International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802247

A Comparative Analysis of Regression Models for used Car Price Prediction

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Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: The accurate calculation of used cars prices is still a major problem in the online market and intelligent transportation because market and car characteristics are not homogeneous hence dictate price variation. Strong regression modelling can help in improving transparency, trust, and decision-making process of both consumers and vendors significantly. The paper involves comparative analysis of deep learning and many regression models, using the CarDekho data of vehicles to predict the prices of used cars. The whole data preprocessing process includes null value cleaning, duplicate trimming of data, target variable logarithmic transformation, feature cleaning, IQR used to remove outliers, and labelling encoding. Classical and modern paradigm of learning are all viable and applicable, and each of these models can be evaluated. The efficacy of the model is assessed using the MAE, MAPE, RMSE and R 2 indicators. The outcomes of the experiment show that the quality of prediction of tree-based and ensemble models is higher. The MAPE of the Voting Regressor is 13.1 and it has R 2 of 95.7 whereas the random forest model has a R 2 of 93.4. SHAP and LIME are AI techniques that can be explained and are applied to estimate the contribution of features to improve the transparency of models or explain the behaviour of prediction. Moreover, the application that is being used to practically implement the trained models is a Flask-based web application, with SQLite-supported authentication to offer real-time predictions of the uploaded data, which is provided by the users.

KEYWORDS: Used car price prediction, regression analysis, ensemble learning, deep learning models, explainable artificial intelligence, LIME and SHAP, Flask-based deployment, machine learning evaluation metrics.”

I. INTRODUCTION

The second one is the development of the used car market, which has grown significantly due to the increase in online markets and the need to acquire cheaper cars. There is an urgent need that buyers and vendors of this industry conform to the right pricing because this directly affects the financial decisions, the fairness of transactions and the overall efficiency of the market. The factors that lead to determination of the prices of vehicles include age, mileage, engine capacity, type of gasoline, gearbox, the history of ownership and brand reputation. The calculation of the price of cars is a complicated and difficult task since the variation of these features is broad, and the market tendencies are subject to changes. The failure of the traditional manual method of valuation due to the inability to consider all of the contributing factors is often the cause of inconsistent or inaccurate pricing results [1].

The development of machine learning and data analysis has enabled more systematic ways of predicting the prices of vehicles. Linear regression approaches allow finding linear relationships between price and features and get the simplified datasets with interpretable results [2]. More advanced models including decision trees and ensemble models can also be improved by using nonlinear relationships and interactions between vehicle characteristics to increase the predictive accuracy [3]. DL models can be applied to predict sequential patterns and temporal trends in vehicle history, such as recurrent neural networks, long short-term memory networks, and offer better predictive potential due to their

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improved performance with complex datasets [4]. Also, the predictability of the price estimation systems has been improved by exploring the simulation-based procedures of verifying the predictive performance in dynamic contexts [5]. Current systems surveys indicate that the artificial intelligence practices are currently being used to automate valuation procedures in order to enhance the effectiveness and uniformity of used vehicle prices [6]. The possibility of integrating both structured and unstructured data to make interpretable and precise predictions is shown with methods that are used in similar areas, e.g., traffic flow forecasting [7], cryptocurrency price forecasting [8], and electric vehicle energy estimation [9] [10].
The main aim is to design a smart system to estimate price of the used cars whereby more than one predictive model is used, raw car data is processed in an efficient way and features are converted to formatted data to guarantee the price prediction. The system aims at ensuring interpretability through the provision of a user-friendly real-time interface to enable the easy input and output of data, and at giving clear descriptions of the contribution of features to the prediction of prices. It discusses the need to make well-founded estimates based on reliable data to enable the informed choices of both buyers and sellers in the resale market of the automobile industry.

II. RELATED WORK

Predictive analysis based on machine learning has been successfully applied in various areas and allows making decisions based on data and contributing to the important information. Kumar, Kedam, Kisi, Alsulamy, Khedher and Salem [11] performed a comparative analysis of the machine learning models used in predicting daily and weekly rainfall. The paper highlighted the efficiency of regression models and ensemble models in the handling of temporal data. This article demonstrates how predictive models can be able to establish complex patterns and generate accurate forecasts with time. It strictly applies to the sequential and time-related data, i.e. vehicle usage patterns inside the automotive market. Noferesti and Mirzahossein [12] explored the use of ML to predict preferences of locations to live and emphasize the role of using structured data and diverse features to recreate decision-making procedures. Their approach also focuses on the idea of taking into account multiple input variables and interactions between the features and can be utilised in the context of the prognosis of the used car prices, in which the final valuation is determined based on various vehicle attributes.

Hussain, Ching, Uttraphan, Tay, Noor, and Memon [13] focussed on the optimisation of electric vehicle energy consumption prediction by applying machine learning and ensemble methods. Their effort proved the possibility of the combination of different models to enhance predictive accuracy and reliability. This is also an indication of the merit of ensemble models in nonlinear relationships and shrinkage of variance which is especially beneficial in the handling of the heterogeneous nature of vehicle datasets. Anderson, Alharbi, Chinnathambi, PJ, and Gavurova [14] used a linear regression model as well as a LSTM model to forecast thrust, fuel consumption, and emissions of micro gas turbines. The paper highlights the interpretability and sequential complexity advantages of the traditional regression methods and the deep learning models respectively, which are aligned with hybrid models in automotive pricing prediction.

Oukhouya, Angour, Aboutabit, and Hafidi [15] provided an example of the effectiveness of ensemble and advanced forecasting models in volatile and dynamic data in a comparative analysis of ARDL, LSTM, and XGBoost forecasting models in the stock market. This study hypothesizes that it is possible to combine deep learning and regression models in order to generate more accurate forecasts in complex areas, like used-car pricing. Yacaman Mendez, Zhou, Brynedal, Gudjonsdottir, Tynelius, Trolle Lagerros, and Lager [16] applied cluster analysis and traditional prediction models to carry out their study on risk stratification of cardiovascular diseases. Their study puts a lot of emphasis on the fact that interpretability and model comparison are very important aspects of understanding how features play out in prediction of any predictive structure including vehicle valuation.

The focus of Mousaei and Naderi [17] was to predict the optimal location of electric vehicle charging stations through the ML approach, especially spatial and structured feature modelling. The approach demonstrates the way in which predictive systems may be improved in terms of accuracy and dependability through the incorporation of numerous features and regression approaches. The same can be applied to the modelling of vehicle pricing which is affected by a multiplicity of factors. Sivabalan and Minu [18] developed a multi-anchor temporal convolutional neural network with optimisation in predicting automobile sales. This piece of work shows how effective hybrid DL architectures are in the ability to capture complicated patterns and time-related data in vehicle-related datasets. This implies that sequential learning coupled with feature extraction would be better when it comes to price prediction.

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Ordenshiya and Revathi [19] compared the traditional M L and hybrid fuzzy inference systems in their study to forecast air quality indexes. They placed emphasis upon model selection, feature importance and interpretability. Their findings highlight the importance of predictive results that are understandable as a key issue in the delivery of insights into the estimates of vehicle prices. The application of regression, ensemble, and hybrid methods in the cost and price estimation in the field of transportation was strengthened by the fact that the same study by Amicosante, Avenali, D'Alfonso, Giagnorio, Manno, and Matteucci [20] examined the use of ML techniques to cost predict local public bus transport services. The research points out the possibility of structured data modelling and predictive models in determining the exact price of used vehicles.

III. MATERIALS AND METHODS

The purpose of the system is to employ advanced data-driven methods to produce a smart system of the correct and interpretable estimation of the prices that are paid on used vehicles. It uses preprocessing, feature cleaning and encoding to transform raw vehicle data into format which can be easily used in modelling. To find linear and nonlinear correlations between the vehicle characteristics, different predictive models are applied, including (but not limited to) LR, RF, RNN, LSTM, CNN integrated with LSTM (CNN+LSTM), and an ensemble Voting Regressor. To ensure explainability, Explainable AI methods, such as SHAP and LIME, are used that provide an idea of the effects of individual factors on the prices predicted. Moreover, with the help of a web interface, which is developed on the basis of Flask, the user has an opportunity to enter the data about the vehicle in CSV format and obtain real-time predictions which are immediate, thus enhancing accessibility and usability. The system provides solutions of price estimation which are easy to use, transparent, and accurate through incorporation of viable deployment, sound modelling, and explanation of features [21]. The method has been informed through comparative research on predictive modelling in the transportation and market analysis sectors [22][23].

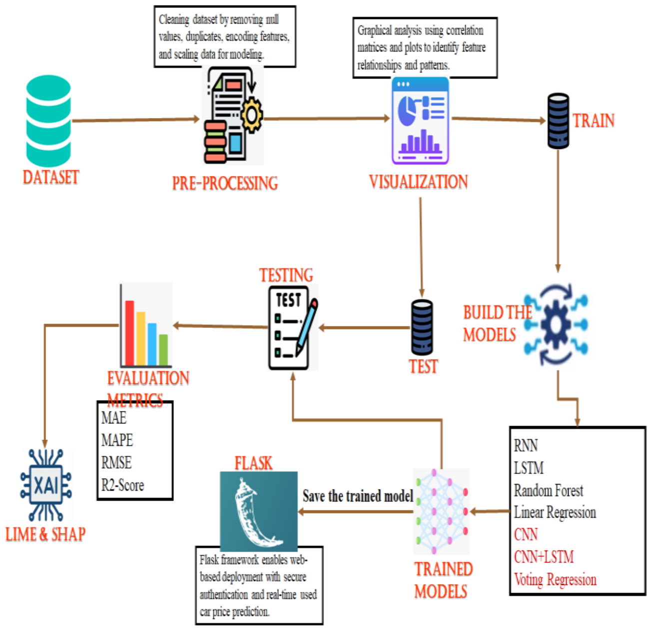

Fig.1 System Architecture

Fig. 1 depicts that ML pipeline starts with dataset pre-processing, which involves cleansing and scaling data. The data is separated into training and assessment after the visualisation is conducted to outline trends. Several models are formed and trained such as RF and RNN. Finally, the performance is measured with evaluation measurements and XAI tools before being deployed with Flask.

A) Dataset Collection:

The data used is a structured set of data on used cars in India as shown in Fig. 2. The table has five sample values (coded 0-4) and twenty categorical and numerical items of each vehicle. The Honda, Maruti Suzuki, Hyundai, and Toyota are a few of the brands that are represented in the major sections, Make, Model, Price and Year. You will have a great variety of cars, starting with affordable ones such as the 2011 Hyundai i10 which costs ₹220,000 and the high-end ones, such as the 2018 Toyota Innova which sells at ₹1,950,000. It contains the following technical specifications:

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Fuel Type (Petrol /Diesel), Transmission (All Manual), Engine displacement (cc), Max Power, and Mileage. The whole profile is created by capturing the physical size, seating capacity, and utilisation history by use of readings on the number of kilometres, besides the seller details. This data is the keystone to predictive modelling, as it allows examining the vital characteristics on which the price of a vehicle depends, and it is also used to carry out the forecasting tasks in real time.

	Make	Model	Price	Year	Kilometer	Fuel Type	Transmission	Location	Color	Owner	Seller Type	Engine	Max Power	Max Torque	Drivetrain	Length	Width	Height	Seating Capacity	Fuel Tank Capacity
0	Honda	Amaze 1.2 VX i-VTEC	505000	2017	87150	Petrol	Manual	Pune	Grey	First	Corporate	1198 cc	87 bhp @ 6000 rpm	109 Nm @ 4500 rpm	FWD	3990.0	1680.0	1505.0	5.0	35.0
1	Maruti Suzuki	Swift DZire VDI	450000	2014	75000	Diesel	Manual	Ludhiana	White	Second	Individual	1248 cc	74 bhp @ 4000 rpm	190 Nm @ 2000 rpm	FWD	3995.0	1695.0	1555.0	5.0	42.0
2	Hyundai	i10 Magna 1.2 Kappa2	220000	2011	67000	Petrol	Manual	Lucknow	Maroon	First	Individual	1197 cc	79 bhp @ 6000 rpm	112.7619 Nm @ 4000 rpm	FWD	3585.0	1595.0	1550.0	5.0	35.0
3	Toyota	Glanza G	799000	2019	37500	Petrol	Manual	Mangalore	Red	First	Individual	1197 cc	82 bhp @ 6000 rpm	113 Nm @ 4200 rpm	FWD	3995.0	1745.0	1510.0	5.0	37.0
4	Toyota	Innova 2.4 VX 7 STR [2016-2020]	1950000	2018	69000	Diesel	Manual	Mumbai	Grey	First	Individual	2393 cc	148 bhp @ 3400 rpm	343 Nm @ 1400 rpm	RWD	4735.0	1830.0	1795.0	7.0	55.0

Fig.2 Dataset

B) Pre-Processing:

Preprocessing of data is a necessary task that ensures that the data is uniform, clean and is ready to undergo modelling. To increase the model accuracy and reliability, it is required to deal with anomalies, remove duplicates, transforming the target variable, and missing values.

Data Preprocessing: The data is first analyzed in terms of null values and those that are not present are removed so that the integrity of data would be maintained. To reduce bias when training the model, the duplicate records are located and removed. Logarithmic transformation is used to bring the objective variable, Price, to the normal form and reduce the prediction variance which is excessively skewed. The IQR process is used to detect outliers in numerical characteristics and they are then removed in order to avoid the distortion of the model by extreme values. Together, these processes ensure that the data set is coherent, accurate and sufficiently ready to undergo an unbiased, accurate modelling.

Feature Cleaning: The feature cleaning process involves transformation of the raw data into a structured and numerical format that fits the ML models. Textual columns like Engine and Power often contain units like cc or bhp. The numbers are pulled out and the units are thrown away in order to make computation easy. Consistency between features is ensured through conversion of columns with varying data types to numerical values. The task during this stage is also involved with the standardisation of categorical representations, elimination of inconsistencies, and handling of any irregularities that might potentially hinder the training of the model. By cleansing and transforming features into a suitable format, the dataset can be made more understandable, predictable and suitable to the regression and DL-based models.

Label Encoding: Label encoding is applied in order to transform categorical variables into numeric ones that can be acted on by ML models. The individuality of each category is maintained without adding bias by coding the columns of Make, Model, Fuel Type, and Seller Type as an integer. This technique makes algorithms like RF, LR, RNN and LSTM useful at interpreting categorical data. Encoding is particularly important to those features with more than two categories since it ensures that the transduced relationship among the variables is accurately represented. Transforming the categorical columns into numeric values will fully manage to make the dataset model-ready, preserving the semantic meaning of each category, and will allow the efficient training and effective predictions.

Data Visualization: To understand how preprocessing steps, correlations and feature distributions affect each other, the data visualisation is applied. Normalisation tested on the distribution of the target variable, Price, in the pre-logarithmic and post-logarithmic forms. To determine the relationships among the target and independent features, correlation matrices are created with the focus on the key variables affecting car prices. Visualisations like histograms, boxplots and scatter plots are used and allow trends to be revealed, identify residual anomalies and feature selection. Such visual insights prove useful in the choice of models, detection of multicollinearity, and maintenance of important variables. As a result, visualisation will allow forming a deeper understanding of the data set and enhance the interpretability and the possibility to make informed decisions.

Train & Test Split: The subsets of features are divided into training and testing data after preparation and preprocessing of the data to evaluate the effectiveness of the model. A 80/20 split is done where 80% of the data is used in training the

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model and 20% in testing and validating of the model. This would ensure that the models have been trained on a substantial amount of the data and then tested with respect to unobserved entries and therefore would provide an impartial evaluation of the predictive performance. Stratification and random shuffling is applied in order to maintain representative distributions of objective variables and features. This split allows free training of powerful models, avoiding overfitting and allows accurate assessment of all regression and deep learning models.

C) Algorithms:

Linear Regression: LR is a statistical technique, which includes the estimation of a linear equation to describe the correlation among a dependent variable and an independent variable, or a combination of independent variables. It predicts a continuous target value using a weighted average of features of the input. LR is employed to determine price of used cars by analyzing how vehicle attributes such as engine capacity, mileage and age influence price pattern. It is also computationally fast, interpretable, and simple, which makes it suitable in making predictions at the baseline. The distinctive feature of the analysis is that it allows the estimation of vehicle prices with fair precision in the case when the relationships are mostly linear by offering prompt information about the importance of features through the understanding of linear relationships among the features and price. However, its predictive quality is limited with regard to its capacities to determine complex nonlinear tendencies in a range of data sets.

Random Forest: RF is also an ensemble learning method that boosts the accuracy and generalisation of predictions as well as by building up many decision trees and combining the resulting outputs. It is also useful in regression and classification because it reduces overfitting by using bootstrapped sampling and random selection of features. Random Forest estimates used car prices by evaluating a wide range of decision streams depending on the characteristics of the vehicles and thus produce robust and accurate price estimates. It can successfully handle heterogeneous data types, feature to feature interactions, and nonlinear relationships. The random forest also provides feature importance measurements to aid in determining the most important attributes. It is the favorite one concerning complex datasets with various numerical and categorical variables, as it is the ensemble-based method that ensures outstanding performance and stability.

Recurrent Neural Network (RNN): A RNN is a type of DL network that is supposed to handle sequential data by learning temporal relationships on the basis of hidden states. This is because feedback connection is made in RNNs, and thus the information is capable of existing even in time increments. RNNs have the ability of learning the pattern in series of car characteristics or past price patterns in order to determine the amount of used cars. They are especially good at identifying dependencies where the inputs in the past affect the outputs in the future, hence they are suitable in datasets that have time or sequence. The potential of RNNs is compromised by the fact that they are prone to vanishing gradient problems, and also face challenges with long-term dependencies. These provide a structure of the sophisticated acquisition of sequential interactions which exceed the capacity of traditional models.

Long Short-Term Memory (LSTM): LSTM is also an advanced version of RNN which is designed to mitigate the vanishing gradient problems by incorporating memory cells and gating mechanisms which regulate the information flow. The longest sequences of data are retained and the irrelevant data is ignored in LSTM networks. Applied to used car pricing, LSTM can discover temporal patterns or sequential dependencies between the characteristics of a vehicle, e.g. maintenance history or price development patterns. They can model a complex, nonlinear relationship and long-term effects leading to better predictions than traditional RNNs. LSTMs are specifically good in case the dependencies between inputs are also ordered, as they allow making more accurate price forecasts and can identify more nuanced trends that other models or linear methods can fail to do.

CNN + LSTM: CNN and LSTM CNN and LSTM are a hybrid DL model, which uses CNN to extract hierarchical features representations and then LSTM layers to extract sequential dependencies. The LSTM layers can maintain information on the context of a sequence of data, whereas CNN layers can examine regular patterns of features, finding local relationships between vehicle features. This combined strategy improves the precision of forecasts since the model is capable of learning complex interactions of features and temporal relationships that can be used to price cars used in different applications. It particularly finds application with sequential, categorical or numerical patterns of data. The combination of the feature extraction and sequence learning by CNN + LSTM can model more complicated dependencies than the single-method approaches, which makes the predictions more accurate.

Voting Regressor: VR is an ensemble method that combines prediction of several models by using the results of the models to come up with a final estimate. It exploits the resources of individual regressors and at the same time corrects their vices. It uses the findings of the models like the LR, the RF, and the LSTM to provide more accurate and

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consistent predictions in the prognosis of used car prices. The ensemble method is resistant to overfitting, controls complex relationships, and minimizes variance. A mixture of different models, Voting Regressor uses the complementary learning strategies to reach complementary optimal balance between predictive power, interpretability and simplicity. It often performs better than single models, and it offers a reliable performance to a dataset that has diverse feature types and distributions.

IV. EXPERIMENTAL RESULTS

MAPE: Mean Absolute Percentage Error is a performance measurement index, which is used to locate the accuracy of a predictive or forecasting model. It eases the interpretation of average deviation between predicted and actual value by presenting prediction errors in percentage. The lower the MAPE, the more accurate the model.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - P_i}{A_i}\right| \times 100 \qquad (1)$$

RMSE: Root mean square error is used in quantifying the average difference between predicted and actual values of a statistical model. In mathematics, it is the standard deviation of the residuals. Residuals are the distance between the regression and the data elements.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left|\left|y(i) - \hat{y}(i)\right|\right|^2}{N}} \qquad (2)$$

MAE: The absolute error is the size of the error that you made during your measurements. The difference between the measured and the true value is what it is called. As an example, when one scale displays that you are 90 pounds whereas you know that your true weight is 89 pounds, the scale makes an absolute error of 1 pound or 90 pounds- 89 pounds.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (3)$$

R2 Score: The sum squared regression is the sum of the squares of the residuals and the total sum of squares is the sum of the distance between the data and the mean, squared.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad (4)$$

Table.1 Performance Evaluation Table

Model	MAPE	RMSE	MAE	R2-Score
Random Forest	0.169	377,134.009	190,301.427	0.934
Linear Regression	0.238	708,484.392	310,401.070	0.767
Voting Regressor	0.131	304,982.527	152,963.785	0.957
LSTM	0.925	1,648,008.530	1,018,028.776	-0.261
RNN	0.987	1,457,810.933	952,555.687	0.013
CNN + LSTM	0.865	1,906,706.320	1,262,343.295	-0.688

Table 1 contains model performance measures, including MAPE, RMSE, MAE, and R 2.

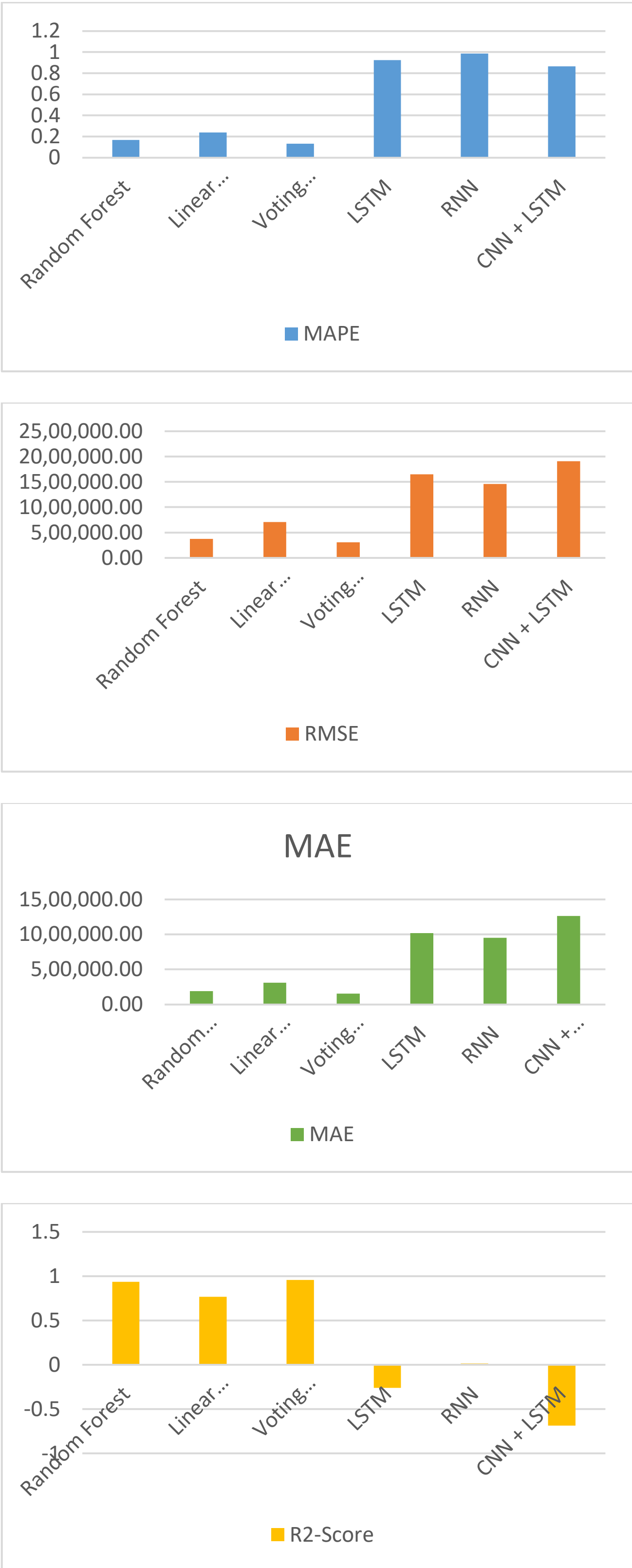

Fig.3 Comparison Graph

Fig. 3 shows different model performance metrics in regression and deep learning architecture.

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V. CONCLUSION

The performed analysis has proven that sound preprocessing, transformation of target, and model selection are significantly better than strong preprocessing in predicting the prices of used cars in highly variable real world datasets. It is seen that predictive stability of the models is greatly increased by the ability to resolve skewed price distribution with the aid of logarithmic transformation and the removal of noise with the help of IQR-based outlier removal. The best methods that have been evaluated are ensemble and tree-based learning methods. The Voting Regressor is the most performing since its R2 value of 95.7%, low MAPE of 13.1 and RMSE are low. This implies that the model can be generalised to a wide range of vehicle profiles. The random Forest model has a R 2 value of 93.4, and hence it can be used to handle the heterogeneous features as well as nonlinear relationships. Explainable AI techniques enhance the interpretability of the model, comprising of the instance-level explanation of LIME and the global feature importance analysis of SHAP. This facilitates the explicit determination of influencing factors, including the age of vehicles, the mileage, and the engine specifications. Such interpretability builds more confidence in model predictions, as well as, supports decision-making based on data. Besides that, the user- uploaded data is integrated with the trained model to ensure the real-time predictions are also supported by the use of the model in the Flask-based web interface and SQLite authentication. This fills the gap between the modelling and the reality of usage. Finally, the findings highlight the fact that there is a trustworthy, explainable, and implementable way of estimating the prices of used cars when operating in a dynamic marketplace.

The way forward can be focused on how to increase the flexibility and strength of predictions in diversity to the evolving market conditions. The best way to enhance model generalisation and reduce regional bias is to add a larger number of datasets across different geographic areas. Advanced feature engineering methods can further be used to capture the reality of pricing which include depreciation curves of the vehicles and modelling of temporal price trends. Hybrid ensemble strategies that combine gradient boosting, stacking and meta-learning could be used to improve accuracy compared to existing models. In addition to that, the combination of uncertainty modeling and probabilistic regression may produce the confidence interval of expected prices which will make it easier to make risk-sensitive decisions. Real-time: to ensure flexibility to market volatility, real-time ingestion of online market news can be used as well as regular retraining of the model. Besides that, the exploration of light and optimised DL models can minimise the computational cost without affecting the predictive ability.

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