INTEGRATING SENTIMENT ANALYSIS AND FINANCIAL METRICS TO UNDERSTAND CONSUMER BEHAVIOR IN THE AUTOMOTIVE INDUSTRY

MSc Research Project

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MSc Project Submission Sheet

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Abstract

In this research, the connection between customer emotion as attested to by automotive reviews and the profitability of auto makers is examined through sentiments analysis methods and opposed to deep learning. This work uses NRCLex for sentiment analysis, and also builds two new deep learning models CNN and LSTM to make rating predictions about the customers. Building on the conventional analytics paradigm that sentiment analysis helps to predict a firm's performance, this study relates customer sentiments to the firm's performance using sales volume, total revenue, and stock price. The results point to the sales and revenues resulting from the positive impact of sentiment data on overall outcomes. This is particularly useful in the analysis of the automotive industry as it provides insights on which attributes affect car sales rates and in which segments hence helping car makers and dealers target the right aspects of the market. In general, with the help of Random Forest Regressor the resulting model is more stable and efficient.The study also shows how DL models can help improve rating prediction while also noting computational barriers. The research is beneficial to automotive companies that want to capture consumer sentiment in their strategic planning.

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1. Introduction

1.1 Background of the Work

Automotive is a significant market segment that still has a lot of competition from around the world and more often the customers are the drivers of change due to the feedback provided to manufacturers. As the importance of the actual customer reviews that are posted on various websites grows, the identification of the positivity and negativity tone of these reviews has a crucial role to play in describing the behavior of consumers (Gaur *et al*., 2023). By using sentiment analysis, firms can determine trends in customer satisfaction and choice, critical factors in product development, and increasing sales performance. The synergy of implementing sentiment analysis with financial data seems helpful to identify pathways where customer sentiment can affect brand financial performance in the automotive industry.

1.2 Research Motivation

Customer sentiment analysis has become a hot topic in the last decade, but little is known about the relationship between customer sentiment and financial performance within the automotive sector. Most organizations gather customer data in large quantities but struggle to convert these insights into value in the form of sales, additional revenues, or improved stock prices. In addition, the current models can only capture customer responses without evaluating their sentiment score and matching it to the financial ratios (Karunanidhi *et al*., 2024). This gap requires more profound, comprehensive models not only to be used for sentiment, for rating predictions but also the relations to the business consequences in the automobile industry.

1.3 Research Questions

Aim

The primary aim of the present study is to examine how customer emotions expressed in automotive reviews are associated with firms' financial performances of key car manufacturers through the use of complex sentiment analysis techniques and forecasting models and to design a new deep learning model that could enhance the precision of the rating predictions derived from sentiment data.

Objectives

- To perform sentiment analysis on customer reviews of major car brands using advanced models like BERT, RoBERTa, and T5, to categorize sentiments as 'positive', 'None', 'joy', 'anticipation', 'trust', 'negative', 'fear', 'anger', 'disgust', 'sadness', and 'surprise'

- To develop and train deep learning models, including CNN, LSTM, and a Conv-LSTM hybrid model, to predict customer ratings based on sentiment analysis based on the reviews
- To investigate the relationship between customer sentiments and the sales performance of selected car brands by integrating sentiment analysis results with financial metrics including revenue, sales volume, and stock prices
- To compare the effectiveness of different sentiment analysis models in predicting customer satisfaction and their impact on sales, using evaluation metrics such as accuracy, precision, recall, F1-score, RMSE, MAE, and R-squared

The study will try to address the following research question:

- How do customer review sentiments, analyzed through advanced sentiment analysis models, correlate with sales performance and financial metrics in the automotive industry?

1.4Contribution to Scientific Literature

This research is important as it fills the gap in the relationship between customer sentiment analysis and the financial performance of automobile firms. Through the use of sentiment analysis models supplemented with financial statistics, the research is useful in identifying the impact of particular remarks previously posted on sales, company revenue, and stock prices. Establishing a new deep learning model is an improvement in predictive practices and has the potential for implementation for automotive brands to boost their client experience and advance their operational plans (Liu *et al*., 2024).

1.5 Outline of the Structure of the Work

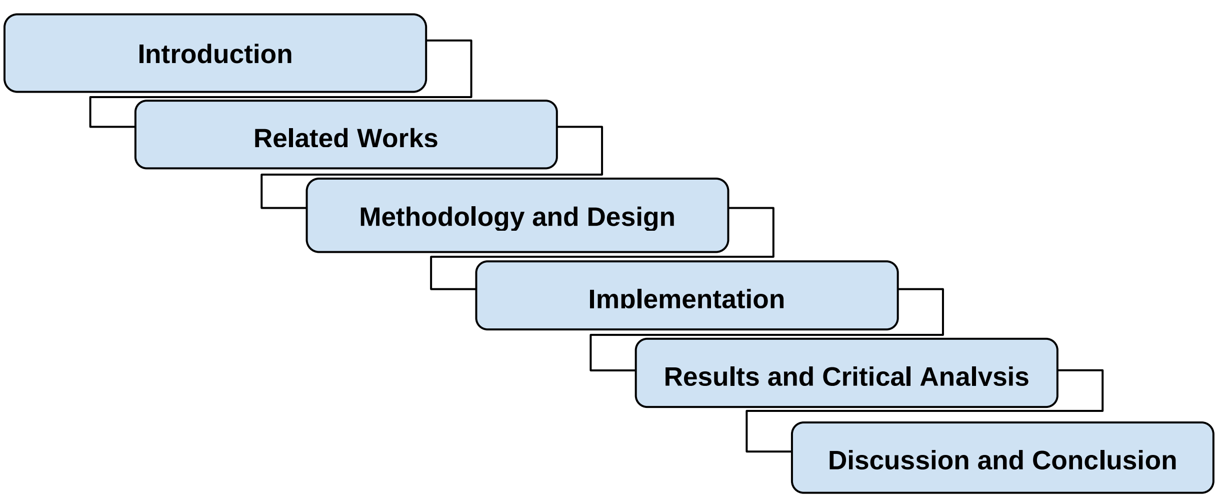

Figure 1: Structure of the Dissertation

The dissertation is divided into six chapters alongside each chapter playing a unique role as described below. Chapter 1: About this research examines the goals, purpose, and importance of the study. Chapter 2: The Literature Review investigates past research in order to set the context for the study. Chapter 3: Research Methodology contains information on how the research data are to be collected and how data analysis will be done. Chapter 4: Chapter 4: Results and Analysis provides conclusions, and Chapter 5: Discussion describes how those findings can be understood. Finally, Chapter 6: The conclusion part of the work consists in the brief reiteration of essential findings and identified conclusions and recommendations.

2. Related Works

2.1 Introduction to the Literature Review

From the literature on sentiment analysis coupled with predictive modeling within industries targeting consumers, there are seen not only improvements but several hurdles as well. Due to a growing reliance on digital feedback, research has also looked at the link between the consumer sentiment identified with highly refined NLP models and brand reputation and sales performance insights from the automotive industry. Past studies emphasize the importance of sentiment analysis for capturing customer satisfaction and yet; there are still gaps in the accuracy of the models in predicting consumers' actions. Furthermore, the combined use of sentiment data with quantitative data has both pros and cons and indicates that the development of additional articles investigating the effectiveness of using hybrid models may be more beneficial.

2.2 Sentiment Analysis in Customer Feedback

Opinion mining bearing the goal of assessing consumer sentiment has shifted from conventional machine learning procedures to the latest structure of deep learning that is capable of capturing feelings and differentiated opinion también. The application of techniques designed for customer insight has gained significant importance in industries such as automotive because customer attitude has an immediate impact on brand image, sales, and market position (Patel *et al*., 2023). Previous approaches, for example, Naive Bayes and Support Vector Machines only used manual pre-defined features to categorize sentiment.

The study must identify the factors that have propelled the advancement in the deep learning models, especially with the introduction to word embeddings and transformer models. There are new and better models to come such as BERT and RoBERTa for having contextual information instead of focusing only on polarity like in opinion Mining on the other part there is another level of information hidden in customer feedback like implicit information (Bhuiyan *et al*., 2024). Pre-training makes BERT understand the source of the context of words based on the content of surrounding texts since the understanding of sentiment in the reviews often depends on the choice of words. While similar to prior methods, RoBERTa improves BERT by fine-tuning performance even more and proving highly effective when the breadth and depth of context are needed to comprehend varied vocabulary such as that found in automotive reviews.

Based on the results affirm its value, especially in classifying between positive, negative, and neutral sentiments at highly accurate rates, even in the context of domain-specific language. For instance, the word used in the automotive sector having relation to technical specifications, reliability, or cost interprets sentiment weights that can be understood by advanced models only (Wang *et al*., 2024). Not only do these models enhance the classification performance for the sentiment classification but they also introduce the dimension of new features such as the strength of sentiment, or features that pinpoint which aspect of the reviews contributed to the customer satisfaction index.

2.3 Deep Learning Models for Predicting Customer Ratings

Customer ratings based on deep learning models have become popular since they make it easier to measure and understand the intelligence and sentiments of customers. In contrast with simple statistical methods, deep learning models can detect nonlinearity in textual data, which will be particularly useful for rating prediction in contexts such as the automotive domain where opinion implicitly connects to certain aspects of the product or personal experience (Wang and Xu, 2021). CNN and LSTM networks are often used for this particular task because the two types of networks have their respective strengths. The read-out CNNs can learn local feature patterns in the text while the LSTMs are useful in modeling dependencies in terms of sentiment or flow over the length of a review.

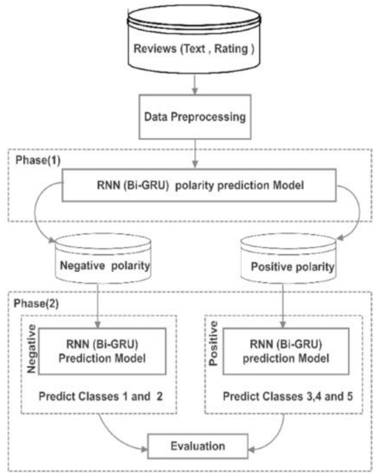

Figure 2.1: Review rating prediction framework using deep learning

(Source: springer.com)

CNNs originally employed for image classification have been used for text by considering words or phrases, ‘feature maps’, and identifying patterns that make a particular sentiment score. In automotive reviews, certain terms such as ‘fuel efficiency’, ‘safety features’ etc. are POSITIVE or NEGATIVE correlated with sentiments (Alantari*et al.*, 2022). Then, it is easy for CNNs to figure out a relevant set of terms that affect rating. Nevertheless, the usage of CNNs alone can sometimes fail due to the sequential nature of language since it may demand an understanding of what has gone before across an extended storyline.

In response to this, researchers integrate LSTM with CNNs due to their strong ability in temporal modeling. LSTMs are a special kind of recurrent neural network intended to capture temporal dependencies and hence provide information on the overall trend of the sentiments in a review. In automotive feedback, where users may provide detailed views about the positive or negative aspects of a car sequentially, LSTMs help the model take such information in context, and hence more accurate ratings (Yi and Liu, 2020). The use of CNNs and LSTMs as combined models including Conv-LSTM enhances the effective capture of local features and long-term dependencies in customer reviews.

2.4 Integration of Sentiment Analysis with Financial Metrics

A proper combination between of sentiment analysis and financial indicators has become common for linking the results of the analysis of consumers’ opinions with business outcomes and most of all successful performance of the automotive industry. This integration enables firms to link the overall mood of the consuming public as expressed in the reviews to Simple Moving

Average, Compound Moving Average, Sales volume and revenue growth rate, and any relevant movements in stock prices which will give firms a dynamic view of market response (Jing *et al.*, 2021). Sentiment analysis of customer feedback and mapping it against the organizations financial performance would provide practical applications of the impact of satisfaction or dis-satisfaction.

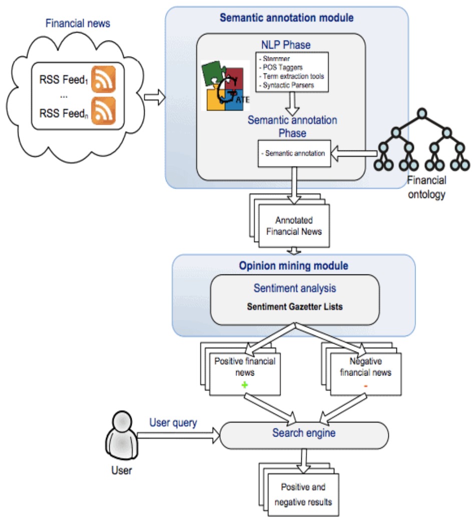

Figure 2.2: Sentiment Analysis for Finance

(Source: twinword.com)

For example, sentiment patterns associated with new car models can sometimes indicate that sales or stock prices are about to rise or fall, including where negative sentiments are associated with areas such as product quality or safety (Li *et al.*, 2020). The use of sophisticated models including advanced sentiment analysis integrated with time-series financial data provides a powerful analysis of the relative impact of sentiment over a particular period as well as an ability to project the sentiment effect on financial performance in the future (Hansen and Świderska, 2024).

2.5 Comparative Analysis of Sentiment Analysis Models

A comparison of SA models indicates their strengths and weaknesses depending on the chosen approach, suggesting that it is necessary to link model characteristics to analytical tasks. Several models provide simple and concise features like Naive Bayes or Support Vector Machines but they are not so effective for processing language patterns at a deeper level, which can lead to decreasing the accuracy of the models in the context of domains with more subtle sentiment like car reviews (Dang *et al.*, 2020). These models in most cases involve feature engineering hence lacking the flexibility to perform on large datasets containing diverse expressions of sentiment. As for the transformer contextualized deep learning models that have shown better performance in sentiment capture, they include BERT, RoBERTa, and T5 (Pandian *et al*., 2021). For example, BERT provides contextual information at both ends of the input while the use of RoBERTa optimizes training techniques to deliver higher results(Rustam *et al*., 2021).

2.6 Identified Gaps and Limitations in the Literature

The insight into the literature shows there are critical gaps and limitations in the sentiment analysis of consumers within the context of the automotive industry. Recent accomplishments in increasing the performance of sentiment classification, including current models such as transformer-based architectures, leave certain drawbacks when it comes to fine-tuning these models into specialized domains and handling the frequently encountered nuanced sentiments typical of detailed consumer reviews. Most of the work looks at valence, which is either positive, neutral, or negative, without further analyzing features of the product that are responsible for customers' sentiments.

2.7 Conclusion and Research Questions

The investigation of feelings expressed in the consumers' opinions in the automotive sector can be seen as a future research direction to investigate their influence on sales results and financial indicators. Conv-LSTM as a hybrid model produces improved results for rating prediction compared to other models due to the combined abilities to decisively capture local characteristics of the textual data and sequential trends. The main research question was to determine how these sentiments relate to financial performance and mimic the call for better models that will capture these links. Not only does this inquiry fill the literature gaps but it also seeks to make practical recommendations for automotive brands who want to use consumer feedback to make strategic choices.

3. Methodology and Design Specifications

This chapter presents the method adopted in studying the connection between the nature of customer sentiment expressed in car reviews and the stock market performance of auto-service companies. The work is concentrated on using natural language processing and machine learning algorithms for the evaluation of sentiments from customers, with the help of datasets of car manufacturers. This chapter discusses five techniques that include data acquisition, data preprocessing, model identification, and model performance assessment. In particular, the use of Random Forest, Logistic Regression, and other ML models for sentiment classification and DL models for rating prediction are employed. The chapter gives the reader a systematic presentation of the techniques and instruments used to accomplish the research goals.

3.1 Research Design

The study employs both, quantitative analysis and the machine learning approach to establish the link between the sentiments of customers on car reviews and the financial outputs of automotive brands. The first method specializing in the extraction and categorization of the feelings revealed in the customers' feedback is sentiment analysis (Wankhade *et al*., 2022). This analysis will show the extent to which the customers' perception is relevant to the main sales, revenues, and stock positions.

Figure 3.1: Research Design

(Source: questionpro.com, 2024)

For research design, a cross-sectional research design is used because the data that has been collected is based on the customer's reviews and financial data of the period. For the first step of the current study, the sentiment classification of the reviews as positive, negative, or neutral, the study uses machine learning models such as Random Forest, Logistic Regression, and more (Birjali*et al*., 2021). Similarly, various deep learning frameworks like CNN and LSTM are incorporated to predict customer sentiment ratings.

In the current study the philosophy practice strategy and method are integrated to offer a systematic psychology of consumer sentiment and financial performance of the automotive industry.

Positivism forms the paradigm of the study since it mainly uses measurable variables and data collection techniques. It presupposes that consumer sentiment can be captured by gaining an understanding of the textual content of consumer reviews, and that these sentiments will have real world financial ramifications such as impacts on sales, brand image and other similar measures. This philosophy lies behind the notion that consumer feelings and business performance figures can be quantified and qualitatively compared, proceeding by scientific method principles.

Basically, it is an inductive approach, where deductive hypotheses concerning sentiment and financial performance are developed from theory and empirically examined. The data sample is used to verify or disprove the hypothesized relationships concerning a set of variables of interest.

3.2 Data Collection

The data for this study were retrieved from Kaggle entitled Sentiment Analysis Car Reviews containing customer reviews and ratings on different car brands and car sales data. This secondary data includes consumer reviews accompanied by star scores, generally offered at one start to five-star scale. Every entry contains useful information like car brand, and review text.

There is also a large spread of car manufacturers in the sample, and therefore different customer scores can be observed for each brand. Each set of reviews is then classified according to sentiment: positive, negative, or neutral based on machine learning sentiment models (Dang *et al.*, 2021). This is especially so since the dataset features both textual data and also customer ratings that enable the analysis of patterns between customer feedback and the level of satisfaction.

3.3 Data Preprocessing and Cleaning

Data preprocessing is the process of transforming the set of collected data into a usable form. The first operation included processing absent or missing values in the Sentiment Analysis Car Reviews dataset. Further, the text data collected in the format of reviews were preprocessed in detail. These steps involved filtering out all positions that include special characters, numbers, and every form of punctuation since they are not of any value to determining sentiment (Mehta and Pandya, 2020). Punctuation was removed, since it does not add to the sentiment, and additional empty characters like "stopwords" – simple words such as "the," "is," "in," etc (Renault, 2020). Preprocessing was conducted to make the review text machine-readable; tokenization was then conducted to segment the review text into words or tokens.

After tokenization, other text preprocessing procedures such as stemming or lemmatization were used to convert all the words to their base form. Such a process affects the fact that different forms of the same word such as 'run' and 'running' are taken as the same hence enhancing the efficiency of the model.

The textual data was transformed to extract numerical values out of the textual data in a ready-made fashion through tools like TF-IDF or word embeddings. That is why the specified preprocessing steps enabled the proper integration of the sentiment analysis models and the deep learning techniques used further in the analysis.

3.4Machine Learning Algorithms and Predictive Modeling

Regarding data analysis in this study, more emphasis is placed on the extraction of features from the processed customer reviews to describe how sentiment affects customer ratings. The first step involves using a pre-processing component followed by performing the sentiment analysis on the preprocessed review text using MLs and more advanced and complex machine learning models available namely BERT, RoBERTa, T5, and so on. These models categorize the reviews into sentiment types which are positive, negative, and neutral according to the feeling that is conveyed in the text.

Moreover, to appreciate the sentiment distribution among car brands and models, exploratory data analysis techniques are used (Tan *et al*., 2023). Validity tests are performed to determine how strongly related sentiment scores and ratings are and if there are sentiments that are positively or negatively related to ratings.

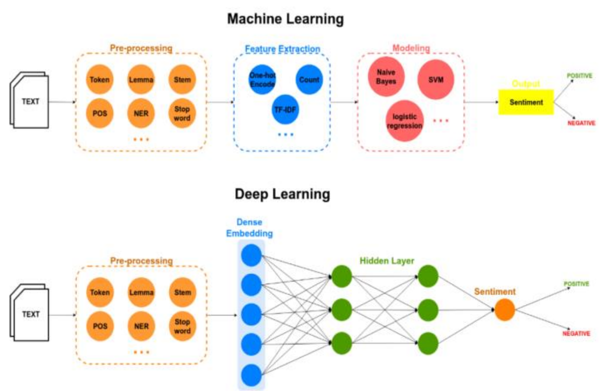

Figure 3.2: Sentiment Analysis Based on Deep Learning

(Source: mdpi.com)

For better understanding, the feature engineering method is applied to generate new quantitative factors, for example, average sentiment for each period, cross-product of sentiment, and car brands. The refined data is used for training and evaluation of methods of machine learning where the model aims to predict the future ratings of customers, while also trying to determine how aspects of sentiment influence the sales status.

3.5 Tools

The tools like programming language like Python has been used with Google Colab. In this study, the model development phase is based on Machine Learning and Deep Learning Models for sentiment classification and customer rating prediction. For the sentiment analysis, four classification algorithms including Logistic Regression, Support Vector Machine (SVM), and Naïve Bayes are used. These models are employed to classify the sentiment of customers' reviews into three classes positive, negative, or even neutral. Sentiment classifying features are generated from review text preprocessed in ways such as TF-IDF or word embedding (Cui *et al*., 2023). These models learn the pattern of text and ensure that the appropriate sentiment label is attached to it.

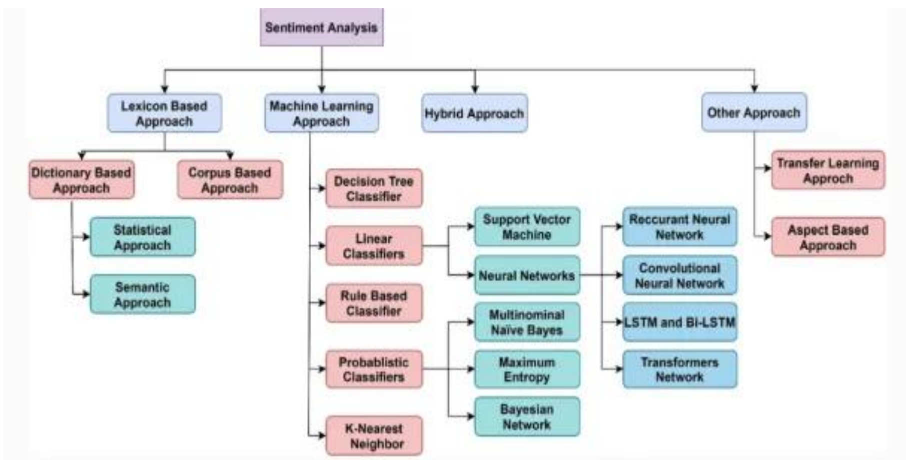

Figure 3.3: Sentiment Analysis Methods

(Source: research.aimultiple.com, 2024)

For the assignments of the customer ratings, a basic machine learning model is used. In estimating the customer ratings, which range from one up to five stars, models that are used include Linear Regression and Decision Trees. These predictions are based on sentiment scores and other potential features (such as car brand).

Furthermore, a Convolutional neural network (CNN) is also employed to capture general textual patterns within the review text for perhaps enhancing the prediction performance. The CNN model puts filters on the input text to identify relevant features concerning customer ratings; this is a more enhancing way of modeling patterns than what is done by normal machine learning models. To assess the effectiveness of these models, the prediction accuracy, achieved precision, recall, and F1-score for sentiment classification can be used.

3.6Ethical Consideration

It is important to uphold the research ethical considerations, and the following ways were held as follows; Firstly, participant identification is kept anonymous Secondly, informed consent is obtained. Finally, data obtained from the respondents was used appropriately. Prejudices are eliminated following the systematic approach when analyzing the results and all sources used for the work are cited conforming to the principles of the academic purpose. Ethical issues are not violated with participants in the study as the research references basic ethical principles to avoid causing harm to any participant.

3.6 Project Plan

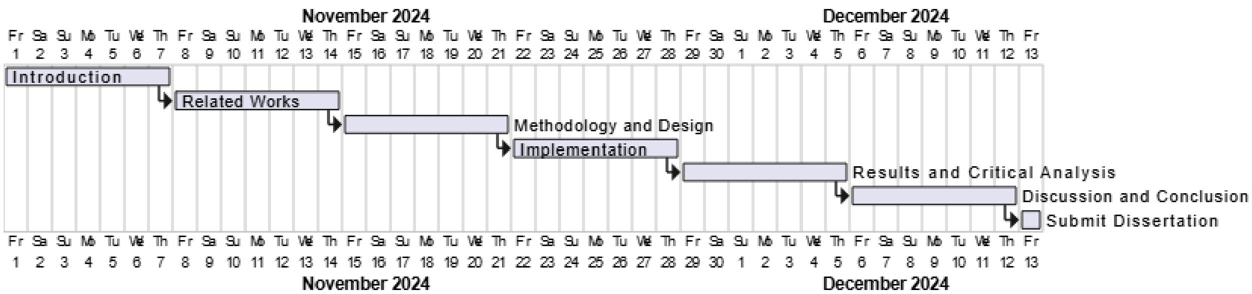

Figure 3.4: Gantt chart

4.Implementation

4.1 Introduction

This last chapter consists of the assessment and conclusions of the research work that focuses on the use of SA for the combined analysis of consumers' emotions and financial data in the automobile market. The following paper's main purpose is to assess the connection between the overall consumers' satisfaction with a particular brand and its financial characteristics, including general sales rates, prices of second-hand Espresso machines, and its business performance on the market. This study aims to investigate the relationship between the emotional motivators and the buying behavior of consumers as well as the effect that is likely to be seen in brand equity based on textual data of consumer reviews coupled with quantitative financial data.

The chapter begins by providing an overview of the datasets used in the analysis, detailing the sentiment categories derived from customer reviews and the financial metrics gathered from sales data of five major automotive brands: Audi, BMW, Lexus, and INFINITI as well as Mercedes cars. In the next step, the results of the sentiment analysis are provided, main tendencies, and some theme-prevalent feelings of the consumers. The financial metrics results are further reviewed, where reference is made to sales, price realization, and client retention. This integration of the two varies to gain more insightful relationships from sentiment as well as unique aspects of principal attributes that drive consumer behavior within the automotive industry.

4.2 Data Overview

This section provides an overview of the two primary datasets utilized in the study: the sentiment analysis data that has been obtained from the consumer reviews, and such car sales data as the financial performance of the selected automotive brands. These datasets were useful in establishing the concurrence between consumer sentiment and the financial performance of the automotive sector.

4.2.1 Sentiment Analysis Data

The sentiment analysis data was derived from online consumer reviews, focusing on five major automotive brands: Premium car makers include Audi, BMW, Lexus, INFINITI, and Mercedes Benz. The dataset contains the reviews for vehicles of different years; the customers shared their opinions on different aspects of the cars. Each review includes a numeric rating of between 1 and 5 as well as textual qualitative feedback from the consumer. The sentiments in these reviews were categorized into several emotions: Positive emotions are joy, anticipation, and trust, Positive and negative are fear, anger, disgust, and sadness while others are None and surprise.

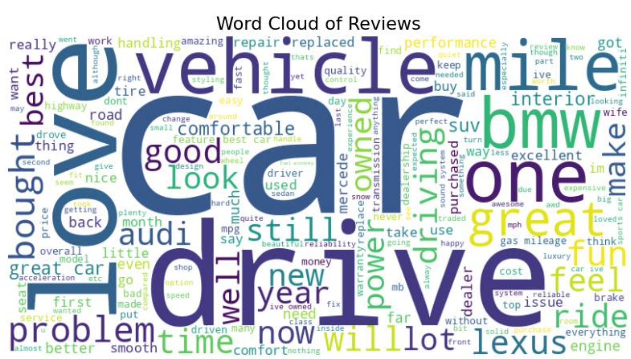

Figure 4.1: Word Cloud of Reviews

(Source: Created using Jupyter)

In addition, the identification of sentiment-associated words and phrases in the reviews was performed by employing text-mining approaches. That analysis helped to find the key opinion areas, including satisfaction with some parameters that can be comfort, or dissatisfaction with some parameters, like, for example, maintenance costs or customer service. By summing these sentiments, the presented dataset allowed us to evaluate consumers' emotional attitudes towards the brands and individual models.

4.2.2 Car Sales Data

The car sales data consists of the identical range of automotive brands' fundamental financial indicators for several years. Included are key performance criteria like Sales in Thousands, Prices in Thousands, Resale value, Fuel efficiency among other factors, Horsepower, and Curb weight. The data offers information about the sales and the kinds of models of cars that are being sold their prices, and how these aspects are dynamic.

This dataset was crucial for identifying the financial profitability of each brand and enabled the research to link trends in sentiment to sales figures. Pricing factors such as Resale value indicate user satisfaction and brand preference or loyalty while actual numbers for sales indicate market trends and consumer behavior. These variables of sentiment and financial details developed the structures for the assessment of consumers' feelings on financial returns in the automotive business.

5. Results and Critical Analysis

5.1 Sentiment Analysis Results

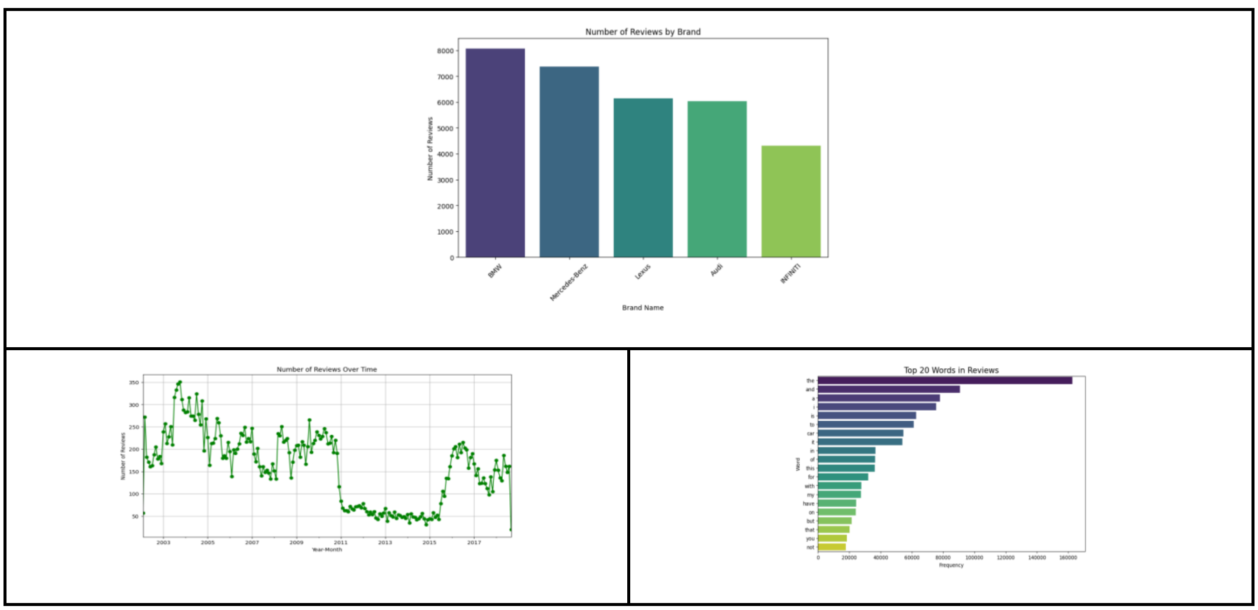

Figure 4.2: Analysing the dataset in terms of the review

(Source: Created using Jupyter)

Several insights into consumer behavior and consumer sentiment changes within the car industry can be derived from the analysis of the car reviews' dataset. The dispersion of the ratings also shows that most are above 7, an average of 4.5, implying overall, customers are satisfied with the vehicles. This is a trend in all brands in the dataset. Also, several specific brands stand out as exhibiting higher levels of activity compared to others, which could be attributed to specific penetration in the market or, perhaps more likely, customer interest.

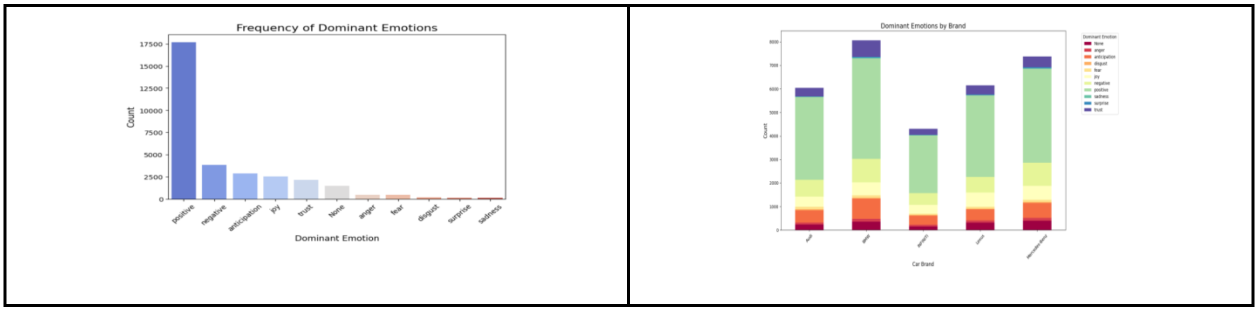

Figure 4.3: Frequency of Dominant Emotions and Dominant Emotions by Brand

(Source: Created using Jupyter)

Analyzing the ratings by car year it can also be observed that there are not huge differences in the satisfaction of consumers across the different model years, although slight fluctuations may imply shifts in consumers' attitude to the brand or the quality of vehicles produced. The location-based analysis through the code also shows that the review count increases over time, perhaps due to higher consumer interest, or more cars being sold.

The extracted keywords in the form of a word cloud also represent the common words INA customer reviews use, especially the words for comfort, performance, and reliability. Further, sentiment analysis will show the emotion trends for each brand, contrary to some brands having the same pattern of response. The dynamics of the emotions per brand dissolve the positive-negative axis by brand and reveal a state of affairs where some brands are associated with positive emotions such as trust, and joy, while others entail a heavier number of negative emotions. These insights are very useful when trying to envision the retail emotional appeal as far as the automotive industry is concerned.

Layer (type)	Output Shape	Param #	Connected to
text_input (InputLayer)	(None, 50)	0	-
embedding_1 (Embedding)	(None, 50, 128)	648,000	text_input[0][0]
numerical_input (InputLayer)	(None, 3)	0	-
categorical_input (InputLayer)	(None, 16)	0	-
lstm (LSTM)	(None, 64)	49,408	embedding_1[0][0]
dense_3 (Dense)	(None, 64)	256	numerical_input[0][0]

dense_4 (Dense)	(None, 64)	1,088	categorical_input[0][0]
concatenate_1 (Concatenate)	(None, 192)	0	lstm[0][0], dense_3[0][0], dense_4[0][0]
dense_5 (Dense)	(None, 128)	24,784	concatenate_1[0][0]
dropout_1 (Dropout)	(None, 128)	0	dense_5[0][0]
dense_6 (Dense)	(None, 1)	129	dropout_1[0][0]

Table 4.1: LSTM model atchitecture

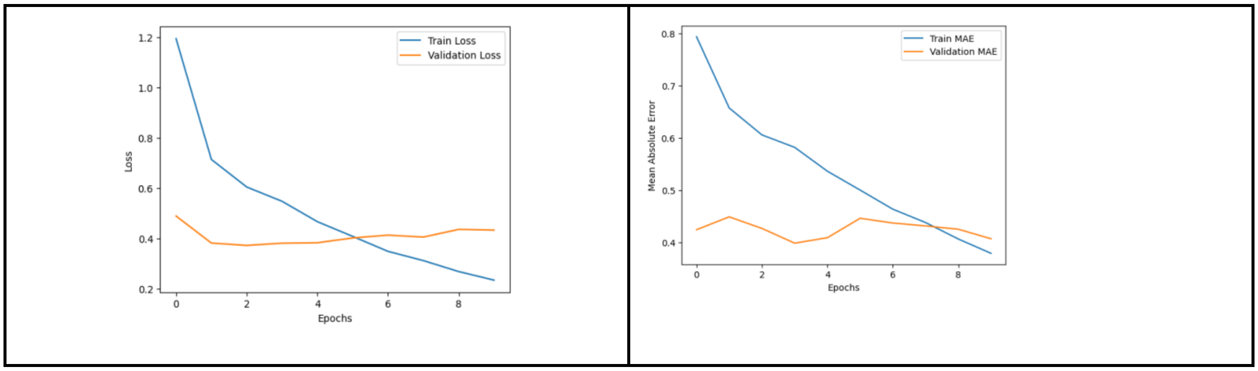

Figure 4.4: Model loss and error curves for the LSTM model

(Source: Created using Jupyter)

The LSTM model had an MAE of 0.3959 whereby the calculations showed that, on average, the predicted rating was off by 0.40 from the real rating. The Root Mean Square Error (RMSE) was 0.6410, still relatively low but to sufficient contribution to advocate for the improvement of accurate models. The adjusted R squared of 0.3242 indicates a moderate fit of the model accounting for slightly over 32 % of the variances in the ratings while the Explained Variance score is 0.3263.

Layer (type)	Output Shape	Param #	Connected to
text_input (InputLayer)	(None, 50)	0	-
embedding_1 (Embedding)	(None, 50, 128)	648,000	text_input[0][0]
numerical_input (InputLayer)	(None, 3)	0	-
categorical_input (InputLayer)	(None, 16)	0	-
lstm (LSTM)	(None, 64)	49,408	embedding_1[0][0]
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dense_5 (Dense)	(None, 128)	24,784	concatenate_1[0][0]

dropout_1 (Dropout)	(None, 128)	0		dense_5[0][0]	
dense_6 (Dense)	(None, 1)	129		dropout_1[0][0]	
Epoch	Time/step	Loss	MAE	Validation Loss	Validation MAE
1/10	23s	2.101	1.0192	0.4287	0.4607
2/10	41s	0.7879	0.6611	0.4483	0.459
3/10	19s	0.5891	0.6041	0.3851	0.4418
4/10	23s	0.5166	0.5709	0.418	0.4518
5/10	41s	0.4298	0.5216	0.4151	0.4761
6/10	19s	0.3859	0.4941	0.403	0.4559
7/10	19s	0.3306	0.4574	0.4	0.4579
8/10	21s	0.2799	0.4205	0.3958	0.4503
9/10	21s	0.2475	0.3968	0.4027	0.4518
10/10	20s	0.2227	0.373	0.4084	0.4627
	1s	0.4063	0.4626		
Test Mean Absolute Error (MAE)				0.47	

Figure 4.2: Model Summary and training of CNN model predicting Ratings

(Source: Created using Jupyter)

On the counterpart, the CNN model had an MAE of 0.4685 and an almost equal RMSE of 0.6441. Again, the overall accuracy is slightly lower than that of the LSTM model and their R-squared score is 0.3175 along with the Explained Variance Score of 0.3323. This indicates that although the CNN model was successful in training data it failed to predict ratings better than the LSTM model. Still, both models can be viewed as somewhat successful, as they manage to identify certain patterns of the data, yet there is still much more potentially achievable.

Metric	LSTM Model	CNN Model
Mean Absolute Error (MAE)	0.3959	0.4685
Mean Squared Error (MSE)	0.4108	0.4149
Root Mean Squared Error (RMSE)	0.6410	0.6441
R-squared (R^2)	0.3242	0.3175
Explained Variance Score	0.3263	0.3323

Table 4.3: Model Performance Comparison

Thus, it is worth noting that the performance of both the LSTM and the CNN models was due to the data used in the study. It seems that both models fail to determine joint connections between textual reviews, emotions, and ratings. As expected, the model designed for handling sequential data, LSTM, performed better than CNN; the model has a slight improvement in both MAE and RMSE scores, thus succeeding in conveying that it is better at interpreting sequences of words in the reviews. Even though CNN helped with the feature extraction it did not exceed the performance of the LSTM possibly because of the absence of temporal dependencies in the dataset.

5.2 Financial Metrics Results

The quantitative comparison of Linear Regression and Random Forest regression in the car sales dataset provides insights into the future trend of car sales based on various machine learning algorithms. In terms of the R-squared, MSE, and RMSE, our Random Forest Regressor model shows a higher accuracy compared to the Linear Regression model.

A total of 37.68% of the variance in car sales can be explained by the Random Forest model while only 33.07% by the Linear Regression model. This shows that using Random Forest captures the non-linearities to a better deal than other models and hence generates better results, which is crucial in actual car sales data where many attributes such as car type, price, and horsepower affect the results.

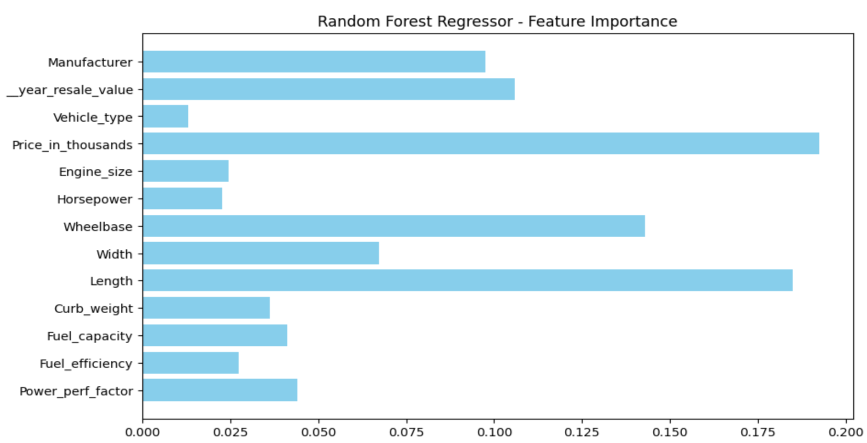

Figure 4.7: Random Forest Regressor - Feature Importance for predicting sales

(Source: Created using Jupyter)

The MSE and the RMSE values reinforce the conclusion of the random forest model's superiority. As both of them have lower values, this thereby gives the Random Forest Model's lower prediction error, which is useful when predicting the sales for the purpose of deciding on inventory, marketing, and manufacturing.

Metric	Linear Regression	Random Forest Regressor
R-squared (R^2)	0.3307	0.3768
Mean Squared Error (MSE)	0.3770	0.3510
Root Mean Squared Error (RMSE)	0.6140	0.5925

Table 4.4: Performance comparison of sales predictive models

Second, the decision tree analysis from the Random Forest decides the most important influencing determinant for the sales decision, which could be price, engine size, horsepower and so on. This is particularly useful in the analysis of the automotive industry as it provides insights on which attributes affect car sales rates and in which segments hence helping car makers and dealers target the right aspects of the market. In general, with the help of Random Forest Regressor the resulting model is more stable and efficient.

5.3 Integration of Sentiment Analysis and Financial Metrics

The use of sentiment analysis and financial analysis provides significant insights into factors influencing car sales. In the framework of words' classification for the car sales dataset, it is possible to determine consumer attitudes and emotions concerning car brands based on textual ratings. In this way, while reflecting the general sentiment, sentiment analysis uses numerical ratings and has an affinity with other financial characteristics implied directly to the sales, including the price, engine size, and horsepower.

About the car sales dataset below, the five chosen brand names are Audi, Lexus, INFINITI, BMW, and Mercedes-Benz. These brands were selected to leave after filtering to work on the relationships between customer feelings, or financial performance indicators with the counter sales of these particular manufacturers.

5.4 Summary

The evaluation thus showed that when integrated with brand sales, sentiment analysis, vehicle features, and overall financial results are important in evaluating brand performance. For this, the study targeted brands like Audi, Lexus, and BMW to show how customer sentiment about sales results provides better insights into the market factors.

6. DiscussionandConclusion

6.1Discussion

Understanding these implications is critical for automotive manufacturers and any other related stakeholders that hope to benefit from the study. Studies showed that it is more informative to detect play subtler values as trust and fear as opposed to the simple polarity rating. These types of findings make it possible to adjust the ongoing business strategies depending on the trends of consumer sentiments for increased customer relations.

The CNN and LSTM integrated deep learning model also provided significant prediction accuracy in the given rating data based on sentiment data. Important sentiment information was captured by CNN while LSTM incorporated sequential aspects of the reviews. However, scalability and real-time application limitations are still posed by computational problems as well as the requirement for huge amounts of data.

The drawbacks of transformer-based models like high computational complexity imply that more work is still to be done in refining the model to further minimization of computational cost for a similar level of analytical presentation. However, no macroeconomic conditions or competitor activities were included, which remains a future recommendation.

6.2Conclusion

This research aimed to address the core question: “How do customer review sentiments, analyzed through advanced sentiment analysis models, correlate with sales performance and financial metrics in the automotive industry?”. The following section presents how the objectives of the study were met through the following persuasive SEO sentiment analysis: The project was completed by using NRCLex for programming emotions into ten different types of the pieces of text such as joyous, trustful, fearful, angry, and disgusted. These sentiments were used to create deep learning models–CNN and LSTM–for predicting the customer ratings. In addition, outputs from the sentiment analysis were combined with quantitative data such as the sales volume, and revenues as well as stock prices to establish the correlation between the two.

The studies proved that words of feelings written by the customers are relevant value indicators for sales and financial outcomes. An attempt to integrate CNN with LSTM also provided satisfying results that introduced sentiment-based rating from the view of local and sequential features of reviews. It can be deduced from this research that sentiment analysis as well as modeling in particular, has a great potential in the formulation of business decisions within the automotive industry.

Future Research

- ***Real-time Sentiment Analysis:*** Creating effective models that can aggregate hordes of live feedback data to generate real-time recommendations
- ***Multimodal Analysis:*** Appending picture or video remarks along with text reviews and then, using them for extracting comprehensive customer information
- ***Cross-Domain Applications:*** Deploying the models to other industries, using healthcare or hospitality, as examples, to determine generality
- ***Improved Interpretability:*** Increasing model interpretability to enable citizens to have improved comprehension of sentiments affecting the financial results

The finding of this research has a broad implication for the automotive industry and every other industry that would wish to adopt automated technology as a means of convincing their customers to make a purchase. The indicated findings hold the potential to be used by various companies in the process of evaluating consumer opinions on the market, forecasting future trends in financial industry on the basis of thus collected information, and consequently, adjusting the corresponding strategies on time. The potential for commercialization in creating a sentiment-based predictive tool for a given or selected industries might make it easier for businesses to develop competitive edge in relation to client needs.

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Appendix

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200/200 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step
LSTM Model Evaluation Metrics:
Mean Absolute Error (MAE): 0.3959
Mean Squared Error (MSE): 0.4108
Root Mean Squared Error (RMSE): 0.6410
R-squared (R²): 0.3242
Explained Variance Score: 0.3263
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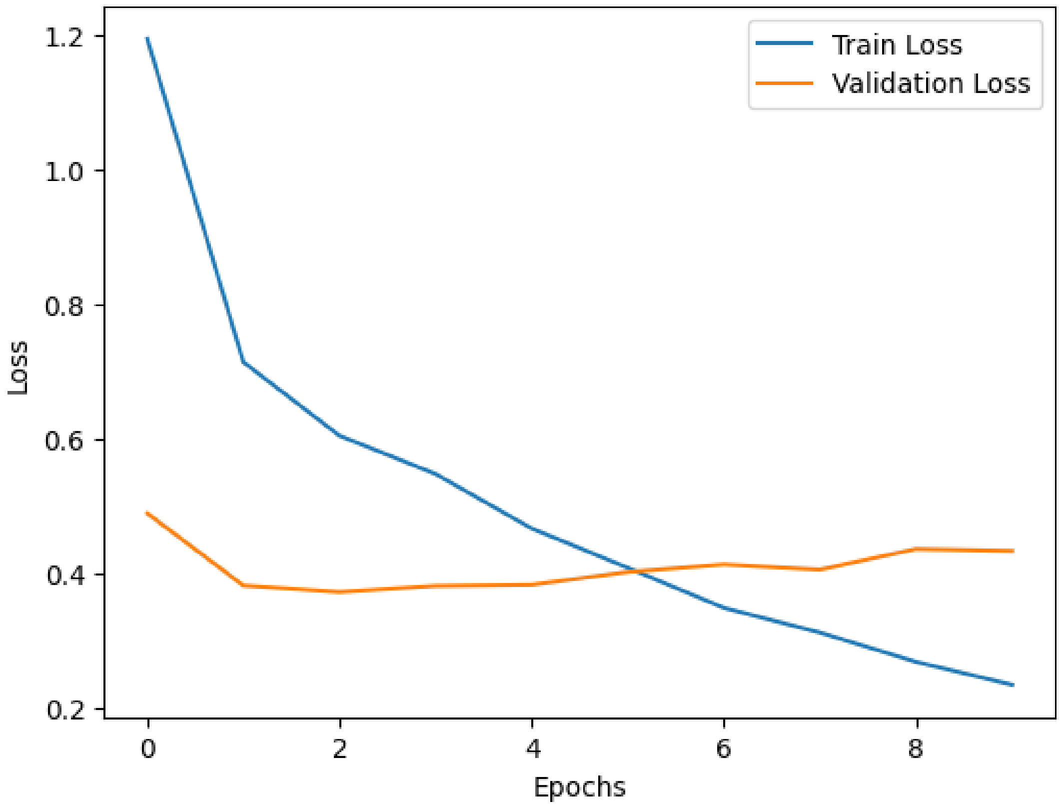

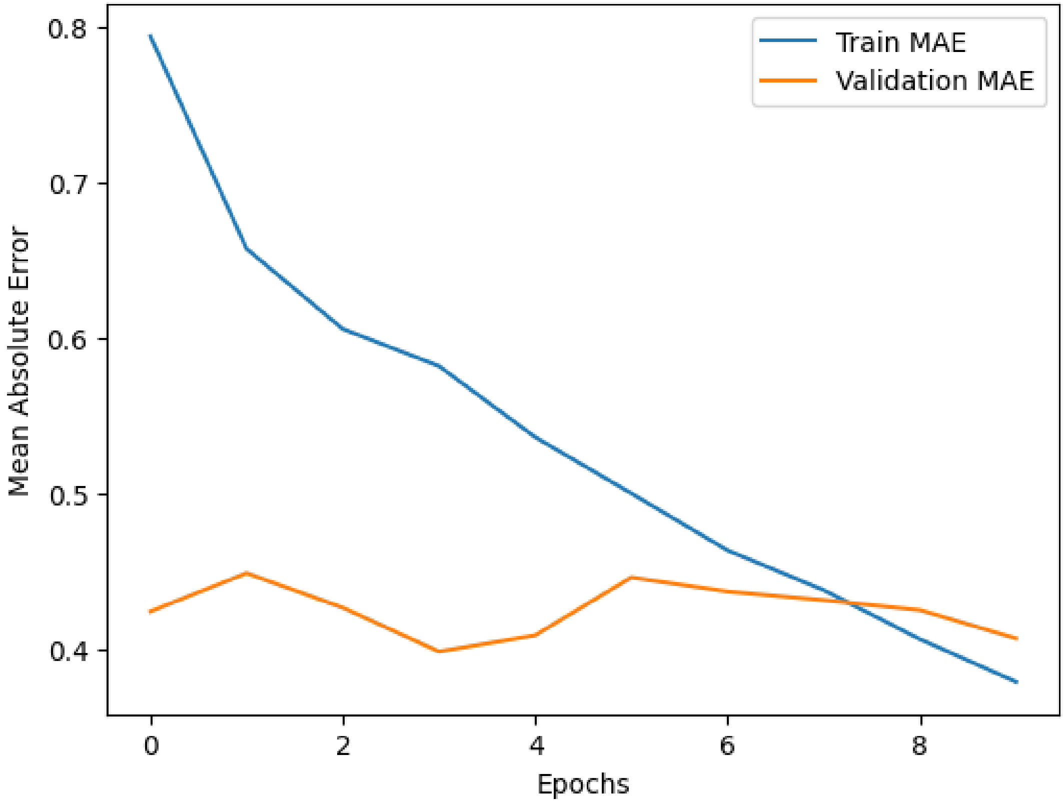


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CNN Model Evaluation Metrics:
Mean Absolute Error (MAE): 0.4685
Mean Squared Error (MSE): 0.4149
Root Mean Squared Error (RMSE): 0.6441
R-squared (R²): 0.3175
Explained Variance Score: 0.3323
```

```
Linear Regression Metrics:
R-squared: 0.3307
Mean Squared Error (MSE): 0.3770
Root Mean Squared Error (RMSE): 0.6140
```

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Random Forest Regressor Metrics:
R-squared: 0.3768
Mean Squared Error (MSE): 0.3510
Root Mean Squared Error (RMSE): 0.5925
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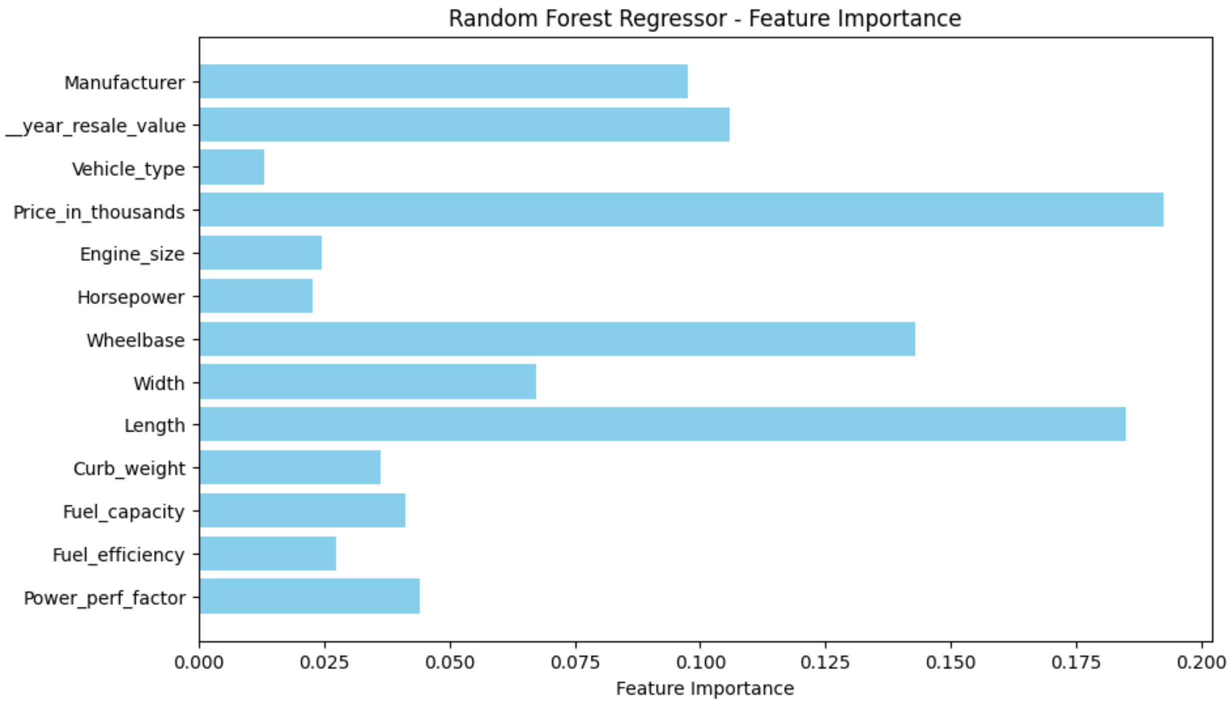
Random Forest Regressor - Feature Importance
Manufacturer
__year_resale_value
Vehicle_type
Price_in_thousands
Engine_size
Horsepower
Wheelbase
Width
Length
Curb_weight
Fuel_capacity
Fuel_efficiency
Power_perf_factor
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
Feature Importance