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Deep Learning and Regression Based Approach for Predicting Target Customer Segments in The Automobile Industry

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ABSTRACT

The automobile industry has witnessed significant advancements over the years, with manufacturers striving to understand and cater to the preferences of various customer segments. Predicting target customer segments is crucial for tailoring marketing strategies, designing products, and optimizing inventory levels. Traditional approaches often rely on surveys and market research, but the emergence of machine learning and regression techniques offers a more data-driven and accurate approach. Traditional methods for customer segmentation in the automobile industry typically rely on market research, surveys, and demographic studies. While these approaches provide valuable insights, they may not always capture the full spectrum of consumer preferences, and they can be time-consuming and resource-intensive. The primary challenge is to develop a predictive model that can accurately identify the customer segments most likely to be interested in specific automobile models or features. This involves analyzing various factors such as demographic data, purchasing history, and market trends to make accurate predictions. As the automobile market becomes increasingly competitive, it's essential for manufacturers to precisely target their products and marketing efforts towards the right customer segments. Accurate predictions can lead to improved sales, reduced marketing costs, and enhanced customer satisfaction by offering products that align with consumer preferences. The project aims to revolutionize customer segmentation by leveraging advanced data analytics and machine learning techniques. By training models on extensive datasets of customer information and purchasing behavior, this research endeavors to develop a system capable of autonomously and accurately predicting target customer segments. The integration of deep learning-based algorithms allows for the identification of key factors influencing customer preferences, enabling manufacturers to make data-driven decisions. This advancement holds great promise for optimizing marketing strategies, product design, and inventory management in the automobile industry, ultimately leading to increased customer satisfaction and profitability.

Keywords: Customer segmentation, Resource-Intensive, Deep learning, Regression, Product design.

1. INTRODUCTION

Deep learning and regression-based approaches are utilized in the automobile industry to predict target customer segments. Deep learning employs neural networks to automatically learn intricate patterns from diverse datasets, enabling accurate segmentation based on customer attributes like demographics and purchasing behavior. Regression models, on the other hand, offer interpretable solutions by analyzing features such as age, income, and vehicle preferences to predict segment memberships. Both techniques involve data collection, preprocessing, model training, and validation, culminating in the deployment of predictive models into marketing and CRM systems. By leveraging deep learning and regression, automakers can optimize marketing strategies, improve customer relations, and drive business growth in a highly competitive industry. The automobile industry is a highly competitive sector

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that constantly seeks ways to improve marketing strategies and customer relations. Predicting the right group of customers for automobile industries is crucial for targeted marketing, sales, and product development. Traditional methods of customer segmentation often involve manual processes and are limited in their ability to handle complex data. Deep learning and regression approaches offer a data-driven and automated solution to this problem.

2. LITERATURE SURVEY

Customer segmentation is a critical marketing strategy that involves dividing customers into smaller groups based on similar characteristics such as demographics, psychographics, behaviors, and needs [1]. While previous studies on customer segmentation provide valuable insights into consumer behavior, they also have some limitations that will be addressed in this research, such as the use of a broader focus on psychographic and behavioural variables, and a more in-depth analysis of the implications of customer segments for marketing strategy. There are also very limited studies on customer segmentation in Indonesia [2, 3]. Admiration-based segmentation conducted in this study focuses on emotional decision-making factors. This approach recognizes that consumers often make decisions based on how they feel about a product, rather than on purely objective criteria such as price or fuel economy. By identifying the emotional triggers that inspire admiration, automotive companies can design cars that resonate with consumers on a deeper level and create long-term brand loyalty.

Millennials and Gen Z in Indonesia prioritize practicality, technology, and sustainability in their car choices. They value experiences over ownership, customization, and online research. These preferences are shaping the automotive market, leading to a shift towards eco-friendly, tech-savvy, and customizable cars [4]. Millennials and Gen Z are two generations that have grown up in the digital age, with access to technology and information that previous generations did not have. This has led to changes in their behaviors, attitudes, and preferences, including in the automotive market [5]. While previous generations were more loyal to specific car brands, millennials and Gen Z are less so. They are more willing to switch brands based on their changing needs and preferences [6]. To understand how a brand is admired, first marketers have to understand customers characteristics and preferences.

Previous literature reviews show that automotive admiration can vary widely across different countries in Asia due to differences in culture, consumer preferences, and economic development. For example, in developed countries like South Korea and Japan, domestic automakers like Hyundai and Toyota tend to dominate the market due to strong national pride and a desire to support local industries [7]. In contrast, in countries like China and India, there is a growing demand for Western luxury car brands as a status symbol among the growing middle class [8]. Additionally, factors such as government regulations, infrastructure, and consumer education can also affect automotive admiration [9]. For example, in countries with well-developed public transportation systems like Singapore and Hong Kong, car ownership may be seen as less necessary and less desirable than in countries with less developed infrastructure [10].

The ASEAN region, which includes 10 countries in Southeast Asia, is a large and diverse market for cars. The region is home to over 650 million people, and its rapidly growing middle class has become an important driver of car sales in recent years. Japanese car brands have traditionally dominated the ASEAN market, with Toyota, Honda, and Nissan being among the most popular brands [11, 12]. However, in recent years, Korean brands such as Hyundai have also gained significant market share [13]. It's worth noting that customer preferences can vary significantly by country. For example, pickup

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trucks are very popular in Thailand. This is driven by a combination of factors, including their versatility, affordability, cultural significance, and government policies that support the

3. PROPOSED METHODOLOGY

3.1 Overview

This research develops a data science project that focuses on predictive modelling and analysis using a customer dataset for automobiles. It follows a standard data science workflow, starting from data loading and preparation, through exploration and visualization, to machine learning model building and evaluation. an overview of the key components and steps involved in this project:

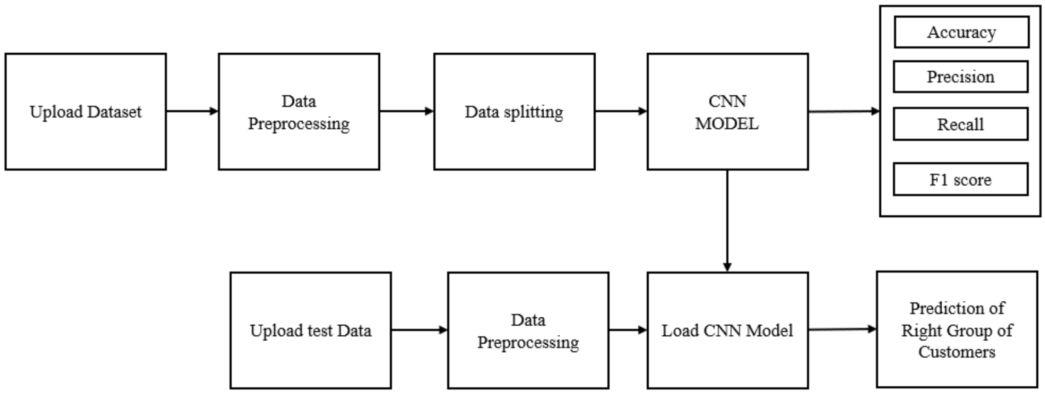

Figure 1: Block Diagram of Proposed Model CNN Model

3.2 CNN model

According to the facts, training and testing of proposed model involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F\left(k_x, k_y, d\right)$. The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map.

ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

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Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Softmax classifier

Generally, as seen in the Fig. 2 softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

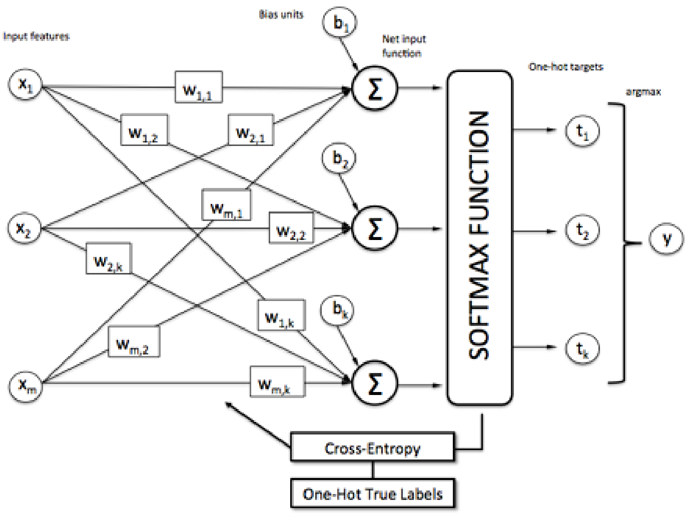

Fig. 2: SoftMax classifier.

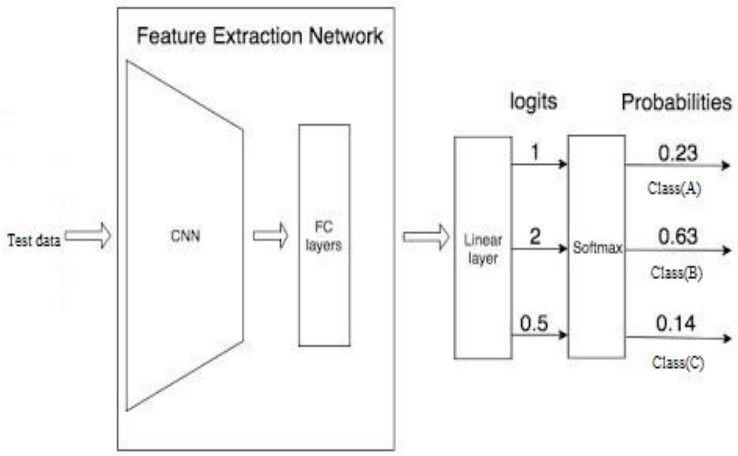

Fig. 3: Example of SoftMax classifier.

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4. RESULTS AND DISCUSSION

Fig. 4 shows that Sample UI Used for Predicting Right Group of Customers represents a sample user interface designed for predicting the right group of customers. The UI includes features and functionalities related to customer prediction, providing a visual representation of the prediction process. Figure 6 shows a count plot visualizing the distribution of customer segmentation in the automobile industry. It provides insights into the distribution of customers across different segments. Figure 7 presents an analysis of the dataset used for predicting the right group of customers. It includes visualizations or insights into key patterns and trends in the data relevant to customer segmentation. Figure 8 displays the user interface presenting the performance metrics of a K-Nearest Neighbors (KNN) model. The metrics includes accuracy, precision, recall, and F1-score, providing an evaluation of the KNN model's performance.

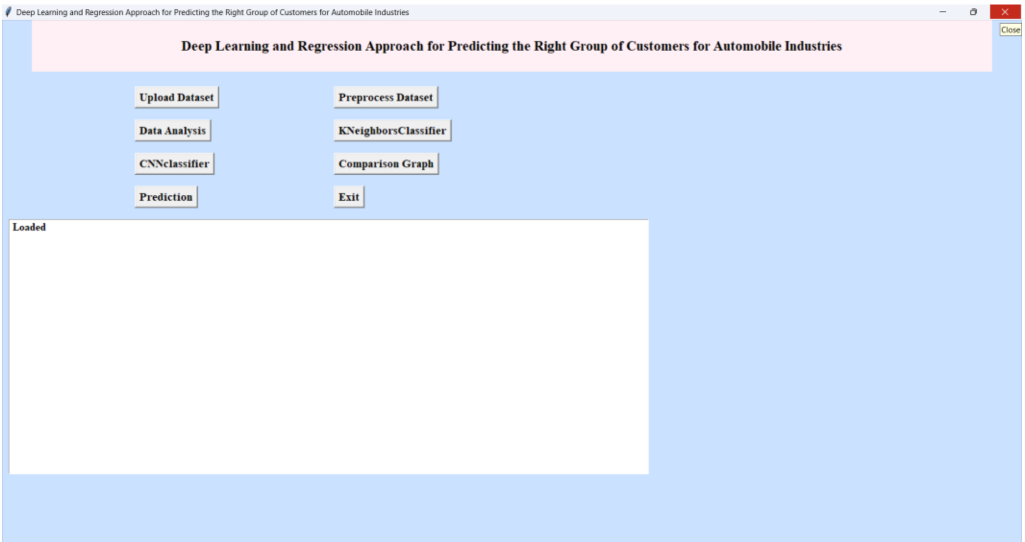

Fig. 4: Sample UI used for predicting right group of customers.

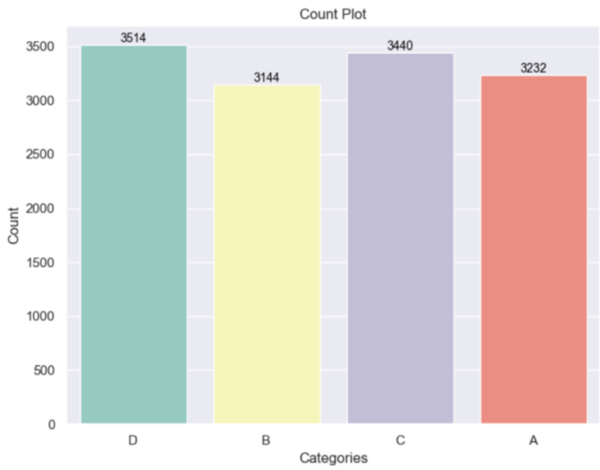

Fig. 5: Count plot of customer segmentation for automobile industries.

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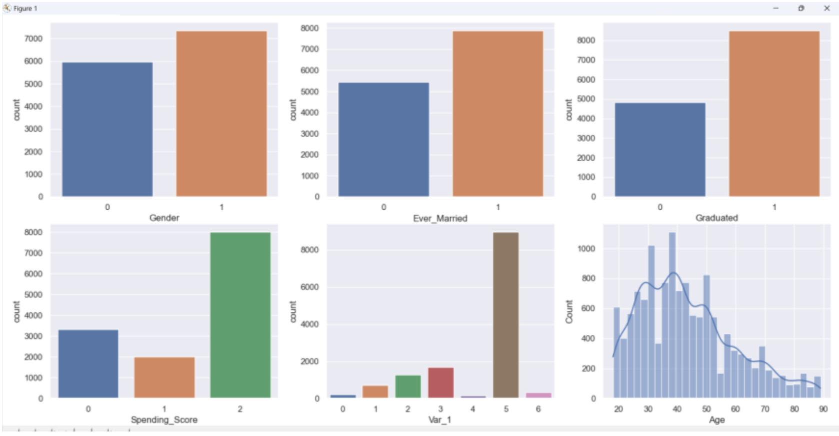

Figure 7: Figure shows Analysis of dataset used for right group of customers

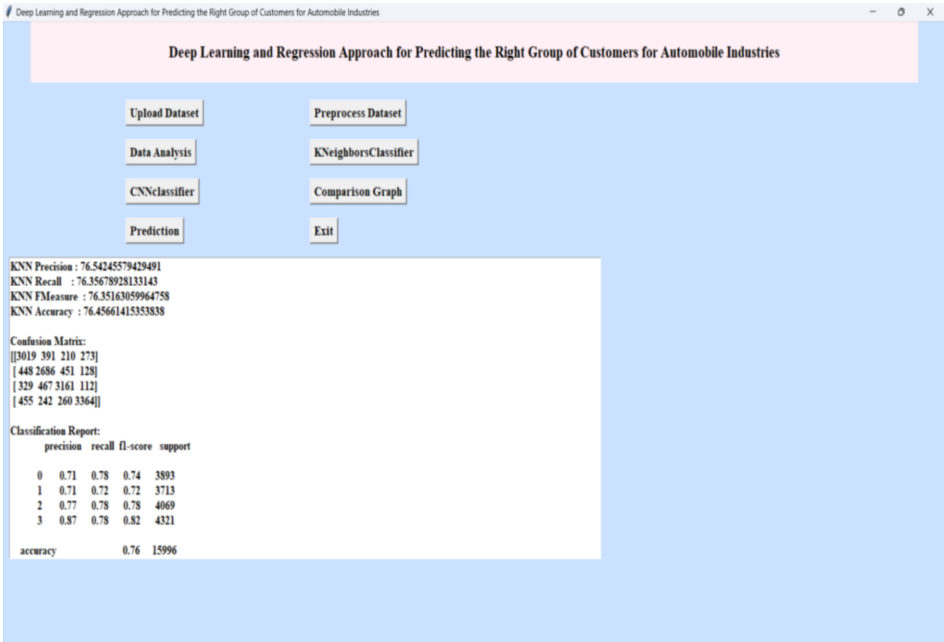

Figure 8: UI shows the performance metrics of KNN Model

Figure 9 showcases the user interface presenting the performance evaluation of a proposed Random Forest Classifier. It includes metrics and visualizations to assess the classifier's effectiveness. Figure 10 presents a comparison graph between the KNN and CNN Model. It illustrates how these models perform across different metrics, aiding in the selection of the most suitable model for customer segmentation. Figure 11 illustrates the user interface presenting the prediction results of the proposed CNN classifier. It includes visualizations or summaries of the model's predictions on the test data, showcasing its ability to predict the right group of customers.

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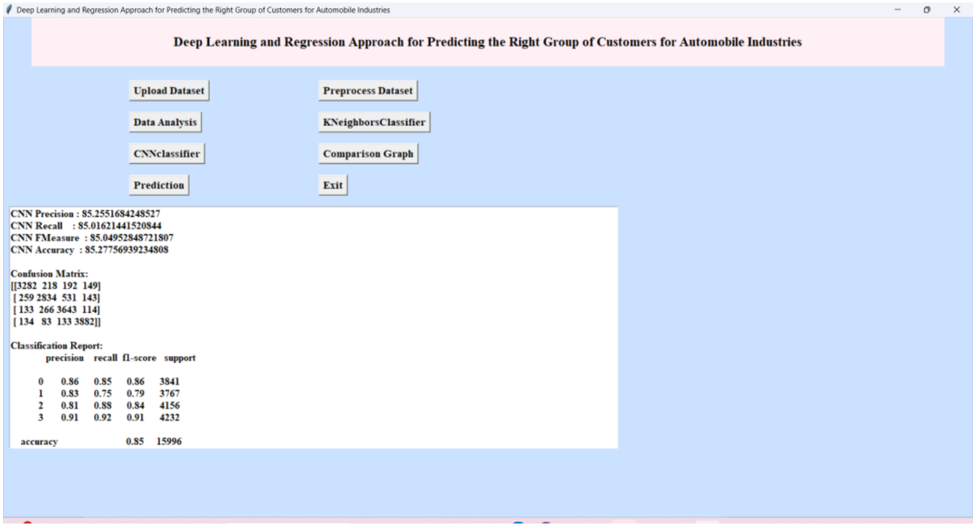

Figure 9: UI shows the performance evaluation of proposed CNN Classifier

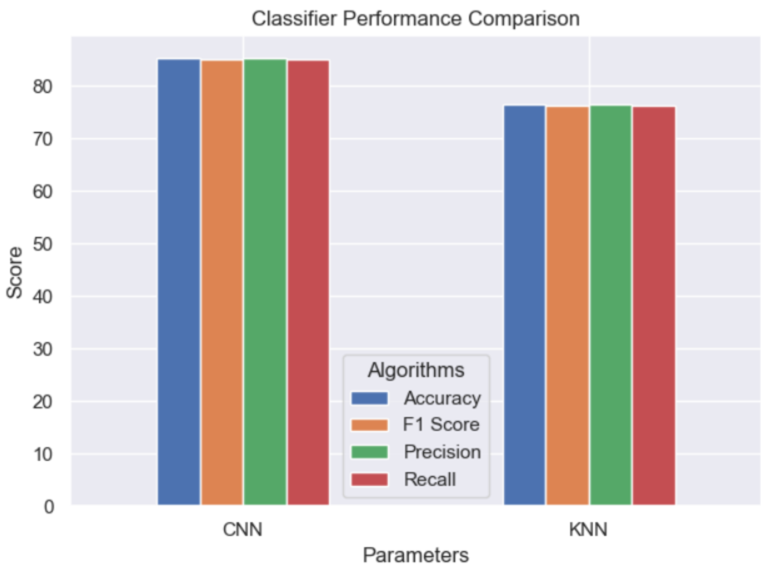

Figure 10: comparison graph of KNN and CNN classifier

Figure 11: The prediction results of proposed CNN classifier

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Table 1: Performance comparison of quality metrics obtained using KNN and CNN model.

Model	KNN	CNN Classifier
Accuracy (%)	76	85
Precision (%)	76	85
Recall (%)	75	85
F1-score (%)	76	85

5. CONCLUSION

In conclusion, the utilization of deep learning and regression-based approaches for predicting target customer segments in the automobile industry presents a significant advancement over traditional methods. By leveraging machine learning techniques and extensive datasets of customer information, manufacturers can better understand consumer preferences and tailor their marketing strategies and product designs accordingly. This not only enhances customer satisfaction but also leads to improved sales and reduced marketing costs. The integration of deep learning algorithms enables the identification of key factors influencing customer preferences, paving the way for more data-driven decisions in the industry. As competition intensifies, accurate predictions of target customer segments become increasingly crucial for manufacturers to stay ahead in the market.

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