Prioritization Of Mobile Car Service Unit Placements Using Neural Networks

MSc Research Project
Data Analytics

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Prioritization Of Mobile Car Service Unit Placements Using Neural Networks

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Abstract

Artificial intelligence has been widely utilized in a variety of corporate fields in recent years, including design, marketing, customer service, inventory management, and stock prediction. The goal of this research is to see how neural networks, specifically Resnet50 may be utilized to improve automobile brand marketing and customer support. The most prevalent brands in vehicle parking lots will be detected using neural networks, which will aid in determining where to locate a mobile car servicing unit in order to optimize its use while also achieving car brand promotion. As part of this research four case studies are carried out using modified RseNet50 model using different input data as normal data, gray scale, selected images(Front/Rear view) and Limited classes. Model run on normal colored data yielded best result with accuracy 94.84% and compared with previous studies carried on same data set.

1 Introduction

One of the most fundamental jobs in computer vision is image classification. And with good reason: it has revolutionized and spurred scientific developments in some of the most important industries, including automobile manufacture, healthcare, and manufacturing. The job of assigning one (single-label classification) or more (multi-label classification) labels to a given image is known as image classification (or image recognition). Applied machine learning is widely recognized and employed in the car industry to generate new intelligent products and improved working practices. The amount of data created by connected automobiles is massive. This information, together with other vehicle information, might be used to develop models that predict when repair is needed or to characterize "driving behavior."

Traditional business models are being challenged by changes in customer behavior and technological advancements. Car makers, dealers, and other organizations in the automotive ecosystem must adapt quickly to the changing environment, embracing challenges and opportunities by leveraging data. The current generation of automobiles are software-enabled, data-generating, networked gadgets, presenting new (data) product and service prospects. It's not only about self-driving cars when it comes to automotive data science. Data science and machine learning technology may help car makers stay competitive by enhancing everything from research to design to manufacturing and marketing.

In the development of any business the marketing and customer service are vital. To reach new clients and to retain old clients It's really important. Marketing part is a little

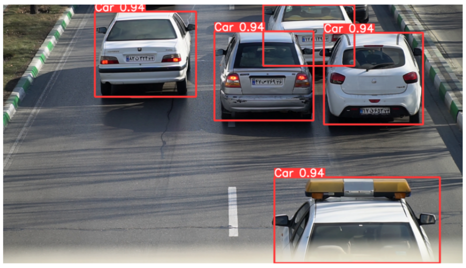


Figure 1: Use Of Deep Learning In Automobile Sector

hard for the car business unlike PUSH marketing strategy used in other industries where customer is pushed to buy some product. The car business therefore largely relies on PULL Marketing. To achieve this the company has to focus on credibility, presentation of knowledge in the field and value for the customer. In the age of e-commerce, when firms are attempting to provide customers with a simple platform and a better purchasing experience, traditional marketing models are antiquated. Prior to it, however, reaching out to target consumers and creating the company's reputation as a reliable and customer-focused brand takes precedence. Your brand is an extension of your mobile marketing vehicles. Regardless of the activation concept or outside branding, the vehicle type chosen has an impact on the message.

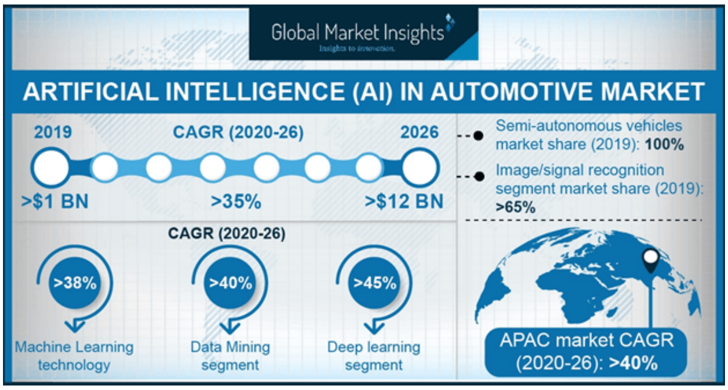


Figure 2: Use Of Deep Learning In Automobile Sector

It may be accomplished by strategically placing mobile vehicle servicing units across parking lots. Placing many mobile service units across the city can assist maintain existing clients by offering easy-to-access service platforms, as well as helping in visual marketing and brand exposure. Marketing costs are decreased since service units will be able to offset their costs by earning their own. Artificial intelligence has been widely utilized in a variety of commercial fields in recent years, including design, marketing, customer service, inventory management, and stock prediction. The goal of this study is to see how neural networks may be utilized to improve automobile brand marketing and customer support.

1.1 Research Question

- How to use ResNet50 model efficiently in identifying locations for Mobile Car Service Units near parking lots using image data classification for better customer reach and brand marketing ?

The research question is to identify and prioritize allocation of mobile car service unit using image data captured. To identify suitable location for placing mobile service unit, image data collected at parking lot entrance can be used to count number of vehicles parked for a specific brand. This data can be used for mobile service unit placement. The Stanford Car Data set will be utilized to build a vehicle recognition predictive model. The ultimate goal of the model is to classify the car make given an input image. This model could be further developed to be used in creating a mobile application that assists users in identifying cars of interest. Partnerships with other car dealership websites could be beneficial in enhancing the application quality, since the recognized vehicle name would be used in searching the partners' database to obtain valuable information such as availability, price and so on. An improved model would result in direct reviews/subscription profit.

2 Related Work

This literature review is an important aspect of research project since it helped position current findings in the context of the previous research carried out. It also aids in increasing the relevance of the collected results by comparing them to previously published studies. It is used to determine how relevant and coherent current research is in comparison to past studies.

2.1 Image Recognition

Computer vision has gotten a lot of attention in recent years, and a lot of research is being done in this sector. The capacity of a computer to process and learn from pictures or movies is known as computer vision. From an engineering standpoint, the goal is to use a computer to automate processes that are analogous to the human visual system. Authors proposed a visual object recognition and detection system based on AI and neural networks in their article Pietrow and Matuszewski (2017). It primarily focuses on comprehending the system's structure and image processing methods. This article examines each algorithm's efficiency, accuracy, and speed, as well as potential future advances.

The author discusses challenges with image recognition and image classification applications, as well as solutions In Dong and Liang (2019), . Machine learning models are compared to deep learning models, including the structure of deep learning algorithms, in this article. The author also points to a rise in the adoption of deep learning models as well as an exponential growth in the amount of research presently being done on deep learning models. This clarifies why deep learning models are important in this study proposal for picture data processing.

To examine the use of deep learning models for picture recognition, concentrating on four fundamental kinds of vehicles: vans, small cars, trucks, and buses is main goal of research Huttunen et al. (2016) . The accuracy of the support vector machine with SIFT is 97 percent, which is substantially greater than any traditional feature extraction approach. The notion of automobile type detection using deep learning model-based image recognition is explained in this study.

To propose smart parking for parking lots, image recognition may be used to recognize automobiles through aerial photos. In Xi et al. (2019), the author has developed a cost-sensitive multi-task convolutional neural network, commonly known as MTCS-CNN, to address this issue (2019). Partition layer with multitask separates object identification jobs into simple enlarged picture object detection tasks, which are less difficult and cost effective in terms of performance. With multitask layer partitioning, this emphasizes the need of deep learning approaches in image identification.

2.2 Use of Artificial Intelligence in Marketing

Machine learning and deep learning models of artificial intelligence are good at detecting patterns and trends in data. It is now also effectively utilized for marketing with adequate data input. Customer behavior trends may be easily recognized through trend identification, and the resulting knowledge can be used to determine future marketing tactics.
The author has addressed an international research of automobile brands and corporate perceptions of automotive brands in Setiono et al. (2006). The major focus of the paper is on re purposing knowledge from one automobile industry into a new automotive market. While retraining the model for a new market, essential knowledge collected through deep learning on one market is kept, and some new local components are added. This generates comparative findings between different automobile markets, revealing similarities and contrasts in transnational automotive markets as well as car brand image perception across all markets covered.

Author used surveys to collect data from 20 automobile market consumers in order to better understand brand image perception in Azcarraga et al. (2008). Customers' perceptions of brands were the subject of one of the survey's questions. The data acquired from these surveys, according to the author, may be utilized to make marketing strategy decisions. Neural networks are employed for knowledge discovery in this case. Based on performance accuracy, neural network models may efficiently handle input attributes, as well as delete or add attributes. This essay focuses mostly on two market applications: categorization and discovering commonalities in brand image perception across different markets. This is simple to apply for national or local markets, highlighting markets with comparable perceptions of automobile brands. In choosing on brand marketing tactics, generated knowledge will be crucial.

Authors main focus is on the benefits and drawbacks of employing artificial intelligence in marketing with knowledge transfer and generation as factors in De Bruyn et al. (2020). The paper examines the use of current neural networks to replace old model techniques. It also illustrates the drawbacks of applying artificial intelligence in organizations, such as the fact that if any of the traits are incorrectly weighted, the environment is biased or unrealistic, or stated functions are not adequately implemented, the firm would suffer greatly. The author focuses on overcoming the obstacles that arise when transferring information from AI to marketing organizations and vice versa.

2.3 Image Classification

When compared to artificial intelligence-powered systems, the manual process of image classification takes a long time. AI can categorize photos and find patterns, which may be used to do tasks such as displaying targeted adverts based on photographs seen by customers, recognizing brands from social media images, and providing accurate product suggestions based on social media image object identification.

The author examined the performance of Noise resilient convolutional neural networks for image classification using image data provided with noise and no pre-processing in Momeny et al. (2021). This operation is carried out with the use of an adjustable resizing and noise map layer in the CNN algorithm's structure. The results reveal that NR-CNN outperforms regular CNN models when it comes to noisy picture categorization.

Author has discussed the performance of a variety of deep learning models, including the Auto Encoder, Restricted Boltzmann Machine, Convolutional Neural Networks, and Deep Belief in Guo et al. (2017). For image classification tasks, CNN gives the best results. The author also discusses how deep learning is being used more often for applications such as picture classification, text recognition, auto encoders, and sparse coding. This article focuses on utilizing CNN to do basic analysis on data sets such as cifar-10 and minist.

The usage of a sandwich convolution neural network for spectral and spatial feature extraction, along with issues with feature extraction such as over fitting, which is caused by insufficient samples is discussed in Gao et al. (2021). The performance of standard approaches is contrasted to that of a lightweight sandwich convolution neural network, which produces better classification results than previous models.

2.4 Image Resolution Impact on Artificial Intelligence

Recent research has found that picking an optimal picture resolution is critical when applying deep learning or neural networks. Using high-quality photos decreases batch size, therefore choosing the best resolution is crucial for improving neural network performance. The influence of picture resolution on neural networks was explored by Sun et al. (2019). The author conducted a series of experiments that comprised training a neural network using a single image data set, either synthetic or camera photos, and then evaluating the model's performance with a separate data set. The results of this experiment reveal that resolution has a significant influence on model generalization and performance for 8-bit pictures, but not for 10-bit images, which have higher bit depth.

The author emphasizes the relevance of super resolution imaging in remote sensing biological or medical imaging, as well as the problems that might be encountered while getting super resolution pictures in Liu et al. (2020). This study investigates high-resolution picture reconstruction utilizing a variety of optimization methods, including AdaGrad, RMSprop, ADAM, and stochastic gradient descent. Study results showed that ADAM model has best performance and count of convolutional layers impacts performance.

3 Methodology

CRISP-DM stands for cross-industry data mining process. The CRISP-DM technique is a strategy for planning a data mining project in an organized way. It's a dependable and tried-and-true strategy. It encourages data miners to concentrate on business objectives in order to guarantee that project outcomes benefit the company. Too frequently, analysts lose sight of the study's ultimate business goal - the analysis may become a goal in and of itself rather than a means to an end. The CRISP-DM method ensures that the project's business goals are kept at the forefront throughout. These six key phases are used to explain the CRISP-DM process or approach.

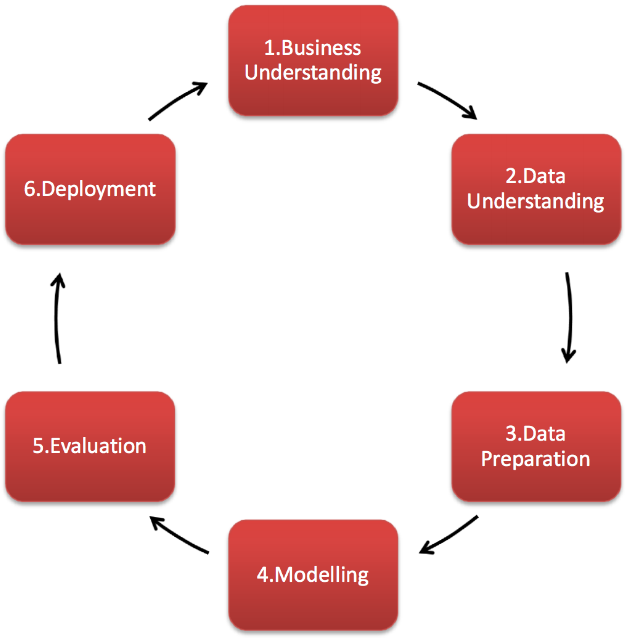


Figure 3: CRISP-DM Steps

3.1 Business Understanding

Neural networks have recently gained popularity as a tool for determining marketing strategy as discussed in Tanveer et al. (2021). The goal of this research is to determine where mobile vehicle service units should be placed. This will in turn reduce marketing and customer service costs. It will save money not just on marketing but also on operating costs for service units. Multiple literature sources are examined in order to determine the optimal method for achieving the goal.

3.2 Data Understanding And Data Preparation

The Stanford Car Data set is a big, fine grain car data set produced by Dr. Jonathan Krause and his Stanford University team Krause et al. (2013). A total of 16,185 automobile pictures are in the public Stanford cars data set. This data set contains a total of 196 vehicle classifications. To create a list of car labels, the authors used an unspecified car website to generate a list of all cars from 1990 to 2012. The data is divided for training and testing. For all pictures, the information comes with class names and bounding boxes. Typical classifications are in the year, production and model categories (for example, 2012 Tesla Model S or 2012 BMW M3). Each picture has its own sizes. In the pre-processing stage, the use of bounding boxes is necessary to produce first pictures focusing on the items of interest, which are the cars in this case. There are no missing data sets, hence there was no need for imputations or data removal owing to image data nature. The class labels were divided in terms of exploratory data analysis to study the levels of individual label make, model, type and year.

3.2.1 Data Set Challenges/ Justification

- Data set considered is from 2013, it does not include new car models in it. But considering scope of this project main focus is to mitigate brand marketing cost using mobile servicing and old car owners tend to opt car servicing more often than new car owners.
- Data set consists of car images from different sides and angles. But for scope of this project input image data will be in fixed format (Font View, Rear View) as it will be acquired from CCTV footage at parking lot. To Tackle this challenge model will be additionally tested using filtered data from original data set having only Font View or Rear-View images.
- Different Image Sizes: standard input size needs to be identified as model performance varies with image size.

3.3 Modeling

As part of this research residual network considered is ResNet50. ResNets are being used in practically every new AI technology to develop cutting-edge systems. ResNets work on the premise of building deeper networks compared to other simple networks while concurrently determining an optimal number of layers to avoid the vanishing gradient problem. ResNeXt has also been used on the CIFAR-10 dataset, with outstanding results. ResNet50 is a residual network with a large number of nodes. The number "50" refers to how many layers it has. It's a type of convolutional neural network, with ResNet being the most often used one for image categorization. ResNet's key innovation is the skip connection. Deep networks typically suffer from vanishing gradients if they aren't adjusted. As the model backpropagates, the gradient grows smaller. Learning might be difficult due to small gradients. By enabling your network to skip through levels that it believes are less significant in training, you may stack extra layers and develop a deeper network, balancing the disappearing gradient.

3.4 Evaluation

As noted in Nighania (2018), several features of the model will be evaluated in the evaluation of the implemented model. It has characteristics including as

- Accuracy is one of the most often used metrics for evaluating a model. However, it is not a reliable indicator of model performance.
- Model Processing Time- The model's overall processing time.
- Precision and Recall- Precision is defined as the ratio of properly recognized positive instances to the total number of positive examples detected, while recall is defined as the ratio of positive instances to the total number of genuine positive instances.
- F1 score is the harmonic mean of accuracy and recall. The F1 score should be greater in order to choose a suitable model.

4 Design Specification

ResNet50 is a ResNet variant of 48 convolutional layers, one MaxPool layer, and one Average Pool layer. The problem of vanishing gradients made training deep neural networks challenging before ResNet. This design supports in the resolution of accuracy deterioration concerns by developing a deep architecture and adding more layers. The flattening layer was used to connect the dense layer to the ResNet50 foundation model. As part of this research two dense layers, each with 256 and 128 nodes, that are completely linked are added. Output of the first base layers is used as input for next dense layers. Finally, the softmax activation function utilized to make output layer dense, which would be used in the classification model. This model is used with different data as input as follow

- Case-I: Cropped images from data set as per given bounding boxes
- Case-II: Black and white cropped images from data set as per given bounding boxes
- Case-III: Selected cropped images (Front view/Rear View)from data set as per given bounding boxes

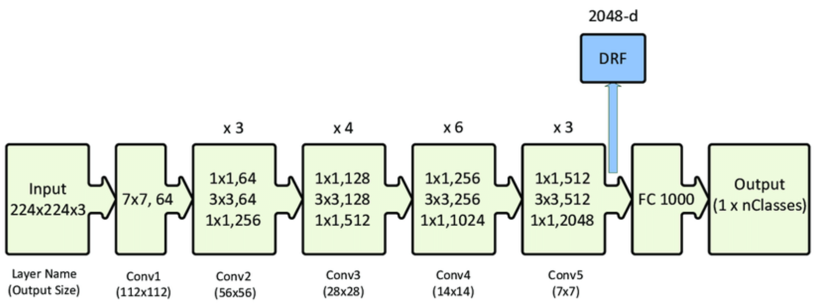


Figure 4: Resnet50 Sample model

5 Implementation

5.1 Data Pre-processing

Analyzing data that hasn't been thoroughly checked for issues might lead to inaccurate conclusions. As a result, before doing any analysis, the representation and quality of data must come first. Data preparation is frequently the most crucial stage of a machine learning project. As part of data pre-processing multiple processes were carried out in this research such as cropping images, converting to black and white, class merge and selecting specific images showing front view or rear view of car. Each step is discussed in detail below

5.1.1 Image Crop

In data set details regarding bounding boxes for images and car names are gives as .MAT file which is imported in pandas data frame. Using this data frame tasks like adjusting data types, plotting bounding boxes and cropping images as per bounding box are performed.

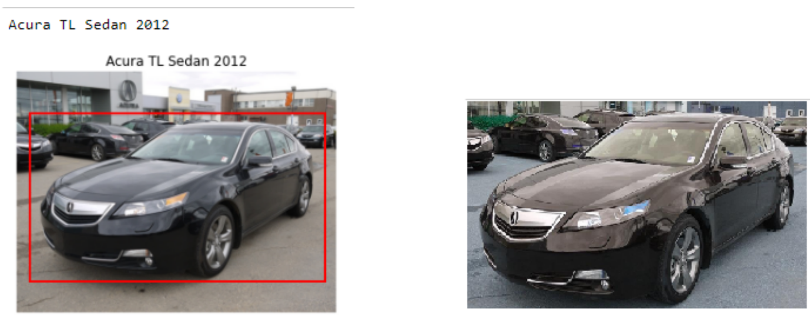


Figure 5: Cropping Images

5.1.2 Converting Images To Black and white

Using python training images are converted to black and white. Use of black and white images can be done in two ways. Either input color scale for model can be changed or giving input as black and white images after converting images first. As part of this research images are converted to black and white first and then given as input to model with all 3 color channels used in model.

5.1.3 Class Merge

As part of this research classes of the cars are merged as many of the car classes provided in data set are not that readily used so practically training model to recognise these car will not yield any actionable output for car company in terms of mobile service unit usage. So previously existing car classes with car make model year in data set are converted to only car brand names and used in model. In return classes present in data are reduced to 32 from 196.

Figure 6: Converting Images To Black and white

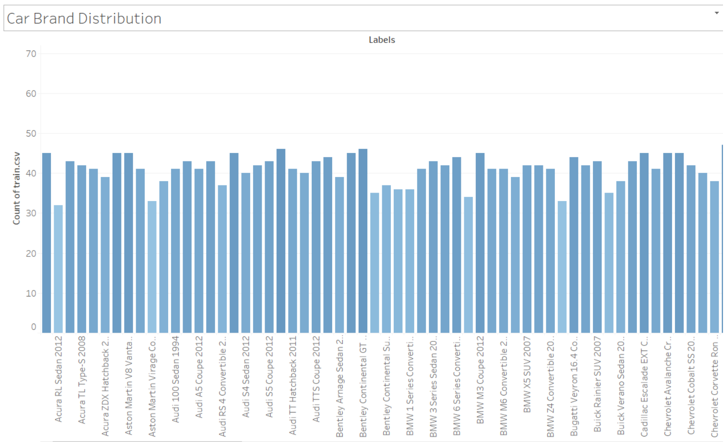


Figure 7: Car Brand Distribution

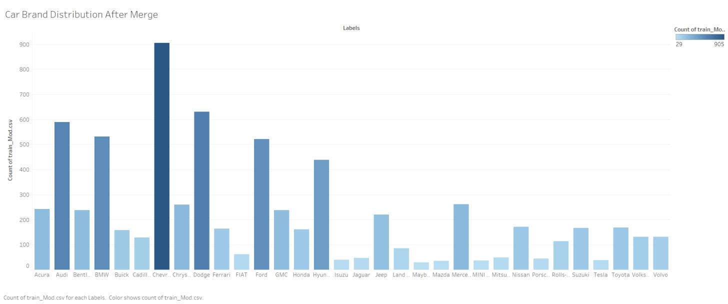


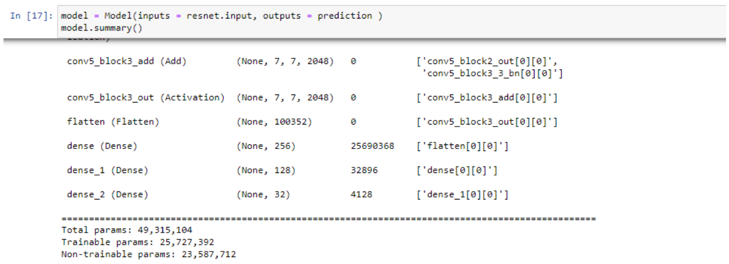
Figure 8: Car Brand Distribution After Class Merge

5.2 Model Implementation

ResNet50 is a ResNet variant with 48 convolutional layers, one MaxPool layer, and one Average Pool layer. Before ResNet, training deep neural networks was difficult due to the problem of vanishing gradients. By establishing a deep architecture and adding more layers, this design aids in the resolution of accuracy deterioration problems. The dense layer was connected to the ResNet50 foundation model via the flattening layer. This research includes the addition of two thick layers, each with 256 and 128 nodes, that are totally coupled. The output of the initial base layers serves as the input for the dense layers that follow. Finally, the softmax activation function was employed to create a dense output layer for the classification model. This model is as following:

5.2.1 Resnet50 Case-I: Colored Data Input

In this implementation Resnet50 with additional linked dense layers is done on normal colored cropped data as shown in Fig[10]. Data is prepared after doing all the processes mentioned in data pre-processing stage like image cropping and resizing.


```
In [17]: model = Model(inputs = resnet.input, outputs = prediction )
         model.summary()

 conv5_block3_add (Add)         (None, 7, 7, 2048)   0          ['conv5_block2_out[0][0]',
                                                                  'conv5_block3_3_bn[0][0]']

 conv5_block3_out (Activation)  (None, 7, 7, 2048)   0          ['conv5_block3_add[0][0]']

 flatten (Flatten)              (None, 100352)       0          ['conv5_block3_out[0][0]']

 dense (Dense)                  (None, 256)          25690368   ['flatten[0][0]']

 dense_1 (Dense)                (None, 128)          32896      ['dense[0][0]']

 dense_2 (Dense)                (None, 32)           4128       ['dense_1[0][0]']

==================================================================================================
Total params: 49,315,104
Trainable params: 25,727,392
Non-trainable params: 23,587,712
```

Figure 9: Resnet50 Case-I

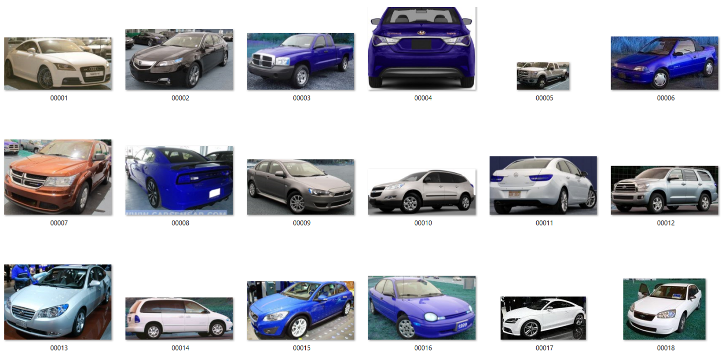


Figure 10: Resnet50 Case-I Input Data

5.2.2 Resnet50 Case-II: Gray Scale Data Input

In this implementation input data is converted to black and white and architecture of model is same as Case-I to check if color of the image is affecting model performance Fig[11]. Basically black and white images are given as input to model having all 3 color channels to check performance.

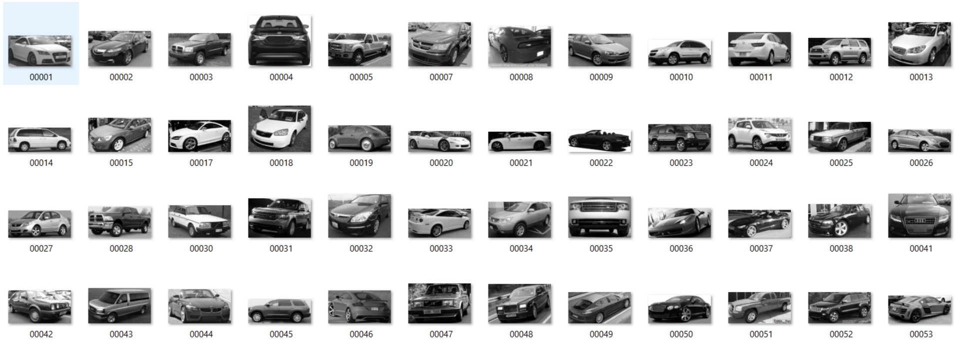


Figure 11: Resnet50 Case-II Input Data

5.2.3 Resnet50 Case-III: Front/Rear View Data Input

Base architecture for this model is same as first model. Only difference is input data given to the model is subset of original data set having cropped images of cars either as front view or rear view of the car. This will help gauge performance of model with images from static recording device as is expected while implementing model in real life for identifying car brand count in particular parking lot Fig[13].

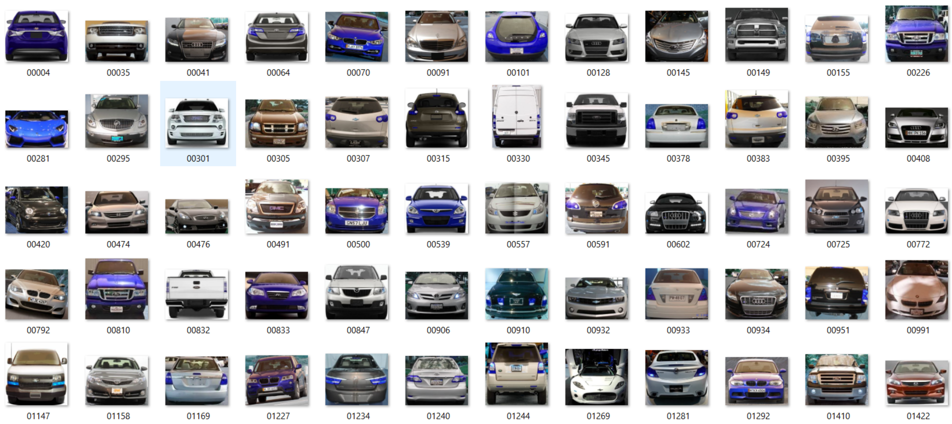


Figure 12: Resnet50 Case-III Input Data

5.2.4 Resnet50 Case-IV: Limited Class Data Input

In this case in attempt to reduce class imbalance and increase validation accuracy classes are limited to 5 where all classes have almost equal number of samples as shown in below Fig[].

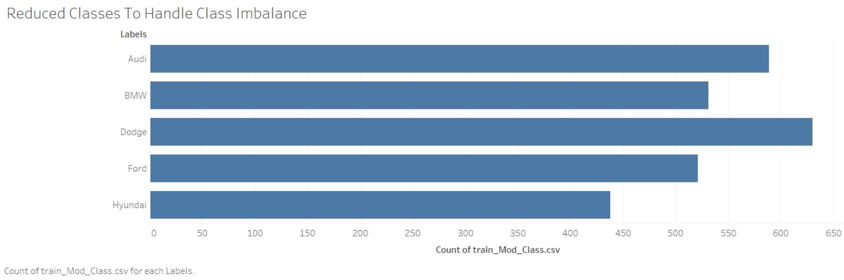


Figure 13: Resnet50 Case-IV Input Data

6 Evaluation

In paper Hu et al. (2017), authors have used Stanford Cars Data set to perform image classification using baseline models with additional swap layers and compared performance with baseline models for AlexNet, VGG16, ResNet50, ResNet101, ResNet50-LMP and ResNet101-LMP. Using results published in Hu et al. (2017) results of ResNet50 model used in current research are compared.

Type	Methods	Acc. on Model
Baselines	AlexNet	78.9%
	VGG16	85.4%
	ResNet50	89.7%
	ResNet101	90.9%
	ResNet50-LMP	91.6%
	ResNet101-LMP	92.9%
Previous	Chai *et al.* [28]	78.0%
	FV-CNN [29]	82.7%
	B-CNN [2]	91.3%
	Krause *et al.* [1]	92.6%
Ours	AlexNet-swp	83.6%
	VGG16-swp	90.7%
	ResNet50-swp	92.3%
	ResNet101-swp	93.1%

Figure 14: Resnet50 Previous Research Model

6.1 Case-I: Colored Data Input

Model returned 94.84% training accuracy with validation accuracy score around 50% after training for 99 epochs.Average epoch run time is 20 seconds. Low validation is generally caused by using different training and validation data or model is over fitting. In an attempt to increase validation accuracy different regularizers were implemented but it did not impact the results in any major way. F1 score for this models is very low 0.26 with low precision and recall suggesting model is not able to classify based on classes distinctly. This case yielded best result and increased accuracy compared to previous study Hu et al. (2017).

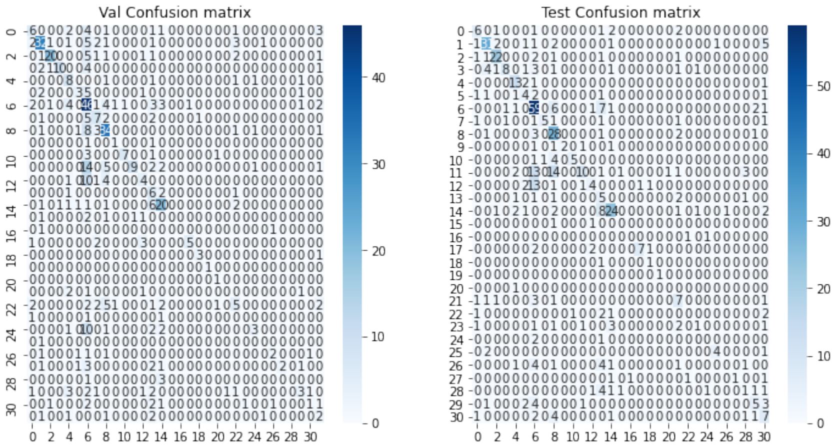


Figure 15: Loss And Accuracy

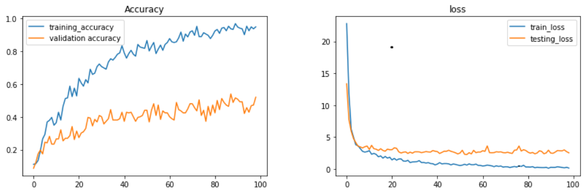
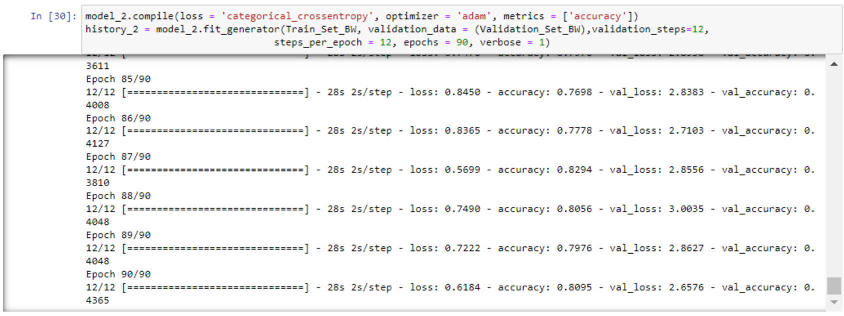


Figure 16: Loss And Accuracy

6.2 Case-II: Gray Scale Data Input

Model returned 80.95% training accuracy with validation accuracy score around 43% after training for 90 epochs with average epoch run time as 19 seconds. In this model input data is converted to black and white, prior to training the model. But all color channels in model are kept intact and used with black and white colors. This model accuracy is less than Case-I where normal color images were given as input to model.



```
In [30]: model_2.compile(loss = 'categorical_crossentropy', optimizer = 'adam', metrics = ['accuracy'])
         history_2 = model_2.fit_generator(Train_Set_BW, validation_data = (Validation_Set_BW),validation_steps=12,
                                           steps_per_epoch = 12, epochs = 90, verbose = 1)
3611
Epoch 85/90
12/12 [==============================] - 28s 2s/step - loss: 0.8450 - accuracy: 0.7698 - val_loss: 2.8383 - val_accuracy: 0.
4008
Epoch 86/90
12/12 [==============================] - 28s 2s/step - loss: 0.8365 - accuracy: 0.7778 - val_loss: 2.7103 - val_accuracy: 0.
4127
Epoch 87/90
12/12 [==============================] - 28s 2s/step - loss: 0.5699 - accuracy: 0.8294 - val_loss: 2.8556 - val_accuracy: 0.
3810
Epoch 88/90
12/12 [==============================] - 28s 2s/step - loss: 0.7490 - accuracy: 0.8056 - val_loss: 3.0035 - val_accuracy: 0.
4048
Epoch 89/90
12/12 [==============================] - 28s 2s/step - loss: 0.7222 - accuracy: 0.7976 - val_loss: 2.8627 - val_accuracy: 0.
4048
Epoch 90/90
12/12 [==============================] - 28s 2s/step - loss: 0.6184 - accuracy: 0.8095 - val_loss: 2.6576 - val_accuracy: 0.
4365
```

Figure 17: Resnet50 Case-II

6.3 Case-III: Front/Rear View Data Input

As part of this research, assumption is image data will be collected from static CCTV or any other method but all images will be taken from from fixed angle and perspective that is either front view of the car or rear view of the car. So to replicate real life scenario images were selected from data set which have either front view or rear view. This model yielded accuracy of 95.74% when run for 15 epochs with average epoch run time as 13 seconds. But this data has high class imbalance as classes are not evenly distributed.

```
Found 209 validated image filenames belonging to 30 classes.
Found 36 validated image filenames belonging to 30 classes.
Epoch 1/15
9/9 [==============================] - 16s 2s/step - loss: 7.0127 - accuracy: 0.0585 - val_loss: 6.3546 - val_accuracy: 0.1111
Epoch 2/15
9/9 [==============================] - 13s 1s/step - loss: 5.3558 - accuracy: 0.2553 - val_loss: 4.8319 - val_accuracy: 0.2500
Epoch 3/15
9/9 [==============================] - 13s 1s/step - loss: 3.8440 - accuracy: 0.6596 - val_loss: 3.6513 - val_accuracy: 0.4167
Epoch 4/15
9/9 [==============================] - 13s 1s/step - loss: 2.9496 - accuracy: 0.8511 - val_loss: 3.0091 - val_accuracy: 0.3056
Epoch 5/15
9/9 [==============================] - 13s 1s/step - loss: 2.3476 - accuracy: 0.9202 - val_loss: 2.4440 - val_accuracy: 0.4167
Epoch 6/15
9/9 [==============================] - 13s 1s/step - loss: 1.9013 - accuracy: 0.9574 - val_loss: 2.0510 - val_accuracy: 0.3611
Epoch 7/15
9/9 [==============================] - 13s 1s/step - loss: 1.5910 - accuracy: 0.9681 - val_loss: 1.7242 - val_accuracy: 0.4444
Epoch 8/15
9/9 [==============================] - 13s 1s/step - loss: 1.3741 - accuracy: 0.9521 - val_loss: 1.5406 - val_accuracy: 0.4444
Epoch 9/15
9/9 [==============================] - 13s 1s/step - loss: 1.2252 - accuracy: 0.9787 - val_loss: 1.4563 - val_accuracy: 0.3056
Epoch 10/15
9/9 [==============================] - 13s 1s/step - loss: 1.1182 - accuracy: 0.9521 - val_loss: 1.2815 - val_accuracy: 0.3333
Epoch 11/15
9/9 [==============================] - 13s 1s/step - loss: 1.0355 - accuracy: 0.9309 - val_loss: 1.1916 - val_accuracy: 0.3611
Epoch 12/15
9/9 [==============================] - 13s 1s/step - loss: 0.9683 - accuracy: 0.9628 - val_loss: 1.1114 - val_accuracy: 0.4167
Epoch 13/15
9/9 [==============================] - 13s 1s/step - loss: 0.9141 - accuracy: 0.9468 - val_loss: 1.0388 - val_accuracy: 0.4722
Epoch 14/15
9/9 [==============================] - 13s 1s/step - loss: 0.8548 - accuracy: 0.9628 - val_loss: 1.0260 - val_accuracy: 0.4722
Epoch 15/15
9/9 [==============================] - 13s 2s/step - loss: 0.8159 - accuracy: 0.9574 - val_loss: 1.0160 - val_accuracy: 0.3056
```

Figure 18: Resnet50 Case-III

6.4 Case-IV: Limited Class Data Input

For this case implementation input data is selected from five classes namely Audi,BMW,Dodge, Ford and Hyundai which have almost same number of samples. Model was implemented with 30 epochs with average epoch run time of 30 seconds per epoch. As shown in below figure Fig[19] model performance is not desirable showing very less accuracy and all cars are classified under one class as shown in confusion matrix. More analysis need to be done as to how performance can be improved.

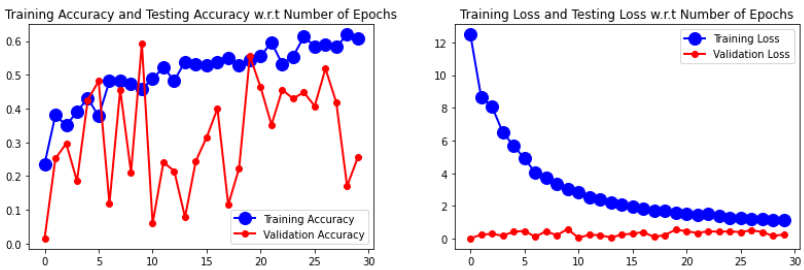


Figure 19: Resnet50 Case-IV

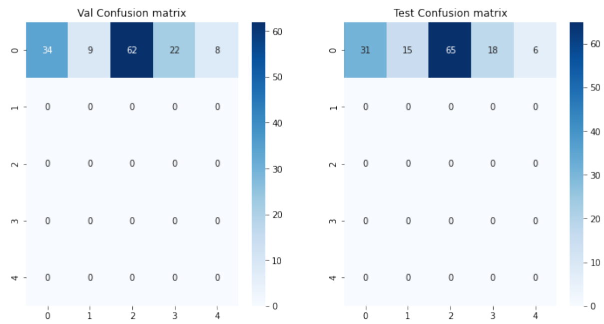


Figure 20: Resnet50 Case-IV

6.5 Discussion

In this model architecture ResNet50 is used as baseline model with additional dense layers with 256,128 nodes respectively which are fully linked. Three different input data set, which are subsets of original data set were given as training data for the model. Out of three cases, Case-I has highest training accuracy and validation accuracy, for this model normal cropped image data with additional dense layers was given. Training accuracy is higher for Case-III and Case-IV having selected view images of car but it can not be taken into consideration because of the class imbalance and model over fitting. Case-II is trained using black and white images as source but removing color gradient for image yielded less accuracy so its advisable to use normal colored images as input. Further analysis is required to enhance model validation accuracy.

7 Ethical Concerns

As image recognition becomes increasingly popular, it presents lots of new ethical concerns regarding its application. Image-recognition algorithms may be used to spy on the people, as they were recently in China, raising concerns about privacy and how it is abused. Such data use blurs the line between ethics, data ownership, and what is socially acceptable due to its lack of regulation and protection of personal information. One alternative for the data set used by the authors would have been to blur out license plates and faces during data collection. Standard ethical norms are followed during execution and will continue to be followed throughout the project's life cycle. The Cars Data set, a public data collection made accessible for academic purposes by Stanford University, is being examined for this study project. In addition, a relevant research work is referenced in the bibliography.

8 Conclusion and Future Work

Goal of this research is to identify suitable model for identifying car brands from data collected from parking lot. Using this data, number of cars can be identified for different brands. Using this suggested model car companies can manage their mobile service unit placement in more efficient way. It will not only help provide better service to existing customers but also it will reduce marketing costs. Out of the three suggested models

Case-I yielded highest accuracy 94.84% with validation accuracy around 50%. Compared to other two models which incorporated use of black white(accuracy 80.95%) and selected images (accuracy 95.74%)keeping the base architecture same. Case-III shows highest training accuracy but it can not be consider as good fit as there is class imbalance in selected subset. During implementation of the model main challenge was data pre-processing as it has to be done on complete data set of around 8000 images. Adding dropouts, batch normalization, weight regularization and other generalization and regularization approaches can help increase validation accuracy.

Further analysis can be done by adjusting layers or building model from scratch instead of using pre-trained model. Other aspect need to be analysed more regarding use of swap layers or gap layer with batch normalization. Current model incorporates baseline ResNet50 with added linked dense layers(256,128). Output of first layer is given as input to next layer but instead of that if we can achieve greater accuracy with reduced layers will not only reduce processing time but operational costs as well.

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