Movie Recommender System with Cascade Hybrid Filtering Using Convolutional Neural Network

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ABSTRACT

The current technological advancements have made it easier to watch movies, especially through online streaming platforms such as Netflix. Social media platforms like Twitter are used to discuss, share information, and recommend movies to other users through tweets. The user tweets from Twitter are utilized as a film review dataset. Film ratings can be used to build a recommendation system, incorporating Collaborative Filtering (CF) and Content-based Filtering (CBF). However, both methods have their limitations. Therefore, a hybrid filtering approach is required to overcome this problem. The filtering approach involves CF and CBF processes to improve the accuracy of film recommendations. No current research employs the Cascade Hybrid Filtering method, particularly within the context of movie recommendation systems. This study addresses this gap by implementing the Cascade Hybrid Filtering method, utilizing the Convolutional Neural Network (CNN) as the evaluative instrument. This research presents a significant contribution by implementing the Cascade Hybrid Filtering method based on CNN. This research uses several scenarios to compare methods to produce the most accurate model. This study's findings demonstrate that the application of Cascade Hybrid Filtering, incorporating CNN and optimized with RMSProp, yields a movie recommendation system with notable performance metrics, including an MAE of 0.8643, RMSE of 0.6325, and the highest accuracy rate recorded at 86.95%. The RMSprop optimizer, facilitating a learning rate of 6.250551925273976e-06, enhances accuracy to 88.40%, showcasing a remarkable improvement of 6.00% from the baseline. These outcomes underscore the significant contribution of the paper in enhancing the precision and effectiveness of movie recommendation systems.

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1. INTRODUCTION

In the current era of technological advancement, watching films has become increasingly widespread, with easy access through online streaming platforms such as Netflix and Disney+ [1]. Social media, particularly Twitter [2], [3], has become the main platform for users to discuss, express opinions, and recommend films through tweets. As the amount of available film information grows, users often struggle to choose the next film to watch. For example, when accessing Netflix's movie service, a user may be required to view several trailers before successfully finding a movie that matches the user's preferences, resulting in a time-consuming search process [4]. To overcome this obstacle, it is necessary to implement a recommendation system to identify movies consistent with the user's preferences [5].

This study aims to create a movie recommendation system in response to this concern. An effective movie recommendation system is anticipated to improve user experience, particularly in the efficient selection of movies aligning with user behavior. The developed system aims to provide recommendations on movie items, allowing users to choose movies that match their preferences [6]. Recommender systems have several model categories, including Collaborative Filtering (CF), Content Base Filtering (CBF), and Hybrid Filtering recommender systems [7], [8]. CF method utilizes other users' opinions to predict items that users may favor based on previous interactions between users and items [9]. While CBF method is a method that recommends content or information based on the suitability of the content to user preferences [10]. Hybrid Filtering combines a single recommendation system as a sub-component [11]. Hybrid Filtering overcomes some problems by using only one type of recommendation system method [12]. CF faces constraints such as data scarcity, where most users only rate a certain number of items, resulting in a matrix with many empty elements, and cold starts that occur when there are new users who have not rated [11], [13]. CBF faces the challenge of providing unique recommendations, as its focus is on users who give high ratings. A hybrid filtering approach is employed in this study, incorporating both Collaborative Filtering (CF) and Content-Based Filtering (CBF) to address the limitations of each method [14]. Collaborative Filtering enhances adaptability by tailoring recommendations to individual user preferences, ensuring a more personalized and relevant user experience [14]. On the other hand, Content-Based Filtering contributes to a diverse range of recommendations by focusing on the content of items, thereby offering a broader selection that goes beyond the preferences of other users. This combination leverages the strengths of both methods to provide a more robust and effective recommendation system [14].

This research adopts the Cascade Hybrid Filtering method among various approaches within the Hybrid Filtering framework. The selection of Cascade Hybrid Filtering is motivated by the absence of current research within the domain of movie recommendation systems utilizing this method. Cascade Hybrid Filtering is chosen for its step-by-step recommendation process, where the initial recommendation list is generated by the first method and subsequently refined by the second method to produce the final recommendation list [11], [15]. Hybrid Filtering is required because all methods except the first method in this approach can only transpose and remove items in the recommendation list and cannot introduce new items or restore items removed from the previous method to the recommendation list [16].

Deep learning is becoming popular in recommender systems because it provides high-quality performance and recommendations [17]. In addition, DL is a method capable of extracting and learning complex relationships between users and items [18], [19]. Convolutional Neural Network (CNN) is a subset of deep learning that processes text more effectively and can capture critical features that help provide users with more personalized and relevant recommendations [20]. Previous research shows that the movie recommendation system with CNN provides relevant results [8]. In this research, CNN is combined with Cascade Hybrid Filtering.

Film recommendation systems using hybrid filtering with CNN from research [4]. The research provides insight into the use of hybrid filtering and deep learning, specifically convolutional neural networks, in improving the performance of film recommendation systems. Experiments were conducted on MovieTweetings and Open Movie Database datasets, which showed an improvement in the accuracy of the proposed approach compared to existing techniques. However, this study did not include the measurement of word significance and relevance and did not compare the CNN method with several optimizations.

This study introduces a recommendation system that employs the Cascade Hybrid Filtering approach in conjunction with Convolutional Neural Network (CNN) as a classification method to augment precision in predicting rating values. Furthermore, various features, including feature extraction, semantic word embedding, and optimization techniques, will be incorporated into the research. Notably, existing literature does not currently explore the amalgamation of cascade hybrid filtering with CNN, particularly in integrating these features within a recommendation system. Using the RMSprop optimizer in conjunction with CNN and Cascade Hybrid Filtering, the study demonstrates a noteworthy achievement, attaining an accuracy rate of 86.95% in the domain of movie recommendations.

This paper is structured in several sections. Section 2 contains material about the methods used in this research. Section 3 contains the results, the discussion contains the research results, and the last section contains the conclusion.

2. METHODS

The research aims to develop a film recommendation system using hybrid filtering with the Convolutional Neural Network (CNN) method. The performance will be measured using a confusion matrix and evaluated using Mean Absolute Error (MAE). The System Design of the film recommendation system with hybrid filtering using CNN can be seen in Fig. 1. Initially, the obtained data undergoes preprocessing, yielding the pre-processed dataset denoted as "Dataset 1." Subsequently, this dataset undergoes processing within the

Cascade Hybrid Filtering framework, where the data is first processed using collaborative filtering, resulting in "Dataset 2." Following this, "Dataset 2" undergoes further processing in the context of Content-Based Filtering, leading to the derivation of "Dataset 3." The latter is subjected to classification through Convolutional Neural Network (CNN). The model's performance is then assessed through the evaluation metric of accuracy.

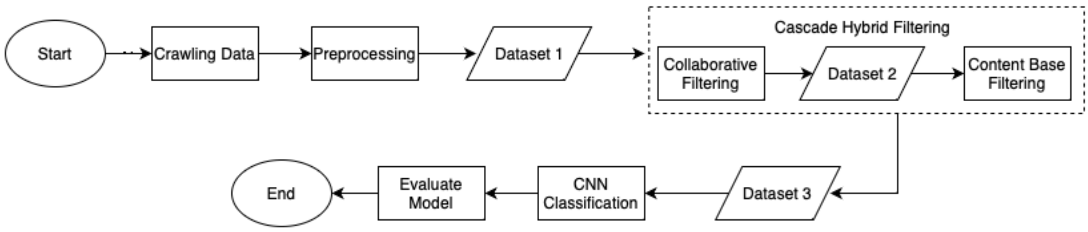

Fig. 1. System Design Hybrid Filtering using CNN Method Scheme Dataset cascade

2.1. Data Crawling

In the modern era, information or data can be collected from anywhere due to the abundance of data sources accessible to everyone. This research used two data types obtained from various sources [21]. Data Crawling is a method used to obtain data from the internet. The first Data Crawling was conducted to obtain film titles from the IMDB website using Netflix and Disney+ filters. Afterward, the data will be feature-extracted using the PyMovieDb Python library. The dataset that has been feature-extracted using PyMovieDb generates several features, such as name, description, and keywords. The second Data crawling was conducted to obtain users' tweet data from Twitter. The obtained tweets are tweets about movie reviews. In this study, Tweet-Harvest did this crawling.

2.2. Preprocessing

Before being used in the system, every dataset must undergo a pre-processing stage [22]. Before being used in the system, every dataset must undergo a pre-processing stage. This process is significantly important because not all datasets meet the requirements of the system to be implemented [23]. Various methods can be applied in dataset pre-processing, such as handling outliers, dealing with null values, scaling data, and other processes [12]. The main objective of this stage is to modify the dataset structure to make it suitable and effectively implementable in the intended system.

Preprocessing is divided into three main stages [24]: translating, cleaning, and calculating blob. During the translate text stage, the tweet's language is adjusted to English using the GoogleTranslator library. During the text cleaning stage, various cleaning actions are taken, including removing the character 'RT,' eliminating emojis, deleting mentions, hashtags, links, non-alphanumeric characters except spaces, and new lines. The text is then converted to lowercase. Subsequently, a blob calculation is performed to determine the sentiment polarity of a review, which is then updated on a scale of 0-5. This process results in 6479 lines of data.

2.3. Hybrid Filtering

Hybrid Filtering combines two or more recommendation systems to improve recommendation performance and address potential issues arising from using a single method [15]. This study employs a Hybrid Filtering approach by combining Collaborative Filtering (CF) and Content-Based Filtering (CBF) to enhance the quality of the resulting recommendations [25].

The Collaborative Filtering (CF) method utilizes user opinions to predict items that may be liked by the user based on their previous interactions with items [19], [25]. Collaborative Filtering (CF) exhibits both merits and constraints. An inherent advantage lies in its adaptability, facilitating tailored recommendations that align closely with individual user preferences. However, this approach contends with certain limitations, notably data scarcity issues. Data sparsity manifests when a substantial proportion of users provide ratings for only a limited set of items, yielding a matrix replete with vacant elements. Additionally, CF confronts challenges posed by cold starts, instances wherein novel users have not yet supplied ratings [11], [13].

The Content-Based Filtering (CBF) method recommends content or information based on its relevance to the user's preferences [23]. CBF relies on item descriptions to provide recommendations and often filters items based on their similarity to the user's preferred content [26].

This approach has various implementation methods. This study uses the hybridization pipeline approach with the Cascade method for CF and CBF. The System Design of the film recommendation system with hybrid filtering can be seen in Fig. 2.

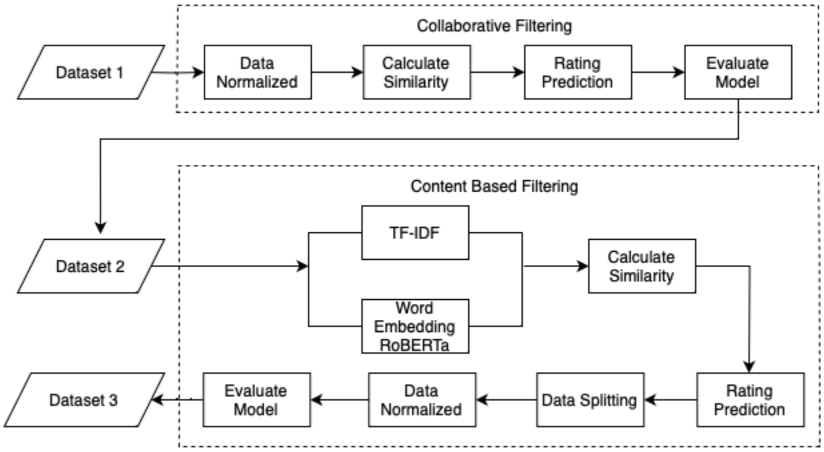

Fig. 2. System Design Hybrid Filtering Method Scheme

2.3.1. Collaborative filtering

In the system design figure above, collaborative filtering has 4 stages: Data Normalization, Calculate Similarity, Rating Prediction, and Evaluate Model [27], [28].

a. Data Normalized is a data transformation method that positively impacts algorithm accuracy and efficiency. This method is also useful in avoiding redundancy or duplication of data in a dataset.
b. Computing Similarity involves determining similarity scores for both users and items to ascertain the degree of resemblance between them. These similarity scores, ranging from -1 to 1, signify the extent of similarity, with values approaching 1 indicating a high degree of resemblance. In this study, the Pearson Correlation Coefficient method is consistently utilized for computing similarity. This method assesses similarity by calculating linear correlations between two distinct datasets. The choice of the Pearson Correlation Coefficient method is driven by its ability to capture linear relationships between variables, providing a robust measure of similarity that is particularly relevant in collaborative filtering scenarios. The method's capability to discern the strength and direction of associations between items makes it a suitable choice for evaluating similarity in the context of the current research.
c. The Rating Prediction stage predicts a user's ranking for an empty item. The choice of the value of n in topN corresponds to selecting the n value that yields the optimal RMSE (Root Mean Square Error) value.
d. The evaluation of a model using Mean Absolute Error (MAE) is a method for calculating the accuracy level of a system's rating prediction against the actual rating given by the user. The evaluation of a model using Mean Absolute Error (MAE) is a method for calculating the accuracy level of a system's rating prediction against the actual rating given by the user. This method is required to evaluate the created model accuracy. MAE is obtained by calculating the absolute value of N pairs of actual and predicted ratings and then taking the average. The closer the MAE value is to 0, the better the prediction results.

From the four processes carried out, 'Dataset 2' was produced. This dataset will be used as input for the next process.

2.3.2. Content Based Filtering

In the system design figure above, collaborative filtering has 6 stages [29]: TF-IDF or Word Embedding RoBERTa, Calculate Similarity, Rating Prediction, Data Splitting, Data Normalized, Evaluate Model. The system design figure above uses 2 models using TF-DF and RoBERTa word embedding model:

a. TF (Term Frequency) plays a role in determining how often a word appears in a document [30]; if the frequency of the word is high, it can be concluded that the word has importance and can be used in the formation of item profiles. This method measures the value or weight of each word. This method could improve the recommendation system by the weight of each words that shows the similarity of each tweet or text. The formula for the TF-IDF is:

$$TF_{ij} = \frac{f_{ij}}{max_k f_{kj}} \tag{1}$$

$$IDF_i = log\ log\ \frac{N}{n_i} \tag{2}$$

$$\text{TF-IDF } Score\text{: } w_{ij} \text{ - } TF_{ij} \times IDF_i \tag{3}$$

b. Word embedding converts words into numerical vector representations [31], [32]. The purpose of word embedding is to obtain semantic and syntactic relationships between words so that similar words in a particular context have vector representations that are close to each other [32], [33]. RoBERTa is a development of BERT that uses word embedding with a contextualized word embedding approach.

The result of combining Collaborative Filtering and Content-Based Filtering is "Dataset 3" which will be used as input in the CNN classification process.

2.4. Data Balancing

SMOTE, which stands for Synthetic Minority Over-sampling Technique, is a systematic method employed to artificially increase the size of a provided dataset [34]. This method adds data from the minority class to improve its representation. One variant of the SMOTE technique is known as SMOTEN [35]. In addition to oversampling, data points or examples that are close to the majority class will be removed. This action is carried out before oversampling the minority class, aiming to avoid including excessive data [36]. The implementation of SMOTE is essential to address the imbalance within the dataset. The dataset's imbalance adversely impacts machine learning's efficacy, as indicated by existing research [35].

2.5. Convolutional Neural Network

CNN is one of the deep learning architectures based on the human brain. Deep learning has become popular in recommendation systems because it provides high-quality performance and recommendations [37], [38]. Convolutional Neural Network (CNN) is a part of deep learning that processes text more effectively and can capture important features that help provide more personalized and relevant recommendations to users [39]. Based on previous research, the movie recommendation system with CNN provides quite relevant results [40]. It has proven very efficient in learning features from users' textual reviews to model latent user and item factors. In the context of text classification, the input is a word vector formed through a word concatenation method [41], like the approach applied to image classification. As more and more people use CNN methods, Google designed a framework known as TensorFlow to support machine learning because tensors play a crucial role in the process. The concept of tensors allows the generalization of vectors and matrices to various dimensions with a higher degree of flexibility [42]. This research develops various CNN model structures by utilizing the Keras library within the scope of TensorFlow.

The feature extraction layer is formed of two main components, namely the Convolutional layer and the Pooling layer. These two layers perform the data encoding process, converting the input information into a vector format [43]. The Convolutional layer, as a key element in the CNN classification model, uses a filter or kernel to take a small portion of the input, which is then processed across the entire input [43]. Its main function is to perform multidimensional matrix calculations [44].

The result of the Convolutional layer then passes through the Pooling layer, which aims to reduce the output sample of the previous layer and reduce the number of operations on the next layer [44]. The output of this feature extraction layer is an activation map in the form of a multidimensional array [45]. Therefore, the next step is to use flatten to convert it back into a single vector that can be used as input for the Fully Connected layer [46].

Overall, the CNN architecture used in this context is a type of 1D-CNN (One Dimensional Convolutional Neural Network) specifically designed to handle one-dimensional data. In this model, architecture consists of Input, convolution layers, leakyRelU layers, maximum pooling layers (max pooling), flatten layers, dense layers, dropout layers, and output layers. These functions play a role in the CNN process.

The data input is processed through convolutional layers. Embedding is also used to convert word or token representations into numerical vectors. Next, embedding converts word or token representations into a numerical vector. With Conv1d, the model can extract more complex patterns and features from the layers above it, allowing the identification of simple patterns in the observed data [47]. Next, The LeakyReLU (Rectified Linear Unit) activation function addresses potential issues with the conventional ReLU (Rectified Linear Unit) activation function. LeakyReLU is a modification of the ReLU activation function, frequently employed within Convolutional Neural Networks (CNNs). Its utility is preserving information within negative values, thereby mitigating the risk of the model stagnating in local minima. This attribute contributes to enhanced generalization, improving performance across tasks, including but not limited to the classification of

ECG abnormalities and classifications involving diverse target data [51]. In the next step, GlobalMaxPooling1D takes the maximum value of the pooling window to reduce the dimensionality of the data. In the next step, dropout prevents overfitting by silencing a random number of neurons during training. To generate class probabilities independently, the model is equipped with a dense layer of three units and uses sigmoid activation. The System Design of the Convolutional Neural Network can be seen in Fig. 3.

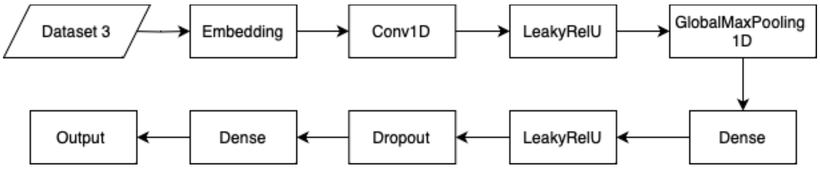

Fig. 3. System Design Convolutional Neural Network Method Scheme

2.6. Performance

During the performance measurement stage, accuracy values will be calculated using the confusion matrix method. The confusion matrix contains information that compares the classification results obtained by the system with the subsequent classification results. The confusion matrix method will calculate accuracy values during the performance measurement stage. This method is used to measure the performance of a classification method [48]. The confusion matrix method will calculate accuracy values during the performance measurement stage. The system's performance is usually evaluated using data in the matrix [49]. The confusion matrix details the real classifications and the predictions generated by the classification system. A tabular representation includes four distinct combinations of predicted and actual values. When assessing performance using the confusion matrix, there are four terms denoting the outcomes of the classification process: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Table 1 illustrates the confusion matrix for a two-class classifier.

Table 1. Confusion Matrix

Table Head	**Predict**	
	Positive	**Negative**
Positive	TP (True Positive)	FN (False Negative)
Negative	FP (False Positive)	TN (True Negative)

In the provided table, True Negative (TN) signifies the count of correctly identified negative data. In contrast, False Positive (FP) denotes negative data incorrectly identified as positive. On the other hand, True Positive (TP) represents accurately detected positive data. False Negative (FN) is the inverse of True Positive (TP), indicating instances where positive data is mistakenly identified as negative [50]. The performance accuracy can be derived from this confusion matrix. Accuracy is the ratio of correctly classified data to all data. The accuracy can be achieved by method (4).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

The next performance measurement will use the Mean Absolute Error (MAE) method [28], which is used to calculate the accuracy level of the system's rating prediction against the actual rating given by the user. MAE is obtained by calculating the absolute value of N pairs of actual and predicted ratings and then taking the average. The closer the MAE value is to 0, the better the predicted result. The MAE score can be achieved by method (5), pi which stands for prediction and ri stands for true value.

$$MAE_i = \frac{1}{n}\sum_{i \in E} (|pi - ri|) \tag{5}$$

3. RESULTS AND DISCUSSION

The research aims to develop a film recommendation system using hybrid filtering with Convolutional Neural Network. The research consists of several stages: data crawling, preprocessing, Hybrid Filtering, and CNN. The data preparation stage involves crawling data from Twitter, preprocessing, and labeling data before using them in the CF and CBF stages. Next, the CF stage predicts items the user may like based on their previous interactions. The output of CF is then used as input for CBF, which aims to recommend content or information based on its relevance to the user's preferences. Finally, the CNN classification process is carried out with several different optimizations to determine the best MAE, RMSE, and accuracy.

3.1. Data Crawling Result

The data preparation stage resulted in two datasets: a film dataset and a film review dataset. The film dataset from IMDB comprises 854 films with 18 features after feature extraction using PyMovieDb, as shown in Table 2.

Table 2. Film Crawling Result

Film	Genre	…	Date Published	Duration
14 Cameras	["Crime", "Horror", "Thriller"]	…	2018-07-27	PT1H30M
17 Again	["Comedy", "Drama", "Fantasy"]	…	2009-04-17	PT1H42M
…	…	…	…	…
3 Days to Kill	["Action", "Comedy", "Drama"]	…	2014-02-25	PT1H57M
3 Idiots	["Comedy", "Drama"]	…	2009-12-25	PT2H50M

The film review dataset was obtained by crawling Twitter using Twitter-Harvest. Data crawling was performed on 39 Twitter accounts that specialize in reviewing films. resulting in 34,086 tweets. The tweets contain three features, as shown in Table 3.

Table 3. Tweet Crawling Result

Username	Film	Text
AnakNonton	Drive	"Drive" was awesome. Recommended! ;) RT @wilfredcullen: @AnakNonton drive oke ga sih filmnya ? :)
CenayangFilm	Wind River	Penata Efek Visual Terbaik Wind River asik juga. Film drama tapi deg degan nontonnya
…	…	…
moviemenfes	The Machine	mvs kalian yg belum nonton ayo cobain. ini seru, lucu, terharu 😍 😍 judul : The Mitchells vs the machine https://t.co/jWjecis85k
winseulbear	The Social Dilemma	@leejaeropark @collegemenfess yg menurutku bgus: the king's speech sama the social dilemma😀 👍

3.2. Preprocessing Result

In the context of this research, review transformation is performed through a series of data-cleaning steps. These steps include removing irrelevant information, such as emoticons, tags, mentions, and links. After the data cleaning, the purified dataset was translated into English using the Google Translator library. This process simplified the reviews, eliminated non-essential elements, and converted text to lowercase, as shown in Table 4.

Preprocessing was then performed on the film review dataset. This preprocessing focuses on converting film reviews on a scale of 0 to 5. The preprocessing produces 6479 data. The following are the results of the preprocessing data, as shown in Table 4.

Table 4. Cleaned Dataset

Username	Film	Text
AnakNonton	Drive	Drive was awesome recommended drive is the film okay
CenayangFilm	Wind River	Wind river is cool too drama film but excited to watch
…	…	…
moviemenfes	The Machine	Those of you who heavent watched lets try it this is exciting funny moving title the mitchells vs the machine
winseulbear	The Social Dilemma	Which I think is good the king speech and the social dilemma

The calculation of polarity score used the TextBlob library, producing a score in the range of 0-5 representing the user's rating of the movie. After the preprocessing stage, the movie review data became a rating dataset with a size of 6479×4, as shown in Table 5. Next, the dataset was aggregated and converted into a 514×45 matrix, which represents the number of films and users. Where the dataset columns reflect the users (which include Twitter accounts such as IMDB, Rotten Tomatoes, and Metacritic), the additional Twitter account regularly provides movie reviews. This dataset was combined with previous research. The dataset's rows list the films' names. The values in the dataset reflect the polarity and rating value of the website in question. This dataset is the result of the data preparation stage and is named "Dataset 1", as shown in Table 6.

Table 5. Preprocessing Result

Username	Film	Score
AnakNonton	Drive	5.0
CenayangFilm	Wind River	3.34
…	…	…
moviemenfes	The Machine	3.8
winseulbear	The Social Dilema	3.41

Table 6. Dataset 1

Username	Film	Score
AnakNonton	Drive	5.0
CenayangFilm	Wind River	3.34
…	…	…
moviemenfes	The Machine	3.8
winseulbear	The Social Dilema	3.41

3.3. Hybrid Filtering Result

The hybrid filtering process involves two stages: The first stage involves processing using the Collaborative Filtering method, which retrieves the top 50 data. The Collaborative Filtering process resulted in a low error rate, which an MAE of 0.1374 and an RMSE of 0.1853. Both MAE and RMSE have values near zero. The dataset obtained from the Collaborative Filtering process will be used as input data for the Content-Based Filtering process. The following are the results of the preprocessing data, as shown in Table 7.

Table 7. Collaborative Filtering Result

Nama Film	AnakNonton	…	IMDB	zavvi
14 Cameras	0.000	…	0.479167	0.0
17 Again	0.000	…	0.666667	0.0
…	…	…	…	…
3 Days to Kill	0.568	…	0.645833	0.0
3 Idiots	0.000	…	0.875000	0.0

The second stage involves processing with Content-Based Filtering. The Content-Based Filtering method employs two scenarios: TF-IDF and Word Embedding RoBERTa. The first scenario, which uses TF-IDF, produces an MAE of 0.2888 and an RMSE of 0.6564. The following are the results of the preprocessing data, as shown in Table 8. The second scenario, which utilizes Word Embedding RoBERTa, yields an MAE of 0.0012 and an RMSE of 0.001. The following are the results of the preprocessing data, as shown in Table 9.

Table 8. First scenario with TF-IDF

Film	AnakNonton	…	IMDB	zavvi
14 Cameras	1.060647	…	2.946794	1.060647
17 Again	1.060647	…	3.684851	1.060647
…	…	…	…	…
3 Days to Kill	3.296469	…	3.602845	1.060647
3 Idiots	1.060647	…	4.504915	1.060647

Table 9. Second scenario with RoBERTa

Film	AnakNonton	…	IMDB	zavvi
14 Cameras	0.0	…	2.3	0.0
17 Again	0.0	…	3.2	0.0
…	…	…	…	…
3 Days to Kill	2.84	…	3.1	0.0
3 Idiots	0.8928	…	4.2	0.0

The second scenario, employing Word Embedding RoBERTa, demonstrates better performance, evidenced by its lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). This improvement can be attributed to RoBERTa's incorporation of self-attention mechanisms, facilitating a nuanced comprehension of word contexts within sentences. The accuracy of the chosen method assumes significance in the context of Cascade Hybrid Filtering, as the outcomes of this method serve as input for the subsequent stages in the Cascade Hybrid Filtering process. Consequently, this method is designated as the output for the Cascade Hybrid Filtering model.

3.4. Convolutional Neural Network Result

After passing the recommendation system process, the next step is classification using Convolutional Neural Network. The first step is to process data for classification. The following data has been classified as shown in Table 10.

Table 10. Data For Classification CNN

Film	AnakNonton	…	IMDB	zavvi
14 Cameras	0.0	…	0.0	0.0
17 Again	0.0	…	1.0	0.0
…	…	…	…	…
3 Days to Kill	0.0	…	1.0	0.0
3 Idiots	0.0	…	1.0	0.0

In the classification process, 32996 rating data with a value of 0 and 5434 rating data are obtained. Therefore, it is necessary to carry out the SMOTE process to systematically over-sample the given data set. After that, optimization will be carried out with several optimizations to get the highest accuracy value.

In this experiment, SMOTE was used to increase the number of samples in the minority class or decrease the number of samples in the majority class. This step aims to achieve optimal results by utilizing the ratio as a divider. In this study, the ratios used include 90:10, 80:20, 70:30, and 60:40. Table 11 shows the baseline and SMOTE results for the CNN model.

Table 11. Comparisons

Split Ratio	Accuracy (%)
90: 10	81.90
80:20	81.84
70:30	**82.40**
60:40	81.69

This was done to address data imbalance, which can result in inaccurate classification results. The table indicates that the highest accuracy was achieved when the data was divided at a ratio of 70:30, which was 81.90%. Therefore, the consistent use of the 70:30 ratio will be applied in the following scenarios.

CNN classification uses several optimizations from Keras Optimizer, namely Adam, SGD, RMSProp, Adamx, and Nadam. In this study, the authors used CNN Conv1D using training data epochs of 15, and batch_size of 64. The following is a table of results from several optimizations that have been carried out classified as shown in Table 12.

The optimization results show that the RMSProp method outperforms the others with low Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values, along with the highest accuracy rate of 86.95%. On the other hand, the Adamx method shows a low RMSE value, although its MAE is relatively high. Although the Adam and Nadam methods have slightly higher accuracy rates, they exhibit relatively high MAE and RMSE values. The following is an image of the MAE and RMSE plots of the five optimizations used, as shown in Fig. 4.

Table 12. Optimizations Result

Optimizer	MAE	RMSE	Accuracy (%)
Adam	0.5015	0.8974	85.27 (+2.87)
SGD	1.4880	1.1668	85.19 (+2.97)
RMSProp	**0.8643**	**0.6325**	**86.95 (+4.55)**
Adamx	0.9018	0.4762	85.19 (+2.79)
Nadam	0.9041	0.4783	85.61 (+3.21)

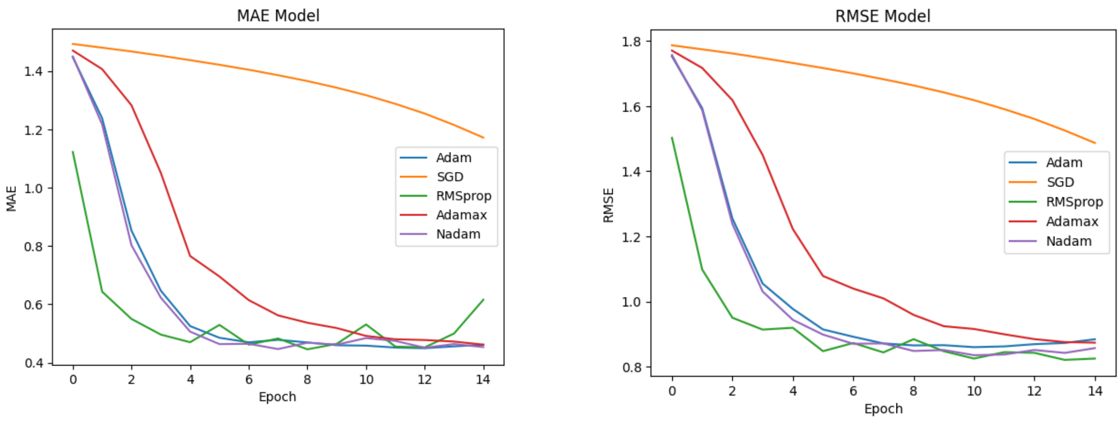

Fig. 4. Line chart MAE and RMSE

The last experiment finds the optimal value for the learning rate in each optimization. Table 13 reflects a very significant improvement in the results from optimizing RMSprop. The findings show that the RMSprop optimization approach achieved the highest accuracy, and this strategy proved successful in improving accuracy. the results of the experiment have increased can be seen in Fig. 5. The goal of this optimization is to achieve the lowest possible values for MAE and RMSE, therefore the RMSProp method can be considered a better choice.

Table 13. Best Learning Rate of RMSprop

Optimizer	Learning Rate	Accuracy (%)
RMSprop	6.250551925273976e-06	88.40 (+4.00)

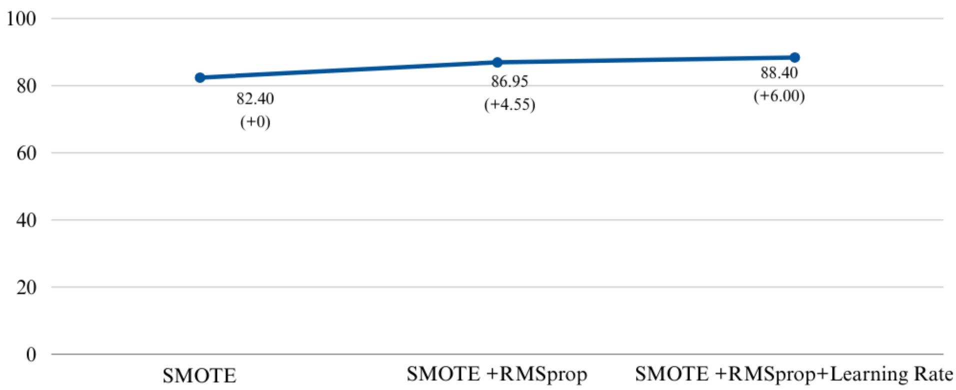

Fig. 5. Line chart result from scenario

4. CONCLUSION

In this research, the development of Cascade Hybrid Filtering method combined with Convolutional Neural Network method has been conducted. This research uses several testing scenarios aimed at optimizing the performance of the CNN model as a classification model.

The Cascade hybrid filtering process with some of the best scenarios, namely by using RoBERTa word embedding, produces MAE of 0.0012 RSME of 0.001 which is then classified using CNN with several optimizations to determine the performance of the optimizations used. This research concludes that Cascade Hybrid Filtering using CNN can be a movie recommendation system with an accuracy of 82.40% on the base model. Optimizer RMSprop contributes to the enhancement of the baseline model accuracy, where the initial accuracy of the basic model stands at 82.40%. Applying RMSprop results in an increased accuracy rate of 86.95% with MAE 0.8643 and RMSE 0.6325. Furthermore, when RMSprop is employed with a specific learning rate of 6.250551925273976e-06, the model achieves an accuracy of 88.40%, signifying a noteworthy improvement of 6% from the baseline accuracy without any optimizer.

This research provides an opportunity for further exploration and application of hybrid filtering techniques in improving recommendation systems in movie watching and other areas.

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