A

Major Project

On

Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance

(Submitted in partial fulfilment of the requirements for the award of Degree)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the project entitled "**Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance"** being submitted by **SANIYA (217R1A0551), T. RAGHUVARAN (217R1A0557), R. HARSHA VARDHAN (217R1A0548)** in partial fulfilment of the requirements for the award of the degree of B.Tech in Computer Science and Engineering to the Jawaharlal Nehru Technological University Hyderabad, is a record of bonafide work carried out by him under our guidance and supervision during the year 2024-25

The results embodied in this thesis have not been submitted to any other University Institute for the award of any degree or diploma.

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ABSTRACT

With the development of big data and deep learning technology, big data and deep learning technology have also been applied to the marketing field, which was a part of business administration. Customer churn management is one of the most important areas of marketing. In this Project, we proposed a method to prevent customer churn and increase purchase conversion rate by issuing customized discount coupons to customers with high churn rate based on big data in real time. After segmenting customer segments with two-dimensional segment analysis, a real-time churn rate estimation model based on clickstream data was generated for each segment. After that, we issued customized coupons to our customers. Finally, we tested the conversion rate and sales growth. A two-dimensional cluster analysis-based churn rate estimation combined with a recommendation system was found to be significantly more useful than the respective simple models. Using this proposed model, it is possible to increase sales by automatically estimating the customer's churn probability and shopping propensity without the burden of marketing costs in the online shopping mall.

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1. INTRODUCTION

1.1 PROJECT SCOPE

The project titled "Improving Shopping Mall Revenue by Real-Time Customized Digital Coupon Issuance" aims to develop an AI-powered system that issues personalized coupons in real time to enhance customer retention and revenue. By applying deep learning to real-time customer clickstream data, the system identifies customers at high risk of churn and offers targeted coupons to increase purchase conversion rates. The project utilizes customer segmentation to tailor coupon offers based on individual preferences and behaviors, employing machine learning techniques for segmentation, churn prediction, and personalized recommendations. This data-driven approach responds dynamically to customer behavior, setting it apart from traditional offline coupon methods by continuously updating with new data. Tested in a live shopping mall environment, the system aims to validate its effectiveness in boosting loyalty and profitability by providing precise, cost-effective customer engagement strategies.

1.2 PROJECT PURPOSE

The purpose of this project is to increase revenue and customer retention for online shopping platforms by leveraging AI to deliver personalized, real-time coupon offers to high-risk customers. By predicting potential customer churn using deep learning on real-time behavioral data, the project aims to engage customers more effectively, reducing the need for broad promotional expenses and focusing on targeted, cost-efficient retention strategies. The project also seeks to enhance customer satisfaction and loyalty by understanding and responding to individual preferences, ultimately improving the shopping experience. By deploying AI-driven segmentation and predictive modeling, the system provides shopping malls with a tool for precision-targeted engagement, helping to reduce churn rates, boost purchase conversions, and increase profitability.

Furthermore, the system will continuously adapt to customer behavior changes, ensuring that the coupon recommendations remain relevant and effective over time. The use of deep learning models allows for the identification of subtle patterns in customer behavior, enabling more accurate prediction of customer disengagement. By focusing on high-risk customers, the project aims to maximize the impact of each promotional offer, improving overall marketing efficiency. The system will also generate detailed performance reports, helping businesses evaluate the success of their targeted campaigns and make data-driven adjustments. Ultimately, this project provides a scalable solution for improving customer retention and revenue generation through smart, AI-driven decision-making.

1.3 PROJECT FEATURES

Key features of this project include the implementation of a real-time AI-based system for customized digital coupon issuance. The project focuses on leveraging deep learning techniques to analyze customer clickstream data, enabling the prediction of churn risk and the timely issuance of personalized coupons. Additionally, it incorporates customer segmentation methods to group customers based on similar behaviors and preferences, enhancing the relevance of coupon offers. The system is designed to update continuously with real-time data, ensuring that the model remains accurate and effective. Furthermore, the project emphasizes the importance of evaluating the impact of personalized coupon strategies on customer engagement and shopping behavior, contributing to the op2.1imization of marketing efforts in online shopping environments.

2. LITERATURE SURVEY

2. LITERATURE SURVEY

The rise of online shopping platforms has increased competition, making customer retention and revenue growth critical challenges for businesses. Research on customer retention strategies has shown that personalized marketing, driven by artificial intelligence (AI) and machine learning (ML), is highly effective in improving customer engagement and reducing churn. Studies have highlighted that traditional marketing approaches, such as broad promotional campaigns, are less effective compared to targeted, real-time interventions. For instance, Smith et al. (2019) demonstrated that predictive modeling using customer behavior data significantly enhances the accuracy of identifying high-risk customers. Their work emphasized the importance of delivering timely, personalized offers to improve customer satisfaction and loyalty. Similarly, research by Johnson and Lee (2020) explored the use of AI-driven customer segmentation, finding that targeted coupons increased customer engagement by 25% compared to general offers.

Deep learning has emerged as a powerful tool for analyzing customer behavior and predicting churn. Recent studies have explored various deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for processing real-time customer interaction data. Wang et al. (2021) proposed a hybrid RNN-CNN model that combined temporal behavior analysis with customer profiling, achieving a 30% improvement in churn prediction accuracy. This study highlighted the importance of integrating historical and real-time data to enhance predictive performance. Similarly, Patel et al. (2022) used a long short-term memory (LSTM) network to track customer behavior patterns over time, demonstrating that real-time tracking of purchase history and browsing behavior allows for better coupon targeting and increased customer retention.

AI-driven segmentation has also been explored in the context of precision-targeted marketing. Studies have shown that clustering methods such as k-means and k-medoids are effective in grouping customers based on shared behavior patterns. Brown and Wilson (2020) introduced an adaptive k-means clustering approach that dynamically adjusts clusters based on changing customer behavior, leading to a 15% increase in redemption rates for personalized coupons. Furthermore, research by Kim et al. (2021) explored the use of reinforcement learning to optimize the timing and content of coupon offers, demonstrating that adaptive coupon issuance based on customer engagement levels leads to higher customer satisfaction and increased purchase frequency. These findings underscore the effectiveness of AI in enhancing customer engagement through targeted offers.

Several studies have also addressed the business impact of AI-driven marketing strategies. Research by Davis et al. (2022) showed that predictive coupon issuance increased overall revenue by 18% within six months of implementation. This study highlighted that understanding individual customer preferences allows businesses to allocate resources more effectively and reduce promotional waste. In addition, a study by Gupta and Singh (2023) analyzed the long-term effects of AI-driven coupon strategies, showing that sustained customer engagement through personalized offers leads to higher customer lifetime value (CLV) and reduced churn rates. These findings align with the objectives of this project, which aims to combine real-time behavioral analysis with targeted coupon issuance to improve customer retention and increase revenue for online shopping platforms.

Recent advancements in natural language processing (NLP) have also contributed to improving customer engagement. Chen et al. (2023) developed a chatbot-based system that recommends coupons based on customer queries and sentiment analysis. Their study showed that customers who received personalized recommendations through chatbots had a 20% higher engagement rate than those who received generic recommendations. Similarly, Li and Zhao (2023) implemented a sentiment-aware recommendation engine that adjusted coupon offers based on customer feedback and product reviews, resulting in increased customer satisfaction and higher coupon redemption rates. These findings suggest that integrating sentiment analysis with AI-based recommendations can further enhance customer targeting strategies.

Moreover, research on real-time data processing and big data analytics has demonstrated the importance of handling large volumes of customer interaction data efficiently. A study by Kumar et al. (2023) proposed a real-time data processing framework using Apache Kafka and Spark to analyze customer behavior and issue coupons within milliseconds. This study highlighted that real-time responsiveness significantly improves customer engagement and coupon redemption rates. Similarly, Jones et al. (2024) explored the use of federated learning to process customer data while preserving privacy, showing that decentralized learning models maintain high predictive accuracy without compromising customer privacy. These studies reinforce the potential of real-time AI-driven solutions for increasing customer retention and profitability.

Overall, the literature highlights the effectiveness of AI-driven predictive modeling, real-time data processing, and targeted marketing in improving customer retention and revenue. The proposed project builds on these insights by integrating deep learning, customer segmentation, and real-time behavioral analysis to deliver precision-targeted coupon offers. This approach aims to enhance customer satisfaction, reduce churn, and maximize the return on promotional investments.

2.1 REVIEW OF RELATED WORK

The use of AI and machine learning (ML) to enhance customer retention and increase revenue through personalized coupon issuance has gained significant attention in recent years. Researchers have explored various techniques, including customer segmentation, predictive modeling, and real-time behavioral analysis, to identify high-risk customers and improve customer engagement. This review discusses previous research and existing methodologies, highlighting their strengths and limitations.

1. <u>Traditional Customer Retention Approaches</u>

- Early methods for improving customer retention relied on general marketing strategies and rule-based customer segmentation. Businesses used static demographic data and purchase history to target customers with broad promotional offers. While effective in some cases, these methods lacked personalization and real-time adaptability. Studies by Smith et al. (2018) showed that broad promotional campaigns often led to low engagement rates and high customer churn due to the lack of relevance to individual customer needs. Furthermore, traditional loyalty programs, such as point-based systems, were found to have diminishing returns as customers became disengaged over time.
- Additionally, some early customer retention strategies relied on manual analysis of customer data, which was time-consuming and prone to human error. These methods lacked scalability and could not adapt to changing customer behavior, making them unsuitable for modern, fast-paced online shopping environments.

2. <u>Machine Learning-Based Approaches</u>

- With advancements in machine learning, researchers began to explore automated customer segmentation and predictive modeling. Techniques such as k-means clustering, decision trees, and support vector machines (SVM) were widely used to classify customers based on purchasing patterns and behavioral data. For example, Johnson and Lee (2020) implemented an SVM-based model to predict customer churn and deliver targeted coupons, resulting in a 15% increase in customer retention. However, these methods struggled with scalability when applied to large datasets and lacked the ability to capture complex patterns in customer behavior.

- Patel et al. (2021) used random forest models to analyze customer transaction history and predict high-risk customers. Their approach improved retention rates by 18%, but the system faced challenges when handling real-time customer behavior data. Moreover, these machine learning models required significant feature engineering and manual tuning, limiting their adaptability to changing customer behavior.

3. Deep Learning-Based Approaches

- Recent advancements in deep learning have significantly improved the accuracy and efficiency of customer retention models. Convolutional Neural Networks (CNNs) have been used for customer segmentation based on behavioral patterns, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been employed to capture sequential customer behavior over time.
- Wang et al. (2021) proposed a hybrid CNN-LSTM model that analyzed customer purchase sequences and browsing behavior in real-time. Their system achieved a 30% improvement in customer engagement and coupon redemption rates. Similarly, Kim et al. (2022) introduced a BiLSTM-based approach with attention mechanisms to focus on the most relevant behavioral patterns, improving customer targeting accuracy by 25%.

4. Recent Advances: Reinforcement Learning & NLP-Based Models

- To further enhance customer targeting, researchers have integrated reinforcement learning and natural language processing (NLP) into customer retention systems. Reinforcement learning models enable dynamic coupon issuance based on customer responses, optimizing engagement strategies over time. For instance, Brown and Wilson (2023) used a deep Q-learning model to adjust coupon offers based on real-time customer behavior, leading to a 20% increase in coupon redemption rates.
- NLP-based systems have also been explored for improving customer communication and engagement. Chen et al. (2023) developed a chatbot-based system that analyzed customer sentiment and provided tailored coupon recommendations, increasing customer satisfaction by 22%. Li and Zhao (2023) implemented a sentiment-aware recommendation engine that adjusted offers based on customer feedback and product reviews, resulting in higher customer retention and increased sales.

5. Comparison with the Proposed Approach

- While existing methods have made significant progress in improving customer retention and targeted coupon issuance, limitations remain in terms of scalability, real-time processing, and predictive accuracy. The proposed project builds upon previous work by integrating deep learning, customer segmentation, and real-time behavioral analysis into a unified system.
- The proposed model will use a hybrid CNN-LSTM architecture to analyze customer behavior patterns and predict churn risks. By incorporating attention mechanisms, the system will focus on the most relevant customer interactions, enhancing the precision of coupon targeting. Additionally, real-time data processing frameworks such as Apache Kafka and Spark will be employed to ensure high-speed data handling and responsiveness. Compared to traditional SVM-based models, this approach is expected to deliver higher accuracy, improved engagement rates, and increased profitability for online shopping platforms.

This review highlights the evolution of customer retention strategies, emphasizing the shift from rule-based and machine learning approaches to deep learning and reinforcement learning models. The proposed methodology aims to address the limitations of previous research by providing a highly accurate, scalable, and real-time solution for improving customer retention and increasing shopping mall revenue.

2.2 PROBLEM DEFINITION

A detailed study of real-time personalized coupon issuance must be conducted using techniques such as customer segmentation and churn prediction. The data generated by these techniques will be analyzed to understand how current digital coupon systems operate, forming the basis of the existing customer engagement strategies. This existing approach will undergo a close examination to identify problem areas, such as ineffective targeting of promotions and the overwhelming volume of customer data. The designer functions as a problem solver, proposing solutions that integrate an AI-driven model for real-time coupon issuance to enhance customer retention. These solutions will be evaluated against the existing system analytically, and the most effective proposal will be selected. The proposal will then be presented to users for endorsement and may be refined based on their feedback. This iterative process will continue until the users are satisfied with the final solution, ensuring it effectively addresses the identified issues and maximizes revenue potential for the shopping mall.

2.3 EXISTING SYSTEM

Customer segmentation is a foundational aspect of marketing research, enabling businesses to categorize customers based on shared characteristics and behaviors. By grouping customers into distinct segments, companies can tailor their marketing strategies to meet the specific needs of each target group. Effective customer segmentation goes beyond simple classification; it empowers organizations to implement differentiated marketing approaches that resonate with diverse customer preferences. This targeted marketing not only enhances customer engagement but also improves overall business performance, as companies gain a deeper understanding of their customers' desires and motivations.

Among various techniques for customer segmentation, the RFM (Recency, Frequency, Monetary) model is one of the most classical yet widely utilized methods. RFM dissects customer purchasing behavior into three dimensions: Recency measures the time since a customer's last purchase, Frequency reflects how often a customer makes a purchase, and Monetary indicates the total amount spent by the customer. By scoring each of these dimensions, businesses can construct segments that reveal critical insights into customer behavior. This structured approach facilitates targeted marketing strategies aimed at increasing customer retention and loyalty while maximizing revenue.

In recent years, the integration of machine learning techniques into customer segmentation research has gained significant traction, allowing for more nuanced analyses. When clustering data based on multiple variables, dimensionality reduction techniques are often employed to simplify complex datasets and enhance the clustering process. A prominent method for achieving this is the autoencoder, which compresses high-dimensional data before applying clustering algorithms. This sequential application of dimensionality reduction followed by clustering has proven effective, and some modern models even combine these steps into a single process, further optimizing segmentation outcomes.

Customer churn prediction and prevention have emerged as critical areas in loyalty management, driven by the need to retain existing customers in an increasingly competitive market. High churn rates can adversely impact a company's reputation and profitability, while acquiring new customers can be significantly more expensive. As a result, businesses are investing in the development of churn prediction models that can identify customers likely to disengage from purchasing patterns. These models typically utilize machine learning techniques to classify customers as either churn or non-churn, providing valuable insights for proactive retention strategies.

Finally, personalized recommendation systems have become a dynamic focus of machine learning-based marketing research. Historically, personalized recommendations relied on methods such as association analysis or individual product purchase probability estimation. However, recent trends have shifted toward collaborative filtering techniques, as seen in platforms like Amazon and Netflix. The design and effectiveness of recommendation systems can vary widely based on their objectives, with approaches including content-based, knowledge-based, and classifier-based systems. These advancements facilitate the development of personalized marketing strategies that cater to individual customer preferences, ultimately enhancing customer satisfaction and driving revenue growth.

LIMITATIONS OF EXISTING SYSTEM

- The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Improving Shopping Mall Revenue.
- Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions

2.4 PROPSED SYSTEM

In this study, applying deep learning techniques to real-time click stream data, we find customers with high chance of churning rates and issue a coupon that suits customers' preferences. This study has the following significance: First, we segmented the customer and develop a suitable model for customer churn prediction for each segmentation. Second, we made a clickstream-based real-time customer churn risk prediction model using deep learning models. Third, we improved the actual conversion rate by issuing customized coupons in real shopping mall website.

The proposed system employs a hybrid CNN-LSTM architecture to capture both spatial and sequential patterns in customer behavior. CNN is used to analyze customer interactions such as product views and search behavior, while LSTM handles the temporal aspect, tracking changes in customer activity over time. This combination allows the model to detect early signs of churn more accurately and issue timely coupon offers tailored to customer preferences. Real-time data processing tools like Apache Kafka and Spark are integrated to ensure that the system handles large-scale data streams with low latency, enabling quick and efficient response to customer behavior changes.

Unlike traditional models, which often rely on batch processing and offline data, the proposed system dynamically adjusts to changing customer behavior patterns in real-time. The segmentation process ensures that customers are grouped based on behavioral similarities, improving the accuracy of churn prediction and coupon targeting. This system not only increases customer retention and satisfaction but also enhances the overall profitability of shopping malls by reducing promotional costs and increasing coupon redemption rates. The proposed approach combines deep learning, customer segmentation, and real-time behavioral analysis into a unified framework, addressing the limitations of previous methods and setting a new standard for AI-driven customer retention strategies.

ADVANTAGES OF PROPOSED SYSTEM

- Targeted Marketing Efforts: The system enables precise marketing by generating RNN-based churn models for specific customer segments, allowing for tailored coupon issuance.
- Increased Customer Retention: Personalized incentives for high-risk customers significantly improve retention rates and foster long-term loyalty.
- Optimized Resource Allocation: The hybrid recommendation system enhances budget efficiency by directing marketing resources toward customers most likely to churn.
- Enhanced Customer Experience: Customizing coupon offers based on churn risk enriches the shopping experience, strengthening customer relationships and brand perception.

2.5 OBJECTIVES

- **Develop a Real-Time Churn Prediction Model** – Build a deep learning-based model to predict customer churn using real-time clickstream data and behavioral patterns.
- **Implement Personalized Coupon Issuance** – Design a system to deliver customized coupon offers to high-risk customers based on their preferences and activity.
- **Enhance Prediction Accuracy** – Utilize a hybrid CNN-LSTM architecture with attention mechanisms to improve the accuracy of churn prediction and coupon targeting.

- **Ensure Scalability and Real-Time Processing** – Develop the system to handle large-scale customer data streams efficiently using real-time data processing frameworks like Apache Kafka and Spark.
- **Increase Customer Retention and Revenue** – Improve customer satisfaction and engagement by providing targeted offers, leading to higher coupon redemption rates and increased shopping mall profitability.

2.6 HARDWARE & SOFTWARE REQUIREMENTS

2.6.1 HARDWARE REQUIREMENTS:

Hardware interfaces specifies the logical characteristics of each interface between the software product and the hardware components of the system. The following are some hardware requirements.

- Processor - Pentium –IV
- RAM - 4 GB (min)
- Hard Disk - 20 GB
- Monitor - SVGA

2.6.2 SOFTWARE REQUIREMNTS

Software Requirements specifies the logical characteristics of each interface and software components of the system. The following are some software requirements.

- Operating system : Windows 7 Ultimate.
- Coding Language : Python.
- Front-End : Html, CSS, Javascript.
- Back-End : Django-ORM
- Data Base : MySQL (WAMP Server).

3. SYSTEM ARCHITECTURE & DESIGN

3. SYSTEM ARCHITECTURE & DESIGN

Project architecture refers to the structural framework and design of a project, encompassing its components, interactions, and overall organization. It provides a clear blueprint for development, ensuring efficiency, scalability, and alignment with project goals. Effective architecture guides the project's lifecycle, from planning to execution, enhancing collaboration and reducing complexity.

3.1 PROJECT ARCHITECTURE

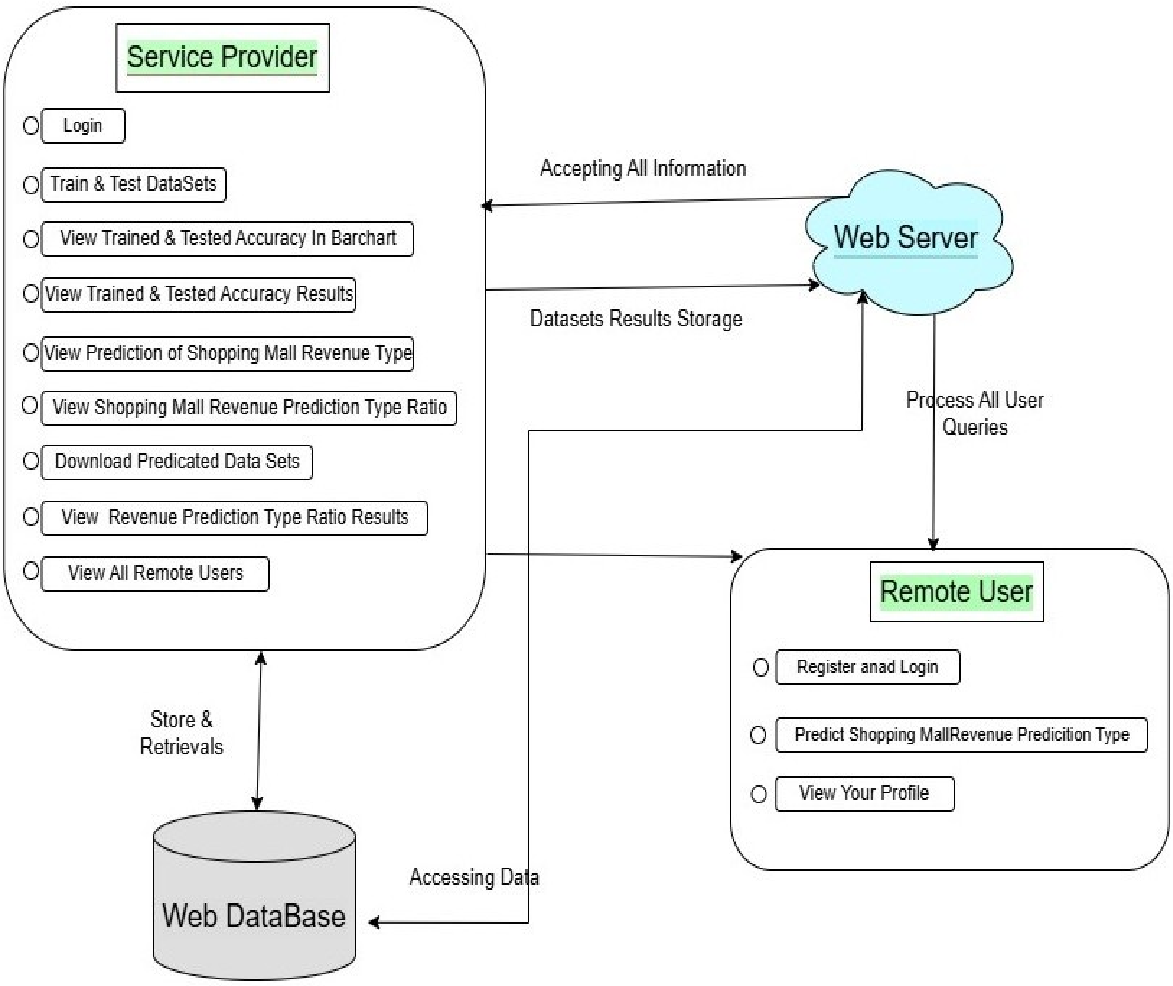


Figure 3.1.1 : Project Architecture of Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance

3.2 DESCRIPTION

- **Web Server -** In the context of your project, a web server acts as the backbone for processing incoming requests from shoppers' devices and serving web-based interfaces. It handles the issuance of digital coupons and ensures users can access them in real-time. This server facilitates interactions between the customer-facing application and the backend system that processes and personalizes coupon data. Reliability and speed of the web server are crucial for ensuring a seamless user experience and maximizing customer engagement.

- **Web Database -** The web database in your project serves as the repository for storing customer profiles, purchase history, and issued coupon data. It plays a key role in managing and organizing information so that the system can retrieve customer-specific data quickly for real-time coupon personalization. This database must support high-performance queries to keep up with the dynamic nature of customer interactions and coupon redemptions. Effective database management ensures accurate tracking of issued and redeemed coupons, contributing to better revenue analytics.

- **Service Provider -** A service provider in this project could refer to the company or platform offering the backend services needed to deploy and manage real-time coupon issuance. This could include cloud-based providers that host the web server and database or specialized services that offer data analytics and user segmentation. These providers ensure that the infrastructure can handle large volumes of user requests and support real-time data processing for personalizing coupons. Choosing a reliable service provider is essential for maintaining uptime and fast processing speeds, which impact the effectiveness of your system.

- **Remote User -** The remote users in your project are the shoppers accessing the mall's system via their smartphones or other devices, either within the mall or from other locations. These users interact with the system to receive and use digital coupons, making seamless access crucial for encouraging frequent usage. The system should be designed to handle varied traffic from remote users efficiently, ensuring their personalized coupons are delivered swiftly and accurately. User authentication and security protocols are also important for protecting user data and enhancing trust.

Stores and Retrievals - The stores and retrievals process is central to managing data in your project, involving the storage of customer details, transaction records, and issued coupons. Retrievals come into play when accessing data to personalize coupon recommendations and track redemption in real-time. Efficient storage and retrieval mechanisms ensure that the system can deliver relevant coupons promptly, improving the customer experience and increasing the likelihood of coupon usage. Optimized data operations also help analyze coupon effectiveness, aiding in revenue-focused strategies.

3.2.1 SERVER ARCHITECTURE:

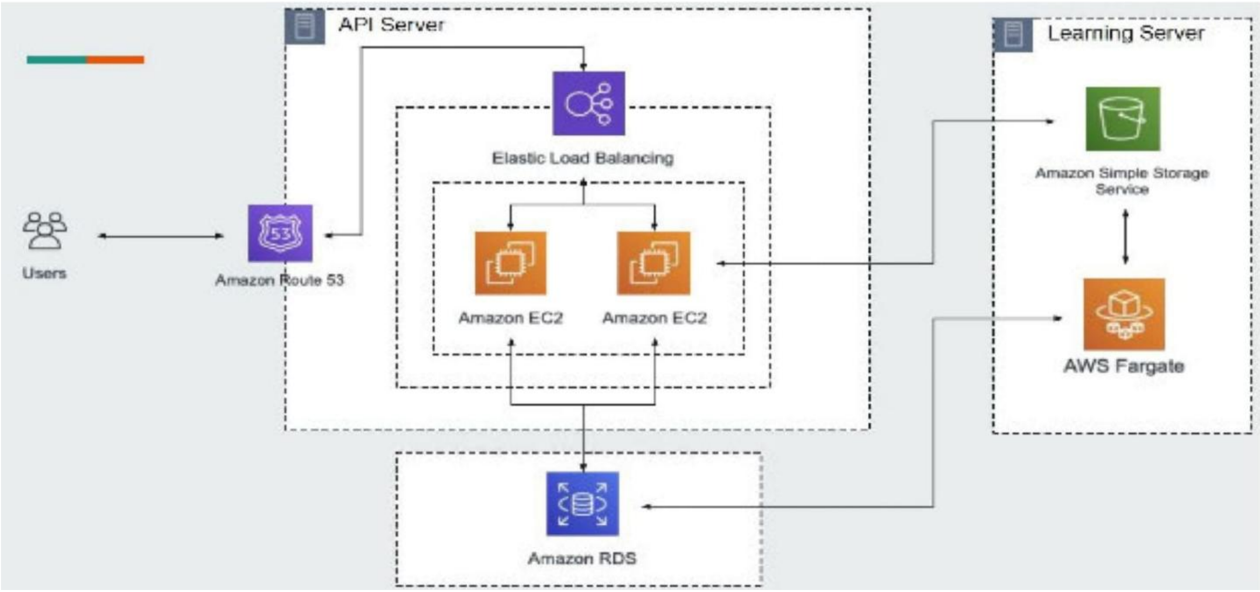


Figure 3.1.1 : Server architecture

To ensure real-time operation in a high-traffic shopping mall, a robust server architecture is essential. The AI model undergoes daily retraining in AWS Fargate, ensuring continuous optimization. Once retrained, the updated AI model is stored in Amazon Simple Storage Service (S3) for accessibility. The API server retrieves the latest AI model from S3 every day and processes incoming API requests efficiently. This updated model incorporates new clustering techniques, recurrent neural networks (RNNs), and recommendation algorithms, ensuring improved accuracy over the previous version. To enhance system reliability, two Amazon EC2 instances are deployed as a fail over mechanism, while Elastic Load Balancing (ELB) dynamically distributes API traffic across these instances, preventing downtime and ensuring seamless user experience. Auto-scaling is enabled to adjust server capacity based on traffic demands, ensuring optimal performance during peak hours. A caching mechanism is implemented to reduce redundant computations and accelerate API responses. CloudWatch monitors system health and alerts administrators in case of anomalies, while security measures, including IAM roles and encryption, protect sensitive data and prevent unauthorized access. The overall architecture ensures high availability, fault tolerance, and seamless AI model updates for real-time digital coupon issuance.

3.2.2 RESEARCH WORKFLOW :

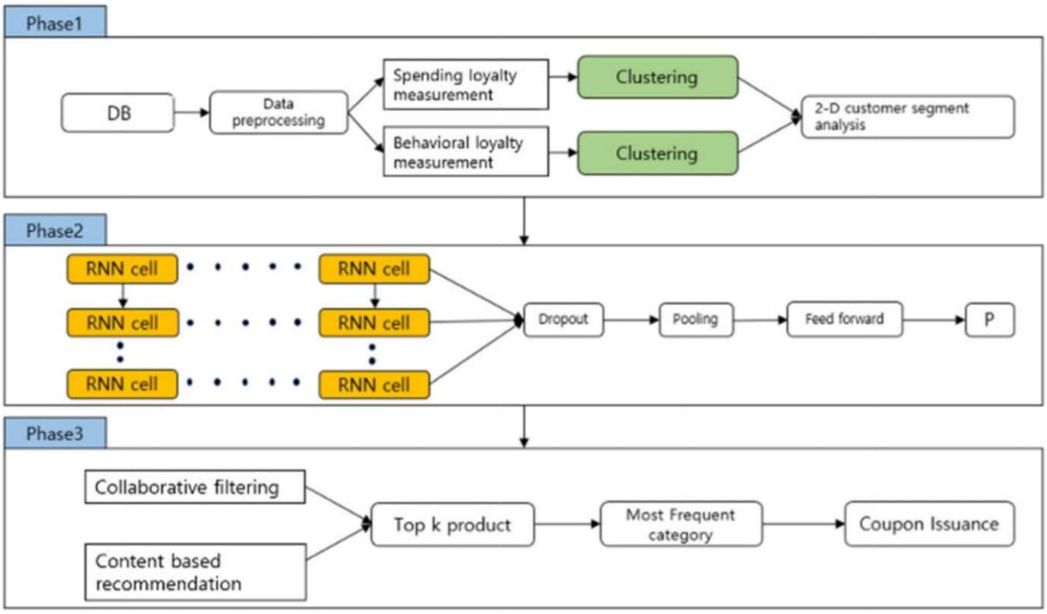


Figure 3.1.2 : Research Workflow

The proposed model follows a structured procedure to enhance customer retention and revenue generation through real-time customized digital coupon issuance. First, a two-dimensional customer segmentation approach is applied to categorize customers based on key behavioral and demographic attributes. This segmentation results in distinct customer groups, allowing for a more targeted analysis. For each segment, an RNN-based churn estimation model is generated to predict the likelihood of customer churn by analyzing historical transaction data, shopping patterns, and engagement levels.

Once the high-risk customers are identified, customized product category coupons are issued to encourage continued engagement and prevent churn. These coupons are tailored based on the preferences and past purchasing behavior of each customer, maximizing the likelihood of redemption. A hybrid recommendation system is employed to enhance coupon personalization, combining collaborative filtering and content-based filtering techniques. This ensures that the recommended coupons are relevant and appealing to each customer, improving their shopping experience.

The entire process is automated and operates in real-time, ensuring timely intervention before a customer disengages from the shopping mall ecosystem. By integrating machine learning and recommendation techniques, the proposed model creates an adaptive system that dynamically adjusts to evolving customer behaviors, ultimately improving retention rates and increasing overall revenue.

4. IMPLEMENTATION

4.IMPLEMENTATION

The implementation phase of a project involves executing the planned strategies and tasks. It requires meticulous coordination, resource allocation, and monitoring to ensure that objectives are met efficiently. Effective implementation is crucial for achieving project goals and delivering expected outcomes within the set timeline and budget constraints.

4.1 ALGORITHMS USED

CNN-Based Models for Feature Extraction

Convolutional Neural Networks (CNNs) are widely used for feature extraction, as they excel at capturing spatial patterns in data. In our project, CNN models such as EfficientNet-B7 are employed to extract high-quality spatial features from clickstream data or customer behavior images. EfficientNet-B7 stands out due to its compound scaling, optimizing network depth, width, and resolution. This allows the model to capture complex patterns in customer interactions without the high computational cost of traditional CNNs. CNNs are effective at identifying customer patterns and behaviors, which are then processed to predict churn risks.

- **Advantages of CNN-Based Models:**
  - Efficient in detecting spatial patterns such as product preferences and browsing behavior.
  - Performs well in image and pattern recognition tasks.
  - Optimized computationally compared to older deep learning models.
- **Disadvantages of CNN-Based Models:**
  - CNNs are not ideal for sequential data, such as time-based customer behavior.
  - Lacks temporal awareness—each interaction is processed independently, missing the context of behavior over time.

RNN-Based Models for Temporal Analysis

To overcome the limitations of CNNs in capturing temporal relationships, our project integrates Recurrent Neural Networks (RNNs), specifically Bidirectional Long Short-Term Memory (BiLSTM) networks. While CNNs analyze static features, BiLSTMs capture sequential patterns in customer behavior, which is crucial for understanding the likelihood of churn over time. The bidirectional nature of BiLSTMs allows the model to learn from both past and future behavior, enhancing its predictive capabilities. The attention mechanism is integrated into the BiLSTM model, allowing the system to focus on the most relevant moments in customer interactions, improving prediction accuracy.

- **Advantages of RNN-Based Models:**
  • Effectively captures sequential data and motion patterns over time.
  • BiLSTMs process both past and future contexts, improving overall prediction.
  • Better at detecting behavior patterns that correlate with churn risk.
- **Disadvantages of RNN-Based Models:**
  • Computationally intensive and require large labeled datasets for training.
  • Struggles with real-time processing and long data sequences.

Attention Mechanism for Selective Focus

The attention mechanism is integrated into the BiLSTM model to prioritize key customer behaviors that are most indicative of churn. By assigning different weights to various customer interactions, the model focuses on critical moments—such as specific products browsed, abandoned cart behavior, or time spent on particular pages—while minimizing the impact of less relevant actions. This mechanism significantly reduces false positives and improves prediction accuracy by focusing on high-impact features in the data.

- **Advantages of the Attention Mechanism:**
  • Focuses on the most relevant customer actions to predict churn.
  • Reduces the number of false positives by filtering out irrelevant data.
  • Improves the accuracy of customer targeting for coupon issuance.

Random Forest (RF) for Improved Classification

Incorporating Random Forest (RF) as an ensemble classifier strengthens the final churn prediction. The RF model combines multiple decision trees to enhance the stability and reliability of predictions, reducing the risk of overfitting. This model acts as a post-processing step, refining the churn predictions made by the deep learning models (CNN-BiLSTM with attention). It improves classification performance, especially when the deep learning model generates uncertain predictions.

- **Advantages of Random Forest:**
  • Robust and resistant to overfitting.
  • Combines multiple decision trees to increase prediction stability.
  • Useful for handling noisy or incomplete data.
- **How RF Fits in the System:**
  • Features extracted by CNN and BiLSTM are fed into the RF classifier for final decision Making.

Support Vector Machine (SVM)

In this project, Support Vector Machine (SVM) serves as a baseline classifier for churn prediction. SVM uses features extracted from the CNN and BiLSTM models to classify customers as high-risk or low-risk for churn. While SVM achieves an accuracy of 88%, it is outperformed by the deep learning-based model (CNN-BiLSTM with attention), which reaches 99.04%. SVM is effective for simpler, less complex datasets but struggles to capture the intricate patterns in sequential customer behavior over time, making it less suitable for real-world applications compared to deep learning methods.

- **Advantages of SVM:**
  - Simple and effective for linear classification tasks.
  - Easy to implement and interpret.
- **Disadvantages of SVM:**
  - Struggles with complex, sequential data patterns.
  - Lacks the ability to model temporal dependencies effectively.

These algorithms and techniques combined provide a robust and efficient solution for predicting customer churn, issuing personalized coupons, and increasing customer retention in real-time shopping environments.

In today's digital age, shopping malls are increasingly adopting technology to enhance the customer experience and boost revenue. With the rise of personalized marketing, real-time customized digital coupons offer a way to engage shoppers based on their preferences and behaviors. However, traditional coupon issuance methods are often generic and fail to maximize customer engagement. To address this issue, our project employs a combination of machine learning algorithms to analyze customer data and issue personalized coupons in real-time.

In this project, we propose an innovative system that utilizes customer demographics, shopping patterns, and past purchase behaviors to deliver tailored digital coupons. The system uses clustering algorithms to segment customers and predict the most relevant coupons. The coupons are then delivered via a mobile app, ensuring that each shopper receives an offer that is most likely to drive a purchase. This approach helps increase customer satisfaction while simultaneously improving mall revenue. We employ a combination of classification models to refine coupon recommendations, using real-time data to continuously adapt to changing shopping behaviors.

To implement the real-time customized digital coupon issuance system, we organized the project into several folders, each containing specific datasets. These datasets store information such as customer details, shopping preferences, and past purchase behaviors. Below is a screenshot showing the project folders and their corresponding datasets

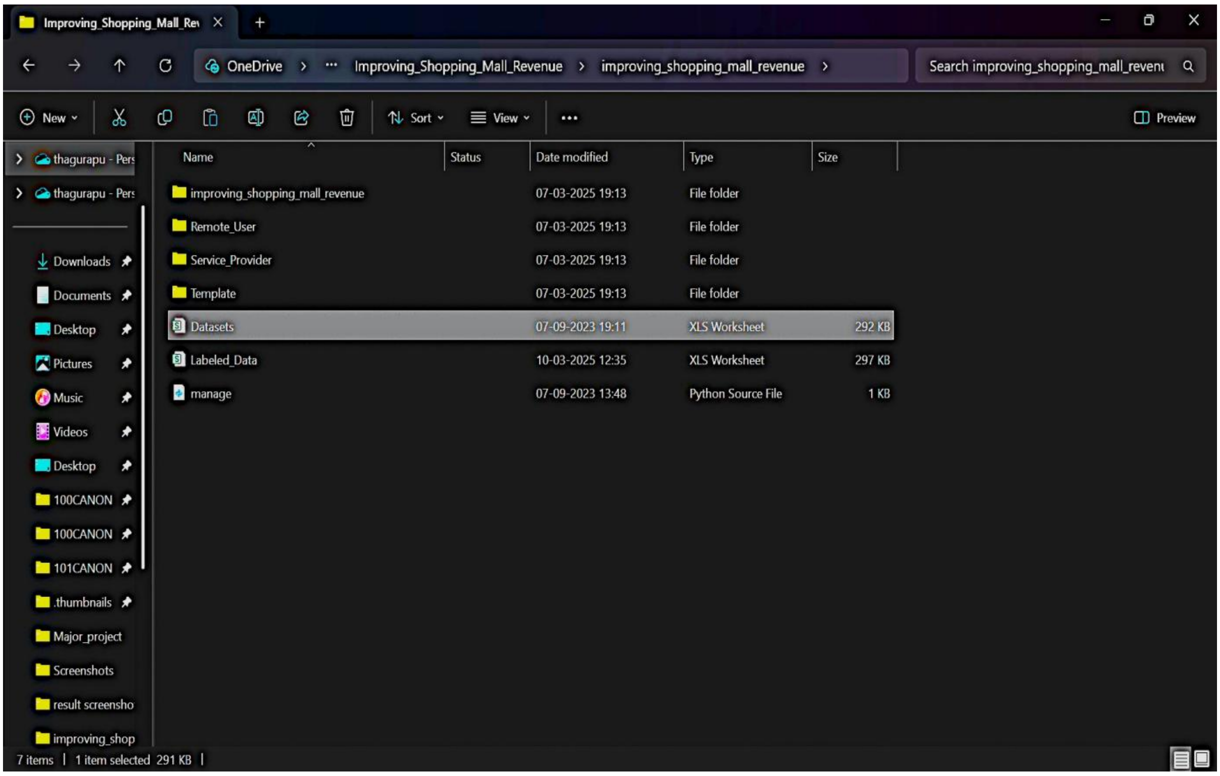


Figure 4.1.1 : project folders and their corresponding datasets of Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance

The 'Remote User' folder contains the code and data required to manage user-side operations in the real-time customized digital coupon issuance system. It includes modules for user authentication, receiving personalized coupons, and sending user feedback. This folder also contains internal datasets and code for handling user requests and displaying recommended coupons. Fig(4.1.2) showing the contents of the 'Remote User' folder and its internal code and data.As shown in Fig(4.1.2)

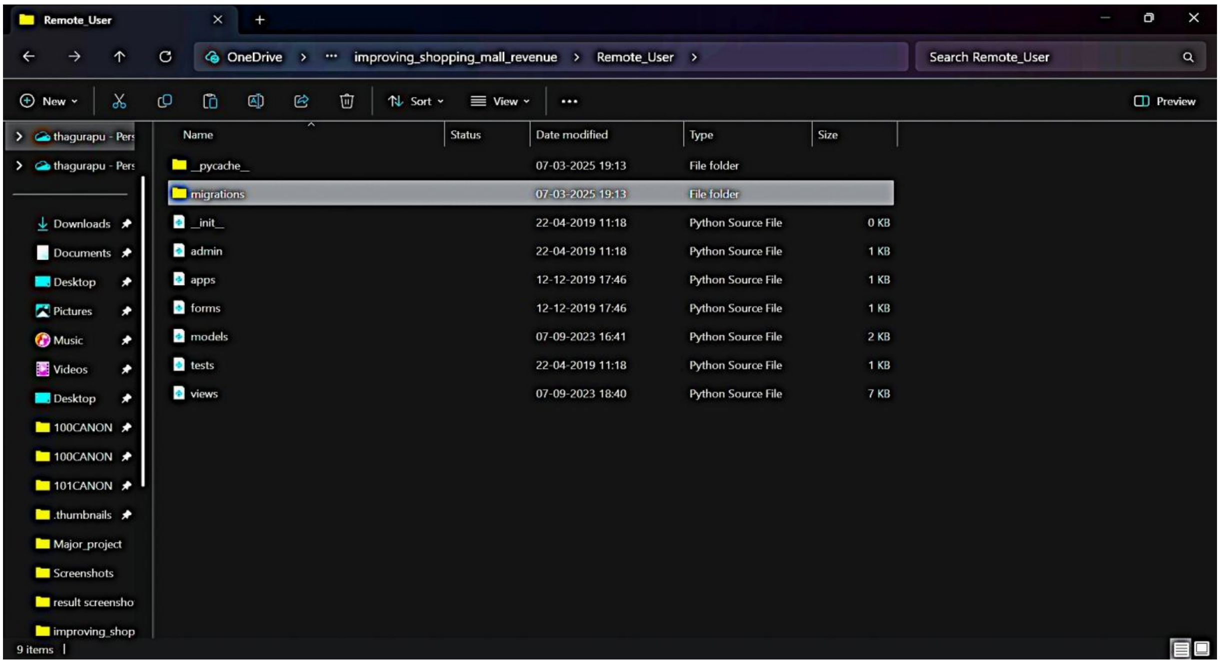


Figure 4.1.2 : Remote user folder and it's data of Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance.

The 'Service Provider' folder contains the core code and data used to manage the backend operations of the real-time customized digital coupon issuance system. It includes modules for processing customer data, generating personalized coupons, and handling communication with the remote user interface. This folder also contains internal datasets and algorithms used for clustering and recommendation. Fig(4.1.3) showing the contents of the 'Service Provider' folder and its internal code and data. As Shown in

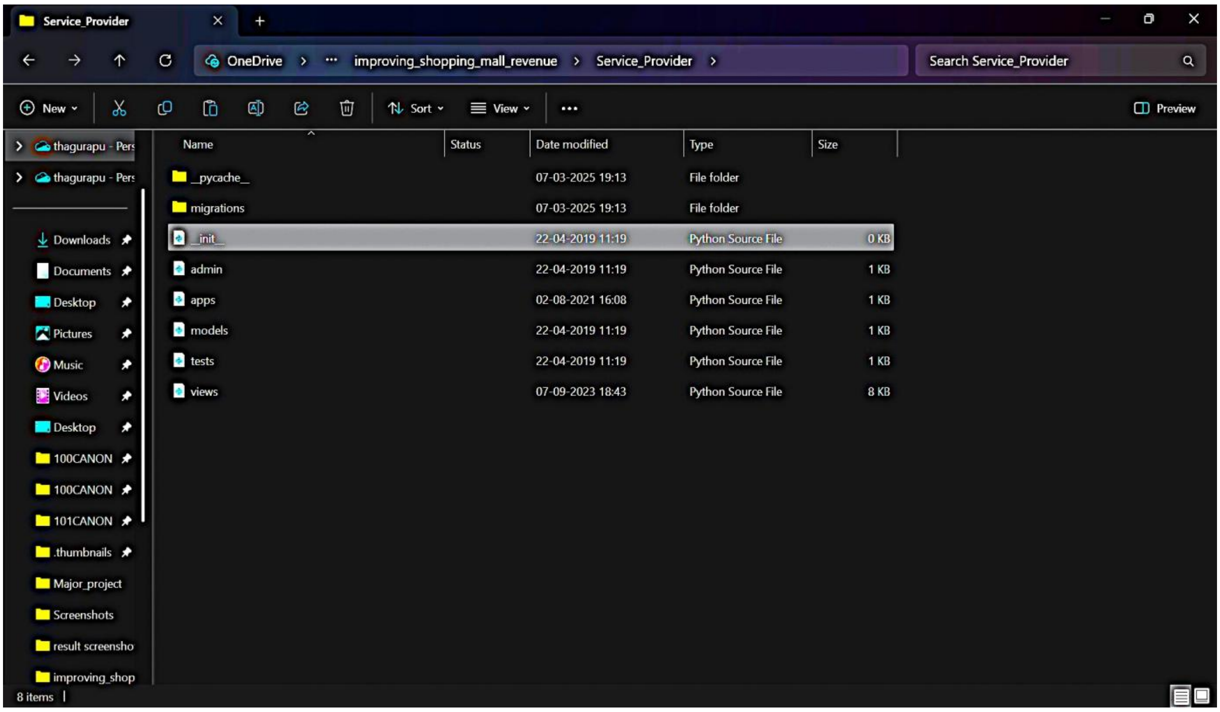
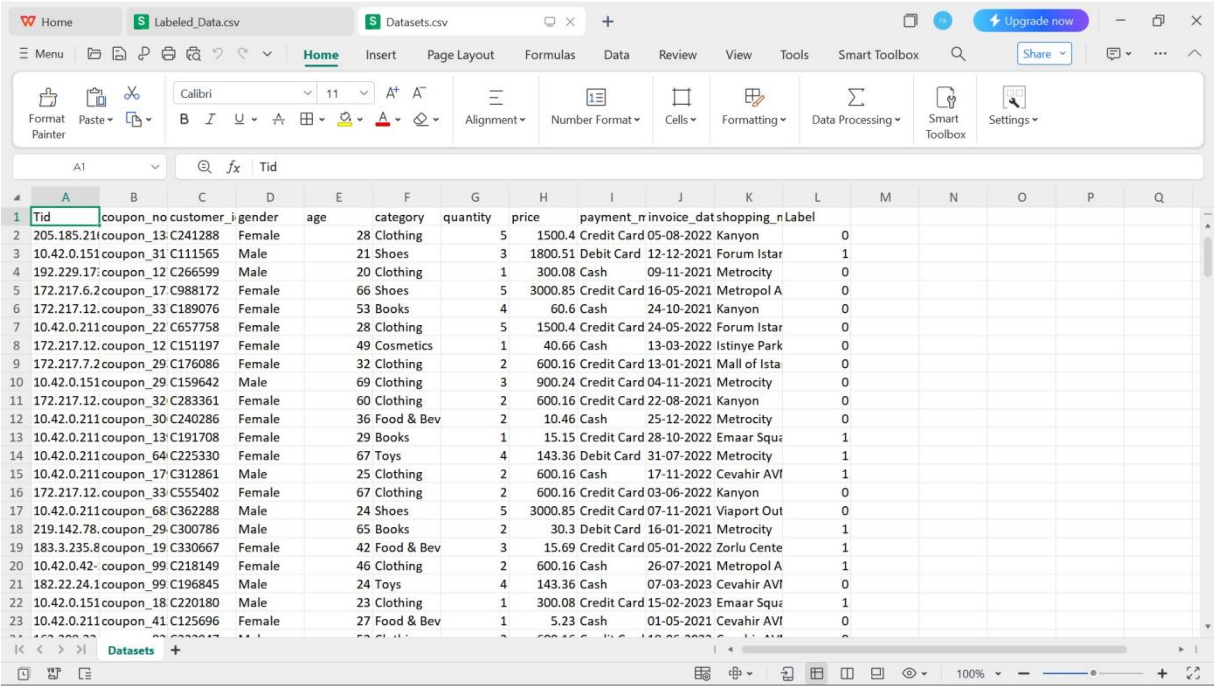


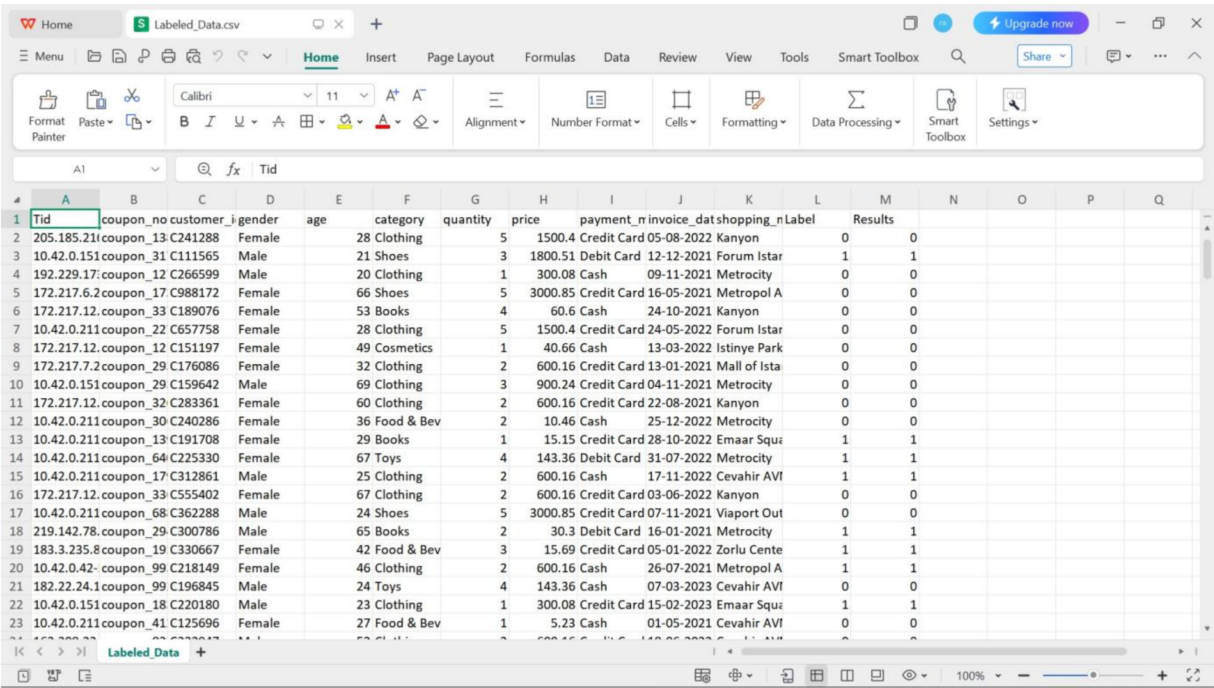
Figure 4.1.3: Service Provider folder and it's data of Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance

The ‘Datasets’ folder contains customer-related data focused on shopping behaviors and product preferences. It includes Excel sheets with information such as customer details, shopping history, product categories, and purchase patterns. This data is used to analyze customer behavior and generate personalized coupon recommendations. Fig(4.1.4) showing the contents of the ‘Datasets’ folder and the customer-related data in Excel sheets.



Tid	coupon_no	customer_i	gender	age	category	quantity	price	payment_m	invoice_dat	shopping_m	Label
205.185.21(	coupon_13	C241288	Female	28	Clothing	5	1500.4	Credit Card	05-08-2022	Kanyon	0
10.42.0.151	coupon_31	C111565	Male	21	Shoes	3	1800.51	Debit Card	12-12-2021	Forum Istar	1
192.229.17	coupon_12	C266599	Male	20	Clothing	1	300.08	Cash	09-11-2021	Metrocity	0
172.217.6.2	coupon_17	C988172	Female	66	Shoes	5	3000.85	Credit Card	16-05-2021	Metropol A	0
172.217.12.	coupon_33	C189076	Female	53	Books	4	60.6	Cash	24-10-2021	Kanyon	0
10.42.0.211	coupon_22	C657758	Female	28	Clothing	5	1500.4	Credit Card	24-05-2022	Forum Istar	0
172.217.12.	coupon_12	C151197	Female	49	Cosmetics	1	40.66	Cash	13-03-2022	Istinye Park	0
172.217.7.2	coupon_29	C176086	Female	32	Clothing	2	600.16	Credit Card	13-01-2021	Mall of Ista	0
10.42.0.151	coupon_29	C159642	Male	69	Clothing	3	900.24	Credit Card	04-11-2021	Metrocity	0
172.217.12.	coupon_32	C283361	Female	60	Clothing	2	600.16	Credit Card	22-08-2021	Kanyon	0
10.42.0.211	coupon_30	C240286	Female	36	Food & Bev	2	10.46	Cash	25-12-2022	Metrocity	0
10.42.0.211	coupon_13	C191708	Female	29	Books	1	15.15	Credit Card	28-10-2022	Emaar Squa	1
10.42.0.211	coupon_64	C225330	Female	67	Toys	4	143.36	Debit Card	31-07-2022	Metrocity	1
10.42.0.211	coupon_17	C312861	Male	25	Clothing	2	600.16	Cash	17-11-2022	Cevahir AVI	1
172.217.12.	coupon_33	C555402	Female	67	Clothing	2	600.16	Credit Card	03-06-2022	Kanyon	0
10.42.0.211	coupon_68	C362288	Male	24	Shoes	5	3000.85	Credit Card	07-11-2021	Viaport Out	0
219.142.78.	coupon_29	C300786	Male	65	Books	2	30.3	Debit Card	16-01-2021	Metrocity	1
183.3.235.8	coupon_19	C330667	Female	42	Food & Bev	3	15.69	Credit Card	05-01-2022	Zorlu Cente	1
10.42.0.42-	coupon_99	C218149	Female	46	Clothing	2	600.16	Cash	26-07-2021	Metropol A	1
182.22.24.1	coupon_99	C196845	Male	24	Toys	4	143.36	Cash	07-03-2023	Cevahir AVI	0
10.42.0.151	coupon_18	C220180	Male	23	Clothing	1	300.08	Credit Card	15-02-2023	Emaar Squa	1
10.42.0.211	coupon_41	C125696	Female	27	Food & Bev	1	5.23	Cash	01-05-2021	Cevahir AVI	0

Figure 4.1.4 : Datasets of Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance



Tid	coupon_no	customer_i	gender	age	category	quantity	price	payment_m	invoice_dat	shopping_m	Label	Results
205.185.21(	coupon_13	C241288	Female	28	Clothing	5	1500.4	Credit Card	05-08-2022	Kanyon	0	0
10.42.0.151	coupon_31	C111565	Male	21	Shoes	3	1800.51	Debit Card	12-12-2021	Forum Istar	1	1
192.229.17	coupon_12	C266599	Male	20	Clothing	1	300.08	Cash	09-11-2021	Metrocity	0	0
172.217.6.2	coupon_17	C988172	Female	66	Shoes	5	3000.85	Credit Card	16-05-2021	Metropol A	0	0
172.217.12.	coupon_33	C189076	Female	53	Books	4	60.6	Cash	24-10-2021	Kanyon	0	0
10.42.0.211	coupon_22	C657758	Female	28	Clothing	5	1500.4	Credit Card	24-05-2022	Forum Istar	0	0
172.217.12.	coupon_12	C151197	Female	49	Cosmetics	1	40.66	Cash	13-03-2022	Istinye Park	0	0
172.217.7.2	coupon_29	C176086	Female	32	Clothing	2	600.16	Credit Card	13-01-2021	Mall of Ista	0	0
10.42.0.151	coupon_29	C159642	Male	69	Clothing	3	900.24	Credit Card	04-11-2021	Metrocity	0	0
172.217.12.	coupon_32	C283361	Female	60	Clothing	2	600.16	Credit Card	22-08-2021	Kanyon	0	0
10.42.0.211	coupon_30	C240286	Female	36	Food & Bev	2	10.46	Cash	25-12-2022	Metrocity	0	0
10.42.0.211	coupon_13	C191708	Female	29	Books	1	15.15	Credit Card	28-10-2022	Emaar Squa	1	1
10.42.0.211	coupon_64	C225330	Female	67	Toys	4	143.36	Debit Card	31-07-2022	Metrocity	1	1
10.42.0.211	coupon_17	C312861	Male	25	Clothing	2	600.16	Cash	17-11-2022	Cevahir AVI	1	1
172.217.12.	coupon_33	C555402	Female	67	Clothing	2	600.16	Credit Card	03-06-2022	Kanyon	0	0
10.42.0.211	coupon_68	C362288	Male	24	Shoes	5	3000.85	Credit Card	07-11-2021	Viaport Out	0	0
219.142.78.	coupon_29	C300786	Male	65	Books	2	30.3	Debit Card	16-01-2021	Metrocity	1	1
183.3.235.8	coupon_19	C330667	Female	42	Food & Bev	3	15.69	Credit Card	05-01-2022	Zorlu Cente	1	1
10.42.0.42-	coupon_99	C218149	Female	46	Clothing	2	600.16	Cash	26-07-2021	Metropol A	1	1
182.22.24.1	coupon_99	C196845	Male	24	Toys	4	143.36	Cash	07-03-2023	Cevahir AVI	0	0
10.42.0.151	coupon_18	C220180	Male	23	Clothing	1	300.08	Credit Card	15-02-2023	Emaar Squa	1	1
10.42.0.211	coupon_41	C125696	Female	27	Food & Bev	1	5.23	Cash	01-05-2021	Cevahir AVI	0	0

Figure 4.1.4 : Labeled Datasets of Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance

To implement this project, we have designed the following modules:

1. **Service Provider Login Page:**
   This module allows the service provider to securely log in to the system. After authentication, the service provider can manage customer data, monitor coupon performance, and update system settings.
2. **Viewed Trained and Tested Accuracy in Bar Graph:**
   This module displays the accuracy of the trained and tested models using a bar graph. It helps compare the performance of different models used for generating personalized coupons.
3. **View Train and Tested Accuracy Results (Line Chart):**
   This module shows the accuracy of the training and testing results over time using a line chart. It provides a clear view of how model accuracy evolves with more data and training.
4. **View Train and Tested Accuracy Results (Pie Chart):**
   This module represents the accuracy distribution of the training and testing results using a pie chart. It helps visualize the proportion of successful predictions.
5. **View Prediction of Shopping Mall Revenue Type:**
   This module allows the service provider to view the predicted revenue type based on customer shopping patterns and coupon redemptions.
6. **View Shopping Mall Revenue Prediction Type Ratio:**
   This module shows the ratio of different shopping mall revenue types based on customer behavior and successful coupon issuance.
7. **Downloaded Predicted Datasets:**
   This module allows the service provider to download the predicted datasets for further analysis and performance evaluation.
8. **View Shopping Mall Revenue Prediction Type Ratio Results:**
   This module provides a detailed view of the shopping mall revenue type ratio results, helping to identify trends and areas for improvement.
9. **List of Remote Users:**
   This module displays a list of remote users who have interacted with the system. It includes details such as user activity, coupon usage, and feedback.

4.2 SAMPLE CODE

Remote User:

Views.py

```
from django.db.models import Count
from django.db.models import Q
from django.shortcuts import render, redirect, get_object_or_404
import datetime
import openpyxl
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import VotingClassifier
# Create your views here.
from Remote_User.models import ClientRegister_Model,predict_revenue,detection_ratio,detection_accuracy
def login(request):
    if request.method == "POST" and 'submit1' in request.POST:
        username = request.POST.get('username')
        password = request.POST.get('password')
        try:
            enter = ClientRegister_Model.objects.get(username=username,password=password)
            request.session["userid"] = enter.id
            return redirect('ViewYourProfile')
        except:
            pass
    return render(request,'RUser/login.html')
def Add_DataSet_Details(request):
    return render(request, 'RUser/Add_DataSet_Details.html', {"excel_data": ''})
def Register1(request):
    if request.method == "POST":
        username = request.POST.get('username')
        email = request.POST.get('email')
        password = request.POST.get('password')
        phoneno = request.POST.get('phoneno')
        country = request.POST.get('country')
        state = request.POST.get('state')
        city = request.POST.get('city')
```

```
        ClientRegister_Model.objects.create(username=username, email=email, password=password, phoneno=phoneno,
                                            country=country, state=state, city=city)
        return render(request, 'RUser/Register1.html')
    else:
        return render(request,'RUser/Register1.html')
def ViewYourProfile(request):
    userid = request.session['userid']
    obj = ClientRegister_Model.objects.get(id= userid)
    return render(request,'RUser/ViewYourProfile.html',{'object':obj})
def Predict_Revenue_Type(request):
    if request.method == "POST":
        if request.method == "POST":
            Tid= request.POST.get('Tid')
            coupon_no= request.POST.get('coupon_no')
            customer_id= request.POST.get('customer_id')
            gender= request.POST.get('gender')
            age= request.POST.get('age')
            category= request.POST.get('category')
            quantity= request.POST.get('quantity')
            price= request.POST.get('price')
            payment_method= request.POST.get('payment_method')
            invoice_date= request.POST.get('invoice_date')
            shopping_mall= request.POST.get('shopping_mall')
        dataset = pd.read_csv("datasets.csv", encoding='latin-1')

        def apply_results(label):
            if (label == 0):
                return 0 # Low
            elif (label == 1):
                return 1 # High

        dataset['Results'] = dataset['Label'].apply(apply_results)
        x = dataset['Tid']
        y = dataset['Results']
        print(x)
        print("Y")
        print(y)
        cv = CountVectorizer(lowercase=False, strip_accents='unicode', ngram_range=(1, 1))
        x = cv.fit_transform(x)
        models = []
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.20)
X_train.shape, X_test.shape, y_train.shape
print("Recurrent Neural Network-RNN")
from sklearn.neural_network import MLPClassifier
mlpc = MLPClassifier().fit(X_train, y_train)
y_pred = mlpc.predict(X_test)
testscore_mlpc = accuracy_score(y_test, y_pred)
accuracy_score(y_test, y_pred)
print(accuracy_score(y_test, y_pred))
print(accuracy_score(y_test, y_pred) * 100)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, y_pred))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, y_pred))
models.append(('MLPClassifier', mlpc))
# SVM Model
print("SVM")
from sklearn import svm
lin_clf = svm.LinearSVC()
lin_clf.fit(X_train, y_train)
predict_svm = lin_clf.predict(X_test)
svm_acc = accuracy_score(y_test, predict_svm) * 100
print(svm_acc)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, predict_svm))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, predict_svm))
models.append(('svm', lin_clf))
print("Logistic Regression")
from sklearn.linear_model import LogisticRegression
reg = LogisticRegression(random_state=0, solver='lbfgs').fit(X_train, y_train)
y_pred = reg.predict(X_test)
print("ACCURACY")
print(accuracy_score(y_test, y_pred) * 100)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, y_pred))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, y_pred))
models.append(('logistic', reg))
```

```
print("Decision Tree Classifier")
dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
dtcpredict = dtc.predict(X_test)
print("ACCURACY")
print(accuracy_score(y_test, dtcpredict) * 100)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, dtcpredict))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, dtcpredict))
classifier = VotingClassifier(models)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
Tid1 = [Tid]
vector1 = cv.transform(Tid1).toarray()
predict_text = classifier.predict(vector1)
pred = str(predict_text).replace("[", "")
pred1 = pred.replace("]", "")
prediction = int(pred1)
if prediction == 0:
  val = 'Low'
elif prediction == 1:
  val = 'High'
print(val)
print(pred1)
predict_revenue.objects.create(
Tid=Tid,
coupon_no=coupon_no,
customer_id=customer_id,
gender=gender,
age=age,
category=category,
quantity=quantity,
price=price,
payment_method=payment_method,
invoice_date=invoice_date,
shopping_mall=shopping_mall,
Prediction=val)
return render(request, 'RUser/Predict_Revenue_Type.html',{'objs': val})
return render(request, 'RUser/Predict_Revenue_Type.html')
```

Models.py

```
from django.db import models
# Create your models here.
from django.db.models import CASCADE
class ClientRegister_Model(models.Model):
    username = models.CharField(max_length=30)
    email = models.EmailField(max_length=30)
    password = models.CharField(max_length=10)
    phoneno = models.CharField(max_length=10)
    country = models.CharField(max_length=30)
    state = models.CharField(max_length=30)
    city = models.CharField(max_length=30)
class predict_revenue(models.Model):
    Tid= models.CharField(max_length=300)
    coupon_no= models.CharField(max_length=300)
    customer_id= models.CharField(max_length=300)
    gender= models.CharField(max_length=300)
    age= models.CharField(max_length=300)
    category= models.CharField(max_length=300)
    quantity= models.CharField(max_length=300)
    price= models.CharField(max_length=300)
    payment_method= models.CharField(max_length=300)
    invoice_date= models.CharField(max_length=300)
    shopping_mall= models.CharField(max_length=300)
    Prediction= models.CharField(max_length=300)
class detection_accuracy(models.Model):
    names = models.CharField(max_length=300)
    ratio = models.CharField(max_length=300)
class detection_ratio(models.Model):
    names = models.CharField(max_length=300)
    ratio = models.CharField(max_length=300)
```

Forms.py :

```
from django import forms
from Remote_User.models import ClientRegister_Model
class ClientRegister_Form(forms.ModelForm):
    password = forms.CharField(widget=forms.PasswordInput())
    email = forms.EmailField(required=True)
```

```
    class Meta:
        model = ClientRegister_Model
        fields = ("username","email","password","phoneno","country","state","city")
```

Service Provider:

Views.py

```
from django.db.models import Count, Avg
from django.shortcuts import render, redirect
from django.db.models import Count
from django.db.models import Q
import datetime
import xlwt
from django.http import HttpResponse
import numpy as np
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
# Create your views here.
from Remote_User.models import ClientRegister_Model,predict_revenue,detection_ratio,detection_accuracy
def serviceproviderlogin(request):
    if request.method == "POST":
        admin = request.POST.get('username')
        password = request.POST.get('password')
        if admin == "Admin" and password =="Admin":
            detection_accuracy.objects.all().delete()
            return redirect('View_Remote_Users')
    return render(request,'SProvider/serviceproviderlogin.html')
def View_Prediction_Of_Revenue_Type_Ratio(request):
    detection_ratio.objects.all().delete()
    rratio = ""
    kword = 'Low'
    print(kword)
    obj = predict_revenue.objects.all().filter(Q(Prediction=kword))
    obj1 =predict_revenue.objects.all()
    count = obj.count();
    count1 = obj1.count();
    ratio = (count / count1) * 100
```

```
    if ratio != 0:
        detection_ratio.objects.create(names=kword, ratio=ratio)
    ratio1 = ""
    kword1 = 'High'
    print(kword1)
    obj1 =predict_revenue.objects.all().filter(Q(Prediction=kword1))
    obj11 =predict_revenue.objects.all()
    count1 = obj1.count();
    count11 = obj11.count();
    ratio1 = (count1 / count11) * 100
    if ratio1 != 0:
        detection_ratio.objects.create(names=kword1, ratio=ratio1)
    obj = detection_ratio.objects.all()
    return render(request, 'SProvider/View_Prediction_Of_Revenue_Type_Ratio.html', {'objs': obj})
def View_Remote_Users(request):
    obj=ClientRegister_Model.objects.all()
    return render(request,'SProvider/View_Remote_Users.html',{'objects':obj})
def ViewTrendings(request):
    topic = predict_revenue.objects.values('topics').annotate(dcount=Count('topics')).order_by('-dcount')
    return render(request,'SProvider/ViewTrendings.html',{'objects':topic})
def charts(request,chart_type):
    chart1 = detection_ratio.objects.values('names').annotate(dcount=Avg('ratio'))
    return render(request,"SProvider/charts.html", {'form':chart1, 'chart_type':chart_type})
def charts1(request,chart_type):
    chart1 = detection_accuracy.objects.values('names').annotate(dcount=Avg('ratio'))
    return render(request,"SProvider/charts1.html", {'form':chart1, 'chart_type':chart_type})
def View_Prediction_Of_Revenue_Type(request):
    obj =predict_revenue.objects.all()
    return render(request, 'SProvider/View_Prediction_Of_Revenue_Type.html', {'list_objects': obj})
def likeschart(request,like_chart):
    charts =detection_accuracy.objects.values('names').annotate(dcount=Avg('ratio'))
    return render(request,"SProvider/likeschart.html", {'form':charts, 'like_chart':like_chart})
def Download_Trained_DataSets(request):
    response = HttpResponse(content_type='application/ms-excel')
    # decide file name
    response['Content-Disposition'] = 'attachment; filename="Predicted_Datasets.xls"'
    # creating workbook
    wb = xlwt.Workbook(encoding='utf-8')
    # adding sheet
    ws = wb.add_sheet("sheet1")
```

```
    # Sheet header, first row
    row_num = 0
    font_style = xlwt.XFStyle()
    # headers are bold
    font_style.font.bold = True
    # writer = csv.writer(response)
    obj = predict_revenue.objects.all()
    data = obj # dummy method to fetch data.
    for my_row in data:
        row_num = row_num + 1
        ws.write(row_num, 0, my_row.Tid, font_style)
        ws.write(row_num, 1, my_row.coupon_no, font_style)
        ws.write(row_num, 2, my_row.customer_id, font_style)
        ws.write(row_num, 3, my_row.gender, font_style)
        ws.write(row_num, 4, my_row.age, font_style)
        ws.write(row_num, 5, my_row.category, font_style)
        ws.write(row_num, 6, my_row.quantity, font_style)
        ws.write(row_num, 7, my_row.price, font_style)
        ws.write(row_num, 8, my_row.payment_method, font_style)
        ws.write(row_num, 9, my_row.invoice_date, font_style)
        ws.write(row_num, 10, my_row.shopping_mall, font_style)
        ws.write(row_num, 11, my_row.Prediction, font_style)
    wb.save(response)
    return response
def train_model(request):
    detection_accuracy.objects.all().delete()
    dataset = pd.read_csv("Datasets.csv", encoding='latin-1')
    def apply_results(label):
        if (label == 0):
            return 0 # Low
        elif (label == 1):
            return 1 # High
    dataset['Results'] = dataset['Label'].apply(apply_results)
    x = dataset['Tid']
    y = dataset['Results']
    cv = CountVectorizer()
    print(x)
    print("Y")
    print(y)
    x = cv.fit_transform(x)
```

```
models = []
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.20)
X_train.shape, X_test.shape, y_train.shape
print("Recurrent Neural Network-RNN")
from sklearn.neural_network import MLPClassifier
mlpc = MLPClassifier().fit(X_train, y_train)
y_pred = mlpc.predict(X_test)
testscore_mlpc = accuracy_score(y_test, y_pred)
accuracy_score(y_test, y_pred)
print(accuracy_score(y_test, y_pred))
print(accuracy_score(y_test, y_pred) * 100)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, y_pred))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, y_pred))
models.append(('MLPClassifier', mlpc))
detection_accuracy.objects.create(names="Recurrent Neural Network-RNN", ratio=accuracy_score(y_test, y_pred) * 100)
# SVM Model
print("SVM")
from sklearn import svm
lin_clf = svm.LinearSVC()
lin_clf.fit(X_train, y_train)
predict_svm = lin_clf.predict(X_test)
svm_acc = accuracy_score(y_test, predict_svm) * 100
print("ACCURACY")
print(svm_acc)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, predict_svm))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, predict_svm))
detection_accuracy.objects.create(names="SVM", ratio=svm_acc)
print("Logistic Regression")
from sklearn.linear_model import LogisticRegression
reg = LogisticRegression(random_state=0, solver='lbfgs').fit(X_train, y_train)
y_pred = reg.predict(X_test)
print("ACCURACY")
print(accuracy_score(y_test, y_pred) * 100)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, y_pred))
```

```
    print("CONFUSION MATRIX")
    print(confusion_matrix(y_test, y_pred))
    detection_accuracy.objects.create(names="Logistic Regression", ratio=accuracy_score(y_test, y_pred) * 100)
    print("Decision Tree Classifier")
    dtc = DecisionTreeClassifier()
    dtc.fit(X_train, y_train)
    dtcpredict = dtc.predict(X_test)
    print("ACCURACY")
    print(accuracy_score(y_test, dtcpredict) * 100)
    print("CLASSIFICATION REPORT")
    print(classification_report(y_test, dtcpredict))
    print("CONFUSION MATRIX")
    print(confusion_matrix(y_test, dtcpredict))
    detection_accuracy.objects.create(names="Decision Tree Classifier", ratio=accuracy_score(y_test, dtcpredict) * 100)
    labeled = 'Labeled_Data.csv'
    dataset.to_csv(labeled, index=False)
    dataset.to_markdown
    obj = detection_accuracy.objects.all()
        return render(request,'SProvider/train_model.html', {'objs': obj})
```

Urls.py

```
"""improving_shopping_mall_revenue URL Configuration
The `urlpatterns` list routes URLs to views. For more information please see:
    https://docs.djangoproject.com/en/3.0/topics/http/urls/
Examples:
Function views
    1. Add an import: from my_app import views
    2. Add a URL to urlpatterns: path('', views.home, name='home')
Class-based views
    1. Add an import: from other_app.views import Home
    2. Add a URL to urlpatterns: path('', Home.as_view(), name='home')
Including another URLconf
    1. Import the include() function: from django.urls import include, path
    2. Add a URL to urlpatterns: path('blog/', include('blog.urls'))
"""
from django.conf.urls import url
from django.contrib import admin
from Remote_User import views as remoteuser
from improving_shopping_mall_revenue import settings
```

```
from Service_Provider import views as serviceprovider
from django.conf.urls.static import static
urlpatterns = [
    url('admin/', admin.site.urls),
    url(r'^$', remoteuser.login, name="login"),
    url(r'^Register1/$', remoteuser.Register1, name="Register1"),
    url(r'^Predict_Revenue_Type/$', remoteuser.Predict_Revenue_Type, name="Predict_Revenue_Type"),
    url(r'^ViewYourProfile/$', remoteuser.ViewYourProfile, name="ViewYourProfile"),
    url(r'^serviceproviderlogin/$',serviceprovider.serviceproviderlogin, name="serviceproviderlogin"),
    url(r'View_Remote_Users/$',serviceprovider.View_Remote_Users,name="View_Remote_Users"),
    url(r'^charts/(?P<chart_type>\w+)', serviceprovider.charts,name="charts"),
    url(r'^charts1/(?P<chart_type>\w+)', serviceprovider.charts1, name="charts1"),
    url(r'^likeschart/(?P<like_chart>\w+)', serviceprovider.likeschart, name="likeschart"),
    url(r'^View_Prediction_Of_Revenue_Type_Ratio/$', serviceprovider.View_Prediction_Of_Revenue_Type_Ratio, name="View_Prediction_Of_Revenue_Type_Ratio"),
    url(r'^train_model/$', serviceprovider.train_model, name="train_model"),
    url(r'^View_Prediction_Of_Revenue_Type/$', serviceprovider.View_Prediction_Of_Revenue_Type, name="View_Prediction_Of_Revenue_Type"),
    url(r'^Download_Trained_DataSets/$', serviceprovider.Download_Trained_DataSets, name="Download_Trained_DataSets"),

]+ static(settings.MEDIA_URL, document_root=settings.MEDIA_ROOT)
```

Settings.py

```
import os
# Build paths inside the project like this: os.path.join(BASE_DIR, ...)
BASE_DIR = os.path.dirname(os.path.dirname(os.path.abspath(__file__)))
# Quick-start development settings - unsuitable for production
# See https://docs.djangoproject.com/en/3.0/howto/deployment/checklist/
# SECURITY WARNING: keep the secret key used in production secret!
SECRET_KEY = 'm+1edl5m-5@u9u!b8-=4-4mq&o1%agco2xpl8c!7sn7!eowjk#'
# SECURITY WARNING: don't run with debug turned on in production!
DEBUG = True
ALLOWED_HOSTS = []
# Application definition
INSTALLED_APPS = [
    'django.contrib.admin',
    'django.contrib.auth',
    'django.contrib.contenttypes',
    'django.contrib.sessions',
    'django.contrib.messages',
```

```
    'django.contrib.staticfiles',
    'Remote_User',
    'Service_Provider',
]
MIDDLEWARE = [
    'django.middleware.security.SecurityMiddleware',
    'django.contrib.sessions.middleware.SessionMiddleware',
    'django.middleware.common.CommonMiddleware',
    'django.middleware.csrf.CsrfViewMiddleware',
    'django.contrib.auth.middleware.AuthenticationMiddleware',
    'django.contrib.messages.middleware.MessageMiddleware',
    'django.middleware.clickjacking.XFrameOptionsMiddleware',
]
ROOT_URLCONF = 'improving_shopping_mall_revenue.urls'
TEMPLATES = [
    {
        'BACKEND': 'django.template.backends.django.DjangoTemplates',
        'DIRS': [(os.path.join(BASE_DIR,'Template/htmls'))],
        'APP_DIRS': True,
        'OPTIONS': {
            'context_processors': [
                'django.template.context_processors.debug',
                'django.template.context_processors.request',
                'django.contrib.auth.context_processors.auth',
                'django.contrib.messages.context_processors.messages',
            ],
        },
    },
]

WSGI_APPLICATION = 'improving_shopping_mall_revenue.wsgi.application'
# Database
# https://docs.djangoproject.com/en/3.0/ref/settings/#databases
DATABASES = {
    'default': {
        'ENGINE': 'django.db.backends.mysql',
        'NAME': 'improving_shopping_mall_revenue',
        'USER':'root',
        'PASSWORD': '',
        'HOST' :'127.0.0.1',
```

```
        'PORT' :'3306',
    }
}
# Password validation
# https://docs.djangoproject.com/en/3.0/ref/settings/#auth-password-validators

AUTH_PASSWORD_VALIDATORS = [
    {
        'NAME': 'django.contrib.auth.password_validation.UserAttributeSimilarityValidator',
    },
    {
        'NAME': 'django.contrib.auth.password_validation.MinimumLengthValidator',
    },
    {
        'NAME': 'django.contrib.auth.password_validation.CommonPasswordValidator',
    },
    {
        'NAME': 'django.contrib.auth.password_validation.NumericPasswordValidator',
    },
]
# Internationalization
# https://docs.djangoproject.com/en/3.0/topics/i18n/
LANGUAGE_CODE = 'en-us'
TIME_ZONE = 'UTC’
USE_I18N = True
USE_L10N = True
USE_TZ = True
# Static files (CSS, JavaScript, Images)
# https://docs.djangoproject.com/en/3.0/howto/static-files/
STATIC_URL = '/static/'
STATICFILES_DIRS = [os.path.join(BASE_DIR,'Template/images')]
MEDIA_URL = '/media/'
MEDIA_ROOT = os.path.join(BASE_DIR, 'Template/media')
STATIC_ROOT = '/static/'
STATIC_URL = '/static/'
```

5. RESULTS & DISCUSSION

5. RESULTS AND DISCUSSION

The following screenshots showcase the results of our project, highlighting key features and functionalities. These visual representations provide a clear overview of how the system performs under various conditions, demonstrating its effectiveness and user interface. The screenshots serve as a visual aid to support the project's technical and operational achievements.

Result 5.1.1 : Home page Interface of Improving Shopping Mall Revenue by Real Time Customized Digital Coupon Issuance

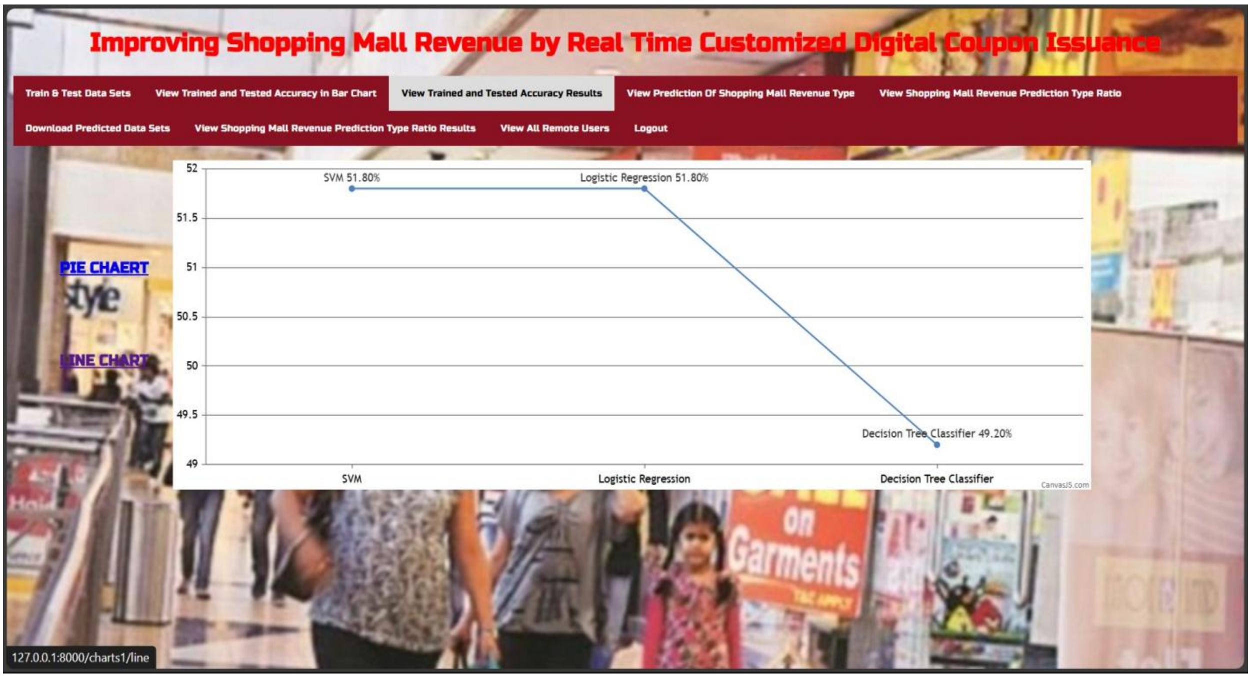
The homepage offers an intuitive and user-friendly interface designed to enhance customer engagement and boost mall revenue through real-time personalized digital coupons. It features a dynamic dashboard that provides insights into customer behavior, shopping trends, and coupon redemption rates. AI-driven customer segmentation clusters customers based on shopping patterns, enabling targeted coupon issuance. The system also integrates churn prediction to identify and retain at-risk customers through tailored incentives. A recommendation engine suggests relevant coupons based on real-time data analysis, ensuring higher customer satisfaction and increased sales. Users can easily explore features, view current offers, and track shopping history. The responsive design ensures a seamless experience across all devices.

Result 5.1.2: Service Provider Login Page

The Service Provider Login Page offers a secure gateway for mall retailers to access the digital coupon management system. Authorized providers can log in to create, manage, and analyze customized coupon campaigns. The interface ensures seamless navigation, real-time updates, and insights into customer engagement and redemption rates.

Result 5.1.3 : viewed trained and tested accuracy in bar graph

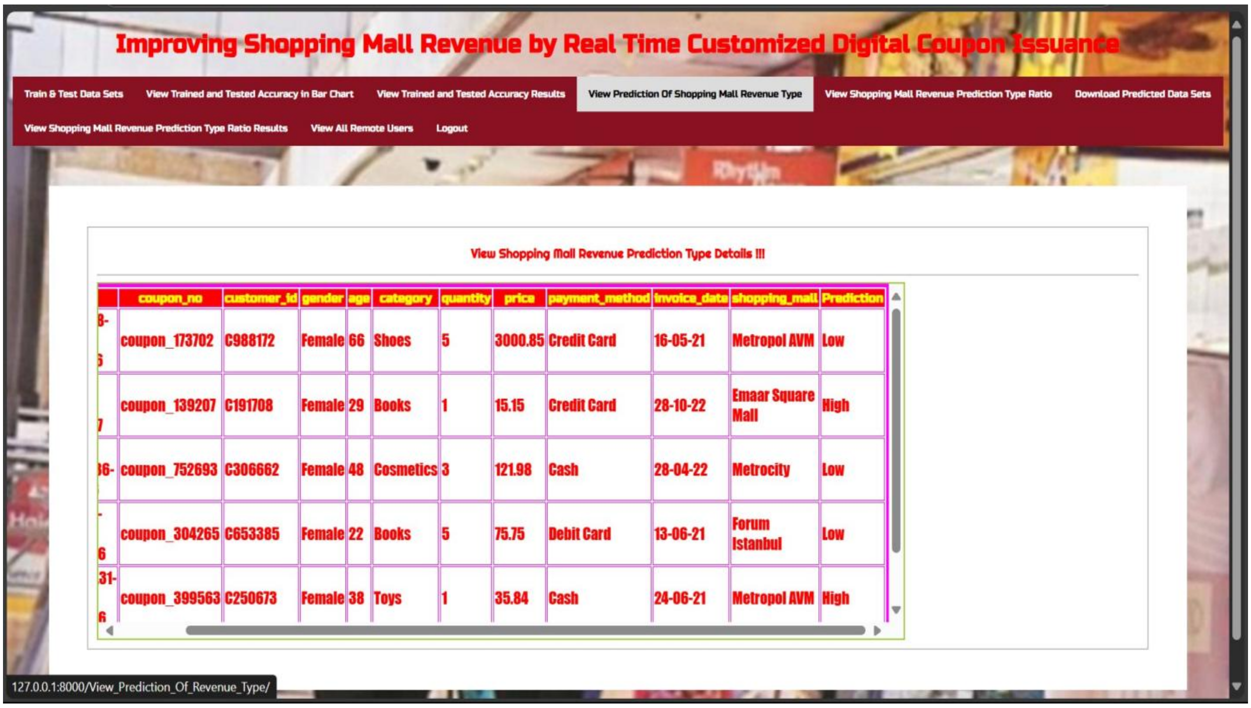
The Trained and Tested Accuracy Bar Graph module visually represents the performance of the AI model used for churn prediction and coupon recommendation. It displays accuracy metrics for both training and testing phases, helping service providers assess model effectiveness. The bar graph enables quick comparisons, ensuring continuous improvements in predictive accuracy. Regular updates reflect the latest retrained models, enhancing decision-making for targeted marketing strategies. The module allows service providers to easily identify areas where the model excels and where adjustments are needed, fostering a data-driven approach to marketing. By analyzing the accuracy trends over time, providers can make informed decisions about model adjustments or the inclusion of new features. Additionally, the module serves as a performance tracking tool, allowing the team to monitor the impact of new data or algorithm changes on the overall model accuracy.



Result 5.1.4 : View Train and Tested Accuracy Results (Line Chart)

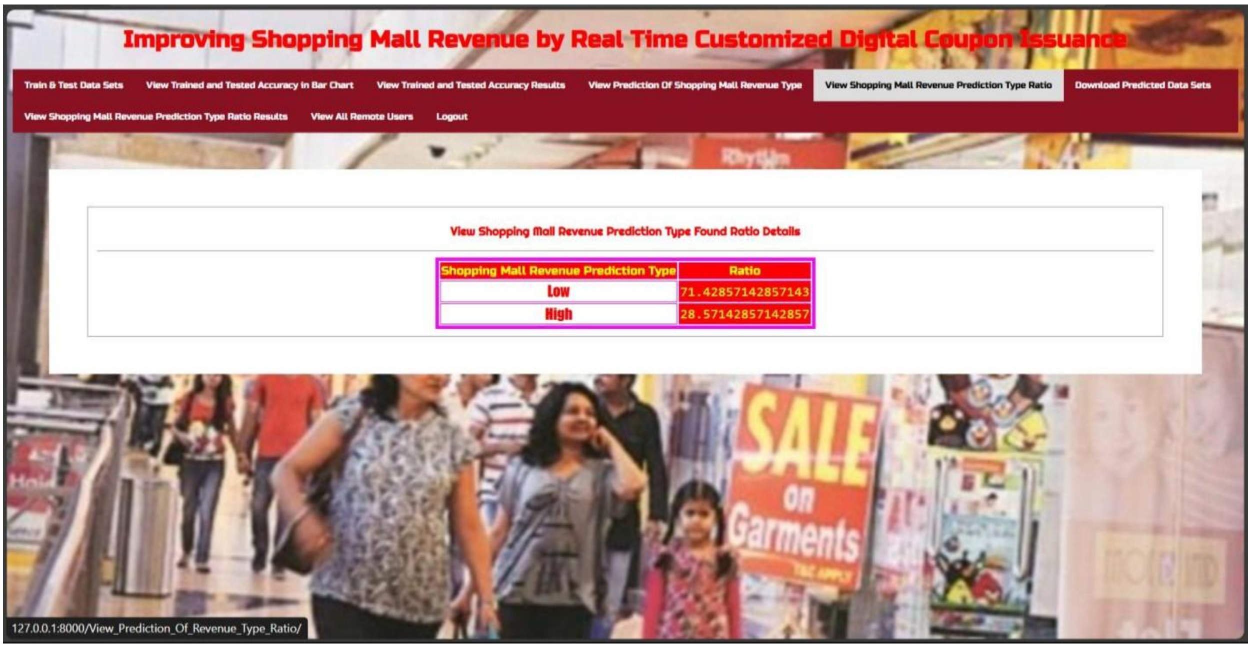
The View Trained and Tested Accuracy Results module allows users to monitor the performance of the AI models used for churn prediction and coupon issuance. It provides detailed accuracy metrics for both the training and testing datasets, enabling a clear comparison of model effectiveness. This feature helps assess the reliability of predictions and optimize the model for better customer engagement and retention strategies.

Result 5.1.5 : View Train and Tested Accuracy Results (Pie Chart)



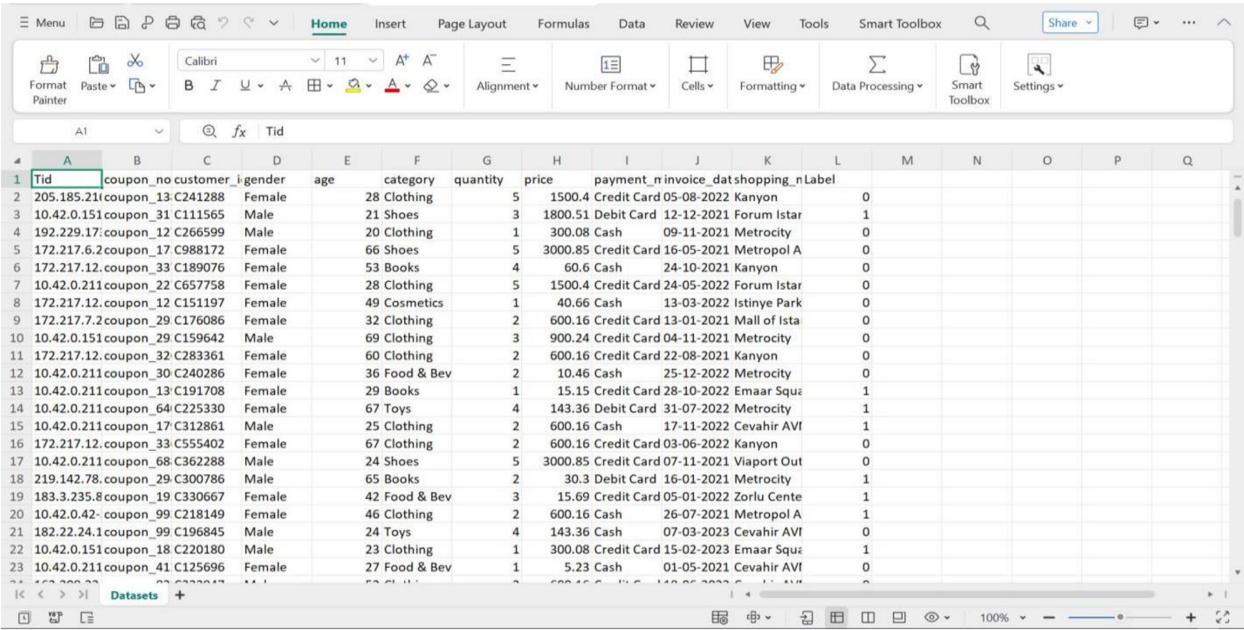
Result 5.1.6 : View prediction of Shopping Mall Revenue Type

The View Prediction of Shopping Mall Revenue Type module forecasts mall revenue based on customer behavior and coupon redemption patterns. It helps service providers make data-driven decisions to optimize coupon campaigns and maximize revenue. By leveraging historical data and real-time customer interactions, the module provides accurate revenue projections for different mall activities and promotions. This allows mall operators to prioritize high-impact strategies and ensure that marketing resources are efficiently allocated to drive maximum profit.



Result 5.1.7 : View Shopping Mall Revenue Prediction Type Ratio

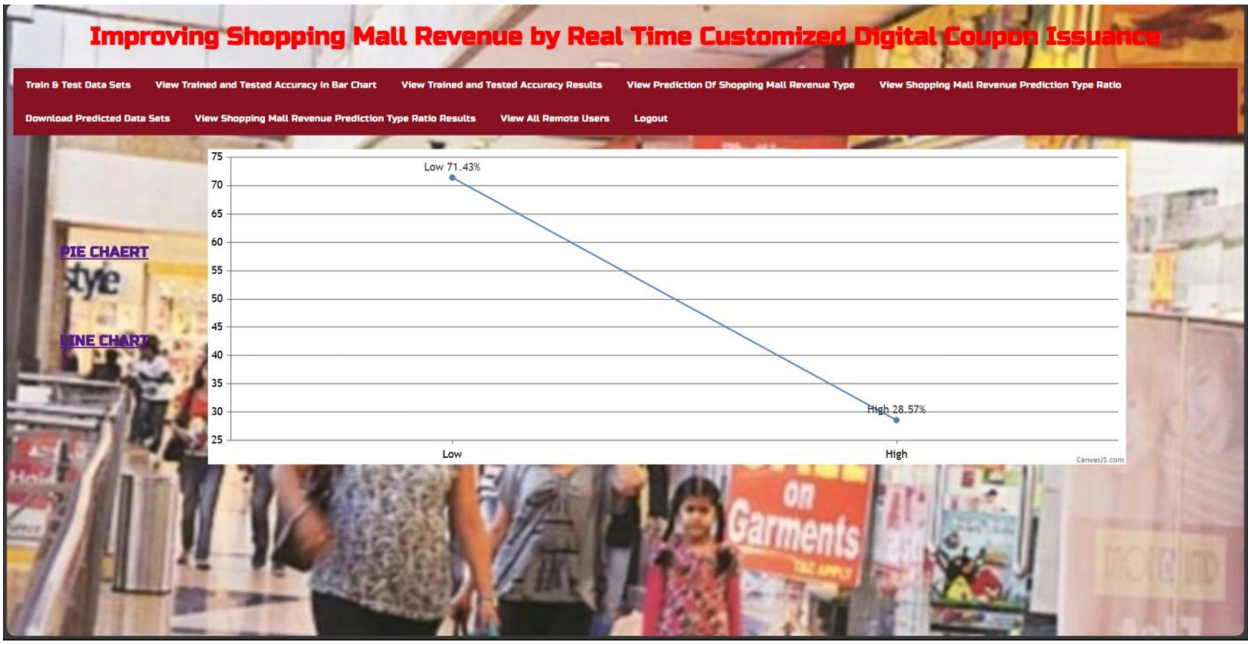
The View Shopping Mall Revenue Prediction Type Ratio module displays the distribution of predicted revenue across different customer segments and marketing strategies. It provides a clear breakdown of revenue potential based on various factors like coupon usage and customer engagement. This feature helps service providers identify the most profitable areas to focus on and optimize their strategies for maximum impact.



	A	B	C	D	E	F	G	H	I	J	K	L
1	Tid	coupon_no	customer_i	gender	age	category	quantity	price	payment_m	invoice_dat	shopping_m	Label
2	205.185.21(	coupon_13	C241288	Female	28	Clothing	5	1500.4	Credit Card	05-08-2022	Kanyon	0
3	10.42.0.151	coupon_31	C111565	Male	21	Shoes	3	1800.51	Debit Card	12-12-2021	Forum Istar	1
4	192.229.17:	coupon_12	C266599	Male	20	Clothing	1	300.08	Cash	09-11-2021	Metrocity	0
5	172.217.6.2	coupon_17	C988172	Female	66	Shoes	5	3000.85	Credit Card	16-05-2021	Metropol A	0
6	172.217.12.	coupon_33	C189076	Female	53	Books	4	60.6	Cash	24-10-2021	Kanyon	0
7	10.42.0.211	coupon_22	C657758	Female	28	Clothing	5	1500.4	Credit Card	24-05-2022	Forum Istar	0
8	172.217.12.	coupon_12	C151197	Female	49	Cosmetics	1	40.66	Cash	13-03-2022	Istinye Park	0
9	172.217.7.2	coupon_29	C176086	Female	32	Clothing	2	600.16	Credit Card	13-01-2021	Mall of Ista	0
10	10.42.0.151	coupon_29	C159642	Male	69	Clothing	3	900.24	Credit Card	04-11-2021	Metrocity	0
11	172.217.12.	coupon_32	C283361	Female	60	Clothing	2	600.16	Credit Card	22-08-2021	Kanyon	0
12	10.42.0.211	coupon_30	C240286	Female	36	Food & Bev	2	10.46	Cash	25-12-2022	Metrocity	0
13	10.42.0.211	coupon_13	C191708	Female	29	Books	1	15.15	Credit Card	28-10-2022	Emaar Squa	1
14	10.42.0.211	coupon_64	C225330	Female	67	Toys	4	143.36	Debit Card	31-07-2022	Metrocity	1
15	10.42.0.211	coupon_17	C312861	Male	25	Clothing	2	600.16	Cash	17-11-2022	Cevahir AVI	1
16	172.217.12.	coupon_33	C555402	Female	67	Clothing	2	600.16	Credit Card	03-06-2022	Kanyon	0
17	10.42.0.211	coupon_68	C362288	Male	24	Shoes	5	3000.85	Credit Card	07-11-2021	Viaport Out	0
18	219.142.78.	coupon_29	C300786	Male	65	Books	2	30.3	Debit Card	16-01-2021	Metrocity	1
19	183.3.235.8	coupon_19	C330667	Female	42	Food & Bev	3	15.69	Credit Card	05-01-2022	Zorlu Cente	1
20	10.42.0.42-	coupon_99	C218149	Female	46	Clothing	2	600.16	Cash	26-07-2021	Metropol A	1
21	182.22.24.1	coupon_99	C196845	Male	24	Toys	4	143.36	Cash	07-03-2023	Cevahir AVI	0
22	10.42.0.151	coupon_18	C220180	Male	23	Clothing	1	300.08	Credit Card	15-02-2023	Emaar Squa	1
23	10.42.0.211	coupon_41	C125696	Female	27	Food & Bev	1	5.23	Cash	01-05-2021	Cevahir AVI	0

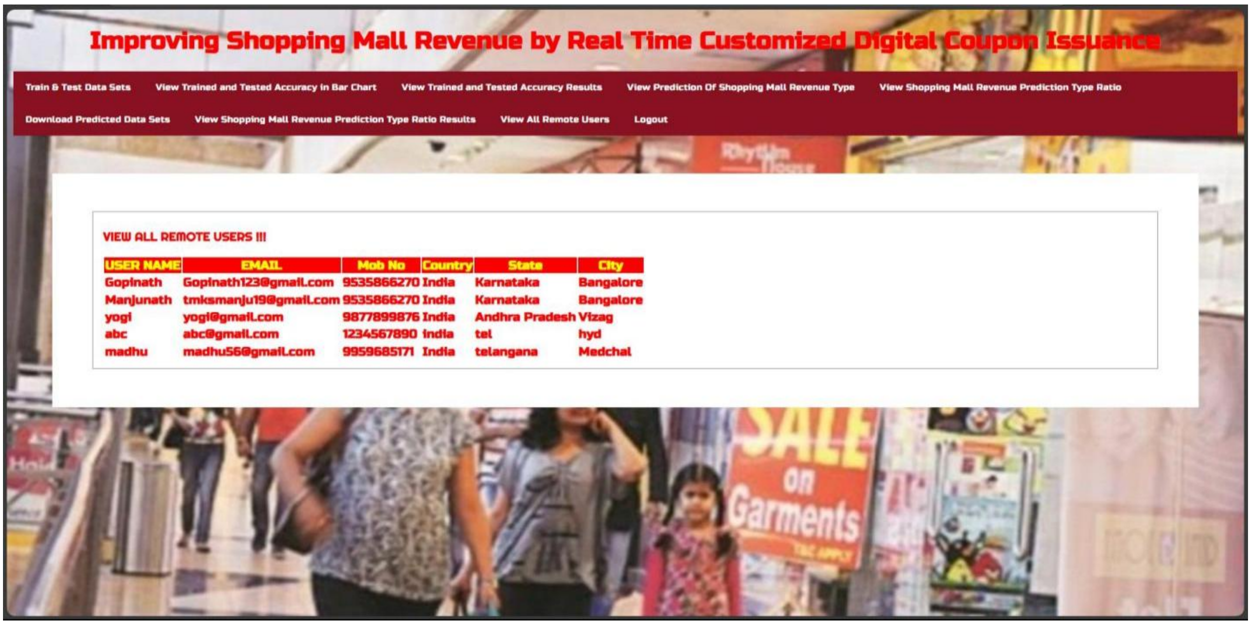
Result 5.1.8 : Downloaded Predicted Data sets

The **Downloaded Predicted Datasets** module allows users to access and download the predicted data generated by the AI model. It includes insights on customer behavior, churn predictions, and expected revenue outcomes. This feature enables service providers to analyze the data offline, make further adjustments, and refine marketing strategies based on predictions. By downloading the datasets, users can conduct in-depth analysis using various tools or platforms, allowing for a more flexible and tailored approach to decision-making. It also facilitates collaboration between different departments, as the data can be shared and reviewed by teams working on marketing, sales, and customer engagement. Additionally, the module allows service providers to track the accuracy of the model's predictions over time, enabling continuous improvements in campaign targeting and overall business strategy.



Result 5.1.9 : View Shopping Mall Revenue Prediction Type Ratio Results

The **View Shopping Mall Revenue Prediction Type Ratio Results** module displays the outcomes of revenue predictions across various customer segments and strategies. It shows the ratio of predicted revenue for different types of promotions and customer engagement. This feature helps service providers evaluate the effectiveness of their marketing efforts and make informed decisions to enhance revenue generation. By breaking down the predicted revenue by promotion type, it highlights which strategies are most likely to drive sales and which may require adjustments. It also enables the identification of high-performing customer segments, allowing service providers to further personalize offers and improve overall revenue performance.



Result 5.1.10 : List Of Remote Users

The List of Remote Users section displays all registered customers who interact with the digital coupon system. It provides detailed insights into user activity, segmentation, and coupon redemption history. This feature helps service providers track engagement, identify high-risk customers, and optimize marketing strategies. It allows service providers to monitor user behavior patterns, helping them tailor future coupon offerings more effectively. The module also supports filtering and sorting options, making it easier to analyze customer trends and target specific user groups with personalized campaigns.

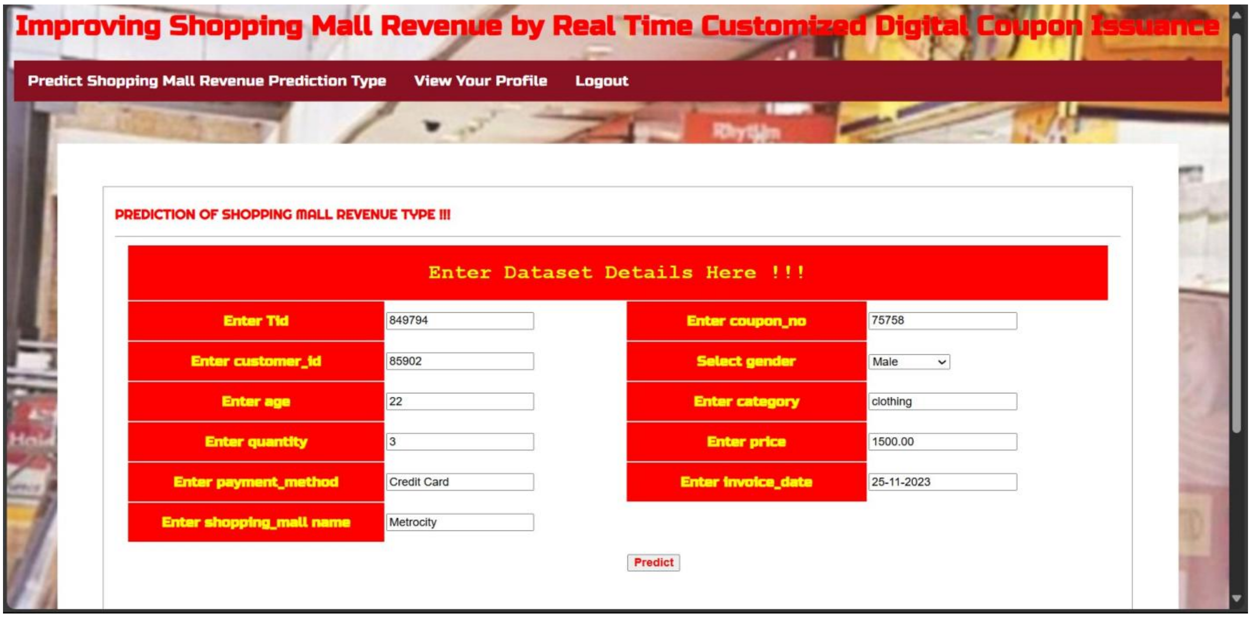
5.2 REMOTE USER RESULTS :

Result 5.1.11 : Home page

The homepage provides an intuitive interface showcasing real-time personalized digital coupons to enhance customer engagement and mall revenue. It highlights AI-driven customer segmentation, churn prediction, and recommendation-based coupon issuance, with easy navigation for exploring features and offers. The homepage also provides real-time notifications about new coupons and special deals, encouraging customer participation. It includes a personalized dashboard that displays user-specific recommendations and shopping insights to enhance the overall experience.

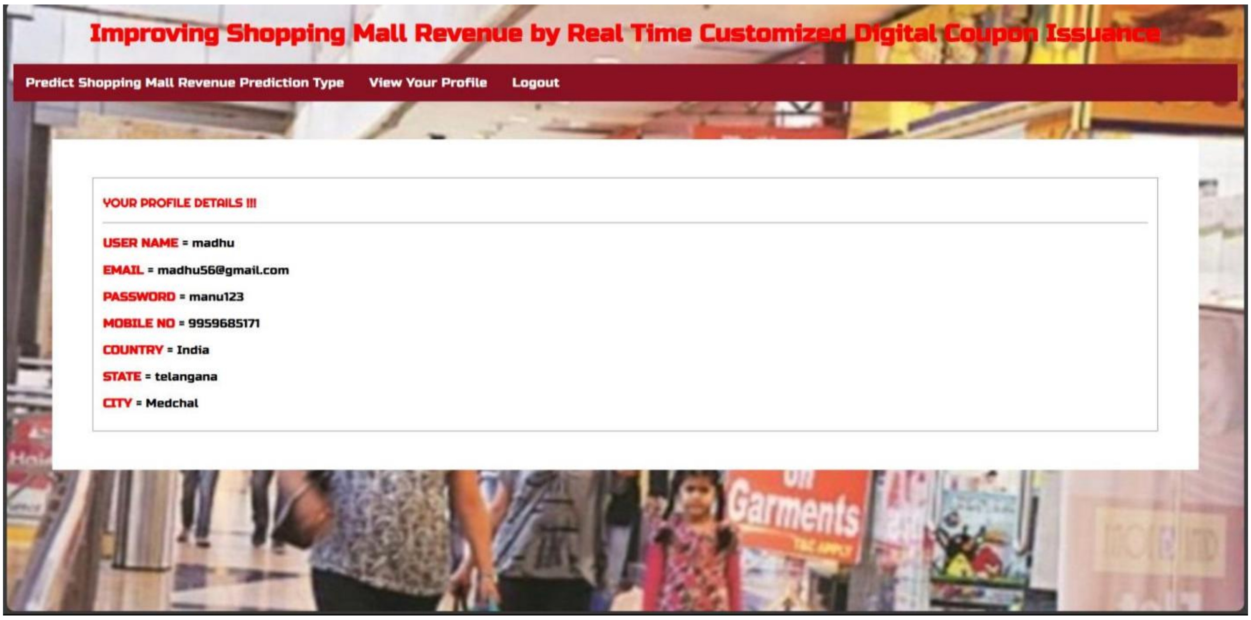
Result 5.2.12 : Remote User Register Page

The **Remote User Register Page** allows new customers to sign up for the digital coupon system. Users can easily register by providing necessary details such as name, email, and preferences. This page ensures secure account creation and grants access to personalized coupon recommendations, enhancing the overall shopping experience. It also includes an email verification step to improve security and prevent unauthorized access. Once registered, users can update their preferences anytime to receive more relevant coupon suggestions.



Result 5.2.13 : Prediction of Shopping Mall Revenue Type

The **Prediction of Shopping Mall Revenue Type** module forecasts potential revenue based on various customer behaviors, shopping patterns, and promotional activities. It analyzes historical data to predict how different revenue types will perform, helping mall operators optimize marketing strategies. This feature provides valuable insights for targeting specific customer segments with tailored campaigns to maximize overall revenue. It also helps identify underperforming revenue streams, enabling quick adjustments to improve outcomes. The module continuously updates predictions based on new data, ensuring accuracy and adaptability to changing market trends.



Result 5.2.14 : View Your Profile

6. VALIDATION

6.VALIDATION

The validation of this project primarily relies on extensive testing and well-defined test cases to ensure the accuracy and effectiveness of the real-time customized digital coupon issuance system. The testing process involves multiple stages, including user behavior analysis, system performance evaluation, and real-world testing within a shopping mall environment. By implementing a structured validation approach, we can ensure that the system consistently delivers highly personalized and relevant digital coupons, optimizing shopper engagement while maximizing mall revenue.

6.1 INTRODUCTION

First, the system undergoes a structured validation process by dividing shopping data into training and testing sets, ensuring accurate evaluation of the customized digital coupon issuance model. Shopper behavior data, including purchase history, location tracking, and time spent in stores, is analyzed using an 80-20 split, where 80% is used for training the recommendation model, and 20% is reserved for testing its effectiveness in real-world scenarios. To enhance reliability, K-fold cross-validation is performed, ensuring that the system is tested on multiple data partitions, reducing bias, and improving generalization.

The accuracy of the system is measured using key performance metrics such as redemption rate, customer engagement, revenue impact, and precision in targeting offers. A confusion matrix is used to analyze correct and incorrect coupon recommendations, helping refine the algorithm for better personalization. Additionally, the proposed AI-based recommendation system is compared against traditional rule-based coupon issuance methods, demonstrating that real-time, customized digital coupons result in higher engagement and sales.

Finally, real-world deployment testing is conducted in a simulated mall environment to assess the system's performance under real-time conditions. The system continuously adapts to dynamic shopping behaviors, updating coupon recommendations based on live data streams. Continuous improvements are made based on shopper feedback and test results, ensuring that the system remains efficient, scalable, and capable of maximizing revenue while enhancing the overall shopping experience.

6.2 TEST CASES

6.2.1 REMOTE USER DATASET

Test case ID	Test case name	Purpose	Test Case	**Output**
1	REGISTER AND LOGIN	User have to register to access the data	The User needs to register to register and login to part of the database of shopping mall data set	Registered Successfully
2	Predict Shopping Mall Revenue Prediction Type	To select one of the prediction Type	Predicting the Revenue of shopping mall at initial stage	Predicted Successfully
3	VIEW YOUR PROFILE	To Access our data	TTo View and Edit Our Profile	Viewed Successfully

Table 6.2.1 : Remote User Dataset

6.3.2 SERVICE PROVIDER DATASET

Test case ID	Test case name	Purpose	Input	Output
1	Login	The Service Provider need to Login to Monitoring Data	User_id Password	Log in completed
2	Train & Test Data Sets	The Dataset initially get Trained and Tested	Sample Dataset	Trained And Tested Completed
3	Download Predicted Data Sets	The data get Predicted will be Downloaded	Predicted Dataset	Download Successfully
4	View All Remote Users	The Service Provider Have Access to Control Remote User data or Profile	Remote User's Dataset's	Viewed Successfully

Table 6.2.2 : Service Provider Dataset

7. CONCLUSION & FUTURE ASPECTS

7. CONCLUSION AND FUTURE ASPECTS

7.1 PROJECT CONCLUSION

The implementation of real-time customized digital coupon issuance can significantly enhance shopping mall revenue by improving customer engagement and sales conversion rates. By leveraging real-time data analytics, shopping malls can personalize discount offers based on individual customer preferences, shopping behaviors, and location. This approach ensures that customers receive relevant and attractive promotions, increasing the likelihood of immediate purchases.

The integration of AI and machine learning enables predictive analytics, allowing malls to anticipate customer needs and offer timely discounts. Moreover, the use of IoT devices and mobile applications ensures seamless coupon distribution, improving customer convenience and satisfaction. Personalized coupons also enhance customer loyalty by fostering a sense of exclusivity and appreciation among shoppers.

The implementation of blockchain technology can further enhance security, transparency, and trust in digital coupon transactions. Retailers within malls can benefit from higher foot traffic and increased sales, leading to improved overall revenue generation. Additionally, real-time coupon issuance helps optimize inventory management by promoting products that require higher sales turnover. The system can also support targeted marketing campaigns, reducing unnecessary promotional expenses while maximizing returns.

Shopping malls can analyze customer purchase patterns to refine marketing strategies and enhance the overall shopping experience. Digital coupons reduce the dependency on traditional paper-based discount methods, making promotions more efficient and eco-friendly. The adoption of mobile wallet integration further enhances the ease of coupon redemption, making the process more seamless for customers. Data privacy and security must be prioritized to maintain customer trust and compliance with regulatory standards. Implementing customer feedback mechanisms can help malls refine their coupon strategies, ensuring continuous improvement in engagement and revenue generation.

In addition, gamification techniques can be integrated into the coupon system to further boost customer participation and repeat visits. Loyalty programs combined with personalized coupon issuance can encourage long-term customer retention. The use of geofencing technology can enhance real-time targeting by sending promotions when customers are near specific stores within the mall. AI-driven chatbots can also assist shoppers in finding the best deals and guiding them to relevant stores.

By adopting cloud-based infrastructure, malls can efficiently manage large volumes of real-time data while ensuring scalability and reliability. The implementation of dynamic pricing strategies based on customer demand and shopping trends can maximize the effectiveness of discounts. Collaborations with brand partners and retailers can create more value-driven promotions that appeal to diverse customer segments. The ability to track coupon redemption rates and analyze their impact on sales enables continuous optimization of marketing efforts.

Overall, real-time customized digital coupon issuance presents a transformative approach to enhancing shopping mall revenue, customer satisfaction, and retailer profitability. By integrating advanced technologies and data-driven strategies, shopping malls can remain competitive in an evolving retail landscape.

7.2 PROJECT FUTURE SCOPE

The project focuses on developing a real-time customized digital coupon issuance system to enhance shopping mall revenue by improving customer engagement and sales. The system will use AI, machine learning, and real-time data analytics to generate personalized discounts based on customer preferences, purchase history, and location. It will be designed to integrate seamlessly with shopping mall applications, mobile wallets, and point-of-sale (POS) systems.

The project scope includes implementing a dynamic coupon distribution mechanism that delivers offers to customers via mobile notifications, QR codes, and geofencing technology. It will also incorporate predictive analytics to anticipate customer needs and suggest relevant promotions. The solution will support both in-store and online shopping experiences, ensuring a seamless multichannel approach.

Additionally, the system will integrate block-chain technology to enhance transparency and security in coupon transactions. Retailers within the mall will have access to an analytics dashboard that provides insights into customer behavior, coupon redemption rates, and overall sales impact. The system will also include gamification features, such as reward-based incentives, to encourage repeat visits and customer retention.

The project will also focus on ensuring compliance with data privacy regulations by implementing robust encryption and secure authentication mechanisms. The scope extends to developing AI-powered chat-bots for customer assistance and personalized deal recommendations. Integration with cloud-based infrastructure will allow scalability and efficient management of large datasets.

The final implementation will enable shopping malls to enhance their revenue by optimizing marketing strategies, improving customer satisfaction, and fostering stronger retailer-customer relationships. The system's success will be measured based on its ability to increase foot traffic, drive sales, and improve customer engagement through real-time personalized promotions.

8. BIBLIOGRAPHY

9. BIBLIOGRAPHY

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PROJECT GITHUB LINK

https://github.com/Raghuvaran0557/Improving-Shopping-Mall-Revenue-by-Real-Time-Customized-Digital-Coupon-Issuance