Developing an Enhanced Recommendation System for Women's Clothing in E-Commerce: A Comparative Analysis of Traditional Machine Learning and Deep Learning Approaches

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1 Introduction

Customer reviews play an important role in the e-commerce sector. These reviews serve as an important tool for understanding customer sentiment. These reviews provide valuable insights into consumer preferences, experiences, and satisfaction levels, thereby enabling e-commerce businesses to make informed decisions. By analyzing customer feedback, companies can identify trends, improve product offerings, and improve the overall shopping experience [1]. This not only helps build a loyal customer base but also drives business growth and competitiveness in a crowded market. Therefore, leveraging customer reviews is crucial for women's clothing e-commerce platforms that aim to stay in tune with their customers' needs and preferences.

However, customer reviews have problems that need to be addressed, such as a variety of different feature types, namely text, categorical, and numeric. A lot of data is missing, such as the text in the review title where the solution must use adjective extraction to get a better meaning [2]. In the feature selection process, there are 10 important features, including: Title, Review Text, Rating, Recommended IND, etc [3]. Selecting the Recommended IND feature as a label is important because it shows whether customers recommend the product, which is a key indicator of customer satisfaction. Using the Rating feature is also very important because it provides direct information regarding customer assessments of products, which helps in analyzing sentiment in review text and title text to decide on business policies.

The problem of data imbalance in customer review datasets requires special handling to ensure that the machine learning model being built is not biased. This imbalance can cause the model to be more likely to predict the majority class, ignoring the minority class which is also important [4]. To balance the dataset, methods such as K-Means or Synthetic Minority Over-sampling Technique (SMOTE) can be used [5]. K-Means can help with clustering and then re-sampling to balance the classes, while SMOTE works by synthesizing new samples from the minority class to increase the number until it is more balanced with the majority class [6]. These two techniques help create a more balanced dataset, ultimately improving the model's performance and accuracy in predicting outcomes in both classes.

The recommendation flow starts with a simple Logistic Regression[7] with TF and TF-IDF [8] feature extraction, also the other comparing text representation using GloVe embeddings[9], to ensure fix length on features some approach are use i.e mean, median, max, midpoint, and absolute max pooling. after that the best pooling are combined to TF-IDF to see whether the performance are get better or not. But ML models still fail to capture complex patterns in textual data. Convolutional neural networks (CNNs) [10] excel at recognizing local patterns, Recurrent neural networks (RNN) [11] is good for processing sequential data, while Long short term memory [12] is able to handle long-term dependencies in text. The combination of CNN-LSTM with GloVe Embedding provides rich word representation and deep contextual understanding, resulting in highly accurate and reliable predictions.

2 Methods and Eksperiments

2.1 Datasets Analysis

The Datasets

The dataset utilized for this analysis is the Women's Clothing E-Commerce Reviews. It comprises reviews authored by genuine customers and has undergone anonymization. Table 1 displays the distribution of features and the label (Recommended IND) within the dataset.

Feature	Unique Count
Clothing ID	1172
Age	77
Review Text	22621
Rating	5
Recommended IND	2
Positive Feedback Count	82
Division Name	3
Department Name	6
Class Name	20

Table 1: Frecuency Distribution of Datasets Fetures

Statistical Descriptive on numerical feature

Feature	Mean	Std. Deviation	Coef. Variance	Type
Age	42.282	12.328	29.156%	Integer
Rating	4.183	1.115	26.655%	Categorical
Recommended IND	0.818	0.385	47.066%	Categorical
Positive Feedback	2.631	5.787	219.955%	Integer

Table 2: Statistical Descriptive of Datasets Features

It appears that our label distribution is unbalanced. With a mean of 0.818, it's evident that the majority of instances are labeled as 1. Additionally, positive feedback is concentrated within certain values, suggesting that relying on these features may not be advisable moving forward.

2.2 Preprocessing Data

1. Missing Value Handling, punctuation removal and lowercasing

   To handle missing values, we first perform punctuation removal and lowercasing on each data entry. For blank review texts, we drop the entries since our main feature is text features, and we observed that if the review text is blank, the title is also usually blank, so these entries are removed. Additionally, information on product division, department, and class name is dropped. For other missing value titles, we fill them by extracting only the adjectives from the review text, the example is :

Review Text	Absolutely wonderful - silky and sexy and comfortable
Title (After Extract Adjective)	wonderful sexy comfortable

Table 3: example missing value handling on blank title

2. Feature Selection

   Rating and Recommended IND exhibit a high correlation score, while the remaining features display low positive or negative correlations. Hence, solely Rating and Recommended IND suffice as features. Furthermore, age is excluded as a feature since product recommendation is independent of age. Ratings carry significant importance for subsequent sentiment analysis, as they provide clarity in distinguishing between positive and negative reviews.

2.3 Features Engineering

Text data is unstructured text also, it's more not straight forward as usual on tabular data, where it can directly fed into model, hence choosing some proper techniques are necessary to ensure better performance on our model.

Feature engineering plays a pivotal role in transforming raw text into structured numerical representations that machine learning algorithms can effectively analyze. Techniques such as tokenization, vectorization, and embedding are employed to extract meaningful features from text, enabling tasks such as sentiment analysis, classification, clustering, and information retrieval. Employ a variety of techniques to transform raw textual information into structured features, enabling effective machine learning model training and inference.

2.3.1 Features Extraction

1. **Bag-Of-Words Representation**

   BOW is a corpus text representation where using word as features and also each document will represent by a vector. The BoW model represents text as a collection of words and their frequency in a given document or corpus. It does not consider the order or context in which the words appear, and therefore, it may not capture the full meaning of the text. The BoW model is simple and easy to implement, but it has limitations in capturing the meaning of language.

   (a) **Term Frequency (TF)**

   Measures how frequently a term appears in a document.

   $$TF(t,d) = \frac{number\,of\,times\,t\,appears\,in\,d}{total\,number\,of\,terms\,in\,d}$$

   (b) **Term Frequency - Index Document Frequency (TF-IDF)**

   Weighs a term's frequency in a document against its frequency across all documents, highlighting important terms unique to each document.

   $$TF-IDF(t,d) = TF(t,d) * IDF(t) \qquad IDF(t) = \log \frac{N}{1+df}$$

   to prevent the curse of dimensionality where weird words, typo words on corpus, then for the features are setted to be appears for each words appears 10 times.

   ```
   count_vect =  CountVectorizer(min_df = 10)
   tfidf_vect = TfidfVectorizer(min_df = 10)
   ```

2. **Global Vectors for Words Representation**

   GloVe (Global Vectors for Word Representation) is an unsupervised learning algorithm for generating word embeddings by aggregating global word-word co-occurrence statistics from a corpus. The Core Idea is this methods using Matrix Factorization to construct co-occurence matrix X, where X_{ij} denotes how often word j appears in the context of word i. Then this matrix is factorized into word vectors W and context vectors C such their dot product approximates the logarithms of the co-occurence probabilities $X_{ij} \approx exp(W_i^T C_i)$. GloVe provides an effective way to learn dense vector representations of words from large text corpora, capturing semantic similarities and relationships between words.[9].

2.3.2 Re-balancing Using SMOTE and K Means

Our Analysis has detected some common problem about unbalanced label, unbalance label can lead some major effect that found, our model cannot learn on minority patterns data, hence to address this problem, use Synthetic Minority Oversampling Technique (SMOTE) and K-Means to deal with this data, at the and the problem solved with increasing F1-Score on Zero classes prediction.

1. **Synthetic Minority Over-sampling Technique**

   SMOTE is a method used to address class imbalance in machine learning datasets by generating synthetic samples for the minority class. It works by creating new instances of minority class samples by interpolating between existing minority class instances, thus helping to balance the class distribution and improve the performance of classifiers, especially in scenarios where the minority class is underrepresented.[5]

   The Equation for generating a syntetic sample can be represented as:

   $$New\,Samples = Sample + (Random\,Value \times (Neighbor - Samples)) \tag{1}$$

   the visualization of SMOTE is given by

   As we can see that SMOTE sucessfully increase performance for zero classes, hence it will use SMOTE for all result

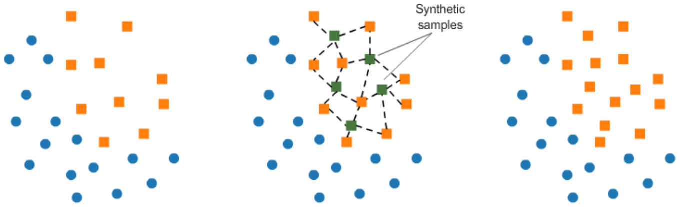
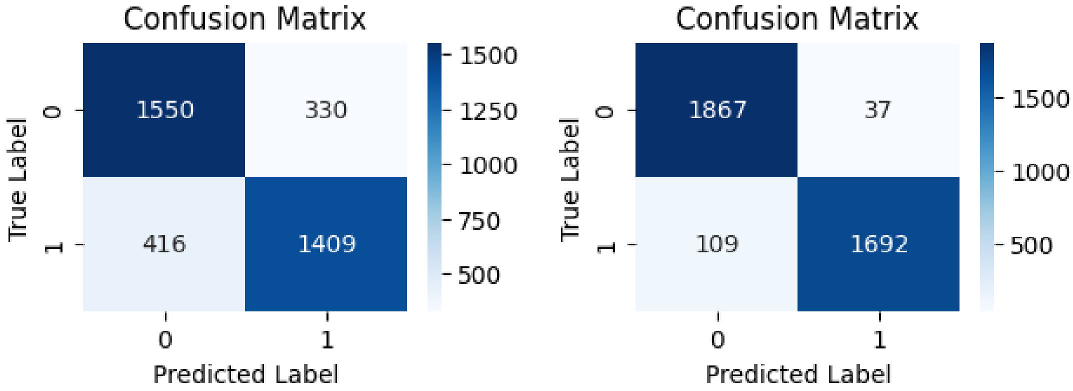


Figure 1: SMOTE Generating Data Visualization



(a)

(b)

Figure 2: Confusion Matrices prediction with Logistic Regression Model: (a) without SMOTE, (b) with SMOTE.

2. **K-Means Clustering**

   K-Means Clustering [6] is an Unsupervised Machine Learning algorithm, which groups the unlabeled dataset into different clusters to explore the fundamentals and working of k mean clustering along with the implementation. Let there is a set of n d-dimensional data $x \in \mathbb{R}^d, i = 1, 2, ..., n$. It is assumed that there are K (must $\leq n$) clusters $S_1, S_2, ..., S_k$, K-means clustering hopes to minimize the sum of squares of the erros beetween the data within the cluster and the cluster center. The mathematical formula is a follows:

$$\text{argmin}_\mu \sum_{c=1}^{K} \sum_{i=1}^{n_c} \|x_i - \mu_c\|^2 \tag{2}$$

   The visualization of data without K-Means and with K-Means

   the Figure 3 (a) shows unbalanced reviews of clustering women's clothing e-commerce reviews, while the Figure 3 (b) shows the results of clustering women's clothing e-commerce reviews using offset K-Means. The Figure 3 (b) shows that with K-Means, data can be balanced so that the analysis and model applied are more accurate and fair, while the Figure 3 (a) shows the risk of bias from original data that is not balanced so that it cannot predict more accurately, as evidenced by the recommendation prediction results as follows Figure 4:

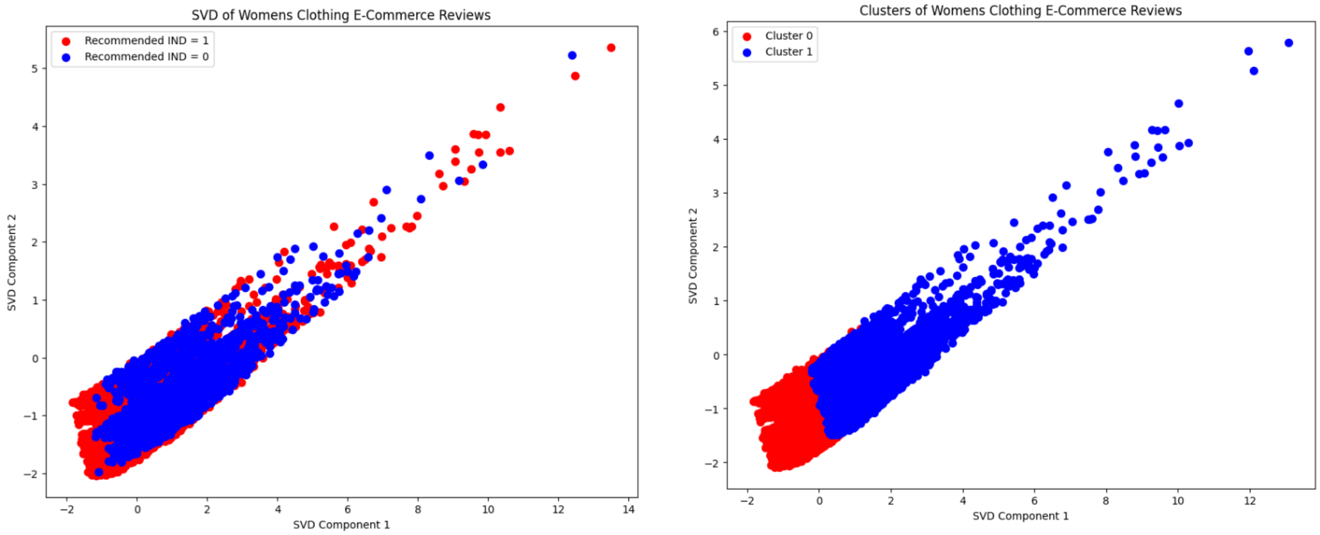
2.3.3 Pooling

In order to convert bunch of vectors to tabular data, so it can train on fix length features, the techniques can be easily achive by only averaging in common way, but to take other approach tried more way like take median, mid point, max, and absolute max pooling. given a sentence that every word of the sentence can be represent by vectors using GloVe. let x_{ij} be a vectors of words i with dimension D

1. **mean pooling:** this approach can be done by take average of the vectors with unfixed length sentence n of each data

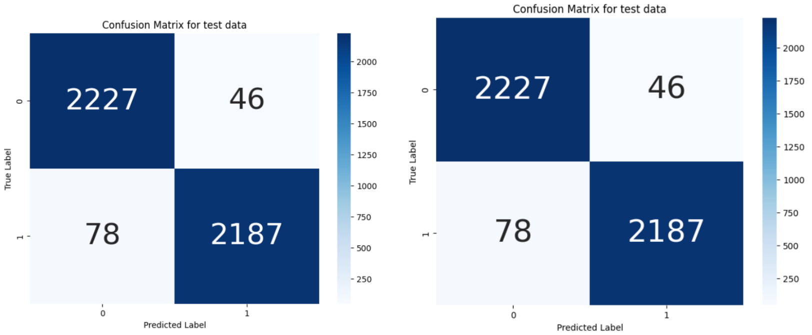
$$\sum_{i=1}^{n} \frac{x_i}{n} \in \mathbb{R}^D$$

2. **median pooling:** this approach is take the median of each features



(a) (b)

Figure 3: A visualization of visualization of data (a) without K-Means, (b) with K-Means.



(a) (b)

Figure 4: A visualization of prediction recommendation data : (a) without K-Means, (b) with K-Means.

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{D1} & a_{D2} & \cdots & a_{Dn} \end{bmatrix}_{D\times N} \xrightarrow{convert\,to} \begin{bmatrix} median(a_{1j}, \forall j \leq n) \\ median(a_{2j}, \forall j \leq n) \\ \vdots \\ median(a_{Dj}, \forall j \leq n) \end{bmatrix}$$

3. **max pooling**: this approach can be done by find the max value of each features in every vectors

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{D1} & a_{D2} & \cdots & a_{Dn} \end{bmatrix}_{D\times N} \xrightarrow{convert\,to} \begin{bmatrix} max(a_{1j}, \forall j \leq n) \\ max(a_{2j}, \forall j \leq n) \\ \vdots \\ max(a_{Dj}, \forall j \leq n) \end{bmatrix}$$

4. **midpoint pooling:** this approach can be done by finding midpoint of each features

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{D1} & a_{D2} & \cdots & a_{Dn} \end{bmatrix}_{D\times N} \xrightarrow{convert\,to} \begin{bmatrix} max(a_{1j}) - min(a_{1j}), \forall j \leq n \\ max(a_{2j}) - min(a_{2j}), \forall j \leq n \\ \vdots \\ max(a_{Dj}) - min(a_{Dj}), \forall j \leq n \end{bmatrix}$$

5. **absolute max pooling:** this approach done by absoluting all value on matrices then do max pooling

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{D1} & a_{D2} & \cdots & a_{Dn} \end{bmatrix}_{D\times N} \xrightarrow{convert\,to} \begin{bmatrix} max(abs(a_{1j}, \forall j \leq n)) \\ max(abs(a_{2j}, \forall j \leq n)) \\ \vdots \\ max(abs(a_{Dj}, \forall j \leq n)) \end{bmatrix}$$

2.4 Model Workflow

1. **Machine Learning with Logistic Regression Workflow**

   Machine Learning with Logistic Regression Workflow below is diagram of ML workflow of our process. Then the result will evaluate with metrics like accuracy, precision, recall, F1-Score, and loss in figure 5 :

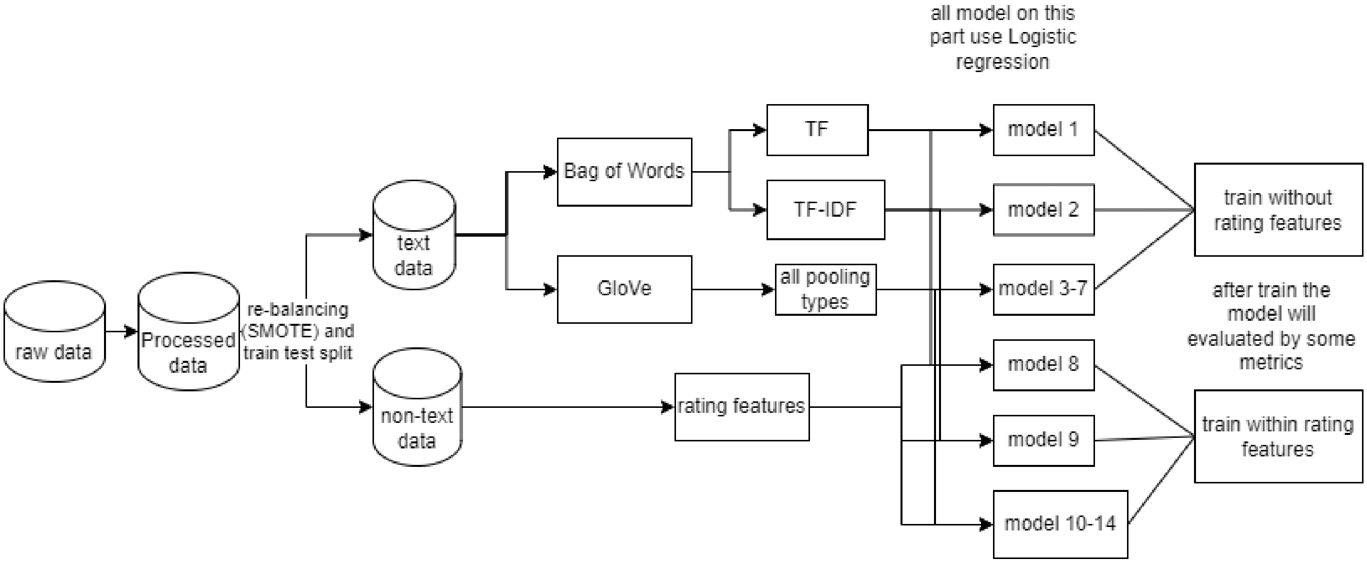

all model on this part use Logistic regression
raw data
Processed data
re-balancing (SMOTE) and train test split
text data
non-text data
Bag of Words
GloVe
rating features
TF
TF-IDF
all pooling types
model 1
model 2
model 3-7
model 8
model 9
model 10-14
train without rating features
after train the model will evaluated by some metrics
train within rating features

Figure 5: Machine Learning Workflow

2. **Deep Learning CNN-LSTM workflow (proposed method)**

   Deep Learning with Neural Networks Workflow below is diagram of DL workflow of our process. Then the result will evaluate with metrics like accuracy, precision, recall, F1-Score, and loss in figure 6 :

2.5 Result and Analysis

1. Result of machine learning approach using logistic regression without rating features, from the table 4 some point that we can learn:

   (a) The result wasn't overfitted evenly without regularization the difference accuracy only 1-3%, but not show here to save more space

   (b) **TF and TF-IDF** alone also perform well, with TF achieving slightly better overall scores than TF-IDF in terms of Accuracy and F1-Score.

   (c) GloVe 200D with mean pooling shows a good performance but falls short **compared to the other approach.**

   (d) **Mean pooling** consistently outperforms other pooling methods (median, midpoint, and abs max pooling).

   (e) **Dimension Impact**: Increasing the dimensionality of GloVe embeddings from 50D to 200D improves performance, as seen with GloVe 50D, 100D, and 200D. The higher-dimensional GloVe 200D with mean pooling performs better than lower-dimensional counterparts.

   (f) **Best Performance:** The combination of GloVe 200D embeddings with TF and mean pooling achieves the highest overall performance across all metrics. It has the highest Accuracy (0.934), Precision (0.950), Recall (0.913), F1-Score (0.931), and the lowest Loss (0.1959). This indicates that combining TF features with GloVe embeddings and using mean pooling effectively leverages the strengths of both methods.

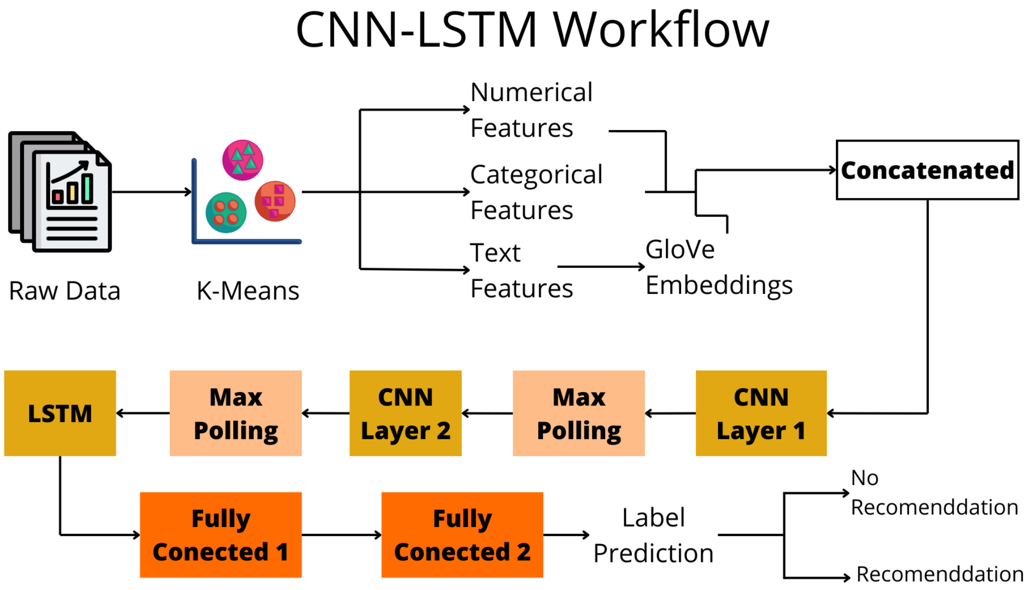


Figure 6: Deep Learning Workflow

Text Representation	Accuracy	Precision	Recall	F1-Score	Loss
TF	0.928	0.927	0.926	0.926	0.2249
TF-IDF	0.925	0.940	0.903	0.921	0.2338
GloVe 50D + mean pooling	0.777	0.785	0.745	0.764	0.4631
GloVe 100D + mean pooling	0.821	0.830	0.794	0.812	0.4062
GloVe 200D + mean pooling	0.848	0.857	0.825	0.840	0.3668
Glove 200D + median pooling	0.827	0.832	0.806	0.819	0.3984
GloVe 200D + midpoint pooling	0.758	0.755	0.743	0.749	0.5005
GloVe 200D + abs max pooling	0.764	0.758	0.754	0.756	0.5029
GloVe 200D + TF + mean pooling	**0.934**	**0.950**	**0.913**	**0.931**	**0.1959**
GloVe 200D + TF-IDF + mean pooling	0.927	0.944	0.904	0.924	0.2288

Table 4: Performance Metrics for different Text Representation with LogisticRegression Without Rating Features

2. Result of machine learning approach using logistic regression with rating features, from the table 5 some point that can explain:

   (a) Introducing rating features leads to an improvement in performance metrics across all text representations. Accuracy, precision, recall, and F1-scores are generally higher, and loss values are lower compared to the models without rating features.

   (b) Interestingly, GloVe 50D with mean pooling shows a significant improvement when rating features are included, reaching an accuracy of 0.961 and an F1-score of 0.959. This suggests that even lower-dimensional embeddings can perform well when complemented with additional informative features like ratings.

   (c) GloVe 200D + TF + mean pooling continues to be the best-performing combination, achieving the highest metrics with an accuracy of 0.967, precision of 0.979, recall of 0.952, F1-score of 0.965, and the lowest loss of 0.1136.

3. Result of Deep Learning Approach

   The table 6 presents the performance of various neural networks models using GloVe embedding in women's clothing e-commerce review analysis, with accuracy, precision, recall, F1-score, and loss metrics measured for each model. The models compared include GloVe CNN, GloVe RNN, GloVe LSTM, and a combination of GloVe CNN LSTM. Based on the table 6, the performance of the neural networks model with GloVe embedding shows very good results in analyzing women's clothing e-commerce reviews. The GloVe CNN model achieved accuracy, precision, recall, and F1-score of 0.9703 with a loss of 0.1658, showing consistent performance but with slightly

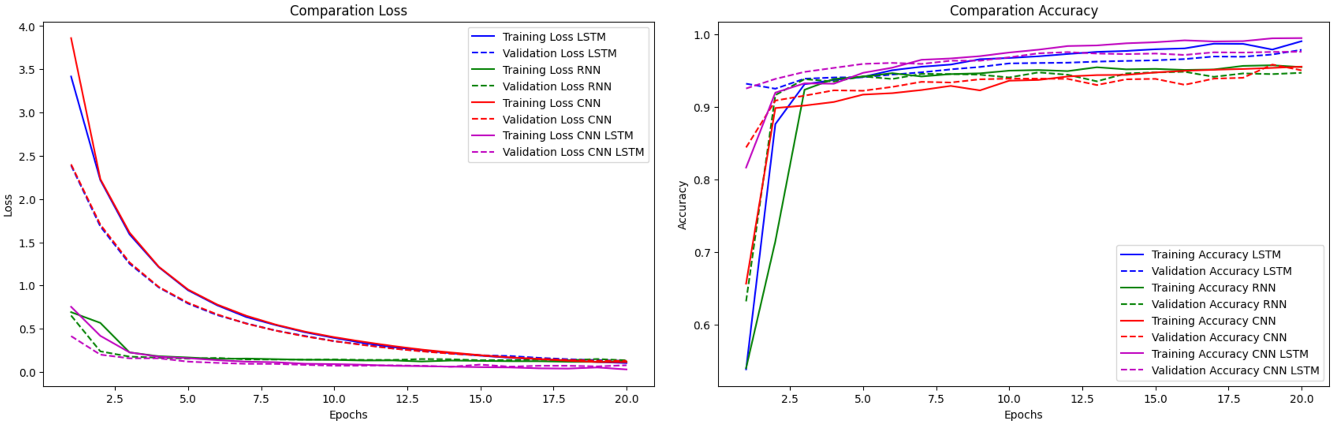
Text Representation	Accuracy	Precision	Recall	F1-Score	Loss
TF	0.958	0.952	0.962	0.957	0.1272
TF-IDF	0.958	0.968	0.944	0.956	0.1297
GloVe 50D + mean pooling	0.961	0.979	0.939	0.959	0.1398
GloVe 100D + mean pooling	0.958	0.975	0.938	0.956	0.1397
GloVe 200D + mean pooling	0.958	0.972	0.940	0.956	0.1375
GloVe 200D + TF + mean pooling	**0.967**	**0.979**	**0.952**	**0.965**	**0.1136**
GloVe 200D + TF-IDF + mean pooling	0.958	0.967	0.947	0.957	0.0598

Table 5: Performance Metrics for different Text Representation with LogisticRegression Without Rating Features

higher loss than the other models. The GloVe RNN model improves the performance metrics slightly higher with a value of 0.9726 and a reduction in loss to 0.1397, while the GloVe LSTM model shows further improvement with a value of 0.9735 and a loss of 0.1298, indicating better ability in handling long-term dependencies in text data. Finally, the GloVe CNN LSTM model shows the best performance with all metrics of 0.9764 and the lowest loss of 0.0688, combining the strengths of CNN in capturing local features and LSTM in handling sequential context, thus providing the most accurate and efficient results.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Loss**
GloVe CNN	0.9703	0.9703	0.9703	0.9703	0.1658
GloVe RNN	0.9726	0.9726	0.9726	0.9726	0.1397
GloVe LSTM	0.9735	0.9735	0.9735	0.9735	0.1298
GloVe CNN LSTM	**0.9764**	**0.9764**	**0.9764**	**0.9764**	**0.0688**

Table 6: Performance metrics for different models



(a)

(b)

Figure 7: A visualization of learning curve Neural Networks model in : (a) Loss Curve (b) Accuration Curve

The learning curve in the figure 7 shows a comparison of loss and accuracy between various neural networks models that use GloVe embedding in women's clothing e-commerce review analysis. In figure 7 (a), which shows the loss curve, it can be seen that the GloVe CNN model has the highest loss value on both training and validation data, while the GloVe CNN LSTM model has the lowest loss and quickly converges, showing superior performance in reducing errors. In the figure 7 (b) , which shows the accuracy curve, the GloVe CNN LSTM model also shows the highest and stable accuracy on both training and validation data, followed by GloVe LSTM, GloVe RNN, and GloVe CNN. The GloVe CNN model shows slower and less stable accuracy improvement than other models.

3 Conclusion

1. Re-Balancing data is a must because model can't learn the minority classes pattern, it can be seen on the lack of precision and recall on zero classes before rebalanced, on this project we provide 2 approach, first the common method SMOTE used on logistic regression and KNN clustering on deep learning part. both of the method helps significantly enhances our performance model on zero classes.

2. Of the 10 available features, the features that have the most influence in this prediction are the review text, title text and rating features which are useful for giving weight to review sentiment and title text. These features provide important insights into customer opinions and satisfaction levels. Analyzing sentiment in review text and headlines, as well as ratings, enables a nuanced understanding of customer feedback, which can significantly increase the predictive power of a model.

3. On Machine Learning part especiall logistic regression, importance of combining features the combination of traditional text representation methods (TF, TF-IDF) with advanced embeddings (GloVe) significantly enhances model performance. Mean pooling consistently outperforms other pooling strategies for GloVe embeddings, both with and without rating features. included rating features leads to a substantial improvement in all performance metrics, highlighting the value of additional contextual information.

4. Machine Learning models using Logistic Regression succeeded in predicting labels well with **best accuracy**, but Deep Learning models were still superior in predicting labels in sentiment analysis with **highest accuracy** of women's clothing recommendations. Logistic Regression, although effective, has limitations in capturing complex patterns and relationships in data. On the other hand, Deep Learning models, with their ability to learn complex patterns through multiple layers, provide more accurate and robust predictions in sentiment analysis tasks. The superior performance of Deep Learning models makes them more suitable for applications that require high accuracy and detailed understanding, such as personalized clothing recommendations.

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