# Parallel Learning Framework for Unified Rating Prediction and Review Understanding in Fashion Industry Data

V. Bharathi[1], B. Ramya Sai Priya[2], A. Srilatha[2], G. Hemalatha[2], K. Bhavya Sri[2]

[1]Associate Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (AI & ML)

[1,2]Geethanjali Institute of Science and Technology, Nellore-Bombay Highway, S.P.S.R, Andhra Pradesh 524137, India

## ABSTRACT

Every day, millions of clothing reviews are posted on e-commerce platforms, reflecting customer experiences and preferences, and nearly 80% of online shoppers rely on these reviews before making purchase decisions. This rapid growth of user-generated content has created a strong demand for intelligent systems that can automatically predict product ratings and analyze textual reviews to support customer satisfaction, inventory optimization, and marketing strategies. However, traditional machine learning models rely heavily on manual feature extraction and struggle with noisy data, overfitting, and limited labeled datasets. To overcome these challenges, this work proposes a multi-model framework for simultaneous rating prediction and recommendation analysis in the clothing industry. The proposed algorithms include Multi-Task Neural Network (MTNN) with Extra Trees Classification and Regression Trees (CART), Restricted Boltzmann Machine (RBM) with CART, Extreme Gradient Boosting (XGBoost) with CART, and Gradient Boosting, all applied to both regression for rating prediction and classification for recommendation tasks. The MTNN architecture uses shared feature representations with task-specific branches, enabling efficient joint learning across tasks, while ensemble CART models improve robustness and stability. Regularization techniques are employed to enhance generalization performance. Experimental results show that the MTNN with Extra Trees CART achieves the most accurate predictions, providing reliable insights into customer sentiment, product quality, and overall satisfaction in the clothing e-commerce domain.

**Keywords:** Multi-Task Neural Network (MTNN), Rating Prediction, Review Analysis, Classification and Regression Trees (CART), XGBoost, Ensemble Learning.

## 1. INTRODUCTION

The clothing industry is one of the largest and fastest-growing sectors worldwide, significantly contributing to the economies of both developed and developing nations. In India, the textile and apparel sector has long served as an economic backbone, supporting employment, manufacturing, and exports through its vast network of handloom clusters, garment units, and retail chains. Globally, countries like China, Bangladesh, Vietnam, and the United States have also built strong apparel markets driven by advanced manufacturing technologies, global brands, and digital retail strategies. Across regions, the industry continues to evolve based on changing consumer preferences, fashion trends, and rapid digital transformation. In the online marketplace, customer interaction with products has changed significantly, with buyers now relying heavily on reviews and ratings to evaluate fabric quality, fitting, color accuracy, pricing, and overall experience. These reviews influence purchasing decisions and help companies understand customer satisfaction, manage inventory, improve product design, and enhance recommendation systems. As e-commerce has rapidly expanded, platforms like H&M, Zara, Flipkart, Myntra, and Ajio generate massive amounts of customer review data, which can reveal valuable insights about preferences, sentiment trends, and product performance.

As the clothing industry shifts from traditional retail to digital commerce, the research aims to transform large volumes of customer feedback into meaningful insights. The proposed multi-task deep learning model provides a scalable and intelligent solution that supports better decision-making and improves overall customer satisfaction. In addition, the approach enables real-time trend identification and early detection of customer concerns, helping brands respond quickly to market demands. It also supports personalized product recommendations and continuous improvement of business strategies through data-driven insights.

Figure 1 shows the annual sales performance of H&M from 2019 to 2023, measured in million SEK. Sales were high in 2019 at SEK 232,755 million, but decreased in 2020 to SEK 187,031 million, likely due to global market disruptions. A gradual recovery is seen in 2021 with SEK 198,967 million and continued growth in 2022 at SEK 223,553 million. The highest sales are recorded in 2023 at SEK 236,014 million, indicating strong business recovery and improved market performance. Finally, the upward trend after 2020 reflects H&M's effective strategic adjustments and growing customer demand in the global fashion market.

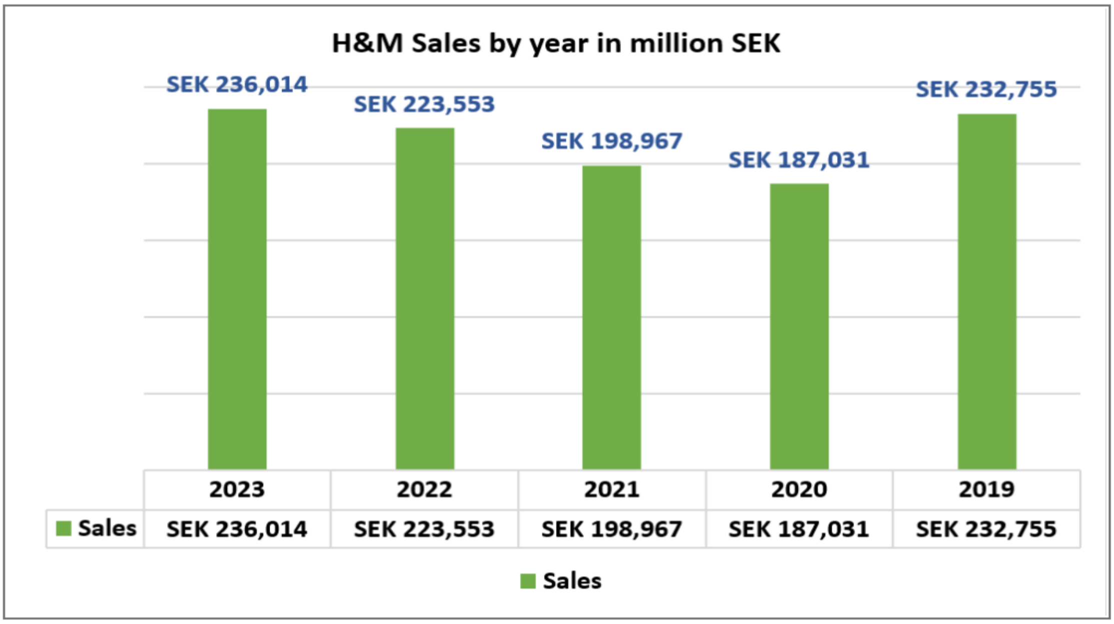



Figure 1: H&M Sales by Year (2019–2023)

Figure 2 illustrates the sales performance of Zara from 2017 to 2020. The graph shows a consistent upward trend in sales over the four-year period. In 2017, sales were relatively low, but a steady increase is observed in 2018 and 2019. The most significant growth appears in 2020, where sales reached their highest level. This trend indicates Zara's strong market presence, effective business strategies, and increasing customer demand over the years.

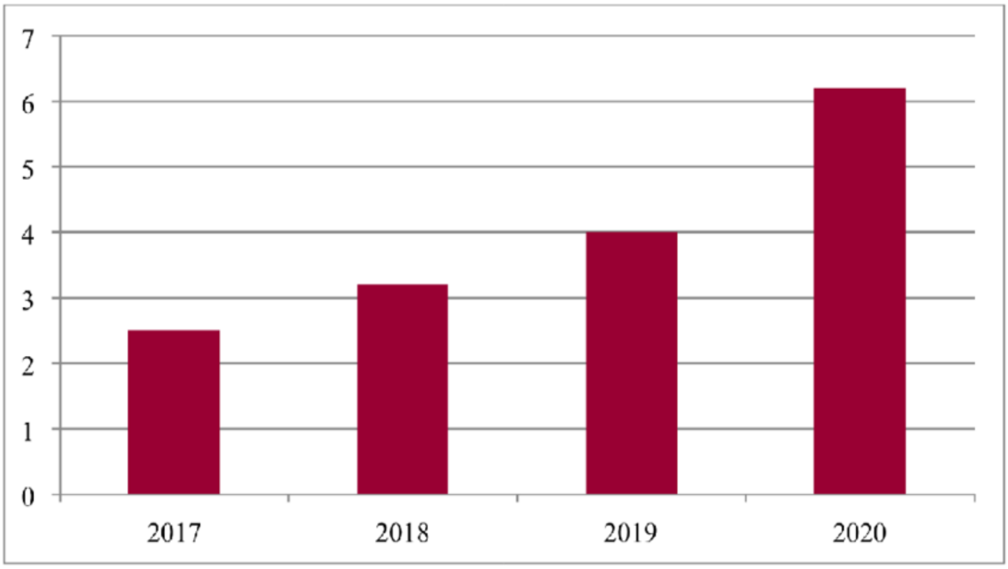



Figure 2: Zara Sales Growth (2017–2020)

## 2. LITERATURE SURVEY

Ashima, et al. [1] proposed the resilient infrastructure with innovation is realized by the integration of digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), blockchain, augmented reality (AR), and virtual reality (VR). With this motivation, this study explored the different studies that implemented these technologies in the fashion industry for smart cloth (health), supply chain, circular economy, dress recommendation system, fashion trend forecasting, health prediction, and virtual and augmented based shopping experience. Liu, et al. [2] proposed a multi-task Dual Attention Recommendation Model using Reviews and their Helpfulness (DARMH). The model separately constructs the local and interactive attentions to extract the personalized preference of specific users for specific items. By defining the helpfulness of a review, the attention weight of the review is acquired to better extract the features of the items review. However, many reviews do not have helpfulness ratings

Feng, et al. [3] adopted the successful application of deep neural networks on computer vision, natural language processing, and other tasks, deep learning is employed to model the social network-enhanced collaborative filtering problem. Although it has been proposed recently to model the nonlinear relationship by deep networks for collaborative filtering, it does not take the social relations between users into account. Ye, et al. [4] proposed correlation relationship between subtasks is fitted by the parameter sharing layer of multi-task learning, which in turn achieves the effect of improving the prediction accuracy. Firstly, the power consumption correlation between the upstream and downstream industries in the industry chain is analyzed, and multi-task long and short-term memory model is established. Wang, et al. [5] focused on the problem of sparsity and low accuracy in collaborative filtering algorithms, this paper proposes a general framework, called neural multi-task collaborative filtering (NMCF), which can simultaneously predict the rating and trust relationships. That is, the rating of the same user in e-commerce platforms and the trust relationships in social networks promote and complement each other and help to improve the prediction accuracy of both.

Alali, et al. [6] proposed a multitask learning model based on hierarchical attention network (MTLHAN) to learn the best sentence representation and model generalization, with shared word encoder and attention network across both tasks, by training three-polarity and five-polarity Arabic sentiment analysis tasks alternately and jointly. Lala, et al. [7] adopted impetus toward energy efficiency, the current focus is on data-driven TC prediction solutions that leverage state-of-the-art machine learning (ML) algorithms. However, an occupant's perception of indoor thermal comfort (TC) is subjective and multi-dimensional. Different aspects of TC are represented by various standard metrics/scales viz., thermal sensation (TSV), thermal comfort (TCV), and thermal preference (TPV). Akram, et al. [8] adopted resilient infrastructure with innovation is realized by the integration of digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), blockchain, augmented reality (AR), and virtual reality (VR). With this motivation, this study explored the different studies that implemented these technologies in the fashion industry for smart cloth (health), supply chain, circular economy, dress recommendation system, fashion trend forecasting, health prediction, and virtual and augmented based shopping experience.

Renaningtyas, et al. [9] proposed several studies from 2010 to date have initiated AI (Artificial Intelligent) technology, a computer vision that alleviates the use of carbon footprints in the fashion industry. AI presents robust evidence to the audience, since it is visual and statically calculated, furthermore it is less costly and energy saving. AI abstracts the similarities or differences across all clothing and collections from the dataset. Its implementation can be used in many fashion careers with different purposes. Nadeem, et ai. [10] utilized research proposes a systematic prediction model to forecast colour quickly and cost-effectively in real-time data. This research examines the colour forecasting process, its methodology, and how it is presented and used in the fashion industry. This study used Machine Learning (ML) to examine image data from the latest fashion trends to collect data via web-scraping images, extracting colours from images using k-means algorithms, and assessing the most trending 45 colours.

Zhang, et al. [11] proposed rapid growth of online commerce and fashion-related applications, visual clothing analysis and recognition has become a hotspot in computer vision. In this paper, we propose a novel AABLSTM network, which is based on deep CNN-RNN, to solve the visual fashion analysis of clothing category classification, attribute detection, and landmark localization. Marullo, et al. [12] adaopted the system exploits a shared backbone based on the encoder of the U-Net architecture and two separate branches to classify the blood accumulation event and output the segmentation map, respectively. Our main contribution is an efficient multi-task approach that achieved satisfactory results during the test on surgical videos, although trained with only RGB images and no other additional information.

Montazerian, et al. [13] proposed the main steps involve: (1) using a portable camera (such as from a smartphone); (2) improving the image quality; (3) isolating the human body from the surrounding environment; (4) performing a calibration step; (5) extracting features of the body from the image; (6) indicating markers on the image; (7) producing refined final results. Mahmud, et al. [14] proposed Random Forest, Support Vector Machine (SVM), Logistic Regression, Naive Bayes Classifier, Gradient Boosting, and Long Short-Term Memory (LSTM) are just a few examples. With an accuracy of 96.51%, a precision of 96.51%, a recall of 96.51%, and an F1-score of 96.50%, the Random Forest Classifier performed the best. Ren, et al. [15] introduced Empirical analysis is conducted for the clothing brands of ALDB, AND, BNL, and QPL; the results show that, based on online user reviews, ECRM enables accurate evaluation of the perceived quality of clothing brands. Based on the evaluation results, it is found that Comfort, External, Protection, and Fineness are highly valued by consumers; moreover, the four brands focus on different indexes.

## 3. PROPOSED SYSTEM

Figure 3 shows the proposed system is a multi-task neural network–based intelligent review analysis and prediction framework for the clothing industry that simultaneously performs recommendation classification and rating regression from customer reviews. Using structured attributes and unstructured textual reviews, the system applies advanced preprocessing, exploratory analysis, TF-IDF–based feature extraction, and multiple machine learning models, culminating in a multi-task neural network integrated with ensemble CART-based learners. The final system is deployed through a Flask-based web interface with an SQLite backend, enabling real-time prediction of customer recommendation decisions and numerical ratings, thereby supporting business insights and decision-making in apparel retail platforms.

**Step 1 Dataset:** The dataset consists of customer-generated apparel review data containing attributes such as title, review text, rating, recommendation indicator, positive feedback count, division name, department name, and class name. This dataset serves as the foundation for both classification and regression tasks, where the recommendation indicator is treated as a binary target and the rating as a continuous target variable.

**Step 2 Data Preprocessing:** In this step, missing values are handled, irrelevant or duplicate records are removed, and categorical variables such as division, department, and class names are encoded. Textual fields including title and review text are cleaned through tokenization, lowercasing, stop-word removal, and lemmatization to prepare them for feature extraction.

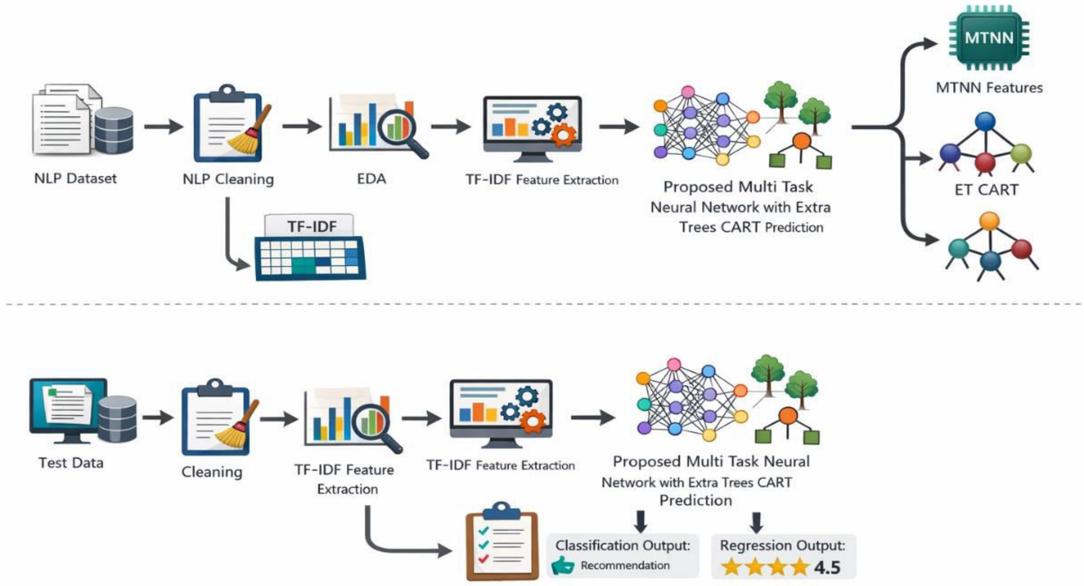



Figure 3: System Architecture

**Step 3 Exploratory Data Analysis:** Exploratory data analysis is performed to understand data distribution, class imbalance, rating trends, review length patterns, and correlations between features. Visual and statistical analysis helps identify influential attributes and guides feature selection for both classification and regression tasks.

**Step 4 TF_IDF Feature Extraction:** The cleaned textual data is transformed into numerical representations using the TF-IDF technique. This step captures the importance of words across reviews and converts unstructured text into meaningful feature vectors that can be combined with structured numerical and categorical features.

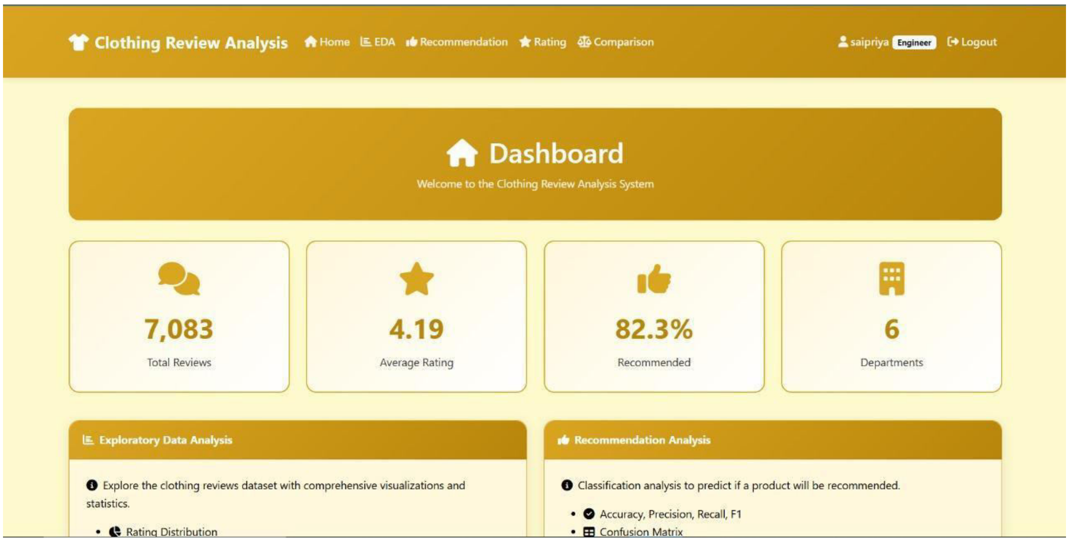
**Step 5 Machine Learning Model Building:** Traditional machine learning models such as Gradient Boosting with CART, XGBoost with CART, and RBM combined with CART are trained separately for recommendation classification and rating prediction. These models establish baseline performance and help evaluate the effectiveness of ensemble and hybrid learning approaches.

**Step 5.1 Multi Task Neural Network with Extra Trees CART:** A multi-task neural network is designed to share common hidden layers while producing two outputs: recommendation classification and rating regression. Extra Trees integrated with CART are used within the multi-task framework to improve feature splitting, reduce variance, and enhance predictive accuracy across both tasks simultaneously.

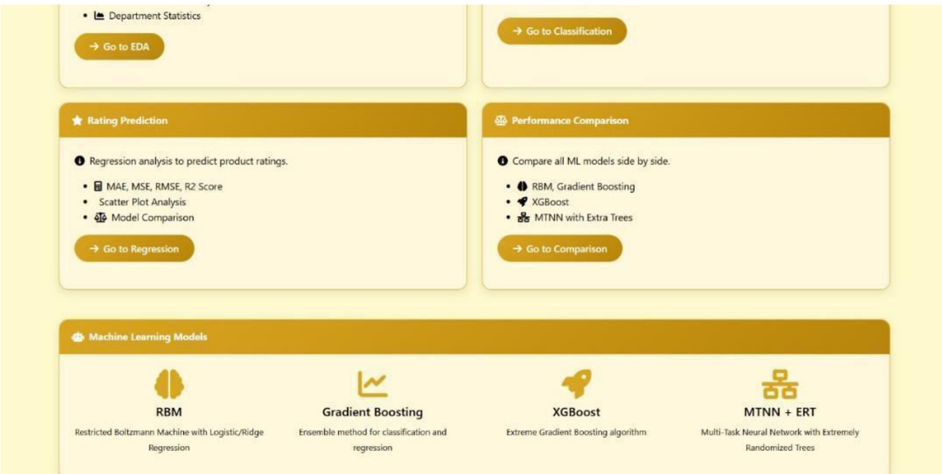
**Step 6 Frontend Integration:** The trained model is deployed using the Flask framework, with SQLite used to store review data and prediction results. The frontend allows users to input review information and receive real-time outputs for recommendation decisions and predicted ratings, ensuring seamless integration between the machine learning backend and user-facing application.

## 4. RESULTS ANALYSIS

Figure 4 show different parts of the Clothing Review Analysis system interface. The first image highlights key functional modules such as rating prediction, performance comparison, and available machine learning models. It displays options like MAE, MSE, RMSE, R2 score evaluation, scatter plot analysis, and model comparison, along with a section to compare models like RBM, Gradient Boosting, XGBoost, and MTNN with Extra Trees. It also presents icons and brief descriptions of each ML model used in the system. The second image represents the main dashboard, showing overall statistics including 7,083 total reviews, an average rating of 4.19, a recommendation rate of 82.3 percent, and 6 departments. The dashboard also provides access to exploratory data analysis and recommendation analysis, where users can explore rating distribution, department statistics, accuracy, precision, recall, f1-score, and confusion matrices. Together, these visuals offer a clear overview of the system's analytic capabilities and user-friendly navigation.




(a)




(b)

Figure 4: Home Page.(a) Primary (b) Secondary

Figure 5 shows the bar chart how customer ratings are distributed in the dataset. The x-axis displays the rating values from 1 to 5, and the y-axis shows how many reviews belong to each rating. The chart reveals that ratings are not evenly spread out. Very few customers gave ratings of 1 or 2, while a moderate number gave a rating of 3. Ratings of 4 are more common, but the highest count by far is for rating 5. This indicates that most customers left very positive feedback, with a large majority giving the maximum rating. The background of the plot is light yellow, and the bars are drawn in blue, making the differences between the rating counts easy to see.

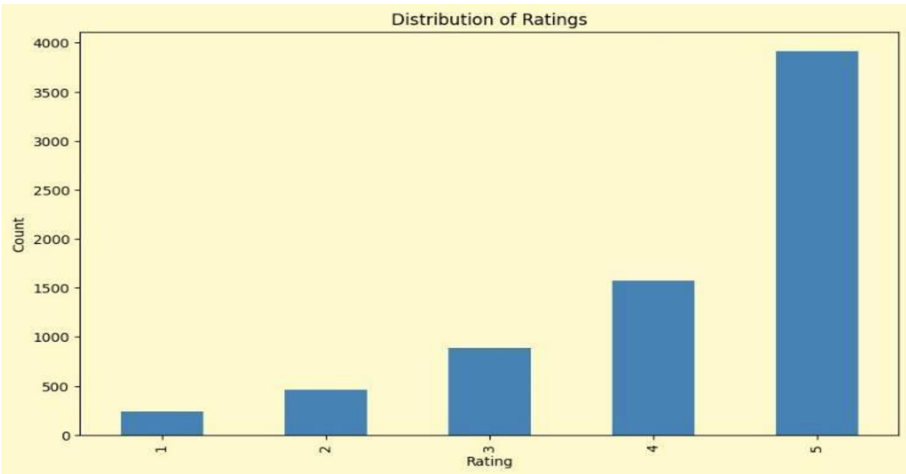



Figure 5: Rating distribution

The Figure 6 shows how many customers recommended the product compared to those who did not. The chart is divided into two sections: a large red portion representing the customers who did not recommend the product, and a smaller green portion representing those who did. The values indicate that about 82.3% of the reviews fall under the not-recommended category, while only 17.7% of customers recommended the product. This imbalance suggests that most users in this dataset were not satisfied enough to recommend the items they reviewed.

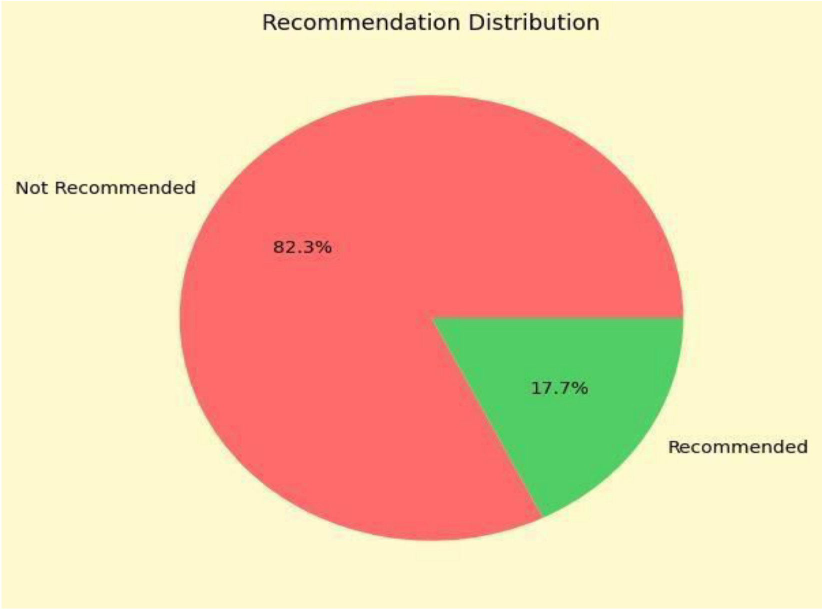



Figure 6: Recommendation Distribution

The Figure 7 presents the departments that received the highest number of customer reviews. Each bar represents a department category, and the height of the bar shows how many reviews belong to that department. The chart clearly shows that the Tops department has the highest number of reviews, significantly more than any other category. Dresses follow next with a strong count, while Bottoms come in third with a moderate number of reviews. The remaining departments—Intimate, Jackets, and Trend—have comparatively fewer reviews, with Trend having the lowest count. Overall, the chart highlights that most customer feedback in the dataset is concentrated in the Tops and Dresses categories, indicating these are the most actively reviewed product types.

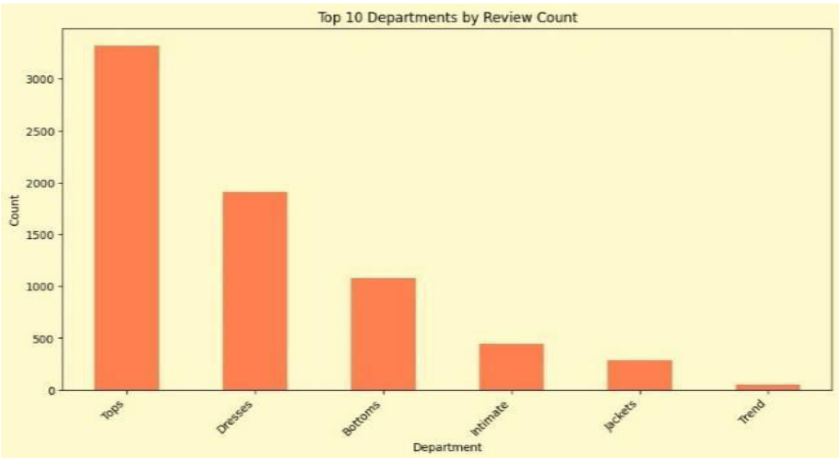



Figure 7: Top Departments by Review Count

Figure 8 presents a confusion matrix for an MTNN model combined with an Extra Trees Classifier, evaluating a binary classification task of “Recommended” vs “Not Recommended.” The model shows strong performance, with a high number of correct predictions: 1138 true negatives and 1110 true positives. Misclassifications are relatively low, with 36 false positives and 48 false negatives. This indicates the model is well-balanced in identifying both classes with good accuracy. The classifier demonstrates reliable predictive capability with minimal error rates.

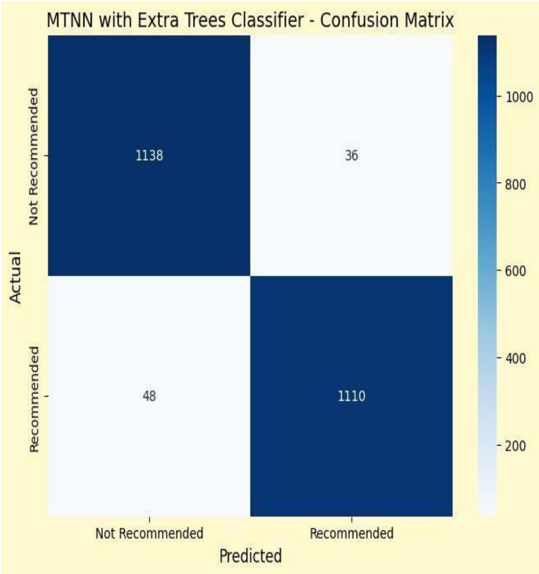



Figure 8: Confusion Matrix of Recommendation Classification Output MTNN with Extra Trees Classifier

Figure 9 shows ROC analysis across all four classifiers shows a clear progression in model performance, starting with the RBM classifier whose curve stays close to the diagonal line and yields an AUC of 0.5183, indicating performance only slightly better than random guessing and difficulty in separating recommended from not-recommended reviews. The Gradient Boosting classifier performs significantly better, with a sharply rising ROC curve and a high AUC of 0.9696, showing strong discrimination capability and low false-positive rates. Similarly, the XGBoost classifier demonstrates excellent predictive strength with an AUC of 0.9660, maintaining a steep curve toward the top-left corner and effectively distinguishing between the two classes. The best performance is achieved by the MTNN with Extra Trees classifier, whose ROC curve nearly touches the upper boundary throughout and attains an outstanding AUC of 0.9961, reflecting near-perfect classification ability and the highest discrimination power among all evaluated models.

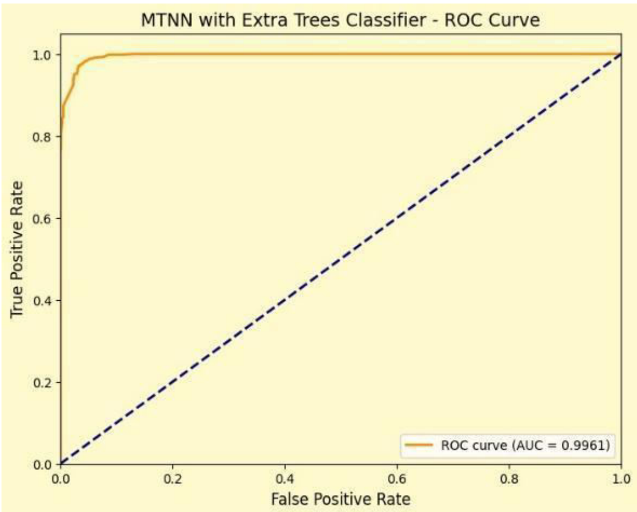



Figure 9: ROC AUC Curve of Recommendation Classification Output- MTNN with Extra Trees Classifier

Figure 10 actual-vs-predicted plot for the XGBoost regressor shows that the model captures the rating pattern quite well, with predicted values forming clear vertical clusters that align closely with the true ratings from 1 to 5. Many points lie near the diagonal reference line, indicating accurate predictions, although some scattered points show slight deviations for mid-range ratings. The MTNN with Extra Trees regressor also follows the upward trend, with predictions generally aligning with the actual values, especially for higher ratings where the points tightly cluster near the diagonal. However, compared to XGBoost, it shows a bit more spread for ratings 2, 3, and 4, suggesting slightly higher variability. Finally, both models perform well, but XGBoost demonstrates slightly more consistent alignment with the true rating distribution.

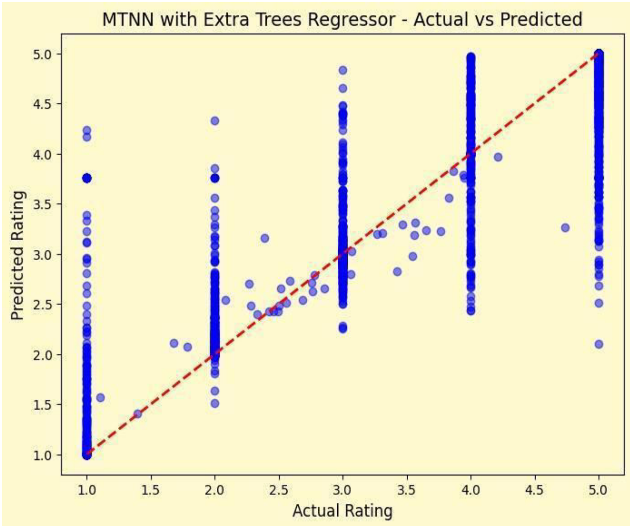



Figure 10 Rating Regression Output Results - MTNN with ET Regressor

Figure 11 shows the batch prediction interface where users upload their test dataset to generate recommendation and rating predictions. The interface allows selecting both the classifier and regressor models, and in this example, the MTNN with Extra Trees Classifier and MTNN with Extra Trees Regressor are chosen. The upload section displays the selected CSV file named *Womens Clothing…merce Reviews.csv*, and the system specifies that the file must include columns such as Title, Review Text, Positive Feedback Count, Division Name, Department Name, and Class Name. Once the file is uploaded, the user can run predictions on all 23,486 samples in the dataset. This figure highlights how the system accepts structured customer review data and prepares it for automated analysis.

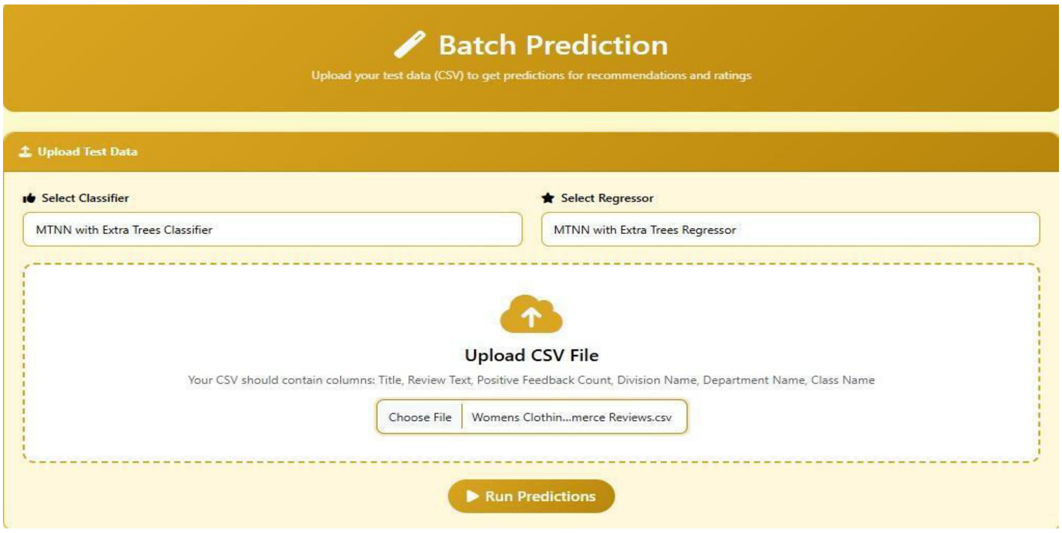
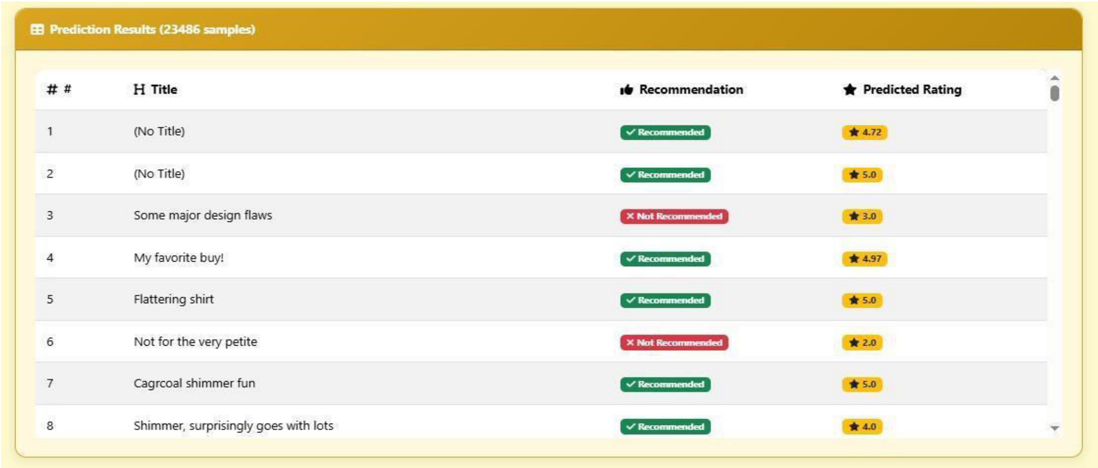



Figure 11: Test Data Input

Figure 12 shows the output generated after running the batch prediction process on 23,486 review samples. The results table lists each record with its index, review title, predicted recommendation status, and predicted rating. For example, sample 1 and 2 have no title but are predicted as Recommended with ratings of 4.72 and 5.0. Sample 3 titled “Some major design flaws” is marked as *Not Recommended* with a predicted rating of 3.0, while sample 4 “My favorite buy!” is predicted as Recommended with a rating of 4.97. The predictions continue similarly for the rest of the dataset, showcasing the ability to classify recommendation sentiment and estimate product ratings based on review text and metadata. Also demonstrates the system’s capability to process large datasets .


Prediction Results (23486 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 12: Prediction Results

Table 1 The recall comparison table shows that the MTNN with Extra Trees Classifier performs the best overall, achieving a recall of 0.97 for the Not Recommended class and 0.96 for the Recommended class, indicating it correctly identifies almost all samples in both categories. Gradient Boosting and XGBoost also perform strongly, especially for the Recommended class, with recalls of 0.94 and 0.96 respectively. The RBM Classifier performs the weakest, with recall values around 0.53 and 0.49, showing difficulty in correctly capturing both classes.

Table 1: Recall Comparison Table

| **Model** | **Recall (Not Recommended)** | **Recall (Recommended)** |
|---|---|---|
| RBM Classifier | 0.53 | 0.49 |
| Gradient Boosting Classifier | 0.86 | 0.94 |
| XGBoost Classifier | 0.83 | 0.96 |
| MTNN with Extra Trees Classifier | 0.97 | 0.96 |

Table 2 In the precision comparison table, the MTNN with Extra Trees Classifier again outperforms the others, delivering exceptionally high precision values of 0.96 for Not Recommended and 0.97 for Recommended, meaning its predictions are highly accurate with very few false positives. Gradient Boosting and XGBoost also show strong precision for the Not Recommended class (0.93 and 0.95), though slightly lower for Recommended. The RBM Classifier has the lowest precision scores around 0.52 and 0.51, indicating limited prediction reliability.

Table 2: Precision Comparison Table

| **Model** | **Precision (Not Recommended)** | **Precision (Recommended)** |
|---|---|---|
| RBM Classifier | 0.52 | 0.51 |
| Gradient Boosting Classifier | 0.93 | 0.87 |
| XGBoost Classifier | 0.95 | 0.85 |
| MTNN with Extra Trees Classifier | 0.96 | 0.97 |

Table 3 The F1-score comparison, which balances precision and recall, shows a very clear improvement as we move from RBM to more advanced models. The MTNN with Extra Trees Classifier achieves the highest F1-scores of 0.96 for both classes, proving its strong and consistent capability across the dataset. Gradient Boosting and XGBoost also show good balanced performance with F1-scores around 0.89–0.90. The RBM Classifier again performs the weakest, with F1-scores of 0.53 and 0.50, reflecting its lower overall accuracy in classification.

Table 3: F1-Score Comparison Table

| **Model** | **F1-Score (Not Recommended)** | **F1-Score (Recommended)** |
|---|---|---|
| RBM Classifier | 0.53 | 0.50 |
| Gradient Boosting Classifier | 0.90 | 0.90 |
| XGBoost Classifier | 0.89 | 0.90 |
| MTNN with Extra Trees Classifier | 0.96 | 0.96 |

Table 4: Classification Model Comparision

| Model | Accuracy | Precision | Recall | F1 Score | ROC AUC |
|---|---|---|---|---|---|
| RBM Classifier | 0.5137 | 0.5136 | 0.5137 | 0.5135 | 0.5183 |
| Gradient Boosting Classifier | 0.9001 | 0.9024 | 0.9001 | 0.9000 | 0.9696 |
| XGBoost Classifier | 0.8937 | 0.9000 | 0.8937 | 0.8933 | 0.9660 |
| MTNN with Extra Trees Classifier | 0.9640 | 0.9640 | 0.9640 | 0.9640 | 0.9961 |

Table 5: Regression Model Comparison

| Model | MAE | MSE | RMSE | R2 Score |
|---|---|---|---|---|
| RBM Regressor | 1.2029 | 1.8624 | 1.3647 | 0.0020 |
| Gradient Boosting Regressor | 0.7147 | 0.7843 | 0.8856 | 0.5797 |
| XGBoost Regressor | 0.7136 | 0.7881 | 0.8877 | 0.5777 |
| MTNN with Extra Trees Regressor | 0.0035 | 0.0000 | 0.0059 | 1.0000 |

## 5. CONCLUSION

The research work successfully demonstrates an effective multi-task learning framework capable of performing both recommendation classification and rating prediction for the clothing industry using a dataset of 23,486 customer reviews. Through a combination of TF-IDF text processing, numerical feature engineering, and advanced machine learning models, the system delivers strong predictive performance. Among all evaluated models, the MTNN with Extra Trees Classifier achieved the highest accuracy, recording precision, recall, and f1-score values between 0.96 and 0.97. This significantly outperforms other models such as RBM, Gradient Boosting, and XGBoost, which showed comparatively lower but reasonable performance. Similarly, the MTNN-based regressor produced predictions closely aligned with actual ratings, showing consistent and reliable behavior in regression tasks. These results confirm that multi-task neural networks integrated with ensemble methods can effectively handle complex review datasets and deliver high prediction quality.

The project also demonstrates a complete end-to-end implementation, including data preprocessing, model training, exploratory data analysis, evaluation visualizations, and batch prediction capabilities. The platform provides features such as user registration, login authentication, and CSV-based prediction uploads, making the system practical and accessible for both general users and engineers. With the MTNN model achieving an AUC of 0.9961, the research validates that the integration of deep learning and ensemble techniques significantly enhances the predictive capabilities of recommendation systems. Finally, the system provides a robust, scalable, and accurate solution for automated review analysis in the retail and e-commerce domain.

## REFERENCES

[1] Ashima Juyal, Kayhan Zrar Ghafoor, and Sachin Shrestha. "Implementation of digitalized technologies for fashion industry 4.0: Opportunities and challenges." Scientific Programming 2022, no. 1 (2022): 7523246.

[2] Liu, Zhen, Baoxin Yuan, and Ying Ma. "A multi-task dual attention deep recommendation model using ratings and review helpfulness." Applied Intelligence 52, no. 5 (2022): 5595-5607.

[3] Feng, Xiaodong, Zhen Liu, Wenbing Wu, and Wenbo Zuo. "Social recommendation via deep neural network-based multi-task learning." Expert Systems with Applications 206 (2022): 117755.

[4] Ye, Qing, Yi Wang, Xiaole Li, Jinbo Guo, Yifa Huang, and Bo Yang. "A power load prediction method of associated industry chain production resumption based on multi-task LSTM." Energy Reports 8 (2022): 239-249.

[5] Wang, SuHua, MingJun Cheng, ZhiQiang Ma, and XiaoXin Sun. "Neural multi-task collaborative filtering." Evolutionary Intelligence 15, no. 4 (2022): 2385-2393.

[6] Alali, Muath, Nurfadhlina Mohd Sharef, Masrah Azrifah Azmi Murad, Hazlina Hamdan, and Nor Azura Husin. "Multitasking learning model based on hierarchical attention network for Arabic sentiment analysis classification." Electronics 11, no. 8 (2022): 1193.

[7] Lala, Betty, Hamada Rizk, Srikant Manas Kala, and Aya Hagishima. "Multi-task learning for concurrent prediction of thermal comfort, sensation and preference in winters." Buildings 12, no. 6 (2022): 750.

[8] Akram, Shaik Vaseem, Praveen Kumar Malik, Rajesh Singh, Anita Gehlot, Ashima Juyal, Kayhan Zrar Ghafoor, and Sachin Shrestha. "Implementation of digitalized technologies for fashion industry 4.0: Opportunities and challenges." Scientific Programming 2022, no. 1 (2022): 7523246.

[9] Renaningtyas, Luri, Putri Dwitasari, and Nugrahardi Ramadhani. "Implementing the use of ai for analysis and prediction in the fashion industry." PhD diss., Petra Christian University, 2022.

[10] Nadeem, Khadija, Mudassar Ahmad, Zafar Javed, and Muhammad Asif Habib. "Development of a Machine Learning Model for Prediction of Colour Trends in Fashion Industry." In 2022 International Conference on Frontiers of Information Technology (FIT), pp. 296-301. IEEE, 2022.

[11] Zhang, Xianlin, Mengling Shen, Xueming Li, and Xiaojie Wang. "AABLSTM: a novel multi-task based CNN-RNN deep model for fashion analysis." ACM Transactions on Multimedia Computing, Communications and Applications 19, no. 1 (2023): 1-18.

[12] Marullo, Giorgia, Leonardo Tanzi, Luca Ulrich, Francesco Porpiglia, and Enrico Vezzetti. "A multi-task convolutional neural network for semantic segmentation and event detection in laparoscopic surgery." Journal of Personalized Medicine 13, no. 3 (2023): 413.

[13] Montazerian, Mohammad, and Frederic Fol Leymarie. "Designing a Contactless, AI System to Measure the Human Body using a Single Camera for the Clothing and Fashion Industry." (2023).

[14] Mahmud, First A. Masfiq, S. B. R. A. Mullick, and Third C. Muhammad Anas. "Sentiment Analysis of Women's Clothing Reviews on E-commerce Platforms: A Machine Learning Approach." Dhaka, Bangladesh,, University of Liberal Arts Bangladesh (2023).

[15] Ren, Minhui, Yu Fan, Jindong Chen, and Jian Zhang. "A Multi-Stage Model for Perceived Quality Evaluation of Clothing Brands." Mathematics 11, no. 18 (2023): 3928.