



Research Paper

ReviewFusion-AI: An Integrated CART Framework for Automated Consumer Review Intelligence in E-Commerce

I. Vasantha Kumari^{1*}, Karupothula Praneeth², Daripelli Sri Harsha², Chunduri Sai Shashi Kumar²

¹Assistant Professor, ²UG Student, ^{1,2}Department of Computer Science and Engineering (AI & ML),

^{1,2}Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: I. Vasantha Kumari (vasantha.mytrayasa@gmail.com)

Abstract

Customer reviews are a vital component of modern e-commerce platforms, offering meaningful insights into customer satisfaction, product quality, and overall user experience. With the rapid growth of online shopping, a massive volume of textual feedback is generated daily. Traditional evaluation methods, such as average ratings and review counts, provide only a general overview and fail to capture the deeper sentiments expressed in textual reviews. As a result, a large portion of valuable customer feedback remains underutilized. Moreover, manual analysis of large-scale review data is time-consuming and inefficient, emphasizing the need for automated analytical solutions. To address these challenges, this research proposes a machine learning-based framework for analysing customer review data and predicting both recommendation outcomes and product ratings. The system incorporates data preprocessing, exploratory data analysis, and text representation using Term Frequency–Inverse Document Frequency (TF-IDF). Multiple machine learning models are implemented, including Restricted Boltzmann Machine (RBM) combined with Logistic Regression (LR) for classification, RBM with Ridge Regressor (RR) for regression, Gradient Boosting (GB), Extreme Gradient Boosting (XGB), and Multi-Task Neural Network with Extra Trees (MTNN-ET) these models are works with Classification and Regression Tree (CART) Model. Experimental results demonstrate that the proposed MTNN-ET-CART model achieves superior performance, with a classification accuracy of 0.9640 and a regression R^2 score of 1.0000. The framework effectively processes large-scale review datasets and generates reliable predictions, enabling enhanced decision-making and improved customer experience in e-commerce platforms.

Keywords: Customer reviews, E-commerce, Machine learning, Feature extraction, TF-IDF, MTNN-ET

1. Introduction

The use of artificial intelligence (AI) technology within the fashion and textiles industry is growing, with potential applications often focusing on consumer experience (e.g., virtual try-on and digital avatars) to consumer insights, forecasting, and trend analysis [1]. AI is a powerful tool that brands may employ to drive sales, improve consumer experience, and increase efficiency [2]. However, there is also enormous scope for the use of AI within the industry to drive and develop new sustainability initiatives, divert waste, and re-circulate second-hand goods. The global fashion and textile (F&T) industry is a significant contributor to environmental pollution and degradation, largely driven by the fast fashion model that promotes rapid production and consumption cycles. The exact volume of

textile wastes this sector generates annually is unknown; 92 million tons is frequently referenced, much of which is either incinerated, exported or ends up in landfills, as shown in figure 1, exacerbating the environmental crisis [3]. Currently, these pathways are challenged as export markets are becoming oversaturated, with the volumes of textiles being exported, dumped, and landfilled beginning to exceed capacities [4]. Economically, the premature disposal of clothing represents a loss exceeding USD 400 billion annually, highlighting inefficient resource use and missed recycling opportunities. Socially, developing countries often receive large quantities of second-hand clothing, overwhelming local markets and contributing to waste management challenges and public health issues.



Figure 1: Types of textiles in fashion industry

Environmentally, the decomposition of synthetic fabrics in landfills releases harmful chemicals, exacerbating pollution and environmental injustice. Addressing these challenges requires innovative approaches that extend the lifecycle of textiles and garments, emphasizing reuse, repair, and recycling infrastructures and technology. A circular economy (CE) framework offers a promising solution, aiming to minimize waste and resource usage by creating closed-loop systems.

2. Literature Survey

Nisa et al. [5] presented a detailed analytical review focusing on datasets utilized in artificial intelligence applications within the fashion and textile domain. The authors systematically categorized existing datasets and organized them into a structured framework, enabling better understanding and accessibility for future research. Their analysis revealed that most datasets predominantly consist of small-scale fabric swatches, with nearly twenty studies relying on such samples, while comparatively fewer works only around seven focused on full garment representations. This imbalance highlights a critical limitation in dataset diversity and real-world applicability. The review emphasized that although AI has strong potential to improve quality assessment in second-hand clothing markets, optimize textile sorting for recycling and donation systems, and reduce overall waste, the lack of comprehensive and large-scale datasets restricts model generalization. The study further outlined future research directions, particularly stressing the need for more diverse, high-quality datasets to support the transition toward a sustainable and circular fashion economy. In [6], a textile-based Planar Inverted-F Antenna (PIFA) was introduced, incorporating a coplanar frequency reconfiguration mechanism. The design integrates a compact printed circuit board with an embedded active tuning

circuit connected through snap-on buttons, enabling seamless interaction between electronic components and textile materials. The proposed antenna demonstrates a wide operational bandwidth, achieving approximately 70% frequency coverage, making it highly suitable for wearable technology applications. Complementing this, [7] proposed a coupled-mode substrate-integrated cavity (CMSIC) antenna capable of radiation pattern reconfiguration at 2.45 GHz. The design employs passive switching using snap-on buttons, allowing the antenna to alternate between a high-gain broadside radiation pattern (9.2 dBi) and an omnidirectional pattern (3.1 dBi). These innovations highlight advancements in smart textile electronics and wearable communication systems.

Park et al. [8] developed a data-driven size recommendation and coding system tailored for online fashion retail platforms. The primary objective was to address high product return rates caused by inaccurate sizing, which significantly impacts inventory management and operational costs. The system integrates size extraction algorithms and recommendation modules supported by an interactive user interface. It utilizes standardized body measurement systems such as the Chinese GB/T standard to accommodate diverse body types within large populations. Building on this, deep learning techniques [9] have significantly enhanced performance in domains such as image recognition and recommendation systems. Their ability to learn complex patterns from large datasets has led to improved personalization in information retrieval. Expanding on this trend, [10] reviewed deep learning-based fashion recommendation systems developed between 2016 and 2020, highlighting architectures that either rely solely on deep learning or combine it with traditional machine learning approaches. The review summarized key models and emphasized their effectiveness in delivering personalized fashion recommendations.

The design and styling of garments, particularly in traditional attire such as the salwar kameez, have been explored in [11], where both aesthetic coordination and structural design were identified as critical factors in women's clothing. The historical evolution of the kameez since the 13th century reflects its cultural and functional significance in South Asia. Technological advancements, including computer-aided design (CAD) and pattern-making software, have transformed garment manufacturing by improving precision, reducing fabric wastage, and enhancing efficiency in marker planning [12]. Naveed et al. [13] extended this research by quantitatively analyzing the integration of traditional kameez structures with modern sleeve designs. Their study involved the development of thirty-three garment variations combining different kameez styles with multiple sleeve geometries. The results demonstrated measurable impacts on fabric utilization, production cost, and overall efficiency, providing valuable insights for apparel manufacturing optimization. Chaudhary et al. [14] examined the adoption of CAD technology within the Indian textile and apparel industry, highlighting its role in improving design accuracy, reducing production time, and enabling seamless integration with computer-aided manufacturing (CAM) systems. The study also evaluated the broader business implications, including cost reduction and productivity enhancement. Similarly, Špelic et al. [15] investigated the relatively slow adoption of CAD/CAM technologies despite their proven advantages. Their research identified barriers such as high initial investment and lack of technical expertise while emphasizing the potential of these technologies to support mass customization and personalized production. Together, these studies underscore the transformative impact of digital technologies in modernizing the textile and apparel industry while identifying key challenges that must be addressed for wider implementation.

3. Proposed Methodology

The research establishes a systematic framework for analysing customer review data obtained from online clothing retail platforms to understand customer satisfaction and product evaluation patterns.

The methodology follows a structured analytical pipeline that begins with data collection, preprocessing, and feature extraction, followed by machine learning based analysis and predictive modelling. Textual customer feedback and associated numerical attributes are transformed into structured representations using feature extraction techniques so that meaningful patterns can be identified. Multiple machine learning models are integrated to analyse recommendation behaviour and rating patterns from review data as presented in figure 2. A lightweight storage mechanism ensures efficient data handling while a web-based interface allows users to interact with the analytical system, upload data, view exploratory analysis results, and obtain prediction outputs. Continuous analytical evaluation enables the framework to adapt to new data patterns and maintain effective analysis of customer feedback over time.

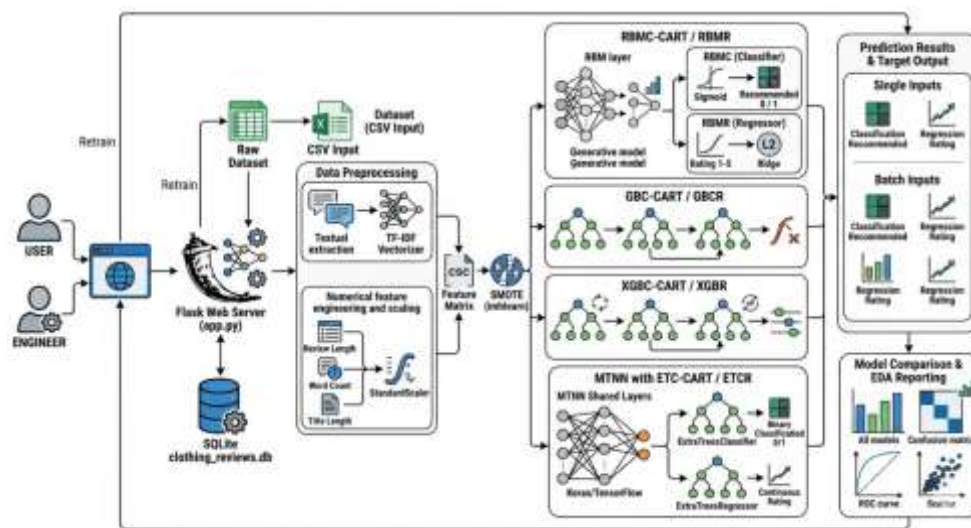


Figure 2: System architecture.

User Interface (Web Browser)

- The user interacts with the system through a browser-based graphical interface.
- Users can perform operations such as login, dataset upload, viewing exploratory data analysis (EDA) results, and generating predictions from review data.
- All user actions are converted into HTTP requests and transmitted to the Flask web server for processing.

Flask Web Server (app.py)

- The Flask backend receives user requests from the interface and routes them to the appropriate processing modules.
- It manages user authentication, prediction requests, data processing tasks, and model execution.
- The server acts as a communication layer between the interface, the machine learning modules, and the database.

SQLite Database (clothing_reviews.db)

- The database stores persistent information required for system operation.

- It maintains records of registered users and related authentication information.
- The database communicates with the Flask server to retrieve and store information efficiently.

Dataset Input (CSV File)

- The customer review dataset serves as the primary input source for analysis.
- It contains attributes such as review title, review text, rating, recommendation indicator, product category information, and feedback count.
- This dataset is forwarded to the preprocessing and feature extraction module for further analysis.

Data Preprocessing and Feature Extraction

- The raw dataset undergoes preprocessing steps including cleaning missing values and combining textual attributes.
- Textual review content is transformed into numerical features using TF-IDF feature extraction.
- Additional numerical attributes such as feedback count, review length, title length, and word count are standardized.
- The processed feature set forms the input for the machine learning models.

Machine Learning Models

RBM-CART

- RBM-CART combines Restricted Boltzmann Machine based feature learning with classification and regression techniques.
- RBMC (RBM + LR): Performs recommendation classification.
- RBMR (RBM + RR): Predicts rating values based on extracted features.

GB-CART

- GB utilizes an ensemble of decision trees based on CART principles.
- It sequentially improves classification performance by correcting errors from previous trees.
- The model is used to identify whether a product is recommended by customers.

XGB-CART

- XGB is an optimized boosting algorithm designed for high efficiency and performance.
- It constructs multiple decision trees to learn complex relationships between review features and recommendation patterns.

MTNN-ET-CART

- The MNTT extracts latent representations from input features using deep neural layers.
- These features are provided to an ET that performs recommendation prediction based on CART decision tree ensembles.

Prediction Output

- After model processing, the system generates predictions for recommendation status and rating values.
- These results are presented through the user interface for interpretation.
- The output includes prediction labels, estimated rating values, and model evaluation results.

Model Evaluation and Monitoring

- The system evaluates model performance using metrics such as Accuracy, Precision, Recall, and F1-score for classification tasks.
- Regression models are evaluated using metrics including MAE (Mean Absolute Error), MSE, RMSE, and R2 score.
- These evaluation results help in comparing model performance and selecting the most effective analytical approach for customer review analysis.

3.1 TF-IDF

TF-IDF is a widely used technique in NLP for converting textual information into numerical form so that it can be analysed by machine learning models. Customer reviews usually consist of unstructured text that cannot be directly processed by analytical algorithms. TF-IDF helps measure the importance of words within individual reviews while considering how frequently those words appear across the entire dataset, as presented on figure 3. By assigning weights to words based on their significance, this technique highlights important terms and reduces the influence of commonly occurring words. As a result, textual review data is transformed into a structured numerical representation suitable for further analysis.

Text Tokenization: The first step involves breaking the review text into smaller units known as tokens, which are usually individual words. Each review sentence is separated into meaningful words that can be analysed individually. This step helps prepare the text for calculating word frequency within the document.

Term Frequency Calculation: Term Frequency measures how often a particular word appears in a single review. Words that appear more frequently within a document receive higher importance at this stage. This step helps identify the prominent words present in individual customer reviews.

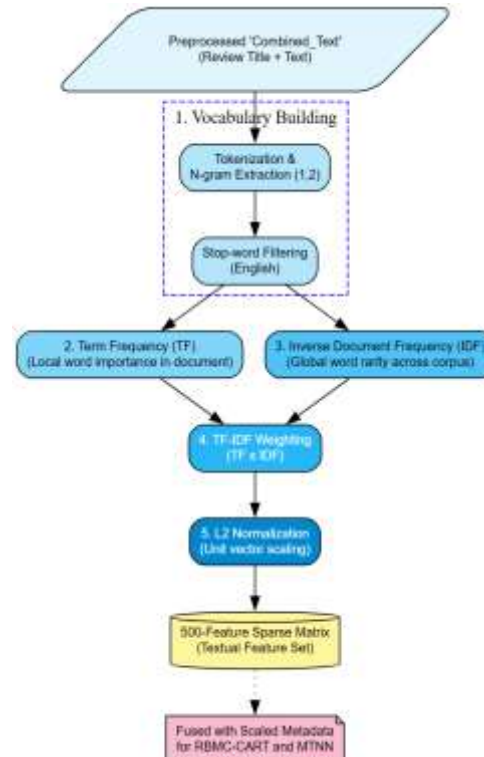


Figure 3: Internal workflow with TF-IDF

Inverse Document Frequency Calculation: Inverse Document Frequency evaluates how common or rare a word is across the entire dataset. Words that appear in many reviews receive lower importance, while rare words receive higher importance. This helps highlight distinctive terms that carry more meaningful information.

TF-IDF Weight Computation: In this step, the Term Frequency and Inverse Document Frequency values are combined to calculate the final TF-IDF weight for each word. The resulting score represents the importance of each word within a review relative to the entire dataset. Higher TF-IDF values indicate more informative words.

Feature Vector Generation: Finally, the calculated TF-IDF values are arranged into a numerical vector representing each review. Each word in the vocabulary corresponds to a numerical weight within this vector. These vectors serve as structured input for machine learning models used in further analysis.

4. Results description

The results obtained from the customer review analysis framework demonstrate the effectiveness of machine learning models in understanding customer feedback and predicting product recommendation behaviour. After performing data preprocessing, feature representation, and dataset partitioning, multiple analytical models were trained and evaluated using the prepared dataset. Models including RBM CART, GB CART, XGB CART, and MTNN-ET CART. were applied to analyse textual review information and related attributes. The experimental results highlight the ability of these models to capture patterns within customer reviews and generate reliable prediction outputs. Performance evaluation was carried out using standard classification and regression metrics to measure model effectiveness. Visualization techniques were also used to illustrate prediction accuracy, confusion matrices, and comparative model performance. The obtained results provide

useful insights into customer opinion patterns and demonstrate the capability of the analytical framework to process large-scale review datasets effectively.

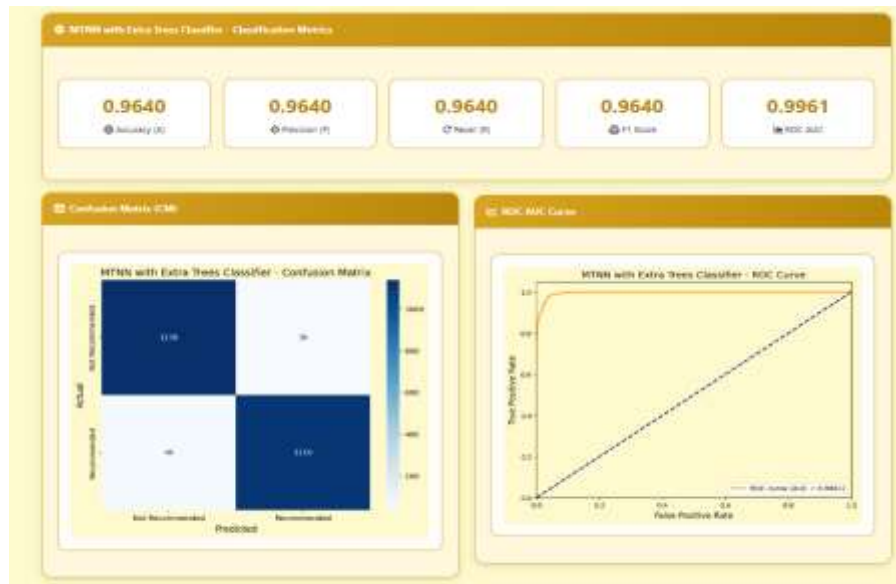


Figure 4: MTNN-ET classification performance results

Figure 4 illustrates the classification performance results obtained from the MTNN-ET model applied to the customer review dataset within the analytical framework. The figure presents key evaluation metrics including accuracy, precision, recall, F1-score, and ROC-AUC, which measure the effectiveness of the hybrid model in predicting product recommendation outcomes. These metrics indicate the capability of the model to accurately classify customer reviews as recommended or not recommended based on the learned feature representations. The confusion matrix visualization further shows the distribution of correct and incorrect predictions generated by the model during evaluation. Additionally, the ROC curve graph illustrates the relationship between the true positive rate and false positive rate, demonstrating the classification strength of the model. The presented results highlight the improved predictive performance achieved by the MTNN-ET model compared with other classification approaches in the system.

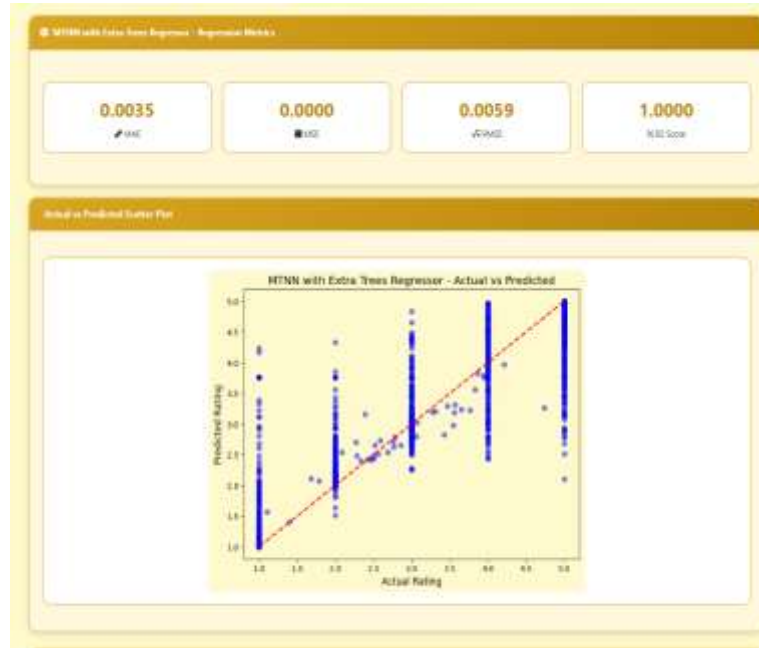


Figure 5: MTNN-ET Regression Performance Results

Figure 5 illustrates the regression performance results obtained from the MTNN-ET model applied for product rating prediction within the customer review analysis framework. The figure presents important regression evaluation metrics including mean absolute error, mean squared error, root mean squared error, and R^2 score, which measure the accuracy of the regression model in estimating rating values from customer review data. These metrics provide insight into the difference between predicted ratings and the actual ratings present in the dataset. The scatter plot visualization further demonstrates the relationship between actual rating values and the predicted ratings generated by the model. This graphical representation helps assess how closely the predicted values align with the true rating values. The results indicate the strong predictive capability of the MTNN-ET model for rating estimation within the analytical framework.

Table. 1: Classification Model Comparison

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
RBM Classifier	0.5137	0.5136	0.5137	0.5135	0.5183
EB Classifier	0.9001	0.9024	0.9001	0.9000	0.9696
XGB Classifier	0.8937	0.9000	0.8937	0.8933	0.9660
MTNN-ET Classifier	0.9640	0.9640	0.9640	0.9640	0.9961

Table 1 presents the performance comparison of different classification models used for recommendation prediction in the customer review analysis framework. The RBM Classifier achieves an accuracy of 0.5137, with precision of 0.5136, recall of 0.5137, F1 score of 0.5135, and ROC-AUC value of 0.5183, indicating relatively lower predictive capability compared to the other models. The EB Classifier demonstrates a significant improvement with an accuracy of 0.9001, precision of 0.9024, recall of 0.9001, F1 score of 0.9000, and ROC-AUC value of 0.9696, showing strong classification performance. Similarly, the XGB Classifier achieves an accuracy of 0.8937 along with precision of 0.9000, recall of 0.8937, F1 score of 0.8933, and ROC-AUC value of 0.9660, indicating

effective prediction capability for recommendation analysis. Among all models, the MTNN-ET Classifier achieves the highest performance with an accuracy of 0.9640, precision of 0.9640, recall of 0.9640, F1 score of 0.9640, and ROC-AUC value of 0.9961, demonstrating superior classification accuracy and overall predictive performance in the framework.

Table. 2: Regression Model Comparison

Model	MAE	MSE	RMSE	R ² Score
RBM Regressor	1.2029	1.8624	1.3647	0.0020
GB Regressor	0.7147	0.7843	0.8856	0.5797
XGB Regressor	0.7136	0.7881	0.8877	0.5777
MTNN with ET Regressor	0.0035	0.0000	0.0059	1.0000

Table 2 presents the performance comparison of different regression models used for predicting product rating values in the customer review analysis framework. The RBM Regressor records a MAE of 1.2029, MSE of 1.8624, RMSE of 1.3647, and an R² score of 0.0020, indicating lower prediction accuracy and higher error compared to the other models. The GB Regressor shows improved performance with a MAE of 0.7147, MSE of 0.7843, RMSE of 0.8856, and an R² score of 0.5797, demonstrating moderate predictive capability for rating estimation. Similarly, the XGB Regressor achieves a MAE of 0.7136, MSE of 0.7881, RMSE of 0.8877, and an R² score of 0.5777, indicating comparable performance to the gradient boosting regression model. Among all the regression models, the MTNN with ET Regressor achieves the best performance with a MAE of 0.0035, MSE of 0.0000, RMSE of 0.0059, and an R² score of 1.0000, demonstrating highly accurate prediction capability for estimating product rating values.

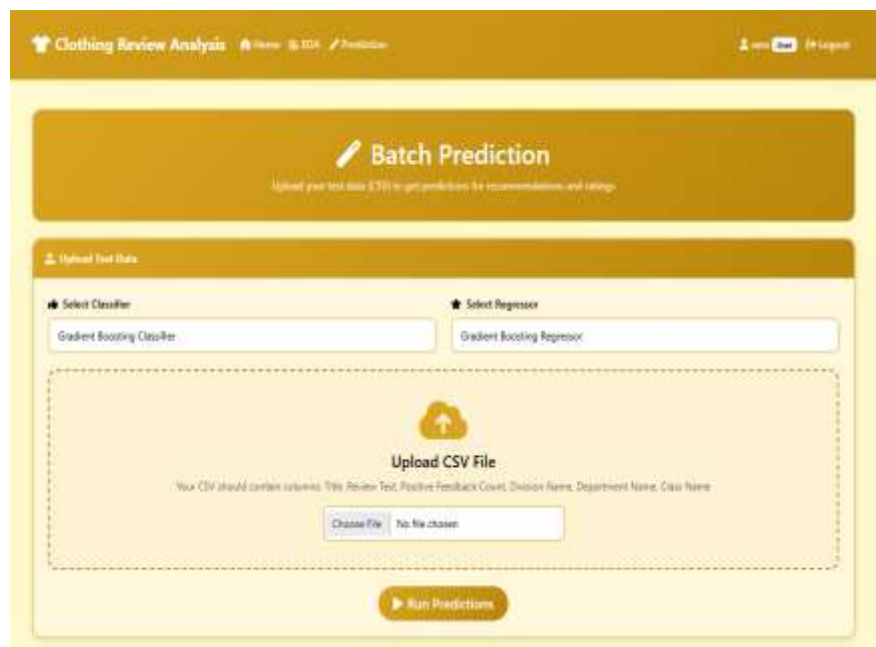
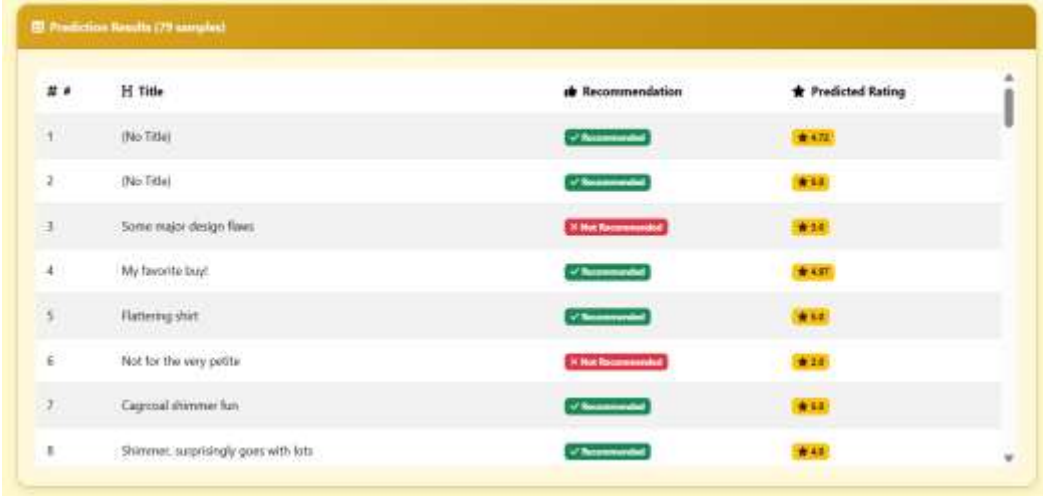


Figure 6: Batch prediction interface for review dataset

Figure 6 illustrates the batch prediction interface of the clothing review analysis framework, which enables users to generate prediction results using trained machine learning models. The interface

allows users to select the classification and regression models that will be applied for recommendation prediction and rating estimation tasks. After selecting the desired models, users can upload a test dataset in CSV format containing the required review attributes. The uploaded dataset is processed by the system to generate prediction outputs based on the trained analytical models. This interface supports automated prediction for multiple review records at once, allowing efficient analysis of customer feedback data. The batch prediction functionality enables users to evaluate recommendation outcomes and rating predictions for new review datasets within the system.



#	Title	Recommendation	Predicted Rating
1	(No Title)	✓ Recommended	★ 4.72
2	(No Title)	✓ Recommended	★ 3.8
3	Some major design flaws	✗ Not Recommended	★ 3.0
4	My favorite buy!	✓ Recommended	★ 4.87
5	Flattering shirt	✓ Recommended	★ 3.8
6	Not for the very petite	✗ Not Recommended	★ 3.8
7	Casual swimmer fun	✓ Recommended	★ 3.8
8	Shimmer, surprisingly goes with lots	✓ Recommended	★ 4.8

Figure 7: Prediction results for customer reviews

Figure 7 illustrates the prediction results interface generated by the clothing review analysis framework after processing the uploaded test dataset. The figure presents the prediction outcomes for multiple review samples, including the review title, recommendation result, and predicted rating value. The recommendation column indicates whether a product review is classified as recommended or not recommended by the selected classification model. The predicted rating column displays the estimated rating values produced by the regression model based on the review features. This tabular representation allows users to easily observe and analyse the prediction results for each review instance. The displayed results demonstrate the system's ability to automatically evaluate customer reviews and generate recommendation and rating predictions using machine learning models.

5. Conclusion

The customer review analysis framework demonstrates the effective use of machine learning techniques for analysing product reviews and predicting both recommendation outcomes and rating values. The system integrates preprocessing, exploratory data analysis, feature representation, and predictive modelling within a unified analytical environment. Multiple machine learning models including RBM CART, GB CART, XGB CART, and MTNN-ET CART. were implemented and evaluated to analyse customer review data. Experimental results show that advanced ensemble and hybrid models significantly improve prediction accuracy compared to basic models. In the classification task, the MTNN-ET model achieved the highest performance with an accuracy of 0.9640 and ROC-AUC of 0.9961, demonstrating strong capability in identifying recommendation patterns. Similarly, in the regression task, the MTNN with ET Regressor produced highly accurate rating predictions with minimal prediction error and an R^2 score of 1.0000. These results indicate that combining neural network-based feature learning with ensemble tree models improves predictive performance and model reliability. The framework provides an efficient and scalable solution for analysing customer review data and generating meaningful prediction insights.

Reference

- [1] Ramos, L.; Rivas-Echeverría, F.; Pérez, A.G.; Casas, E. Artificial intelligence and sustainability in the fashion industry: A review from 2010 to 2022. *SN Appl. Sci.* 2023, 5, 387.
- [2] Ramírez-Escamilla, H.G.; Martínez-Rodríguez, M.C.; Padilla-Rivera, A.; Domínguez-Solís, D.; Campos-Villegas, L.E. Advancing Toward Sustainability: A Systematic Review of Circular Economy Strategies in the Textile Industry. *Recycling* 2024, 9, 95.
- [3] Singh, S. Artificial Intelligence in the Fashion and Apparel Industry. *Tekstilec* 2024, 67, 225–240.
- [4] Papamichael, I.; Voukkali, I.; Economou, F.; Loizia, P.; Demetriou, G.; Esposito, M.; Naddeo, V.; Liscio, M.C.; Sospino, P.; Zorpas, A.A. Mobilisation of textile waste to recover high added value products and energy for the transition to circular economy. *Environ. Res.* 2024, 242, 117716.
- [5] Nisa, H.; Van Amber, R.; English, J.; Islam, S.; McCorkill, G.; Alavi, A. A Systematic Review of Reimagining Fashion and Textiles Sustainability with AI: A Circular Economy Approach. *Appl. Sci.* 2025, 15, 5691. <https://doi.org/10.3390/app15105691>
- [6] Dang, Q.H.; Chen, S.J.; Ranasinghe, D.C.; Fumeaux, C. A Frequency-Reconfigurable Wearable Textile Antenna with One-Octave Tuning Range. *IEEE Trans. Antennas Propag.* 2021, 69, 8080–8089.
- [7] Cui, J.; Liu, F.; Zhao, L.; Dou, W. Textile Fixed-Frequency Pattern-Reconfigurable Coupled-Mode Substrate-Integrated Cavity Antenna. *IEEE Antennas Wirel. Propag. Lett.* 2022, 21, 1916–1919.
- [8] Yuan, Y.; Park, M.-J.; Huh, J.-H. A Proposal for Clothing Size Recommendation System Using Chinese Online Shopping Malls: The New Era of Data. *Appl. Sci.* 2021, 11, 11215. <https://doi.org/10.3390/app112311215>
- [9] Amin, M.S.; Wang, C.; Jabeen, S. Fashion sub-categories and attributes prediction model using deep learning. *Vis. Comput.* 2023, 39, 3851–3864.
- [10] Khan, S.U.R.; Asif, S.; Bilal, O.; Ali, S. Deep hybrid model for Mpox disease diagnosis from skin lesion images. *Int. J. Imaging Syst. Technol.* 2024, 34, e23044.
- [11] Ho, S. Salwar Kameez. Singapore Infopedia. Available online: <https://www.nlb.gov.sg/main/article-detail?cmsuuiid=ce2a4b6a-6aea-46d3-917f-81fe0f1b1d56> (accessed on 1 October 2025).
- [12] Rasheed, A. Textile Engineering: An Introduction; Nawab, Y., Shaker, K., Eds.; Walter de Gruyter GmbH & Co KG: De Gruyter Oldenbourg, Germany, 2023; pp. 137–158.
- [13] Naveed, T.; Khan, A.; Ramzan, M.B.; Ilyas, R.; Shahid, A.; Khan, I.A.; Awais, M.; Javed, K. Fabric Utilization of Women's Kameez Designs with Different Types of Sleeves in the Apparel Industry. *Textiles* 2025, 5, 48. <https://doi.org/10.3390/textiles5040048>

- [14] Chaudhary, S.; Kumar, P.; Johri, P. Maximizing performance of apparel manufacturing industry through CAD adoption. *Int. J. Eng. Bus. Manag.* 2020, 12, 184797902097552.
- [15] Špelic, I. The current status on 3D scanning and CAD/CAM applications in textile research. *Int. J. Cloth. Sci. Technol.* 2020, 32, 891–907.