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COURSE: UNDERSTANDING ARTIFICIAL INTELLIGENCE

EXERCISE 1:

Analysing Second Hand Car Sales Data with Supervised and Unsupervised Learning Models

Abstract

Our goal is to uncover hidden patterns and insights within the large dataset of second hand car transactions. Using supervised learning models, we predict and understand the key factors that influence pricing of second hand cars. On the other hand, using unsupervised learning Models, we uncover hidden structures and connections within the data, giving us a comprehensive view of the dynamics of second hand car market. By analyzing this data, we not only improve our understanding of consumer behaviour and market forces, but we also harness the predictive powers of machine learning in a rapidly changing automotive industry. This paper contributes to the larger discussion on how to use data analytics to make better decisions in the world of secondhand car sales.

Introduction

The market value of used cars is increasing day by day. In fact, it has almost doubled in the last couple of years. With the advent of online portals like AutoTrader, Cazoo, Lookers, The AA, and many more, it has become easier for both the buyers and sellers to understand the trends and the patterns that affect the value of used cars on the market.

Machine Learning algorithms are used to predict a car's retail value based on a set of parameters. Training statistical models for the purpose of predicting the prices makes it easy to get a rough estimation of the price. (Chen et al) conducted an empirical investigation and compared two techniques, namely linear regression and random forest.

In this paper, we are going to use different prediction models and compare their level of accuracy.

Data Processing

The data set used for the prediction models was an imaginary mock dataset of second hand car sales in the UK. The dataset had 50000 rows with each row corresponding to the sale of a second hand car. The dataset had the following features(Columns):

Manufacturer – the name of the manufacturer.
• Model – the name of the model.
• Engine size – the size of the engine, in litres.
• Fuel type – the type of fuel.
• Year of manufacture – the year in which the car was made.
• Mileage – the total number of miles that the car has been driven.
• Price – the price that the car was sold for, in Pound Sterling (GBP).

From fig 1, it can be seen that the most represented car manufacturer are:

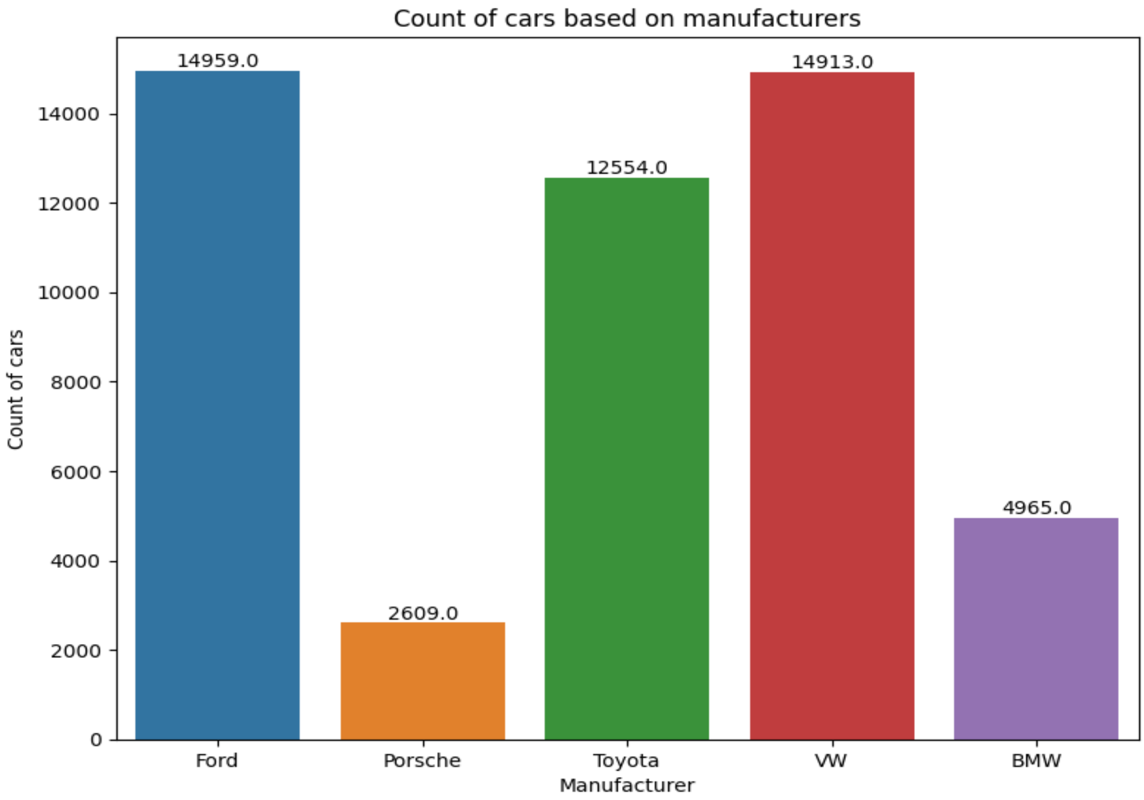


Fig 1 . *Distribution of the number of vehicles in the data set classified by the manufacturer.*

Figure 2 shows the number of car manufacturers and their prices attached. It can be seen that the most priced cars are Porche and BMW:

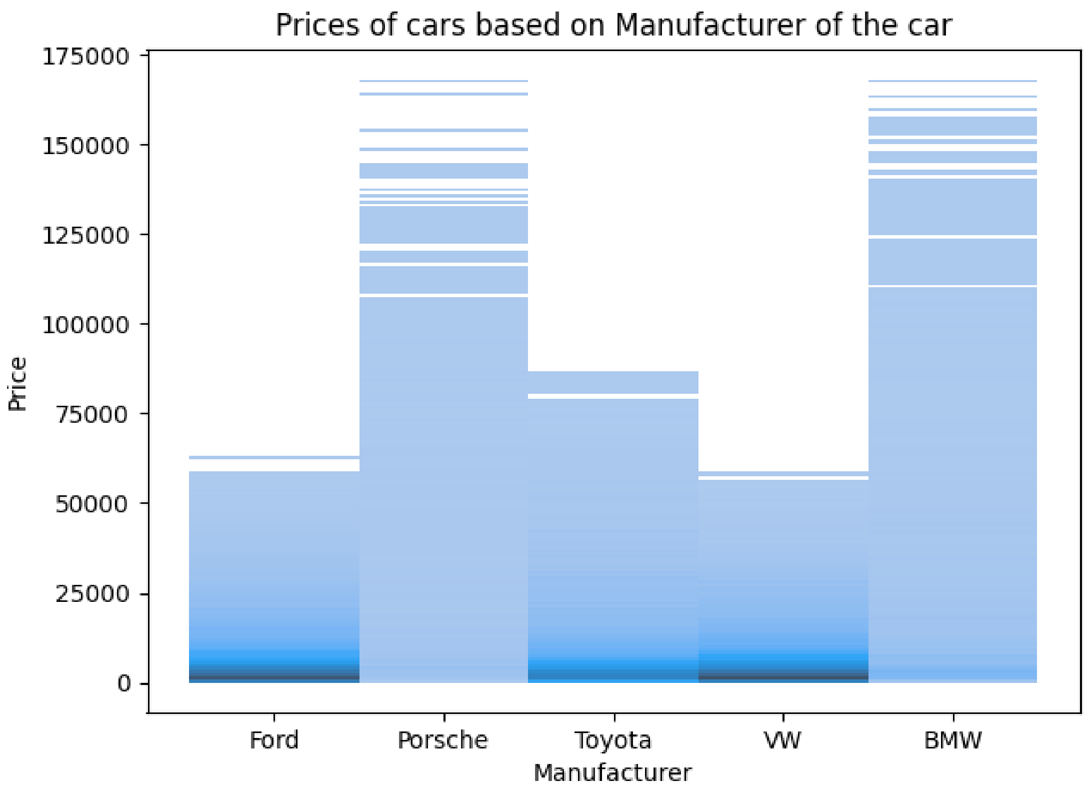
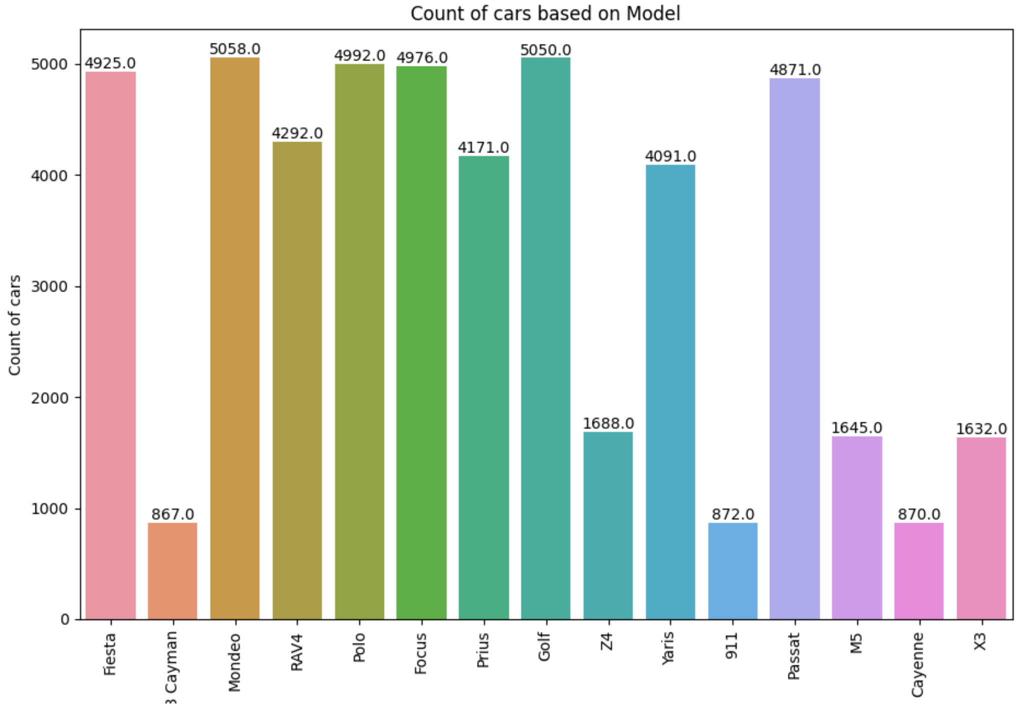


Figure 2: Manufacturer Vrs Price



From fig 3, it can be seen that the most represented car model:

Machine Learning

ML usually provides systems with the ability to learn and enhance from experience automatically without being specifically programmed and is generally referred to as the most popular latest technologies in the fourth industrial revolution (4IR or Industry 4.0) (Sarker et al

The learning algorithms can be categorized into four major types, such as supervised, unsupervised, semi-supervised, and reinforcement learning in the area (Mohammed M, Khan MB, Bashier Mohammed BE. Machine learning: algorithms and applications. CRC Press; 2016.), discussed briefly in below.

Methodology

PART 1

In this study, comparisons will be made between different linear regression models which will take different independent variables as input to determine the model that produces the most accurate predicted outcomes of used car prices.

Table 1: Table showing regression models and input parameters

Regression model	Input Feature
Simple linear regression	Engine Size
Simple linear regression	Year of Manufacture
Simple linear regression	Mileage
Polynomial Regression model	Engine Size

Polynomial Regression model	Year of Manufacture
Polynomial Regression model	Mileage

A supervised learning model is said to be good if:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |x_i - x|$$

Mean Absolute error is low

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Coefficient of Determination (R2) is closer to 1

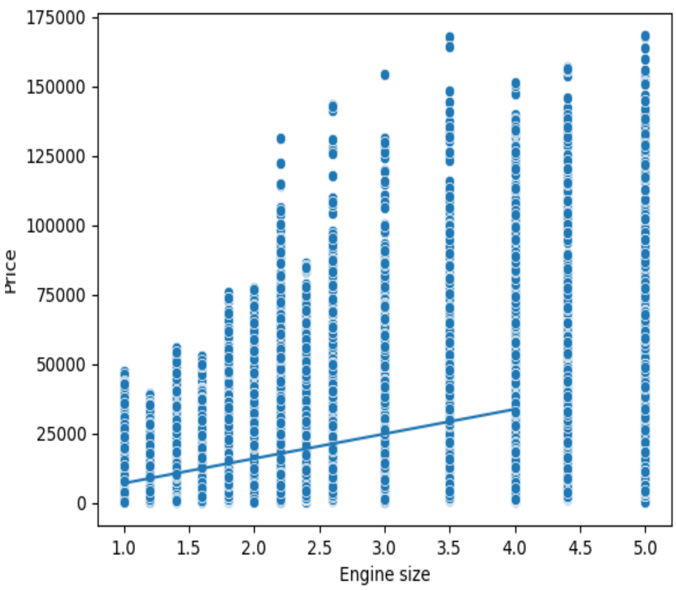
1. (a) Summary of Results and Analysis (Using one Input variable)

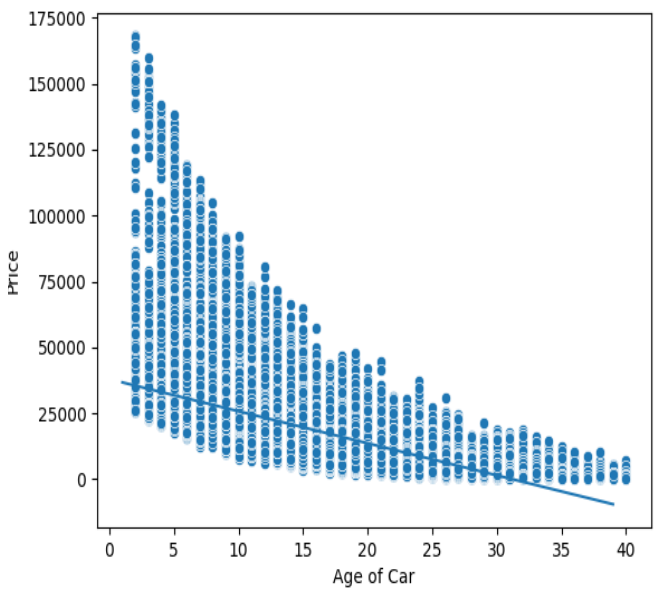
This model predicted the prices of used cars. Our focus is evaluating and comparing the performance of the model. The table below shows the evaluation metrics of the simple linear regression models which takes various numearical inputs as independent variables.

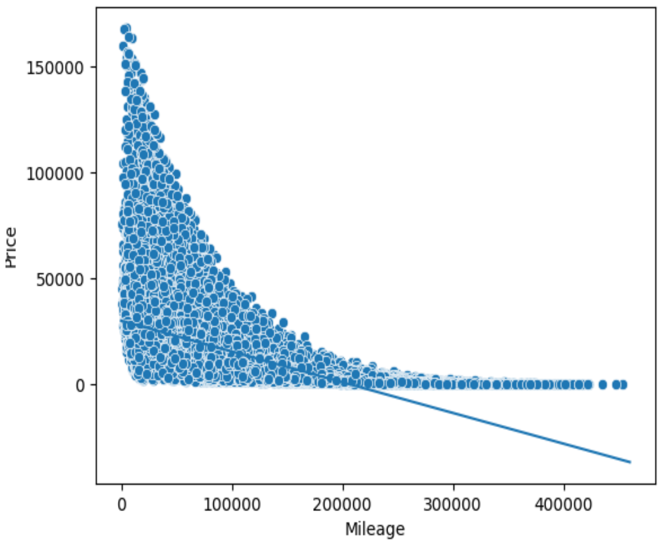
Table 2: Simple Linear Model Evaluation Metrics

Model	MAE	Coefficeient of Determination r2
Simple linear Regression of input ‘Engine size’	10670.30717	0.15781
Simple linear Regression of input ‘Year of Manufacture’	7013.02687	0.51405
Simple linear Regression of input ‘Mileage’	7877.33653	0.40727

Figures : Plot of Linear Regression with various numerical inputs as independent variables.





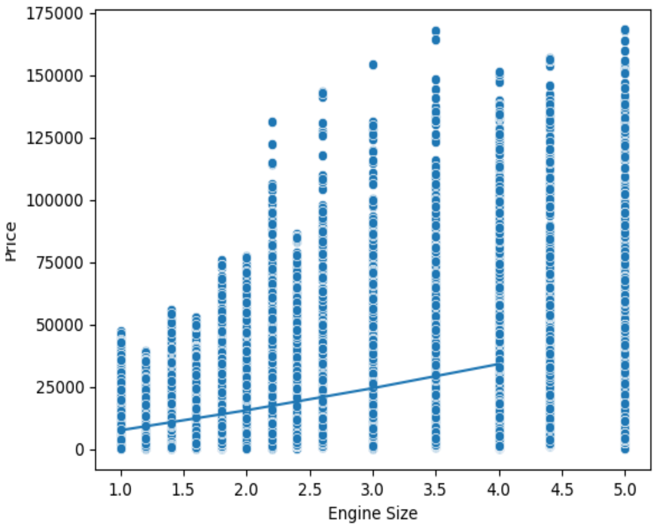


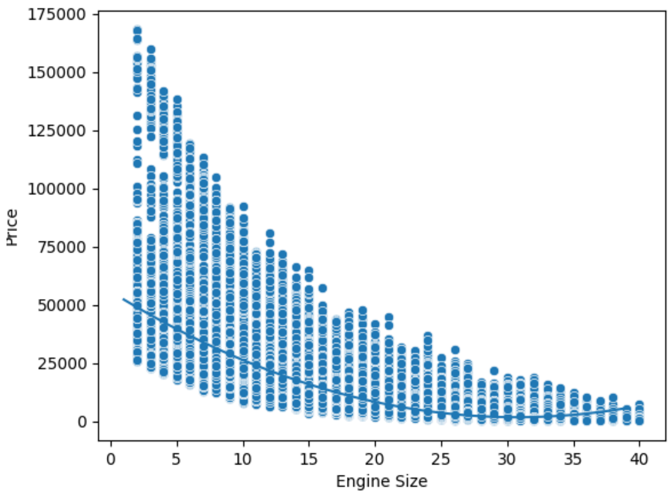
Comparing the evaluation metrics from the above table, the simple regression model with input ' Year of Manufacture ' performs better than the other models because it satifies the evaluation metrics criteria, followed by the other models. This is so because it has greater r2 score of 0.51 than the other models.

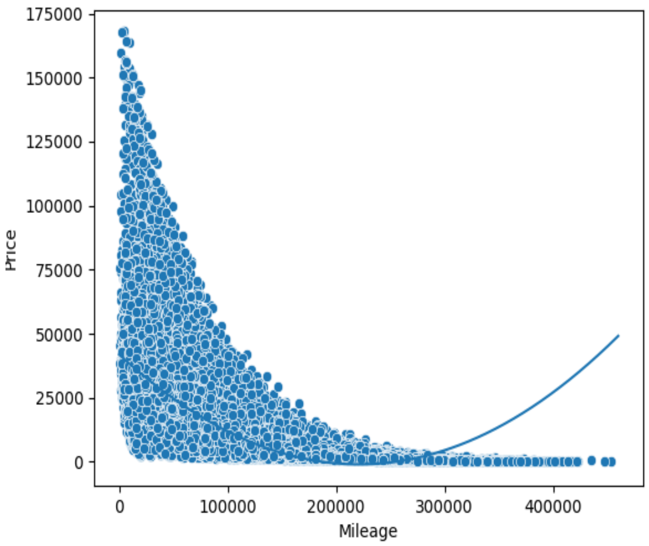
Polynomial Regression model

The model predicted prices of cars using polynomial regression of degree 2. The table below shows the summary of the MAE and coefficient of determination (r2) of degree 2 for all numerical features.

Model	MAE	Coefficeient of Determination r2
Polynomial Regression of input 'Engine size'	10661.05311	0.15869
Polynomia Regression of input 'Year of Manufacture'	5389.41952	0.60970
Polynomia Regression of input 'Mileage'	6380.89394	0.52199







Figures: The figures above shows plots of polynomial regression models of numerical features.

From the above, the price is better fit by polynomial regression model (Non-linear regression model). The polynomial regression had higher scores for the coefficients of determination (r2) and lower Mean Absolute Error (MAE)

PART 2 (Using Multiple Input Variables)

The model predict the price of a used a used using all numerical features as an independent variable.

The following table shows the model used.

Model	Input feature
Linear regression	'Engine size', 'Year of manufacture', 'Mileage'
Random Forest Regression	'Engine size', 'Year of manufacture', 'Mileage'

The summary of the coefficient of determination (r2) and Mean absolute error of this model is as follows:

Model	MAE	Coefficeient of Determination r2
Linear Regression of all numerical input features	6022.54523	0.68060
Random Forest Regression	2252.5614	0.92955

From the table above, the price of a used car is better fit by Random Forest Regressor model using multiple numerical inputs as independent variables as compared to using one input variable. This model had an r2 score of 0.68060 and MAE of 6022.5452 when using Linear Regression and r2 score of 0.92955 and MAE of 2252.5614 when using Random Forest Regressor, which is better comparing our previous models.

PART C (Using both Categorical and Numerical features)

This model uses both categorical and numerical features of the dataset to predict the price of a used car. The input variables were "Manufacturer", "Model", "Fuel type", “Engine size”, “Year of Manufacture”, “Mileage”. The table below shows the summary of the coefficient of determination (r2) and Mean absolute error of this model is as follows.

Model	MAE	Coefficeient of Determination r2
Linear Regression of all input features	5682.2889	0.71873
Random Forest Regression	289.0691	0.99849

From the table above, the price of a used car is better fit by Random Forest Regressor model using all inputs as independent variables as compared to using one input variable or multiple numerical variables. This model had an r2 score of 0.71873 and MAE of 5682.2889 when using Linear Regression and r2 score of 0.99849 and MAE of 289.0691 when using Random Forest Regressor, which is better comparing our previous models.

PART D Using Artificial Neural Network

This model uses deep learning algorithms to predict the prices of used cars.

Architecture:

Number of neurons equal to the number of features (6 layers)

Hyperparameter Tuning:

Learning Rate: Experiment with 0.001..

Batch Size: It was set to None.

Epochs: Train for a 200 number of epochs.

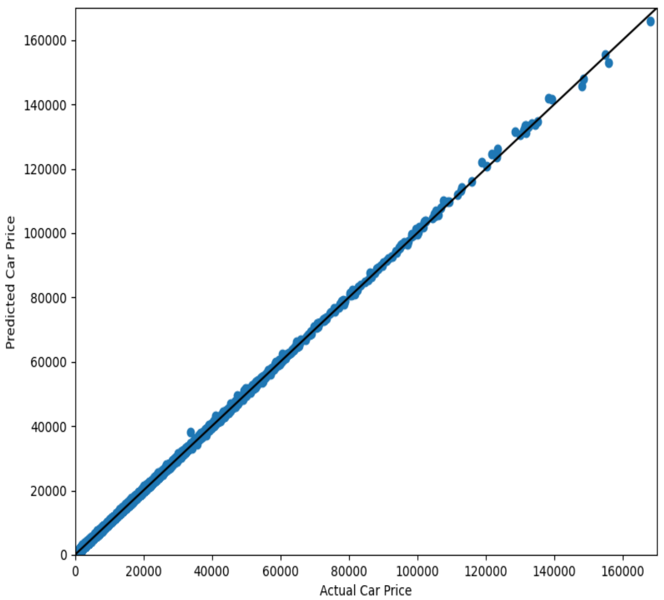
Early stopping: This was set to patience of 20.

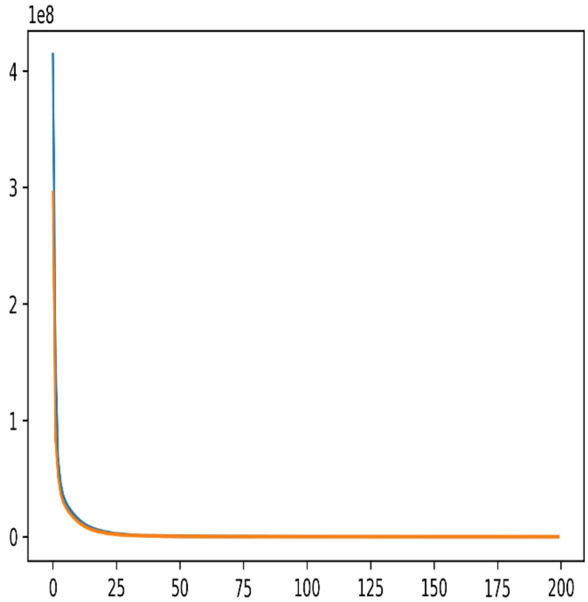
The table below shows the summary of the coefficient of determination (r2) and Mean absolute error of this model is as follows:

Model	MAE	Coefficeient of Determination (r2)
Artificial Neural Network	154.12756	0.99981

PART E

Based on this analysis, Artificial Neural Network is the best model for predicting the price of a car. This model achieved an r2 score of 0.99981 and MAE of 154.12756





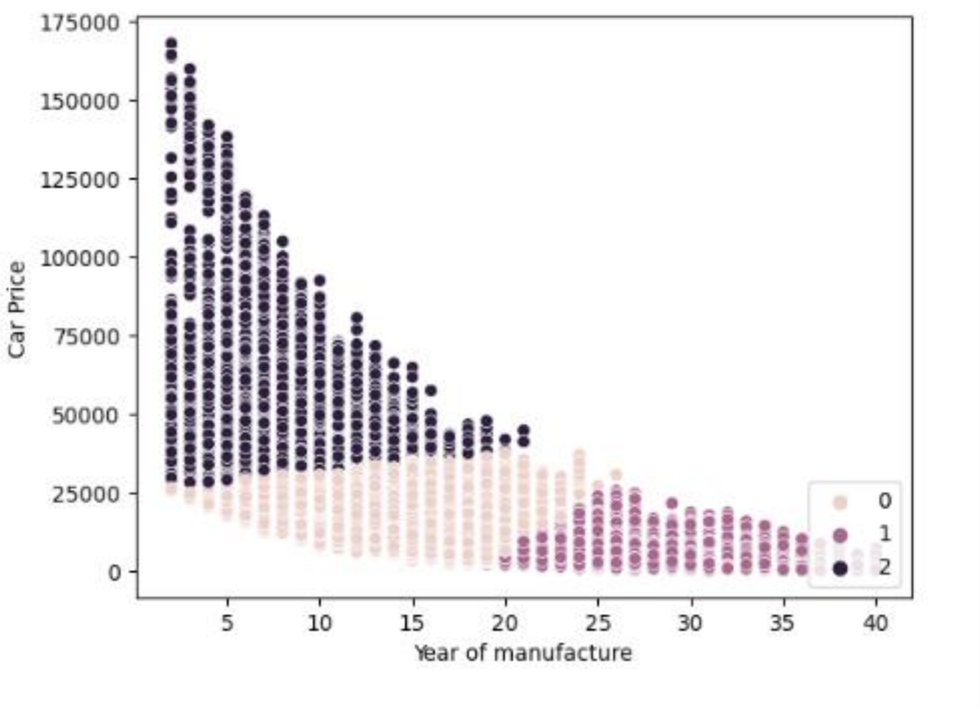
PART F Unsupervised Learning Model

This section utilizeed unsupervised learning technique to identify clusters of prices based on the data given. Using the K-Means clustering and DBSCAN clustering taking in inputs to predict Prices of used cars. The accuracy of the model is determined by the following criteria:

a. Davis Bouldin Index: A low score or value indicates a better performing model
b. Silhouette Coefficient: This ranges from -1 to +1 where a high score indicates a better performing model.

Model	Davies Bouldin Index	Silhouette Coefficient
K-means (Engine Vrs Price)	0.8982	0.4727
K-means (Year Vrs Price)	0.6866	0.5139
Simple linear Regression of input 'Mileage'	0.6870	0.4786

From the above table, K-Means clustering for the Year of manufacture vrs Price produces the best clustering results. This is so because Silhouette coefficient is greater and Davies Bouldin Index is smaller than the other clustering models.



PART G

Other clustering models used is DBSCAN. This produced the following evaluation metrics after modelling Engine size vrs Price.

```
Davies Bouldin Index: 2.6414
Silhouette Coefficient: 0.0608
```

Comparing this to other clustering models used, this produced worst results. The K-Means produced better results.

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EXERCISE 2:

Report on Image Recognition to Identify Species of Flowers

Introduction

The purpose of this study, Image Recognition to Identify Species of Flowers, is to create a CNN model that can recognize a flower's species from a picture. Tensor Flow's tf_flowers dataset was used to train the model..

The Convolutional Neural Network (CNN) is one of the most impressive types of ANN design. CNNs are generally employed to handle complex image-driven pattern recognition problems, and their exact but basic design makes it easier to get started with ANNs (Keironand Ryan,2015).

All of these parameters have a significant impact on classification performance in terms of accuracy, precision, and recall. The combination of convolution layers, number of pooling layers, number of filters, filter size, stride rate, and location of pooling layer determines an appropriate convolutional neural network architecture. Suitable parameter selection is entirely manual, requiring a significant amount of time and high computer resources such as GPUs for training and testing parameter combinations repeatedly (Mohammad et al,2022).

Methodology

Exploratory Data Analysis

This dataset contains 3670 colour photographs of flowers, consisting of five different species- Daisy, Dandelion, Roses, Sunflowers, Tulips.

Once the data was loaded, it was already divided into a "train" set and a "test" set. The picture data is stored in multi-dimensional arrays called x_train and x_test. Then I looked at the dimensions. It prints a tuple providing the array's size in each dimension. The x_train and x_test arrays have just four dimensions, with the fourth dimension having a size of three, representing the Red, Green, and Blue channels.

Define the class names an apply label encoding, Took a look at the class labels of the first five images of the training dataset in y_train to see these if labels agree with what is expected from the images that plotted above.

Data Pre-Processing & Data Augmentation

Normalizing the pixel values, combined with adjustments for data augmentation such as rotating, flipping, cropping and so on.

The input image arrays were then normalized, bringing the pixel values inside the range of 0 and 1. The arrays called x_train and x_test were divided by 255 because pixels ranged in value from 0 to 255.

Next, the picture alterations that will be applied to the data augmentation were defined.

The processes listed below are utilized to generate sets of image data: rotating by sixty degrees and repositioning the image by ten percent in both the height and breadth. The ranges for zoom, shear, and horizontal flips are 10%, respectively. ImageDataGenerator class was created to define these transformations. A a validation split of 20% was specified, the transformation was fitted to the normalized images from the training dataset.

Image Classification With CNN Model

Architecture of the CNN model

Building of the model started with the use of the following architecture .

First, a 2-dimensional Convolution layer (Conv2D) with 256 filters, a kernel size of 3x3,
32 filter was used because has been the standard starting point and besides since its moderate, it help balance the model capacity

ReLU activation function.Ensured that the input shape matches the shape of the input images, i.e. (width_npix, height_npix, 3), where width_npix and height_npix are the width and height, respectively, of each image in pixels. ReLU activation function non linearity to the mode, it allows the model to learn properly and approximate more functions

A 2-dimensional Max Pooling layer (MaxPooling2D) with a pool size of 2x2.
Using the max Pooling Layer helps prevent over-fitting, it makes the model more efficient.

A second 2-dimensional Convolution layer with 128 filters, a kernel size of 3x3, and the ReLU activation function. The additional convolutional added help the model capture more features

A 2-dimensional Max Pooling layer (MaxPooling2D) with a pool size of 2x2.The 2x2 pool size , helps in down sampling of the spatial dimensions of the future maps .

A third 2-dimensional Convolution layer with 96 filters, a kernel size of 3x3, and the ReLU activation function. The 96 filters can potentially capture broad feature. Though one should be care so it does snot result to over fitting .
A 2-dimensional Max Pooling layer (MaxPooling2D) with a pool size of 2x2

A fourth 2-dimensional Convolution layer with 64 filters, a kernel size of 3x3, and the ReLU activation function
A 2-dimensional Max Pooling layer (MaxPooling2D) with a pool size of 2x2.

A fifth 2-dimensional Convolution layer with 32 filters, a kernel size of 3x3, and the ReLU activation function
A 2-dimensional Max Pooling layer (MaxPooling2D) with a pool size of 2x2

A Flatten layer, which will flatten the outputs of the final convolution and pooling
This is important when transitioning from convolutional area. It reshapes the output layers into 1 dimension, ready for the fully connected part of the network.

A Dense layer with 128 neurons and the ReLU activation function.
connected to every neuron in the former layer , it helps to helps in dimensional reduction

Apply a dropout rate of 50% to this layer. This helps to prevent over-fitting

A final Dense layer with 5 neurons and the Softmax activation function. The outputs from this layer gave probability distribution of the 10 possible class labels

Imported classes from the tensor flow library to star building the model, created an instance like earlier done import the following classes from the Tensor Flow library.

The summary was then printed.

Compile the model (Compilation Stage) & Train the model (Training Stage)

The CNN model using the Adam optimiser, with a learning rate of 0.01. Set the loss function to 'categorical_crossentropy' and the metrics to 'accuracy'.

The model was trained for 100 epochs, using batches of randomly transformed images generated from the training data, with a batch size of 32.

When the training was done, the training and validation losses versus Epoch was plotted. Also plot the training and validation accuracies versus epoch was also plotted.

Hyperparameter Tuning

In each case, use appropriate evaluation metrics to determine the optimal choice for each hyperparameter.

- Trained the model using a batch size of 32. Now create a new model with
- the same CNN architecture, but increase the batch size to 128

- The model was repeated with a stride length of 2 in all three convolutional layers, in both the horizontal and vertical directions. Padding was applied to each convolutional layer.

- So far we have used convolutional layers with a kernel size of 3x3. The model was repeated,
- but with convolutional layers that use a kernel size of 5x5.

- Instead of using Max Pooling method for the
- pooling layers. the Average Pooling method in was used in each each pooling layer

Which hyperparameters have the strongest effect on the performance of your model? Use suitable figures to visualise the accuracy and performance of your final model.

Regularization method Used

Regularization used to avoid over fitting making the model more generalist to new data. Used:

- Used Batch Normalization is the process of normalizing the outputs of a layer to have a mean of zero and a standard deviation of one. Used an option parameter starting from 0.9.

- Trained the model with a learning rate reduced by a factor of 10, i.e. with a learning rate of 0.001.

The best model was used to predict the class labels from the testing dataset. The model predictions may then be used to generate a Classification Report, which summarizes several evaluation indicators including the precision, recall and F1-score for each class label and for the dataset as a whole.

How do they affect the accuracy of your results?

Predictions

Visualize the results using confusion matrix

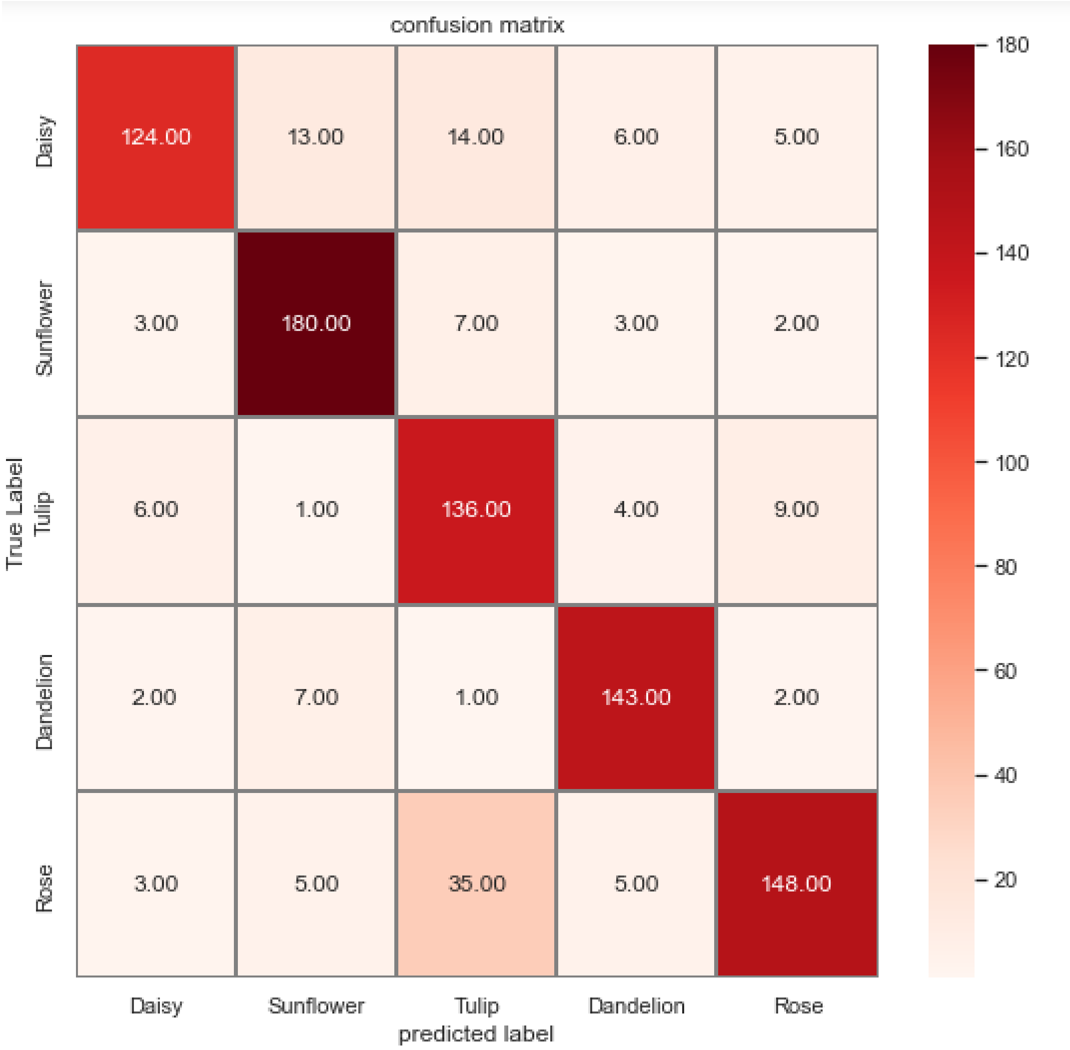
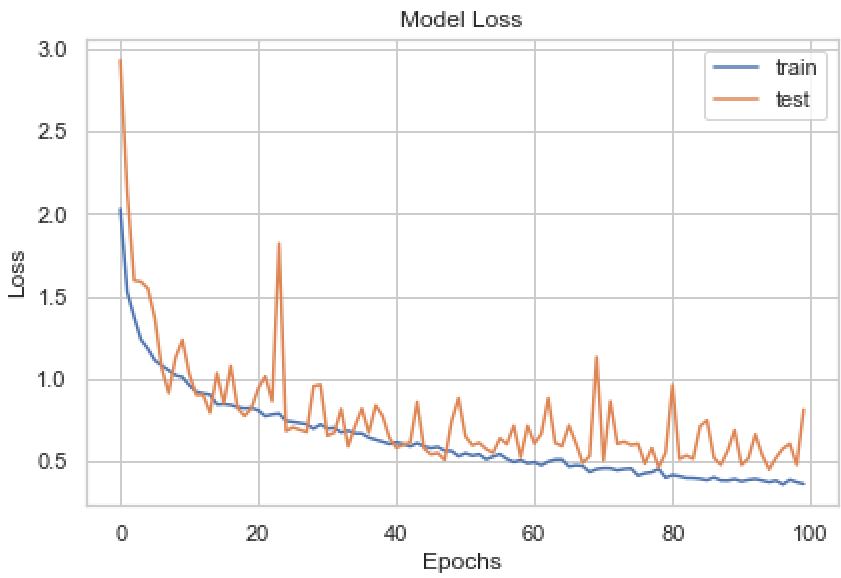


Figure1: Confusion Matrix

d. Was there any evidence of over-fitting in any of your models? Justify your answer with suitable figures.

There was overfitting in the model since there was higher training accuracy and lesser validation accuracy.

Figure 2 Train Test Loss



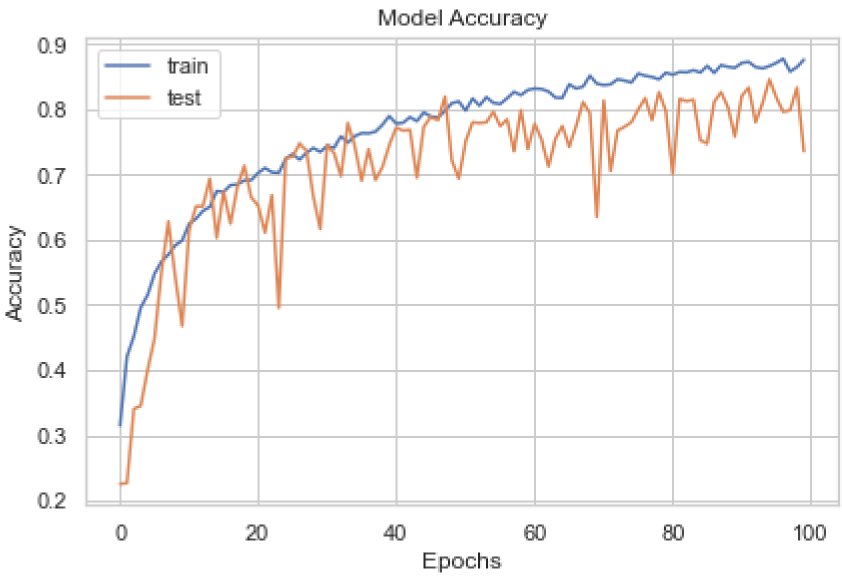


Figure 2 Train Test accuracy

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LITERATURE REVIEW

INTRODUCTION

Artificial intelligence (AI) enables computers to execute tasks that are easy for people to perform but difficult to describe formally (Pandl et al. 2020). Although Artificial Intelligence (AI) has been developed and studied for many years, it is mainly the recent developments in the sub-disciplines of Machine Learning (ML) and Deep

Learning that not only lead to many opportunities to improve the well-being of individuals, as well as the growth and development of organizations and societies, but also to a variety of new ethical, legal and social issues that, if not managed properly, could seriously limit the value contribution of AI. There are many examples of problems related to the rapid growth and adoption of AI. They range from risks of infringing individuals' privacy (e.g., swapping people's faces in images or videos via DeepFakes (Turton and Martin 2020) or involuntarily tracking individuals over the Internet via the Clearview AI (Hill 2020)), or the presence of racial bias in widely used AI-based systems (Obermeyer et al. 2019), to the rapid and uncontrolled creation of economic losses via autonomous trading agents (e.g., the loss of millions of dollars through erroneous algorithms in high-frequency trading (Harford 2012)).

TRUSTWORTHY IN ARTIFICIAL INTELLIGENCE

Aims of Trustworthy in Artificial Intelligence

Explore the ethical implications of AI technologies, ensuring that AI systems align with moral principles and respect human values. This involves addressing issues such as bias, discrimination, and fairness in AI algorithms

Success of the article

It presents a ground-breaking idea of fusing Distributed Ledger Technology (DLT) with Artificial Intelligence (AI) to produce a new paradigm for reliable AI and envisions a time when transparent, decentralised AI systems run on networks akin to blockchains, reducing the risks and promoting trust that come with centralised AI.

It offers a convincing vision for an AI environment that is more dependable, safe, and accountable.

It explains in great detail and with insight how DLT can be used to address important issues like explainability, bias reduction, and data security that are important to building trust in AI.

Challenges

Although there are potential mechanisms for combining DLT with AI discussed in the paper, there are still concerns regarding how well these solutions can scale to handle massive datasets and sophisticated models.

In a DLT-based AI ecosystem, the essay recognises the necessity of decentralised governance mechanisms but doesn't go into great detail about how they should be created or implemented.

Reaching a consensus on decision-making in the network is a major difficulty, especially when it comes to delicate AI models.

Suggested solutions to Challenges.

Investigate integrating with well-known DLT systems like Ethereum 2.0 or Hyperledger Fabric, which provide well-developed scalability options.

Examine more closely at the creation and modelling of decentralised governance models for the advancement of AI on the DLT network.

To strike a balance between data security and openness, consider using privacy-preserving strategies like federated learning and differential privacy.

Conclusion

In summary, the search for reliable AI is essential to guaranteeing the responsible advancement and application of AI technology. This article has dug into numerous fundamental purposes, spanning from ethical considerations and openness to accountability, privacy, and bias reduction. We may work to create AI systems that not only improve human skills but also do so in a way that is just, dependable, and considerate of individual rights by addressing these important aspects.

Building Trustworthy AI Solutions: A Case for Practical Solutions for Small Businesses

Aims

Taking into account the particular resources and constraints faced by small enterprises, discuss and offer workable ideas that make AI technology useful and accessible to them.

In order to ensure that the technology is utilized responsibly and in accordance with moral values, emphasize the significance of ethical issues in small enterprises' use of AI.

Successes

Recognizing the limited uptake of Trustworthy AI (TAI) principles and tools within small and medium-sized enterprises (SMEs) despite their importance for ethical AI development.

By conducting qualitative consultations with SMEs, the article identifies specific challenges and needs they face in implementing TAI, contributing valuable insights for researchers and policymakers.

Instead of focusing on high-level guidelines, the article advocates for practical, actionable solutions tailored to the constraints and capabilities of SMEs, increasing the feasibility and likelihood of TAI adoption within this crucial segment.

Highlighting the need for a more inclusive approach to TAI that considers the specific needs of diverse organizations, including SMEs, fosters broader and more responsible AI development.

Challenges and Gabs

Although the paper advocates for pragmatic solutions, it may not offer SMEs enough specific and doable steps to successfully apply TAI in their local environments. Including case studies, toolkits, or actual examples could increase the article's applicability.

Although the article discusses the initial obstacles to TAI adoption, it may not adequately address longer-term issues such as updates, continuous maintenance, and possible resource limitations in smaller enterprises. Taking care of these issues could support SMEs' ongoing TAI adoption.

SMEs may face a wide range of demands and difficulties depending on their industry and type of operation. It would be beneficial for the article to acknowledge this variation and provide customized frameworks or solutions that are suited to particular industries or situations.

Suggestions to bridge the gabs

Perform studies, either qualitative or quantitative, using a larger sample of SMEs that span various industries, sizes, and locations. This will produce broadly applicable insights and customize solutions to meet particular requirements.

Promote alliances with AI suppliers, academic institutions, or business associations to give SMEs with continuing assistance and information exchange.

Examine the particular difficulties and recommended procedures for implementing TAI in various company structures and industries.

Provide tools and advice that are suited to the unique requirements and uses of various SME industries.

Conclusions

In summary, the process of incorporating AI into small firms is not just a technology development but also a critical strategic move. The significance of developing reliable artificial intelligence solutions especially for small organizations has been emphasized by this article. Through tackling the distinct obstacles encountered by smaller businesses, we may provide a path for extensive implementation that is both pragmatic and morally sound.

Improving Trustworthiness of AI Solutions: A Qualitative Approach to Support Ethically-Grounded AI Design

AIMS

The main goal of the paper is to highlight any potential biases and weaknesses in the AI models that are used to forecast recidivism. It does this by showing how adversarial attacks can take advantage of these flaws and produce results that could be erroneous and biased. This attempts to increase awareness of the risks associated with biased AI in delicate fields like criminal justice.

Success

The essay makes connections between ideas from several academic fields, such as computer science, social justice, and law. This multidisciplinary method adds depth to the study and creates new directions for investigation and conversation.

The paper does more than just point out issues; it also promotes responsible AI development and application. It highlights the necessity of responsibility, fairness, and transparency when using AI to forecast recidivism.

In the context of recidivism prediction, the authors suggest specific actions to reduce the dangers of adversarial attacks and encourage ethical AI research. Policymakers and practitioners may find these recommendations—such as data pre-processing and model explainability—to be helpful.

Challenges and gabs

The technical components of adversarial attacks against particular recidivism models are the main emphasis of this essay. It may not go into great detail about the wider ethical, legal, and social ramifications of these attacks, such as possible systemic biases or effects on individual rights.

While it is important to show vulnerabilities in controlled environments, there may be a lack of research on the viability and ramifications of adversarial assaults in the real world. Including possible mitigation techniques and countermeasures could increase the article's usefulness.

Because the paper only examines particular models and datasets, it is unclear whether the results can be applied to other recidivism models and situations. The effect and application of the article might be improved by broadening its scope to take into account a variety of models and data sources.

Suggestions

Examine the wider social effects of adversarial attacks, such as how they affect individual rights, institutional biases, and legal frameworks for the use of AI in criminal justice.

Examine the viability and possible outcomes of adversarial attacks in practical contexts, taking into account user behavior, system security, and defenses.

Examine the generalizability of results by conducting tests on a variety of recidivism prediction models and datasets from various settings and nations.

Conclusion

The gap between technical understanding and practical application can be closed by addressing the problems and shortcomings that have been found. The article's important message can direct the development of responsible AI technologies in the critical field of recidivism prediction by broadening the scope, strengthening theoretical foundations, customizing solutions, and setting priorities for future study.

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