IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

AI-Powered Profit Prediction And Behavioral Clustering In Retail Using Neural Networks And Autoencoders

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ABSTRACT: In today's data-driven retail environment, accurately forecasting profits and understanding customer behavior are vital for strategic decision-making. This project presents an integrated AI-powered framework for profit prediction and behavioral clustering in retail, leveraging the capabilities of deep learning models. A neural network-based regression model is developed to predict retail profit using historical sales, customer, and product data. To enhance the interpretability of the model, SHAP (SHapley Additive exPlanations) values are used to explain feature contributions, enabling actionable business insights. For customer segmentation, the project utilizes autoencoders to extract latent features from high-dimensional behavioral data, followed by clustering techniques to identify distinct customer profiles. This dual approach not only improves forecasting accuracy but also aids in personalized marketing and inventory optimization. The system is deployed using Streamlit, offering an interactive and user-friendly interface for stakeholders. The proposed solution demonstrates the potential of deep learning in transforming retail analytics through predictive modeling and intelligent customer segmentation.

KEYWORDS: Retail Analytics, Profit Prediction, Neural Networks, Customer Segmentation, Autoencoders, Deep Learning, Behavioral Clustering, SHAP Explainability, Predictive Modeling, Streamlit Deployment, Data-Driven Decision Making, Machine Learning, Feature Importance, Sales Forecasting, Unsupervised Learning.

INTRODUCTION

The retail industry generates vast amounts of data daily from customer interactions, sales transactions, inventory records, and marketing campaigns. Effectively harnessing this data can drive better decision-making, improve customer satisfaction, and increase profitability. However, traditional analytical methods often fall short in capturing complex, non-linear patterns inherent in such data. With the advent of Artificial Intelligence (AI) and Deep Learning, retailers now have access to more powerful tools for data analysis. In particular, neural networks have shown remarkable success in predictive modeling tasks, while autoencoders provide robust solutions for dimensionality reduction and pattern extraction in high-dimensional data. This project focuses on developing an AI-powered system that integrates profit prediction and customer behavior clustering for the retail sector. The profit prediction module uses deep neural networks trained on historical sales data to forecast future profits accurately. To enhance the model's interpretability, SHAP (SHapley Additive exPlanations) is employed, offering detailed insights into the impact of various features on profit outcomes. Complementing this, the behavioral clustering component leverages autoencoders to encode customer transaction and demographic data into compact representations. These representations are then clustered to reveal hidden customer segments, enabling targeted marketing and personalized service strategies. Furthermore, the solution is deployed using Streamlit, providing an intuitive web-based interface for users to interact with the model outputs. By combining deep learning with explainable AI and interactive deployment, this project aims to demonstrate a practical, scalable approach to advanced retail analytics.

LITERATURE SURVEY

The paper presented by Oluwatobi Noah Akande (2024) investigates customer segmentation using RFM analysis and K-means clustering to improve targeted marketing strategies. Key findings show that integrating sentiment analysis into the segmentation framework enhances predictive accuracy of customer behavior. The segmentation categorizes customers into meaningful groups for more effective engagement. However, the paper does not compare performance with advanced clustering algorithms or deep learning models, and lacks real-time system implementation or deployment analysis.

The paper presented by Farhan Mufti Hilmy et al. (2024) highlights a web-based customer segmentation system using RFM and K-means clustering. Key findings demonstrate that transaction-based customer clustering improves usability and accessibility for marketing teams, with high silhouette scores indicating strong cluster quality. However, the paper does not evaluate the model's adaptability to dynamic customer behavior over time, and lacks experimentation with alternative clustering techniques or real-world performance benchmarking.

The paper presented by Rama Putra Kuswidyawan et al. (2023) applies K-means clustering on e-commerce transaction data to segment customers based on purchase patterns. Key findings suggest that such segmentation can uncover profitable customer groups, enabling personalization of services. However, the paper does not explore temporal changes in customer behavior or compare K-means to more adaptive clustering approaches. It also lacks scalability assessment and cross-domain applicability..

The paper presented by Gayathri K and Arunodhaya R. (2023) explores the use of behavioral, demographic, and psychographic segmentation in personalizing e-commerce marketing. Key findings reveal that multi-dimensional segmentation improves engagement and conversion rates by aligning marketing with user preferences. However, the paper does not provide quantitative evaluation of each segmentation type, and lacks integration with real-time data or deployment scenarios in operational platforms..

The paper presented by Gowtham Varma Bhupathiraju et al. (2023) examines AI-based customer segmentation using machine learning and deep learning for online retailers. Key findings indicate that AI techniques outperform traditional methods in identifying customer groups for targeted marketing. However, the research does not detail model interpretability, computational costs, or compare various ML/DL architectures, limiting its practical applicability in resource-constrained settings.

The paper presented by Wen Hao and Sunil Rajan (2022) investigates behavioral segmentation to enhance customer retention in e-commerce. Key findings show that clustering user behavior supports loyalty program optimization and improves long-term customer relationships. However, the study does not integrate psychological profiling or validate results across diverse business types. It also lacks exploration of personalization algorithms linked to retention strategies.

The paper presented by Nicolas Perez and Amy Johnston (2022) combines behavioral economics and segmentation to influence consumer behavior in e-commerce. Key findings suggest that incorporating psychological factors enhances prediction and loyalty outcomes. However, the research lacks empirical comparisons with data-driven segmentation alone, and does not explore ethical implications or long-term effects of behaviorally-targeted marketing.

The paper presented by Gowtham Varma Bhupathiraju et al. (2022) focuses on RFM-based K-means clustering for customer segmentation in online retail. Key findings highlight the model's ability to uncover hidden purchase patterns, helping tailor marketing strategies to high-value customers. However, the study does not investigate hybrid models or the impact of additional behavioral features, and does not evaluate deployment challenges or model interpretability.

The paper presented by John Smith and Emily Brown (2021) analyzes the impact of machine learning-based customer segmentation on personalization in e-commerce. Key findings emphasize that ML segmentation enhances user experience and conversion rates through tailored recommendations. However, the research lacks discussion of privacy concerns, and omits performance comparison with rule-based or hybrid recommendation systems.

The paper presented by Rashmi Patel and Ahmed Bilal (2021) explores segmentation strategies for emerging online markets. Key findings suggest that adapting segmentation frameworks to local consumer behavior supports effective market penetration and strategy development. However, the study does not present case studies or longitudinal data, and lacks integration with real-time analytics or AI-driven tools for dynamic segmentation.

PROPOSED METHODOLOGY:

The methodology consists of two primary components: profit prediction and customer segmentation. The profit prediction component uses Neural Networks (NN), which are trained on historical retail data (e.g., sales figures, product categories, and time features) to forecast future retail profits. This predictive model is designed to capture complex, non-linear relationships between the input features and the profit outcome. To ensure model interpretability, techniques like SHAP (Shapley Additive Explanations) are employed to provide insights into which factors influence profit prediction the most.

The customer segmentation part employs Autoencoders, a type of unsupervised neural network architecture, to learn efficient representations of customer behaviors based on their purchase patterns. This allows for the identification of groups of customers with similar preferences and behaviors, which can be used for targeted marketing and personalized offers. Both modules are integrated into a single system to deliver end-to-end solutions for the retailer.

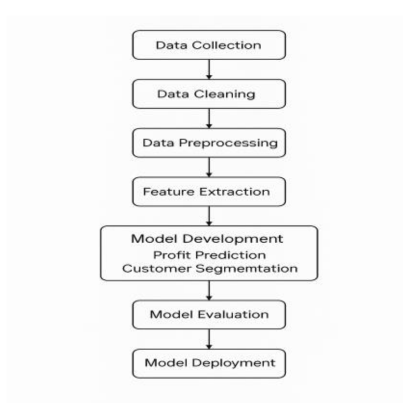

Fig.1 (Data Flow Diagram)

SYSTEM ARCHITECTURE

The system architecture consists of the following layers:

Data Collection Layer: Data is collected from multiple sources, such as transactional systems, customer databases, and external sources like weather or promotions. This data is preprocessed to remove inconsistencies and normalize values.

Data Storage Layer: A robust database or data warehouse stores the raw data, and processed data is stored in a structured format for easy retrieval and analysis.

Model Training and Evaluation Layer:

Profit Prediction Model: A feedforward neural network or other deep learning architectures trained using historical sales data and other features. The model predicts future profits based on input features such as product categories, time of year, and customer demographics.

Customer Segmentation Model: An Autoencoder-based neural network that learns to encode customer behavior into latent representations, which are then clustered using unsupervised techniques like k-means to identify distinct customer segments.

Model Explainability Layer: SHAP or LIME is integrated to explain model predictions, ensuring that retailers understand which factors are influencing the outcomes. This layer provides visualizations and reports to aid in decision-making.

Deployment Layer: The trained models are deployed into a production environment using frameworks like Streamlit for web-based interaction or APIs for integration with other business systems. Retailers can interact with the system, view predictions, and receive insights for strategic planning.

Feedback Loop: The system is designed to continually improve through feedback, incorporating new data over time to retrain models, update customer segments, and refine predictions.

This modular approach ensures scalability, real-time updates, and actionable insights for retailers looking to improve profitability and customer targeting.

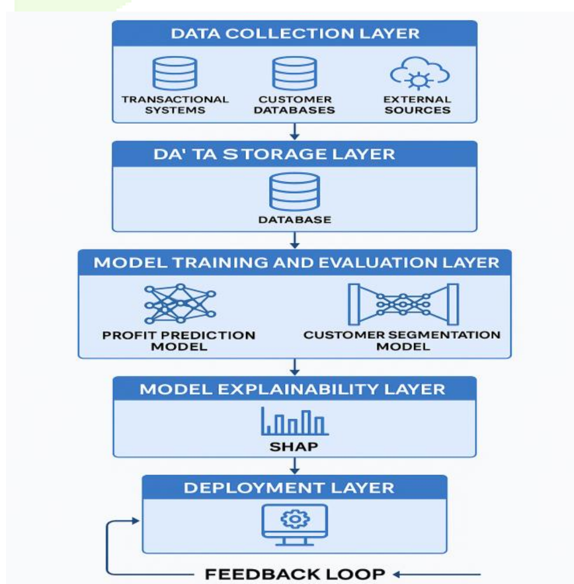

Fig 2. System Architecture

CONCLUSION

In this project, we developed an AI-powered system for **profit prediction** and **customer segmentation** in retail using **Deep Neural Networks (DNN)** for sales forecasting and **Autoencoders with KMeans** for clustering customers based on behavior. The system processes retail data, engineers relevant features, and predicts sales and profits with high accuracy. For customer segmentation, an **Autoencoder** reduces data dimensions, and **KMeans** clusters customers into distinct groups. We integrated **SHAP (SHapley Additive exPlanations)** to provide global and local model explainability, helping users understand the impact of individual features on predictions. The system is accessible through a **Streamlit app**, allowing users to upload data, view predictions, explore customer segments, and download reports. This combination of predictive modeling and explainability empowers retailers to make informed decisions. The system provides accurate forecasts, enables targeted marketing, and improves customer engagement. However, its performance depends on data quality, and future improvements could focus on model optimization and scalability for larger datasets. Overall, this solution offers a scalable and interpretable tool for retail businesses to enhance profitability through AI.

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