

**Sales Forecast of Manufacturing Companies using Machine
Learning Navigating Pandemic**

at

**Sathyabama Institute of Science and Technology
(DEEMED TO BE UNIVERSITY)**

Submitted in partial fulfillment of the requirements for the award of
Bachelor Engineering Degree in Computer Science and Engineering

By

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY (DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC I12B

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March- 2021



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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Professional Training Report is the bonafide work of **Nandaluri Prabhas (38110351)**, **Balineni Dileep Kumar (38110070)** who carried out the project entitled “**Sales Forecast of Manufacturing Companies using Machine Navigating Pandemic**” under our supervision from November 2020 to April 2021

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External Examiner

DECLARATION

I, **NANDALURI PRABHAS (37110351)** hereby declare that the project entitled **“SALES FORECAST OF MANUFACTURING COMPANIES USING MACHINE LEARNING NAVIGATING THE PANDEMIC”** done by me under the guidance of Ms. **Dr. T. JUDGI** at **Sathyabama Institute of Science and Technology** is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering.

DATE:

PLACE: CHENNAI

SIGNATURE OF THE CANDIDATE

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ABSTRACT

The paper is concerned with statistical models to forecast resale prices of used cars. An empirical study is performed to explore how different degrees of freedom in the modeling process contribute toward forecast accuracy. First, a comparative analysis of alternative prediction methods evidences that random forest regression is particularly effective in resale price forecasting. It is also shown that the use of linear regression, the prevailing method in previous work, should be avoided. Second, empirical results evidence the presence of heterogeneity in resale price forecasting and identify methods that can automatically overcome its detrimental effect on forecast accuracy.

Finally, the study confirms that the sellers of used cars possess informational advantages over market research agencies, which enable them to forecast resale prices more accurately. This implies that sellers have an incentive to invest into an in-house forecasting solution, instead of basing pricing decisions on externally generated residual value estimates.

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CHAPTER 1

INTRODUCTION

1.1 OUTLINE OF THE PROJECT

In many developed countries, it is common to lease a car rather than buying it outright. A lease is a binding contract between a buyer and a seller (or a third party – usually a bank, insurance firm or other financial institutions) in which the buyer must pay fixed installments for a pre-defined number of months/years to the seller/financier. After the lease period is over, the buyer has the possibility to buy the car at its residual value, i.e. its expected resale value. Thus, it is of commercial interest to seller/financiers to be able to predict the salvage value (residual value) of cars with accuracy. If the residual value is under-estimated by the seller/financier at the beginning, the installments will be higher for the clients who will certainly then opt for another seller/financier. If the residual value is over-estimated, the installments will be lower for the clients but then the seller/financier may have much difficulty at selling these high-priced used cars at this over-estimated residual value.

Predicting the resale value of a car is not a simple task. It is trite knowledge that the value of used cars depends on a number of factors. The most important ones are usually the age of the car, its make (and model), the origin of the car (the original country of the manufacturer), its mileage (the number of kilometers it has run) and its horsepower. Due to rising fuel prices, fuel economy is also of prime importance. Unfortunately, in practice, most people do not know exactly how much fuel their car consumes for each km driven. Other factors such as the type of fuel it uses, the interior style, the braking system, acceleration, the volume of its cylinders (measured in cc), safety index, its size, number of doors, paint colour, weight of the car, consumer reviews, prestigious awards won by the car manufacturer, its physical state, whether it is a sports car, whether it has cruise control, whether it is automatic or manual transmission, whether it belonged to an individual or a company and other options such as air conditioner, sound system, power steering, cosmic wheels, GPS navigator all may influence the price as well. Some special factors which buyers attach importance in Mauritius is the local of previous owners, whether the car had been involved in serious accidents and whether it is a lady-driven car. The look and feel of the car certainly contributes a lot to the price. As we can see, the price depends on a large number of factors. Unfortunately, information about all these factors are not always available and the buyer must make the decision to purchase at

a certain price based on few factors only. In this work, we have considered only a small subset of the factors mentioned above. More details are provided in Section III. This paper is organised as follows. In the next section, a review of related work is provided. Section III describes the methodology while in section IV, we describe, evaluate and compare different machine learning techniques to predict the price of used cars. Finally, we end the paper with a conclusion with some pointers towards future work.

1.2 RELATED WORK

Surprisingly, work on estimated the price of used cars is very recent but also very sparse. In her MSc thesis, liztiani showed that the regression mode build using support vector machines (SVM) can estimate the residual price of leased cars with higher accuracy than simple multiple regression or multivariate regression. SVM is better able to deal with very high dimensional data (number of features used to predict the price) and can avoid both over-fitting and underfitting. In particular, she used a genetic algorithm to find the optimal parameters for SVM in less time. The only drawback of this study is that the improvement of SVM regression over simple regression was not expressed in simple measures like mean deviation or variance. In another university thesis, Richardson working on the hypothesis that car manufacturers are more willing to produce vehicles which do not depreciate rapidly. In particular, by using a multiple regression analysis, he showed that hybrid cars (cars which use two different power sources to propel the car, i.e. they have both an internal combustion engine and an electric motor) are more able to keep their value than traditional vehicles. This is likely due to more environmental concerns about the climate and because of its higher fuel efficiency. The importance of other factors like age, mileage, make and MPG (miles per gallon) were also considered in this study.

Gonggi proposed a new model based on artificial neural networks to forecast the residual value of private used cars. The main features used in this study were: mileage, manufacturer and estimate useful life. The model was optimized to handle nonlinear relationships which cannot be done with simple linear regression methods. It was found that this model was reasonably accurate in predicting the residual value of used cars.

CHAPTER - 2

LITERATURE SURVEY

2.1 In 2011, Yuan Qingyu, Peng Geng, Liu Ying, Lv Benfu presented a paper on titled:

“A prediction study on the car sales based on web search data” The automobile industry is a pillar industry in the national economy, so it's of important significance to predict accurately car sales. On the basis of building theoretical frame of web search data and car sales, this paper selects keywords with the technology of auto recommendation, composes the keywords into composite index which can be used in the regression model of this paper, analyzes the relationship between the sales of car in different price ranges and the corresponding composite index, makes the prediction test.

2.2 In 2021, Yun Dai; Jinghao Huang presented a paper on titled:

“A Sales Forecast Method for Products with No Historical Data” With the acceleration of demand changes, the life cycle of products has been significantly shortened, and new product releases frequently. Thus, enterprises have an urgent demand for sales forecast of new products with no historical data. This article presents a forecasting approach based on the idea of “commodities with similar characteristics, sales may be similar”. We use similarity measures, consistency checks, and feature random search methods to predict sales in the first N months after launch. To illustrate the performance, we employ the model on a car sales dataset. The results show that compare with a series of machine learning models, the proposed method increased the forecast performance in a relatively short time, and it can be used in small size dataset that expands the scope of use and meets the actual business demands.

2.3 In 2019, Philipp Wachter; Tobias Widmer; Achim Klein presented a paper titled as

“Predicting Automotive Sales using Pre-Purchase Online Search Data” Sales forecasting is an essential element for implementing sustainable business

strategies in the automotive industry. Accurate sales forecasts enhance the competitive edge of car manufacturers in the effort to optimize their production planning processes. We propose a forecasting technique that combines keyword-specific customer online search data with economic variables to predict monthly car sales. To isolate online search data related to pre-purchase information search, we follow a backward induction approach and identify those keywords that are frequently applied by search engine users. In a set of experiments using real-world sales data and Google Trends, we find that our keyword-specific forecasting technique reduces the out-of-sample error by 5% as compared to existing techniques without systematic keyword selection. We also find that our regression models outperform the benchmark model by an out-of-sample prediction accuracy of up to 27%.

2.4 In 2015, Khutso Mashigo; Richard Weeks; Louwrence D. Erasmus presented a paper on titled:

“Evaluation of the vehicle after-sales services offered in South Africa by competing brands”The South African automotive industry is the third largest sector

in the national economy, This industry employs a significant number of people and it accounts for about 7.6% of the country's GDP. It operates in a highly competitive and dynamic environment that is growing at a tremendous rate due to international competition and changing demands of the customers. Furthermore, new competitors are countinuously entering the market introducing new competing brands which make it even more difficult for different brands to be competitive and profitable. A combination of a literature review and narrative enquiry was used in this study, that is qualitative and non-statistical in nature. The objective is to evaluate strengths and weaknesses of the servitization strategies adopted by competing brands in the after-sales service industry in South Africa to understand factors that give the competing brands a competitive advantage.

CHAPTER 3

AIM AND SCOPE OF THE PROJECT

3.1 AIM

The aim of the project is to create a model that can accurately predict the car sales for who are willing to buy their won liked model having a specific measures. So, client can buy either new or used cars by his won choice which is comfortable for to use and also comfortable form the investing in that car.

3.2 OBJECTIVE

From this machine learning model it is all about prediction of sales of a company cars using machine learning. it can easily predict the next outcome in terms of turnover or whichever is equivalent to it. For this particular project, an Indian automobile industry has been selected for car sales prediction. This project shows, if every other thing remains constant, what will be the sales trend for various automobile companies. By using various machine learning techniques.

3.3 SYSTEM REQUIREMENTS

The System requirements are the minimum hardware and software requirements needed for the implementation and execution of the model.

3.3.1 HARDWARE REQUIREMENT

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by the software engineers as the starting point for the system design. It shows what the system does and not how it should be implemented

	dual core 2.4 GHz (i5 or i7 series Intel processor or equivalent AMD)
SYSTEM	:
RAM	:8GB
HARD DISK	: 120 GB

3.3.2 SOFTWARE REQUIREMENTS

The software requirements document is the software specification of the system. It should include both a definition and a specification of a requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the team's progress throughout the development activity.

OPERATING SYSTEM : WINDOWS 10

PROGRAMMING LANGUAGE : PYTHON

TOOLS : PYCHARM, PYTHON, PIP 2.7

3.4 SOFTWARE FEATURES

The software features gives a detailed about all the software tools and database used in the model.

3.4.1 Python

Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object oriented, imperative, functional and procedural, and has a large and comprehensive standard library. Python interpreters are available for many operating systems. CPython, the reference implementation of Python, is open source software and has a community-based development model, as do nearly all of Python's other implementations. Python and CPython are managed by the non-profit Python Software Foundation Python is a multi-paradigm programming language. Object-oriented programming and structured programming are fully supported, and many of its features support functional programming and aspect-oriented programming

Python uses dynamic typing, and a combination of reference counting and a cycle-detecting garbage collector for memory management. It also features dynamic name resolution, which binds method and variable names during program execution. Python's design offers some support for functional programming in the Lisp tradition. It has filter(), map(), and reduce() functions; list comprehensions, dictionaries, and sets; and generator expressions. The standard library has two modules that implement functional tools borrowed from Haskell and Standard ML.

Libraries Used for this Project include –

- **Pandas**
- **NumPy**
- **Matplotlib**
- **Seaborn**
- **ScikitLearn**

3.4.2 Pycharm

PyCharm is a dedicated Python Integrated Development Environment (IDE) providing a wide range of essential tools for Python developers, tightly integrated to create a convenient environment for productive Python, web, and data

science development. PyCharm is cross-platform with windows , macOS and linux ver with Windows, macOS and Linux versions. The Community Edition is released under the Apache License and there is also Professional Edition with extra features – released under a subscription-funded proprietary license and also an educational version.

PyCharm provides an API so that developers can write their own plugins to extend PyCharm features. Several plugins from other JetBrains IDE also work with PyCharm. There are more than 1000 plugins which are compatible with PyCharm.

3.4.3 HTML

HTML (Hypertext markup Language) is the code that is used to structure a web page and its content. For example, content could be structured within a set of paragraphs, a list of bulleted points, or using images and data tables. As the title suggests, this article will give you a basic understanding of HTML and its functions.

HTML elements are the building blocks of HTML pages. With HTML constructs, images and other objects such as interactive forms may be embedded into the rendered page.

HTML provides a means to create structured documents by denoting structural semantic for text such as headings, paragraphs, lists, links, quotes and other items. HTML elements are delineated by *tags*, written using angle brackets.

3.4.4 Flask server

Flask is a micro web framework written in Python. It is classified as a micro framework because it does not require particular tools or libraries. It has no database no database abstraction layer, form validation, or any other components where pre-existing third-party libraries provide common functions. However, Flask supports extensions that can add application features as if they were implemented in Flask itself. Extensions exist for object-relational mappers, form validation, upload handling, various open authentication technologies and several common framework related tools.

3.5 ALGORITHM

3.5.1 KNN

K-nearest neighbour (IBk in Weka) is a machine learning technique in which the new (unknown) data is compared to all the existing records in order to locate the best match(es). Despite its apparent simplicity, a lot of care has to be taken in pre processing the data otherwise we can easily go off-track. Only three attributes were considered namely the make, year and cylinder volume. However, the data set was split into different sets, one containing only Toyota cars and the other only Nissan cars. This was done because most software cannot handle nominal values appropriately

but this allowed us to compare the performance on each make. In general, it was also

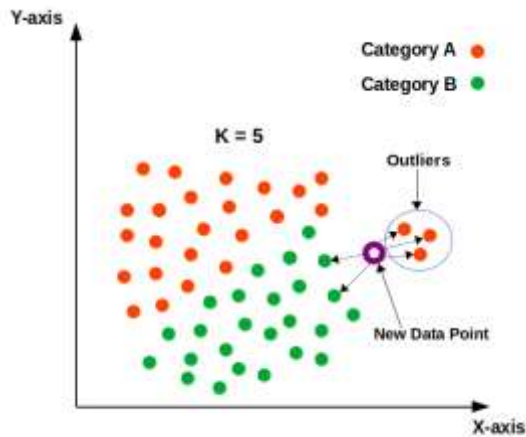
found that Toyota cars of the same age and cylinder are more expensive than Nissan cars with the same features. The data for year and cylinder had to be normalized to prevent large values (from one feature) from over-shadowing smaller values (from another feature). Thus, the following formulae were applied for normalizing the data. There were two options for normalizing the year.

1. Normalized value for Year = $(\text{Year of Manufacture} - 2014) / 19 + 1$

2. Normalized value for Year = $(\text{Year of Manufacture} - 2010) / 15 + 1$

The second option was chosen because most used cars are more than 4 years old. Used cars which are less than 4 years old are very likely to be outliers and may significantly affect the prediction performance. The divisor is the span of years from the newest car to the oldest car in the database. One (1) is then added to the quotient

to bring the value between 0 and 1 and to make sure that newer cars have higher normalized values than older cars.



3.1 KNN figure

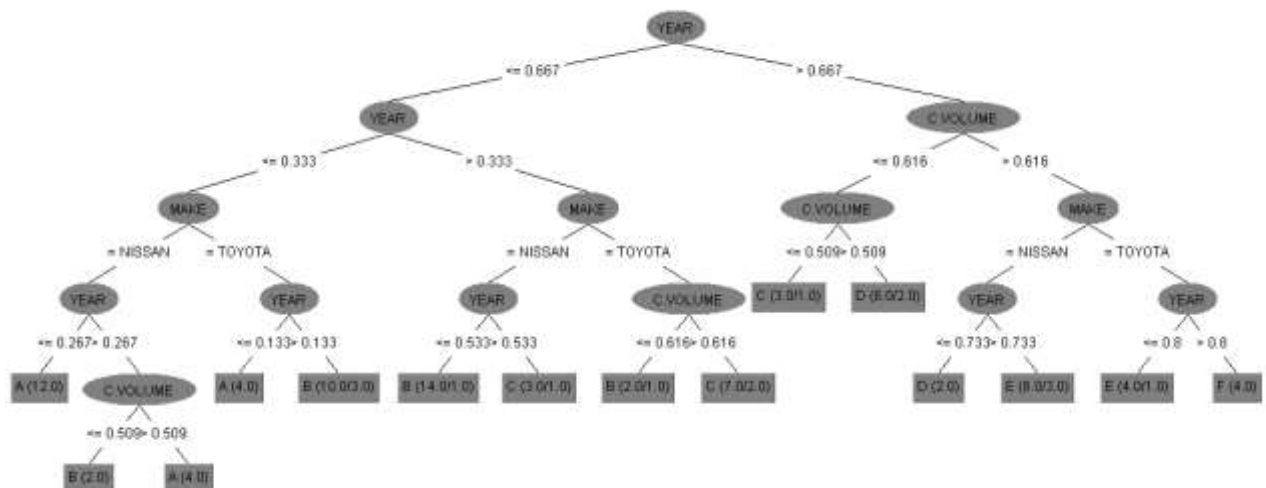
3.5.2 Decision Tree

Only Nissan and Toyota cars were considered for building the decision tree. The prices were grouped into six nominal categories as most of the popular decision tree algorithms cannot handle numeric outputs. There are many gaps in the ranges that have been defined because there were no cars within these ranges although it is certainly possible to get new data which fits within these zones. These large gaps have

been useful in determining the boundaries for the classes. The defined ranges can certainly be extended when more data is available. J48 is a free Java implementation of

the C4.5 decision tree algorithm which is found in Weka. The following attributes were

used to build the tree: make, model, cylinder volume, year and price.



3.2. Decision tree setup without car model

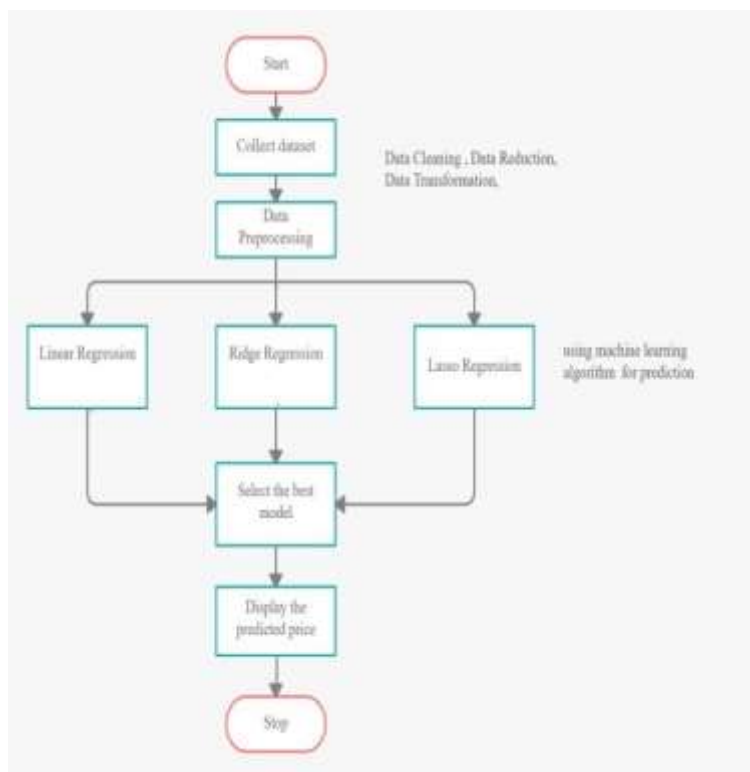
CHAPTER-4

METHODOLOGY

4.1 EXISTING SYSTEM

- Forecasting Based on Your Current Funnel
- Forecasting Based on Lead Scores and Multiple Variables
- Lead Scoring Tools
- Qualitative techniques
- Time series analysis and projection
- Casual Models

4.2 PROPOSED SYSTEM



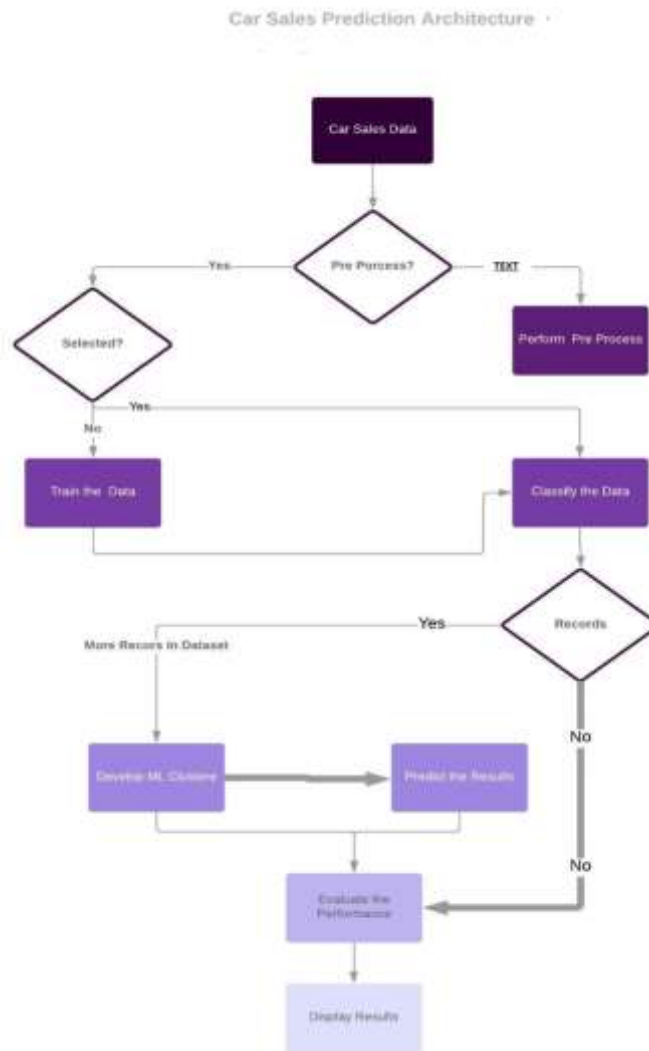
4.1 Proposed system

The process starts by collecting the dataset. The next step is to do Data Preprocessing which includes Data cleaning, Data reduction, Data Transformation. Then, using various machine learning algorithms we will predict the price. The algorithms involve Linear Regression, Ridge Regression and Lasso Regression. The best model which predicts the most accurate price is selected. After selection of the best model the predicted price is displayed to the user according to user's inputs. User can give input through website to for used car price prediction to machine learning model.

4.2.1 ADVANTAGES OF PROPOSED SYSTEM

- It has been growing tremendously and have a very bright future.
- it can easily predict using before data.
- the condition is, in real life, there are many factors affecting the production and sale of a company.
- It is very useful for future sales for company.
- The use of regression approaches for sales forecasting can often give us better results compared to time series methods.
- The accuracy on the validation set is an important indicator for choosing an optimal number of iterations of machine-learning algorithms.
- Can be used to make sales prediction when there is a small number of historical data for specific sales time series.

4.3 SYSTEM ARCHIITECTURE



4.2 System Architectural design

4.4 MODULES

The modules for this study involved seven data mining tasks,

1. Data collection
2. Data Pre-processing
3. Training and Testing
4. Performance Evaluation
5. Prediction

These steps help to ensure the models are optimal and prevent against overfitting. A range of variables were considered in the model building, with the final variables decided upon based on previous studies, significance in the models, and the impact of inclusion on the performance of the model. The final models consisted of variables describing whether the cars measurements are suitable for in the giver dataset or not.

4.5 Module Description

To build the complete prediction model, it is essential to carry out step-by-step execution of all required modules.

4.5.1 Data Collection

The process of gathering data depends on the type of project we desire to make, if we want to make an ML project that uses real-time data, then we can build an IoT system that using different sensors data. The data set can be collected from various sources such as a file, database, sensor and many other such sources but the collected data cannot be used directly for performing the analysis process as there might be a lot of missing data, extremely large values, unorganized text data or noisy data. Therefore, to solve this problem Data Preparation is done.

We can also use some free data sets which are present on the internet. Kaggle and UCI Machine learning Repository are the repositories that are used the most for making Machine learning models. Kaggle is one of the most visited websites that is used for practicing machine learning algorithms, they also host competitions in which people can participate and get to test their knowledge of machine learning.

4.5.2 Data Pre-processing

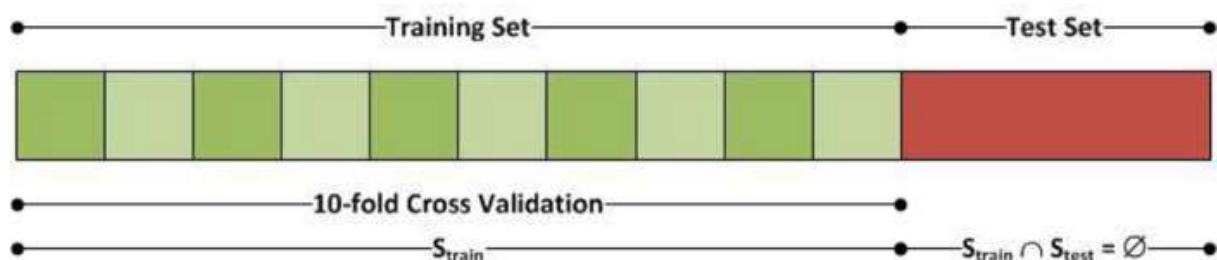
Collecting the data is one task and making that data useful is another vital task. Data collected from various means will be in an unorganized format and there may be a lot of null values, invalid data values and unwanted data. Cleaning all these data and replacing them with appropriate or approximate data and removing null and missing data and replacing them with some fixed alternate values are the basic steps in pre processing of data. Even data collected may contain completely garbage values. It may not be in exact format or way that is meant to be.

All such cases must be verified and replaced with alternate values to make data meaningful and useful for further processing.

Data must be kept in an organized format.

4.5.3 Training and Testing

For training a model we initially split the model into three sections which are 'Training data', 'Validation data' and 'Testing data'. You train the classifier using 'training data set', tune the parameters using 'validation set' and then test the performance of your classifier on unseen 'test data set'. An important point to note is that during training the classifier only the training and/or validation set is available. The test data set must not be used during training the classifier. The test set will only be available during testing the classifier.



4.3 Train and testing validation

4.5.4 Performance Evaluation

In this module, we evaluate the performance of trained machine learning model using performance evaluation criteria such as F1 score, accuracy and classification error. In case the model performs poorly, we optimize the machine learning algorithms to improve the performance. Performance Evaluation is defined as a formal and productive procedure to measure an employee's work and results based on their job responsibilities. It is used to gauge the amount of value added by an employee in terms of increased business revenue, in comparison to industry standards and overall employee return on investment (ROI).

All organizations that have learned the art of “winning from within” by focusing inward towards their employees, rely on a systematic performance evaluation process to measure and evaluate employee performance regularly. Ideally, employees are graded annually on their work anniversaries based on which they are either promoted or are given suitable distribution of salary raises

Performance evaluation also plays a direct role in providing periodic feedback to employees, such that they are more self-aware in terms of their performance metrics.

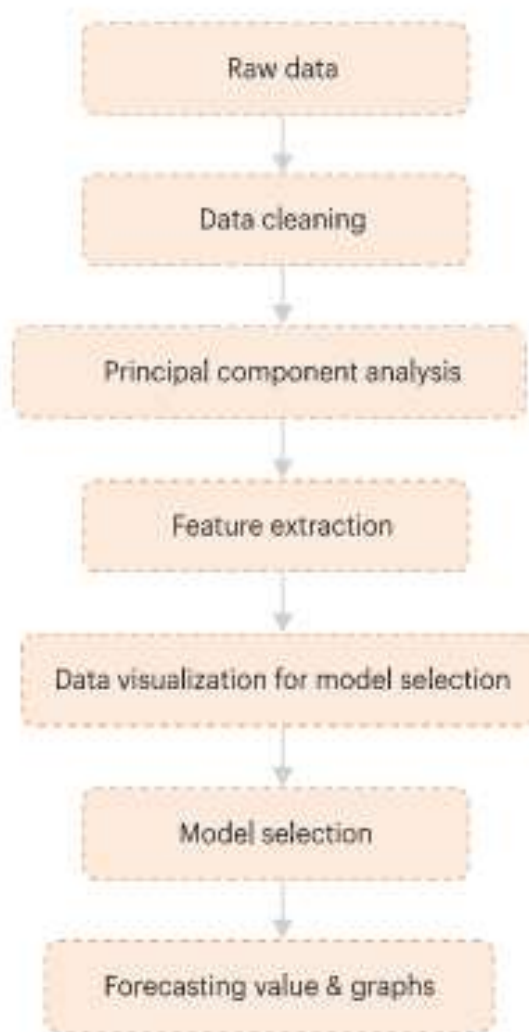
4.5.5 Prediction

Prediction refers to the output of an algorithm after it has been trained on a historical dataset and applied to new data when forecasting the likelihood of a particular outcome, such as whether or not a customer will churn in 30 days. The algorithm will generate probable values for an unknown variable for each record in the new data, allowing the model builder to identify what that value will most likely be.

The word “prediction” can be misleading. In some cases, it really does mean that you are predicting a future outcome, such as when you're using machine learning to determine the next best action in a marketing campaign.

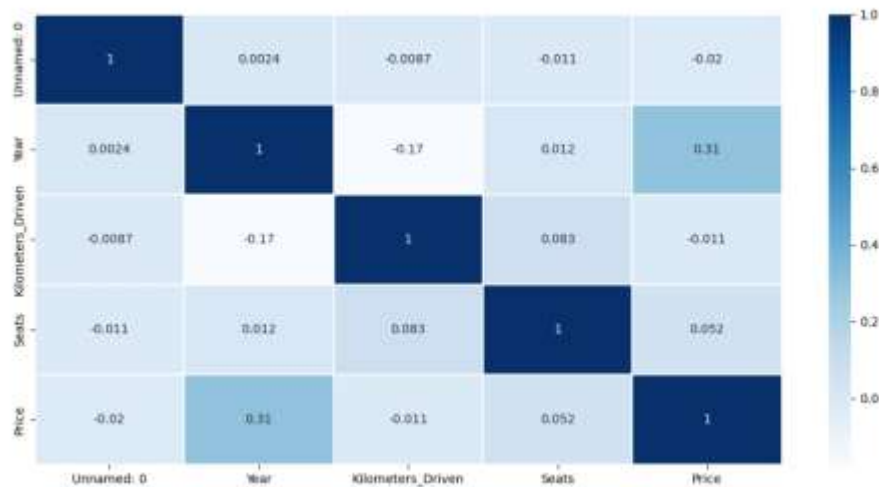
Other times, though, the “prediction” has to do with, for example, whether or not a transaction that already occurred was fraudulent. In that case, the transaction already happened, but you're making an educated guess about whether or not it was legitimate, allowing you to take the appropriate action.

4.6. DATA FLOW DIAGRAM



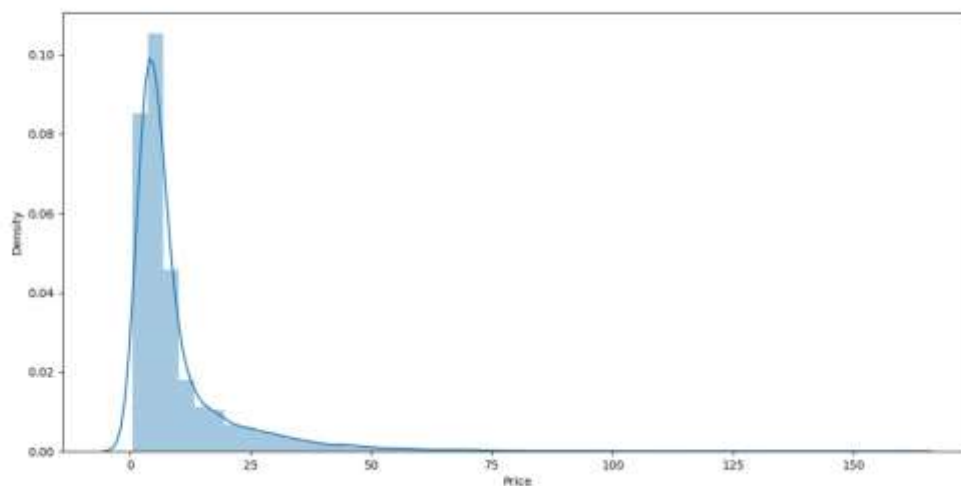
4.4 Data flow chart

The above data flow diagram will be predict about how the process is happening in a particular order with the given tools. First step collecting the raw data from the website which will be suitable for to demonstrate the values to predict. Next cleaning the data from the dataset because a lot of unwanted junk file will be in the dataset which we don't either used or not. Later considering the algorithm principles used to specify the perfect accuracy to predict the values from the dataset. From the considered algorithm have to select the model selection here the model had used were KNN regression had found high accuracy comparing with linear regression and forest regression. Then we can get the values represented in a formatical graph.



4.5 Used price value

The above graph shows the consumption of material for price, seat, kilometresdriven and no. of years used. Can easily analyze the value of the car with the above graph.



4.6 Density price graph

The above mentioned graph demonstrate about the density of the product will changes based the price. The more price will increase the consumers will be goes down i was showed as density. So, the prices always have to be in limited sometimes it may higher due the material used for the car to make it luxurious by that price will be automatically will be higher.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 EXPERIMENTAL RESULTS

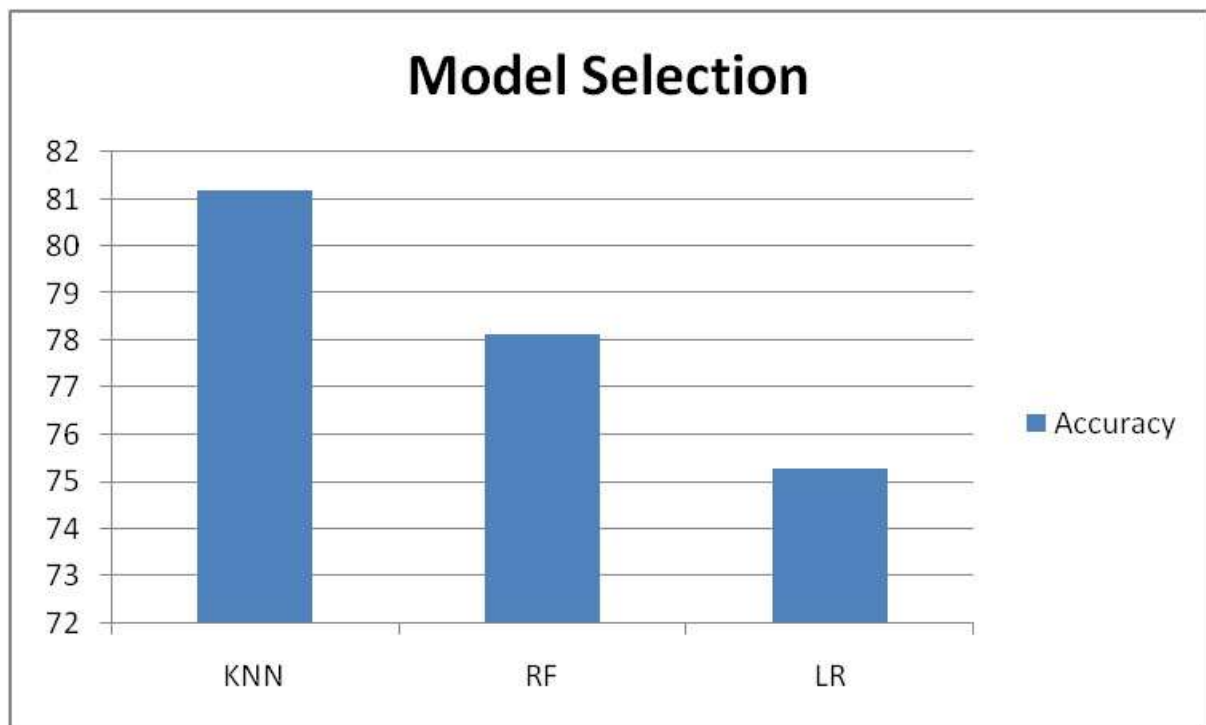
	Name	Location	Year	Kilometers	Fuel_Type	Transmission	Owner_Ty	Mileage	Engine	Power	Seats	New_Price	Price
1	0 Maruti Wagon	Mumbai	2002	72000	CNG	Manual	First	26.6 kmpl	888 CC	58.16 bhp	5	6.75	
2	1 Hyundai C-Di	Pune	2015	41000	Diesel	Manual	First	19.87 kmpl	2582 CC	128.2 bhp	5	12.5	
3	2 Honda City	Chennai	2015	66000	Petrol	Manual	First	18.2 kmpl	1599 CC	88.7 bhp	5	8.60 Lakh	8.5
4	3 Maruti Ert	Chennai	2012	87000	Diesel	Manual	First	20.77 kmpl	1248 CC	88.76 bhp	7	6	
5	4 Audi A4	No Coimbatore	2011	40670	Diesel	Automatic	Second	15.2 kmpl	2968 CC	148.8 bhp	5	17.74	
6	5 Hyundai Elantra	Hyderabad	2012	75000	LPG	Manual	First	21.1 kmpl	854 CC	55.2 bhp	5	2.35	
7	6 Nissan Micra	Jaipur	2015	86999	Diesel	Manual	First	23.98 kmpl	1381 CC	63.1 bhp	5	5.5	
8	7 Toyota Inn	Mumbai	2014	36000	Diesel	Automatic	First	11.36 kmpl	2755 CC	175.6 bhp	8	21 Lakh	17.5
9	8 Volkswagen	Pune	2013	64430	Diesel	Manual	First	20.54 kmpl	1598 CC	103.6 bhp	5	5.2	
10	9 Tata Indico	Chennai	2012	62942	Diesel	Manual	Second	22.3 kmpl	1248 CC	74 bhp	5	1.85	
11	10 Maruti Cio	Kochi	2018	25692	Petrol	Manual	First	21.36 kmpl	1402 CC	103.25 bhp	5	10.85 Lakh	9.95
12	11 Honda City	Kolkata	2012	40000	Petrol	Automatic	First	16.6 kmpl	1497 CC	114.1 bhp	5	4.48	
13	12 Maruti Sui	Jaipur	2013	64424	Diesel	Manual	First	25.2 kmpl	1248 CC	74 bhp	5	5.8	
14	13 Land Rover	Delhi	2014	72000	Diesel	Automatic	First	12.7 kmpl	2179 CC	187.7 bhp	5	17	
15	14 Land Rover	Pune	2012	87000	Diesel	Automatic	Second	0.0 kmpl	2179 CC	135 bhp	5	17.5	
16	15 Mitsubishi	Delhi	2014	110000	Diesel	Manual	First	13.3 kmpl	2477 CC	175.56 bhp	7	32.85 Lakh	13
17	16 Honda Am	Kochi	2014	58950	Diesel	Manual	First	25.8 kmpl	1498 CC	86.0 bhp	5	5.4	
18	17 Maruti Sui	Jaipur	2017	25000	Diesel	Manual	First	28.4 kmpl	1248 CC	74 bhp	5	5.98	
19	18 Renault D	Kochi	2014	77468	Diesel	Manual	First	20.45 kmpl	1481 CC	83.8 bhp	5	6.14	
20	19 Mercedes	Bangalore	2014	78500	Diesel	Automatic	First	14.84 kmpl	2143 CC	187.62 bhp	5	28	
21	20 BMW 3 Se	Kochi	2014	32984	Diesel	Automatic	First	22.68 kmpl	1995 CC	190 bhp	5	17.87 Lakh	18.55
22	21 Maruti S C	Bangalore	2015	55382	Diesel	Manual	Second	23.85 kmpl	1248 CC	88.5 bhp	5	8.25	
23	22 Audi A4	Mumbai	2015	53985	Petrol	Automatic	First	13.51 kmpl	2984 CC	177.01 bhp	5	25.5	
24	23 Hyundai U	Kolkata	2014	42807	Petrol	Manual	First	18.5 kmpl	1107 CC	80 bhp	5	1.87	
25	24 Volkswagen	Kolkata	2012	57000	Petrol	Automatic	First	15.4 kmpl	1398 CC	101.6 bhp	5	2.85	
26	25 Honda City	Mumbai	2013	51920	Petrol	Manual	First	16.8 kmpl	1497 CC	114.2 bhp	5	4.35	
27	26 Nissan Micra	Hyderabad	2012	54000	Diesel	Manual	First	23.08 kmpl	1301 CC	63.1 bhp	5	4.25	
28	27 Maruti Aio	Hyderabad	2011	54000	Petrol	Manual	Second	20.82 kmpl	888 CC	67.1 bhp	5	2.75	
29	28 Honda WR	Kochi	2018	37432	Petrol	Manual	First	17.5 kmpl	1109 CC	86.7 bhp	5	10.37 Lakh	9.8
30	29 Toyota Inn	Mumbai	2009	262000	Diesel	Manual	Fourth & 5	12.8 kmpl	2488 CC	152 bhp	7	6	
31	30 Renault D	Bangalore	2013	63000	Diesel	Manual	First	18.37 kmpl	1881 CC	108.25 bhp	5	7.15	

5.1 Train Dataset

The above data set were collected from the kaggle website which had predicted recently. The dataset contains car model, location, year, fuel type, kilometres driven, owner type, power, mileage, seat capacity, price.

	Name	Location	Year	Kilometers	Fuel_Type	Transmission	Owner_Ty	Mileage	Engine	Power	Seats	New_Price	Price
1	0 Maruti Aio	Delhi	2014	40528	CNG	Manual	First	32.26 kmpl	998 CC	58.2 bhp	4		
2	1 Maruti Aio	Coimbatore	2015	54433	Petrol	Manual	Second	24.7 kmpl	796 CC	47.3 bhp	5		
3	2 Toyota Inn	Mumbai	2017	36000	Diesel	Manual	First	13.68 kmpl	2491 CC	167.8 bhp	7	25.27 Lakh	
4	3 Toyota Inn	Hyderabad	2012	130000	Diesel	Manual	First	23.59 kmpl	1364 CC	84 bhp	5		
5	4 Hyundai U	Mumbai	2014	74669	Petrol	Manual	First	16.5 kmpl	1167 CC	82.85 bhp	5		
6	5 Marutiva	Coimbatore	2016	85608	Diesel	Manual	Second	16.0 kmpl	2179 CC	140 bhp	7		
7	6 Toyota Inn	Pune	2015	59600	Diesel	Automatic	First	12.35 kmpl	2682 CC	168.7 bhp	7		
8	7 Hyundai El	Jaipur	2012	65000	Petrol	Manual	First	21.1 kmpl	814 CC	55.2 bhp	5		
9	8 Honda City	Mumbai	2011	66800	Petrol	Manual	Second	17.0 kmpl	1497 CC	118 bhp	5		
10	9 Marutiva	Coimbatore	2015	54684	Diesel	Manual	First	15.1 kmpl	2179 CC	140 bhp	7		
11	10 Audi Q5	Mumbai	2012	78800	Diesel	Automatic	Second	12.8 kmpl	1968 CC	167.8 bhp	5		
12	11 Hyundai G	Jaipur	2014	21000	Petrol	Manual	First	18.9 kmpl	1107 CC	82 bhp	5		
13	12 Toyota C	Chennai	2007	90000	Petrol	Manual	Third	15.4 kmpl	1704 CC	125 bhp	5		
14	13 Maruti Sui	Coimbatore	2008	87628	Diesel	Manual	First	17.8 kmpl	1248 CC	75 bhp	5		
15	14 Nissan Terr	Mumbai	2014	40500	Petrol	Manual	First	12.24 kmpl	1508 CC	102.1 bhp	5		
16	15 BMW X1	y Coimbatore	2015	30188	Diesel	Automatic	First	17.05 kmpl	1995 CC	189 bhp	5		
17	16 BMW 3 Se	Hyderabad	2015	39524	Diesel	Automatic	First	19.59 kmpl	1595 CC	184 bhp	5		
18	17 Ford Focus	Chennai	2009	130000	Diesel	Manual	First	13.8 kmpl	1589 CC	68 bhp	5		
19	18 Maruti Sui	Kochi	2019	15408	Petrol	Automatic	First	22.0 kmpl	1107 CC	81.85 bhp	5		
20	19 Maruti Sui	Jaipur	2015	36162	Petrol	Manual	First	17.5 kmpl	1298 CC	85.8 bhp	5		
21	20 Maruti R	Pune	2016	200000	Diesel	Manual	First	22.2 kmpl	1248 CC	73.94 bhp	5		
22	21 Nissan Mic	Delhi	2010	70000	Petrol	Manual	First	18.06 kmpl	1158 CC	75 bhp	5		
23	22 Maruti Aio	Kochi	2017	26765	Petrol	Manual	First	24.7 kmpl	796 CC	47.3 bhp	5		
24	23 Honda L	Bangalore	2009	72000	Petrol	Manual	Second	17.5 kmpl					
25	24 Honda Cio	Bangalore	2011	40006	Petrol	Manual	Second	15.5 kmpl	1798 CC	132 bhp	5		
26	25 Ford Focus	Pune	2005	47000	Petrol	Manual	Second	13.8 kmpl	1298 CC	70 bhp	5		
27	26 Maruti Aio	Pune	2014	91549	Petrol	Manual	Second	19.7 kmpl	796 CC	46.3 bhp	5		
28	27 Honda Jaz	Pune	2013	52080	Diesel	Manual	First	27.3 kmpl	1408 CC	98.6 bhp	5		
29	28 Nioche R	Jaipur	2015	56429	Diesel	Automatic	Second	21.86 kmpl	1498 CC	105.52 bhp	5		
30	29 Hyundai U	Mumbai	2011	133000	Petrol	Manual	Second	17.0 kmpl	1107 CC	80 bhp	5		
31	30 Volkswagen	Bangalore	2013	65000	Diesel	Manual	Second	21.08 kmpl	1881 CC	111.88 bhp	5	8.55 Lakh	

5.2 Test Dataset



5.3 Accuracy

For using above mentioned algorithms linear regression, random forest regression and KNN . using these mentioned models for a better output prediction . comparing with linear regression and random forest, KNN got highest accuracy with 81% for to get better output.

A screenshot of a web application titled 'Car Price forecasting'. The interface features a background image of a white car on a road with mountains in the background. A semi-transparent form is overlaid on the image, containing input fields for various car specifications. The inputs are as follows:

- Year: 2
- Driven Kilometers (e.g. 10000) in KM: (empty)
- Mileage (e.g. 15) KM/L: (empty)
- Engine (CC): (empty)
- Power (BHP): (empty)
- Company: Bmw
- Seats (e.g. 4-5): (empty)
- Model: Volkswagen Polo Diesel Combi
- Location: Coimbatore
- Fuel Type: Lpg
- Transmission: Manual
- Owner Type: First

A blue 'FORECAST' button is located at the bottom left of the form.

5.4 Output

CHAPTER 6

CONCLUSION

The project has successfully met its aim and is ready to predict all the future behavior and trends of the market based on the then scenario. By this prediction model one can easily find out the possibility of the growth and sales of the company and can take actions accordingly. This model is ready to serve the purpose of fulfilling the prediction of sales and production after the impact of the corona virus outbreak. Further if anything this sort or any other pandemic hit again then this model is going to suggest how to save the companies worth by providing the required details through its predictions. The model has been currently at a base level and covers few factors currently so it depends upon many circumstances and conditions. Further it has a lot of area to be worked upon and lots of factors to be taken care of and considered to give more accurate results. The basic purpose of making this model is to save companies from pandemic. They can be insured with this type of a model and takes the necessary steps according to the benefit of the company in the upcoming time. The model has been predicting the possibility of saving the worth of a company and preventing them economically by not misusing their wealth. It gives a financial preparation to the company by predicting the future outcomes. The automobile industry has been in a very delicate situation, they need to listen to their customers to move forward treading carefully. Listening to the demand has been the only variable option for them to create sales in such times. If they stay patient then surely the tides will turn and the situation will get better, it has been just a matter of sticking to the basics.

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APPENDIX

A. Source Code

Application python file

```
import numpy as np

from flask import Flask, request, jsonify, render_template

import pickle

import json


app = Flask(__name__)

model = pickle.load(open('model.pkl','rb'))

myjson=open('columns.json','r')

jsonData=myjson.read()

obj=json.loads(jsonData)

r=0

for x in obj:

    if isinstance(obj[x], list):

        r += len(obj[x])


def predict_price(year, kilometers_driven, mileage, engine, power, seats,
company, name, location, fuel_type, transmission, owner_type):

    x2 = [0]*r

    x2[0] = int(year)

    x2[1] = kilometers_driven

    x2[2] = mileage

    x2[3] = engine

    x2[4] = power

    x2[5] = seats
```

```

l=[]
for w in obj:
    for y in obj[w]:
        l.append(y)
w=l
for i in range(6,r):
    if w[i]==company:
        x2[i] = 1
    if w[i]==name:
        x2[i] = 1
    if w[i]==location:
        x2[i] = 1
    if w[i]==fuel_type:
        x2[i] = 1
    if w[i]==transmission:
        x2[i] = 1
    if w[i]==owner_type:
        x2[i] = 1
result = ([x2])
return result

def xyz(ash):

c=predict_price(ash[0],ash[1],ash[2],ash[3],ash[4],ash[6],ash[5],ash[7],ash[8],ash[9
],ash[10],ash[11])

return c

@app.route('/')
def home():

```

```

    return render_template('index.html')

@app.route('/predict',methods=['POST'])
def predict():

    int_features = [x for x in request.form.values()]
    final_features = list(int_features)
    k=xyz(final_features)

    prediction = model.predict(k)

    output = prediction[0]

    return render_template('index.html',prediction_text='Price is ₹ {}
lakhs'.format(output))

if __name__ == "__main__":
    app.run(debug=True)

```

HTML CODE

```

<html>
    <head>
        <title>Sell Car Price ion</title>

        <style type="text/css">
            .input {
                width: 98%;
                height: 33px;

```

```

border-radius: 03px;
border: solid 1px #000;
background: transparent;
color: #000;
font-weight: bold;
padding: 05px;
font-size: 20px;
text-transform: capitalize;
}
.ab {
width: 100%;
background: #38516f;
height: 39px;
border: solid 1px #111165;
font-size: 15px;
color: #000;
font-weight: bold;
cursor: pointer;
}
</style>

```

```

<link rel="stylesheet"
href="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/css/bootstrap.min.css">
<!-- jQuery library -->
<script
src="https://ajax.googleapis.com/ajax/libs/jquery/3.5.1/jquery.min.js"></script>
<!-- Latest compiled JavaScript -->
<script
src="https://maxcdn.bootstrapcdn.com/bootstrap/3.4.1/js/bootstrap.min.js"></script>
>

```

```

</head>

<body class="img-fluid" style="background-
image:url('static/images/bg.jpg');background-repeat:no-repeat;background-
size:cover" >

    <div style="height: 680px;width: 700px;position: absolute;left: 50px;top:
50px;border-radius: 5px;background: #d2d2d2b3;padding: 15px;color:
#000;margin-left:25%">

        <div>

            <h1 class="article-title__title" style="text-align: center; font-
family:Brandon Text,-apple-system,BlinkMacSystemFont,Segoe
UI,Roboto,Oxygen-Sans,Ubuntu,Cantarell,Helvetica Neue,sans-serif">Car Price
forecasting </h1>

            <hr>

            <form action="{{ url_for('predict')}}"method="post">

                <div style="float: left; width: 48%">

                    <label style="text-align: left; margin-bottom:
05px">Year</label>

                    <select name="year" class="input" style="height: 35px;"
required>

                        <option value="2">2</option>
                        <option value="3">3</option>
                        <option value="4">4</option>
                        <option value="5">5</option>
                        <option value="6">6</option>
                        <option value="7">7</option>
                        <option value="8">8</option>
                        <option value="9">9</option>
                        <option value="10">10</option>
                        <option value="11">11</option>
                        <option value="12">12</option>
                        <option value="13">13</option>
                        <option value="14">14</option>

```

```

<option value="15">15</option>
<option value="16">16</option>
<option value="17">17</option>
<option value="18">18</option>
<option value="19">19</option>
<option value="20">20</option>
<option value="21">21</option>
<option value="22">22</option>
<option value="23">23</option>
</select> <br><br>
<label style="text-align: left;">Driven Kilometers (e.g 10000) In KM</label>
<input type="text" name="driven_kilometeres" class="input"
required>
<br><br>
<label style="text-align: left;">KM/L</label>
Mileage (e.g 10)
<input type="text" name="mileage" class="input"
required>
<br><br>
<label style="text-align: left;">Engine (CC)</label>
<input type="text" name="engine" class="input"
required>
<br><br>
<label style="text-align: left;">Power (BHP)</label>
<input type="text" name="power" class="input"
required>
<br><br>

```

35px;" required>

```
<label style="text-align: left;">Company</label>
```

```
<select name="company" class="input" style="height:
```

```
<option value="bmw">bmw</option>
```

```
<option value="fiat">fiat</option>
```

```
<option value="tata">tata</option>
```

```
<option value="datsun">datsun</option>
```

```
<option value="volvo">volvo</option>
```

```
<option value="honda">honda</option>
```

```
<option value="mitsubishi">mitsubishi</option>
```

```
<option value="audi">audi</option>
```

```
<option value="force">force</option>
```

```
<option value="toyota">toyota</option>
```

```
<option value="ford">ford</option>
```

```
<option value="smart">smart</option>
```

```
<option value="ambassador">ambassador</option>
```

```
<option value="isuzu">isuzu</option>
```

```
<option value="nissan">nissan</option>
```

```
<option value="mercedes-benz">mercedes-benz</option>
```

```
<option value="mini">mini</option>
```

```
<option value="skoda">skoda</option>
```

```

        <option value="jaguar">jaguar</option>
    <option value="chevrolet">chevrolet</option>
    <option value="volkswagen">volkswagen</option>
        <option value="porsche">porsche</option>
        <option value="jeep">jeep</option>
        <option value="hyundai">hyundai</option>
        <option value="land">land</option>
        <option value="maruti">maruti</option>
        <option value="bentley">bentley</option>
        <option
value="lamborghini">lamborghini</option>
        <option value="mahindra">mahindra</option>
        <option value="renault">renault</option>
        <option value="isuzu">isuzu</option>
    </select> <br><br>
</div><div style="float: right; width: 48%">
    <label style="text-align: left;">Seats (e.g 4,5)</label>
    <input type="text" name="seats" class="input"
required>

    <br><br>
<label style="text-align: left;">Model</label>
    <select name="model" class="input" style="height: 35px;" required>
        <option value="volkswagen polo diesel
comfortline 1.2l">volkswagen polo diesel comfortline 1.2l</option>
        <option value="volkswagen vento diesel
highline">volkswagen vento diesel highline</option>
        <option value="audi a6 2011-2015 2.0 tdi
premium plus">audi a6 2011-2015 2.0 tdi premium plus</option>
        <option value="hyundai i10 magna 1.2">hyundai
i10 magna 1.2</option>

```

i20 1.2 magna</option>	<option value="hyundai i20 1.2 magna">hyundai
magna</option>	<option value="hyundai i10 magna">hyundai i10
lxi">maruti alto 800 2016-2019 lxi</option>	<option value="maruti alto 800 2016-2019
ls</option>	<option value="chevrolet beat ls">chevrolet beat
vtec sv</option>	<option value="honda city i vtec sv">honda city i
lt</option>	<option value="chevrolet beat lt">chevrolet beat
wagon r lxi cng</option>	<option value="maruti wagon r lxi cng">maruti
swift dzire vxi</option>	<option value="maruti swift dzire vxi">maruti
amaze s i-vtech</option>	<option value="honda amaze s i-vtech">honda
i10 sportz 1.2</option>	<option value="hyundai i10 sportz 1.2">hyundai
i20 1.2 sportz</option>	<option value="hyundai i20 1.2 sportz">hyundai
crdi">hyundai i20 asta 1.4 crdi</option>	<option value="hyundai i20 asta 1.4
titanium">ford ecosport 1.5 dv5 mt titanium</option>	<option value="ford ecosport 1.5 dv5 mt
1.2">hyundai i20 asta option 1.2</option>	<option value="hyundai i20 asta option
sportz">hyundai grand i10 1.2 kappa sportz</option>	<option value="hyundai grand i10 1.2 kappa
i20 sportz 1.2</option>	<option value="hyundai i20 sportz 1.2">hyundai

celerio vxi at</option>	<option value="maruti celerio vxi at">maruti
santro xing gls</option>	<option value="hyundai santro xing gls">hyundai
1.5 v mt</option>	<option value="honda city 1.5 v mt">honda city
highline">volkswagen polo 1.2 mpi highline</option>	<option value="volkswagen polo 1.2 mpi
magna">hyundai grand i10 crdi magna</option>	<option value="hyundai grand i10 crdi
zdi</option>	<option value="maruti swift zdi">maruti swift
asta">hyundai grand i10 at asta</option>	<option value="hyundai grand i10 at
highline">volkswagen polo 1.5 tdi highline</option>	<option value="volkswagen polo 1.5 tdi
wagon r lxi</option>	<option value="maruti wagon r lxi">maruti
line">bmw 5 series 520d luxury line</option>	<option value="bmw 5 series 520d luxury
city i vtec cvt vx</option>	<option value="honda city i vtec cvt vx">honda
rxl">renault duster 85ps diesel rxl</option>	<option value="renault duster 85ps diesel
220d avantgarde edition c">mercedes-benz new c-class c 220d avantgarde edition c</option>	<option value="mercedes-benz new c-class c
sportz</option>	<option value="hyundai i10 sportz">hyundai i10
tone">maruti vitara brezza zdi plus dual tone</option>	<option value="maruti vitara brezza zdi plus dual
eon era plus</option>	<option value="hyundai eon era plus">hyundai

wagon r vxi</option>	<option value="maruti wagon r vxi">maruti
petrol zxi</option>	<option value="ford figo petrol zxi">ford figo
diesel exi</option>	<option value="ford figo diesel exi">ford figo
swift dzire vdi</option>	<option value="maruti swift dzire vdi">maruti
tdi</option>	<option value="audi a4 2.0 tdi">audi a4 2.0
verna 1.6 sx</option>	<option value="hyundai verna 1.6 sx">hyundai
diesel zxi</option>	<option value="ford figo diesel zxi">ford figo
lxi</option>	<option value="maruti alto lxi">maruti alto
4wd">mahindra xuv500 w8 4wd</option>	<option value="mahindra xuv500 w8
vdi</option>	<option value="maruti ritz vdi">maruti ritz
lxi bsiii</option>	<option value="maruti alto lxi bsiii">maruti alto
plus">audi q7 3.0 tdi quattro premium plus</option>	<option value="audi q7 3.0 tdi quattro premium
grand i10 asta</option>	<option value="hyundai grand i10 asta">hyundai
(o)">hyundai verna 1.6 sx crdi (o)</option>	<option value="hyundai verna 1.6 sx crdi
swift dzire vxi</option>	<option value="maruti swift dzire vxi">maruti
swift dzire vdi</option>	<option value="maruti swift dzire vdi">maruti
sdrive20d</option>	<option value="bmw x1 sdrive20d">bmw x1

<option value="hyundai creta 1.6 crdi sx
 option">hyundai creta 1.6 crdi sx option</option>

<option value="maruti swift vxi bsiv">maruti swift
 vxi bsiv</option>

<option value="toyota fortuner 4x2
 manual">toyota fortuner 4x2 manual</option>

<option value="hyundai i10 era">hyundai i10
 era</option>

<option value="toyota innova crista 2.8 zx
 at">toyota innova crista 2.8 zx at</option>

<option value="hyundai creta 1.6 crdi
 sx">hyundai creta 1.6 crdi sx</option>

<option value="volkswagen polo petrol
 comfortline 1.2l">volkswagen polo petrol comfortline 1.2l</option>

<option value="hyundai grand i10
 sportz">hyundai grand i10 sportz</option>

<option value="maruti wagon r vxi bs iv">maruti
 wagon r vxi bs iv</option>

<option value="honda city i dtec vx">honda city i
 dtec vx</option>

<option value="maruti ertiga vdi">maruti ertiga
 vdi</option>

<option value="ford ecosport 1.5 dv5 mt titanium
 optional">ford ecosport 1.5 dv5 mt titanium optional</option>

<option value="maruti swift vdi">maruti swift
 vdi</option>

<option value="honda amaze vx i-dtec">honda
 amaze vx i-dtec</option>

<option value="honda brio s mt">honda brio s
 mt</option>

<option value="mahindra xuv500 w6
 2wd">mahindra xuv500 w6 2wd</option>

wagon r lxi bs iv</option> <option value="maruti wagon r lxi bs iv">maruti

plus">audi a4 2.0 tdi 177 bhp premium plus</option> <option value="audi a4 2.0 tdi 177 bhp premium

1.2l">volkswagen polo diesel trendline 1.2l</option> <option value="volkswagen polo diesel trendline

2wd">mahindra xuv500 w10 2wd</option> <option value="mahindra xuv500 w10

series 320d</option> <option value="bmw 3 series 320d">bmw 3

seater">toyota innova 2.5 v diesel 7-seater</option> <option value="toyota innova 2.5 v diesel 7-

eon d lite plus</option> <option value="hyundai eon d lite plus">hyundai

k10 vxi</option> <option value="maruti alto k10 vxi">maruti alto

1.5 s mt</option> <option value="honda city 1.5 s mt">honda city

800 lxi</option> <option value="maruti alto 800 lxi">maruti alto

sportz">hyundai grand i10 crdi sportz</option> <option value="hyundai grand i10 crdi

1.2l">volkswagen polo diesel highline 1.2l</option> <option value="volkswagen polo diesel highline

<option value="other">other</option>

at">skoda superb elegance 1.8 tsi at</option> <option value="skoda superb elegance 1.8 tsi

seater">toyota innova 2.5 g (diesel) 8 seater</option> <option value="toyota innova 2.5 g (diesel) 8

vxi">maruti alto k10 2010-2014 vxi</option> <option value="maruti alto k10 2010-2014

figo diesel titanium</option> <option value="ford figo diesel titanium">ford

swift dzire ldi</option>	<option value="maruti swift dzire ldi">maruti
vdi bsiv</option>	<option value="maruti swift vdi bsiv">maruti swift
xf 2.2 litre luxury</option>	<option value="jaguar xf 2.2 litre luxury">jaguar
fortuner 3.0 diesel</option>	<option value="toyota fortuner 3.0 diesel">toyota
vtvt">hyundai verna 1.6 sx vtvt</option>	<option value="hyundai verna 1.6 sx
vtec v</option>	<option value="honda city i vtec v">honda city i
2wd">mahindra xuv500 w8 2wd</option>	<option value="mahindra xuv500 w8
rxz">renault duster 110ps diesel rxz</option>	<option value="renault duster 110ps diesel
crdi">hyundai i20 sportz 1.4 crdi</option>	<option value="hyundai i20 sportz 1.4
highline">volkswagen vento petrol highline</option>	<option value="volkswagen vento petrol
1.2l">volkswagen polo petrol highline 1.2l</option>	<option value="volkswagen polo petrol highline
fortuner 4x2 at</option>	<option value="toyota fortuner 4x2 at">toyota
line">bmw 3 series 320d luxury line</option>	<option value="bmw 3 series 320d luxury
highline">volkswagen vento 1.5 tdi highline</option>	<option value="volkswagen vento 1.5 tdi
rxt</option>	<option value="renault kwid rxt">renault kwid
amaze s i-dtech</option>	<option value="honda amaze s i-dtech">honda
(o)">hyundai verna 1.6 sx vtvt (o)</option>	<option value="hyundai verna 1.6 sx vtvt

```

                                <option value="maruti ertiga zdi">maruti ertiga
zdi</option>

                                </select> <br><br>

                                <label style="text-align: left;">Location</label>

                                <select name="location" class="input" style="height:
35px;" required>

                                <option
value="coimbatore">coimbatore</option>

                                <option value="chennai">chennai</option>

                                <option
value="ahmedabad">ahmedabad</option>

                                <option value="hyderabad">hyderabad</option>
                                <option value="jaipur">jaipur</option>
                                <option value="pune">pune</option>
                                <option value="delhi">delhi</option>
                                <option value="kolkata">kolkata</option>
                                <option value="kochi">kochi</option>
                                <option value="bangalore">bangalore</option>
                                <option value="mumbai">mumbai</option>

                                </select> <br><br>

                                <label style="text-align: left;">Fuel Type</label>

                                <select name="fuel_type" class="input" style="height:
35px;" required>

                                <option value="lpg">lpg</option>

                                <option value="diesel">diesel</option>

                                <option value="petrol">petrol</option>

                                <option value="cng">cng</option>

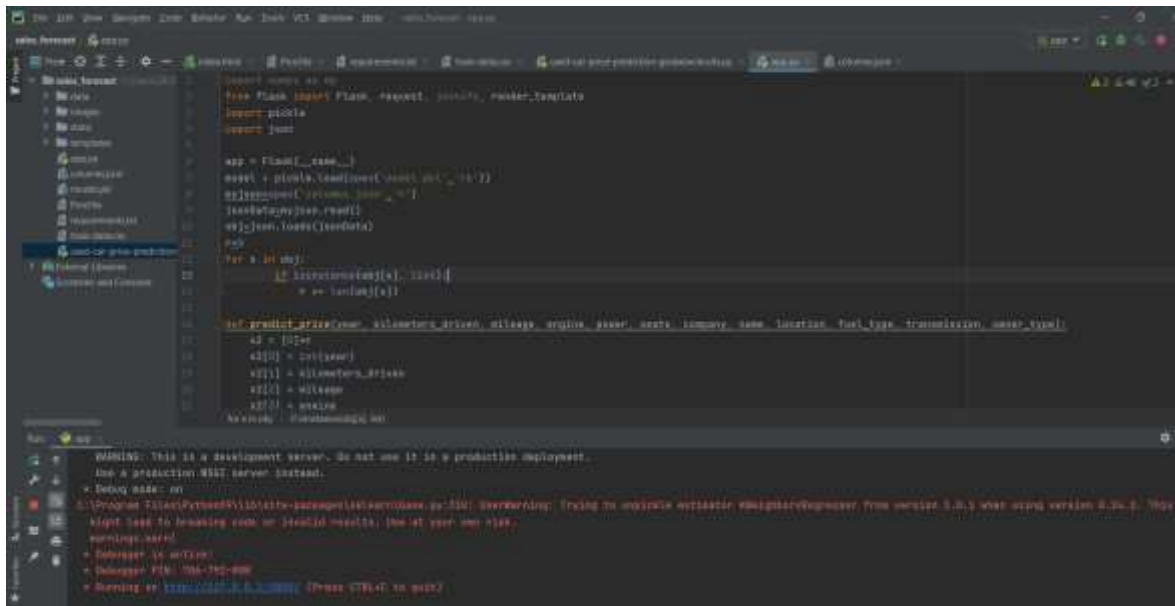
                                </select> <br><br>

                                <label style="text-align: left;">Transmission</label>

                                <select name="transmission" class="input" style="height:
35px;" required>

```


B. Screenshots



The screenshot shows a Jupyter Notebook interface with a file explorer on the left and a code editor in the center. The code defines a Flask application for car price forecasting. It includes imports for Flask, jsonify, render_template, pickle, and json. A Flask route is defined for '/predict' which loads a trained model and predicts the price based on input features. The output is rendered as an HTML page. The bottom of the notebook shows a warning message about the development server and a list of installed packages.

```
from flask import Flask, request, jsonify, render_template
import pickle
import json

app = Flask(__name__)

model = pickle.load(open('model.pkl', 'rb'))

@app.route('/predict', methods=['POST'])
def predict():
    json_data = request.get_json()
    features = json_data['features']

    # Predict the price
    price = model.predict(features)

    return jsonify({'price': price})

if __name__ == '__main__':
    app.run(debug=True)
```

6.1 Server file



The screenshot shows a web application titled "Car Price forecasting". It features a form with various input fields for car specifications. The background image shows a white car driving on a road with mountains in the background.

Year	Seats (e.g 4.5)
2	

Driven Kilometers (e.g 10000) in KM	Model
	Volkswagen Polo Diesel Comt

Mileage (e.g 10) KM/L	Location
	Coimbatore

Engine (CC)	Fuel Type
	Lpg

Power (BHP)	Transmission
	Manual

Company	Owner Type
Bmw	First

FORECAST

6.2 Final output