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Film Genre Classification Based on Poster Using Convolutional Neural Network

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Abstract: **-** This study proposes a method for classifying film genres based on their posters using Convolutional Neural Networks (CNNs). Film posters are valuable visual representations that encapsulate key elements of a movie's genre. The CNN model is trained on a dataset comprising diverse film posters and their corresponding genres. The model learns to extract relevant features from the posters and classify them into predefined genres. Experimental results demonstrate the effectiveness of the proposed approach in accurately classifying film genres solely based on their posters, showcasing the potential for automated genre classification systems in the film industry.

Keywords: Convolutional Neural Network (CNN), Film Genre Classification, Poster Analysis

INTRODUCTION

Nowadays, the topicality and popularity of films also have a special place among the public because of their aesthetic combination of colors and interesting stories. Based on data sourced from Indonesian Films which has been collected by lokadata, it is proven that the development of audiences in Indonesia from 2008 to 2019 has increased along with the development of films circulating and showing in cinemas. The number of film viewers in 2019 reached 51.9 million people with 129 films showing. This number is calculated based on films shown in network and independent cinemas (excluding online platforms, limited screenings and roadshow screenings outside cinemas).

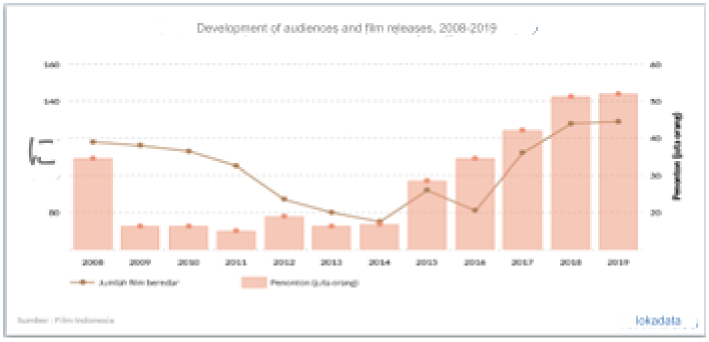

Figure 1.1 Development of audience and film screenings 2008-2019

(Lokadata sourced from Film Indonesia)

Other data related to interest in watching Indonesian films involving 411 respondents via electronic survey media distributed throughout Indonesia throughout July 2019 by IDN Times obtained the highest interest results in the East Java region with 31.4%, West Java following with the most respondents, namely 14.6%, DKI Jakarta with 14.4%, Central Java with 10% and DIY with 7.8%. Other regions also participated, such as North Sumatra with 3.6% and also South Sulawesi with 1.9%. Meanwhile, in the gender category, 61.6% were women and the remaining 38.4% were men. Most were aged 20-27 years with a percentage of 51.6%, 10-19 years 34.1%, 28-35 years 12.9% and only 1.5% were over 35 years old. Interest in watching is also dominated by millennials, 59.1% of whom work as students, while the remaining private employees, entrepreneurs, government employees and jobseekers total 40.9%.

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Figure 1.2 Interest in Watching Indonesian Films 2019 (IDN Times)

Film posters are the main and leading promotional media that deal directly with the target audience in conveying message information before the launch of a film, both offline and online. However, not all film posters provide sufficient information regarding the rating given or the genre of the film, so often potential viewers who are interested in the film through the film poster are misled in determining or understanding the genre given. Some streaming services also do not show the film genre on the poster directly, instead there is a separate menu that must be pressed to get a list of film genres or the film poster must be pressed to enter the detailed description version. It is very interesting if by using a mobile phone you can find out directly about the film genre just from the film poster displayed on the site without having to navigate within the site.

From this, deep learning technology is considered good for helping predict the genre of a film poster which sometimes at first glance is only an aesthetically attractive image but it turns out the content of the film is different. Different studies in recent years using the Convolutional Neural Network (CNN) method have produced a good level of accuracy in image recognition. Multilayered convolutional neural network (CNN) for film poster classification which will then be attached to the genre based on the poster classification obtained an accuracy rate of 91.15% with an F1 score of 0.22, followed by a hamming loss of 0.1 and a zero one loss of 0.75 in research on film genre classification with deep neural network using poster images (Hossain et all, 2021). An accuracy level of 84.82% with a loss of 0.4892 was obtained for multi-label genre detection from a movie poster using InceptionV3 Transfer Learning in research on multi-label movie genre detection from a movie poster using knowledge transfer learning (Kundalia et al., 2020). Meanwhile, evaluation of several methods such as Multi-label kNN (MLkNN), Binary Relevance (BR), Classifier Chains (CC), Random k-labELsets (RAkELd) and Label Powerset (LP) combined with the Multinomial Naïve Bayes (MNB) classifier, C-Support Vector Classification (SV) and Random Forest Classifier (RF) in film genre classification from posters got a Jaccard score of 41.78% for the Label Powerset (LP) method with Multinomial Naïve Bayes (MNB) in film genre research in multi-label classification using semantic extraction from only movie poster (Sirattanajakarin et al., 2019). Meanwhile, a comparison of the use of the Long Short-Term Memory (LSTM) method which was trained with a film synopsis and Long Short-Term Memory (LSTM) which was trained with the text of the entire film (subtitles) concluded that the Long Short-Term Memory (LSTM) method which was trained with text on the entire film (subtitles) is better and produces an F-score of 0.674 and an AUC-PR of (0.725) (Mangolin et al., 2022).

Based on several research results, a lot of research has been developed in multi-label classification of film genres and produces good accuracy, but this research often uses large architectures such as VGGNet, InceptionV3, ResNet and the like where these architectures require large parameters and large computing power. or large infrastructure too, so there is still an opportunity to research methods that can produce good genre recognition results from film posters but by utilizing low computing power, so that this research will later contribute data from evaluation results and can be applied to mobile phones. has limited computing capabilities. This research will make multi-label classification technology increasingly developed, especially on mobile devices that have a small architecture which can provide good results. This is also relevant to current developments where mobile devices have become tools that must be available and used both for work and entertainment. In addition, this research will contribute a new dataset taken from the streaming service platform and add to the existing dataset on Kaggle.

Apart from the things above, this research can have an impact on improving user experience if implemented on a film streaming platform, automatic identification of film genres can help users find more accurate film recommendations according to user preferences compared to using conventional genre filters. Apart from influencing the user experience, this research can also be implemented to facilitate the management of grouping film data based on posters. If research is not carried out, the use of resources cannot be done efficiently, so it costs more time and money if data grouping is done manually. Therefore, this research is important to improve efficiency, user experience and contribute to the development of AI, especially for multi-label classification on mobile devices.

Based on the description in the background, the research problem to be solved can be formulated as follows: How to collect a dataset of film posters from paid video streaming services and label the data based on film genre? How to model multi-label classification of film genres based on poster images using Convolutional Neural Network (CNN) techniques? How to evaluate a multi-label classification model for film genres from poster images?

Based on the problem formulation above, the research objectives are structured as follows: Collecting a dataset of film posters originating from paid video streaming services and labeling the data based on film genres. Carry out multi-label classification modeling of film genres based on poster images using Convolutional Neural Network (CNN) techniques. Evaluate the multi-label classification model for film genres from poster images.

The research carried out is expected to contribute to the following benefits: Adding data on film posters from various different types of posters, even with the same film name on several platforms such as Netflix, Disney+, Hulu or Prime Video. Makes it easier for film viewers to quickly determine which films to watch based on genre. Adding evaluation results from the proposed multi-label classification model of film genres from poster images. Becomes the basis for developing integration with gadget operating systems.

Library Review

Research on the topic of comparing Convolutional Neural Network architectures, namely MobileNet and MobileNetV2, was carried out by (K. Dong et al, 2020), where the models were compared for image classification. This research is intended to prove that the performance of the MobileNetV2 architecture is better than the previous generation. Evaluation is visualized using T-SNE. The results of this research show that the accuracy of MobileNetV2 is higher compared to the MobileNet architecture.

Research conducted by (Alshehri et al., 2019) used Deep Attention Neural Network implemented with the Channel and Spatial Attention Mechanisms method for classification of multi-label images from Unmanned Aerial Vehicles (UAV), obtaining an accuracy rate of 83.59% for the dataset obtained. above the science faculty building at the University of Trento (Italy) where in the Trento dataset, there are 13 classes with 1,000 images used for training data and 3,000 images used for testing data. Meanwhile, an accuracy rate of 86.93% was obtained by a dataset obtained near the city of Civezzano (Italy) for 14 classes with 1,000 images for training data and 3,105 images for testing data.

Research conducted by (Sirattanajakarin et al., 2019) implemented Semantic Extraction which produced 12 features containing information, with a total of 18 genres and used Multinominal Naive Bayes with Label Power set to get a Jaccard score of 41.78% compared to 1.11% results without applying Use feature extraction to get information on the poster.

Research conducted by (Kundalia et al., 2020) classified film genres using Deep Learning with the Convolutional Neural Network (CNN) method using Inception-V3 with Knowledge Transfer Learning as well as a dataset that has 12 film genres with more than 30,000 poster images where Each genre has 2,500 poster images and each poster image has a resolution of 960 x 600 pixels, resulting in an accuracy rate of 84.82% with a loss of 0.4892.

Research conducted by (Lydia & Francis, 2020) used VGG-Net combined with Sigmoid as a binary classifier to be able to carry out multi-label recognition to obtain an accuracy rate of 98% with the Color Clothes dataset and an accuracy rate of 96% on the Fruits & Vegetables dataset. Both datasets were obtained from Google and improvised using manual pruning for relevance and balanced samples in each category. The Color Clothes dataset consists of 1800 images with 6 classes, each class has 300 data samples. The Fruits & Vegetables dataset consists of 450 images for each category. Performance is evaluated with the standard Binary Cross-Entropy metric.

Research conducted by (Park et al., 2020) for multi-label classification of various image sizes uses a Convolutional Neural Network where the Dilated Residual Network (DRN) is modified to obtain a higher feature map resolution and Horizontal Vertical Pooling (HVP) which is designed to combine position information more efficiently from feature maps, obtaining the highest level of accuracy from the evaluation results of 3 other models (ResNet-18, DRN-C-26 and DRN-D-22), namely 95.11%.

Research conducted by (Wang, Yang, et al., 2020) regarding multi-label classification using a Custom Convolutional Neural Network on Fundus images with EfficientNet which functions as feature extraction where the output from the two models is combined to form a probability as the final recognition result, obtained an accuracy level of 0.89 using the dataset provided by ODIR 2019 (Peking University International Competition on Ocular Disease Intelligent Recognition).

Research conducted by (Hossain et al., 2021) in classifying film genres using Multilayered Convolutional Neural Network (MCNN) obtained an accuracy rate of 91.15%, F1 Score of 0.22, Precision of 0.67, Hamming loss of 0.1 and zero one loss of 0.75. The dataset used comes from IMDB with a total of 7,254 film posters from 1980 to 2015.

Research conducted by (Prasanna et al., 2021) for multi-label classification using a Convolutional Neural Network on labeled images that had been collected by researchers, obtained an accuracy level of 0.55. The dataset used consists of 2,000 images consisting of various objects such as cars, trees or mountains.

Research conducted by (Mangolin et al., 2022) in classifying film genres not only uses film posters, but also uses video clips trailers, subtitles and synopses from a total dataset of 152,622 film titles obtained from The Movie Database (TMDb) . Each film in the dataset was labeled along with 18 film genres. By using various methods such as Mel Frequency Cepstral Coefficients (MFCCs), Statistical Spectrum Descriptor (SSD), Local Binary Pattern (LBP), Long-Short Term Memory (LSTM) and Convolutional Neural Network (CNN). After that, the BinaryRelevance and ML-kNN classifiers are used. From the results of the combination of various existing methods, the combination of Long-Short Term Memory (LSTM) with synopsis and Long-Short Term Memory (LSTM) with film subtitles obtained the best results, namely an F-score of 0.674 and an AUC-PR of 0.725.

Research conducted by (Kim, Y. T., et al., 2020) compared several oversampling methods such as SMOTE, borderline-SMOTE and adaptive synthetic (ADASYN) in the case of heart failure prediction. The data used comes from New York Heart Association class III and IV (203 patients still alive and 96 patients dead) with a total of 299 patients. The time span for treatment of patients is between 4-285 days or an average of 130 days. The research results show that before oversampling the F-score had a value of 0.55. After oversampling, the F-score value increased by around 0.05 with details of SMOTE 0.63, borderline-SMOTE 0.60, and ADASYN 0.62. So the best oversampling algorithm that can be applied to this research is SMOTE.

From previous research using various methods and architectures, the use of deep learning is an approach that has been proven to be widely used in the 2-dimensional image classification process. The methods studied often focus on producing a high level of accuracy without limitations on computing power. So research regarding the use of Convolutional Neural Networks (CNN) with limited computing power such as mobile or gadgets will be very interesting and the evaluation results can be known.

METHOD

3.1 Research Stages

By focusing on classifying film genres based on posters, this research will be able to contribute to the evaluation process of the Convolutional Neural Network (CNN) method which has fewer parameters than existing methods but can still make good genre predictions with limited computing power on mobile or gadgets. . This research will be carried out in research stages which are divided into four stages, namely planning, initiation, training, and ending with an overall performance evaluation in testing data. The research stages in this study are given in Figure 3.2.

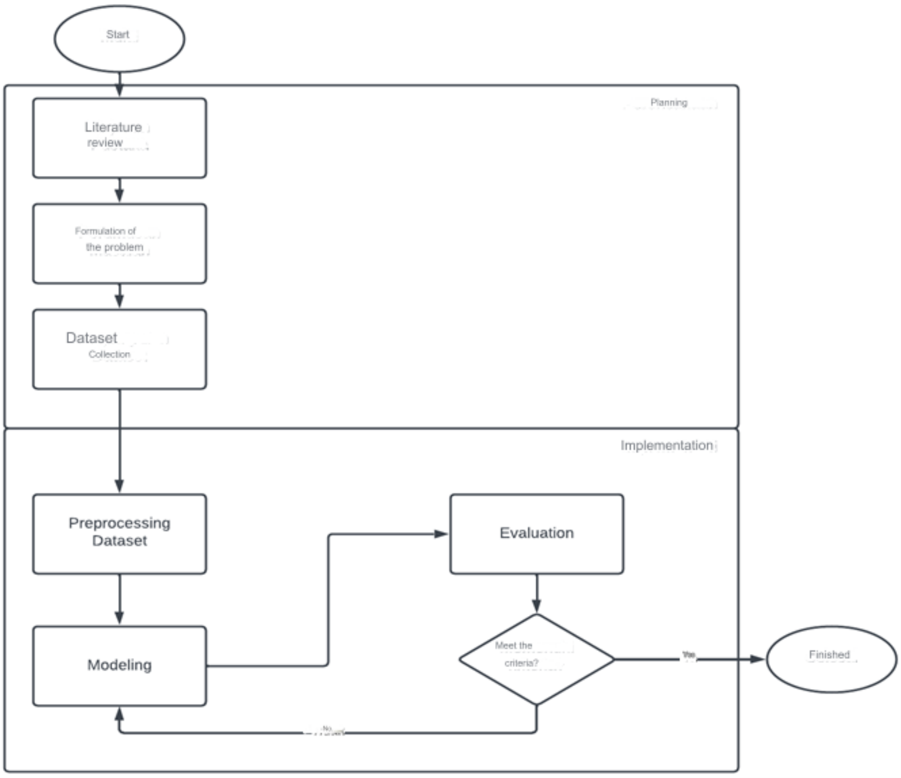

Figure 3.2 Scheme of Research Stages

In the planning process, the stages of literature study, problem formulation and dataset collection are carried out. A literature study was carried out on various related research and models that will be used in the research as explained in Chapter 2. So that a formulation of the research problem that will be discussed and developed can be created, namely regarding multi-label classification using the method proposed in Chapter 1. Next At the initiation stage, the activities carried out were collecting film poster datasets on the Kaggle site and adding new datasets sourced from online platforms such as Netflix, Disney+ or so on, then labeling all new datasets.

Then the next process is implementation by carrying out the dataset preprocessing, modeling and evaluation stages. Preprocessing is carried out on the dataset so that the data is optimal for modeling. Then the model building stage is carried out which will be continued with the model training stage using training data. The final step of the research is the evaluation stage which functions to test the model with testing data and measure the model's performance to be reported in the research report. If the resulting model is not optimal, a new model creation process will be carried out using hyperparameter tuning.

3.2 Dataset Collection

The film poster dataset used in the research is data obtained from the Kaggle site where this data comes from IMDb which consists of various films with various genres and a total of 40,108 posters that have been labeled with their genre. The film posters contained in the Kaggle dataset come from the period 1874 – 2018. Apart from that, film posters from online platforms in the period 2022-2023 were also added, thereby enriching the existing dataset.

RESULTS AND DISCUSSION

4.1 **Dataset**

4.3.1 Dataset Preparation

The dataset used is divided into two, namely the Kaggle dataset (training and validation) and the streaming service dataset (testing). At the dataset preparation stage, the process of downloading film posters in the Kaggle dataset is carried out using the poster link provided in the dataset and creating a testing dataset using the streaming service dataset. The total data in the Kaggle dataset used is 40,108 data. An example of the Kaggle dataset used can be seen in Figure 4.1.

	imdbId	Imdb Link	Title	IMDB Score	Genre	Poster
0	114709	http://www.imdb.com/title/tt114709	Toy Story (1995)	83.0	Animation|Adventure|Comedy	https://images-na.ssl-images-amazon.com/images...
1	113497	http://www.imdb.com/title/tt113497	Jumanji (1995)	69.0	Action|Adventure|Family	https://images-na.ssl-images-amazon.com/images...
2	113228	http://www.imdb.com/title/tt113228	Grumpier Old Men (1995)	66.0	Comedy|Romance	https://images-na.ssl-images-amazon.com/images...
3	114885	http://www.imdb.com/title/tt114885	Waiting to Exhale (1995)	57.0	Comedy|Drama|Romance	https://images-na.ssl-images-amazon.com/images...
4	113041	http://www.imdb.com/title/tt113041	Father of the Bride Part II (1995)	59.0	Comedy|Family|Romance	https://images-na.ssl-images-amazon.com/images...

Figure 4.1 Example of a Kaggle dataset dataframe

The process of downloading the Kaggle dataset produces poster data totaling 34,985 posters. An example of a poster resulting from the Kaggle dataset download process can be seen in Figure 4.2.

Figure 4.2 Example of Kaggle dataset poster results

Streaming service datasets or testing datasets are created manually. The genre of each film follows the original genre on the streaming service. The dataset has a slightly different structure. However, in this study the structure of the dataset used will follow the structure of the testing dataset. So, several features such as IMDB link, IMDB Score, and Poster will be deleted in the Kaggle dataset because they are no longer used in the next process. The amount of data in the streaming service dataset used is 457 data. An example of the testing dataset used is shown in Figure 4.3.

	imdbId	Title	Genre
0	71100000	If anything happens I love you	Drama
1	71100001	Blue Miracle	Drama
2	71100002	Garuda di dadaku	Drama
3	71100003	Dad wanted	Drama
4	71100004	A christmas prince the royal baby	Drama

Figure 4.3 Example of a streaming service dataset dataframe

Taking posters for the testing dataset was done manually on several streaming platforms, namely Disney +, Netflix and Prime. For example, the steps for taking a poster on the Netflix platform using the Google Chrome browser are as follows.

1. Login using the account that will be used to collect posters. After logging in, the home screen will appear as shown in Figure 4.4.

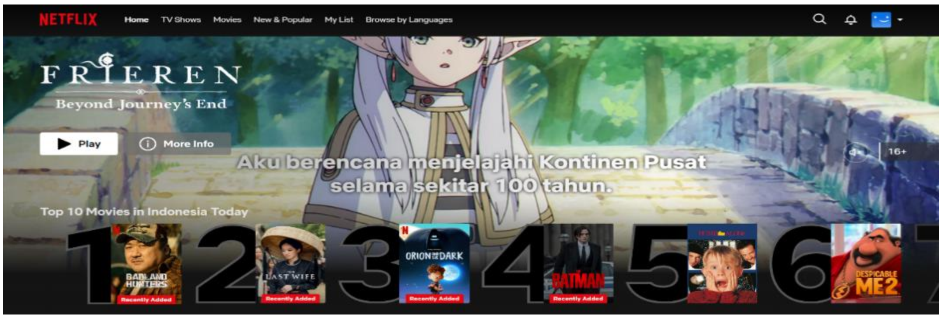

Figure 4.4 Netflix home page display

2. For example, if we want to take a poster as marked in Figure 4.4, just right click on the poster. Then the option to save the image will appear as shown in Figure 4.5.

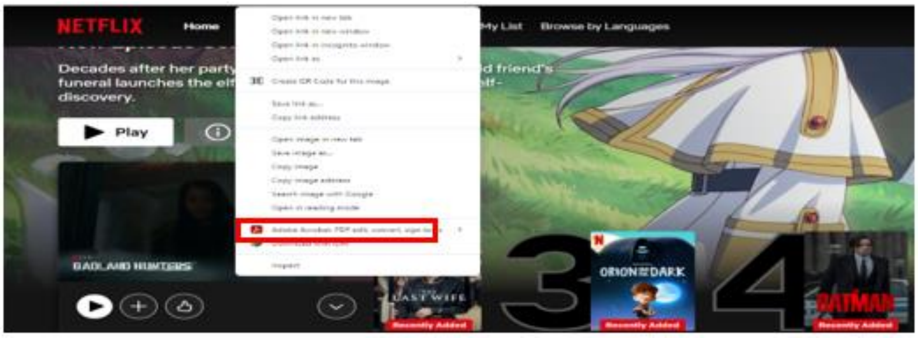

Figure 4.5 Save image as option

3. Select save image as as marked in Figure 4.5. Then a pop up window will appear to select the storage location shown in Figure 4.6.

Figure 4.6 Pop up window saving files

4. The final step is to change the image name according to the ImdbId that has been determined in the streaming service dataset shown in Figure 4.6.

The film posters used for testing data were obtained from each streaming platform which is shown in Table 3.4 with a total of 457 posters. An example of a poster used for data testing is shown in Figure 4.7.

Figure 4.7 Example of a streaming service dataset poster

The name of each poster file has the same name as the ImdbId in the Kaggle dataset and streaming service dataset. So that each poster has a unique code and preprocessing can be carried out at the next stage.

4.3.2 Preprocessing

Preprocessing is the data cleaning stage carried out on the two previous datasets. Data cleaning was carried out to check null data on the Kaggle dataset and streaming services. So the final data amount is 39,246 data for Kaggle data and 457 data for streaming service data.

After the cleaning process has been carried out at this stage, the poster file is also checked to see whether the poster file to be used is in good condition. After checking, there are no corrupt or damaged files for the poster data that will be used.

Then the image identification process is carried out by adding the location of the poster file to the Kaggle dataset and streaming service dataset. An example of a dataset after the image identification process has been carried out can be seen in Figure 4.8.

	imdbId	Genre	Title	Image_Paths
0	1000095	Animation|Action|Adventure	PokÌ©mon Ranger and the Temple of the Sea (2006)	Posters/1000095.jpg
1	100014	Fantasy	Liu jai yim taam (1987)	Posters/100014.jpg
2	100024	Comedy|Drama	Life Is Sweet (1990)	Posters/100024.jpg
3	100046	Drama|History	The Long Walk Home (1990)	Posters/100046.jpg
4	100049	Drama|Romance	Longtime Companion (1989)	Posters/100049.jpg

Figure 4.8 Example of a dataset resulting from image identification

The number for the Kaggle dataset was reduced to 34,985 data due to several image files not being found at the time of identification and for the streaming service dataset it remained the same, namely 457 data.

After identification on the Kaggle dataset, a label separation process is carried out because each film title can have more than one genre. An example of a Kaggle dataset after the label separation process has been carried out can be seen in Figure 4.9.

	imdbId	Genre	Title	Image_Paths
0	1000095	Other	PokÌ©mon Ranger and the Temple of the Sea (2006)	Posters/1000095.jpg
1	1000095	Action	PokÌ©mon Ranger and the Temple of the Sea (2006)	Posters/1000095.jpg
2	1000095	Other	PokÌ©mon Ranger and the Temple of the Sea (2006)	Posters/1000095.jpg
3	100014	Other	Liu jai yim taam (1987)	Posters/100014.jpg
4	100024	Comedy	Life Is Sweet (1990)	Posters/100024.jpg

Figure 4.9 Example of a dataset resulting from label separation

After the label separation process was carried out, the amount of data in the Kaggle dataset changed to 75,485 data. With final class data, namely action 4,691 data, comedy 11,163 data, drama 17,601 data, comedy 5,355 data, crime 4,577 data, and other 32,098 data. Then the Kaggle dataset will be split into 70% for training, 30% for validation and for testing using 457 streaming service data where the label separation process is not carried out.

4.2 Modeling

The modeling stage is the stage of creating a classification model using CNN, MobileNetV1 and MobileNetV2. The scenario applied in the modeling process is resizing the image size to 224 pixels, using a learning rate of 10^-3, Adam optimizer, batch size 32 and running for 50 epochs. Then implemented hyperparameters using learning rates 10^-4 and 10^-5 and the SGD optimizer. Examples of images before and after resizing are shown in Figure 4.10.

Figure 4.10 Example of poster resizing results

During the modeling process using the Google Collab Pro platform, a runtime error occurred (session crashed) which caused the training to not be completed. Error due to excessive RAM usage. This error appears during the SMOTE process of large amounts of data (before reduction). The resources used for model training are 51 GB RAM, V100 GPU and T4 GPU and 166.8 GB disk.

To overcome this, a process of training data reduction and validation is carried out so that training can be completed. Data reduction is carried out randomly on each label. The optimal dataset that can be applied is 7,300 data, with details for each class: action 1,000 data, drama 1,200 data, romance 1,450 data, crime 1,100 data, comedy 1,250 data and other 1,300 data. Then do the split with the same ratio as before. The distribution of the optimal dataset used is shown in Figure 4.11.

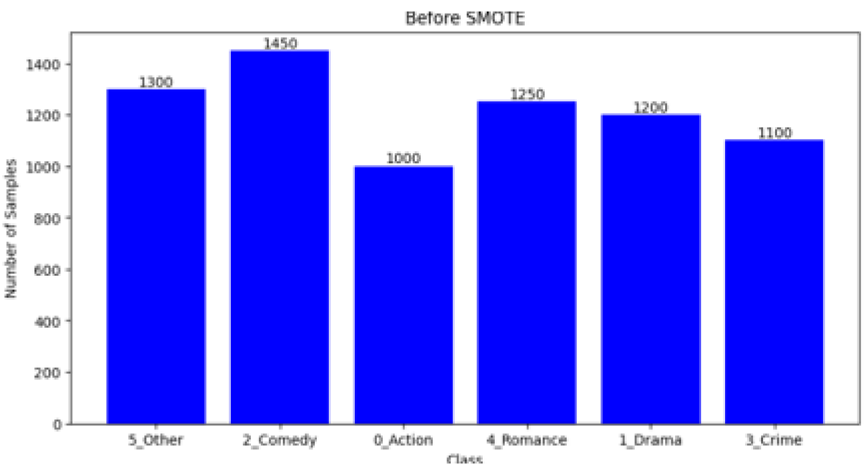

Figure 4.11 Data distribution before SMOTE

To overcome data imbalance, oversampling was carried out using SMOTE. So the total data used was 6,869 data with the total data for each class being 1,143. The optimal dataset distribution after SMOTE is shown in Figure 4.12.

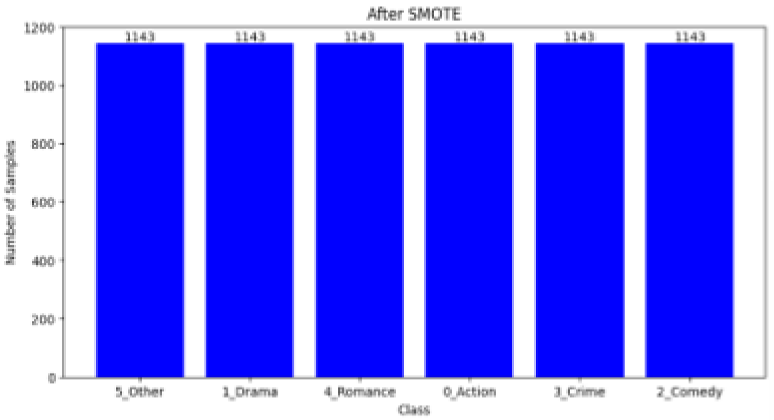

Figure 4.12 Data distribution after SMOTE

Then model training of three classification models was carried out using the optimal dataset and the SMOTE optimal dataset.

4.3 Evaluation

Evaluation is the testing stage of the model that has been created at the modeling stage. The models that will be evaluated are six models with model details, namely CNN, MobileNetV1, MobileNetV2, CNN + SMOTE, MobileNetV1 + SMOTE MobileNetV2 + SMOTE. The evaluation results are explained in sub-chapters 4.3.1 – 4.3.2.

4.3.1 Validation

Validation is the application testing stage using 30% of the total training dataset. This stage will analyze the accuracy results as well as macro average precision, recall and f1-score from the classification report. The validation process measures model performance using poster data in each class. Posters will be placed in folders that have been named according to the number of genres that will be used as classes, namely action, drama, romance, crime, comedy and other. For example, if a poster has more than one genre, namely action and comedy, it will be put in the action and comedy folder for that one poster. So that validation results can provide understanding in implementing models with or without hyperparameters and can be used to select the best model. Following are the validation results for each model using a predetermined scenario.

1. Model CNN

Table 4.1 CNN model validation results

Parameter		**Accuracy %**	***Precision %***	***Recall %***	***F1-Score %***
Optimizer	**Learning Rate**				
Adam	**10^-3**	**23**	**23**	**23**	**22**
Adam	10^-4	23	22	22	21
Adam	10^-5	23	22	23	21
SGD	10^-4	21	14	18	9
SGD	10^-5	20	8	17	6

From the validation results for each scenario shown in Table 4.1, it can be concluded that the CNN model has the best performance with the Adam optimizer and a learning rate of 10^-3 (default parameters) with results of accuracy of 23%, precision of 23%, recall of 23% and f1-score of 22 %. The validation results show that there are no significant changes with the implementation of hyperparameters by changing the optimizer and learning rate. Even the implementation of the SGD optimizer has decreased.

2. Model MobileNetV1

Table 4.2 MobileNetV1 model validation results

Parameter		*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*
Optimizer	***Learning Rate***				
Adam	10^-3	17	16	17	16
Adam	10^-4	18	17	18	17
Adam	**10^-5**	**18**	**18**	**18**	**18**
SGD	10^-4	17	17	17	16
SGD	10^-5	17	17	16	16

From the validation results for each scenario shown in Table 4.2, it can be concluded that the MobileNetV1 model has the best performance with the Adam optimizer and a learning rate of 10^-5 (hyperparameters) with results of 18% accuracy, 18% precision, 18% recall and 18% f1-score. The validation results show that there are no significant changes with the implementation of hyperparameters by changing the optimizer and learning rate. Even the implementation of the SGD optimizer has decreased.

3. Model MobileNetV2

Table 4.3 MobileNetV2 model validation results

Parameter		*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*
Optimizer	***Learning Rate***				
Adam	10^-3	17	16	16	15
Adam	10^-4	17	16	16	16
Adam	**10^-5**	**18**	**17**	**17**	**17**
SGD	10^-4	17	17	17	17
SGD	**10^-5**	**18**	**17**	**17**	**17**

From the validation results for each scenario shown in Table 4.3, it can be concluded that the MobileNetV2 model has the best performance with the Adam and SGD optimizers with a learning rate of 10^-5 (hyperparameters), producing 18% accuracy, 18% precision, 18% recall and f1-score. 18%. The validation results show that there are changes with the implementation of hyperparameters by changing the learning rate to 10^-5 in both types of optimizer. These results show the same performance results between the two optimizers on the MobileNetV2 model.

4. Model CNN + SMOTE

Table 4.4 CNN + SMOTE model validation results

Parameter	*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*

Optimizer	*Learning Rate*				
Adam	10^-3	22	21	23	20
Adam	**10^-4**	**25**	**24**	**25**	**23**
Adam	10^-5	24	26	25	23
SGD	10^-4	18	15	18	13
SGD	10^-5	19	24	19	12

From the validation results for each scenario shown in Table 4.4, it can be concluded that the CNN + SMOTE model has the best performance with the Adam optimizer and a learning rate of 10^-4 (hyperparameters) with results of 25% accuracy, 24% precision, 25% recall and f1-score. 23%. The validation results show that there are no significant changes with the implementation of hyperparameters by changing the optimizer and learning rate to 10^-5. Even the implementation of the SGD optimizer has decreased.

5. Model MobileNetV1 + SMOTE

Table 4.5 MobileNetV1 + SMOTE model validation results

Parameter		*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*
Optimizer	*Learning Rate*				
Adam	10^-3	15	16	15	15
Adam	**10^-4**	**17**	**17**	**17**	**17**
Adam	10^-5	16	16	16	16
SGD	**10^-4**	**17**	**17**	**17**	**17**
SGD	10^-5	16	16	16	16

From the validation results for each scenario shown in Table 4.5, it can be concluded that the MobileNetV1 + SMOTE model has the best performance with the Adam and SGD optimizers with a learning rate of 10^-4 (hyperparameters), producing 17% accuracy, 17% precision, 17% recall and f1 -score 17%. The validation results show that there are changes with the implementation of hyperparameters by changing the learning rate to 10^-4 in both types of optimizers. These results show the same performance results between the two optimizers on the MobileNetV1 + SMOTE model.

6. Model MobileNetV2 + SMOTE

Table 4.6 MobileNetV2 + SMOTE model validation results

Parameter		*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*
Optimizer	*Learning Rate*				
Adam	10^-3	15	15	15	15
Adam	10^-4	16	16	16	16
Adam	10^-5	17	17	17	17
SGD	**10^-4**	**18**	**18**	**18**	**18**
SGD	10^-5	17	17	17	16

From the validation results for each scenario shown in Table 4.6, it can be concluded that the MobileNetV2 + SMOTE model has the best performance with the SGD optimizer with a learning rate of 10^-4 (hyperparameters), producing 18% accuracy, 18% precision, 18% recall and f1-score. 18%. The validation results show that there are changes with the implementation of hyperparameters by changing the learning rate to 10^-4 and the optimizer type to SGD. However, the implementation of the learning rate of 10^-5 has decreased again.

Tabel 4.7 Summary validation six model

Model	**Parameter**		***Accuracy %***	***Precision %***	***Recall %***	***F1-Score %***
	Optimizer	***Learning Rate***				
CNN	Adam	10^-3	23	23	23	22
MobileNetV1	Adam	10^-5	18	18	18	18
MobileNetV2	Adam	10^-5	18	17	17	17
	SGD	10^-5	18	17	17	17
CNN + SMOTE	**Adam**	**10^-4**	**25**	**24**	**25**	**23**
MobileNetV1 + SMOTE	Adam	10^-4	17	17	17	17
	SGD	10^-4	17	17	17	17
MobileNetV2 + SMOTE	SGD	10^-4	18	18	18	18

From the best scenario validation results of the six models which are summarized in Table 4.7, it can be concluded that based on the accuracy, precision, recall and f1-score values, the CNN + SMOTE model is the best model that can be applied with the accuracy, precision, recall and f1-score values respectively – also namely 25%, 24%, 25%, and 23% with hyperparameter implementation using the Adam optimizer and learning rate 10^-4. It can be seen that implementing hyperparameters with a learning rate of 10^-4 can improve model performance, especially in models that implement SMOTE. Then the use of the Adam optimizer is overall better than SGD in poster genre classification.

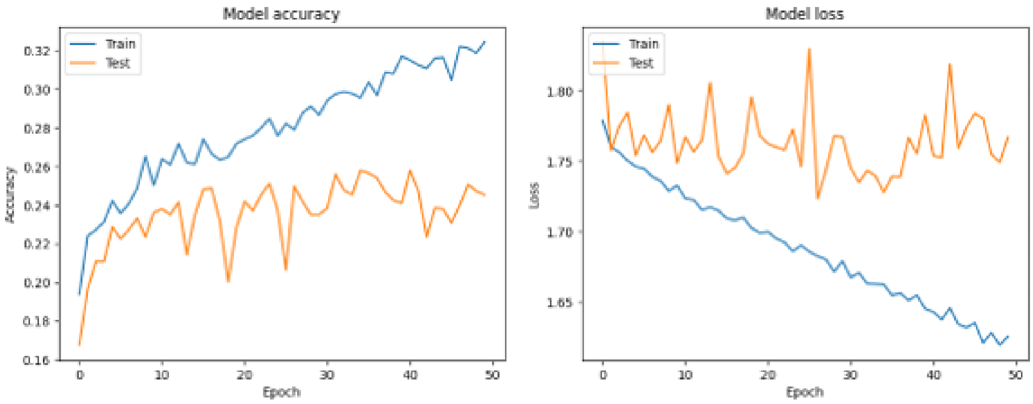

Figure 4.13 Accuracy dan loss training validation CNN + SMOTE

From the comparison of the accuracy and loss training validation accuracy graphs shown in Figure 4.13, it can be concluded that the CNN + SMOTE model is experiencing underfitting. Because the accuracy value of CNN + SMOTE only reaches 0.34, which means that the CNN + SMOTE model is too simple.

4.3.2 Testing

Testing is the application testing stage using 457 data obtained from the streaming service platform. The testing process measures the model's performance in predicting multi-model posters. Using the same approach as validation, the testing results consider the macro average accuracy, precision, recall and f1-score values for each model testing result. The testing results of the six models in each scenario are shown as follows.

1. Model CNN

Table 4.8 CNN model testing results

Parameter		**Accuracy %**	***Precision %***	***Recall %***	***F1-Score %***
Optimizer	**Learning Rate**				
Adam	**10^-3**	**19**	**19**	**16**	**17**
Adam	10^-4	15	17	13	14
Adam	10^-5	17	17	14	15
SGD	10^-4	21	13	16	7
SGD	10^-5	23	4	17	6

From the testing results for each scenario shown in Table 4.8, it can be concluded that the CNN model has the best performance with the Adam optimizer and a learning rate of 10^-3 (default parameters) with results of accuracy of 19%, precision of 19%, recall of 16% and f1-score of 17 %. The testing results show that there is a significant change in the accuracy value by implementing hyperparameters by changing the optimizer and learning rate. However, other values such as precision and f1-score experienced a significant decrease.

2. Model MobileNetV1

Table 4.9 MobileNetV1 model testing results

Parameter		***Accuracy %***	***Precision %***	***Recall %***	***F1-Score %***
Optimizer	***Learning Rate***				
Adam	**10^-3**	**30**	**28**	**25**	**26**
Adam	10^-4	30	28	24	24
Adam	10^-5	24	28	20	21
SGD	10^-4	24	25	20	22
SGD	10^-5	18	19	15	14

From the testing results for each scenario shown in Table 4.9, it can be concluded that the MobileNetV1 model has the best performance with the Adam optimizer and a learning rate of 10^-3 (default parameters) with results of accuracy of 30%, precision of 28%, recall of 25% and f1-score of 26 %. Testing results show that implementing hyperparameters by changing the optimizer and learning rate causes a gradual decrease in performance.

3. Model MobileNetV2

Table 4.10 MobileNetV2 model testing results

Parameter		***Accuracy %***	***Precision %***	***Recall %***	***F1-Score %***
Optimizer	***Learning Rate***				
Adam	10^-3	23	26	19	22
Adam	10^-4	27	26	23	24

Adam	**10^-5**	**29**	**28**	**24**	**25**
SGD	10^-4	28	27	23	23
SGD	10^-5	16	18	12	12

From the testing results for each scenario shown in Table 4.10, it can be concluded that the MobileNetV2 model has the best performance with the Adam optimizer and a learning rate of 10^-5 (hyperparameters), producing an accuracy of 29%, precision 28%, recall 24% and f1-score 25%. The testing results show that there are significant changes with the implementation of hyperparameters by changing the learning rate to 10^-5, especially in the Adam optimizer.

4. Model CNN + SMOTE

Table 4.11 CNN + SMOTE model testing results

Parameter		*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*
Optimizer	***Learning Rate***				
Adam	**10^-3**	**18**	**22**	**16**	**15**
Adam	10^-4	14	15	12	13
Adam	10^-5	14	15	12	12
SGD	10^-4	13	14	10	7
SGD	10^-5	18	21	14	9

From the testing results for each scenario shown in Table 4.11, it can be concluded that the CNN + SMOTE model has the best performance with the Adam optimizer and a learning rate of 10^-3 (default parameters) with results of 18% accuracy, 22% precision, 16% recall and f1- score 15%. The testing results show that there are no significant changes with the implementation of hyperparameters by changing the optimizer and learning rate. Even the implementation of hyperparameters causes a decrease in model performance.

5. Model MobileNetV1 + SMOTE

Table 4.12 Results of testing the MobileNetV1 + SMOTE model

Parameter		*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*
Optimizer	***Learning Rate***				
Adam	10^-3	27	30	22	23
Adam	10^-4	23	24	20	21
Adam	10^-5	27	28	22	23
SGD	**10^-4**	**29**	**26**	**24**	**22**
SGD	10^-5	19	19	15	14

From the testing results for each scenario shown in Table 4.12, it can be concluded that the MobileNetV1 + SMOTE model has the best performance using the Adam and SGD optimizers with a learning rate of 10^-4 (hyperparameters), resulting in an accuracy of 29%, precision 26%, recall 24% and f1 -score 22%. The testing results show that there are changes with the implementation of hyperparameters by changing the learning rate to 10^-4 and the optimizer to SGD. However, it experienced a significant decrease when implementing a learning rate of 10^-4 on the optimizer.

6. Model MobileNetV2 + SMOTE

Table 4.13 MobileNetV2 + SMOTE model testing results

Parameter		*Accuracy %*	*Precision %*	*Recall %*	*F1-Score %*
Optimizer	***Learning Rate***				
Adam	10^-3	26	26	21	23
Adam	**10^-4**	**32**	**27**	**25**	**25**
Adam	10^-5	29	26	24	24
SGD	10^-4	24	21	18	18
SGD	10^-5	13	20	11	13

From the testing results for each scenario shown in Table 4.13, it can be concluded that the MobileNetV2 + SMOTE model has the best performance using the Adam optimizer with a learning rate of 10^-4 (hyperparameters), producing 32% accuracy, 27% precision, 25% recall and f1-score. 25%. The testing results show that there are changes with the implementation of hyperparameters by changing the learning rate to 10^-4 and the optimizer type to SGD. However, the implementation of the learning rate of 10^-5 has decreased again.

Table 4.14 Summary of testing six models

Model	**Parameter**		**Accuracy %**	***Precision %***	***Recall %***	***F1-Score %***
	Optimizer	***Learning Rate***				
CNN	Adam	10^-3	19	19	16	17
MobileNetV1	Adam	10^-3	30	28	25	26
MobileNetV2	Adam	10^-5	29	28	24	25
CNN + SMOTE	Adam	10^-3	18	22	16	15
MobileNetV1 + SMOTE	SGD	10^-4	29	26	24	22
***MobileNetV2* + SMOTE**	**Adam**	**10^-4**	**32**	**27**	**25**	**25**

Based on Table 4.14, the best model that can be applied is MobileNetV2 + SMOTE with an accuracy of 32%, precision 27%, recall 25% and f1-score 25% in the testing process. Then the confusion matrix results from the best model, namely MobileNetV2 + SMOTE in the testing process, are shown in Figure 4.14.

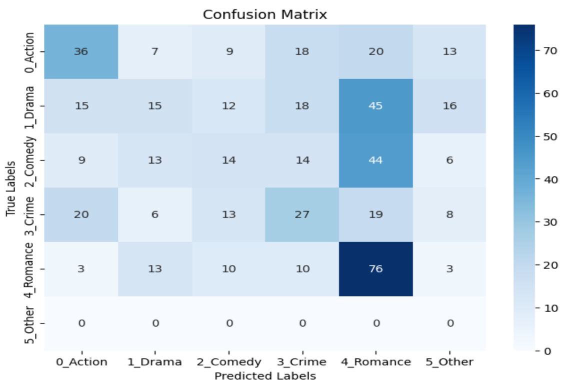

Figure 4.14 Confusion matrix best model

The confusion matrix results shown in Figure 4.14 show that the MobileNetV2 + SMOTE model tends to predict posters as being in the romance genre.

Classification Report:

	precision	recall	f1-score	support
0_Action	0.43	0.35	0.39	103
1_Drama	0.28	0.12	0.17	121
2_Comedy	0.24	0.14	0.18	100
3_Crime	0.31	0.29	0.30	93
4_Romance	0.37	0.66	0.48	115
5_Other	0.00	0.00	0.00	0
accuracy			0.32	532
macro avg	0.27	0.26	0.25	532
weighted avg	0.33	0.32	0.30	532

Figure 4.15 Classification report of the best model

From the results of the classification report shown in Figure 4.15, it can be seen that the macro average accuracy, precision, recall, and f1-score of the MobileNetV1 + SMOTE model are 32%, 27%, 26%, and 25%, respectively. The model still predicts other classes even though the testing dataset does not contain other classes. This is because the model was trained with other classes and there may be similarities between posters between other classes and other classes in the testing data. This causes most models in the testing process to have smaller precision and recall values than validation because the comparison of classification results uses macro average values (the average of the classification results for each class). So you can merge the dataset between the Kaggle dataset and the streaming service dataset to find out the performance results of other genres validly or use a weighted average value.

In the process of testing one image for a scenario where the label on the poster is unknown, this is done using a threshold value approach. This value is used to differentiate between poster genres based on the minimum probability result for each class. Because the prediction results are an array of probabilities for each class.

```
[8.1432354e-01 1.8390144e-01 6.4734936e-02 3.8673069e-02 2.8587203e-04
 9.8566926e-01]
```

Figure 4.16 Example of predicted probability array results

Using an array containing probabilities from six classes as shown in Figure 4.16, classes are taken with predetermined threshold values. The value set for the threshold is 0.5. So if the class prediction result is less than 0.5 then the poster will not be predicted as that class.

```
ID : 71100019 , Title : Think like a dog, Genre : Drama
1/1 [==============================] - 1s 881ms/step
Predicted classes: ['Drama', 'Romance']
Confidence for each class:
0_Action: 0.53
1_Drama: 0.57
2_Comedy: 0.68
3_Crime: 0.10
4_Romance: 0.45
5_Other: 0.54
```

Figure 4.17 Example of MobileNetV2 + SMOTE model prediction with threshold 0.5

Figure 4.17 shows an example of the prediction results for a film poster with the title "Think like a dog" using the MobileNetV2 + SMOTE model. The prediction results for classes other than drama and romance are below 0.5 so the poster is not included in the action, comedy, crime and other genres according to the MobileNetV2 + SMOTE model. Testing a single poster assumes or is carried out in a scenario where the original label on the poster is unknown. The prediction results for the film poster based on the six best models from each scenario for each type of model that have been created are shown in Table 4.15.

Table 4.15 Example of prediction for the poster "Think like a dog" threshold method

Model	**Parameter**		***Actual Genre***	***Prediction Genre***
	Optimizer	***Learning Rate***		
CNN	Adam	10^-3	*Drama*	*Drama|Comedy|Crime*
MobileNetV1	Adam	10^-3	*Drama*	*Drama|Comedy|Other*
MobileNetV2	Adam	10^-5	*Drama*	*Drama|Comedy*
CNN + SMOTE	Adam	10^-3	*Drama*	*Drama|Crime|Romance|Other*
MobileNetV1 + SMOTE	SGD	10^-4	*Drama*	*Action|Romance|Other*
***MobileNetV2* + SMOTE**	**Adam**	**10^-4**	***Drama***	***Drama|Romance***

Based on Table 4.15, the five models created can predict whether the film poster with the title "Think like a dog" has a drama genre according to the original genre apart from the MobileNetV1 + SMOTE model. This is because the threshold value for the drama genre model is below the predetermined value, namely 0.5.

In some film posters, all models cannot predict the poster correctly, one example is for the film poster "Argo" which has an original drama genre. None of the models predict the drama genre but predict the comedy genre. This could happen because there are several similarities with comedy film posters, one of which is the "Bad Trip" film poster shown in Figure 4.18.

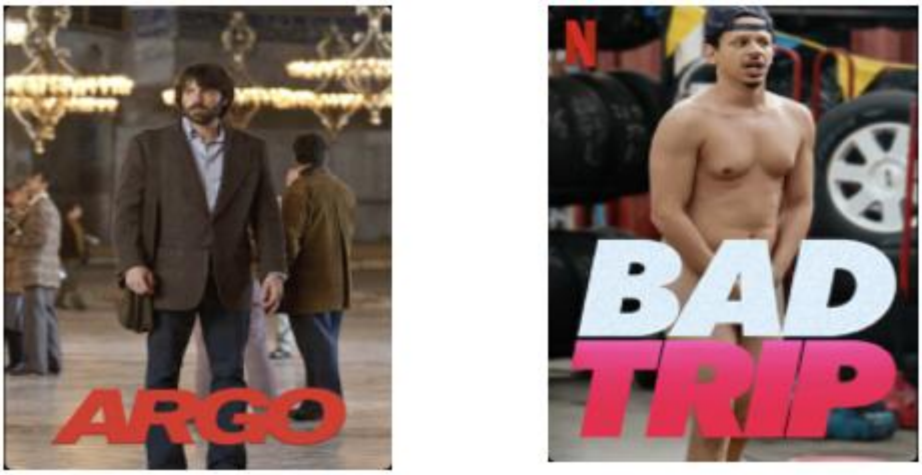

Figure 4.18 Comparison of the film posters for "Argo" and "Bad Trip"

Basically, the MobileNetV2 + SMOTE model uses a CNN architecture, namely MobileNetV2, only there are differences in the dataset used in training the MobileNetV2 model using the SMOTE oversampling technique. Then the best model structure, namely MobileNetV2 + SMOTE, is shown in Table 4.16.

The best model results between validation and testing show different model results. This can be influenced by the use of the dataset in the training and validation process, namely film posters between the years 1874 - 2018 which were chosen randomly. Meanwhile, the testing process uses film posters in 2022-2023. The model performance results can be influenced by differences in poster styles for certain time periods for the same genre. Examples of differences in comedy genre poster styles are shown in Figure 4.19.

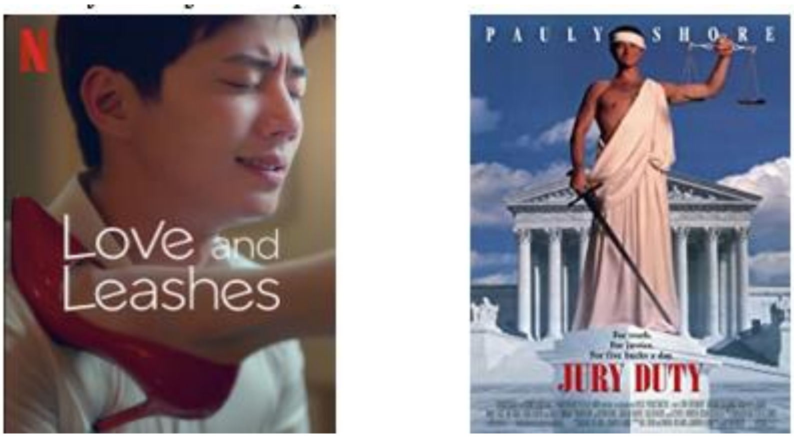

Figure 4.19 Comparison of comedy genre film posters

For example, a film with only a comedy genre, namely "Love and Leashes" in 2022 in the testing data and the film "Jury Duty" in 1995 in the training data has contrasting differences in color and shooting techniques. So the model could have guessed wrongly that the poster was a drama genre. Examples of poster similarities with the comedy and drama genres are shown in Figure 4.20.

Figure 4.20 Comparison of comedy and drama genre film posters

An example of a comparison of comedy and drama genre posters is shown in Figure 4.20, a film with the previous comedy genre, namely "Love and Leashes" in 2022 in the testing data, when compared with a film with the drama genre in the same year in the testing data, namely 1995, such as "Losing Isaiah" has similarities to shooting, namely close ups and similar colors. From the poster comparison, it can be concluded that the 2022 film "Love and Leashes" is more similar to the 1995 drama genre poster in the training data.

From several examples of poster similarity comparisons, it can be concluded that using posters as a dataset must take into account the range of years the film was broadcast. So with a shorter year span, each poster has a style that is similar to each other.

Conclusion

After conducting experiments and evaluating multi-label film genre classification models based on posters using Convolutional Neural Network, the following conclusions were obtained. The collection of film poster datasets from video streaming services was carried out manually by downloading posters for film titles available on the service one by one. Labeling is done manually according to the film genre on the platform. Then an ID is given for each poster obtained in the dataset and the poster file name.

Multi-label classification modeling of film genres based on poster images is carried out using three methods, namely Convolutional Neural Network (CNN), MobileNetV1 and MobileNetV2. Each model is also trained using a reduced dataset with an unbalanced distribution and using a dataset that has undergone SMOTE oversampling. Then the data is divided into 70% for training, 30% for validation and testing data using data obtained from video streaming service platforms. The model was created with a poster resize scenario to 244 pixels, using a learning rate of 10^-3, Adam optimizer, batch size 32 and running for 50 epochs. Then each model is hyperparameter tuned by changing the learning rate to 10^-4 and 10^-5 and using the Stochastic Gradient Descent (SGD) optimizer.

Evaluation of the multi-label classification model for film genres from poster images is carried out in two stages, namely validation and testing. Validation is carried out by paying attention to accuracy, precision, recall and f1-score values using 30% of the Kaggle dataset to determine prediction tendencies and information about model fitting. The best model in the training and validation process is CNN + SMOTE using the Adam optimizer and a learning rate of 10^-4 by looking at accuracy, precision, recall and f1-score values of 24%, 23%, 24% and 23% respectively. However, the best model experienced underfitting. Then the results of the testing process concluded that MobileNetV2 + SMOTE was the best model with accuracy, precision, recall and f1-score values of 32%, 27%, 25% and 25% respectively. The difference in the best model in the training and validation and testing processes is caused by the difference in the poster year range used in the training and validation data with testing. A range of years that is too far apart causes differences in poster styles to occur between the same genre, resulting in different prediction results. Testing one image uses the threshold method with a value of 0.5 for the scenario if the original genre of the predicted poster is not known.

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