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Deep Decision Analytics for Customer Review Understanding and Predictive Opinion Intelligence

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Abstract

Customer reviews play a crucial role in today's e-commerce ecosystem by providing valuable information about customer satisfaction, product performance, and the overall shopping experience. As online retail continues to expand, an enormous amount of textual feedback is generated every day. Conventional evaluation approaches, such as average product ratings and the total number of reviews, offer only a broad assessment and are unable to fully capture the detailed opinions and emotions expressed within review texts. Consequently, a significant amount of useful customer feedback remains unexplored. In addition, manually examining large volumes of review data is both labor-intensive and impractical, creating a strong demand for intelligent automated analysis techniques. To overcome these limitations, this study presents a machine learning-driven framework for customer review analysis that predicts both product recommendation decisions and product ratings. The proposed framework includes data preprocessing, exploratory data analysis, and textual feature extraction using the Term Frequency–Inverse Document Frequency (TF-IDF) technique. Several machine learning algorithms are employed, including Restricted Boltzmann Machine (RBM) integrated with Logistic Regression (LR) for classification, RBM combined with Ridge Regressor (RR) for regression, Gradient Boosting (GB), Extreme Gradient Boosting (XGB), and a Multi-Task Neural Network with Extra Trees (MTNN-ET), where these models operate using the Classification and Regression Tree (CART) methodology. The experimental findings indicate that the proposed MTNN-ET-CART model outperforms the existing approaches, achieving a classification accuracy of 0.9640 and a regression R^2 score of 1.0000. The framework efficiently handles large-scale customer review datasets while delivering accurate prediction results, thereby supporting informed decision-making and enhancing the overall customer experience across e-commerce platforms.

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

1. Introduction

The adoption of artificial intelligence (AI) in the fashion and textile industry has increased significantly, with applications ranging from improving customer experiences through technologies such as virtual try-on systems and digital avatars to enabling consumer behavior analysis, demand forecasting, and fashion trend prediction [1]. AI serves as a valuable technology that enables fashion brands to enhance sales, optimize operational efficiency, and deliver better customer experiences [2]. In addition to these commercial applications, AI offers substantial potential to support sustainability by encouraging innovative waste management practices, improving textile recovery processes, and promoting the reuse and circulation of second-hand clothing. The global fashion and textile (F&T) industry is one of the major contributors to environmental degradation, primarily due to the fast fashion business model that encourages high production volumes and frequent consumption. Although the precise quantity of textile waste generated each year remains uncertain, approximately 92 million tons is widely cited, with a considerable portion being incinerated, exported to other countries, or disposed of in landfills, as illustrated in Figure 1, thereby

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intensifying environmental concerns [3]. At present, these disposal methods are becoming increasingly unsustainable because export destinations are reaching their capacity, while the growing amounts of discarded textiles continue to exceed the capabilities of dumping sites and landfill facilities [4]. From an economic standpoint, the early disposal of clothing results in annual losses of more than USD 400 billion, reflecting inefficient utilization of valuable resources and unrealized recycling potential, as shown in figure 1. From a social perspective, many developing nations receive excessive volumes of second-hand garments, placing pressure on local markets and creating additional challenges related to waste management and public health.



Figure 1: Types of textiles in fashion industry

From an environmental perspective, the breakdown of synthetic textile materials in landfill sites releases hazardous substances that contribute to pollution and environmental inequality. Addressing these issues requires innovative strategies that increase the lifespan of textiles and garments by promoting reuse, repair, and advanced recycling technologies and infrastructure. In this context, the circular economy (CE) model provides an effective approach by reducing waste generation and resource consumption through the establishment of closed-loop production and recycling systems.

2. Literature Survey

Chaudhary et al. [5] explored the implementation of Computer-Aided Design (CAD) technology within the Indian textile and apparel industry, highlighting its effectiveness in improving design precision, shortening production cycles, and facilitating seamless integration with Computer-Aided Manufacturing (CAM) systems. Their findings also demonstrated that CAD adoption contributes to reduced production costs, higher productivity, and improved overall manufacturing efficiency. Likewise, Špelic et al. [6] examined the current status of CAD/CAM adoption in the textile sector and observed that, despite their proven advantages, these technologies are still not widely implemented. The study identified major obstacles such as substantial initial investment and insufficient technical expertise while emphasizing their potential to enable mass customization and personalized garment productionYuan et al. [7] introduced a data-driven clothing size recommendation and coding framework designed for online fashion marketplaces. The proposed approach was intended to reduce product returns caused by incorrect size selection, thereby improving inventory management and customer satisfaction. The framework integrates size extraction methods, recommendation algorithms, and an interactive interface while utilizing standardized body measurement systems such as the Chinese GB/T standard to accommodate diverse body types. Amin et al. [8] demonstrated that deep learning techniques have substantially improved the performance of image recognition and recommendation systems by learning complex patterns from extensive datasets, leading to more effective personalized information retrieval. Similarly, Khan et al. [9] reviewed deep learning-based fashion recommendation systems developed between 2016 and 2020, categorizing methods based on standalone deep learning architectures and hybrid approaches that combine deep learning with conventional machine learning models. Their review summarized prominent techniques and emphasized their capability to provide accurate personalized fashion recommendations. Naveed et al. [10] performed

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a quantitative assessment of integrating traditional kameez structures with modern sleeve styles. Their work produced thirty-three garment variations by combining different kameez patterns with multiple sleeve geometries. The experimental findings demonstrated notable improvements in fabric utilization, manufacturing efficiency, and production cost reduction, providing practical insights for apparel production optimization. Ho [11] examined the design characteristics and historical evolution of traditional garments such as the salwar kameez, emphasizing that both structural design and aesthetic coordination play essential roles in women's apparel. The study also highlighted the cultural significance of the kameez, tracing its development from the 13th century across South Asia. Rasheed [12] discussed how advancements in computer-aided design and digital pattern-making technologies have transformed garment manufacturing by enhancing design precision, minimizing fabric wastage, and improving marker planning efficiency.

Nisa et al. [13] presented a comprehensive review of datasets employed in artificial intelligence applications for the fashion and textile sector. The authors systematically classified available datasets into a structured taxonomy to improve their accessibility for future investigations. Their analysis revealed that most existing datasets consist of small-scale fabric swatches, with nearly twenty studies relying on such samples, whereas only about seven studies utilized complete garment datasets. This imbalance limits dataset diversity and affects the ability of AI models to generalize effectively in practical applications. The review emphasized that although AI offers considerable potential for second-hand clothing quality assessment, textile sorting, recycling, donation management, and waste reduction, the shortage of diverse and large-scale datasets remains a major challenge. The authors also outlined future research directions, highlighting the need for comprehensive datasets to support sustainable and circular fashion systems. Dang et al. [14] proposed a textile-based Planar Inverted-F Antenna (PIFA) 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 efficient interaction between textile materials and electronic components. The antenna achieved an operational bandwidth covering approximately 70% of the frequency range, making it highly suitable for wearable electronic devices. Cui et al. [15] further advanced wearable communication technology by introducing a coupled-mode substrate-integrated cavity (CMSIC) antenna capable of radiation pattern reconfiguration at 2.45 GHz. Through passive switching using snap-on buttons, the antenna can alternate between a high-gain broadside radiation pattern of 9.2 dBi and an omnidirectional radiation pattern of 3.1 dBi, demonstrating significant potential for smart textile electronics and wearable communication applications.

3. Proposed Methodology

The research establishes a systematic framework for analyzing women's clothing reviews using machine learning techniques for both recommendation prediction and product rating estimation. Initially, the review dataset is collected and processed through a structured preprocessing pipeline that removes inconsistencies, extracts textual information, and standardizes numerical attributes for effective learning. The processed data is transformed into TF-IDF feature vectors and combined with scaled numerical features, followed by class balancing using SMOTE to improve model robustness. As illustrated in Figure 2, the engineered features are supplied to multiple machine learning models, including RBM-LR, RBM-RR, Gradient Boosting, XGBoost, and the proposed MTNN with Extra Trees architecture. The trained models are evaluated using classification and regression

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performance metrics, while comparison analysis identifies the most effective approach. Finally, the deployed system enables users to upload new review data and obtain accurate recommendation labels and product rating predictions through the trained inference models, supporting intelligent decision-making in e-commerce platforms.

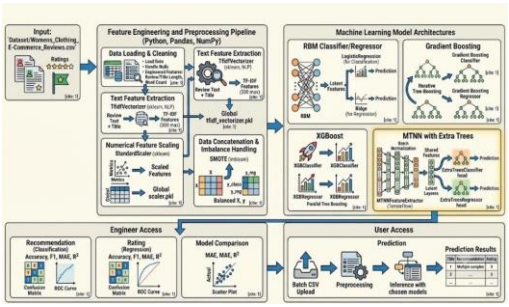


Figure 2: Proposed System architecture.

Data Collection and Preprocessing

The system begins by loading the women's clothing review dataset and performing data cleaning to remove missing values and inconsistent records. Important numerical attributes such as ratings, review length, and word count are extracted, while textual reviews and titles are prepared for further processing. This stage ensures that the input data is complete, consistent, and suitable for feature engineering.

Feature Engineering and Data Preparation

The textual information is converted into numerical representations using the TF-IDF vectorization technique, while numerical attributes are normalized using the StandardScaler algorithm. The generated text features are concatenated with the scaled numerical features to form a unified feature space. SMOTE is then applied to balance the classification dataset, improving the learning capability of classification models.

Machine Learning Model Development

The prepared dataset is used to train multiple learning models, including RBM with Logistic Regression for classification, RBM with Ridge Regression for rating prediction, Gradient Boosting, XGBoost, and the proposed MTNN with Extra Trees architecture. These models learn complex relationships between customer reviews and target variables to perform both classification and regression tasks effectively.

Model Evaluation and Performance Comparison

Each trained model is evaluated using appropriate performance metrics. Classification models are assessed using Accuracy, Precision, Recall, F1-score, ROC curve, and confusion matrix, whereas regression models are evaluated using MAE and R^2 score. Fig. 2 demonstrates that comparative analysis is performed to identify the model achieving the best predictive performance.

Prediction and User Interface

The final trained models are deployed through a user interface that accepts batch CSV uploads containing unseen customer reviews. The uploaded data undergoes the same preprocessing and feature extraction pipeline before inference is performed using the selected trained model. The system then generates recommendation predictions and product rating estimates, providing reliable analytical support for customers and e-commerce administrators.

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,

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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.

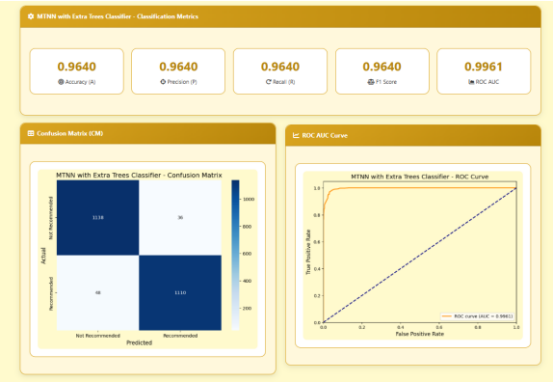


Figure 3: MTNN-ET classification performance results

Figure 3 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 4 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.

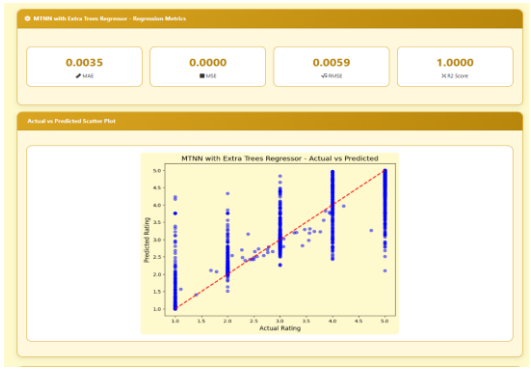


Figure 4: MTNN-ET Regression Performance Results

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

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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 R^2 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 R^2 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 R^2 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 R^2 score of 1.0000, demonstrating highly accurate prediction capability for estimating product rating values.

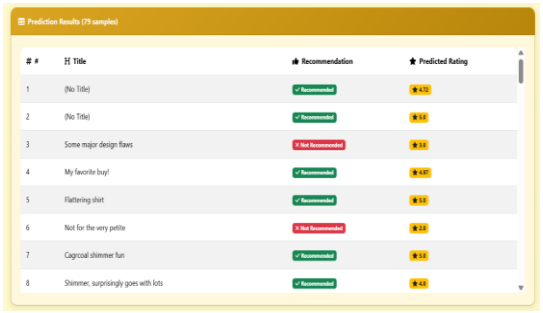


Figure 5: Prediction results for customer reviews

Figure 5 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

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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

This research effectively utilizes machine learning techniques to examine product reviews and accurately predict both customer recommendation decisions and product rating values. The framework combines data preprocessing, exploratory data analysis, feature extraction, and predictive modelling into a single integrated analytical pipeline. Several machine learning models, including RBM-CART, GB-CART, XGB-CART, and the proposed MTNN-ET-CART, were developed and evaluated using customer review data. Experimental evaluation demonstrates that hybrid and ensemble learning approaches deliver superior predictive performance compared to conventional models. For the classification task, the MTNN-ET model achieved the best results, obtaining an accuracy of 0.9640 and a ROC-AUC score of 0.9961, indicating excellent capability in identifying customer recommendation behavior. Likewise, for the regression task, the MTNN integrated with the Extra Trees Regressor generated highly precise product rating predictions, achieving minimal prediction error and an R^2 score of 1.0000. These findings demonstrate that integrating neural network-based feature extraction with ensemble tree learning enhances prediction accuracy, robustness, and overall model reliability. Consequently, the proposed framework offers an efficient, scalable, and dependable solution for large-scale customer review analysis while providing valuable predictive insights to support informed decision-making in e-commerce platforms.

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