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Prediction of Resale Value of Pre-Owned Luxury Cars in the Indian Market Employing Machine Learning Techniques

Ranjith K[1], Rishi Sagar BK[2], Uma Sharma[3]
[1, 2]Students, Department of Business Analytics, RVIM, [3]Assistant Prof, Department of Marketing, RVIM

Abstract: The market for second-hand luxury cars in India is witnessing a significant surge, expected to grow at a rate of 16.30% from 2024 to 2032. This growth is fueled by increased car manufacturing, rising disposable incomes, and a shift in consumer preferences towards luxury brands. However, accurately determining the resale value of these vehicles presents a challenge due to various influencing factors. In this dynamic market, informed decision-making is crucial for luxury car buyers. Digital platforms have revolutionized access to real-time market data, helping both buyers and sellers stay updated on pricing trends. Our research explores the complexities of predicting prices for pre-owned luxury cars and introduces a predictive analytics framework using advanced machine learning algorithms. We collected and preprocessed a comprehensive dataset and conducted an in-depth exploratory data analysis. Various regression techniques, including Linear Regression, Decision Tree, Random Forest, and Extreme Gradient Boosting, were employed to forecast prices. These models were evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to identify the most accurate predictive model. This study offers a systematic solution for price prediction, enhancing the buying process for stakeholders in the second-hand luxury car market

Keywords: Exploratory data analysis, Regression techniques, Linear Regression, Decision Tree, Random Forest, Extreme Gradient Boosting, Artificial Neural Networks (ANN), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE).

I. INTRODUCTION

The Indian market for used cars has nearly doubled in value over the past decade, particularly in the luxury segment. High prices of new cars, influenced by manufacturers and government taxes, make them unaffordable for many, driving the middle class to the pre-owned market. Online platforms like Car Dekho, Quikr, Carwale, and Cars24 have simplified the buying and selling process by providing essential price-influencing information. However, accurately valuing used cars remains challenging due to factors like mileage, manufacturing year, engine size, transmission type, and power. This research leverages artificial intelligence and machine learning algorithms to predict the resale value of pre-owned luxury cars in India, using various prediction models to compare accuracy. By analyzing data from platforms and considering multiple vehicle features, the study aims to establish a reliable method for determining market value. The findings will save time and effort for stakeholders and provide insights into price variations by body type and manufacturing year. Additionally, manufacturers like Mercedes-Benz, Toyota, and Honda can use these data-driven insights to optimize production and stay competitive in the growing pre-owned car market.

A. Related Works

1) Nandan & Ghosh (2023): The current study delves into the application of machine learning methodologies such as linear regression, random forest, and XGBoost in the prediction of used car prices. The assessment of model accuracy reveals the notable effectiveness of XGBoost in the analysis of feature importance.
2) Barlybayev et al. (2023): Concentrating on emerging markets such as Kazakhstan, this investigation delves into a variety of machine learning models, encompassing linear regression, decision trees, and deep neural networks, to forecast used car prices based on variables like mileage, brand, and market demand. While deep learning models exhibit superior accuracy, bagged trees emerge as a viable and cost-efficient alternative.
3) Sharma & Mitra (2023): This particular study sheds light on the less-explored domain of used car pricing within the Indian context. By utilizing Multivariate Adaptive Regression Splines (MARS), the research captures the non-linear price depreciation influenced by factors such as age, mileage, and previous ownership. The findings showcase the superiority of MARS over Ordinary Least Squares (OLS), underscoring the significance of accounting for non-linear price trends.

4) A study by Sharma and Mitra further accentuates the research gap in the realm of used car pricing, particularly in the Indian market. It underscores the constraints of conventional linear models and the efficacy of MARS in achieving a more precise fit for used car prices in India.
5) Alhakamy et al. (2023): This particular research delves into the correlation between used car affordability, sustainability, and pricing. Through the utilization of linear regression, the study scrutinizes features like car specifications, condition, and mileage to unravel the impact of used car prices on sustainable car ownership.
6) Dutulescu et al. (2023) : shed light on the global significance of the used car market by employing deep learning models, such as convolutional neural networks. Notably, these models are not only utilized to analyze the characteristics of cars but also to extract valuable insights from visual information obtained from car images. This innovative approach enables the researchers to capture intricate connections between various car details and their corresponding prices across diverse markets, including Germany and Romania.
7) Enci Liu et al. (2022) : propose a novel PSO-GRA-BP Neural Network model to meet the demand for precise price prediction in online used car marketplaces, this model incorporates Grey Relational Analysis (GRA) to identify crucial price factors, Particle Swarm Optimization (PSO) to optimize the neural network, and a Back-Propagation (BP) neural network for accurate prediction. The researchers claim that their model surpasses existing models in terms of accuracy, demonstrating its effectiveness in addressing the price prediction challenge.
8) Mehmet Bilen (2021) : directs attention towards the intricacies of used car pricing in Turkey's second-hand market. This research delves into the utilization of heuristic algorithms, such as Fisher+ANN, for optimal price prediction. The study emphasizes the significance of heuristic algorithms in comprehending the complex relationships between car features and prices. Additionally, the researchers compile a new dataset specifically tailored for used car price prediction, employing these algorithms to enhance the accuracy of predictions.

II. PROPOSED METHODOLOGY

In the present research inquiry, a prognostic model is formulated through the application of diverse machine learning techniques to predict the costs of previously owned automobiles. This is achieved by taking into account a range of parameters and employing regression analysis. The architecture of the proposed system is depicted in Fig-1 below

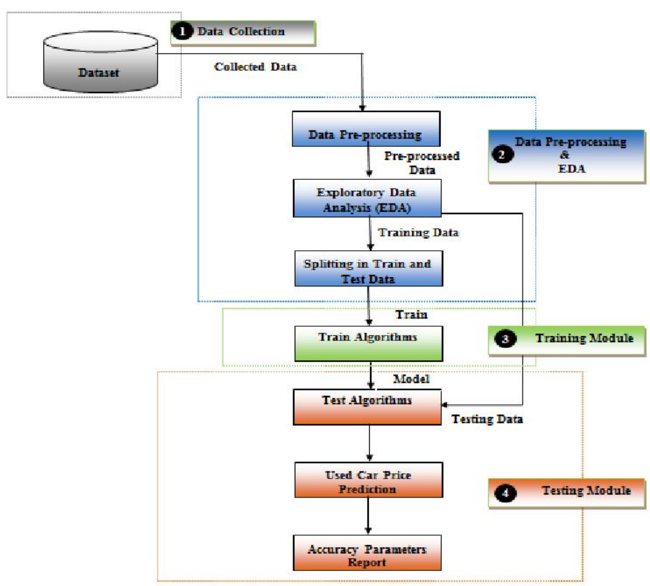

Fig - 1 Control Flow Graph of the Proposed System

A. Data Acquisition

Initially, data from various cars is collected, including both the features and the target variable, which is the price.

B. Data Cleaning

This step involves identifying and removing any null values, filling in missing values, and eliminating outliers from the dataset.

C. Preprocessing

The data is then pre-processed using either normalization or standardization techniques to ensure that all variables are on a similar scale.

D. Exploratory Data Analysis (EDA)

EDA is conducted to gain insights into the data by examining patterns, detecting anomalies, testing hypotheses, and validating assumptions. This is achieved through the use of summary statistics and graphical representations.

E. Division into Training and Testing Sets

The pre-processed dataset is divided into two subsets, namely the training set and the testing set. This division allows for the evaluation of the model's performance on unseen data.

F. Model Training

The training features are used to train the model using various machine learning algorithms, specifically regression techniques.

G. Prediction on the Testing Dataset

The trained model is then used to make predictions on the testing dataset. The predicted values are compared with the actual values to assess the accuracy of the model's predictions, ultimately enabling the prediction of the price.

III. MODELLING AND RESULT ANALYSIS

A. Data Acquisition

The dataset employed in the current study has been downloaded from Kaggle and related to CAR-DEKHO company, the dataset as been transformed, cleaned and filtered to only luxury car market. The Dataset comprises of 1633 used car records and data. And the variables selected for the research is as follows:- car_name , car_brand, model, purchase_year vehicle_age , km_driven, seller_type , fuel_type , transmission_type , mileage, engine_power , max_power, seats, selling_price, inflation_rate and depreciation_rate.

B. Data Cleaning

After transforming the data in excel and filtering out non-luxury cars, we have no null values, and the dataset is ready for the analysis.

C. Unique values and info about the dataset

Now to gain a deeper understanding of our used car data, we'll utilize box plots to explore the distribution of each variable. This will allow us to identify the central tendencies, spread, and potential outliers within the data. Given the inherent variability in used car specifications, encountering outliers is a reasonable expectation. Compared to new cars, used cars naturally exhibit a wider range of values across various features. This very characteristic increases the likelihood of outliers, which can be valuable insights. Analyzing these outliers can reveal unique information about the dataset, potentially leading to unexpected discoveries. By acknowledging the possibility of outliers in our used car data, we can make informed choices during the analysis phase. This might involve selecting statistical methods that are less susceptible to outliers, or alternatively, we can delve deeper to understand the reasons behind their existence. Ultimately, this awareness allows us to extract the most meaningful information from our used car data.

```
mrsl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1632 entries, 0 to 1631
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   car_name           1632 non-null   object
 1   car_brand          1632 non-null   object
 2   model              1632 non-null   object
 3   purchase_year      1632 non-null   int64
 4   vehicle_age        1632 non-null   int64
 5   km_driven          1632 non-null   int64
 6   seller_type        1632 non-null   object
 7   fuel_type          1632 non-null   object
 8   transmission_type  1632 non-null   object
 9   mileage            1632 non-null   float64
 10  engine_power       1632 non-null   int64
 11  max_power          1632 non-null   float64
 12  seats              1632 non-null   int64
 13  selling_price      1632 non-null   int64
 14  inflation_rate     1632 non-null   float64
 15  depreciation_rate  1632 non-null   float64
dtypes: float64(4), int64(6), object(6)
```

Fig - 2 info about the dataset

```
Unique Values in Each Column:
car_name              46
car_brand             17
model                 46
purchase_year         20
vehicle_age           20
km_driven            474
seller_type            2
fuel_type              3
transmission_type      2
mileage              176
engine_power          62
max_power            153
seats                  5
selling_price        454
inflation_rate        20
depreciation_rate      5
dtype: int64
```

Fig – 3 unique values in the dataset

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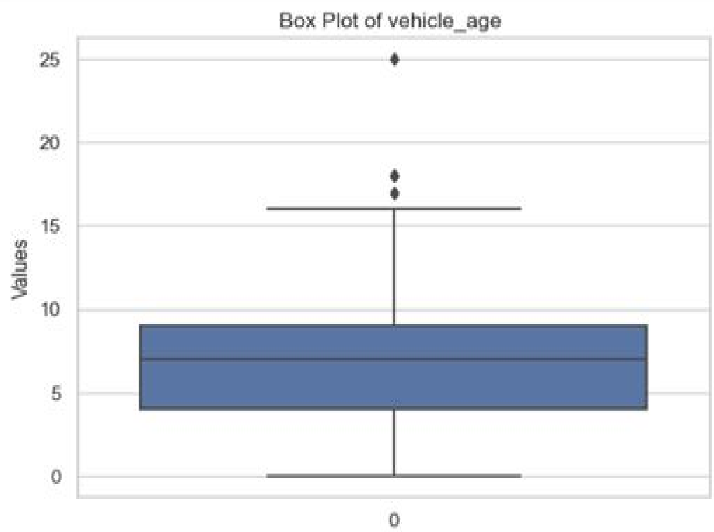

Fig – 4 Box-plot of vehicle age

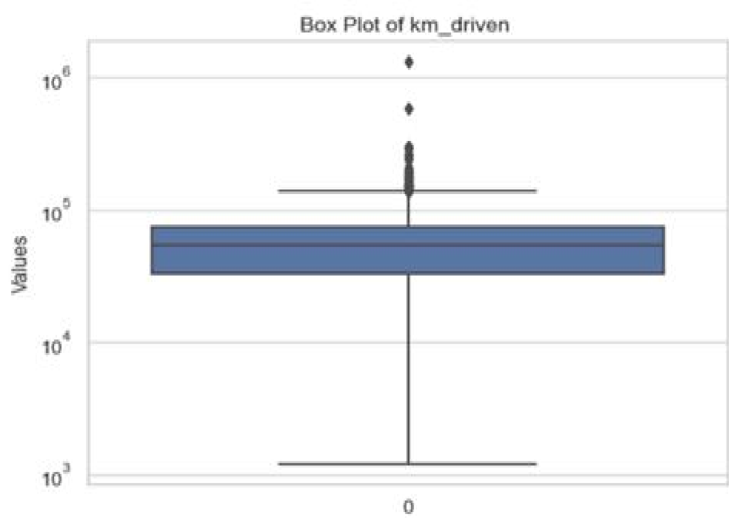

Fig 5 – Box-plot of Kms_driven

The box plot (figure.4) shows that the median vehicle age is around 7 years, with most vehicles aged between 5 and 10 years. The whiskers extend from 0 to 15 years, and a few outliers represent vehicles up to 25 years old. We can see Varied Usage Patterns from box plot of Kms driven (figure.5) Used cars encompass a wide range of prior ownership experiences. Some vehicles may have been driven extensively for business purposes, accumulating high mileage, while others might have been used sparingly for occasional commutes. This inherent variability in usage patterns can contribute to outliers on both ends of the spectrum. The box plot (figure.6) illustrates that the median mileage is approximately 15 km/l, with most vehicles having a mileage between 12.5 and 17.5 km/l. The whiskers range from 5 to 22.5 km/l, and there is one lower outlier at around 5 km/l.

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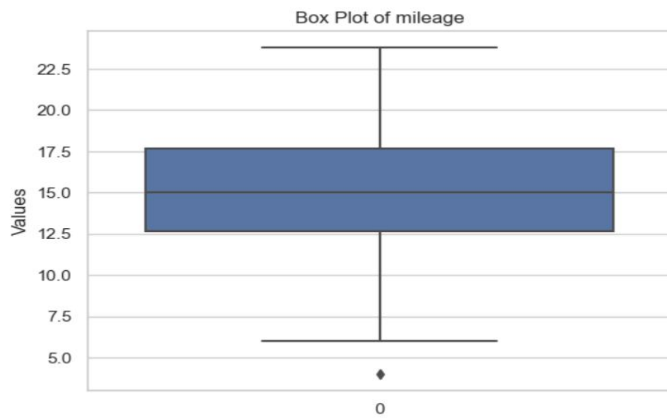

Fig - 6 Box-plot of the mileage

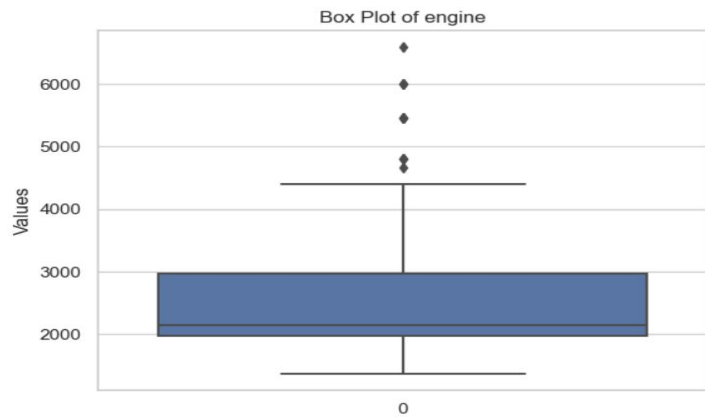

Fig - 7 Box-plot of the engine

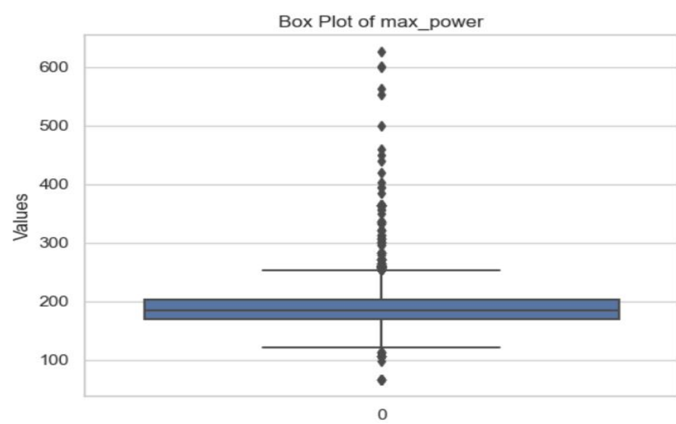

Fig - 8 Box-plot of the max_power

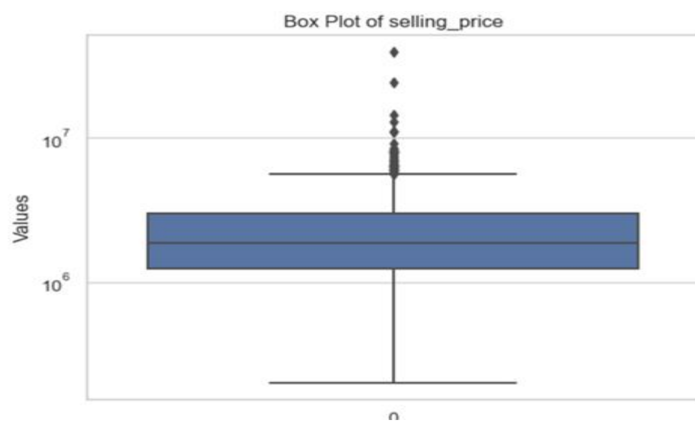

Fig - 9 Box-plot of the selling_price

Outliers in "max_power" (Fig.8) for used luxury cars stem from various factors, with model variations being particularly significant. Luxury car high-performance models naturally boast more horsepower compared to standard models, leading to outliers. Furthermore, advancements over time can result in newer models having more power than older ones within the same brand, potentially causing outliers on the higher end.

Additionally, aftermarket modifications for increased performance can create outliers exceeding original specifications. To understand this spread of power variations, it's important to consider that luxury models often have multiple engine options (Fig.7) with different horsepower levels, and within a model, different trim levels can have varying engine specifications, contributing to outliers in the upper range of the data set.

The box plot of used car selling prices (Fig.9) reveals potential outliers that can be attributed to several factors. Luxury cars naturally command a higher price, placing them on the higher end of the distribution. Similarly, the allure of rarity and collectability associated with classic or limited-edition models can inflate their selling price, making them outliers. Additionally, meticulously maintained cars or those in exceptional condition can fetch a premium, potentially becoming outliers on the higher end.

While less common, data recording errors can also lead to outliers that deviate significantly from the market value. It's important to consider factors like geographic location and time period as well, as these can influence what might be considered an outlier in one context but be typical in another.

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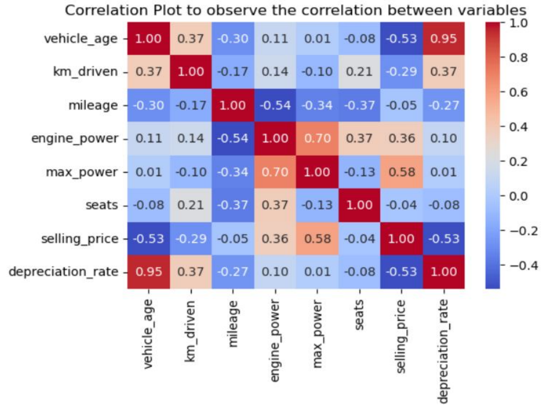

Fig – 10 correlation plots

D. Exploratory Data Analysis

Let us now explore the various Exploratory Data Analysis (EDA) visualizations figure.10 in the current dataset depicts the correlation plot among the various feature variables in the dataset. It can be noted that there is low correlation among the features present in the data. Next, the pair-plots between the various variables are illustrated in figure 11.

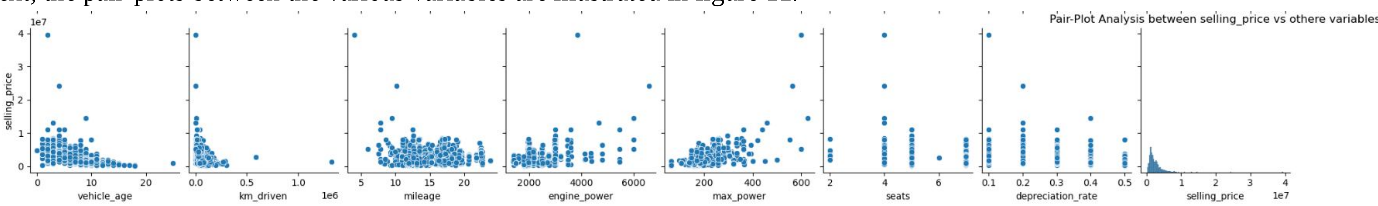

Fig 11 - pair-plots b/w selling price and variables

E. Key Insights from the Pair Plot (Figure-11):

1) Vehicle_age vs. selling_price:

There is a clear negative correlation between vehicle age and selling price. As the age of the vehicle increases, the selling price generally decreases. This is expected as older vehicles typically have lower market value.

2) km_driven vs. selling_price:

There is also a negative correlation between kilometers driven and selling price. Vehicles that have been driven more tend to have lower selling prices, which makes sense because higher mileage often indicates more wear and tear.

3) Mileage vs. selling_price:

There doesn't appear to be a strong correlation between mileage and selling price. The scatter plot shows a wide range of selling prices for different mileage values, suggesting that other factors might play a more significant role in determining the selling price.

4) engine_power vs. selling_price:

There is a positive correlation between engine power and selling price. Vehicles with higher engine power tend to have higher selling prices, which could be due to the perception of higher performance and possibly higher manufacturing costs.

5) max_power vs. selling_price:

Similar to engine power, there is a positive correlation between max power and selling price. Higher max power is associated with higher selling prices.

6) seats vs. selling_price:

There doesn't seem to be a strong or clear pattern between the number of seats and selling price. The plot shows scattered points without a distinct trend, suggesting that the number of seats alone is not a significant determinant of selling price.

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7) depreciation_rate vs. selling_price:

There is a negative correlation between depreciation rate and selling price. Higher depreciation rates are associated with lower selling prices. This indicates that vehicles that depreciate more quickly lose their value faster.

selling_price distribution: The histogram for selling_price shows that most cars have a lower selling price, with a few cars having very high selling prices. This indicates a right-skewed distribution, which is common in price-related data.

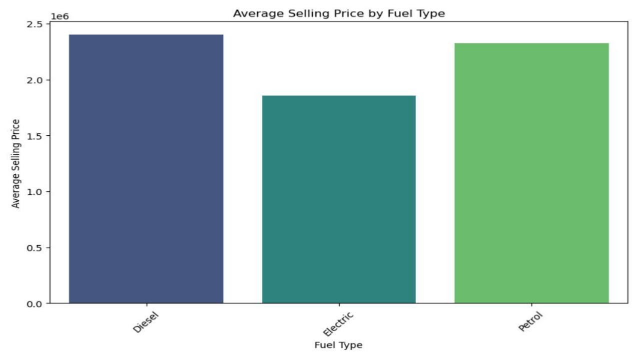


Fig 12 - Bar Plots displaying the price of each fuel type

Now let us see how the factors vary between different fuel type.

Upon analysis of the graph (figure-12), it can be concluded that the cost of diesel cars is higher than that of petrol cars, while electric vehicles are the least expensive. Next The bar plot shows the distribution of vehicle ages across different fuel types. Diesel vehicles (blue) , Petrol vehicles (orange), Electric vehicles (green).

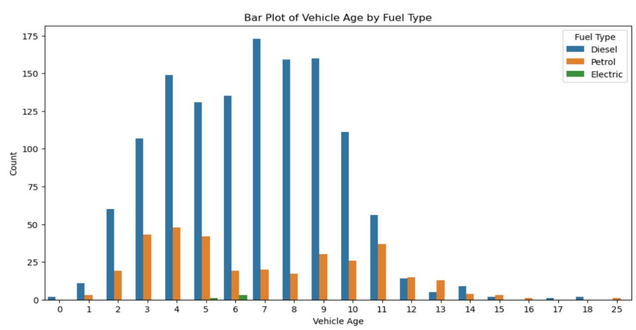


Fig 13 Bar plot of vehicle age by fuel type

The bar plot figure.13 illustrates the distribution of vehicle ages across different fuel types, with a notable dominance of diesel vehicles (blue), particularly within the 4–10-year range and peaking around 7 years. Petrol vehicles (orange) are consistently present but in lower counts compared to diesel, while electric vehicles (green) are relatively rare, appearing only in the 4–6-year range. Figure 14, which details the average age of vehicles by fuel type, indicates that electric vehicles tend to be the newest with an average age of around 5 years, followed by petrol vehicles at around 7 years, and diesel vehicles, which are the oldest on average, at approximately 6.8 years.

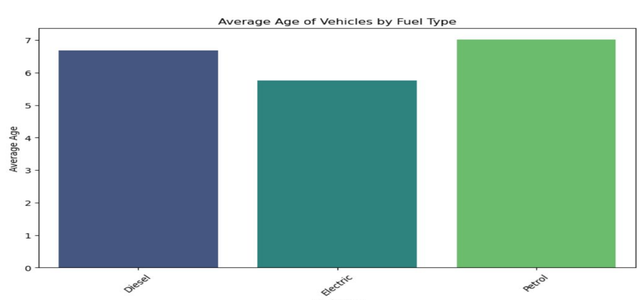


Fig 14 Bar plot of average vehicle age

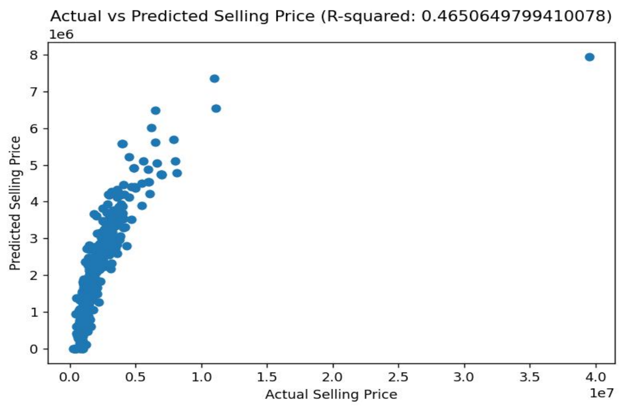
F. Model Generation And Analysis Of The Dataset And Predicting The Resale Price Of The Car

1) Splitting The Dataset into Training and Testing Set

During this procedure, 80% of the data was allocated for the training dataset, while the remaining 20% was designated as the testing dataset.

2) Training with ML Models

The current section involves the utilization of various machine learning algorithms to make predictions about the price of second-hand cars, which serves as the target variable in the present study. To achieve the desired pre-owned car prices, a set of supervised machine learning algorithms is now applied.



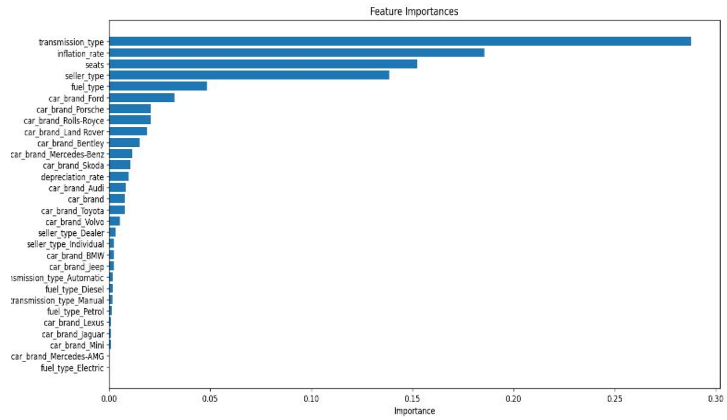


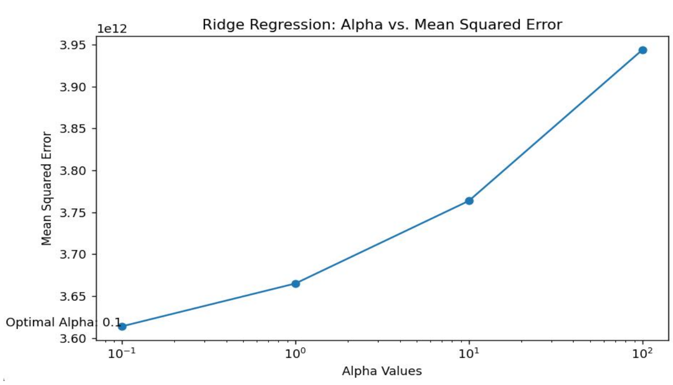
Fig - 15 linear regression performance Fig 16 Feature importance plot

3) Linear Regression

Linear regression is a statistical method used to analyze the relationship between a single outcome variable (dependent variable) and one or more explanatory variables (independent variables). Linear predictor functions are employed to model these relationships, with the unknown parameters being estimated based on the available data. Such models are commonly known as linear models, where the coefficients indicate whether the relationship between a predictor variable and the response variable is positive or negative.

The plot figure 14. displaying the performance of the linear regression on the dataset by obtaining a R-squared value= 0.465064 which implies that that the model explains around half of the variance in the target variable indicating that approximately 46.50% of the variance in the selling prices of the vehicles can be explained by the model. We can see from the plot that there is no linear relationship between actual vs predicted price. And from feature importance plot fig-16 transmission type , inflation rate , seats , seller type are the most critical factors influencing selling price. There might be room for improvement by incorporating additional factors or exploring different machine learning models.

4) Ridge Regression



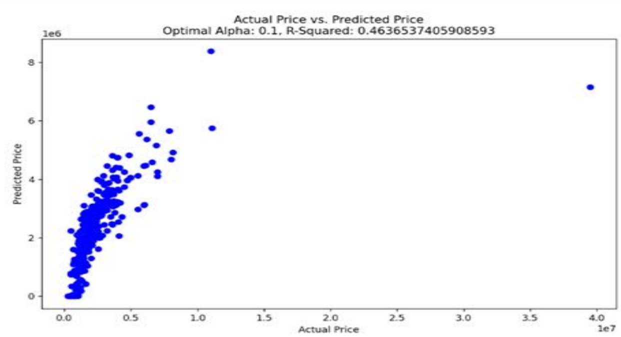


Fig - 17 Ridge Regression plot of Alpha vs Mean Squared Error Fig - 18 Ridge Regression performance

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Ridge Regression is a method used to examine multiple regression data that is affected by multicollinearity. In cases of multicollinearity, the least squares estimates may be unbiased, but their variances are substantial, which can result in values that are significantly different from the actual ones. The Ridge Regression analysis fig-17&fig-18 reveals that the optimal alpha value is 0.1, which yields the highest R-squared value of 0.46. This indicates that, at this level of regularization, the model best balances bias and variance, providing a robust fit that explains 46% of the variance in the selling prices. Thus, an alpha of 0.1 is the most effective parameter for this dataset, optimizing model performance and predictive accuracy.

5) Random Forest

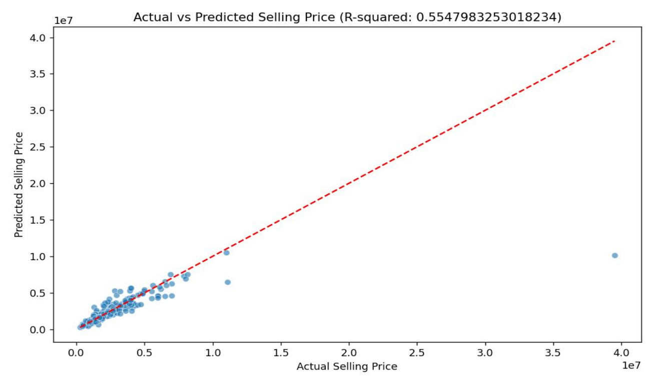

Fig – 19 Random Forest performance

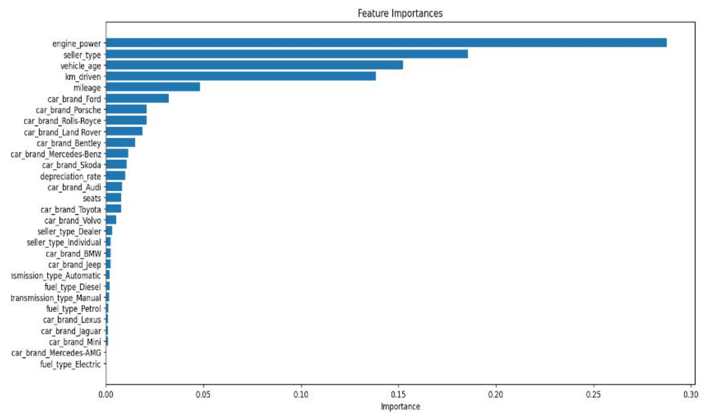

Fig - 20 Feature importance plot

The Random Forest is a classification technique that involves multiple decision trees. To generate a diverse set of trees with uncorrelated predictions, the algorithm employs bagging and feature randomness during tree construction. By aggregating the predictions of all the trees, the Random Forest algorithm aims to produce more accurate results than any single decision tree. The RandomForestRegressor model's scatter plot fig-19 & fig-20, with an R-squared value of 0.555, indicates that it explains approximately 55.5% of the variance in selling prices, demonstrating reasonable accuracy. Most predictions are close to the ideal fit line, especially in the lower and mid-range price segments, though outliers in higher price ranges suggest areas for improvement. We can see the increase in r-square value by 10%. The feature importance analysis reveals that engine power, seller type, vehicle age, and kilometers driven are the most critical factors influencing selling prices. Other features, such as mileage and specific car brands like Ford, Porsche, and Rolls-Royce, have a moderate impact, while fuel type and transmission type have minimal influence. This combined analysis underscores the importance of focusing on the most impactful features to enhance model accuracy and provides valuable insights for refining pricing strategies in the automotive market. Addressing outliers and incorporating additional relevant features could further improve the model's predictive performance and reliability.

6) XG-Booster Regression

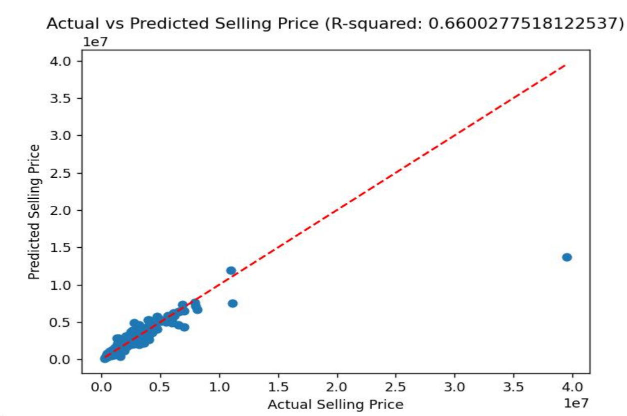

Fig - 21 XG – Booster Performance

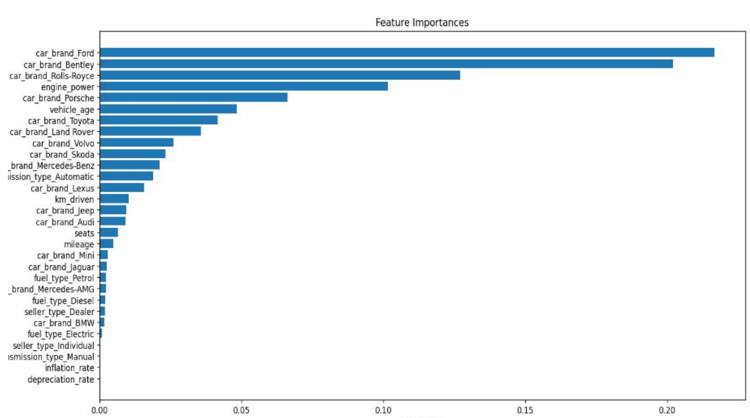

Fig - 22 Feature importance plot

XGBoost fig-21&22 , an ensemble learning technique, employs gradient boosted decision trees. Its primary strength lies in its capacity to rapidly and efficiently learn through parallel and distributed computing, while effectively utilizing memory. The remarkable scalability of this robust algorithm renders it highly appealing for numerous applications.

From figure 21 & 22 pertaining to XGBoost regression model achieved an R-squared value of 0.66, indicating that it can account for approximately 66% of the variability in vehicle selling prices. This level of explanation suggests a satisfactory fit, as the model successfully captures a significant portion of the variance present in the data. Upon conducting a feature importance analysis, it becomes evident that the brand of the car holds a pivotal role in determining the selling price. Brands such as Ford, Bentley, and Rolls-Royce emerge as the most influential factors. Additionally, engine power and vehicle age are shown to have a substantial impact on the model's predictions, underscoring their significance in the valuation of cars. Factors like depreciation rate, inflation rate, and specific seller types exhibit minimal influence on the model's performance. The prominence of certain car brands in the feature importance analysis underscores the premium associated with particular makes and models. Furthermore, the significant effects of engine power and vehicle age emphasize the importance of these physical attributes in the resale market.

7) *ANN-Artificial Neural Network*

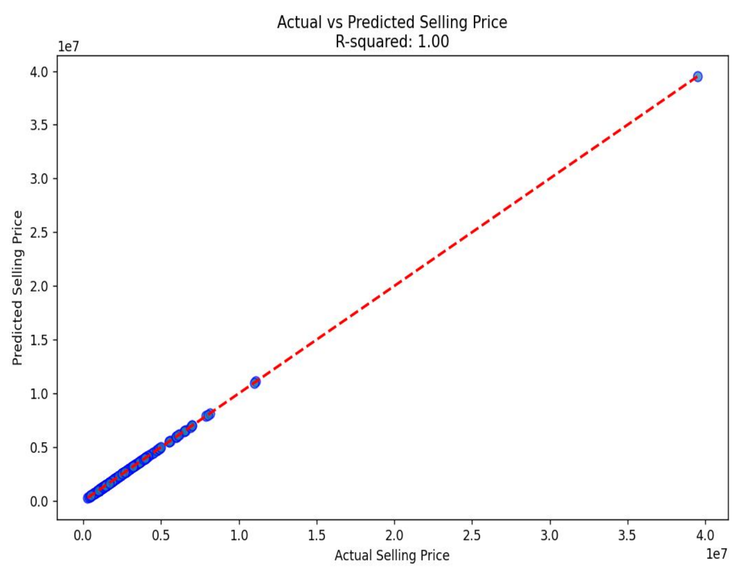

Fig - 23 – ANN Performance

The ANNs, which are machine learning models inspired by the neural networks of the human brain, are widely used for various tasks. These models consist of interconnected nodes, or neurons, organized into layers. In regression tasks, such as predicting selling prices, ANNs typically include an input layer, one or more hidden layers, and an output layer. Each neuron processes input data applies a transformation using learned weights and biases, and passes the result to the next layer, ultimately generating an output prediction. In the specific context of predicting selling prices, the trained ANN model exhibits exceptional performance depicted in figure-23. It achieves an R-squared value of 0.999999967801258, which serves as a metric for evaluating the model's predictive accuracy. The R-squared value, also known as the coefficient of determination, indicates how well the model's predictions explain the variance in the actual selling prices.

A value close to 1 signifies that the model accurately captures the relationships between the input features (such as mileage, engine power, and vehicle age) and the target variable (selling price).

This high R-squared value demonstrates that the ANN has successfully learned complex patterns within the data, enabling it to effectively predict selling prices based on the selected features. The ability of the ANN model to achieve such a high level of performance is of great importance in applications related to the automotive market. Precise predictions are crucial for pricing strategies, as they contribute to competitiveness and profitability. Therefore, the ANN's capability to accurately predict selling prices based on the selected features is highly valuable in this industry.

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8) Comparison of the Performance of ML Models

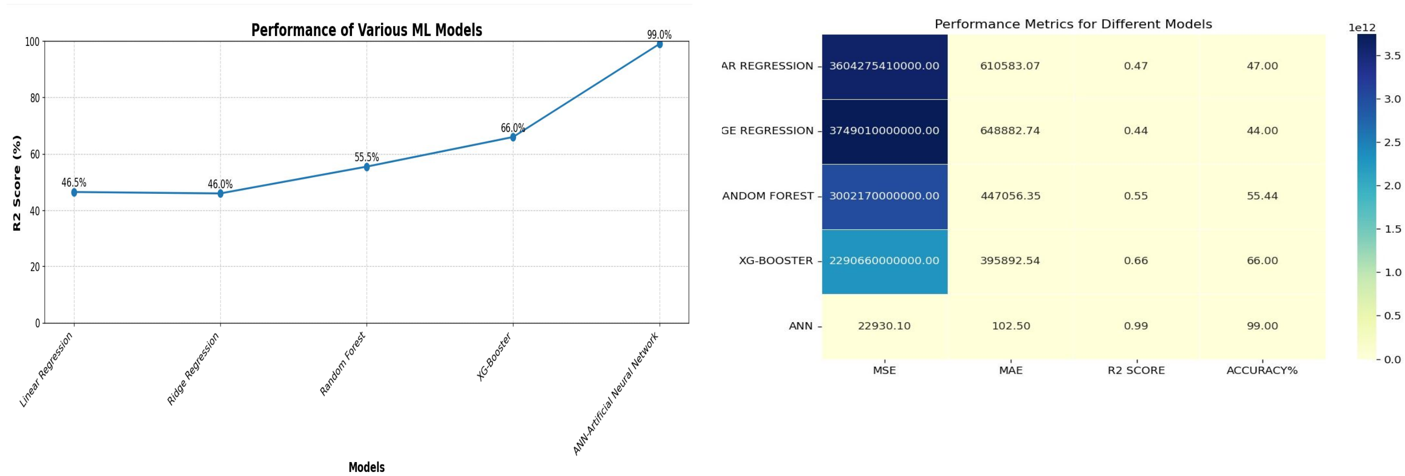

Fig - 24 Comparison of Performance of various models

Based on the figure presented above, the Artificial Neural Network (ANN) model has the highest accuracy among the models shown, with an accuracy of 99.0%. The next highest accuracy is Ridge Regression at 66.0%, followed by Random Forest at 55.5%. Linear Regression has the lowest accuracy among the four models at 46.5%.

IV. CONCLUSION

The study's objective was to predict the prices of used cars using various machine learning models to achieve high accuracy and minimize prediction errors. The process began with extensive data cleaning to remove null values and outliers, ensuring the dataset's integrity. Following the data preparation, multiple machine learning models were employed to forecast resale car prices. A thorough examination of the dataset was performed using data visualization tools, revealing the relationships between different features and aiding in the selection of relevant predictors for the models. The evaluation of these models indicated that the Artificial Neural Network (ANN) model outperformed others in predicting used car prices, achieving an impressive R2-SCORE of 0.99. This high score indicates that the ANN model can explain 99% of the variance in the price prediction, demonstrating its superior capability in handling complex relationships within the data. The success of the ANN model highlights the potential of advanced machine learning techniques in accurately forecasting used car prices. However, this work also recognizes the importance of continuous improvement and proposes future directions for enhancing predictive accuracy. One proposed future scope is the application of deep learning algorithms to the same dataset. Deep learning models, with their ability to capture intricate patterns and relationships in large datasets, could further refine price predictions and reduce errors.

In summary, this study successfully demonstrates the efficacy of machine learning models, particularly ANN, in predicting used car prices. The promising results pave the way for further research using deep learning techniques and diverse datasets, aiming to enhance the accuracy and reliability of price predictions in the used car market. This continuous pursuit of improvement will not only benefit stakeholders in making informed decisions but also contribute to the advancement of predictive analytics in the automotive industry.

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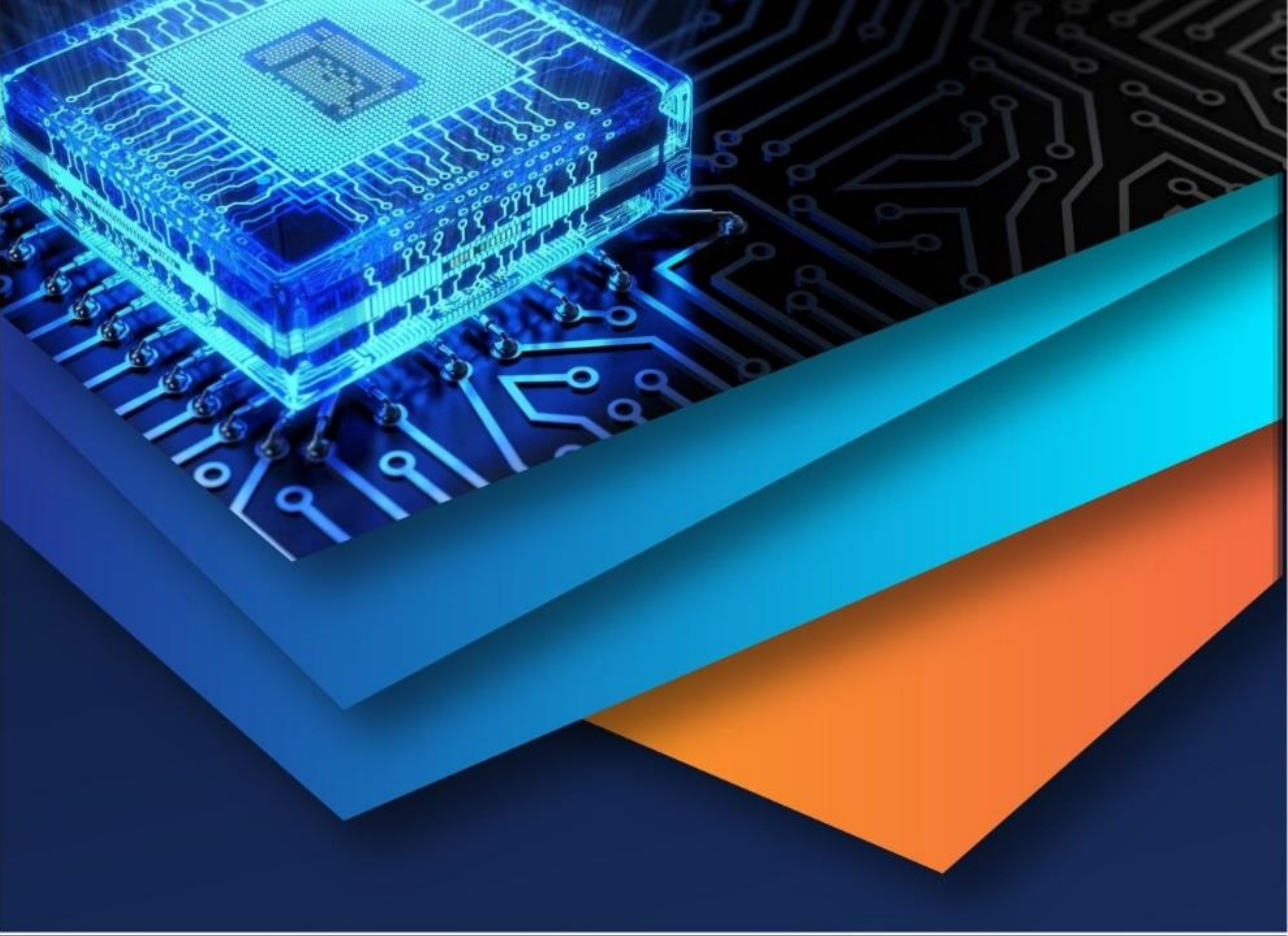

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