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Predictive Pricing Model for Commercial Vehicles using Supervised Learning

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Abstract: Despite the fact that the manufacturer determines the market price for new automobiles, some governments in specific nations incur additional fees in the form of taxes. Customers may be certain they will receive value for their money when purchasing anew vehicle. Used vehicle sales are rising globally, meanwhile, as new automobile costs climb and more people are unable to afford toacquire them. A system that reliably forecasts the price of automobiles based on multiple attributes is therefore urgently needed. In thecurrent system, sellers arbitrarily choose prices without considering the true condition of the car, while purchasers are uninformed of the vehicle's actual market worth. In actuality, neither the asking price nor the value of the automobile are known to the seller. It has highly efficient way to address this issue and this circumstance. Supervised machine learning methods including KNN (K Nearest Neighbor) Regression, Lasso Regression, ANN (Artificial Neural Network), and SVM (Support Vector Machine) are providedfor the analysis of used car expenditure. To train the model, we used pre-owned automobile data that we gathered from a number of websites utilizing a single source. In this experiment, a variety of training-to-test ratios were used to analyses the date. As a consequence,the proposed model's accuracy significantly increased, and it was modified to become the ideal model.

Keywords: *Support Vector Machines, K Nearest Neighbor Regression, Lasso Regression, Machine learning Model, Artificial Neural Network*

1. INTRODUCTION

Despite the fall in the new car market, the used car business has been expanding. According to a recent Indian Blue Book estimate of the country's used car sector, about 4 million used autos were acquired and sold in India in 2018-19. Both buyers and sellers now have businesses thanks to the used automobile industry. Because used automobiles are more reasonably priced and may be sold again after a few years of use for a profit, the majority of people choose to purchase them. The market price of second-hand automobiles will continue to fluctuate. As a result, an evaluation model is needed to forecast the price of second-hand automobiles.

For businesses to succeed in the highly competitive commercial vehicle sales market, pricing tactics must be optimized. In this research, a commercial vehicle forecast pricing model utilizing supervised learning with Support Vector Machines (SVM) is presented. In order to provide precise predictions about future prices, the model makes use of historical data on vehicle characteristics, pricing, and market conditions. The purpose of the suggested approach is to help companies set competitive prices by taking market trends and vehicle characteristics into account. Through the examination of historical pricing data, the SVM model picks up intricate patterns and correlations that let it forecast new car prices with accuracy. It has been validating the model's performance with real-world commercial vehicle datasets through tests. The findings demonstrate that the SVM-based predictive pricing model beats out conventional pricing techniques, giving companies a useful tool for enhancing pricing tactics and boosting revenue in the commercial vehicle sector.

One of the supervised machine learning models developed in this study to predict used car costs is the K-Nearest Neighbor strategy. Simple and small data sets respond nicely to this. For this study, we assembled and analyzed a dataset of second-hand cars. Different training/test set ratios were employed to gauge the model's accuracy after Lasso regression and SVM were used to train the model on the data. Use the easy-to-understand and easy-to-implement K-Fold technique to cross-validate the same model in order to assess model performance. This method even determines basic requirements for increasing the accuracy of the dataset with adding new parameters than the old methodology of algorithms used. Adding additional attributes for development and enhancement of the new policies designed by the government is necessary for determining the accuracy. In this paper, sections are organized as follows, in section 2 literature survey was explained, in section 3 the existing architecture and proposed architecture system was explained. proposed system methodology was discussed in section 4 whereas the section 5 denotes the discussion of the

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proposed work. The section 6 discussed with conclusion .

2. LITERATURE SURVEY

Samerchand Pudaaruth [1] Using machine learning techniques, he claimed, might be a good way to forecast used car values. In this study, prices for used cars in Mauritius were forecasted using historical data obtained from local media utilizing decision trees, K-nearest neighbours, multiple linear regression, and a basic Bayesian method. Nissan, Toyota, and linear regression all had average errors of about Rs 27,000, Rs 45,000, and Rs 51,000, respectively. Depending on the parameters, the accuracy of the decision tree and Naive Bayes models varies, with a training accuracy of 61%. Natis Monburinn et al [2] Advocated using a regression model to calculate the price of old cars. The authors chose data from a German e-commerce website for this study. The main objective of this study is to create a reliable used automobile price forecast model. They evaluated the effectiveness of several machine learning algorithms using the mean absolute error (MAE) as a parameter. They discovered that the gradient-based regression model performed better overall than the random forest linear regression and reduced the error at MAEs of 0.28, 0.55, and 0.35, respectively. He also determines the price of the car can be achieved with good accuracy by using lasso regression. Eniss Gegaic et all [3] An Idea for Using Machine Learning to Forecast Automobile Prices A number of machine learning techniques, including support vector machines, random forests, and artificial neural networks, were combined by the authors of this research to create an ensemble model. These researchers developed a model to forecast used automobile prices in Bosnia and Herzegovina using information from a particular website. The model has an 87% accuracy rate. Kanwaeel Noer and Sadqqat Jann [4] Recommended Machine Learning Methods for Predicting Vehicle Prices. This study put forth a model for predicting vehicle prices using multiple linear regression. They determined which trait was the most important by using the feature selection method, and they eliminated the rest. The recommended model's prediction accuracy was over 98%. Gonggie [5] Presented an ANN-based model for predicting used automotive prices (Artificial Neural Networks). He considered the brand, the estimated vehicle life, and the number of kilometers travelled. The proposed model was created in order to accommodate nonlinear connections in the data, which was not achievable with previous models that employed simple linear regression methodologies. In terms of predicting automotive pricing, the non-linear model outperformed conventional linear models. In [6], [7] completed a research project employing a neuro fuzzy knowledge-based methodology to anticipate automobile prices. Manufacturer, year of manufacturing, and engine type were taken into account. Both their prediction model and a straightforward regression model produced comparable outcomes. Furthermore, created the ODAV expert system since auto dealers frequently wish to sell their inventory at the conclusion of the lease period. Support Vector Machines (SVM) are utilized suggested in [8] to forecast the costs of leased vehicles. When a very large dataset is available, SVM is significantly more accurate at predicting prices than multiple linear regression, according to this study. Additionally, SVM is more effective at handling high-dimensional data and prevents both under fitting and overfitting. Effective spatial patterns of urban attractiveness are revealed by the suggested filtering and actual cross-validation of which limit biased selection and rule out a false-positive classification given in [9]. Useful for executives and analysts looking to better understand how people in cities use public space. Utilized a variety of machine learning methods, including k-nearest neighbor (KNN), decision tree, random forest regression, and light gradient boosting machine (LightGBM), to forecast the value of pre-owned vehicles in India according to a variety of characteristics unique to that consumers in [10], [11]. In [12], [13] build and compare the accuracy of several models, including Multiple Linear Regression, KNN, Random Forest, Gradient Boosting, and XGBoost. With 88% of training data and 87% of test data, XGBoost achieves the greatest r2 score among these classes. In [14], [15], The results show that using algorithms like Decision Tree, Random Forest Regressor, MLP Regressor, and AdaBoost Regressor in an approach that predicts car prices is a good way to figure out how much a used car is worth. The objective of this study is to construct a predictive model for determining the appropriate costs of pre-owned automobiles. This model takes into account several factors such as mileage, production year, fuel efficiency, transmission type, road tax, fuel type, and engine size. This approach has the potential to be advantageous for vendors, purchasers, and automobile manufacturers operating in the used cars market suggested in [16].

3. EXISTING SYSTEM

Predicting used car prices has been the subject of numerous studies, most of which have used support vector machines (SVMs) because of their efficiency with large datasets. Figure 1 shows the representation of the existing system. These investigations have, however, shown limits in the use of fundamental metrics to discriminate between simple and complex SVM regression models.

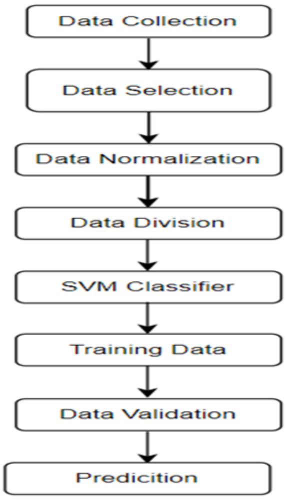

Figure 1. Existing System Structure

Compared to other vehicle types, there is surprisingly little research into the pricing of used cars, and the majority of prediction algorithms in use today rely primarily on machine learning and data mining approaches. For quicker findings, these methods need more comparison approaches due to their lack of precision. Collecting sufficient datasets globally poses a challenge, especially when restrictions limit offline data collection. Because different websites employ different techniques to determine the value of pre-owned cars, there is no common price mechanism. By utilizing statistical models to train, one can obtain a preliminary approximation of the pricing without the need to input specific information into the intended website [17], [18], [19]. The records do not include data regarding vehicles that have remained unused for an extended period. Furthermore, it does not inherently include data regarding previous generations of automobiles. The current system has numerous limitations and challenges that impede the proper determination of a car's price. The manifesto specifics are not compared to the patent automobile details at the showroom.

3.1 PROBLEMS IN CURRENT STRUCTURE

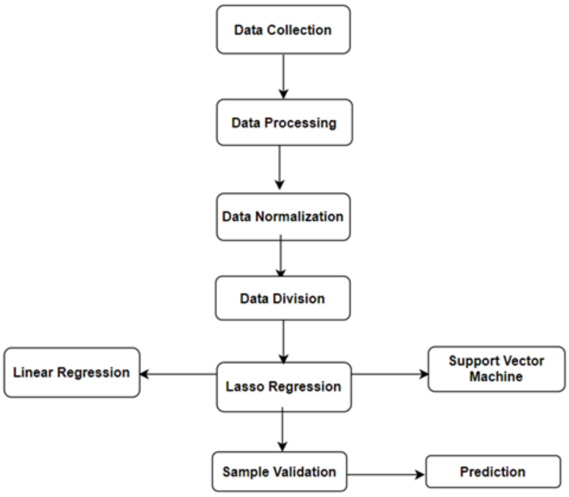

Fig. 2. Proposed Architecture Diagram

Numerous algorithms are used in data mining and machine learning. More qualities are needed in order to forecast the car's pricing [20],[21],[22]. The challenges associated with forecasting pre-owned vehicle prices include the need for additional comparison methodologies, challenges in obtaining geographically dispersed datasets, and limitations in the collection of internet data. This presents an obstacle for people residing in rural regions who are unable to obtain online data. Furthermore, insufficient or obsolete data frequently hinder pricing models, leading to less-than-optimal performance. Current studies on keyword queries mostly examine individual data points, which limits the examination of groups of diverse vehicle points and contributes to system sluggishness. The dearth of efficient query retrieval methods, combined with the lack of SVMs functioning under limitations, worsens these issues. The evaluation of the model can have done by precision and recall [23], [24], [25] and in [26]. The current structure is given in figure 2.

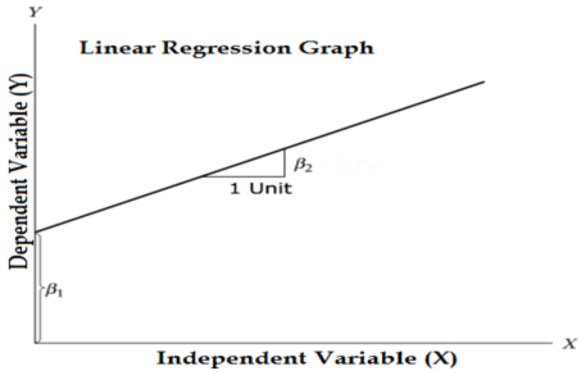

Fig. 3. Graph Representation of the Linear regression algorithm

3.2 PROPOSED METHOD

Most keyword query studies only look at individual points, which makes them inappropriate for many applications that need looking at groups of differentvehicle points. As a result, the system is extremely sluggish. There are no efficient methods for obtaining queries since thereare few SVMs that can function under these conditions. It is more efficient since the algorithm compares vehicle combinations based on cost. The basic proposed architecture is given in figure 2.

3.3. LINEAR REGRESSION ALGORITHM

Linear regression is a statistical technique utilized to represent the correlation between a dependent variable (often labeled as "y") and one or more independent variables (commonly labeled as "x"). The assumption is that the relationship between the independent variables and the dependent variable is linear, indicating that a modification in one independent variable is linked to a consistent modification in the dependent variable, while keeping all other variables constant. The graphical representation of the linear regression is given in the figure 3.

y=β0+β1x+ϵ

y is the dependent variable (e.g., vehicle price)

x is the independent variable (e.g., vehicle age)

β0 is the intercept term (the value of y when is x is zero),

β1 s the slope, ϵ is the error term

3.4 LASSO REGRESSION ALGORITHM

In Lasso regression, a linear regression approach, the ordinary least squares (OLS) objective function is augmented by a regularization factor. The regularization term in this context imposes a penalty on the absolute magnitude of the regression coefficients, resulting in the reduction of certain coefficients to zero. Due to its ability to select and regularize variables, Lasso regression simplifies the model and enhances interpretability. The suggested model utilizes Lasso to collect historical data on commercial vehicle sales, which includes specific details such as vehicle type, manufacturer, model, year, mileage, condition, location, and selling price. Analyse the data by handling any missing values, outliers, and encoding categorical variables. Determine a collection of pertinent characteristics that could impact the pricing of commercial cars. Lasso regression automatically identifies and selects the most significant features throughout the process of fitting the model. Optimize the hyper-

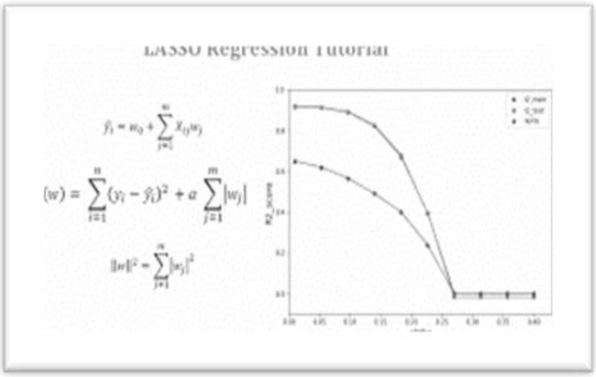

Fig. 4 Graph Representation of the Lasso regression

parameter alpha, which governs the level of regularization in Lasso regression. The evaluation has assessed the performance of the regression model on the testing set using metrics such as mean absolute error (MAE), mean squared error (MSE), or R-squared. Utilizing cross-validation allows for the determination of the ideal alpha value that minimizes the prediction error. Once the model has been trained and evaluated, employ it to predict the prices of new commercial cars based on their attributes. Lasso regression is a regularization method that reduces model complexity. The acronyms for least absolute and selection operator are LASO. The penalty term in this case lacks quadratic weights, which is the sole difference from ridge regression. The slope can be set to zero due to the utilization of absolute numbers. However, ridge regression can only assist in approaching a value closer to zero. This is referred to as L1 regularization as shown in figure 4. The cost's Lasso regression function is represented by the equation.

- n is the number of observations,
- p is the number of features,
- y_i is the observed value of the dependent variable for the ith observation,
- $\hat{y}_i$ is the predicted value of the dependent variable for the ith observation,
- β_j is the coefficient of the jth feature,
- α is the regularization parameter that controls the strength of the penalty term.

3.5 SUPPORT VECTOR MACHINE ALGORITHM

Support Vector Machines, is a commonly used supervise machine learning technique for solving classification and regression issues. It is widely employed in various systems such as intrusion detection, handwriting recognition, protein structure prediction, and steganography detection in digital photos. In this approach, each feature value corresponds to a certain coordinate, and each point is considered a data item in an n-dimensional space. The classification is finalized by determining the degree of hype that differentiates the two classes after plotting. Refer to the diagram provided below in order to comprehend the concept. It is highly efficient methods for developing pricing models that estimate commercial vehicle prices. It collects statistics by aggregating information on commercial vehicle sales, including details such as vehicle type, make, model, year, mileage, condition, location, and sale price. Eliminate any missing values, identify and exclude outliers, and convert categorical variables into a numerical format. Including the feature collection was critical for accurately predicting prices. The key factors to consider are the vehicle's type, make, model, manufacture year, mileage, condition, location of sale, and previous ownership. Additionally, it is crucial to analyze the accident history using the numerical data provided in Figure 5.

	Vehicle_Type	Make	Model	Year	Mileage	Condition \
0	Bus	Ford	Silverado	2021	134537	Excellent
1	Bus	Chevrolet	Sprinter	2008	10246	Fair
2	Bus	Mercedes-Benz	Silverado	2011	140782	Good
3	Truck	Toyota	Corolla	2004	34718	Excellent
4	Truck	Toyota	Sprinter	2007	138916	Fair

	Location	Market_Trend	Economic_Indicator	Seasonality	Competition \
0	New York	Upward	0.959631	Winter	54
1	Chicago	Upward	0.849185	Fall	26
2	Houston	Downward	0.495060	Winter	52
3	Chicago	Downward	0.498482	Winter	84
4	Los Angeles	Upward	0.969134	Summer	86

	Exterior_Color	Interior_Features	Previous_Ownership	Accident_History
0	Blue	Entertainment System	Multiple Owners	Yes
1	Black	Entertainment System	Multiple Owners	No
2	Blue	Entertainment System	Single Owner	No
3	White	Air Conditioning	Single Owner	No
4	Red	Entertainment System	Single Owner	Yes

Fig 5. Features in dataset

Pros of SVM

When dealing with datasets that contain numerous characteristics, SVMs shine in high-dimensional spaces. This is especially true for attributes like car type, make, model, year, and so on denotes to handle high dimensional data. By employing the kernel method, support vector machines are able to effectively conduct regression or classification in non-linear domains, accurately capturing intricate feature-relationships. Because of their versatility, support vector machines are well-suited to many machine learning applications, including predictive pricing modeling.

4. Methodology

The Training phases: Data from the dataset is used to train the system. The Testing phases: Following the receipt of the inputs, the system's functionality is examined. The goal is accuracy. Consequently, the information utilized to develop or verify the model must and should be appropriated. The system must employ the proper algorithms to complete two distinct jobs since it is intended to identify and estimate used automobile pricing. Several algorithms were accurately evaluated before choosing one for future usage.

Steps performed in the algorithm

Data exploration is a crucial process for comprehending patterns, frequently achieved through the use of data visualization techniques. Managing missing values is essential, usually done by imputation or deletion. Data restructuring refers to the process of reorganizing data formats, whereas categorical data encoding entails transforming variables into numerical representations. Preprocessing is the process of preparing data for model fitting. During this procedure, correlation matrices and scatterplots are used to assess the correlations between variables. A system facilitating user management, vehicle categorization, and search functionalities. It allows users, including sellers, to log in, manage users, upload vehicles, and access ratings and transaction details. Administrators can oversee user data, including login rights, and users can view profiles, search for vehicles, and access search history. The system supports online bank account creation and offers various modules for managing and analyzing user and vehicle data.

Data preprocessing:

It is an essential step in building a predictive pricing model for commercial vehicles using the SVM algorithm. It involves cleaning and transforming the raw data into a format suitable for training the model. The key steps in data preprocessing,

Handle the missing values in the dataset

Find the dataset's missing numbers and deal with them. It can fill in empty values (for example, by using the mean, median, or mode) or get rid of rows or columns that have missing values.

Categorical values:

Use methods like one-hot encoding or label encoding to turn categorical variables (like car type, make, and model) into numbers. This has to be done because SVMs need numbers to work.

- n is the number of observations,
- p is the number of features,
- y_i is the observed value of the dependent variable for the ith observation,
- $\hat{y}_i$ is the predicted value of the dependent variable for the ith observation,
- β_j is the coefficient of the jth feature,
- α is the regularization parameter that controls the strength of the penalty term.

Numerical Features

To find the decision limit, SVMs figure out the distance between data points. Larger features can skew the calculation of lengths, which can lead to inaccurate results. Scaling makes sure that all traits add the same amount to the distance calculations. For each numerical feature, compute the mean and standard deviation (for standardization) or the minimum and maximum values (for min-max scaling). Apply the scaling formula to every feature. The efficacy and stability of machine learning models, particularly SVMs, are enhanced through the scaling of numerical features, which guarantees that each feature makes an equal contribution to the model's predictions.

5. Discussion

	Year	Kilometers_Driven	Seats	Price
count	6019.000000	6.019000e+03	6019.000000	6019.000000
mean	2013.358199	5.873838e+04	5.276790	9.479468
std	3.269742	9.126884e+04	0.806346	11.187917
min	1998.000000	1.710000e+02	0.000000	0.440000
25%	2011.000000	3.400000e+04	5.000000	3.500000
50%	2014.000000	5.300000e+04	5.000000	5.640000
75%	2016.000000	7.300000e+04	5.000000	9.950000
max	2019.000000	6.500000e+06	10.000000	160.000000

Fig 6. Numerical Analysis

The dataset has been implemented and description is given in the figure 5. With attributes like price, kilometer, seats, year, Location, owner_type, Mileage Engine, Power, name, fuel-type, Transmission, Power, New price and soon. The numerical features of the data with the analysis has given in the figure 6. The analysis the minimum, maximum and sum and average price of the dataset has highlighted using the algorithm. When working on a predictive pricing model with SVM, it's crucial to thoroughly examine the numerical features in your dataset. This includes studying their distributions, connections to the target variable (price), and identifying any possible factors that could affect the SVM model's accuracy. Below are essential components of numerical analysis for your SVM predictive pricing model. The reprsentation is given in figure 7.

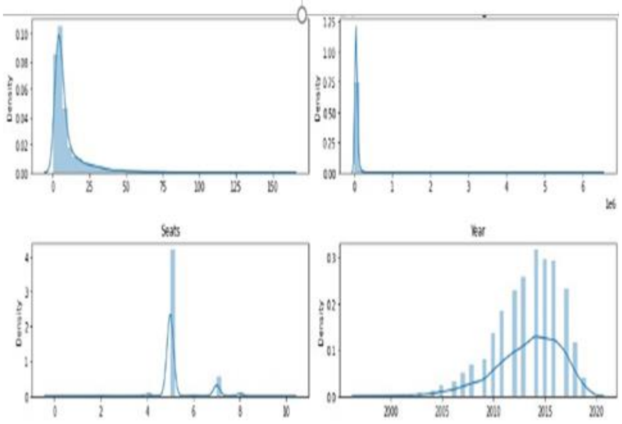

Fig 7. Graphical representation of features

The correlation matrix offers a numerical depiction of the connections among the variables in your collection[23-24]. Main aim to analyze the link between the fuel data and the variables price, kilometers traveled, seat, and year is shown in figure 6. The correlation matrix assigns coefficients that indicate the magnitude and direction of correlations between variables. A value of 1 indicates a strong positive correlation, -1 indicates a strong negative correlation, and 0 indicates no association. The SVM model can incorporate 'Year' if there is a strong positive connection between 'Year' and 'Price'. If there is a negative correlation between 'Kilometers Driven' and 'Price', it may be ecessary to make revisions to the model.

6. Conclusion

The study compared lasso regression, linear regression, and Support Vector Machines (SVM) to forecast pre-owned vehicle prices. SVM showed superior predictive accuracy, capturing intricate patterns in the dataset for more accurate forecasts than lasso and linear regression. Thus, it is advisable to utilize SVM as the most effective method for predicting the pricing of used vehicles. By utilizing the SVM's capacity to process non-linear data and uncover patterns in intricate associations, businesses and purchasers can enhance their ability to create precise estimations in the dynamic used automobile market. This, in turn, enables educated decision-making.

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