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ABSTRACT

The application of the Artificial Intelligence (AI) algorithms has been challenging in the retail industries One of the most intriguing advancements in retail is the advent of AI-powered automated stores, offering a seamless shopping journey for customers. These cutting-edge establishments integrate state-of-the-art technologies to revolutionize customer interactions, streamline operations, and eliminate the traditional checkout process. In this research paper, the Machine Learning (ML) algorithm, i.e., K-NN has been applied to classify three levels of satisfaction among the customer which are Unsatisfied, Neutral, and Satisfied. Here, we have applied the dataset of the customer behavior of Infosys Autonomous Store Simulation results to find that the proposed K-NN algorithm achieves high precision, F1-score, and Recall scores. This research contributes valuable insights of the proposed algorithm as a significant predictor of shopping intention, including perceived ease of use, usefulness, enjoyment, customization, and interactivity.

KEYWORDS

Artificial Intelligence, Automated shopping technology, K-Nearest Neighbour, Machine Learning Algorithm.
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1. INTRODUCTION

The retail industry has witnessed a transformative change by applying different applications of Artificial Intelligence (AI) , Machine learning (ML), Internet of Things (IoT), and Big Data Analytics (BDA), during recent years, which is named as Retail 4.0 [1,2]. As a result, AI can replace human in doing routine jobs whereas the applications related to home and office can be executed by using mobile applications and IoT [3]. Here, the real time data can be stored in the cloud and these data can be analyzed. When IoT operates effectively, it gathers data that is subsequently analyzed to discern customer preferences. This data analysis enables AI to identify users and deliver personalized services. These technological advancements have also found application in agri-food retailing, aiding in the improvement of supply chain sustainability.

In the past two years, the global e-commerce market has experienced a remarkable 45.8% increase in online sales [4]. This surge is particularly significant considering that in 2019, only 13.6% of sales were conducted online.

Forecasts indicate that by 2021, this figure is expected to climb to 19.5%. Furthermore, the proportion of mobile e-commerce sales has risen from 50% in 2018 to 78% in 2022.Recent data from IBM's United States Retail Index highlights how the COVID-19 pandemic has accelerated the shift from physical retail to online shopping by approximately five years [5]. Walmart and Target retailers have capitalized on this trend by considering the strategies, such as grocery pickup and delivery services which resulted in increased sales. Moreover, the IoT industry continues to thrive amidst the ongoing COVID-19 pandemic. "In 2020, the number of IoT connections surpassed that of non-IoT connections, reflecting the widespread adoption of IoT devices like connected cars, smart home devices, and industrial equipment. Additionally, retailers responded to the challenges posed by the COVID-19 pandemic by implementing self-service kiosks to reduce face-to-face interactions and enhance customer safety. These self-service kiosks empower customers to independently access various services, increasing satisfaction by giving them greater control over their purchasing decisions. Equipped with features such as self-checkout options, customers can seamlessly complete transactions using a variety of payment methods, including credit cards, debit cards, mobile phones, Apple Watches, and gift cards. [6,7] This integration of technology, utilizing QR codes, RFID, and smartphone transactions, blurs the line between online and offline shopping experiences, ensuring a consistent and seamless experience for consumers [8,9,10].

Different literature reviews have been conducted on the retail stores by the application of Artificial Intelligence (AI) algorithms. Few of the studies have been explained in this paragraph. In [11,12,13], this review analyzes 219 publications related to AI in fashion e-commerce. The articles are categorized using AI techniques, revealing research gaps and potential areas for further exploration. Key topics include optimizing the retail value chain and enhancing customer expectations through AI. In this study [14,15,16], emerging trends and practices of using AI in retail has been explored. It highlights how AI enhances customer experiences and adds value to retail businesses. The efficiency of AI helps retailers provide better services and respond to customer needs in the era of digitization and intelligence. This systematic literature review provides insights into the current augmented reality (AR) knowledge in retail and e-commerce. It covers topics such as consumer decision-making, consumer experience, self-brand connection, and negative effects related to AR [17,18,19]. In this study, the intention of the customers has an intention for shopping at the AI-Powered Retail Stores. By extending the different technologies, the model is accepted by incorporation of AI context-specific constructs. The technology has been extended to study some of the predictors such as ease of use, useful, enjoy, customization, and interaction [20,21**]**.

From the above literature studies, it has been observed that the involvement of consumer behavior also underscores the utility of the latest technologies for enhancement in the business performance and satisfaction of the customers [22,23,24]. Retailers recognize the need to adapt in changing consumer preferences by offering them as integrated, uniform service across different channels which is stored in mobile platforms. Furthermore, Retail 4.0 emphasizes the significance of digital marketing and social media.

In this research paper, we have applied the utilization of the K-Nearest Neighbors (KNN) algorithm for analyzing the different customer behaviors within the retail environments. KNN plays a important role in comprehending customer preferences and forecasting purchasing trends. Through the examination of real-world data collected from these autonomous stores, we have investigated the potential of KNN in personalizing shopping experiences. There are two contributions in the paper, such as:

- The Emergence of AI-Driven Retail Stores: We have explored the integration of AI technologies by leading retailers like Aditya Birla Retail, Reliance Retail, and Shopper’s Stop in India.
- The Infosys Autonomous Store: In this store, some of the latest solutions that are used to revolutionize traditional environments. Applying the latest computer vision models and GPU acceleration, the shopping experience has the latest experience.

2. DATA DESCRIPTION OF THE INFOSYS AUTONOMOUS STORE (IAS)

The IAS [25] returns the retail stores by incorporating some of the latest technologies in analyzing customer behavior. By exploiting the application of DL-powered models, this innovation interprets the intricate details of customer interactions within the store environment. Through AI-based algorithms, this store can track the different customer movements, and preferences, and purchase the different patterns in real-time conditions. These models are to identify popular product areas, analyse the various times, and detect the different the various patterns in customer navigation. This understanding of customer behavior enables the store for optimizing the layout and product placement for maximum engagement and sales. In this store, AI-driven recommendation systems are employed for personalizing the different shopping experience. By analyzing the past history and demographic information, this store can offer the different product recommendations for customers. In this dataset, the various customer information such as gender, age, city, type of membership, spending nature, items purchased, average rating, discounts, days since last purchase, and level of satisfaction have been explained as shown in the Fig.1.

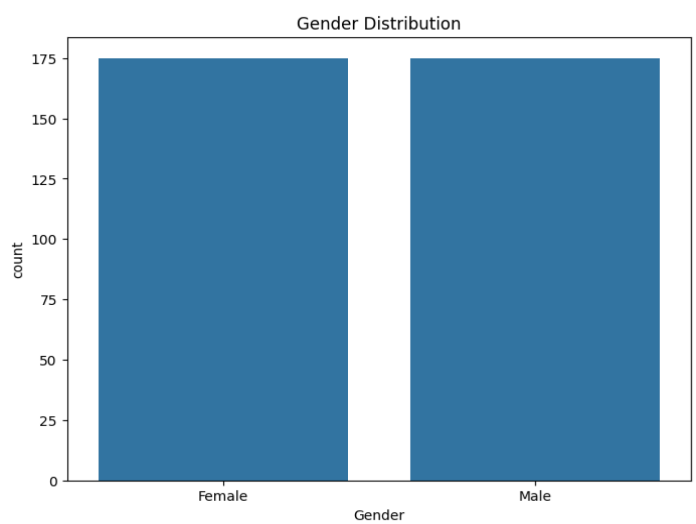

Fig.1 The number of counts of gender distribution (Male/Female)

3. PROPOSED METHODOLOGY

We introduce a model that builds upon the TRAM Model by integrating AI-specific factors. These factors encompass:

- Perceived Enjoyment: Refers to consumers' personal feelings of satisfaction and enjoyment during their interactions with AI-driven stores.

- Customization: Reflects the degree to which stores personalize their offerings according to individual preferences and needs.

- Interactivity: Describes the level of active engagement and responsiveness experienced by shoppers during their interactions within the retail environment.

Here, we proposed K-NN algorithm in order to address factors that are contained in the dataset, such as enjoyment, customization, and interaction. The mathematical formulation of K-NN has been described below.

For the distance calculation, the KNN algorithm computes the distance between data points to determine their similarity. The Euclidean distance expression is expressed in the Eqn.1.

$$d(x,x^{/}) = \sqrt{(x - x^{/})^2 + \cdots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. + (x - x_n^{/})^2} \quad (1)$$

KNN classifies the new data point based on its K neighbors. The parameter (K) represents the number of neighbor's to consider. To choose an appropriate (K), one common rule is to use $\sqrt{(n)}$, where (n) is the total number of data points. If (n) is even, make the value odd by adding or subtracting 1 to ensure better selection.

Algorithm Workflow

Step1: Given a new data point, calculate its distances to all existing data points.
Step 2: Select the K nearest neighbors based on the calculated distances.
Step 3: Use majority voting to assign the new data point to a certain class.
Step 4: The input x gets the value assigned to the class with the highest probability.

$$P(y = j | X = x) = \frac{1}{K} \sum_{i \in A} I\,(y^{(i)} = j) \quad (2)$$

For ex, data points with features "age" and "gender" (0 for male, 1 for female) are represented for classifying a new data point with age 5 and gender 1 (female). The first step is to calculate the Euclidean distances between the new point and the existing points. Based on the K nearest neighbors, the new point is assigned to the majority class.

4. SIMULATION RESULTS & DISCUSSION

In this section, all real time simulations have been carried out by applying Python Integrated Development Environment (IDE) on a personal computer equipped with a 1 TB hard disk, 4 GB of RAM, and an Intel Core i7 processor. The K-Nearest Neighbors (KNN) model exhibits exceptional performance in classifying customer satisfaction levels based on the provided features. The KNN model has achieved a perfect accuracy score of 1.00 (100%) on the test dataset which indicates that it accurately in all classified instances.

For each satisfaction level (Unsatisfied, Neutral, Satisfied), the KNN model has categorized customers into three levels. Precision represents proportionate positive predictions, and recall denotes proportionate actual positive instances, and consistently yielded high values of 1.0. F1-score which is the harmonic mean of precision and recall was calculated to be 1.0. Furthermore, the correlation matrix as depicted in Fig. 2 provides insights into the relationships between different variables that are being used in the analysis[26-33].

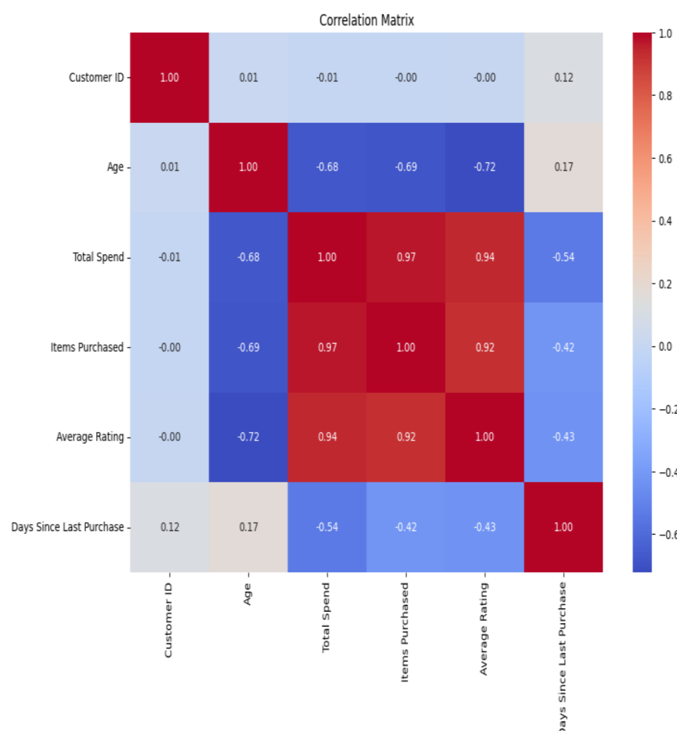

Fig.2 Correlation matrix for different parameters

This heatmap presents the correlation matrix of customer data which focusses on relationships between Customer ID, Age, total spend, Items purchased, Average rating, and days since last purchase. It reveals positive correlations between the purchasing and spending (0.97), total spend an average rating (0.94), and purchasing and rating (0.92), indicating that customers who spend more tend to purchase more items and give higher ratings. Conversely, age exhibits strong negative correlations with Items purchased (-0.69), total spend (-0.68), and average rating (-0.72), suggestion of older customers for buying lesser items, spend less, and provide lower ratings. Last purchase variable shows the weak correlations across all variables, with the highest being with total spend (-0.54). This analysis highlights critical insights into customer behavior, with age significantly impacting spending habits and satisfaction, while spending behavior closely aligns with purchasing volume and satisfaction levels. Here, the confusion matrix representing three labels has been given in Fig.3.

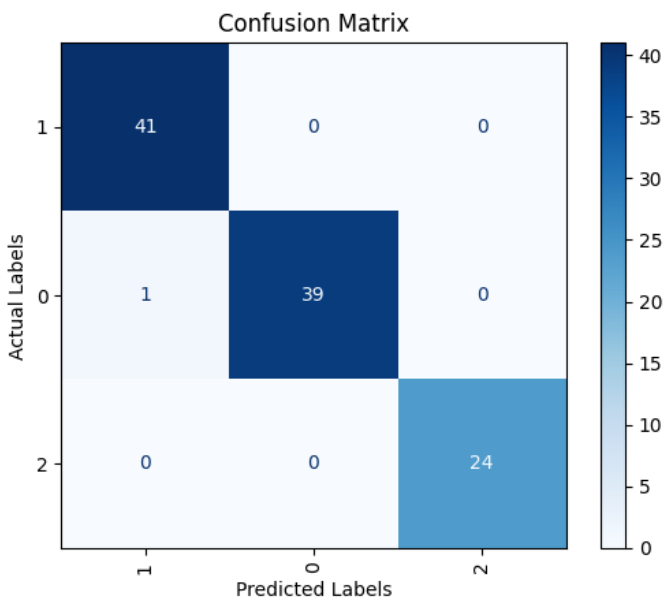

Fig.3 Confusion Matrix for 3 classes

Table 1: Scores of PREC, REC, and F1-score for three classes

Class	**Precision**	**Recall**	**F1-Score**
Satisfied	1.00	1.00	1.00
Neutral	0.96	1.00	0.98
Unsatisfied	1.00	0.97	0.98
Weighted Avg	0.99	0.99	0.99

Table 1 summarizes the performance metrics of a classification model, including Precision, Recall, and F1-Score for each class and their weighted averages. From the Table 1, " Satisfied" achieves a perfect score across all metrics (Precision, Recall, and F1-Score all 1.00). This implies that the model perfectly identified all "Satisfied" instances. Whereas "Neutral" class, precision is high (0.96) but not perfect, while Recall is perfect (1.00). The F1-Score is nearly perfect (0.98), showing that most predictions were accurate with only minor misclassifications. For "Unsatisfied" class, perfect Precision (1.00) and high Recall (0.97), resulting in a high F1-Score (0.98). A small number of "Unsatisfied" instances were missed.

Overall, the model demonstrates excellent classification accuracy, particularly excelling in identifying "Satisfied" instances while also performing very well on the "Neutral" and "Unsatisfied" classes. Retailers can apply the KNN model to predict customer satisfaction levels. Therefore, the KNN algorithm captures patterns in the data which enables the accurate predictions of customer satisfaction. Retailers can apply the model for enhancing personalized experiences.

5. CONCLUSION & FUTURE SCOPE

In this paper, the KNN model was applied to classify customer satisfaction into unsatisfied, neutral, and satisfied categories based on historical data. Using the customer behavior dataset from the IAS dataset, the proposed K-NN algorithm achieved high precision, F1-score, and recall scores. This research provides valuable insights as a significant predictor of shopping intention through the usefulness, enjoyment, customization, and interaction factors.

In future studies, the application of AI in retail holds the potential for enhancing customer satisfaction and operational efficiency. Furthermore, exploring the deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) could provide deeper insights into customer behavior patterns. With the integration of AI-driven predictive analytics fulfil customer needs which enables highly personalized shopping experiences. Additionally, the fusion of AI with augmented reality (AR) and virtual reality (VR) could revolutionize the customers interaction with the different products before making any type of decision.

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