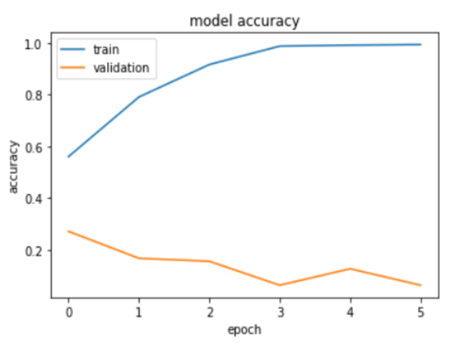

Fig 12: Test accuracy is around 6% and training accuracy is 99%

(3) . Another method of improving accuracy is using efficiency net algorithm.

(4). Test accuracy of the model is around 32%. Finally, Edge Detection is performed on all the images onboth training data and testing data

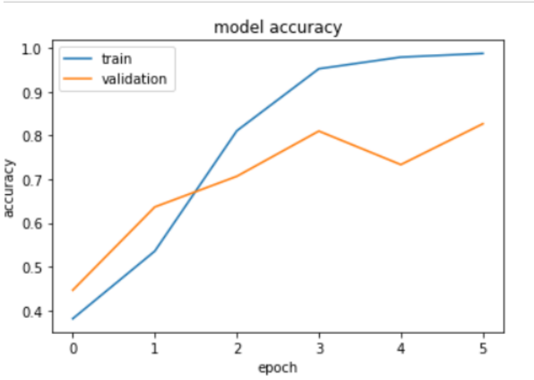

Fig 13: Test accuracy is around 82%

IX. DISCUSSION

Table 1: Accumulated Results

SL.No.	Proposed Approach	Dataset Size	Training Accuracy	Testing Accuracy	Inference
1	Original Dataset Raw Socket Images	1000	95.55%	29.56%	Overfitting
2	Original Dataset Raw Socket Images	2000	99.92%	6.35%%	Data Augmentation does not help in improving accuracy
3	Original Dataset Raw Socket Images	1000	83.51%	32.27%	Efficient Net is not helpful in improving accuracy
4	Original Dataset with edge Detection	1000	98.74%	82.66%	Edge Detection is the best way to get accurate result.

I. First we have used the original dataset of 1000 images and have got the training accuracy as 95% whereas the testing accuracy as 29%. This is known as overfitting.A major issue in machine learning is overfitting, which happens when a model is trained on the training data too thoroughly and starts to fit the noise or random fluctuations in the data instead of the underlying patterns or relationships. The training data are perfectly fit by an overfit model; however, it does not transfer well to test data. This may result in subpar performance on the test data and render the model unusable for practical use.

II. In the second phase we have increased the dataset from 1000 images to 2000 images using data augmentation. By this method the training accuracy is increased to 99% however the testing accuracy has reduced to 6%.

The model appears to be becoming better at identifying and categorising the images in the training set, as seen by the improvement in training accuracy to 99% after adding more images through data augmentation. The model is not generalising well to novel, untried images outside of the training set, as shown by the drop in testing accuracy to 6%.
In this situation, the model has learned to fit the training data too well and has become overly specialized to the training data, which is a classic case of overfitting. As a result, it struggles to perform effectively on fresh, untested data, which is what matters most in practical applications.
Several strategies, including reducing model complexity, regularizing the model, or using more diverse training data, can be used to address overfitting. In this instance, it's feasible that additional regularization approaches will help the model perform better when applied to fresh, untested data.

III. In the third phase to improve the accuracy of the model efficient net is used.The convolutional neural network architecture and scaling technique known as Efficient Net uses a compound coefficient to scale all depth, breadth, and resolution dimensions evenly. The training accuracy achieved is 83% and testing accuracy is 32%.
A class of convolutional neural network (CNN) architectures called Efficient Net was developed to attain cutting-edge accuracy with the least amount of input parameters and processing.
Efficient Net does this by combining a few methods, including:
(i)Compound scaling is the process of scaling the network's depth, width, and resolution in a proportionate manner to achieve the best performance on various tasks and resources.
(ii)To increase model efficiency, mobile inverted bottleneck convolutional (MBConv) blocks use depthwise separable convolution, shortcut connections, and linear bottlenecks.
(iii)Squeeze-and-Excitation (SE) blocks are a type of block that adjusts channel-wise feature responses adaptively to understand the dependencies between channel-wise features.
Efficient Net can handle a variety input image sizes and the resolution can be adjusted by scaling the height, width and depth of the network.
The height and breadth of the input image are typically represented by a number, such as 224x224 or 512x512, to indicate the resolution. Although more computational resources are needed, a higher resolution typically yields better performance.
Fine tuning is also used to improve the accuracy of the model.The practice of further training a pre-trained neural network model on a new, smaller dataset to adjust the model to the new dataset is referred to as fine-tuning. The weights of the previously trained model are utilized as a starting point in this procedure, and the model is then trained on the new dataset using a slower learning rate to let it to gradually adapt to the new dataset.
Fine-tuning is a technique commonly used in transfer learning, which involves taking a pre-trained model that has been trained on a large, general dataset such as ImageNet and then training it further on a specific dataset or task with a smaller amount of data. This can help enhance the model's performance on the new task or dataset, particularly when there is limited data available for training.

IV. In the final phase of the research we have used edge detectionon both training data and testing data. Convolutional neural networks (CNNs), which are taught to learn filters or kernels that can recognize edges in an image, are frequently used in machine learning to detect edges in images. These filters can be used for a variety of applications, including scene interpretation, object recognition, and image segmentation.

X.CONCLUSION

(i)Edge detection is the best method to perform image classification of electric socket for EVs.
Edges contain crucial information about the boundaries and contours of objects in an image, making edge detection a popular technique for feature extraction in image processing and computer vision.
Edges, which depict the transitions between various regions in a picture, are defined as the sudden changes in intensity or color values of adjoining pixels. We can extract significant characteristics like corners, curves, and shapes by identifying the locations and orientations of these transitions by looking for edges in a picture.

(ii)Data Augmentation is not the best method to improve the accuracy of the model.By applying numerous alterations to the original data, including flipping, rotating, cropping, and altering the brightness or contrast of images, the size of a training dataset can be artificially increased using the data augmentation technique, which is frequently employed in machine learning. Although data augmentation has the potential to increase a model's accuracy, it is not always the ideal approach and has significant drawbacks.

(iii)Fine tuning is not the best method to improve the accuracy of the model.Fine-tuning can be a useful strategy for increasing a model's accuracy, but it should be done carefully, considering variables like dataset size, task similarity, data distribution, and pre-trained model selection.

XI. FUTURE ENHANCEMENT

Finally, after doing edge detection on both the training dataset and the testing dataset we have got the test accuracy as 82.66%.Convolutional neural networks (CNN) are a boon to image classification systems as they learn highly abstract characteristics while using fewer parameters. However, using CNN to train the model presents several challenges, such as overfitting, exploding gradients, and class imbalance. Due to these difficulties, the model's performance may decline, which could affect the model's accuracy. However, by taking corrective measures and comprehending them, the model's effectiveness can be raised, and these issues can be largely avoided. The classification of images with varied positions due to different perspectives, multiple coordinate frames, and various different illumination conditions are the major drawbacks of CNN models.

XII. REFERENCES

[1] Miseikis, Justinas, Matthias Ruther, Bernhard Walzel, Mario Hirz, and Helmut Brunner. "3D vision guided robotic charging station for electric and plug-in hybrid vehicles." arXiv preprint arXiv:1703.05381 (2017).

[2] Chen, Tianjin, Xiao-Ping Zhang, Jianji Wang, Jianing Li, Cong Wu, Mingzhu Hu, and Huiping Bian. "A review on electric vehicle charging infrastructure development in the UK." Journal of Modern Power Systems and Clean Energy 8, no. 2 (2020): 193-205.

[3] Kumar K, Jeykishan, Sudhir Kumar, and Nandakumar VS. "Standards for electric vehicle charging stations in India: A review." Energy Storage 4, no. 1 (2022): e261.

[4] Zhang, Hui, and Xiating Jin. "A Method for New Energy Electric Vehicle Charging Hole Detection and Location Based on Machine Vision." In 2016 5th International Conference on Environment, Materials, Chemistry and Power Electronics. Atlantis Press, 2016.

[5].Dhanalakshmi, S., and C. Venkatesh. "Classification of ultrasound carotid artery images using texture features." International Review on Computers and Software (IRECOS) 8, no. 4 (2013): 933-940.

[6] Walzel, Bernhard, Christopher Sturm, Jürgen Fabian, and Mario Hirz. "Automated robot-based charging system for electric vehicles." In 16. Internationales Stuttgarter Symposium: Automobil- und Motorentechnik, pp. 937-949. Springer Fachmedien Wiesbaden, 2016.

[7]Prince Waqas, Khan, and Yung-Cheol Byun. "Blockchain-based peer-to-peer energy trading and charging payment system for electric vehicles." Sustainability 13, no. 14 (2021): 7962.