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# Two-Dimensional Customer Segmentation for Digital Custom Coupon Issuance Approach

**[1]Pitta.Srirama.Pavan Kumar, [2] Mr. Ch. Kodanda Ramu, M. Tech, (Ph.D)**

[1]M. Tech, Dept. of CSE, Miracle Educational Society Group of Institutions, Miracle City, Munjeru Village, Bhogapuram Mandal, Vizianagaram, Andhra Pradesh, India

[2]Associate Professor, Miracle Educational Society Group of Institutions, Miracle City, Munjeru Village, Bhogapuram Mandal, Vizianagaram, Andhra Pradesh, India

**ABSTRACT:** With the improvement of large information and profound learning innovation, enormous information and profound learning innovation have likewise been applied to the showcasing field, which was a piece of business organization. Client agitate the board is one of the main areas of promoting. In this paper, we proposed a technique to forestall client beat and increment buy transformation rate by giving tweaked rebate coupons to clients with high stir rate in light of huge information continuously. In the wake of sectioning client portions with two-layered fragment examination, a continuous beat rate assessment model in light of clickstream information was created for each portion. From that point onward, we gave tweaked coupons to our clients. At last, we tried the transformation rate and deals development. A two-layered group investigation based stir rate assessment joined with a proposal framework was viewed as essentially more helpful than the particular straightforward models. Utilizing this proposed model, it is feasible to increment deals via consequently assessing the client's stir likelihood and shopping penchant without the weight of showcasing costs in the web based shopping center

**KEYWORDS**: big data, machine learning, two layer, shopping.

## I. INTRODUCTION

There has been an expansion in the use of big data and deep learning technologies into management-related domains, such as marketing. Digital coupons have also become a popular promotional tactic due to the rise in internet penetration [1]. The issue of personalized digital coupon issuing is crucial to e-commerce. This is due to the fact that retaining current clients is a higher priority for any firm than bringing in new ones [2]. Keeping current consumers is much more cost-effective than finding new ones [3]. It is really five to six times more expensive to acquire new clients than it is to keep old ones [4]. Businesses that have mastered the art of client retention have a multiplicative impact on both their bottom line and their reputation in the eyes of their target audience [5].

Developing predictive models employing machine learning and artificial intelligence technology has historically been the major focus of customized coupon issuance research, which has been active in highly competitive and urgent areas including the telecoms, banking, distribution, and gaming industries [6]. Artificial intelligence (AI) marketing that makes use of deep learning and large data has also just emerged. Assuming the targeting model is successful in properly measuring user receptivity, AI-driven targeting has the potential to significantly reduce marketing expenses while simultaneously increasing online sales [7].

The typical purchase conversion rate, especially for online shopping centers, is around 2%. The convenience of online shopping malls is undeniable, as they can be simply accessible via PC or mobile web. However, this convenience also comes with the risk of being easily abandoned. Accordingly, a high conversion rate may result in enormous revenues, and even a little decrease in customer turnover rate can achieve this.

It is far easier to get data from online shopping malls than from traditional ones. In real time, the shopping mall's own database may capture all consumer behavioral traits while they purchase online. In light of this, it is feasible to collect extensive data on past purchases and utilize it to deduce patterns in consumer behavior. In conclusion, it is possible to raise customer conversion rates even in the absence of targeted promotions by making use of detailed historical data on consumer habits and preferences.

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Providing clients with instant, customized coupons is the most direct and hassle-free option. It is feasible to enhance sales by raising the buy conversion rate without burdening special costs like promotional events by choosing consumers with a high risk of real-time churn and delivering real-time personalized discount coupons. And you'll need an AI-driven strategy to really implement these plans. Proper coupon issuance is achievable once AI automatically learns consumer histories by detecting individual actions and preferences.

Strategies based on deep learning are one example of an AI methodology that may be put into action. For optimum decision-making, deep learning learns from massive amounts of data, and more data means better results. Online shopping malls collect massive amounts of real-time log data, which may be used to study consumer preferences and habits. In example, using the data that accumulates daily to update and re-train the current model makes it feasible to build a more advanced model on a daily basis.

There are three main categories of AI-powered tailored coupon issuing methods: client segmentation, personalized suggestion, and customer churn prediction.

The term "customer segmentation" refers to the process of dividing up a target audience into subsets defined by shared traits in order to launch targeted, personalized marketing campaigns [8]. Decision trees and other supervised learning models, as well as self-organizing maps (SOMs) and K-means models, are the most common unsupervised learning models used for consumer segmentation [9]. A notable aspect of the latest customer segmentation studies that use machine learning is that these studies are being conducted for relevant marketing research reasons, such predicting customer attrition [10], [11]. One of the primary areas of machine learning-based marketing research is customer churn prediction. The rising tide of customer churn in today's cutthroat business climate has prompted numerous studies to develop new models for accurately predicting customer churn, which has been acknowledged as an important area of study for both marketing and enterprise-wide management strategies [4]. Ensemble models, which interconnect various models, have recently gained more attention, although previous research focused on learning models using individual algorithms like decision trees, logistic regression, and artificial neural networks to forecast customer deviations [12]. As for marketing research based on machine learning, churn prediction and customized recommendation systems are among the most active subjects at the moment [13]. There has been a recent uptick in studies examining the efficacy of tailored suggestions for online retailers and media streaming services. Model development research aiming to improve prediction performance have dominated personalized recommendation studies [13], [14].

Conversely, internet shopping malls may benefit substantially from personalized coupon distribution. Since a huge number of users enter and depart in an instant, real-time performance is necessary for an online shopping mall, in contrast to a traditional mall. Consequently, the conventional method of issuing discount coupons at a physical storefront does not work when applied to an online setting. On top of that, gathering log data online is much more feasible than offline. Consequently, you may create efficient marketing strategies, such a plan for the real-time issue of discount coupons, by using the marketing approach that makes use of AI.

The majority of research treats all customers as a single entity and builds AI prediction models all at once. It is irrational to treat all consumers the same since their behavior varies for reasons that are both obvious and obscure, and because their buying habits are unique. Establishing AI models for each group that shares similar trends according to consumer behavior can greatly enhance its power. Using deep learning methods applied to real-time click stream data, this research identifies clients at high risk of churn and offers them a voucher tailored to their interests. The importance of this research is as follows: We started by breaking the client base down into different groups and then creating a model to predict which groups would be most likely to leave. Secondly, we used deep learning models to create a click stream-based real-time customer churn risk prediction model. Third, by offering personalized discounts on the website of genuine shopping malls, we were able to increase the actual conversion rate.

In contrast to previous research, this study's scientific contribution was a three-step process for preventing customer churn and real-time analysis of consumers utilizing acquired data. The three stages of our concept were also tested in a real-life shopping mall, proving their efficacy and efficiency from an economic perspective.

## II. PROBLEM STATEMENT

Marketing research begins with customer segmentation. Marketing strategies may be developed for each target category when clients are grouped according to their shared features. Segmenting customers is only the beginning;

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following marketing tactics should also be based on segmentation. Businesses that divide their clientele into distinct groups and then create targeted, effective marketing campaigns for each subset tend to do better overall. Furthermore, businesses may learn more about the needs and wants of their customers. When it comes to consumer segmentation, RFM procedures are among the most traditional and widely used options. The RFM assigns ratings to each of the three aspects that make up consumer behavior. The variables R, F, and M stand for the total amount spent, total frequency of purchases, and the duration since the previous transaction, respectively. All three dimensions are used to determine the final scores. Afterwards, it builds segments based on three-dimensional classifications [15], [16], [17], [18].

Machine learning has been the subject of several consumer segmentation studies in recent years, complementing more conventional RFM approaches. It is common practice to reduce dimensionality while clustering with several variables. An example of a deep learning technology that can reduce dimensionality is the autoencoder. Cluster analysis used sequentially after dimensionality reduction with an autoencoder is a common example [19]. Another option is to use modeling techniques that simultaneously include dimensionality and clustering [20], [21].

One of the most important goals of loyalty management has always been to find strategies to reduce client attrition. There are two main reasons why churn prediction is important for companies: The primary rationale is that service providers' credibility and trustworthiness are impacted by high rates of client attrition. Second, it's five to six times more expensive to acquire a new client than it is to keep an existing one. Building a churn prediction model that can identify purchases that don't follow the norm is essential [22]. Instead than using empirical investigations to verify hypotheses, research on customer turnover mostly relies on machine learning approaches [23]. The classification issue, in which each client is either assumed to churn or assumed not to churn, is applicable to the task of churn prediction. A support vector machine and hybrid recommendation strategy architecture for proactive identification of client turnover was presented in reference [24]. Recommendation strategies provide tailored retention activities, while support vector machines forecast e-commerce client turnover. In order to forecast the likelihood and timing of client attrition, reference [25] developed a churn model. The Decision Tree method and Naïve Bayes classification were used by the model. Predicting customer turnover using clickstream data was done using an LSTM model in reference [1].

Among the many areas of marketing research using machine learning, tailored recommendations get a lot of attention. Association analysis or individual product purchase probability calculation were once the major tools used in customized suggestion research []. But recently, content-based approaches and collaborative filtering applied to suggested services like Amazon and Netflix have been the hottest topics in the industry. Research based on deep learning that combines several auxiliary processing algorithms has also been active recently, using hybrid methods [3]. The goal of the system dictates the design of the recommendation system. Due to this, the recommendation system makes use of a broad range of methods. The majority of these systems rely on content and collaborative filtering [4]. Other recommendation systems, such as knowledge-based and constraint-based systems, are also in use [5], [6]. Decision trees, neural networks, naïve bayes, supported vector machines, linear regression models, and classifier-based recommender systems are also used [7], [8], [34]. It also makes use of clustering-based suggestions, including the K-means clustering method [9]. Deep learning recommendation systems have recently become the subject of intensive study [10]. When it comes to time series modeling, nonlinear modeling, and accepting a wide variety of input data types, deep learning recommendation systems really shine. In the context of the social Internet of Things, for instance, [11] suggested a method for recommending smart objects that takes time into account. In order to choose the best spot to build a chain shop, reference [12] suggested a recommendation system. For the purpose of making recommendations about stores, reference [14] suggested a preference learning approach that uses heterogeneous data.

### 2.1 LIMITATION OF EXISTING SYSTEM

Data complexity: In order to identify ways to increase revenue in shopping malls, most current machine learning algorithms need to be able to correctly understand big and complicated datasets.
Access to data: In order for machine learning algorithms to provide reliable predictions, they often need massive datasets. The reliability of the model could be compromised if there is a lack of data in enough amounts.
Mislabeling: The accuracy of current machine learning models is directly correlated to the quality of the input dataset used for training. The model's predictive abilities are severely limited if the data is mislabeled.

## III. PROPOSED SYSTEM

Here, we identify clients at high risk of churn and provide them with a discount that meets their preferences by using

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deep learning methods to data collected in real-time from click streams. The following implications arise from this research: To begin, we broke the client base down into many groups and created a model to predict customer attrition based on each group. Our second project included developing a deep learning model for real-time customer churn risk prediction based on clickstream data. Thirdly, on the website of a genuine retail mall, we increased the real conversion rate by giving out personalized discounts.
The scientific contribution of this research was to go through three processes to reduce customer churn and to assess customers in real time utilizing data obtained in real time. This was different from earlier studies. In addition, we tested our approach in a real-life shopping center, proving that all three stages of our strategy were efficient and cost-effective.

### 3.1 ADVANTAGES OF PROPOSED SYSTEM

After dividing customers into two categories based on their dimensions, the suggested solution used RNNs to create churn estimate models for each category. Customers with a high churn risk were subsequently sent individualized discounts for certain product categories. Customized coupon issuing is made possible via the use of a hybrid recommendation system

## IV. METHODOLOGY

### 4.1 Service Provider

The Service Provider must provide their username and password in order to access this module. Once he logs in, he'll have access to features like Train and Test Data Sets, Check the Bar Chart for Trained and Tested Accuracy, Check Out the Accuracy Results from Training and Testing, See the Type of Revenue Prediction for Shopping Malls, the Ratio of Revenue Prediction for Shopping Malls, and Downloadable Data Sets for Predictions. See All Remote Users, Shop Revenue Prediction Type Ratio Results.

### 4.2 View and Authorize Users

This section allows the administrator to get a complete rundown of all registered users. Here, the administrator may see the user's information (name, email, and address) and grant them access.

### 4.3 Remote User

There are n users in this module at the moment. Registration is required prior to performing any operations. Details will be entered into the database after a user registers. He will be prompted to provide his permitted user name and password upon successful registration. The user will be able to do actions like as Go ahead and sign up! Determine the Type of Revenue Prediction for Shopping Malls, VIEW YOUR PROFILE

## V. SYSTEM ARCHITECTURE

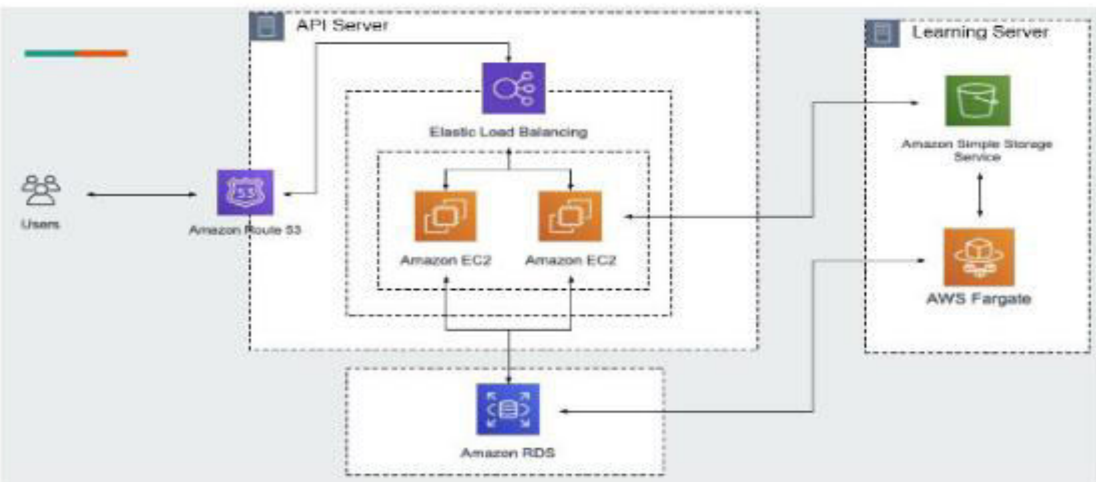


Fig. 5.1 System Architecture

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## VI. ALGORITHMS USED

**6.1 Logistic Regression using Python (scikit-learn)**

The scikit-learn package in Python offers a 4-step modeling approach that simplifies the coding of machine learning classifiers, which is one of its most remarkable features. The Logistic Regression classifier is used in this lesson, however the coding procedure is the same for other sklearn classifiers like Decision Tree and K-Nearest Neighbors. Predicting digit labels from photographs is the focus of this course, which employs Logistic Regression. A large number of training digits (observations) from the MNIST dataset, with known category membership (labels 0-9), are shown in the figure above. An image's label (from 0 to 9) may be predicted using a model trained using logistic regression. to demonstrate the behavior of the logistic regression algorithm and to swiftly demonstrate scikit-learn's 4-step modeling pattern using a toy dataset (digits dataset). Changing a model's default parameters may influence performance (in terms of both time and accuracy of the model). In the second part of the lesson, we walk over a more realistic dataset (MNIST dataset) to quickly demonstrate this effect

**6.2 Naive Bayes Classifier**

Using Bayes Theorem as its foundation, Naive Bayes is a method for statistical categorization. Among supervised learning algorithms, it is among the most basic. The method that is dependable, quick, and accurate is the Naive Bayes classifier. Performing quickly and accurately on massive datasets are naive bayes classifiers.

The naive bayes classifier works on the assumption that each feature's impact on a class is completely separate from any other features. Consider how a borrower's age, geography, income, and history of loans and transactions affect the loan application's desirability. Regardless of whether these traits are reliant on one other, they are nevertheless evaluated separately. This assumption is seen as naïve since it simplifies calculation. What we mean by this is "class conditional independence

**6.3 K Nearest Neighbor Algorithm**

Many different types of organizations make use of K-Nearest Neighbors, or KNN, as it is one of the most basic machine learning algorithms. Lazy learning algorithms like KNN do not need any parameters. A method is considered non-parametric if and only if it does not presume anything about the data it uses. Without respect to the characteristics represented by the numerical values, it selects data points according to their closeness to one another. A lack of training phase is indicative of a lazy learning algorithm. Consequently, we can categorize fresh data pieces as soon as they emerge

**6.4 Decision Tree Classification**

Classification using Decision Trees, metrics for attribute selection, and methods for developing and improving Python Scikit-learn package is used to create a decision tree classifier.If you're a marketing manager, you want to target the people who will buy your product the most. Discovering your target demographic in this way can help you save money on advertising. One of your goals as a loan manager should be to reduce the default rate by identifying applications for loans that pose a risk. A classification issue is the process of sorting consumers into two groups: those who are likely to be profitable and those who are not, or who pose a low risk of defaulting on a loan. There are two stages to classification: learning and prediction. The learning process involves building the model using the provided training data. The prediction stage involves using the model to anticipate the response based on the provided data. If you're looking for a popular and easy-to-understand categorization method, consider Decision Tree. It is applicable to problems involving both classification and regression.

**6.5 Random Forest Algorithm**

A supervised machine learning approach that relies on ensemble learning is random forest. One way to improve your prediction model is to use ensemble learning, which involves combining many methods or running the same algorithm several times. "Random Forest" comes from the fact that it mixes several decision trees—an algorithm of the same type—into a single, larger structure. Regression and classification are two applications of the random forest technique.

**6.6 XGBoostAlgorithm**

Efficient, versatile, and easily transportable, XGBoost is a distributed gradient boosting toolkit with optimizations. The Gradient Boosting framework is used to develop machine learning algorithms. Many data science issues may be quickly and accurately solved using XGBoost's parallel tree boosting (GBDT, GBM).

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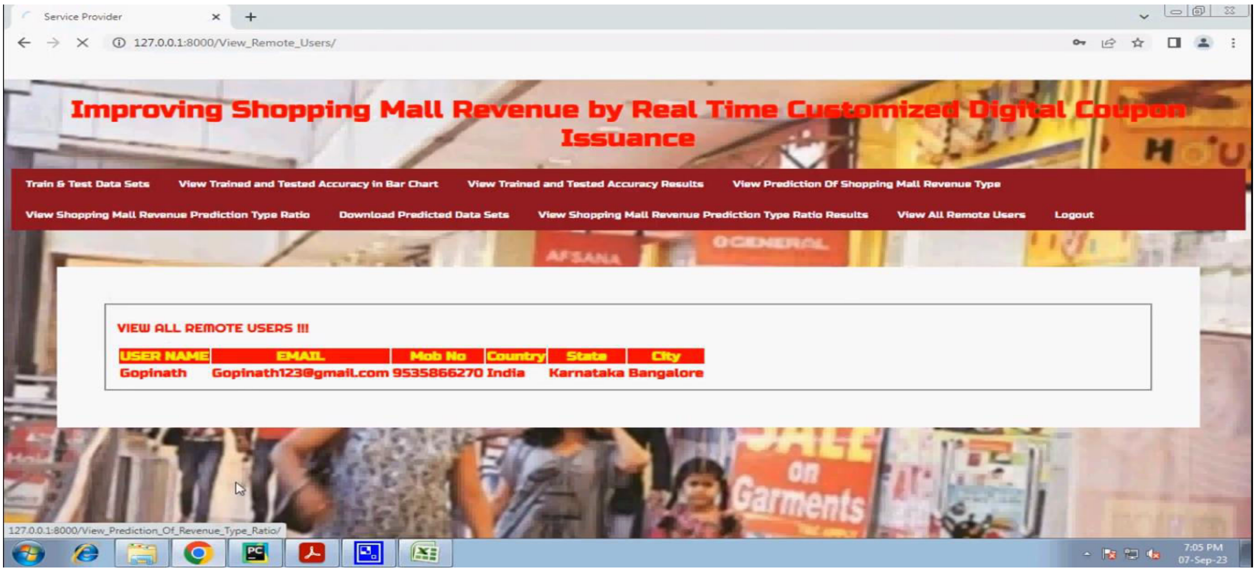
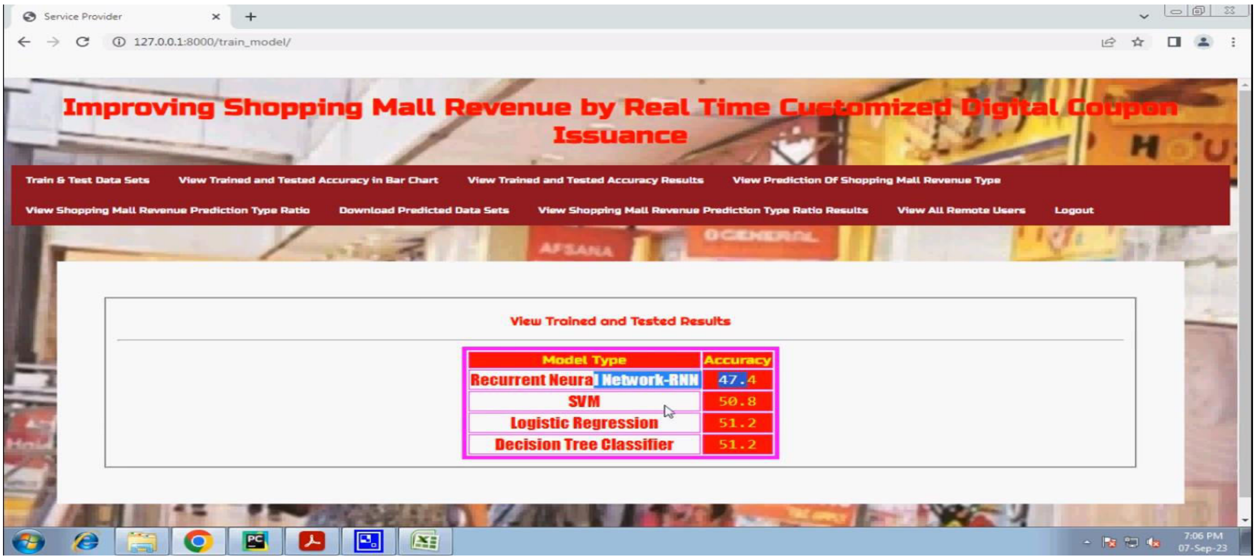
## VII. IMPLEMNTATION RESULTS

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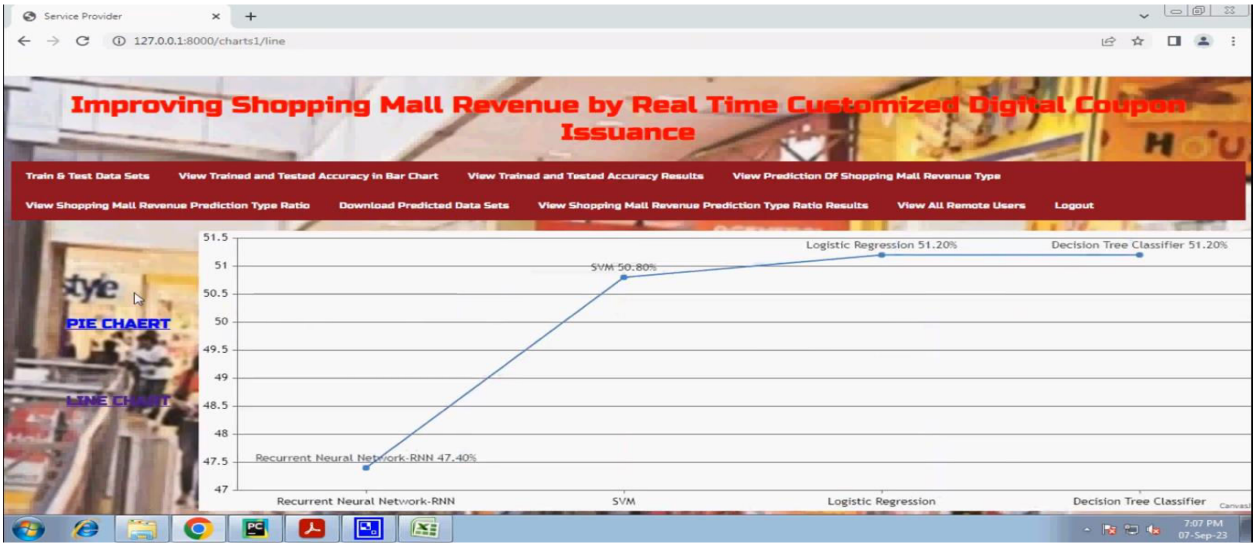


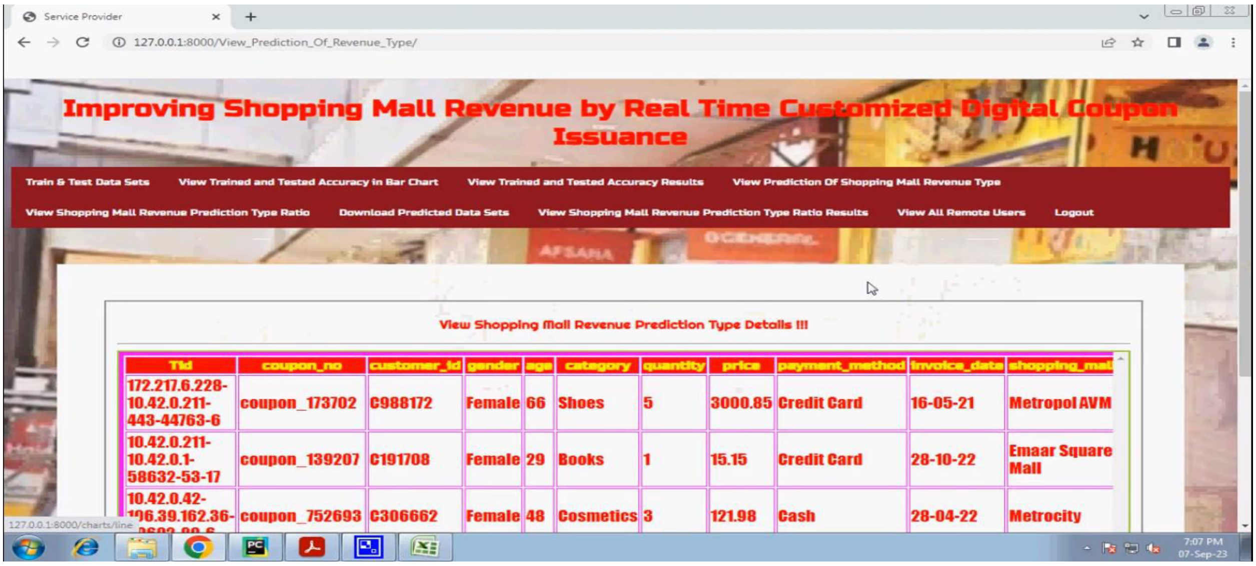


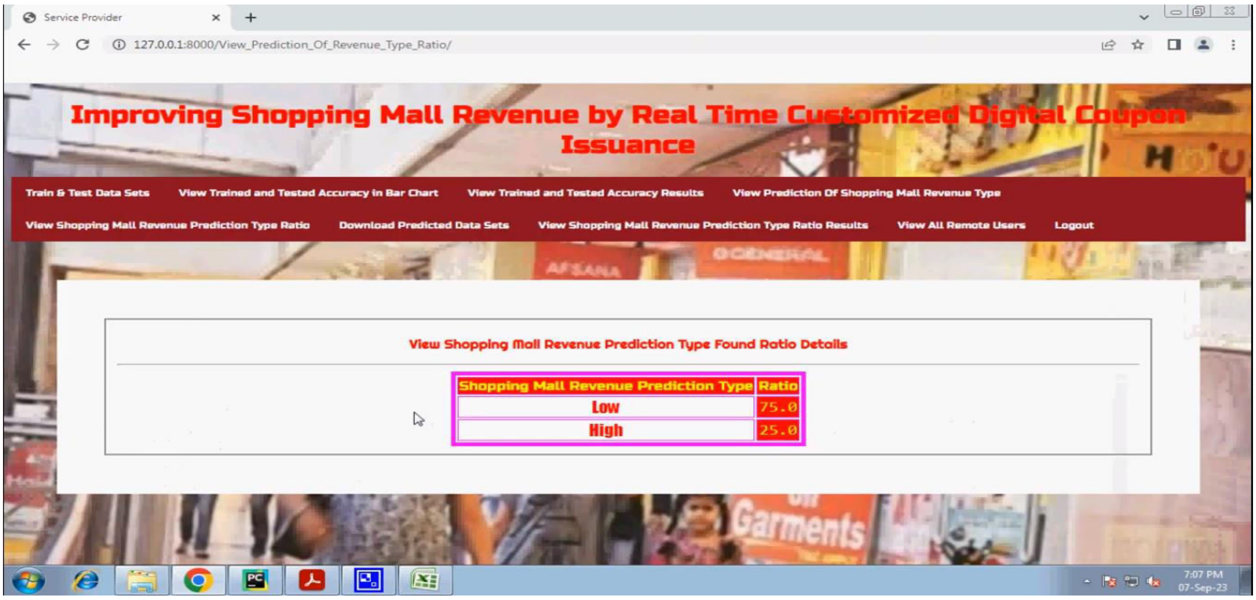

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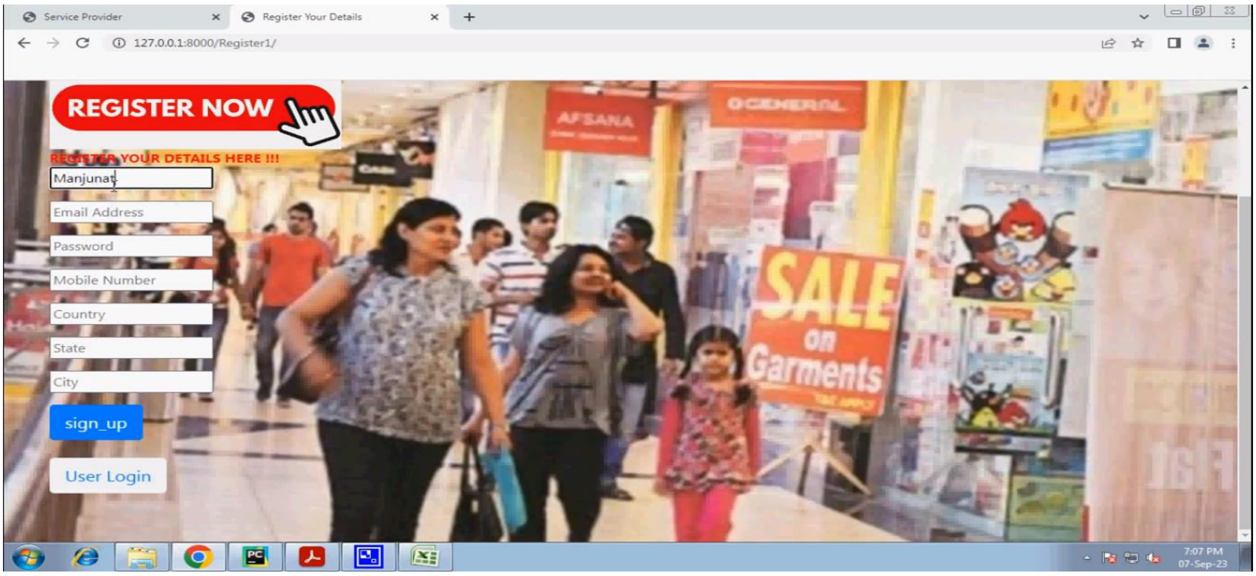


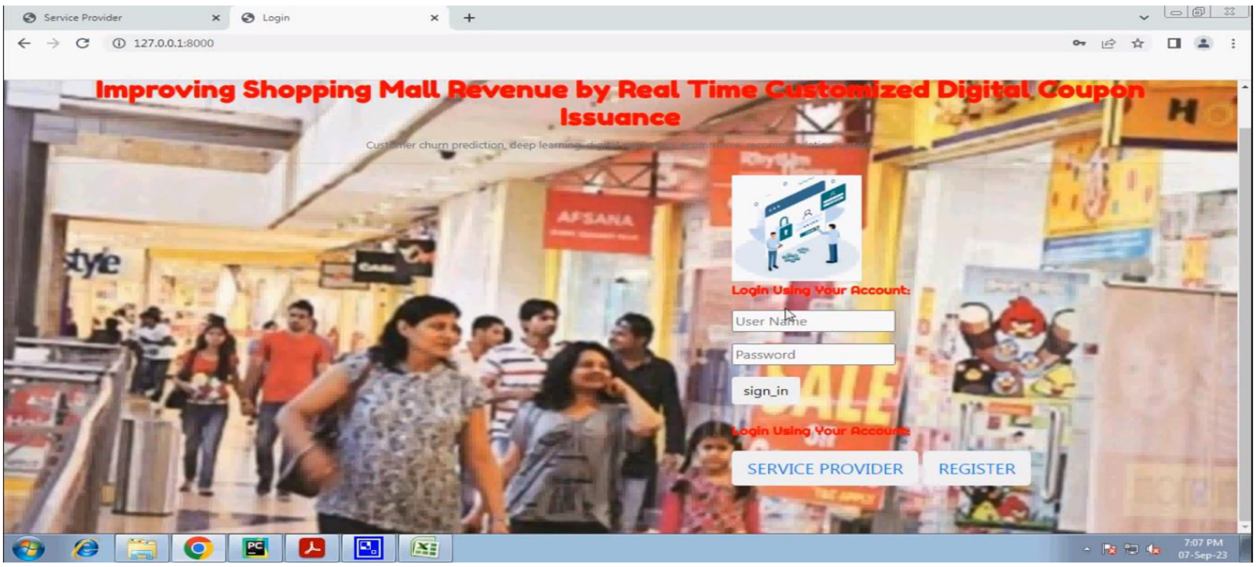

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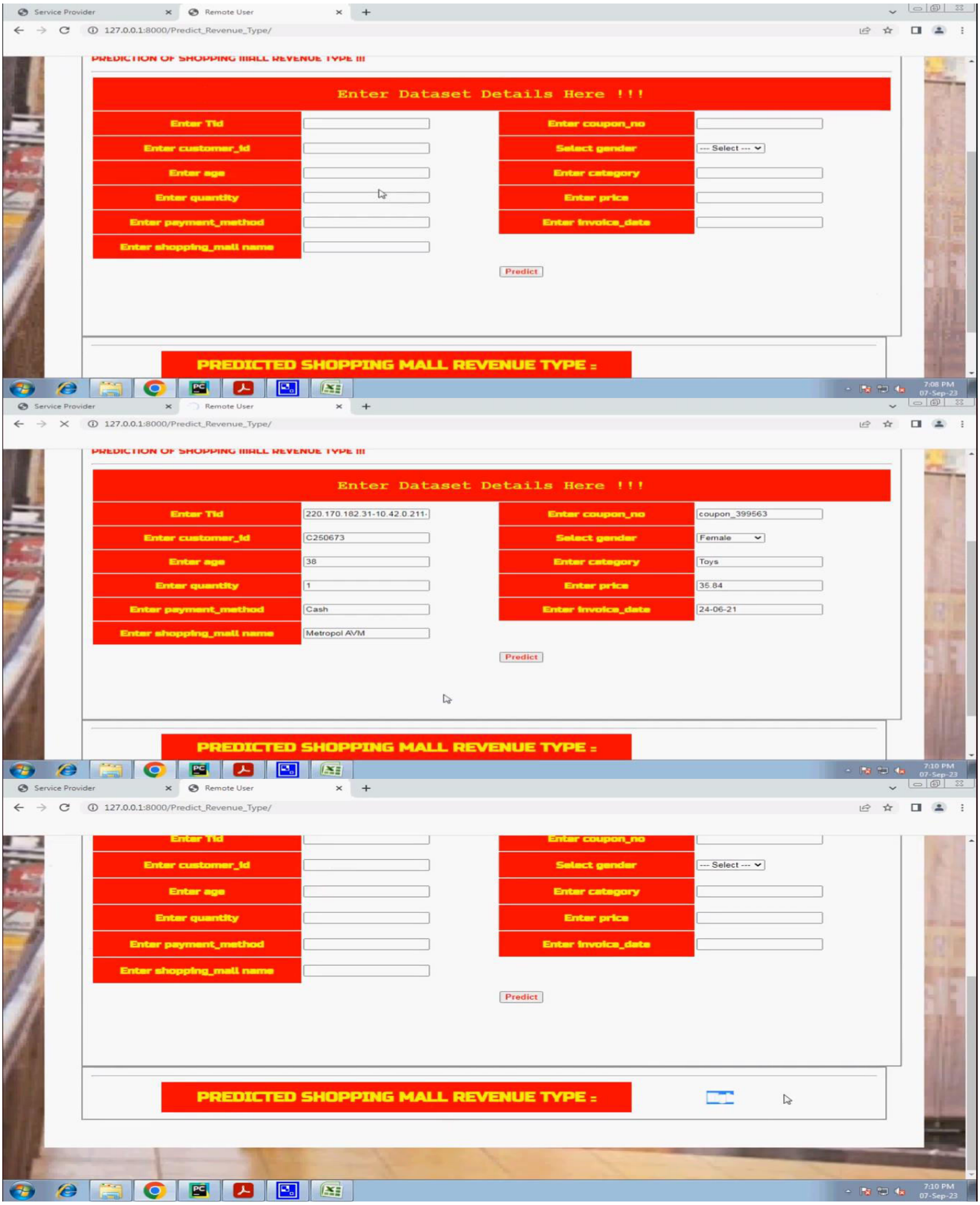


## VIII. CONCLUSION

In order to estimate how users will act on an online store, we looked for prior e-commerce marketing strategies. The use of a deep learning approach to forecast client churn in real time yielded accurate results. In order to increase the

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conversion rate and revenues, we implemented our findings into an online shopping mall. Using a segment model and a tailored suggested digital coupon, we created a framework to quantify the quantity of sales, which we utilized to verify whether our experiment had monetary worth. Scenario1, our model, yielded the highest quality outcomes. We discovered that it works well for online shopping malls to increase sales and conversion rates. Using big data and deep learning, our research demonstrated that marketing—a subfield of management—could be resolved more rapidly and effectively

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