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Content-based filtering movie recommender system using semantic approach with recurrent neural network classification and SGD

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Abstract

The application of recommendation systems has been applied in various types of platforms, especially applications for watching movies such as Netflix and Disney+. The recommendation system is purposed to make it easier for users, especially in choosing a movie because currently the number of movie productions is increasing every day. This research proposed a CBF movie recommendation system by comparing the performance of several semantic methods to be able to get the best rating prediction results. In order to improve the performance quality to get the best rating prediction results, this research utilized semantic feature methods by comparing the performance of the evaluation results produced by the TF-IDF method and word embedding applications, such as BERT, GPT-2, RoBERTa, and implemented RNN model to classify the results of rating prediction. The data were used to generate the recommendation system by involving 854 data movie and 39 accounts with a total of 34,056 movie reviews on Twitter. This research has succeeded in getting a method that produced rating predictions, namely RoBERTa. In the classification process with the RNN model and SGD optimization, the measurement results with confusion matrix by classifying the RoBERTA rating prediction obtained an evaluation value of 0.6514 loss, 95.59% accuracy, and 95.76% precision.

1. Introduction

In the era of rapid development of social media, the role of recommendation systems is needed. Recommendation systems have been implemented in various types of platforms such as, Netflix, Disney +, Youtube, e-Commerce, Twitter (X), and many other platforms. The ability of the recommendation system can make it easier for users to choose an item that is adjusted based on several factors from the user such as preferences, past behavior, item characteristics, and social interactions [1][2]. This research produced a movie recommendation system based on "Tweets" on Twitter containing movie reviews. Twitter can generate a large amount of data every day that is real-time so that it can be used to implement a movie recommendation system [3].

Recommendation System is an information to predict the rating that will be given by a particular user for a particular item [4]. There are several techniques in implementing recommendation systems, such as Content-Based Filtering (CBF), Collaborative Filtering (CF), and Hybrid Approcach. The method applied in this research is CBF recommendation. CBF works by analyzing the user preferences and behaviors that can produce personalized recommendations based on the similarity value of an attribute. CBF method can produce more accurate recommendations than CF, especially if the users are limited or when the recommended items have clear and identifiable features [5][2].

CBF in this research is applied with Term Frequency - Inverse Document Frequency (TF-IDF) which acts to generate weights on words by measuring how important the word is, words that have high weights are considered more important and relevant [6]. This research also applies the use of word embedding to present interactions between users and movie items to understand the content of movie plots from one another [7]. The word embedding method applied are Bidirectional Encoder Representations from transformers (BERT), Genetarive Pretrauned Transformer 2 (GPT-2), Robustly Optimized BERT Pretraining Approach (RoBERTa), which applies the transformer architecture of a deep learning model that uses self-attention mechanism to take into account the relationship between each element in the data sequence [8]. In natural language processing, the four methods will be compared to be able to find the best algorithm in generating recommendations and also apply the classification into the rating prediction results produced by these methods.

The classification method applied in this research with deep learning is the Recurrent Neural Network (RNN) model which has an important role in the process of clasifying sequential data such as text, which has the ability to remember information from previous data and use it to predict the next class label in the sequence [9]. RNN is also capable of identifying flow patterns in the data used to provide recommendation results that are more tailored to user preferences [10].

In previous research, research [5] which was successful in applying the use of CBF resulted in a Mean Absolute Error (MAE) worth 0.72, which is high [5] . Another study [11] applied TF-IDF resulted in recommendations that were effective in improving the accuracy of the CBF recommendation system, but data improving accuracy still required the development of more sophisticated and complex techniques [11].

Previous research also applied the use of word embedding in research [12][13][14], which successfully improved the performance and accuracy on recommendations by applying transformer architecture, Bert, GPT-2, RoBERTa, the 3 models work by generating items that have similarity to the model applied also depends on the quality of the relevance of the input data [12][13][14].

The main contribution of this research is to apply several semantic feature methods as a comparison in order to find the best semantic method in generating CBF-based recommendation systems. The CBF method applied to generate recommendations, TF-IDF, and the application of word embedding BERT, GPT-2, RoBERTa, and applied the using of RNN models as classification and apply SGD optimization. RNN will produce results in the form of a label whether a movie is recommended or not, and measure the evaluation with confusion matrix with accuracy, precision, recall, and F1-Score. My motivation to apply these methods is because throughout the search that has been done, I have not found research that applies a comparison with the use of these methods in producing a recommendation system. Based on the model that I have applied, I managed to increase the TF-IDF evaluation which is higher than previous research [5]. For the application of the RNN model that I applied also resulted in a higher confusion matrix value than the previous researches [3].

Further explanation related to this research will be presented in section 2 Research Method, which will discuss the flow chart of the recommendation system that will be applied and the explanation of the method. Section 3 Result and Discussion will discuss the results that have been applied in this study. Section IV Conclusion will summarize all the research results that have been applied.

2. Research Method

2.1 Research Stage

This research was designed based on a flow chart that as shown in Figure 1 which presents the steps and designs that are applied in order to produce a recommendation system. Starting from collecting data that will form a dataset to produce a model for recommendations.

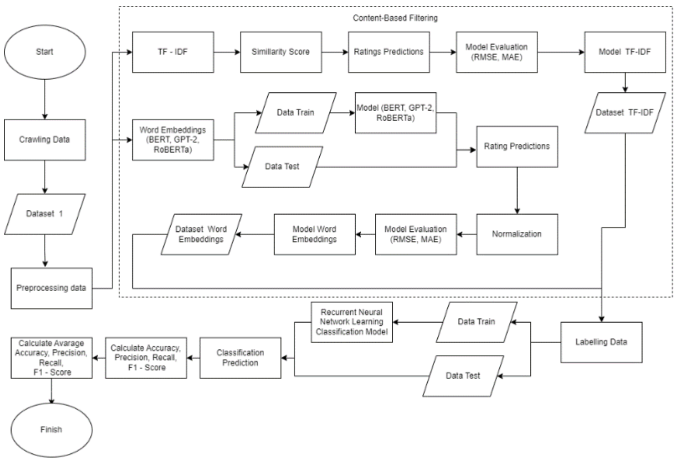

Figure 1. Flow Chart

As Shown in Figure 2, the process begins with data collection through Data Crawling, the results of crawling data are stored into Dataset 1. The data then goes through Preprocessing to clean and process the text. In the process of designing the recommendation system, the TF-IDF method is used to extract important features from the text. Similarity Score is calculated to determine the similarity between items, and Ratings Predictions are made based on content similarity, model evaluation using RMSE and MAE, and for comparison applying language models such as BERT, GPT-2, and RoBERTa, which were used to generate word embeddings from the dataset. Word embeddings from the dataset and models were processed for training and testing the model. The data was divided into train and test, and the rating predictions were normalized. In the classification part with RNN, RNN is used to learn from the data and build a classification model. The model was then used to make classification predictions, and the data was labeled based on the model output. This process also involved dividing the data into train and test. The process was completed after model evaluation and normalization of rating predictions.

2.2 Research Method

The data crawling technique was carried out to produce recommendations using 2 types of data. Movie crawling data and crawling data on Twitter, in the form of user tweets containing reviews of a movie. The process of crawling movie data through the IMDB website by applying Netflix and Disney+ filters. The filter results will obtain information related to 'name', 'description', 'keywords' by applying the Python programming language user using the PyMovieDb library, as show in Table 1.

Table 1. The Results of Movie Data Crawling

Film	Genre	…	Date Published
14 Cameras	[“Crime”, “Horror”, “Thriller”]	…	2018-07-27
17 Again	[“Comedy”, “Drama”, “Fantasy”]	…	2009-04-17
…	…	…	…
1BR	[“Drama”, “Horror”, “Thriller”]	…	2020-04-24

The implementation process of crawling to get tweets containing movie reviews on Twitter by applying the use of Tweet-Harvest to collect movie reviews from users on Twitter who were known for their ability to respond to a movie, the results can be seen in Table 2.

Table 2. The Results of Data Tweet Crawling

Username	Text
djaycoholyc	Grown Ups pertama ini masih asyik. Asyik banget
CenayangFilm	Film biografi indonesia yg paling pas emang baru azrax sih. Baru Gie dan Habibie Ainun.
…	…
danieldokter	Buset. Don't Knock Twice full house. Apa-apaan ini...

2.3 Preprocessing

The preprocessing process was applied to remove missing or inconsistent information, in order to present data that can be applied to produce a recommendation system [15]. The first step in the preprocessing process was to convert movie review data from Twitter into 0-5. This process applied several stages, namely translation, text cleaning, and polarity assessment. For polarity assessment, TextBlob was applied to analyze sentiment in the text to understand the opinions or feelings contained in a text [16].

2.4 Content Based Filtering

Content-Based Filtering (CBF) is a technique in recommendation systems that utilizes information about an item preferred by users to be able to recommend similar items [17]. In this research, as shown in the flowchart of the Figure 1, the steps of applying CBF methods in producing recommendations to produce the best predictions will be further explained by comparing the use of semantic feature methods, TF-IDF, BERT, GPT-2, RoBERTa which will be described for its explanation and application as follows.

2.4.1 TF-IDF

Term Frequency - Inverse Document Frequency (TF-IDF) is one of the weighting techniques that performs calculation by multiplying the frequency of occurrence of words in documents (TF), with a value (IDF) which is the logarithm of the inverse proportion of documents in coripus that contain the word [15][18].

TF-IDF is applied to calculate the weights of words in descriptions, keywords, and genres. The weighted values generated by TF-IDF can be used to compare the similarity between user profiles and applied to recommendation algorithms[17]. The results of the weights obtained by TF-IDF will produce a user profile containing movies that match the attributes of the user. The user profile account is formed by calculating, as show in Equation 1 bellow:

$$Account\_selection\_profile = G * R \,\hat{}\, T \quad (1)$$

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Where G represents the attribute column, R is the user rating value vector with m x 1 where m is the number of movies that will be included in the TF-IDF matrix which represents the numeric of the attribute column words that are taken into account.

The process of calculating the similarity score between user profiles and movies is calculated by applying the calculation, as show in Equation 2:

$$Score\_similiratiy\_i = U * M[:, i] \tag{2}$$

Where Score_similarity_i is the similarity score between the user profile and the i-th movie. U is a vector of user profiles, and M[:, i] is the vector of the i-th movie in the matrix formed from TF-IDF. The scores will be sorted, for the highest score is considered as the most relevant recommendation to the user.

2.4.2 Bert

Bidirectional Encodre Representations form Transformer (BERT) is a natural language processing model that uses transformer technology to learn the relationship between words in a sentence [19]. BERT works by understanding the sequential pattern of user behavior and the relationship between user behavior based on information from items to generate better recommendations [20]. BERT model is applied by utilizing the features in the movie in order to understand the user's preferences along with representing the embedding of ratings using Word Embedding (wembd) and the embedding of movies.

Splitting data to train the model for training data and testing data to test model performance. The model will also predict the rating for all users, then perform normalization by applying MinMaxScaler so that the rating value is in a range of 1 - 5, by applying calculation as show in Equation 3:

$$X_{norm} = (x - min(x) * (b - a)/max(x) - min(x) + a) \tag{3}$$

Where x represents the original data to be normalized, X_norm is data that has been normalized to the range [a, b], min(x) is the smallest value in x data, max(x) is the largest value in x data, and a and b are the lower and upper limits of the desired range. Then it will produce a rating prediction that describes the level of movie preference with the user. By applying CBF, a recommendation system model can be developed, namely by applying the use of BERT [21].

2.4.3 GPT – 2

Generative Pre-trained Transformer - 2 (GPT - 2) is a model that applied pre-training on large data that is trained using unsupervised learning techniques by predicting the items that are most similar to the given item list and acts as an effective CBF model in generating item recommendations [22][23]. The GPT-2 process is similar to the process carried out by the BERT model, the only difference is the use and application of a different model, namely GPT-2.

2.4.4 RoBERTa

Robustly Optimized Bidirectional Transformer (RoBERTa) is created as one of the efforts used to build a model to produce good recommendations according to user preferences. RoBERTa is one of the embedding models to produce better embedding vectors from sentences in the dataset to produce more relevant recommendations [21]. In terms of the process, the process in BERT is also similar, the only difference is the feature and model applied are RoBERTa.

2.5 CBF Model Evaluation

The prediction results generated by the models that have been applied will be measured by applying evaluation measurements, namely Root Mean Square Error (RMSE) which is used to measure the accuracy of the model and Mean Absolute Error (MAE) to evaluate the gap from the original value [24][25]. The following formulas for applying RMSE and MAE calculations as shown in Equation 4 and Equation 5.

$$\boldsymbol{MAE} = \left(\frac{\boldsymbol{1}}{\boldsymbol{N}}\right) \sum_{i=1}^{m} \sum_{j=1}^{m} * \left|\boldsymbol{r}(\boldsymbol{i},\boldsymbol{j}) - \hat{}\boldsymbol{ri},\boldsymbol{j}\right. \tag{4}$$

Where $\boldsymbol{N}$ is the amount of data, $\boldsymbol{m}$ is the number of movies that have been predicted, $\boldsymbol{r}(\boldsymbol{i},\boldsymbol{j})$ is the actual rating value given by the user for item $\boldsymbol{j}$,$\hat{}\boldsymbol{ri},\boldsymbol{j}$ is the rating value predicted by the system for user $\boldsymbol{i}$ on item $\boldsymbol{j}$.

$$\boldsymbol{RMSE} = \sqrt{\frac{\boldsymbol{1}}{\boldsymbol{n}} \sum\nolimits_{i=1}^{n} (\boldsymbol{y}_i - \hat{\boldsymbol{y}}_i)^2} \tag{5}$$

Where n is the number of samples, y_i is the actual value of the $i\ th$ sample, $\hat{y}_i$ is the predicted value for the the $i\ th$ sample. From the formula applied, if the resulting values of RMSE and MAE are lower, the better the performance of the model conceived by the recommendation system [24][25].

2.6 RNN Classification

Recurrent Neural Network (RNN) is a type of deep learning model architecture designed to process sequence data, consisting of one or more units called memory cells, which have the ability to store information from previous sequences which makes it possible to apply the use of RNN in various applications including recommendation systems [26]. To be able to improve the performance results generated by RNN calcification, the use of SGD optimization is applied which is useful for accelerating model convergence, preventing overfitting, by adjusting model weights iteratively, in some cases SGD has succeeded in producing better results when compared to other optimization methods such as Adam [27]. The following as show in Figure 2 which is the RNN architecture:

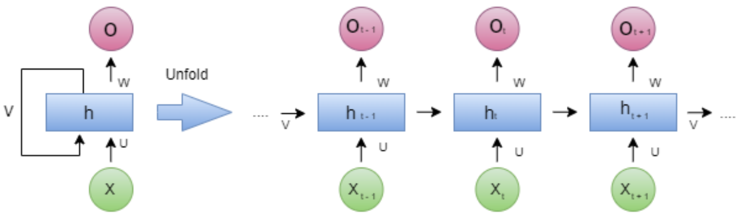

Figure 2. Architecture RNN

As shown in Figure 2 is the RNN architecture for processing data sets, which prioritizes the sequence of data points. Based on the image displayed, RNN consists of 3 main components, namely the green Input Sequence, the blue Hidden State, and the purple Output Sequence. For more details of the architecture applied in this research, it is shown in the Figure 4 below:

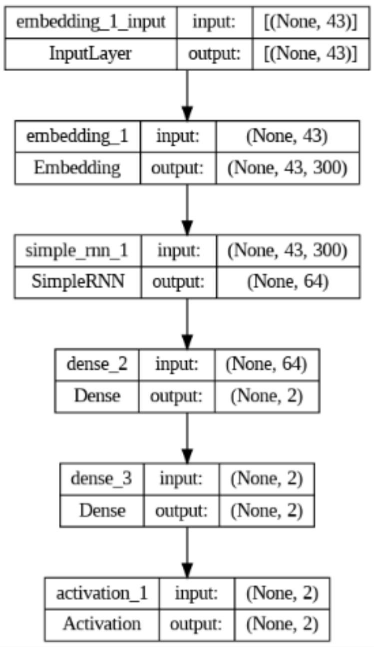

Figure 3. Architecture RNN Model Built

As show in Figure 3 is an illustration of the application of the architecture model built with RNN in this research.

2.7 Perfomance Evaluation

This performance evaluation stage is applied in order to determine the performance results produced by the classification model by applying Confusion Matrix measurements which resulted the Precision, Recall, Accuracy, and F1-Score scores. This evaluation is applied to help evaluate how well the classification model is built in producing relevant and accurate recommendations [3]. The confusion matrix is presented in Table 3 below:

Table 3. Confusion Matrix

Confusion Matrix		Prediction	
		Positif	*Negatif*
Actual	Positif	TP	TN
Value	Negatif	FP	FN

Table 3 showed the number of correct rating predictions and based on the results of the recommendation system, the table defines TP (True Positive), FP (False Negative), TN (True Negative), FN (False Negative). Based on the results of the Confusion Matrix, Precision, Recall, and F1-Score can be calculated to evaluate the performance of classification-based recommendation systems [28].

3. Results and Discussion

In this research there were 5 sections including, crawling results, RMSE and MAE evaluation results generated from several applied models, rating prediction results from the model with the best evaluation score, and classification results using RNN and several applied methods based on rating predictions generated by labeling the rating predictions of each CBF method that has been applied. The RNN model obtained evaluation results with Accuraccy, Precision, Recall, and F1-Score as show in Table 4.

3.1 Dataset

This research has produced a recommendation system using crawling data from the IMBD site with Netflix, and Disney+ filtered, for the time span from January 1, 2022 to November 2, 2023. The crawling resulted were entered into pyMovieDb to apply feature extraction, the results of the feature extraction were combined with the 593 previously conducted research data, so that the total movie data reached up to 854 movies with 15 features. The features used in this study were only 3 features, namely Description, Genre, Keywords, which were put together in one table, namely "Combined" to be processed by the methods that were applied as show in Table 4 below:

Table 4. Film Dataset Final

Film	Genre	…	Combined
Zombieland	['Action', 'Comedy', 'Horror']	…	When an undercover cop is tasked with investigating a historic gold heist in Johannesburg, he’s forced to choose between his conscience and the law. ['Action', 'Adventure', 'Crime'] police procedural crime,team action
3 Idiots	['Comedy', 'Drama']	…	0 ['Comedy', 'Drama'] hairy chest,motivation,coming of age,against the system,papadum
…	…	…	…
3 Days to Kill	['Action', 'Comedy', 'Drama']	…	A dying CIA agent trying to reconnect with his estranged daughter is offered an experimental drug that could save his life in exchange for one last assignment. ['Action', 'Comedy', 'Drama'] spy,violence,dirty bomb,massacre,cough syrup

The next crawling stage obtained 39 movie review accounts, which were combined with the previously conducted research movie review data of 3133 reviews, so that the total tweet reviews as a whole were 34086 with 3 features, as show in Table 5.

Table 5. Twitter Dataset

Username	Film	Text
AnakNonton	Thor: Ragnarok	Dengan $121 juta, 'Thor: Ragnarok' jadi film MCU dgn debut terbesar ke-7 sekaligus memuncaki box-office minggu ini!
AnakNonton	Headshot	Penata Efek Visual Terbaik #FFI2016 : Andi Novianto - 'Headshot' #MalamPuncakFFI2016
…	…	…
zavvi	What If	Well, new animated Marvel show What If...? looks like it will be plenty of fun #DisneyInvestorDay

The preprocessing stage was applied to data from crawling results for review data in the form of tweets on Twitter. There were 3 stages, namely translating the text, cleaning the text, and calculating blob. In the text translation stage, the language in the tweet is converted into English using the GoogleTranslator library. In the text cleaning stage, cleaning was carried out by removing "RT" characters, emojis, mentions, hastags, links, non-alphanumeric characters, line breaks, except spaces, and converting the text to lowercase. Then calculating blob is applied to calculate the sentiment polarity scores of a review and then converted to 0-5. This processed has produced a total of 6479 rows of data which included reviews from five added users, namely IMDB, Metacritic Metascore, Metacritic User Score, Rotten Tomatoes, Tomato Meter, and Rotten Tomatoes Audience Score as show in Table 6:

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Table 6. Twitter Final Dataset

Username	Film	Score
AnakNonton	3 Days to Kill	2.8409
AnakNonton	Posesif	3.6666
…	…	…
zavvi	Elemental	2.8316

3.2 Recommendation System Result

The dataset that has been formed were formed into a matrix to enter the rating prediction results by applying CBF with TF-IDF, BERT, GPT-2, RoBERTa, which were evaluated using RMSE and MAE. The results of RMSE is presented in Figure 4, and MAE is presented in Figure 5.

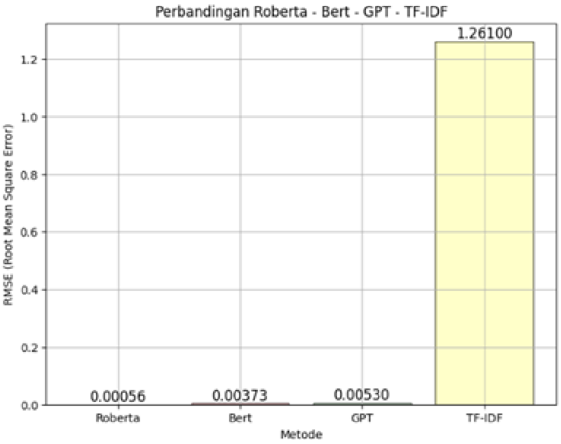

Figure 4. RMSE Evolution

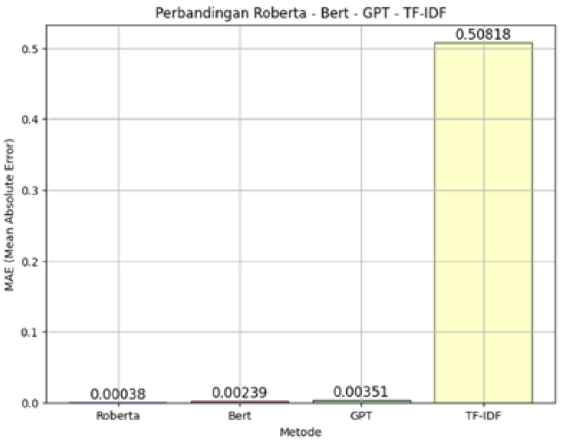

Figure 5. MAE Evolution

Figure 4 shows that TF-IDF produced the highest RMSE value, namely 1.2610. Meanwhile, the application of transformer architecture produced a very low RMSE value with BERT obtained 0.0037 and GPT obtained – 2: 0.0053, and the lowest RMSE value was produced by the RoBERTa model, i.e. 0.0005.

Figure 5 shows that TF-IDF again produced a higher MAE value among other methods, i.e. 0.5081. Meanwhile, BERT, GPT-2, and RoBERTa methods which applied a transformer-based language model produced a very low MAE values, namely 0.0023, 0.0035, and 0.0003 respectively.

It shows that the rating prediction generated by TF-IDF has an error in producing rating predictions that are not suitable/far from the original rating value because it produces high RMSE and MAE values. This happens because of the weakness of TF-IDF, which is vulnerable to irrelevant words so that it can affect the calculation of similarity and produce recommendations that are less accurate [29]. Cosine similarity can be used to provide recommendations for users based on their preferences. [30].

The application of BERT, GPT-2, and RoBERTa methods succeeded in produced lower RMSE and MAE values when compared to the TF-IDF method. The three methods succeeded in producing a smaller error rate and approaching the rating value. This shows that the three methods succeeded in building a more sophisticated language model and have a better understanding of a context so that they can produced more accurate recommendations.

Therefore, it can be concluded that the RoBERTa method succeeded in providing the best performance by producing the lowest RMSE and MAE values among other methods applied. RoBERTa managed to understand the relationship of words and sentences in a document so as to produce a richer and more accurate semantic in performing document embedding [14].

As shown in TABLE NUMBER is the result of RoBERTa rating prediction which has the best evaluation value among other rating predictions, RoBERTa has a very small error value. The following RoBERTa matrix table has a size of 854 rows that display movie titles and 45 columns that are user names.

Table 7. RoBERTa Rating Prediction Score

name	Zombieland	3 Idiots	…	3 Days to Kill
Sir_amirsyarif	1.0035	1.0034	…	1.0034
Rayculz	3.4965	2.9532	…	1.0034
…	…	…	…	…
AnakNonton	1.0033	1.0034	…	3.2729

As shown in the Table 7, not only the RoBERTa results are entered into the classification stage, but also all the rating prediction results generated from the methods that have been applied to find out the resulting performance was good enough, which was proceeded in the following stage.

3.3 Classification Result

The entire dataset generated from rating predictions that have been applied by several methods were labeled 1 and 0. The score of 1 is given if the film is recommended, and 0 is not recommended. After the labeling process, the classification model is applied using RNN, and the evaluation is calculated for the accuracy, precision, recall, and F1-Score. As shown in Table 8 as an example of the labeling result, here is the RoBERTa model.

Table 8. Labelling RoBERTa

name	Zombieland	3 Idiots	…	3 Days to Kill
Sir_amirsyarif	1	0	…	0
Rayculz	1	1	…	0
…	…	…	…	…
AnakNonton	0	0	…	1

As shown in Table 8, the classification model will be built, and the system will calculate the accuracy, precision, recall, and F1-score.

Table 9. RNN Confusion Matrix

Metode	Performance Metrics (%)				
	Loss	*Accuracy*	*Precision*	*Recall*	*F1-Score*
TF-IDF	3.4907	51.84%	78.28%	87.09%	82.42%
BERT	0.6376	86.88%	95.86%	95.40%	95.62%
GPT-2	2.4608	95.27%	86.12%	96.12%	89.46%
RoBERTa	0.6514	95.59%	95.76%	95.41%	95.58%

Table 9 shows that the classification resulted from the RoBERTa method performed quite well. The measurement by confusion matrix for its accuracy, precision, and recall reached high scores, but F1-Score is lower, perhaps this is because there is an imbalance of precision and recall in the model. The following results are the results after running 5 times for each model and divided as a whole.

4. Conclusion

This research has successfully designed a CBF-based recommendation system to be able to produce the best rating prediction, by comparing several semantic methods, TF-IDF, BERT, GPT-2, and RoBERTa, and implementing the RNN model for the classification process. On the evaluation resulted of the movie recommendation system by compared the performance of the methods applied in predicting the rating. The evaluation results show that the RoBERTa model provides the best results because it has the lowest RMSE and MAE values. In the application of classification using the RNN method and SGD optimization, the evaluation results using the confusion matrix metric still prove that the RoBERTa model provides the best results with a loss value of 0.6514, 95.59% accuracy, 95.76% precision, 95.41% recall, and 95.58% F1-Score. Therefore, the purpose of this research was successfully achieved by designing a CBF-based recommendation system by comparing several semantic methods to get the method that produces the best rating prediction.

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Thank you School of Infomatics in Telkom University for being a place for researchers to develop this journal research. Hopefully this research can make a major contribution to the advancement of the development of recommendation systems.

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