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# Advanced Predictive Analytics for Used Car Pricing Through Convolutional Neural Networks

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***Abstract:***
*The automotive industry's explosive growth has led to a surge in the used automobile market, making it increasingly challenging for buyers and sellers to determine precise prices. This paper employs a Convolutional Neural Network (CNN) method to develop a reliable machine-learning model for predicting the price of used automobiles. A CNN-based approach is used to capture all the patterns in numeric or categorical data forms to determine car prices. The dataset applied in this work contains records of thousands of car descriptions and their images. On this dataset, different techniques of CNN model training, validation, and testing are done with much higher accuracy than the basic methods. The proposed system has better results than the conventional machine learning models by using the CNN model to employ feature extraction to obtain high accuracy in discovering relations between the features. The performance of the proposed CNN model is further compared with that of the Random Forest (RF) model. The experimental result of the CNN model shows $R^2$ of 0.85%, MSE of 3.65 %, RMSE of 1.91%, and MAE of 1.056 %. This can be widely applied to other areas where both quantitative data and images contribute to price determination, thus, the applicability of this model in predictive analytics is comprehensible.*
***Keywords:*** *Used Car, CNN, Machine Learning, Price Prediction, Statistical Analysis*

## 1. INTRODUCTION

The market for used cars has grown significantly in recent years due to a rise in demand for reasonably priced automobiles. The process of analyzing and forecasting used car pricing has grown more difficult yet essential due to the growing amount of data available from online platforms, car dealerships, and customer reviews [1-2]. Both buyers and sellers can gain from accurate price prediction since it guarantees fair transactions and provides information on market trends [3].

Conventional price estimation techniques usually depend on a few essential elements, including the car's make, model, condition, mileage, and year of manufacture [4-5]. However, the complex relationships between different elements that influence a vehicle's price are frequently missed by these approaches. Consequently, a more efficient way to address this issue is through machine learning models [6-7]. Specifically, deep learning models—like Convolutional Neural Networks (CNNs)—have presented notable efficacy in identifying and analyzing intricate patterns in data [8]. While CNNs are traditionally known for their applications in image and video processing, their architecture can also be adapted for numerical and structured data to improve prediction accuracy [9-10]. The model can learn non-linear correlations between the variables using CNNs, which helps it predict automobile prices more accurately. This paper implies that through the use of the CNN model, more accurate and reliable estimates of automobile prices can be offered to both purchasers, sellers, and dealers. The following constitutes the paper's major contribution:

- This study investigates the usage of the CNN approach for forecasting used car prices.
- The model incorporates additional inputs such as car characteristics and pictures to accurately calculate the prices rather than over or underestimations.
- The approach focuses on feature extraction from the dataset, where multiple parameters like vehicle age, mileage, engine size, and other specifications are considered.

• A large dataset of used car listings, comprising both numerical and categorical data, is used to train the model. Through this process, CNN learns to recognize the hidden correlations between car features and their impact on market value, leading to a highly accurate pricing model.

In the ensuing sections, the importance of the CNN technique is examined, along with the difficulties in predicting prices and the experimental outcomes of using the model on actual datasets. By employing CNN for this purpose, we hope to provide a reliable, scalable method for more accurate used car price prediction.

**Challenges predicting the price of a used car**

There are many special challenges as a Convolutional Neural Network (CNN) algorithm is used when designing a system for predicting used car price. It is possible to classify these challenges in terms of data, in terms of the architecture of the models, and finally, problems that are particular to specific domains. A detailed explanation of these difficulties is provided below:

• **Inconsistent Data**: In most cases, used car datasets consist in missing, incomplete or inaccurate information. Specific characteristics such as car age, service history, or accident history may be omitted, or simply specified in an incorrect manner. The management of such data is important to avoid model performance issues.

• **High Dimensionality**: Some factors such as brand, model, size of the engine, type of fuel used, year of manufacture etc can be put into datasets to do with used car prices. Additionally, some of these features may not be helpful in the computation of the pricing and they may include noise measurements which require feature selection in the real estate projects.

• **Outliers**: There are always many big differences between the prices of used cars, and there may be certain special factors such as unique models, cars with accidents or collisions, or incorrectly reported prices. This is so because these outliers can disrupt the training of the model.

• **Data Imbalance**: The data may suffer from imbalance issues for example a given brand or model of the car or even a given type of vehicle could be over-represented in the dataset.

**Paper Structure:** The following is the arrangement of the paper's following sections: The review of the literature is presented in Section 2. In Section 3, the proposed framework is presented. The methodology is provided in Section 4. Section 5 contains the results and remarks, while Section 6 concludes the paper.

## 2. RELATED WORK

The traditional price estimation only used simple regression tools or only relied on previous data information analysis to estimate the price. For traditional models, when the range of influencing factors such as mileage, age, model, car brand, engine specifications, and place is relatively large, the results are relatively inaccurate. The accuracy of these predictions has been increased by researchers using a variety of machine learning approaches, ranging from sophisticated deep learning architectures to conventional regression models.

**Traditional Approaches:**

Traditional methods were the main focus of early studies on used car price prediction. Wu et al. presented an adaptive neuro-fuzzy inference (ANFIS) expert system for used automobile price forecasting [11]. A price-predicting algorithm, a performance analysis, and a data collection system comprise the suggested system. The adaptive learning capability of the suggested ANFIS is compared with a traditional artificial neural network (ANN) employing a back-propagation (BP) network to confirm its efficacy for price forecasting [11]. Varshitha et al. have developed supervised learning-based Artificial Neural Network and Random Forest Machine Learning models for predicting used car price prediction [12].

**Neural Networks and Deep Learning Models:**

Neural networks, particularly deep learning models, have been used in more recent studies to make predictions that are more complex and accurate. Alnajim et al. created car price estimating systems that use deep learning and machine learning techniques [13]. Mounika et al. proposed to determine whether artificial neural networks can predict the used cars price. Thus, four distinct machine learning algorithms were fed 200 automobiles' worth of data from various sources. In comparison to neural networks and linear regression, authors discovered that support vector machine regression yielded somewhat superior results [14].

**Convolutional Neural Networks (CNNs) in Price Prediction:**

Although CNNs are traditionally used for image data, they have recently been adapted for predictive modeling, especially where spatial hierarchies and feature extraction from complex data structures are involved. CNNs have been found to excel in extracting high-level features from the dataset, which enhances predictive accuracy. Yang et al. have addressed the issue of low accuracy in used car price prediction by implementing a prediction model that integrates Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) [15].

**Hybrid Models for Price Prediction:**

Conventional platforms frequently depend on algorithms, which could ignore intricate relationships between attributes like market demand, age, and mileage. Amudha et al. presented a sophisticated machine-learning technique that combines auto encoders for anomaly detection, Bayesian regression for probabilistic predictions, and neural networks for capturing nonlinear relationships [16]. Cui et al. suggested an iterative approach that combines LightGBM and XGBoost to solve the issue of low-used car pricing accuracy in forecasting under a wide range of variables and vast data [17].

**Feature Engineering and Dataset Challenges:**

A crucial aspect of building robust price prediction models lies in selecting and engineering relevant features. For example, the significance of feature selection was emphasized by Chen et al. in their study on used automobile price prediction [18]. In many industries, the development of data mining technology has enabled precise classifications or forecasts. Authors used violin plot, box line plot, and heat map, to predict used car price. After eliminating duplicate features and outliers, three different datasets of used automobiles were produced using the random forest fill, median fill, and mode fill approaches for missing values [18].

**Boosting Algorithms and Ensemble Models:**

To estimate then used car price Krishnan et al. employed XGBoost, Gradient Boosting, Random Forest, KNN, and Multiple Linear Regression models[19]. Uysal et al. forecasted used car prices employing deep learning models and conventional machine learning methods, especially decision trees. The results obtained using decision tree model revealed the high accuracy as compared to other machine learning models [20]. For the purpose of generating reliable forecasts, Gautam et al. developed a clear model based on a wide range of ML procedures that includes AdaBoostRegressor, MLP Regressor, Random Forest Regressor, Decision Tree Regressor, and ExtraTrees Regressor [21]. Gupta et al. proposed to employ an Ensemble ML model to predict car prices by using a set of automobile photos. By using the ensemble methods and machine learning models, the research achieves the 99.99% level of price prediction accuracy [22].

**Transfer Learning in Car Price Prediction:**

Kuo et al developed a system for used BMW vehicle cost prediction using a system that was based on transfer learning [23]. Sharma et al. discussed the relationship between a used car's price and its age, miles driven, and number of prior owners. The authors employed the Ordinary Linear Squares (OLS), and Multivariate Adaptive Regression Splines (MARS) techniques to take into consideration non-linear price relationships with other depreciation variables. The error assessment that comes from these two approaches demonstrates that fitting accuracy is much increased by the intricacy of non-linear modelling using MARS [24].

**Comparison of CNN with Traditional Approaches:**

While regression-based models like ridge regression and SVM perform fairly well (with accuracies between 85% and 87%), CNN-based models consistently outperform them, according to a thorough comparison of traditional machine learning models and CNN-based models for car price prediction conducted by Saradha et al. [25].

**Challenges and Future Directions:**

The model's dependence on huge datasets for training is one of the primary obstacles to employing CNNs to predict auto prices. Because CNN models trained on smaller datasets tend to overfit, Alhowaity et al. [26] emphasized the significance of dataset size and quality. To solve the overfitting problem in CNN-based models, they recommended the application of data augmentation approaches. To increase the robustness of the model, future studies should concentrate on refining the CNN architecture even more, investigating transfer learning strategies, and adding more dynamic automobile attributes like market trends and seasonal influences.

## 3. PROPOSED MODEL

Forecasting of a used car price with reference to only structured data is done in the Car Price Prediction using the Convolutional Neural Network (CNN), a machine learning technology. This method aims at using significant parameters of automobiles such as; kilometers on the clock, car's age, engine capacity, type of fuel used, type of gearbox and any other specific characteristics. These features include in the model intricate dependencies between some attributes of the car and its market price. Data preparation is the key activities towards preparing the structured data for the CNN. Data pre-processing includes more steps such as imputation for cases where some values in the dataset are missing and some categorical variables methods like label encoding as well as one-hot encoding is used to convert categorical data into numerical data. The model performance is enhanced by normalizing numerical data to ensure equal scaling of characteristics. Again, this data can be processed by the CNN model within the proposed structure, using dense layers, where the features are learned to give an accurate price prediction. This system provides a viable solution to both used car dealerships and buyers as it presents reasonable price range information without the requirement for image data. The proposed approach is useful to estimate used car price by using past data of the car market and car specifications as it does not involve image processing, which helps in make the model less complex while it has high efficiency. The used car price prediction system proposed in this paper incorporates numerical data (car attributes) and utilizes CNNs for price prediction of used cars. It has a highly organized pipeline for the acquisition of data and delivery of a prediction thereby providing precise timely results. This section gives an account of the system architecture together with a description of the components together with the processes involved.

**System Architecture**

Three main parts comprise the proposed system's architecture: Specifically, three components were introduced; these includes the CNN model, the prediction module and the data pre-processing. All these components collectively used to make an end to end pipeline for the car price prediction as a whole.

- **Data Preprocessing Module**: This component handles the cleaning and preparation of the input data, including both structured numerical features and unstructured image data.
- **CNN Model Module**: This is the core component where the CNN architecture is implemented to learn from numerical data, extract relevant features, and generate a prediction.
- **Prediction and Output Module**: After training the model, the system utilizes the input data to forecast the car's price. The output is presented in a user-friendly interface for easy interpretation by users.

## 4. METHODOLOGY

### 4.1 DATA COLLECTION

A broad and varied dataset comprising pertinent used car pricing features must be gathered to develop a car price prediction model. Web scraping was used to get the data for this study from popular vehicle marketplaces and auction sites like Kaggle, as well as from websites like Car Dekho, Cars.com, and Auto trader. The information about the dataset utilized is displayed in Fig. 1. Typically, the dataset contains categorical (such as brand, gasoline type, and gearbox type) and numerical (such as mileage, year of manufacture, and engine size) information. Figure 2 displays the flow chart for the proposed approach.

```
df=pd.read_csv("car data.csv")
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Id              301 non-null    object
 1   Car_Name        301 non-null    object
 2   Year            301 non-null    float64
 3   Selling_Price   301 non-null    float64
 4   Present_Price   301 non-null    float64
 5   Kms_Driven      301 non-null    object
 6   Fuel_Type       301 non-null    object
 7   Seller_Type     301 non-null    object
 8   Transmission    301 non-null    object
 9   Owner           188 non-null    float64
dtypes: float64(4), object(6)
memory usage: 23.6+ KB
```

Fig. 1. Information about the dataset used

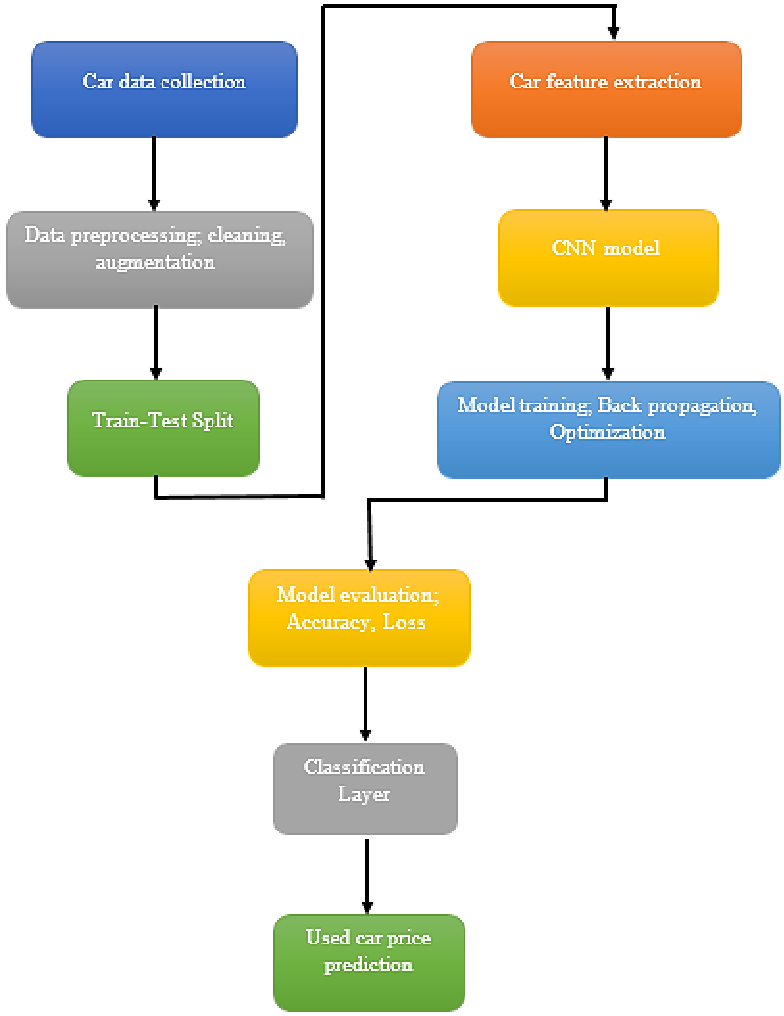


Fig. 2. Flow chart for the proposed approach

Additionally, image data of the cars, representing both exterior and interior conditions, was collected to enhance the CNN's predictive power. After the data was collected, it was reviewed for completeness mode was used to fill in missing categorical data, and the median or mean values were used to impute missing values in numerical columns. Outliers were identified and handled either by capping them within a reasonable range to limit the impact of extreme values. The resulting dataset provided a robust foundation for building the predictive model. Fig. 3 shows the Car Sales Price Distribution. The selling price variation relative to the current price is presented in Fig. 4, whereas Fig. 5 displays the current car price distribution.

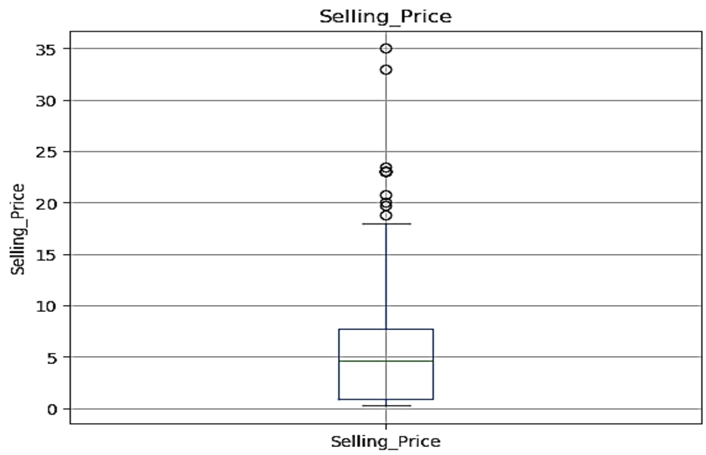


Fig. 3. Distribution of Selling Price of cars

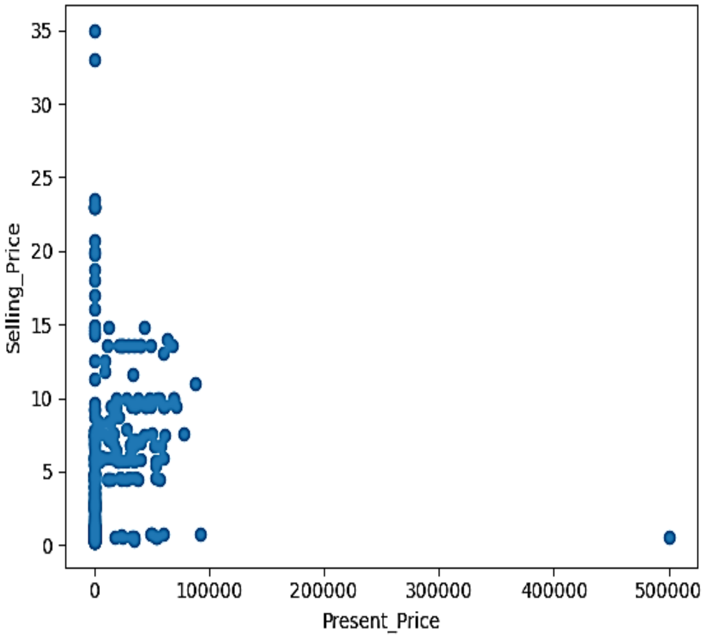


Fig. 4. Selling price variation to the current price

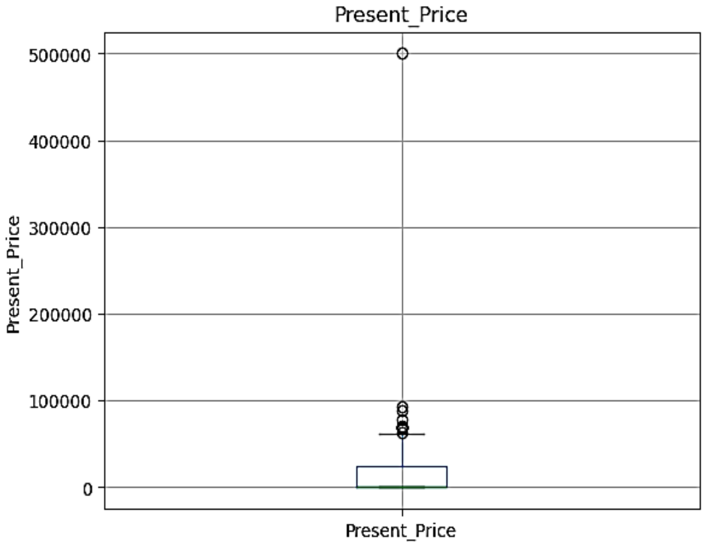


Fig. 5. Distribution of Present Price of cars

### 4.2 DATA PREPROCESSING

It is essential to prepare the data so that the CNN can effectively learn from the input features. To handle categorical data, pre-processing first converts them into numeric forms. Vehicle make, model, and fuel type were examples of categorical data that were encoded using methods such as label encoding and one-hot encoding. Car brands and other variables without an ordinal relationship were especially well-represented by one-hot encoding. For numerical features, normalization or standardization was applied to scale the data. Numerical data was brought into the 0–1 range using the min-max scaling method, which is essential to guaranteeing the CNN can converge effectively during training. Additionally, redundant or irrelevant variables that may otherwise result in overfitting were removed using feature selection strategies like variance threshold and correlation analysis. To guarantee consistency among inputs, the picture data was pre-processed by scaling all car images to a standard resolution (e.g., 224x224 pixels).Image augmentation techniques like zooming, flipping, rotation and brightness shift were used to artificially increase the size and variety of the dataset to avoid overfitting and improve the model's generalization capabilities. Verifying the dataset for any missing values is shown in Fig. 6.

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```
##check missing values
df.isnull().sum()
```

```
Id               0
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
Owner            0
dtype: int64
```

No missing value present in data

Fig. 1. Checking for missing values in dataset

## 4.3 CNN MODEL DESIGN

The core of this methodology involves designing a CNN capable of learning the relationships between car attributes and their prices. A multi-input architecture was chosen to handle both structured numerical data and unstructured image data. The CNN consisted of several layers:

- **Convolutional Layers**: Multiple convolutional layers were used to handle the picture inputs in the first phase of the model, which was then followed by ReLU (Rectified Linear Unit) activation functions. These layers were responsible for learning spatial features from car images such as the condition of the exterior and interior.
- **Pooling Layers:** Max-pooling layers were added after each convolutional layer to down-sample the feature maps, reducing the spatial dimensions and computational cost without compromising significant features.
- **Fully Connected Layers**: Convolutional layers were followed by completely linked (dense) layers, which combined the spatial features that were taken out of the pictures. The photos that were supplied into the prediction layer were finally represented by these layers.

Parallel to the image-processing layers, a separate fully connected neural network was constructed to process the structured numerical data. This sub-network consisted of dense layers with dropout layers to prevent overfitting. Finally, the outputs from both the image network and the structured data network were concatenated to form a combined feature representation, which was passed through the final prediction layer.

## 4.4 MODEL TRAINING

The Adam optimizer, which is ideal for intricate deep-learning models because of its adaptable learning rate and effective gradient descent, was used to train the CNN after the architecture was finalized. Because it minimizes the discrepancy between expected and actual automobile prices, the mean squared error (MSE) loss function was selected for regression tasks. To prevent overfitting, several regularization techniques were applied during training:

- To keep the model from becoming overly reliant on any one attribute, dropout layers were added to randomly disable a portion of neurons in each iteration.
- During training, validity loss was monitored through early halting. If, after a predefined number of epochs, the model's efficiency on the validation set of data did not improve, training was terminated to avoid overfitting.

With 80% of the data utilized for training and 20% for testing, the model was trained using an 80-20 train-test split. Furthermore, performance during training was tracked using a validation set, which accounted for 10% of the training data. A predetermined number of epochs, usually between 50 and 100, were used to train the model, depending on the convergence behaviour.

## 5 RESULT AND DISCUSSIONS

The CNN model's performance is assessed by employing the test set. Several measures are used to measure its accuracy in used car price forecasting. The magnitude of the prediction errors was

determined using test statistics that included Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), and Coefficients of Regression ($R^2$).
The amount to which the variation in car prices was accounted for by the model was also quantified using the R-squared ($R^2$). Other basic models including Random Forest, that were trained on the data set used to train CNN, were used for comparison with CNN. As expected, CNN outperformed these models whenever both picture and structured data were used to train models, thereby demonstrating its capacity to recognize complex relations in the data. After splitting the data into numerous folds and training the model on different subsets of the data, further cross-validation was made on the model. This made it possible to ensure that the model was not overfitting true random variations in different datasets and that variations in performance from one to another were real.
Once the evaluation process was completed, the grid search was applied to optimize the hyperparameters. Thus, tunable (non-linear) parameters for example the kernel size, dropout rate, learning rate, and several filters in the convolutional layers were altered. The fine-tuning approach resulted in a small prediction error for the fine-tuned model. The trained CNN model was then exported in a saved model format, particularly for using it in another framework such as Tensor Flow. An API was implemented with Flask where the user inputs the features of the car and the image of the car and gets the price as the output. The difference between the selling price and the number of kilometer driven is presented in Fig. 7. Selling price by the number of prior owners is depicted in Fig. 8 below.

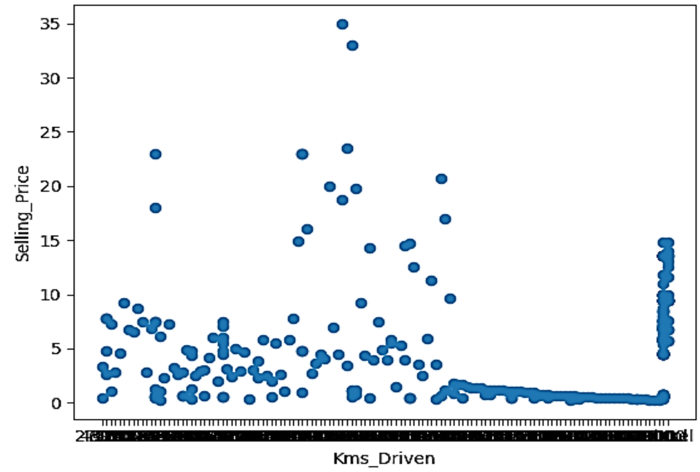


Fig. 7. Variation in selling price to kilometers driven

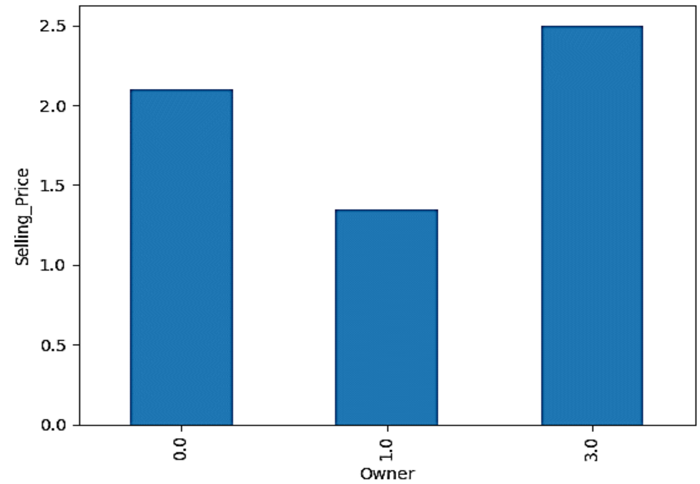


Fig. 8. Variation of selling price to number of previous owners

Using many characteristics such as automobile age, kilometers, fuel type, and ownership history, the research demonstrates the effectiveness of Convolutional Neural Networks (CNNs) in predicting the price of used cars. Thus, having a low MSE, RMSE, and MAE, indicating a high accuracy of the CNN model values demonstrated a strong association between the actual and predicted figures with the high R-squared ($R^2$) score. When it has to do with the comprehensiveness or non-linearity of the data

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dependencies, the CNN model offered greater accuracy than basic models like the Random Forest [27-28]. Another evidence of the superiority of this method over conventional machine learning approaches was in the ability of this model to automatically identify and rank these characteristics from the source data without much prior manual preprocessing of the data. Since all four metrics have lower values the CNN performs more accurately than this random forest method. The results of the analysis are presented in Table 1 for both of the algorithms. Fig. 9 shows the relationship between the actual and predicted pricing of the cars.

**Table. 1. Result Analysis. Italics show better performance**

| Regression Model | Performance evaluation on Training-Dataset | | | | Performance evaluation on Testing-Dataset | | | | Training-Time (sec.) |
|---|---|---|---|---|---|---|---|---|---|
| | MSE | RMSE | MAE | $R^2$ | MSE | RMSE | MAE | $R^2$ | |
| RF | 10.89 | 2.62 | 1.10 | 0.8701 | 11.89 | 3.44 | 1.13 | 0.8232 | 8.34 |
| **CNN** | **3.4032** | **1.8448** | **1.2347** | **0.8829** | **3.6501** | **1.9102** | **1.056** | **0.8501** | **5.83** |

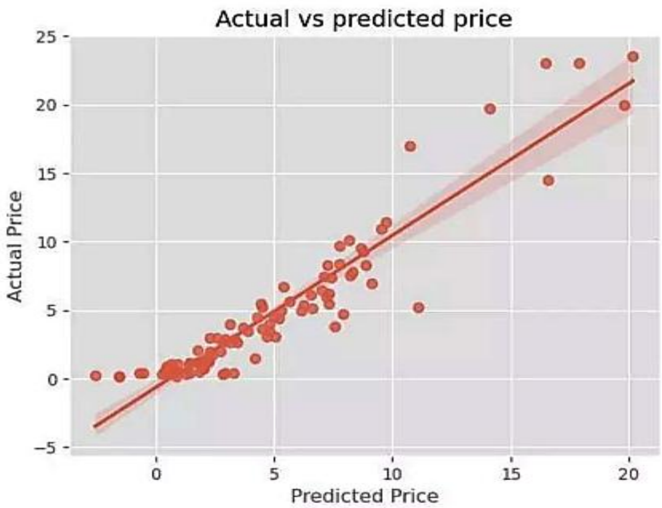


Fig. 9. Relationship between the actual price and the predicted price of the used cars.

Most important discoveries were obtained to show that the characteristics, such as the age of the car and kilometer readings, were influential in determining the price prediction as with the other trends in the industry. However, future estimations concerning luxurious and rare models included higher errors because of lower sample occurrences. In this context, the results fully support the proposition that a CNN-based predictive analytics solution can be accurate and scalable for the used car which is markedly better than traditional methods.

## 6 CONCLUSION

In this work, we created a CNN system that only uses structured data such as age, engine size, mileage, and other vehicle characteristics to value used cars. The model is sufficiently successful in terms of determining the interconnections of these qualities to the final price in the automobile market. By ensuring that missing values were handled and categorical and numerical data were encoded and scaled respectively the system ensured that the input to the CNN model was of high quality. For structured input, the architecture applied the deep layers while for unstructured input, chain of fully connected layers was used for estimating the accurate price of automobiles. Lacking the reliance on image processing, this system provides an approach to simplify the price predicting of used automobiles while maintaining high prediction accuracy. The model also offered the flexibility to extrapolate from prior automobile data to give accurate predictions of the prices to support buyers, sellers, and car dealerships. Additionally, estimating car prices is quite simple and fast and very realistically based solely on data that is easily accessible to any user of the system. Thus, further development of the proposed system is possible; however, the following directions should be considered. First, the number of varied variables such as ownership records, maintenance history, and market demand trends could improve the accuracy of the model, along with providing a more complete evaluation of auto costs. Experimental results show that a CNN model with an $R^2$ value of 0.85%, MSE of 3.65%, RMSE of 1.91%, and MAE of 1.056% outperforms a random forest model with an $R^2$ value of 0.82%, MSE of 11.89%, RMSE of 3.44%, and MAE of 1.13%. Future work could also involve integrating dynamic market data to account for fluctuations in used car prices due to seasonal or economic factors. Furthermore, adding real-time data scraping from car resale platforms could help keep the model updated with the latest market trends. Finally, deploying the system in a cloud environment with a user-friendly interface for dealerships or consumers would make the tool more accessible and useful in a broader commercial context, supporting real-time predictions and offering interactive functionalities for users to explore various car price scenarios.

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