Multi-Task Neural Ensemble Framework for Clothing Review Analysis and Recommendation with Rating Prediction

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ABSTRACT

Customer reviews have become an essential source of information in modern e-commerce platforms, providing valuable insights into customer satisfaction, product quality, and user preferences. However, the rapid growth of online shopping has resulted in a massive volume of unstructured textual data, making manual analysis inefficient and limiting the effectiveness of traditional review systems. Existing approaches often rely on simple statistical measures such as average ratings and review counts, which fail to capture the deeper semantic meaning and sentiment expressed in textual feedback. To address these limitations, this study presents a multi-task neural ensemble framework for clothing review analysis, recommendation prediction, and rating estimation. The proposed framework integrates data preprocessing, exploratory data analysis, and feature extraction using Term Frequency–Inverse Document Frequency (TF-IDF) to convert textual reviews into meaningful numerical representations. It employs a combination of machine learning and deep learning models, including Restricted Boltzmann Machines (RBM), Logistic Regression (LR), Ridge Regressor (RR), Gradient Boosting (GB), Extreme Gradient Boosting (XGB), and a Multi-Task Neural Network with Extra Trees (MTNN-ET). These models are further enhanced using the Classification and Regression Tree (CART) approach to effectively handle both classification and regression tasks within a unified framework. The 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, indicating high prediction accuracy and reliability. The framework successfully captures complex patterns in customer feedback and generates precise recommendation and rating predictions.

Key words: Customer Reviews, E-commerce, Sentiment Analysis, TF-IDF, Ensemble Learning, Multi-Task Neural Network, Recommendation System, Rating Prediction, CART.

1.INTRODUCTION

The adoption of artificial intelligence (AI) in the fashion and e-commerce industry has significantly expanded, particularly in analysing customer reviews to enhance recommendation systems and rating prediction [1]. AI-driven models enable deeper understanding of consumer preferences by extracting meaningful insights from textual feedback, improving personalization and decision-making processes [2].

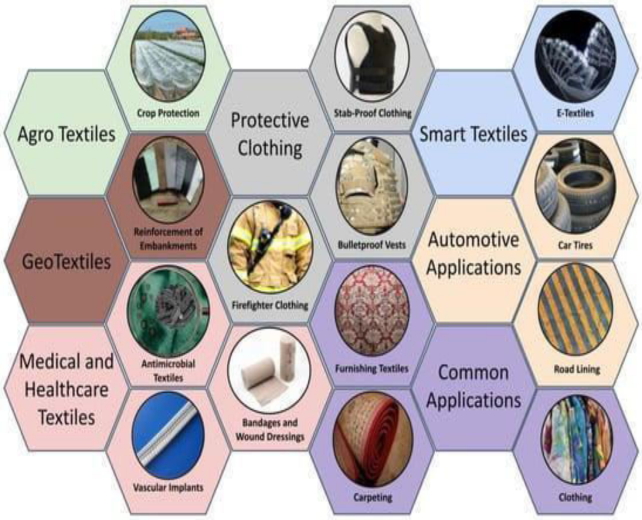


Figure 1: Types of Textiles in Fashion Industry

These intelligent systems not only enhance user experience but also optimize product evaluation through automated review analysis. Furthermore, advanced multi-task learning approaches support efficient handling of large-scale review data for accurate recommendations and rating estimation. The fashion and e-commerce industry generates a massive volume of customer review data, which, if not effectively analysed, leads to underutilization of valuable consumer insights and inefficient decision-making processes [3]. Traditional review management systems primarily focus on storing and displaying textual feedback and ratings, without performing deeper analytical interpretation of the content [4]. As a result, critical information related to customer sentiment, preferences, and product perception remains unexplored.

This limitation affects the accuracy of recommendation systems and reduces the reliability of rating predictions. Additionally, manual analysis of large-scale review datasets becomes increasingly complex and time-consuming as data volume grows. As shown as figure 1 To overcome these challenges, advanced artificial intelligence techniques are required to automatically process and interpret unstructured textual data. Multi-task neural ensemble approaches provide an effective solution by enabling simultaneous analysis of multiple aspects such as sentiment, recommendation behaviour, and rating estimation. These models improve prediction accuracy by capturing complex relationships within the data. Furthermore, such intelligent systems enhance personalization, optimize product evaluation, and support scalable analysis of customer feedback. Integrating AI-driven frameworks significantly improves the efficiency and effectiveness of review understanding in modern e-commerce platforms.

2.LITERATURE SURVEY

Nisa et al. [5] conducted this review as an examination and analysis of datasets that had been used for model development in fashion and textiles, which they categorized and detailed in a comprehensive table to guide future research. Whilst the findings emphasized the potential of AI to enhance quality assurance in second-hand clothing markets, streamline textile sorting for donations and recycling, and reduce waste in the fashion industry, the authors also highlighted gaps in the available datasets, often due to limited size and scope. The types of textiles captured were most commonly swatches of fabric, with 20 studies examining these, whereas whole garments were less frequently studied, with only 7 instances. This review concluded with insights into future research directions and the promising use of AI within fashion and textiles to facilitate a transition to a circular economy.

Dang, et al. [6] is presented by applying a coplanar frequency reconfiguration mechanism. The reconfiguration module includes a compact printed circuit board that embeds the active tuning circuit with snap-on buttons offering the electronic-to-textile connection. The antenna prototype achieves a wide operating frequency range of about 70%. Finally, in [7] a coupled-mode substrate-integrated cavity (CMSIC) antenna is presented. The antenna achieves radiation pattern reconfiguration at 2.45 GHz by employing two snap-on buttons as passive switches. When the buttons are in the OFF state, the antenna generates a broadside radiation pattern with a maximum gain of dBi, while, in the ON buttons state, the radiation pattern is omnidirectional with a maximum gain of dBi.

Park et al. [8] conducted this study to design data-based size recommendation and size coding systems specifically for online shopping malls, with the aim of reducing the burden of holding excessive inventories, which often resulted from the high return rates in these malls. The recommendation system was implemented with a focus on size extraction and recommendation functions, along with a user interface (UI). For the size extraction function, data were required to determine customers' sizes; for example, the system used in China adopted the Chinese standard body size GB/T (Chinese national standard), taking into account the variety of body types in the country's large population. Deep learning algorithms [9], particularly those used for image and video recognition, have significantly improved accuracy across various domains. Interestingly, deep learning techniques are also being applied in information recommendation, with numerous recommendation systems designed to offer tailored suggestions for information retrieval.

This article [10] concentrated on deep learning-based Fashion Recommendation System (FRS) initiatives developed between 2016 and 2020. Researchers have constructed recommendation systems using either exclusively deep learning models or in combination with other machine learning models. The article provides a concise overview of the most noteworthy deep learning models currently employed in recommendation systems (RS). Salwar Kameez et al. [11] They design (creates the outfit) and style (coordinates the esthetic choices for the visual or outer look with accessories) of any garment holds significant importance for women's clothing. In the 13th century, the kameez style (long kameez or tunic) was introduced in South Asia. Technological upgrades, such as the adoption of computer-aided design (CAD), pattern-making software, and manufacturing systems, have been adapted by the apparel industry to improve precision, accuracy and the highest possible efficiencies for fabric cutting, and marker making (efficient nesting of patterns) with a decrease in fabric wastage [12].

Naveed et al. [13] addressed a critical research gap by quantitatively evaluating the impact of fusing traditional South Asian garment construction (the kameez) with varied, Western-inspired sleeve geometries on key manufacturing metrics. Thirty-three distinct women's garment styles, comprising three kameez types (simple, princess-cut, open-front) each paired with eleven different sleeve designs, were developed in the apparel industry to examine the effects on fabric efficiency, wastage, and cost-effectiveness. Chaudhary et al. [14] investigated the adoption of CAD technology in India's textile and apparel manufacturing sector. The study examined how CAD enhances design efficiency, reduces costs, and accelerates production through integration with CAM, while also assessing its impact on design, productivity, and business outcomes. Špelic et al. [15] researched that focused on the underutilization of CAD/CAM systems in the apparel and textile industry despite their potential benefits. It discusses the technology's applicability, benefits, and slow adoption, highlighting its role in enabling customization and shifting industries toward mass customization and personalization.

3. PROPOSED SYSTEM

The research presents a multi-task neural ensemble framework for analysing customer review data from online clothing retail platforms to understand recommendation behaviour and rating prediction patterns. The methodology follows a structured pipeline that includes data collection, preprocessing, and feature extraction, followed by integrated multi-task learning and predictive modelling. Textual reviews and associated attributes are transformed into structured representations using techniques such as TF-IDF to capture meaningful semantic information. Multiple machine learning and neural models are combined within an ensemble framework to simultaneously perform recommendation classification and rating estimation tasks, as illustrated in figure 2. A lightweight data management system ensures efficient handling of large-scale review datasets, while a web-based interface enables users to upload data, visualize analysis results, and obtain predictions. Continuous model evaluation and updating allow the framework to adapt to evolving customer feedback patterns, ensuring consistent performance and accurate review understanding over time.

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.

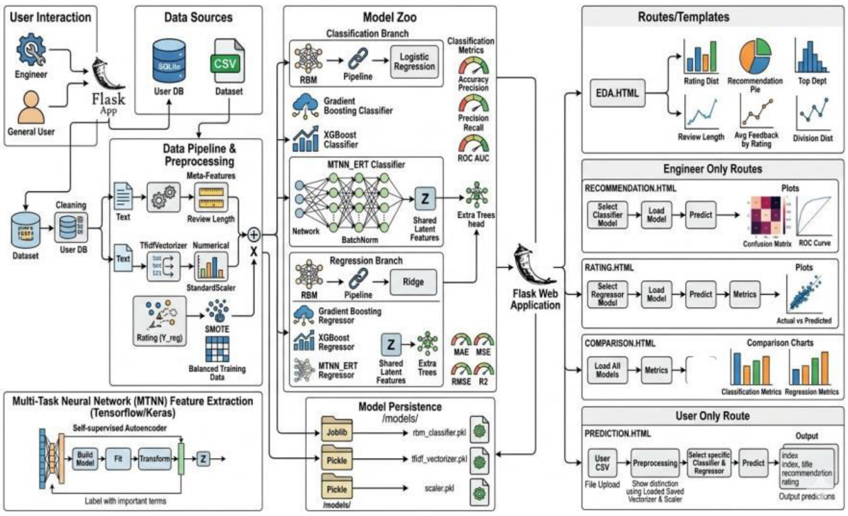


Figure 2: System architecture.

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.

4. RESULTS ANALYSIS

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.

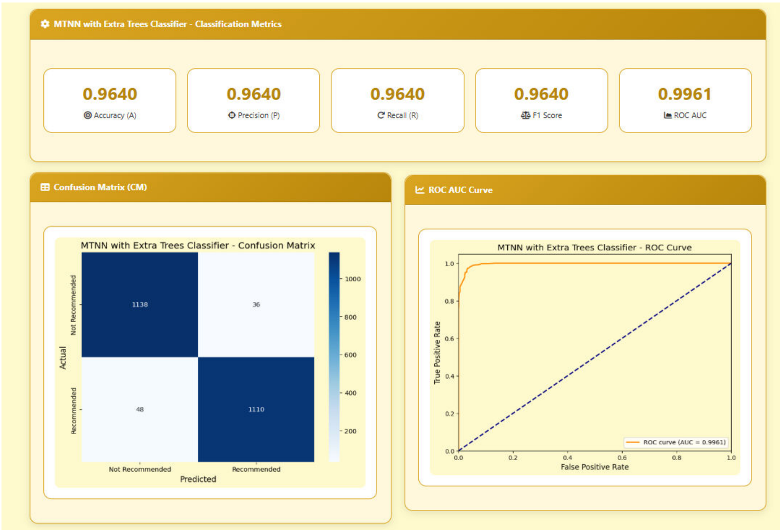


Figure 3: MTNN-ET Classification Performance Results

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.

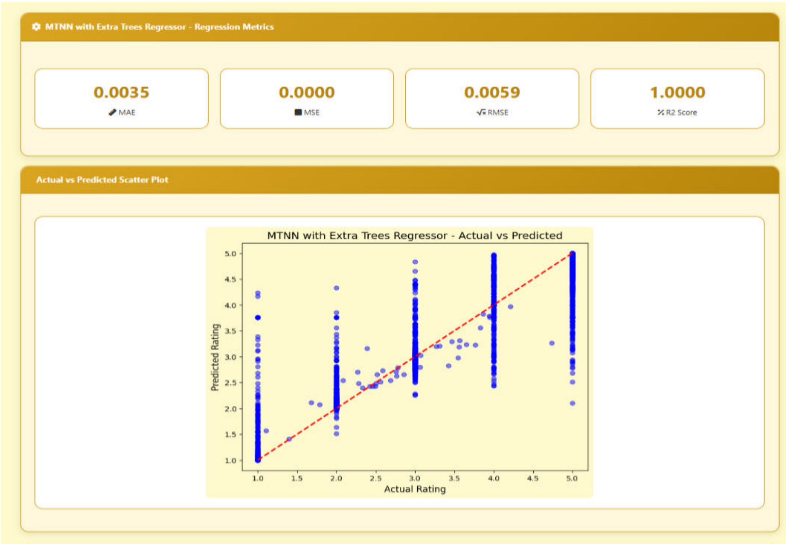
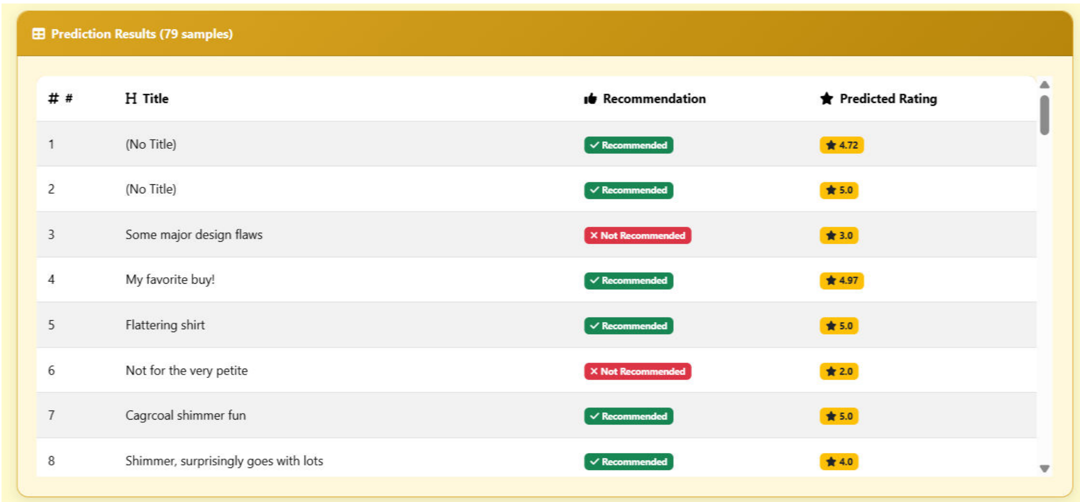


Figure 4: MTNN-ET Regression Performance Results

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.


Prediction Results (79 samples)

#	Title	Recommendation	Predicted Rating
1	(No Title)	Recommended	4.72
2	(No Title)	Recommended	5.0
3	Some major design flaws	Not Recommended	3.0
4	My favorite buy!	Recommended	4.97
5	Flattering shirt	Recommended	5.0
6	Not for the very petite	Not Recommended	2.0
7	Cagrcoal shimmer fun	Recommended	5.0
8	Shimmer, surprisingly goes with lots	Recommended	4.0

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 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.

Comparative Analysis

The comparative analysis evaluates the performance of multiple machine learning models implemented in the customer review analysis framework. This analysis helps determine which model provides the most effective prediction results for recommendation classification and rating estimation tasks. Different models such as RBM, GB, XGB, and MTNN with ET are compared using standard evaluation metrics. For classification, metrics including accuracy, precision, recall, F1-score, and ROC-AUC are used to measure model performance. For regression analysis, metrics such as MAE, MSE, RMSE, and R^2 score are used to assess prediction accuracy. The comparative results provide insights into the strengths and limitations of each model and help identify the most suitable approach for customer review analysis.

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 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.

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.

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