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MOVIE RATING PREDICTION USING NEURAL FACTORIZATION MACHINES (NFM) APPROACH

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ABSTRACT

This research is motivated by the difficulty viewers have in finding movies that suit their tastes amid the large number of movies being produced. Current movie ratings are often based solely on direct assessments by viewers without considering factors such as genre, audience age category, and movie synopsis. This study aims to predict movie ratings using the Neural Factorization Machines (NFM) approach. The research method includes data preparation, which covers dataset file merging, age category mapping, data cleaning, text conversion to lowercase, regular expression removal, removal of non-English text, tokenization, lemmatizing, word embedding, one-hot encoding, and label encoding. The modeling process was carried out by building an NFM model consisting of feature inputs, embedding layers, bi-interaction layers, hidden layers, and prediction scores. Model evaluation was carried out by setting hyperparameters, namely epoch and batch size, to optimize model performance. This study was conducted with 9 tests using a combination of epochs (30, 50, and 100) and batch sizes (64, 128, and 256). The evaluation results show that the lowest MSE value, which means the best, in the training data is 1.181 with a batch size of 256 and an epoch of 100, and in the validation data is 1.230 with a batch size of 256 and an epoch of 100. However, in the test data, the configuration with a batch size of 128 and 50 epochs gave the best MSE of 1.280. Although the model showed the best performance in the training and validation data with a batch size of 256 and 100 epochs, the evaluation graph indicated overfitting. These findings show that the NFM model is capable of predicting movie ratings based on genre, audience age category, and movie plot description.

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1. INTRODUCTION

At present, technology is advancing rapidly, creating a need for things that can make our lives easier, such as smartphones, computers, and other devices. This increasingly sophisticated technology makes it easier for us to find information and communicate with people over long distances. In addition, there are many other things we can enjoy thanks to these technological developments. One of the most interesting technologies that has emerged from these developments is Augmented Reality (AR). Augmented Reality (AR) is a technology that can combine 2-dimensional or 3-dimensional objects into a real environment and then project them in real time [1].

Movie is an audio-visual medium that consists of a series of moving images displayed on a screen. The digital era has evolved, and so has the movie industry, which has grown rapidly worldwide. To date, there are many movies produced in various countries, including Indonesia [1]. Movie has become a form of entertainment that is very popular among Indonesians [2].

The development of the movie industry has undergone a significant transformation, for example in the way movies are accessed, which can now be easily enjoyed by users. There are now many streaming platforms that can be used to access thousands of movies in various genres, release years, and much more. The results of a Jakpat survey emphasize the use of over-the-top (OTT) streaming platforms such as Vidio, Netflix, or Disney+ Hotstar as the main entertainment choice for smartphone users. According to the survey, most of Generation Z, around 89%, use these OTT platforms to enjoy movies [3].

As more movies are produced, it becomes difficult for viewers to find movies that suit their tastes [1]. One of the factors that viewers use as a reference is movie ratings. However, current ratings are often based solely on viewers' direct assessments or personal opinions about a particular movie, without considering other factors. These factors include the movie's genre, the age category suitable for certain viewers, and the movie's plot description.

One solution to this problem is to predict movie ratings based on genre, audience age category, and movie description. Rating predictions can provide additional information about the audience's potential liking for movies they have not seen yet or provide rating estimates before the movie is watched based on the characteristics of movies that the audience is interested in. Rating predictions can also help predict ratings for upcoming movies. One method of predicting ratings is Neural Factorization Machines (NFM). Neural Factorization Machines (NFM) is an approach that integrates the concepts of Factoriation Machines (FM) and Deep Neural Networks (DNN) to model complex interactions between features in a dataset [4]. Factorization Machines (FM) are used to facilitate automatic interaction feature learning by factoring parameters [5]. Meanwhile, DNNs are used to learn more complex representations of data [6]. By using bi-interaction operations, NFM is able to describe more informative interactions between features, including features that rarely appear or are complexly related [4].

Previous studies have shown that the performance of Neural Factorization Machines (NFM) has significantly improved compared to other models such as Collective Matrix Factorization (CMF), SVDFeature, DeepMusic, and CTR. The comparison results show that the MSE (Mean Squared Error) of NFM is lower than other models by around 0.032-0.048[7]. A lower MSE indicates that the evaluation results are better [8].

2. METHOD

2.1. Business Understanding

This stage focuses on setting research objectives through the system to be developed and identifying problems in this study. A description of the needs analysis and limitations is also provided to ensure the achievement of the research objectives. As explained in the previous chapter, this research aims to overcome problems in predicting movie ratings based on genre, audience age category, and movie description using the Neural Factorization Machines (NFM) approach. This research utilizes a dataset that includes features such as movie genre, audience age category, and story description as input attributes for the Neural Factorization Machines (NFM) model. The data will be used to develop a model that can predict movie ratings based on user input, namely genre, audience age category, and movie description.

2.2. Data Understanding

In this study, the data used is movie data with several features, namely movie title, movie genre, audience age category, movie description, and movie rating. The data used was obtained from a dataset collected through web scraping from the IMDb website and is publicly available on the Kaggle website "IMDb Movie Dataset: All Movies by Genre". IMDb is an online movie database, often used as a primary reference in research and movie information searches [20]. The dataset contains 16 files, each of which contains data for different movie genres. This dataset was chosen because it covers various movie genres and provides detailed information on titles, age categories, and movie descriptions that are relevant to this study. The available movie rating data will be used as the prediction target, while other features such as genre, audience age category, and movie description will be used as input for the Neural Factorization Machines (NFM) model.

2.3. Data Preparation

At this stage, several steps are taken to prepare the data before it is used in model training. Data preparation involves combining files, mapping audience age categories, data cleaning, lower casing, removing regular expressions, removing non-English words, tokenizing, lemmatizing, word embedding, one-hot encoding, and label encoding.

2.3.1 Gathering Data

Pada dataset yang digunakan, terdapat 16 file yang masing-masing berisi data untuk genre movie yang berbeda. Untuk memudahkan analisis dan pengolahan data, seluruh file tersebut digabungkan menjadi satu DataFrame. Setelah melakukan penggabungan file, terdapat 368.300 baris data.

2.3.2 Mapping Audience Age Categories

This mapping was carried out by changing the audience age categories to categories that correspond to the movie age classification system in Indonesia. This was done to simplify the data because the audience age categories in the data were too numerous and varied. By carrying out this mapping, the dataset can be simplified so that it is easier to analyze. The process of mapping age categories is based on Indonesia's movie age classification system, which was established under Law No. 33 of 2009 on Movie, Article 7, and Minister of Education and Culture Regulation No. 14 of 2019, Article 17. Based on these regulations, there are audience age classifications or audience age ratings, namely all ages, ages 13 and above, ages 17 and above, and ages 21 and above. The following is an explanation of movie age classifications according to the Indonesian Movie Censorship Institute (LSF):

1. All Ages Category: Movies categorized for all ages are designed with a primary focus on children, but can still be enjoyed by all age groups. Movies in this category must meet criteria that ensure that the themes, titles, visual scenes, and dialogue or monologues are appropriate for children's age development and do not harm their physical and mental health. In addition, movies must contain elements of education, culture, morals, wholesome entertainment, and aesthetic appreciation that can encourage children's curiosity about their surroundings. Movies in this category must avoid scenes of violence, both physical and in dialogue or monologue, that can be easily imitated or followed by children. Scenes that depict dangerous behavior or situations must also be avoided to prevent children from imitating them. Furthermore, movies must not contain visual scenes or dialogue that could encourage children to imitate sexual behavior, be disrespectful to parents or teachers, curse at others, use foul language, or display antisocial behavior such as greed, cunning, and deceit. Other criteria that must be met include the absence of content that could lead children to believe in superstition, occultism, magical spirituality, mysticism, or superstition that is contrary to religious norms. Movies must also not contain horror or sadistic scenes, nor depict elements that could disrupt children's psychological development, such as adultery, suicide, gambling, or the use of narcotics and other addictive substances.
2. Age category 13 years or older (13+): Movies categorized for audiences aged 13 years or older must contain educational values, morals, appreciation, aesthetics, creativity, and positive curiosity. The themes, titles, visual scenes, and dialogues or monologues in these movies must be appropriate for viewers who are transitioning from childhood to adolescence. In addition, movies in this category must ensure that there are no scenes that could be easily imitated by transitional-age viewers, such as dangerous scenes or promiscuous behavior between individuals of different genders or the same gender.
3. Age category 17 years or older (17+): Movies and movie advertisements classified for audiences aged 17 years or older must meet several important criteria. These movies must contain educational, cultural, moral, appreciation, aesthetic values, and foster a positive sense of curiosity.

The themes, titles, visual scenes, and dialogues or monologues must be appropriate for viewers aged 17 and above. In addition, content related to sexuality must be presented in a proportionate and educational manner, while violence must be presented in a proportionate manner. Movies in this category must also not contain scenes of sadism.

4. Age category 21 years or older (21+): Movies categorized for audiences aged 21 years or older must include titles, themes, visual scenes, and dialogue or monologues specifically intended for adults. These movies may explore family themes and issues in depth, with visual scenes and dialogue involving sex, violence, and sadism, as long as they are not presented excessively. These movies should be broadcast on television between 11:00 p.m. and 3:00 a.m. local time, or only shown in movie theaters, except for movie appreciation activities or movie screenings for educational and/or research purposes.

In the audience age category dataset, there are movie categories that do not fall under any age classification. Therefore, these categories have been changed to the Unrated category. The mapped data is stored in a new column/feature.

2.3.3 Text Preprocessing

Text preprocessing is performed on features that are an important stage in text data processing, which aims to organize and normalize raw text before further analysis is carried out. The following are several stages performed in text preprocessing:

1. Lower Casing

At this stage, lower casing is performed, which is the conversion of all letters in the text to lowercase. In text data processing, lowercasing is used to ensure consistency and avoid differences caused by the use of uppercase and lowercase letters. Table 1 represents the results before and after the lower casing process.

Table 1. Lower Casting Process

Before	After
[The people of Wakanda fight to protect their home from intervening world powers as they mourn the death of King T'Challa.]	[the people of wakanda fight to protect their home from intervening world powers as they mourn the death of king t'challa.]

2. Menghapus Regular Expression

This stage involves cleaning up text that contains regular expressions such as punctuation marks. Table 2 shows the results before and after the process of removing regular expressions.

Table 2. Remove Regular Expression

Before	After
[the people of wakanda fight to protect their home from intervening world powers as they mourn the death of king t'challa.]	[the people of wakanda fight to protect their home from intervening world powers as they mourn the death of king tchalla]

3. Menghapus Selain Bahasa Inggris

At this stage, words that are not part of the English language are removed. Table 3 represents the results before and after the process of removing non-English words.

Table 3. Remove Non English

Before	After
[the people of wakanda fight to protect their home from intervening world powers as they mourn the death of king tchalla]	[the people of fight to protect their home from world as they mourn the death of king]

4. Tokenizing

The tokenizing stage aims to break down text into tokens based on words. Table 4 represents the results before and after the tokenizing process.

Table 4. Tokenizing Process

Before	After
[the people of fight to protect their home from world as they mourn the death of king]	[the,people,of,fight,to,protect, their,home,from,world,as,they, mourn,the,death,of,king]

4. Menghapus Stopwords

The process of removing stopwords involves eliminating words that do not provide significant added value. Examples include words such as “the,” “of,” and “to.” Table 5 represents the results before and after the stopword removal process:

Table 5. Stopwords Removal

Before	After
[the,people,of,fight,to,protect,their,home, from, world, as, they, mourn, the,death,of,king]	[people,fight,protect,home, world,mourn,death,king]

4. Lemmatizing

This process involves converting words in the text into their basic form, taking into account the context and meaning of the words. Table 6 shows the results before and after the lemmatizing process:

Table 6. Lemmatizing Process

Before	After
[terrifying] [channeling] [fighting]	[terrify] [channel] [fight]

5. Word Embedding

The purpose of this process is to convert text into numerical representations in order to understand the meaning of words based on their context in the text. These representations are obtained from the Word2Vec model. Word2Vec is a technique in Natural Language Processing (NLP) that is used to convert words into numerical vectors in multidimensional space, or the way data is represented in mathematical space that has more than three dimensions.

In its implementation, the model is trained using a collection of sentences from a dataset, where each word is represented as a 100-dimensional vector. Each word has a unique vector representation that reflects its meaning. For example, words such as “people,” “fight,” “protect,” and “home” will each have a vector representing the position of that word in a 100-dimensional semantic space. Table 7 represents the word embedding process.

Table 7. Word Embedding Process

No.	Words	Dimension 1	Dimension 2	...	Dimension 3	Dimension 4
1	[people, fight, protect, home]	0,05	0,02	...	-0,404	-0,146

The vector value for the first dimension can be illustrated by calculating the average vector. Word2Vec represents word vectors from text data randomly. The following is a brief calculation example for the first dimension average vector of the words “people,” “fight,” “protect,” and ‘home’ in the Word2Vec model. The average value for the first dimension of the words “people,” “fight,” “protect,” and “home” is: 0.05.

6. One-hot Encoding

In this process, movie genre data, which was originally in the form of strings with multiple labels, was converted into binary representation using the one-hot encoding technique. This technique allows each movie to have more than one genre without losing important information. In this process, each unique genre is represented as a separate column. A value of 1 indicates that the movie has the genre in question, while a value of 0 indicates the opposite [21]. Table 8 represents the one-hot encoding process.

Table 8. One-hot Encoding Process

No.	Genre	Action	Drama	Adventure	Comedy
1	Action, Adventure	1	0	1	0
2	Comedy, Romance	1	1	0	1
3	Drama, Adventure, Comedy	0	1	1	1
4	Action, Drama, Comedy, Adventure	1	1	1	1

7. Label Encoding

This process converts audience age category data into numerical representations. Table 9 represents the label encoding process:

Table 9. Label Encoding Process

No.	Before	After
1	13+	0
2	17+	1
3	21+	2
4	All Ages	3
5	Unrated	4

2.4. Modeling

This study uses the Neural Factorization Machines (NFM) approach implemented with the Keras library to model linear and non-linear relationships between features. The model accepts three main types of input, namely: (1) one-hot encoded representations of 24 movie genres, (2) audience age category encoding labels, and (3) 100-dimensional movie description embeddings obtained using Word2Vec.

In the initial stage, a linear regression part is applied to capture the direct contribution of genre and age features. A dense layer is used to generate the weights of each feature before combining them with non-linear interaction components, enabling the model to learn linear and complex influences simultaneously.

Next, the genre and age category features are mapped into a 100-dimensional embedding space. The genre representation, which was originally one-hot encoded, is converted into an embedding through a dense layer with ReLU activation, while the age category is processed using an Embedding layer. This embedding dimension alignment aims to be consistent with the movie description embedding from Word2Vec.

Interactions between features are modeled using a Bi-Interaction Layer, which calculates the interaction of embedding pairs through dot product operations. The three main interactions considered are: genre–age, genre–description, and age–description. The results of these three interactions are then combined using concatenation to form a unified feature vector.

The resulting concatenation vector is then processed by several hidden layers with dense layers activated by ReLU to learn more complex non-linear patterns. Dropout is applied to hidden layers to reduce the risk of overfitting. The output from this neural network is combined with the initial linear regression results. The final output of the model is generated through a dense layer with one neuron and linear activation to predict the rating value.

2.5. Evaluation

After the training is complete, the model is evaluated using Mean Squared Error (MSE) to assess its performance on each data set (train, validation, and test). The MSE results provide an overview of how well the model can predict movie ratings based on the processed features. MSE is a measure of the average of the squared differences between actual values and predicted values, which is used to assess how well the model predicts the actual data.

3. RESULT AND DISCUSSION

The testing was conducted using nine different scenarios to evaluate the performance of Neural Factorization Machines (NFM) in predicting ratings based on genre, audience age category, and movie description. These testing scenarios included variations in epoch and batch size, ranging from 30, 50, and 100 epochs and 64, 128, and 256 batch sizes. The following are the results of evaluating the performance of the Neural Factorization Machines (NFM) approach in predicting ratings based on genre, audience age category, and movie description. Based on the visualization, it can be seen that the y-axis represents loss, which measures how well or poorly the model predicts the correct target value from the given data. Meanwhile, epoch is one full round in which the entire training dataset is used to train the model. MSE is also used to measure how well the model predicts numerical values. A lower value indicates a better prediction.

Table 10. Evaluation Summary

Pengujian ke	Epoch	Batch Size	MSE Training	MSE Validation	MSE Test
1	30	64	1.204	1.232	1.282
2	30	128	1.207	1.233	1.281
3	30	256	1.331	1.334	1.382
4	50	64	1.202	1.233	1.286
5	50	128	1.200	1.232	1.28
6	50	256	1.300	1.311	1.361
7	100	64	1.202	1.242	1.296
8	100	128	1.260	1.292	1.334
9	100	256	1.181	1.230	1.288

Based on the training data evaluation, the best MSE for each batch size is batch size 64, which achieves an MSE of 1.202 at epochs 50 and 100, batch size 128, which achieves an MSE of 1.200 at epoch 50, and batch size 256, which achieves an MSE of 1.181 at epoch 100. Of all the combinations of batch size and epoch tested, the best overall performance on the training data was achieved with a batch size of 256 and an epoch of 100, resulting in the lowest MSE, which means the best, of 1.181.

From the validation data evaluation results, it was found that the best performance for each batch size was for a batch size of 64 at epoch 30, which achieved an MSE of 1.232, for a batch size of 128 at epoch 100, which also achieved an MSE of 1.231, while for a batch size of 256 at epoch 100, it showed the lowest MSE of 1.230. From the overall validation data, batch size 256 with epoch 100 showed the best performance in validation with an MSE of 1.230.

In the test data evaluation results, it was found that the best performance for each batch size in each epoch was for batch size 64 in epoch 30, which produced an MSE of 1.282, for batch size 128 in epoch 50, which had an MSE of 1.280, while for batch size 256 in epoch 100, it showed the lowest MSE of 1.288. These results indicate that in the test data, the configuration of batch size 128 with epoch 50 produced the lowest MSE of 1.280.

The evaluation results show that the combination of hyperparameters with batch size 256 and epoch 100 provided the best performance in the training and validation data, with an MSE in the training data of 1.181 and an MSE in the validation data of 1.230. Meanwhile, on the test data, the best evaluation result was on batch size 128 epoch 50 at 1.280. However, the graph results show overfitting, which means that the model works very well on training and validation data but is less than optimal on test data.

4. CONCLUSION

Based on the results of the study, the application of Neural Factorization Machines (NFM) to predict movie ratings by utilizing genre features, audience age categories, and movie descriptions has been successfully implemented. The NFM model has proven capable of capturing non-linear and complex interactions between features, thereby producing fairly accurate rating predictions. Performance evaluation shows that the configuration with 100 epochs and a batch size of 256 provides the lowest MSE values in the training data (1.181) and validation data (1.230). However, the loss visualization results indicate overfitting, where the model adapts too much to the training and validation data. On the test data, the configuration with 50 epochs and a batch size of 128 produced the best performance with an MSE value of 1.280, although overfitting was still evident, indicating the model's limitations in generalizing to new data.

For further development, it is recommended to explore hyperparameters more broadly, not only limited to epoch and batch size, but also including learning rate, number and size of layers, embedding dimensions, and selection of different activation functions in order to obtain a more optimal model configuration. In addition, the application of early stopping is highly recommended to stop the training process when performance on the validation data begins to decline, thereby reducing overfitting and improving the model's generalization ability to previously unseen data.

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