Jurnal Teknik Informatika (JUTIF)
Vol. 5, No. 1, February 2024, pp. 291-300
DOI: https://doi.org/10.52436/1.jutif.2024.5.1.1729
p-ISSN: 2723-3863
e-ISSN: 2723-3871

FILM RECOMMENDATION USING CONTENT-BASED USING ARTIFICIAL NEURAL NETWORK METHOD AND ADAM OPTIMIZATION

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(Article received: January 15, 2024; Revision: January 20, 2024; published: February 17, 2024)

Abstract

This research aims to develop a more accurate and relevant content-based film recommendation system from the Netflix and Disney+ streaming platforms using the ANN method. Movie recommendation systems are a popular solution to help users find movies that match their preferences. The ANN method develops a model to learn complex patterns from film features. Additionally, Adam optimization is used to improve the speed and accuracy of the model training process. The advantage of using an ANN is its ability to learn complex patterns and improve the performance of the recommendation system over time. Adam Optimization helps improve the speed, accuracy and quality of ANN models. From this research, researchers, based on the evaluation results using the confusion matrix, obtained an accuracy value of 88.30%, using a split ratio of 80:20 and a learning rate of 0.04469992592930794. This means that most classifications can detect correctly according to sufficient data. Combining these two methods allows the film recommendation system to provide better recommendations as more data becomes available.

Keywords: *ANN, Adam, Content-Based, Film, Recommender System.*

1. INTRODUCTION

In the current digital era, entertainment has become a critical need for many people. One popular form of entertainment is watching films [1]. However, deciding which film to watch is often tricky with so many film choices available. As a famous movie streaming platform, Netflix uses a sophisticated recommendation system to help users find movies that match their preferences[2]. Disney has a streaming platform called Disney+. Disney+ offers a collection of films and TV series, including the Disney franchise, Marvel, Star Wars and others. Recommendation systems can help users overcome the problem of information overload and find items they may want. A recommendation system is an application that provides and recommends items that users want in making decisions[3].

Movie recommendation systems have become a top-rated solution to help people find movies that match their preferences[4]. One implementation of ANN that is widely used is for prediction [5]. One type of recommendation system that is most commonly used is a content-based filtering recommendation system, which aims to recommend films based on the genre and rating of the film[6]. This content-based filtering compares two filtering models with the smallest MAE and RMSE values from the word embedding model using RoBERTa and TF-IDF. The MAE and RMSE values represents the average absolute error between the forecast results and the actual value[7]. The smaller (closer to 0) the RMSE value, the more accurate the prediction value[8].

The Artificial Neural Network (ANN) method and Adam optimization are used to improve the quality of the content-based film recommendation system. ANN can learn from experience, generalize over the examples they obtain and abstract the essential characteristics of input even for irrelevant data[9]. The Artificial Neural Network (ANN) method can learn complex patterns from film features [10], while Adam optimization is used to increase the speed and accuracy of the model training process [11].

One study on film recommendations using a content-based approach was carried out by Li in 2019 developed a film recommendation system by utilizing information from films such as genre, synopsis, and actors. The research results show that the content-based approach has relatively high accuracy in recommending similar films [6].

In addition, the Artificial Neural Network (ANN) method is often used in film recommendation research. Santoso in 2018 developed a film recommendation system using a hybrid approach that combines content-based and collaborative filtering with an Artificial Neural Network (ANN). The research results show that the recommendation system has relatively high accuracy in recommending films [12].

The Adam optimization method has been used in research related to film recommendations to develop a film recommendation system by combining collaborative filtering and ANN methods with Adam optimization. The research results show that this method can increase the accuracy of film recommendation [13]. The advantage of using an Artificial Neural Network optimized by Adam in a film recommendation system is its ability to learn complex patterns from the data provided [14]. This allows the recommendation system to provide more accurate and relevant recommendations. In addition, it can improve the performance of the recommendation system over time so that it can give better recommendations as more data becomes available. In Adam, the learning rate is also adaptive. The change in learning rate is calculated from the momentum estimate. Momentum is a value calculated based on the direction of previous training [15].

This research aims to measure the level of accuracy of the ANN model optimized by Adam by comparing the results of the ANN Baseline with the ANN optimized by Adam. In this case, we also look for better accuracy results by looking for the best configuration of the learning rate used. Hopefully, this research can help the movie service system implement a better and more accurate recommendation system to satisfy consumers.

2. RESEARCH METHOD

The following is a general overview or flowchart of a film recommendation system using Content-Based Filtering, Artificial Neural Networks, and Adam Optimization methods. For evaluation using the Confusion Matrix, the research stages of data filtering and method implementation are shown in Figure 1.

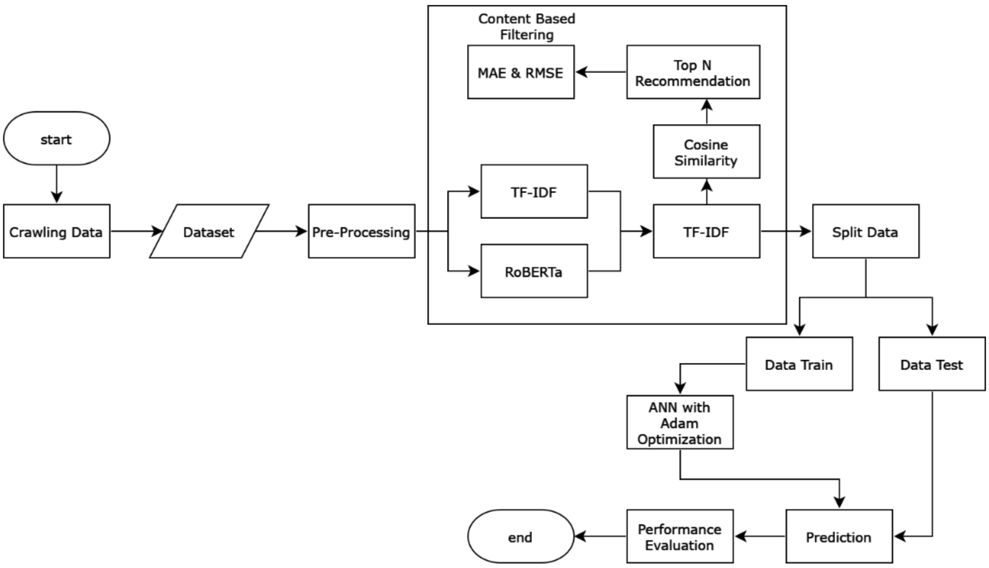

Figure 1. Research Stages

2.1. Recommendation System

A recommendation system is a system or application created to be able to provide and provide recommendations for an item to make a decision desired by the system user [16]. The goal of a recommendation system is to recommend products according to user preferences—classification of Recommendation Systems. Recommendation systems can be classified into three groups based on the approach used to generate recommendations. Collaborative filtering approach and hybrid approach. For the content-based filtering approach, attributes are assigned to each product. By using information retrieval techniques on these attributes, it is possible to obtain similarities between products so that two products with the same qualities have a level of similarity [17].

2.2. Crawling Data

The concept of recommendation systems has been widely used by almost all business areas, where many people need information to make decisions[18]. A recommendation system is software that provides recommendations for several items for users to use. Recommendation systems can increase user satisfaction and loyalty if the recommendations match their tastes[19]. Recommendation systems infer user preferences by analyzing the availability of user data, information about the user and his environment[20]. A recommendation system requires an appropriate recommendation model so that what is recommended matches the user's expectations and makes it easier for users to make the right decisions[21].

This research utilizes two types of data obtained from various sources. Initial data crawling was done to get film titles from the IMDB website using Netflix and Disney+ filters. Additionally, feature extraction is performed using the Python library PyMovieDb, which generates features such as 'name', 'description', and 'keywords'. Table 1 displays some films and their extracted features. The second exploration used Tweet-Harvest to obtain film reviews from Twitter users, known experts in reviewing movies. Table 2 presents a selection of reviews received from Twitter.

Table 1. Crawling data 1 example result

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

Table 2. Crawling data 2 example result

Username	Genre
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. Pre-processing Data

Preprocessing deals with missing or uninformative data caused by user or machine error. The first step in preprocessing is to check for outliers using z-score, and if there is a polarity score of more than 5 in the rating account dataset, then the value will be divided by 2. After checking for outliers, the process of deleting unused columns and empty data is carried out. The next step is to combine the two datasets, namely the film dataset and the account rating dataset, by taking data on film titles, account names and ratings. The final step is data normalization using Min-Max Scaler to change the values in a feature (variable) so that the value range is between 0 and 1. To avoid bias that can arise if several features have very different scales in the data.

2.4. Cosine Similarity

Cosine similarity is a technique that can be used to calculate the similarity value between 2 items[22]. Cosine similarity is used to search for similar documents so that groups of documents are obtained according to their respective topics. From each group of documents, the keywords that represent the group of documents are stored and processed into a complete feature dataset along with their weights[23]. In this case, cosine similarity is used to calculate the similarity value between the name, description, genre and keywords in the film, which can increase the accuracy of the implemented model.

2.5. Content Based Filtering

Content-based Filtering is a recommendation system technique used to recommend items based on user profiles and item characteristics. This technique assumes that users like items with the same characteristics as those they have enjoyed before. In content-based, the features or characteristics of items are analyzed and compared with user preferences to recommend suitable items[24].

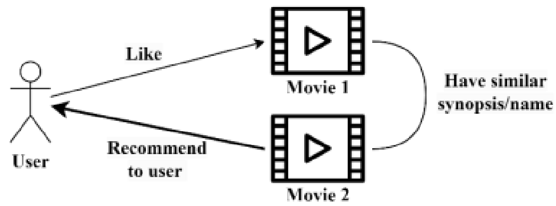

Figure 2. Content-Based Filtering Illustration

Figure 2 shows that users like movie 1. Movie 1 and 2 are identified as similar movies because they have identical attributes. Since the user has yet to interact with Movie 2, movie two will be recommended to the user.

Content-based Filtering has the advantage of overcoming the cold start problem, where the recommendation system does not have enough information about the user or item. In content-based, item characteristics can be analyzed independently without requiring information about the user[25]. However, the downside of this technique is the need for more variety in recommendations, where the system only recommends items with the same characteristics as items the user has previously liked.

2.5.1. Term Frequency – Inverse Document Frequency (TF-IDF)

The TFIDF method is a method for calculating the weight of each word, which is most commonly used in information retrieval. This method is also known to be efficient, easy and has accurate results[26]. The way it works starts by counting the number of words that appear in the data. Then the level of importance of these words is calculated. If the word in question appears frequently, then the word has a high level of importance. The cosine similarity results of TF-IDF are shown in Table 3.

$$W_{dt} = tf_{dt} \times idf_t \quad (1)$$

Table 3. Cosine Similarity TF-IDF Result

Film	AnakNonton	…	zavvi
14 Cameras	1.000000	…	0.000000
17 Again	0.000000	…	0.011559
…	…	…	…
Özel Ders	0.000000	…	1.000000

The explanation for the formula above is Wdt is the weight of the d-th document against the t-th word, tfdt is the number of words searched for in a document, idft is Inverse Document Frequency, N is Total documents, and df is the number of documents containing the searched word.

2.5.2. Word Embedding

Sentence embedding or sentence embedding can be described as a method of mapping sentences into vector form to represent text with real numbers so that it can be processed for machine learning. The sentence embedding method used in the system is built with the SBERT framework using a pre-trained model trained with a more extensive English language dataset. SBERT makes modifications to the BERT network using Siamese and Triplet Network architectures, which can obtain semantically meaningful sentence embeddings [27].

The pre-trained model will undergo a knowledge distillation process to understand sentence embeddings in Indonesian. The knowledge distillation process is carried out by utilizing two models. The first model acts as a teacher model, which is a benchmark for vector representation in a language. Meanwhile, the second model is a student model, which will be trained to produce vectors similar to the teacher model. Sentence pairs in English and Indonesian are used as input. The teacher model will have a vector representation in English. Next, the student model will produce two vectors representing the input sentence in English and a vector for the sentence in Indonesian. The loss function applied to the training process is the Mean Square Error. The structure of this process can be seen in Figure 3. And the cosine similarity results of the Roberta word embedding are shown in Table 4.

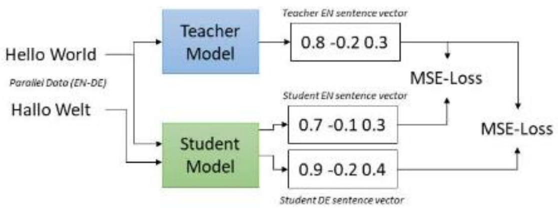

Figure 3. Sentence Embedding Architectur[27]

Table 4. Cosine Similarity roBERTa Result

Film	AnakNonton	…	zavvi
14 Cameras	1.000001	…	0.983691
17 Again	0.976128	…	0.974821
…	…	…	…
Özel Ders	0.983691	…	1.000000

2.6. Mean Absolute Error dan Root Mean Squared Error

Mean absolute error (MAE) is a commonly used method for testing recommendation systems. MAE is used to calculate the difference between the predicted rating value and the actual user rating value[28]. The greater the MAE value, the less accurate the rating predictions from the recommendation system. On the other hand, the smaller the MAE value, the more precise the rating prediction from the MAE recommendation system is calculated using the equation. MAE results produce a number close to 0, indicating that predictions from a calculation method have better accuracy because the error value is almost 0[29].

RMSE is used as a differentiator between predicted and actual values. The higher the resulting RMSE value, the lower the accuracy level; the lower the resulting RMSE value, the higher the accuracy level[30].

2.7. Artifical Neural Network

ANN is short for Artificial Neural Network or Artificial Neural Network. This is a technique in the field of artificial intelligence that is inspired by how the human brain works[31]. Artificial Neural Networks consist of many interconnected information-processing units called neurons, which work together to process information.

Artificial Neural Networks can be used to solve complex or unstructured problems, such as pattern recognition, classification, prediction, and speech recognition[32]. Artificial Neural Networks can learn from data, improving their performance as the data provided increases. Artificial Neural Networks are flexible enough that they can be applied to various types of problems.

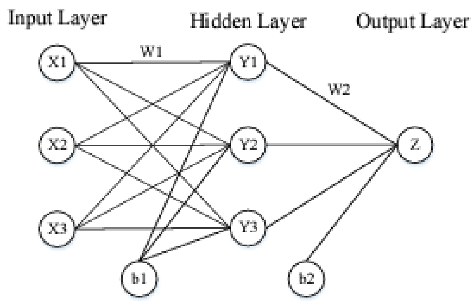

Figure 4. Artificial Neural Network Architecture[33]

Figure 4 illustrates the Artificial Neural Network Architecture, which is designed using three neurons in the input layer: the rice planting area target, rice harvest area target and rice productivity target. The hidden layer consists of three (3) neurons obtained from a trial and error process. The weights used are in the range 0.05 to 0.08. The output layer is a prediction of rice production with one neuron[33].

Artificial Neural Networks can be used for recommendation systems that aim to recommend specific products or services to users based on their preferences and behaviour. Artificial Neural Networks can be used to predict user preferences based on historical user data, such as purchase history, product preferences, or user interactions with the platform[34].

2.8. Adam Optimization

Adam (Adaptive Moment Estimation) is an optimization algorithm used in deep learning to increase convergence speed and model accuracy. Adam combines two optimization techniques, momentum and RMSprop, to achieve better results [35].

Momentum is an optimization technique that speeds up convergence by calculating the average of previous gradients. With momentum, the algorithm can respond to gradient changes more quickly and avoid getting stuck in local minima. RMSprop is another optimization technique that computes the average of previous squared gradients. This allows the algorithm to adjust the learning rate adaptively for each parameter[36].

In Adam, each parameter has a learning rate that is calculated adaptively based on the previous gradient and the previous squared gradient. This allows the algorithm to adjust the learning rate for each parameter individually, thereby speeding up convergence[37]. Adam's momentum mechanism also helps the algorithm respond to gradient changes more quickly and avoid getting stuck in local minima. Adam has proven to be very effective in training neural networks in various tasks such as face recognition, voice recognition, natural language recognition, etc. [38].

2.9. Confusion Matrix Evaluation

Evaluation and validation are the final processes to determine the performance of the prediction system created. Therefore, the author measured the performance of the retweet prediction model using a confusion matrix. Confusion matrix is a table that states the classification of the number of correct test data and the number of incorrect test data[39]. An example of a confusion matrix for binary classification is in Table 5.

Tabel 5. Confusion Matrix

		Prediction Class	
		1	**0**
Class	1	TP	FN
Actual	0	FP	TN

The information from Table 1 is P (True Positive), a number of documents from class 1 that are correctly classified as class 1. TN (True Negative) is a number of documents from class 0 that are correctly classified as class 0. FP (False Positive) is the number of documents from class 0 that were incorrectly classified as class 1. FN (False Negative) is the number of documents from class 1 that were incorrectly classified as class 0 [40]. The formula for calculating the confusion matrix from accuracy, precision, recall, and F1-score is:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$F1\ Score = 2\frac{Recall\ x\ Precision}{Recall+Precission} \quad (5)$$

3. RESULT AND DISCUSSION

In this research, the first step is to calculate the predicted rating value using the content-based filtering method and then evaluate it using the Confusion Matrix. The second step is the classification process using the Artificial Neural Network (ANN) SMOTE algorithm and Content-Based Filtering using a word embedding Roberta, then optimized using Adam to get recommended or not recommended film results, which are then evaluated using accuracy values. Then we compared the Adam optimization method with the baseline model and looked for the best learning rate.

3.1. Crawling Data

The first crawl was obtained from the IMDB website with company filters from Netflix and Disney+ from 1 January 2022 to 2 November 2023. After that, the crawl results were entered into pyMovieDb for feature extraction. Next, the feature extraction data was combined with data from previous research, 593, so the final data for films was 854 with the format as in Table 6.

Table 6. Crawling data 1 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
Özel Ders	[“Comedy”, “Drama”]	…	2009-12-25	PT2H50M

Next, a second crawl was carried out using tweet harvest to get film reviews on Twitter using the film title keywords from 39 film reviewer accounts. Next, the results of the second crawl were combined with review data from previous researchers, which amounted to 3133 reviews, resulting in 34086 reviews, as in Table 7.

Tabel 7. Crawling data 2 result from Twitter

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	Turning Red	Disney Pixar's #TurningRed hits @disneyplus today! Who else is

		watching this cute and cuddly coming of age film?
zavvi	What If	Well, new animated Marvel show What If...? looks like it will be plenty of fun #DisneyInvestorDay

3.2. Content-Based Filtering

At the Content-Based Filtering stage, rating predictions are made based on the similarity of item content. The features used to calculate similarity are keywords, description, and genre. These three features were then extracted using the Word Embedding Roberta language processing method. Because the RMSE results from Roberta are smaller or closer to 0 than the results from the TF-IDF method. The roBERTa word embedding method produces MAE results of 0.001240404701 and RMSE 0.00181130664505. The results of the prediction of the Content-Based Filtering rating using TF-IDF are shown in Table 8. Meanwhile, the results of the prediction of the rating using Word Embedding RoBERTa are shown in Table 9.

Tabel 8. TF-IDF with Content Based Prediction result

Film	**AnakNonton**	**…**	**zavvi**
14 Cameras	0.000000	…	0.000000
17 Again	0.000000	…	0.000000
…	…	…	…
Özel Ders	0.957881	…	0.000000

Tabel 9. RoBERTa with Content Based Prediction result

Film	**AnakNonton**	**…**	**zavvi**
14 Cameras	1.060647	…	1.060647
17 Again	1.060647	…	1.060647
…	…	…	…
Özel Ders	1.060647	…	1.060647

3.3. Classification Result

The classification stage of the Artificial Neural Network model uses a dataset, which is the output of the Content-Based Filtering stage. At this stage, each user-item interaction is assigned to one of two classes: class 0 or class 1. Class 0 represents non-recommended items, while class 1 represents recommended items. Class placement is based on the average score of all user interaction items. Interactions with a value above the average are assigned to class 1, while interactions below the average are assigned to class 0. The average value used to determine the class value is 2.5, which means if an item has a value above or equal to 2.5, the item is assigned to class 1, and vice versa.

Figure 5 shows that the class distribution in the classification data set after the values have been adjusted produces 16.1% of the data classified as class 1 and 83.9% classified as class 0. To find out whether the performance of the test results with Adam optimization has more significant results than other optimization models, we conduct tests using different test data sizes. It aims to find the optimal combination of methods. The test data used are 10%, 20%, 30% and 40%. The Artificial Neural Network method optimized with Adam is implemented using standard parameters.

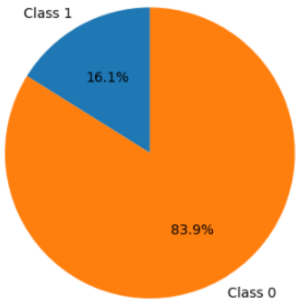

Figure 5. Distribution of Class 1 and 2

3.3.1. ANN Baseline Classification Model

The first experiment was carried out in this research using a baseline ANN model with SMOTE without an optimizer. This stage aims to obtain optimal results on the test data size that corresponds to the highest accuracy results. The comparison of test data sizes consists of 90:10, 80:20, 70:30, and 60:40. For comparison, see Table 10.

Table 10. ANN SMOTE Performance Result

Split Rasio	Accuracy (%)
90:10	86.13%
80:20	**87.20%**
70:30	87.03%
60:40	87.14%

Table 10 shows the results of the ANN Baseline classification model using SMOTE. From the table above, it can be concluded that the scenario with a split ratio of 80:20 gets high accuracy results compared to the others, with an accuracy gain of 87.20%. Therefore, a ratio of 80:20 will be used for the following scenario.

3.3.2. Word Embedding using RoBERTa

At this stage, the same thing is done as in the initial stage, namely running the ANN SMOTE model using a ratio of 80:20 and data that has been normalized using the MinMaxScaler library to create features from the range 0 to 1. And it is using data that has been processed with content-based filtering. It is using word embedding using RoBERTa.

Table 11. ANN SMOTE and Embedding Result

Baseline	Accuracy (%)
Baseline + SMOTE + Embedding	87.69% (+ 0.49%)

Table 11 shows that with the ANN SMOTE model, embedding accuracy has increased from the previous stage to 87.69%, with a difference of 0.49%.

3.3.3. Classification Model using ANN Optimized by Adam

The ANN SMOTE model is used in this second scenario, and the embedding is optimized with Adam. This stage will optimise by comparing the accuracy results of the standard or default learning rate model with several learning rates. A comparison of several learning rates is shown in Table 12.

Table 12. Learning Rate Comparison Result

Optimizer	Learning Rate	Accuracy (%)
Baseline + SMOTE + Embedding	Default	87.69% (+0.49%)
Baseline + SMOTE + Embedding + Adam	Default	87.40% (+0.20%)
Baseline + SMOTE + Embedding + Adam	1	84.77% (-2.43%)
Baseline + SMOTE + Embedding + Adam	0.1	87.64% (+0.44%)
Baseline + SMOTE + Embedding + Adam	**0.044699925 92930794**	**88.30% (1.10%)**

Table 12 shows the comparison results of ANN optimization with Adam using the default learning rate and the best learning rate. In this stage, we get increased accuracy after using the best learning rate with an accuracy result of 88.30%, where we get an increased difference with the first stage experiment of 1.10%.

4. DISCUSSION

Researchers can find combinations and optimizations in the model by carrying out several scenarios to get results with high accuracy. Using SMOTE to overcome unbalanced classes can improve accuracy as well. The baseline Artificial Neural Network model with SMOTE and Content-Based Filtering using roBERTa produces an accuracy of 87.69%. The Artificial Neural Network model increased in accuracy when optimized with Adam at a learning rate of 0.04469992592930794. In the SMOTE ANN model with optimization, Adam achieved an increase in accuracy of 1.10% to 88.30%. The comparison graph for each learning rate is shown in Figure 6 below.

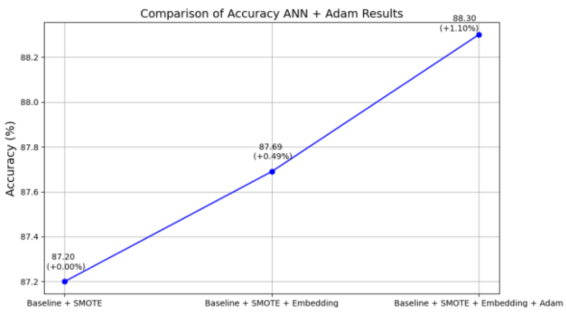

Figure 6. ANN + Adam Accuracy Result

5. CONCLUSION

This research utilizes content-based filtering techniques and a deep learning approach aimed at developing a recommendation system. This research is focused on evaluating recommendations for system improvements by combining and comparing two similarity identification methods, namely using the Roberta word representation and the TF-IDF approach. Next, we analyzed several optimization scenarios aimed at optimizing the performance of the Artificial Neural Network model and optimizing Adam as a classification model. 845 films and 34086 tweets were used in text format and then translated into English using the Google Translator library from 44 Twitter accounts. The data is then processed before further analysis. This research evaluates the results of combining the Content-Based Filtering model using roBERTa with an Artificial Neural Network optimized with Adam. In basic classification testing, an accuracy performance result of 87.69% was obtained, which was achieved using a split ratio of 80:20. Adam showed performance in testing using the optimized Artificial Neural Network method. This is proven by the Adam optimization model, which showed an increase in accuracy from the ANN SMOTE baseline of 1.10% to 88.30%. Implementing the learning rate value in Adam's optimized ANN classification produces optimal performance.

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