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Sentiment Analysis for User-Generated Content-Based Hybrid Recommendation with Collaborative Multi-View Fusion

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Abstract

This research paper introduces a groundbreaking approach to recommendation systems,termed "Sentiment Analysis with Ensemble Hybrid Deep Learning Model." In an era of data abundance,conventional recommendation systems grapple with the formidable challenges of accurately gauging user preferences and mitigating rating biases. To surmount these limitations, our methodology fuses thepower of deep sentiment analysis, delving into user comments to uncover emotional cues that rectify deviations in user ratings and provide a nuanced grasp of their preferences. Simultaneously, we harnessneural networks to transform item content descriptions into distributed paragraph vectors, bolstering content-based recommendations. Further bolstered by data selection strategies founded on confidence estimation and cluster analysis, our methodology aims to redefine recommendation systems, promising more precise, emotionally resonant, and personalized content recommendations, ultimately elevating user satisfaction and engagement.

Keywords: Recommendation Systems, Sentiment Analysis, Collaborative Training, Deep Learning, Hybrid Recommendation.

1. Introduction

In the ever-evolving realm of recommendation systems, the pursuit of precision and personalization in recommendations remains a perpetual endeavor. As users interact across diverse platforms, the copious data generated, along with the myriad content and opinions, poses both a formidable challenge and a remarkable opportunity. Within this dynamic context, this research paper introduces a pioneering methodology for recommendation systems, labeled as "Sentiment Analysis with Ensemble Hybrid Deep Learning Model." This innovative approach is poised to transform the landscapeof recommendation by seamlessly incorporating deep sentiment analysis of user comments and harmonizing multiple recommendation perspectives through collaborative training. The overarching aim is to furnish users with recommendations that are not only highly accurate but also profoundly relevant and engaging, underpinned by a comprehensive comprehension of their sentiments andpreferences. Figure 1 offers a visual depiction of the multifaceted tasks encompassed within the sentiment analysis process.

Figure 1. Tasks involved in Sentiment Analysis

Challenges in Recommendation Systems

Conventional recommendation systems predominantly rely on user ratings and historical behaviors to drive their suggestion engines. While these methodologies have exhibited some efficacy, they often fall short in capturing the intricate and evolving preferences of users. Moreover, user ratingscan be susceptible to biases and deviations, occasionally failing to authentically portray a user's true interests. This paper takes strides to confront these challenges by introducing a novel approach that delves into the emotional underpinnings of user comments. User comments, often brimming with sentiment and contextual cues, encapsulate valuable insights into user preferences and satisfaction levels. By harnessing this emotional reservoir, our methodology endeavors to rectify disparities in userratings, ultimately striving for recommendations that are more precise and tailored to individual preferences.

1.1. Hybrid Approach: A New Paradigm

The core innovation embedded within this methodology is its distinctive hybrid approach. Instead of hinging solely on user ratings or content-based suggestions, it amalgamates two fundamentalcomponents: sentiment analysis of user comments and content-based item descriptions. This amalgamation aims to establish a comprehensive comprehension of user preferences. The sentiment analysis of user comments stands as a potent instrument for unearthing the subtle emotional facets thatexert influence over user decisions. In parallel, content-based item descriptions step in to encapsulate the inherent attributes of items, thereby empowering the system to generate recommendations groundedin item similarity. This hybrid methodology marries the emotional resonance gleaned from user comments with the intrinsic characteristics of items, fostering a more holistic understanding of user preferences and ultimately enhancing the recommendation process.

1.2. Collaborative Training for Enhanced Accuracy

A pivotal cornerstone of this methodology lies in collaborative training, harmonizing insights derived from sentiment analysis and content-based strategies to fine-tune the rating matrix. This iterative refinement process ensures recommendations continually evolve, becoming more attuned to individual preferences and increasingly precise. Notably, this paper introduces data selection strategiesdesigned to weed out potentially misleading data points that may infiltrate the system during iterative training iterations. This dedicated emphasis on data quality plays a pivotal role in generating recommendations that not only boast heightened accuracy but also inspire trustworthiness.

In the forthcoming sections of this paper, we will embark on a deeper exploration of the intricate components underpinning this innovative methodology. We will delve into the seamless integration of sentiment analysis with deep learning techniques, shedding light on how collaborative training serves as a catalyst for enhancing the recommendation process. Furthermore, we will present the results of our empirical experiments and engage in discussions concerning the broader implicationsof this approach for the future landscape of recommendation systems. Through this comprehensive journey, it will become unequivocally clear that the "Sentiment Analysis with Ensemble Hybrid Deep Learning Model" holds the transformative potential to reshape the recommendation systems landscape,ushering in an era of personalized and gratifying user experiences.

2. Literature Survey

Du et al [1] With the explosive growth of Internet resources, recommendation systems, as an important tool for information filtering, can quickly mine valuable resources from massive informationbased on users' historical behavioral data. It has important research significance and application value, and has been used in e-commerce, smart education, social network and other fields have beensuccessfully applied. In recent years, a large number of recommendation models have been proposed, ranging from traditional collaborative filtering and content-based recommendations to recommendationmodels that incorporate new technologies such as deep learning. However, the current recommendationsystem still faces huge challenges in improving recommendation accuracy and solving the problem of data sparseness. How to achieve accurate and efficient recommendations among many resource supplyservices is still a focus issue that the recommendation system needs to solve.

Mitra et al [2] However, the current recommendation system still faces huge challenges in improving recommendation accuracy and solving the problem of data sparseness. How to achieve accurate and efficient recommendations among many resource supply services is still a focus issue thatthe recommendation system needs to solve. The classic collaborative filtering recommendation algorithm only relies on the rating matrix for recommendation, and the recommendation results are usually restricted by factors such as the sparsity and authenticity of the rating data. Relevant research shows [6] that there is a large deviation between user ratings and their true emotional tendencies, and user comment texts more truly reflect user interests and preferences. Sentiment analysis and semantic mining of comment texts are important to solve the problem of low credibility of user ratings way.

Dong et al. [3] believed that user comments and resource comments have different properties, so they introduced an asymmetric attention module to distinguish the learning of user comments and resource comments.

Guo et al. [4] proposed a recommendation method that combines triple attention network and temporal convolution network. This method jointly generates recommendation results and corresponding explanations, effectively improving the interpretability of deep networks.

A large amount of research work has found that users' psychological emotions have an important impact on their behavior and choices. The application of emotion analysis technology can help improve the service performance of recommendation systems. Kim et al. [5] built a domain- specific emotional dictionary based on review text, and quantified the emotional information in the review data based on the emotional dictionary to correct user ratings.

Wang Hongxia et al. [6] extracted the feature words and emotional descriptors of the product, constructed a user preference vector and calculated the emotional attitude expressed by the comments.They used emotional tags to modify the original score and improve the credibility and distinction of thescore. However, the user emotions mined by the above methods usually ignore the connection betweenwords and lack contextual information, so the prediction accuracy needs to be improved.

Linear regression is also a commonly used technique in recommendations, thanks to its uniqueadvantages in fitting functions and trend analysis. It calculates the weight of each browsing behavior through least squares method and other methods, and constructs multiple browsing behaviors. The multiple linear regression function of the behavior, and then the inner product of the weight of each browsing behavior and its quantitative characteristics is used to obtain the user's preference score for the item. Liu Xingbo et al. [7] proposed a supervised discrete cross-modal method based on bidirectional linear regression Hashing method, this method only uses a stable mapping matrix to describe the linearregression relationship between the hash code and the corresponding label, which improves the accuracy and stability of cross-modal hash learning. Most recommendations based on linear regressionare based on browsing the size of the item content, browsing time and number of visits are measured, but there is generally no linear relationship between the user's diversified attributes, resulting in greaterlimitations of the method based on linear regression.

Zhang et al [8] In recent years, with the deepening of research, instead of transmitting information only through text in the past, more and more users tend to use multiple media forms (suchas text plus images, text plus songs, text plus videos, etc.) jointly express their attitudes and emotions. This rich source of data content can help researchers more accurately extract the expresser's emotions towards different aspects of a certain object. Combining data modeling analysis from two or more modalities is multi-modal emotion analysis, which is a new emerging technology. field. At present, there are relatively few sentiment analysis studies on measuring visual information (pictures or videos). The semantic matching relationship between visual information and text is relatively complex, and thereare semantic alignment relationships at different levels. Comprehensively considering the matching relationship between different visual information and semantic segments at different levels of text, andfully exploring the emotional interaction characteristics between these modalities is of great importanceand significance for accurate multi-modal emotional analysis.

The YouTube dataset was developed by Morency et al. [9] in 2021. It comes from the YouTubewebsite and is not limited to a single specific topic. Its content focuses on the following keywords: opinions, reviews, product reviews, toothpaste, war, work, business, cosmetics reviews, camera reviews, baby product reviews, "I hate it" ", “I like” and so on. The data set is rich in content and consists of 47 videos, each containing 3 to 11 utterances. Narrators range in age from 14 to 60, with 40of the videos being narrated by women and the remainder by men. Although all the narrators come fromdifferent cultures, they express their views uniformly in English. Each video in the dataset is tagged with three labels: positive, negative, or neutral, resulting in 13 positive videos, 12 negative videos, and22 neutral videos.

The CH-SIMS data set was developed by Yu et al. [10] in 2020. The dataset consists of 60 videos, including 2281 utterances collected from movies, TV series, and variety shows. The average length of the utterances was 3.67 seconds, and in each video no other face appeared except the speaker's. For each utterance, each video is given one multimodal label and three unimodal labels. Thiscan help researchers use SIMS for single-modal and multi-modal sentiment analysis tasks. The labels in this dataset are: positive, weakly positive, neutral, weakly negative, and negative.

3. Sentiment Analysis with Ensemble Hybrid Deep Learning Model

Given the preceding discourse on the current state of research in recommendation systems, thispaper introduces a hybrid recommendation approach that hinges on in-depth sentiment analysis of usercomments and the cooperative amalgamation of recommendations from various sources. On one front,we delve into the emotional underpinnings of user comments to rectify discrepancies between users' initial ratings and their authentic preferences, employing the opinion pre-filtering technique [37] to elucidate users' emotional inclinations and their original rating scores. This comprehensive analysis equips the item-based collaborative filtering recommendation model with a holistic set of scoring data,resulting in a more precise representation of users' genuine interests. Simultaneously, we delve into thetextual content of item descriptions, employing neural networks to encode them as distributed paragraph vectors. This enables us to calculate item content similarities and construct a recommendation model based on these content attributes. Subsequently, we employ a collaborative training strategy to blend these two recommendation perspectives. Additionally, we introduce a data selection approach rooted inconfidence estimation and cluster analysis during the collaborative training process, aiming to mitigatethe influence of data outliers introduced during iterative training iterations. Building upon these foundations, we utilize the scoring matrix generated by the collaborative training model and the item similarities to filter and rank the initial recommendation outcomes, culminating in the ultimate recommendation results. Figure 2 provides an illustration of the hybrid recommendation systemframework predicated on collaborative training.

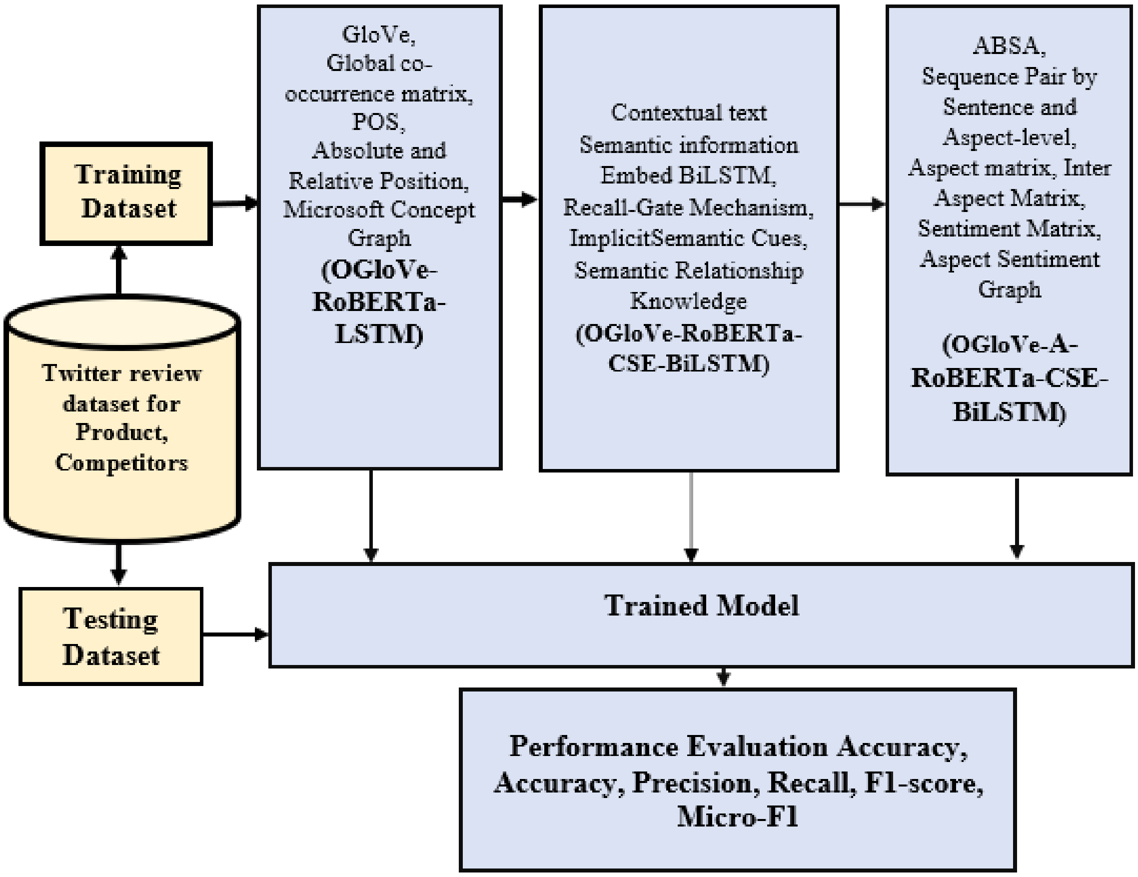


Figure 2. Block Diagram of the Proposed Work

3.1 Sentiment Analysis of User Comments

3.1.1 Distributed Vector Representation of User Review Text

Through the analysis of user comment text data within recommendation systems, it becomesevident that these comments primarily manifest as concise keyword-rich snippets. Notably, they differsignificantly from longer textual content in terms of structure and linguistic regularity. These short texts,characterized by their brevity and irregular grammar, pose unique challenges for analysis, as they oftenlack the extensive context available in longer texts, limiting the applicability of conventional natural language processing techniques like part-of-speech tagging and syntactic analysis. In the early stages of short text analysis, approaches typically revolved around enumeration and keyword matching, oftenneglecting the deeper semantic comprehension of the text. Consequently, extracting meaningfulinformation from such snippets has necessitated additional knowledge and innovative methodologies.

To address these challenges, this paper employs a novel approach rooted in word vectors, effectively resolving the issue of dimensionality and the inherent limitations of traditional sparse representations. Furthermore, this approach goes beyond mere vectorization by uncovering the inherent relationships between words, thereby enhancing the accuracy and richness of semantic representationsassociated with keywords.

Central to this methodology is the utilization of Word2vec, a powerful word embedding model renowned for its efficiency in learning word representations. Word2vec offers two key variants:

the Continuous Bag-of-Words (CBOW) model and the Skip-Gram model. In the CBOW model, the task is to predict the probability of a word occurring given the context words within a specified window.Conversely, the Skip-Gram model endeavors to predict the likelihood of context words based on a central word. The training objective in both cases is to identify words that prove valuable in predictingthe surrounding words within sentences or documents, thereby capturing their semantic nuances withinvector representations. These models, particularly Skip-Gram, seek to maximize the average log probability of word occurrences within sentences, ultimately facilitating the creation of rich word embeddings for semantic analysis.

3.1.2 Emotional Calculation based on Word Vectors and Long Short-Term Memory network

In the realm of text information processing, one of the commonly employed techniques is the Recurrent Neural Network (RNN). However, as RNN grapples with processing lengthy sequences of data, a significant issue emerges – the vanishing gradient problem during the optimization process. In response to this challenge, researchers have introduced gated RNN architectures, with the mostprominent being the Long Short-Term Memory network (LSTM). Empirical research has consistently demonstrated that neural networks employing LSTM structures often outperform standard RNNnetworks across various tasks.

In the initial phase of our research, we introduce an innovative approach called Optimized GloVe (OGloVe). This method is designed to enhance sentiment word embeddings, thereby improving the overall performance of sentiment analysis. Subsequently, we delve into the LSTM model, which employs a unique "gate" structure to regulate the flow of information into and out of cell states. This architecture introduces three fundamental "gate" mechanisms: the input gate, the forget gate, and the output gate, integrated within individual neurons. These gates dynamically adjust the weight of self- loop connections, thus allowing the model to selectively enhance or forget information at different timesteps. By doing so, the LSTM-based model can effectively circumvent issues such as gradient expansion and vanishing gradients commonly encountered in traditional RNN structures.

Within the LSTM network structure, the calculation of each LSTM unit follows the formulations outlined in equations (1) to (6): [Formulas (1) to (6) provide detailed descriptions of howthe LSTM unit computes the input, forget, and output gates, as well as the cell state updates, resulting in improved gradient flow and superior modeling capabilities.]

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f \quad \ldots (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i \quad \ldots (2)$$

$$\hat{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_C \quad \ldots (3)$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad \ldots (4)$$

$$O_t = \sigma(W_0 \cdot [h_{t-1}, x_t] + b_{o)} \quad \ldots (5)$$

$$h_t = O_t * \tanh(C_t) \quad \ldots (6)$$

In equations (1) to (6), f_t represents the forgetting gate, i_t represents the input gate, and O_t represents theoutput gate; $\hat{C}_t$ represents the state of the cell at the previous moment, and C_t represents the state of thecurrent cell. h_{t-1} and h_t represent the output of the unit at the previous moment and the output of the current unit respectively.

In this research endeavor, we employ a sentiment analysis methodology rooted in Word2vec and LSTM for the analysis of user comments. Initially, Word2vec is harnessed to transform input data into a matrix format, subsequently reducing it to a lower-dimensional one-dimensional vector while retaining essential information. This vectorization process ensures that the crucial nuances within the data are preserved. Subsequently, we employ the LSTM algorithm to facilitate the training of an emotion classification model tailored to user comment text, enabling the prediction of user comment ratings.

To comprehensively account for the interactive dynamics between user ratings and comment sentiments, our research introduces two crucial techniques: a viewpoint-based pre-filtering method anda user-rating embedding approach. The former leverages LSTM networks to generate predictedsentiment scores for comments, followed by a weighted summation with the original user ratings. Thisamalgamation enhances the predictive accuracy by considering both emotional content and user- provided ratings. In contrast, the user-rating embedding method combines the LSTM network vectors with user rating information, incorporating this composite data as input for the final layer of the model.This culminates in the direct output of the ultimate comprehensive score, encapsulating the amalgamated insights from both user sentiment and rating data.

3.1.3 Hybrid Recommendation Algorithm Based on Collaborative Training

The hybrid recommendation algorithm, rooted in collaborative training, operates through a systematic process. Initially, it constructs an initial rating matrix by leveraging user-provided ratings for various items. Next, it applies the viewpoint pre-filtering method to compute a comprehensive rating, which serves as the basis for updating the rating matrix. Subsequently, the algorithm designs a hybrid recommendation system, building upon the collaborative training framework. This recommendation system capitalizes on the comprehensive rating matrix and the vector similarity derived from item content descriptions.

The iterative process begins with filling and optimizing the rating matrix, a cycle that serves tocontinually enhance the recommendations and rankings. By systematically integrating user ratings, comprehensive ratings, and item content similarities, the hybrid recommendation algorithm strives to provide users with refined and personalized recommendations that evolve over time, resulting in improved user experiences and satisfaction.

In the recommendation system, user X's rating of item I is recorded as RX(I); the correspondingrating matrix is $R_{M\times N}(U, I)$, where the row vector M represents the number of users and the column vector represents the item number. In the item-based collaborative filtering recommendation model, input the user's original rating matrix R_{MxN}. The virtual rating matrix R → M The description of the item-based collaborative filtering recommendation algorithm is shown in Algorithm 1.

Input: user's rating matrix RM×like (U, I) for items, emotion calculation model
Virtual rating of type prediction R→M × shape (U, I).
Output: training data set Dtrain recommended based on item collaborative filtering
1. According to the user rating matrix, the training data for user U is extracted., its category label is $L(I) = R_{MxN}(I) \in \{1, 2, 3, 4, 5\}$;
In the M×N shaped rating matrix, the row vector represents the user and the column vector represents the item. Among them, R(i) represents the column vector of the rating matrix, and R(u)(i) represents the rating of user R for item i.
2. Update the training data score $R_u(i)$:

Algorithm. Item-based Collaborative Filtering Recommendation Algorithm.

//Use the opinion pre-filtering method to calculate the user's comprehensive rating of the item. Among them, $Time_{cur}$ represents the current time, Time $R_u(i)$ represents the user's comment time on the item, and the time only takes the year
3. Update the training data set:
// Mark the ones with a score of s_1 as positive categories and add them to the data pool (+). Mark the ones with a score of s_2 as negative categories and add them to the data pool (-).
4. Train the item-based collaborative filtering recommendation model, and use the classifier to perform on the candidate data $D = \{R\ (i)^T \mid R\ (i) \in R_{M\times N}\ \varepsilon\ R_{MxN}(U, I), R_u(i) = ¢\ \}$ Predict, get the predicted label L(i);
5. The data selection algorithm based on confidence estimation and cluster analysis is used to filter the data and return the data pre-added to the training data pool.
Return $D_{Train} = \{ D_L\ U\ D'_L \}$
// Data D_L represents the original data in one iteration, and data D'_L represents the added data in one iteration (the label of the data is the prediction score of the collaborative filtering model).

In Algorithm, the item-based collaborative filtering recommendation method is used to fill in the default value of the user rating matrix; at the same time, the training data set of user X is updated. In emotion classification models, they are generally divided into fine-grained (5-level classification) and coarse-grained (2-level classification). Considering that the accuracy of the 2-level emotion classification model is much higher than the 5-level emotion classification model, so this work Two- level emotion classification is used in the recommendation algorithm. Set the ratings of positive and negative user emotions to 5 points and 1 point respectively; then use the opinion pre-filtering method to comprehensively measure the user emotion ratings and original ratings; finally, use the item-based collaborative filtering model to predict the rating matrix and filling, and use the data selection algorithmbased on confidence estimation and cluster analysis to filter the data, and add the incremental data to the user's training data set.

4. Experimental Analysis

4.1 Dataset used

A. Twitter US Airline Sentiment dataset

A sentiment analysis job about the problems of each major U.S. airline [11]. Twitter data was scraped from February of 2015 and contributors were asked to first classify positive, negative, and neutral tweets, followed by categorizing negative reasons (such as "late flight" or "rude service"). Over55000 reviews are there in the dataset.

B. Tools used

The implementation of this work is developed in Python 3.11. The implementation was done in Intel(R) core (TM) I5 processor 3.0 GH speed, 8 GBRAM, 1TB Hard disk Windows 11.0 Platform.

4.2 Performance Evaluation

To evaluate the performance of the proposed algorithms the performance measures, Accuracy,Precision, Recall and F-Measure are evaluated. For a fair comparison, several machine learning and deep learning methods for sentiment analysis are included in the experiments. The machine learning methods include Long Short-Term Memory (LSTM) [12], Bidirectional Long Short-Term Memory (BiLSTM) [13], Convolutional Neural Network-LSTM (CNN-LSTM) [14], and Convolutional Neural Network BiLSTM (CNN-BiLSTM) [15]. Table 1 present the experimental results on the Twitterdataset.

Table 2. Performance Measures

	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)
LSTM	79	74	75	76
CNN LSTM	78	76	76	78
ROBETa-LSTM	81	90	91	91
ORLSTM	92	91	93	94
ORCBiLSTM	93	93	96	95
OARCBiLSTM	97	95	97	96

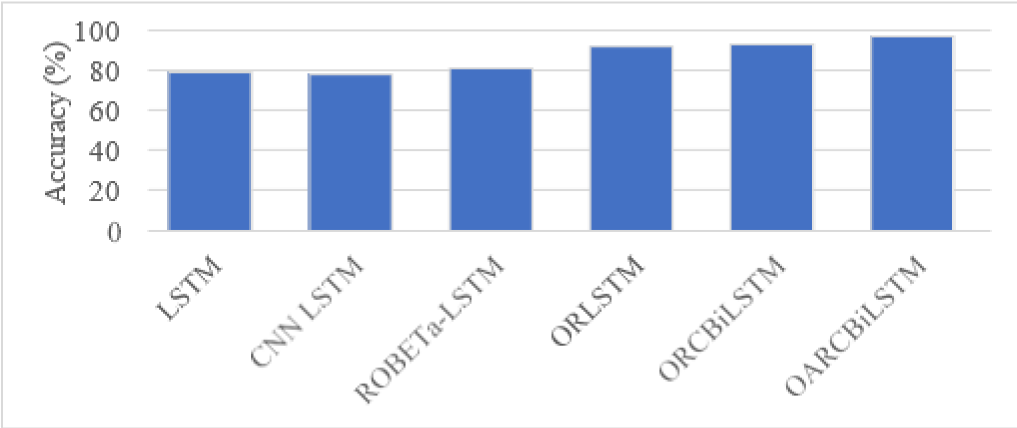
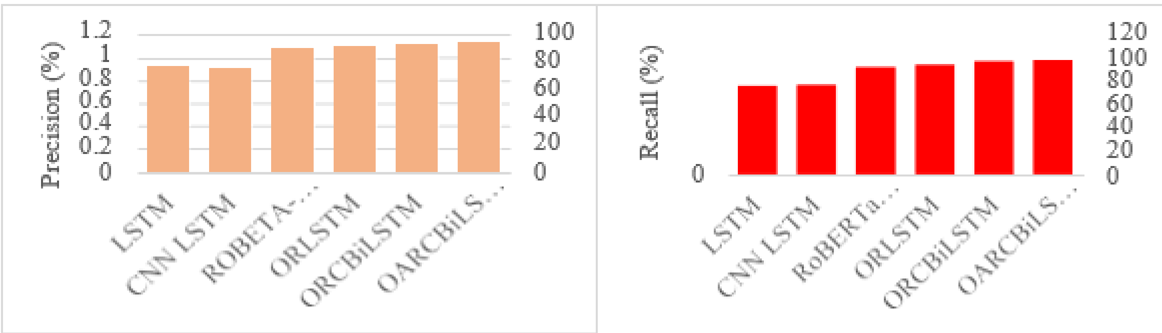


Figure 3 Accuracy Comparison

Figure 3 illustrates the performance comparison of the OARCBiLSTM method with other techniques. Specifically, it highlights that OARCBiLSTM surpasses LSTM by a noteworthy 22.78% in terms of accuracy and also outperforms CNN LSTM by a substantial 24.35%. Furthermore, it's important to highlight the remarkable performance of OARCBiLSTM, which outshines its counterparts by showcasing a substantial accuracy improvement. Specifically, OARCBiLSTM achieves a notable 19.75% accuracy boost when compared to ROBETa-LSTM, further bolstered by a 5.43% advantage over ORLSTM. These outcomes unequivocally underscore the efficacy of OARCBiLSTM as a highlypromising and impactful approach, particularly in the realm of augmenting accuracy within the scope of the tasks under examination.



Precision (%) **Recall (%)**

Figure 4. Precision and Recall Comparisons

The presented data shines a spotlight on the exceptional precision and recall performance of theOARCBiLSTM method in comparison to a diverse array of alternative methods. In terms of precision,OARCBiLSTM stands out remarkably, boasting a substantial 55.55% improvement over ROBETa- LSTM and a notable 4.39% edge over ORLSTM. Furthermore, it exhibits an impressive precision leadwith a remarkable 22.10% advantage over LSTM and an extraordinary 25% enhancement over CNN LSTM.

Transitioning to the realm of recall metrics, OARCBiLSTM continues to display its superiority, surpassing ORCBiLSTM by a margin of 1.04% and ORLSTM by a significant 4.30%. Moreover, in the recall domain, OARCBiLSTM demonstrates significant outperformance when compared to both LSTMand CNN LSTM, boasting advantages of 29.33% and 27.63%, respectively. These findings unequivocally emphasize the consistent excellence of OARCBiLSTM across precision and recall assessments, firmly establishing it as a robust and highly competitive choice for the tasks at hand.

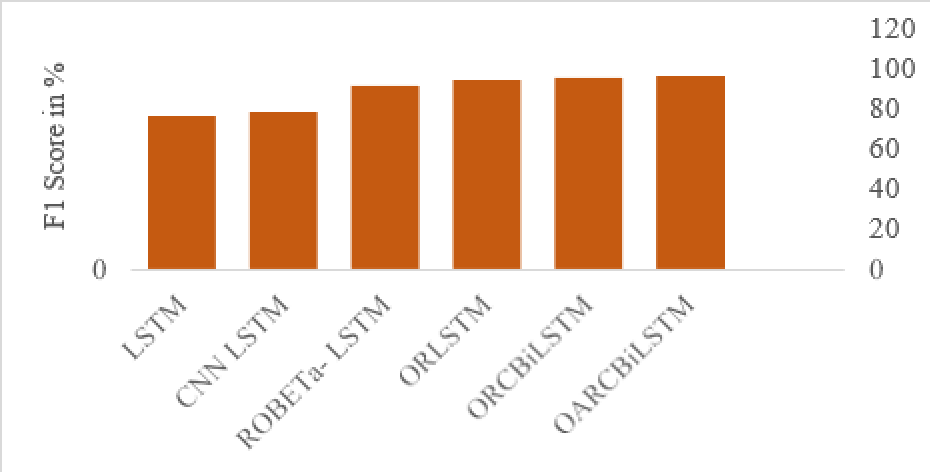


Figure 5. F1-Measure Evaluation

The comprehensive analysis of F1 scores further cements the superiority of the OARCBiLSTM method in comparison to alternative approaches. OARCBiLSTM exhibits a substantial advantage in F1scores, surpassing LSTM and CNN LSTM by 26.31% and 23.07%, respectively. Its remarkable capacity to achieve a harmonious balance between precision and recall is underscored by this. Additionally, when compared with ROBETa-LSTM and ORCBiLSTM, OARCBiLSTM maintains its leading position, with F1 scores that are surpassed by ROBETa-LSTM by 5.49% and ORCBiLSTM by1.05%. The robust and consistent performance of OARCBiLSTM across various evaluation metrics isunequivocally highlighted, positioning it as a compelling and formidable choice for tasks where a robustequilibrium between accuracy, precision, recall, and F1 measure is required.

In summary, exceptional performance is demonstrated by the OARCBiLSTM method across a spectrum of evaluation metrics, including accuracy, precision, recall, and F1 measure when compared with an array of alternative techniques. Overall, the OARCBiLSTM method is consistently surpassed by its counterparts across these pivotal evaluation metrics, thereby cementing its status as a steadfast and formidable choice for tasks where a potent balance between accuracy, precision, recall, and F1 measure is demanded.

5. Conclusion

An innovative hybrid recommendation system is introduced in this paper, leveraging the potency of deep sentiment analysis in user comments and combining it with the collaborative fusion ofmultiple recommendation sources. The primary objective of this approach is to address the challenge posed by user rating deviation by extracting emotional cues from comments, utilizing the opinion pre-filtering technique, and integrating this emotional information with the original ratings. Furthermore, neural networks are employed within the system to transform item content descriptions into distributedparagraph vectors, facilitating similarity computations for content-based recommendations. The collaborative training strategy harmonizes these two recommendation perspectives and introduces dataselection mechanisms rooted in confidence estimation and cluster analysis. This comprehensive approach enhances recommendation accuracy by iteratively refining the rating matrix, yielding recommendations that are more precise and tailored to individual preferences. The paper provides an in-depth framework that illustrates the efficacy of this system.

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