Emotion-Based Movie Recommendation System

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Abstract— **This study presents a novel approach for a movie recommendation system that uses the emotions of a user to recommend movies. To detect user emotions, the system uses both facial expressions and text analysis. To detect facial expressions, several types of pre-trained models were re-trained and evaluated using benchmark datasets (FER2013). The ResNet50 model which has the highest accuracy of 73% was selected as the final model. For text analysis, several classical machine learning models (SVM, RF, MNB) and deep learning models (LSTM, Bi-LSTM, BERT, BERT+CNN) were trained and evaluated for their effectiveness in classifying emotions (using ISEAR). The BERT+CNN model with an accuracy of 78% was ultimately chosen for its high accuracy and efficiency in handling textual data. Final emotion derived by applying soft voting ensemble technique to the results of facial expression model and the text analysis model.**

For making the recommendations, the study incorporated content-based and collaborative filtering techniques to recommend movies based on the users' emotional state. Both methods were combined and adjusted based on the user's emotional state, resulting in more personalized movie recommendations.

To assess the efficiency of the proposed system, feedback was collected from ten users and analyzed. The final system received positive feedback from seven of the ten users. This indicated that the proposed system has the potential to enhance user experience by providing more personalized and relevant movie recommendations based on their emotional state.

Keywords— **Machine Learning, Deep Learning, Image processing, NLP, Recommendation systems**

I. INTRODUCTION

Human-Computer Interaction (HCI) is a field dedicated to optimizing user-computer interactions through the design of interactive interfaces. Emotion-based recommendation systems have gained attention in HCI research, aiming to recommend personalized content based on users' emotional states. Traditional recommendation systems may struggle to accurately recommend movies due to their reliance on historical ratings, making emotion-based systems crucial for providing more tailored recommendations. This study focuses on developing a movie recommendation system that effectively recognizes users' emotional states and suggests suitable movies, addressing the need for further research in this area [1]. The study aimed to build an emotion-based movie recommendation system that identifies user emotions accurately and suggests the most suitable movies for the

identified emotion. To achieve this aim, the study focused on building an emotion recognition model based on facial expressions and text analysis and developing a recommendation system that uses the emotions identified to recommend a personalized set of movies that match the users' emotions.

Numerous advancements have been made in emotion-based recommendation systems for different applications [2]–[4]. However, there is a gap in the existing literature regarding the integration of facial expressions and text analysis for emotion identification in movie recommendation systems, making this study's approach novel.

The Sri Lankan film industry is underrated and overlooked [5]. It is widely believed that local movies are not as popular as international movies among the Sri Lankan youth [6]. A possible reason for this could be the easy access to international movies through platforms like Netflix and Amazon Prime. Therefore, this study attempts to design a movie recommendation system incorporating local movies, which would also help make local movies popular among users (especially among young users), thereby uplifting the local entertainment industry.

The next section provides an overview of the literature review, discussing prior work related to this topic. This is followed by an explanation of the methodology. The project's results are then presented, and the final section is dedicated to the discussion, analyzing the results, and concluding with the research's key findings.

II. RELATED WORK

Facial expressions play a vital role in human communication and are responsible for 55% of the impact of a message[2] . The number of basic emotions remains a topic of debate. Ekman [7] proposed seven emotions initially. However, Jack et.al [8] found similarities between disgust and anger and between fear and surprise in facial expressions. Recognizing these similarities, the authors reduced the initial seven basic emotions into four, which includes anger, fear, sadness and happiness. Following the work of Jack et.al [8], this study also considered anger, fear, sadness, and happiness as the four basic emotions for developing the emotion recognition system. Numerous facial expression datasets have been utilized for training and developing deep learning models in the past, as reported in the literature. However, with the introduction of the FER2013 image dataset, it has become the benchmark for evaluating model performance in emotion recognition [9]. As a result, the study utilized this dataset to create an effective emotion recognition model based on facial expressions.

Different deep learning models, especially Convolutional Neural Networks (CNNs), have been tested with this dataset. Convolutional Neural Network (CNN) variants have achieved remarkable results with a classification accuracy between 65% and 72.7% for the FER2013 dataset [10]–[13]. A study by Pramerdorfer & Kampel [14] compared the performance of three different architectures, Visual Geometry

Group (VGG), Inception and ResNet, on the same dataset, and their results showed that VGG performs best among the different architectures. Another study by Nordén et al. [15] compared five machine learning algorithms for binary classification of facial expressions using the JAFFE and FER2013 datasets.

The algorithms included support vector machine, extreme learning machine, CNN, pre-trained CNN (VGG16), and ResNet. The study revealed that ResNet which is also a pretrained CNN model achieved the highest accuracy for the FER2013 dataset. Convolutional Neural Networks (ConvNets) are extremely effective for image processing applications because they are efficient at identifying local patterns, maintaining translation invariance, and gaining a hierarchical understanding of visual information by gradually learning features [16]. Pramerdorfer & Kampel [14] stated that through their findings it is evident that the pre-trained models outperformed shallow and simple CNN architectures in terms of accuracy. Considering the impact of training dataset size on feature extraction by CNNs, Kaur & Gandhi [17] also highlighted the efficiency of deep CNNs with transfer learning when dealing with limited data. Transfer learning in image classification entails using a pre-trained convolutional neural network (CNN) model as a feature extractor for a new classification task. Given the study's reduced image dataset due to computational limitations, the focus will be on applying transfer learning techniques using diverse pre-trained models to identify the best-performing model, in line with the findings of Kaur & Gandhi [17].

In addition to facial expressions, emotion detection using text detection can be done by examining the writer's input text. Lexicon-based approaches or machine learning-based approaches could be employed for the emotional analysis of text data [18]. After analyzing both approaches, C. Kaushik and A. Mishra [19] concluded that machine-learning models frequently outperform lexicon-based models on emotional analysis tasks when comparing the standard evaluation metrics. Previous studies have also demonstrated that supervised machine learning methods are frequently utilized in text-based emotion identification problems and provide higher detection rates than unsupervised machine learning approaches [20]. Therefore, this study also explored the implementation of supervised machine learning algorithms for analyzing emotions in text.

Additionally, numerous research studies have explored the application of deep learning models for text-based emotion analysis. Ragheb et al. [21] used Bidirectional-Long Short-Term Memory units to detect emotions in textual conversations. Keshavarz & Abadeh [22] utilized a CNN model and achieved significant improvement compared to traditional machine learning approaches. Pre-training models like ELMo, ULM-Fit, and BERT have also been used for text emotion analysis. Abas et al. [23] introduced BERT-CNN, which combined BERT's language model with a CNN for predicting emotions in text. Building on this existing research, our study will also explore various deep-learning techniques to determine the most effective model for emotion recognition through text analysis.

A good recommendation system should precisely capture the demands and tastes of the customer. However, in their study, Ho et al. (2006) emphasized that it can be challenging for customers to describe the desired product features for subjective and complicated products like movies, music, and fragrances. The typical user profile is inadequate to grasp these changes because user preferences for these items also often change in line with their emotions. As a result, several emotion-based recommendation systems have been researched in various domains. Ho et al [2] designed an emotion-based movie recommendation system that utilized a color-based questionnaire to determine user emotions, leading to movie recommendations aligned with those emotions. James et al. [3] proposed a music recommendation system that employed facial expressions for emotion detection and employed a hybrid approach combining content and mood-based filtering for song suggestions. Ayata et al. [4] developed a music recommendation system based on wearable physiological sensors, where user emotions were captured using a wearable device and integrated as supplementary data into collaborative or content-based recommendation engines.

However, to the best of the authors' knowledge, existing literature on movie recommendation systems does not include any system that utilizes both the facial expressions and the input provided by the user to determine the overall emotion of the user, which adds to the novelty of this study. This system also attempted to further improve the performance of the system by incorporating the emotion-based recommendation system with content-based and collaborative filtering techniques.

III. METHODOLOGY

A. Emotion Recognition Using Facial Expressions

This work utilized the FER2013 dataset, originally presented in 2013 and widely used as a benchmark for evaluating machine learning models in emotion recognition from facial expressions. The dataset consists of 28,709 training images and 7,178 testing images, categorized into seven classes: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. However, considering the practicality of the recommendation system, only four classes (fear, anger, sadness, and happiness) were selected for the study, which collectively comprised 20,272 training images and 5,003 testing images. To address the imbalanced nature of the dataset and computational limitations, 10,000 images were randomly chosen, with 2,500 images from each class, for model training. Image pre-processing steps were performed, including reading the images using OpenCV, converting them to RGB channels, resizing them to 224x224 pixels, normalizing the intensity values, and augmenting the data through techniques such as rotations, shifts, and flips. The Haar Cascade algorithm was employed for face detection, and feature extraction was conducted using Convolutional Neural Networks (CNNs). Even though CNNs are the most commonly used approach for image classification, one of the challenges of training a CNN for image classification is the need for a large amount of labelled data. Therefore, in this study, transfer learning techniques were used for image classification, where several different CNN architectures pre-trained on massive datasets were fine-tuned to be suited for the classification task.

B. Emotion Recognition Using Text Analysis

The ISEAR dataset was used for text analysis-based emotion recognition. It consists of responses from student respondents describing instances of seven major emotions which included

joy, fear, anger, sadness, disgust, shame, guilt, joy, and fear. However, only the four fundamental emotions (joy, fear, anger, and sadness) were considered in the study. The dataset included data from around 3000 respondents representing 37 countries. The text pre-processing steps involved tokenization, lowercasing, contraction mapping, part-of-speech tagging, stop word removal, and lemmatization using the NLTK library. Feature extraction techniques used in this study included the Bag of Words (BoW) model, which represents word distribution in documents, and TFIDF (Term Frequency-Inverse Document Frequency), which measures word relevance. The feature extraction techniques were used separately for all classical machine learning models, including the Random Forest classifier, Support Vector Machine (SVM) and Multinomial Naïve Bayes. Additionally, deep learning models, including LSTM, Bi-LSTM, BERT, and BERT-CNN, were also trained to determine the most effective model for emotion recognition.

The combination of the results from the facial expression model and the text analysis model was done using the soft voting ensemble technique. Soft voting is a type of ensemble technique where the final prediction is made by taking the average of the predicted probabilities from each individual model and choosing the class with the highest probability. This ensemble technique has been used in many studies to combine multiple models.[24], [25]. In this study, an equal weight was given to both models when applying soft voting. The possibility of weighting the models based on accuracy was explored, and it was identified through previous work that this procedure was followed for models trained on the same dataset, which was not the case for this study. The following diagram gives the methodology followed in the study to identify the emotion of the user.
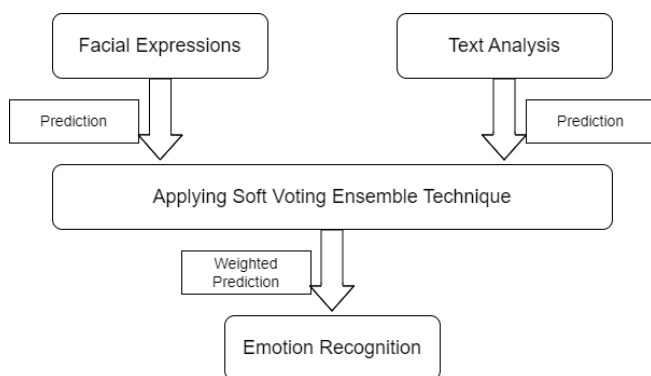

Fig. 1 Proposed methodology to identify the user emotion

C. Building the Recommendation System

The initial step of building a recommendation system was to create a database with information about movies. Web scraping was employed to extract movie information from multiple pages of the IMDB website, which is known for providing verified information about various movies. A total of 800 movies from different languages (Sinhala, Tamil, English, and Hindi) were collected for analysis in this study. Once the database was created, the next step was to recommend the movies to the users. In order to achieve this, both content-based filtering techniques and collaborative filtering techniques were employed in the system. However, since the emotions of the users were also to be considered both these techniques were applied to data that was filtered based on the emotions.

In the content-based filtering process, the movie's description and director's name were vectorized using TFIDF, and genres were one-hot encoded. Cosine similarities were calculated among all movies. When a user logs in, their profile is analyzed, filtering out records relevant to the detected emotion. The movie with the highest rating by the user is selected, and five movies with the highest similarity to the chosen movie are recommended. User feedback on the selected movie is stored in their profile database.

Collaborative filtering is a technique that provides recommendations based on the idea that people who share common preferences in the past will also share the same in the future. Collaborative filtering techniques can be broadly divided into two categories: memory-based collaborative filtering and model-based collaborative filtering. Memory-based filtering uses statistical methods to search for a set of users or items that have similar transaction history or ratings to the active user or item and use this to generate recommendations [26]. Model-based collaborative filtering algorithms learn a model from the training data, and subsequently, this model is used for recommendations. Matrix decomposition model and clustering model are some model-based collaborative filtering techniques [27]. However, since this study initially did not have sufficient information to train a model with a good accuracy, memory-based collaborative filtering was utilized. The item-based approach to collaborative filtering used in this study recommends items based on item similarities. However, item-based collaborative filtering faces the "new community" problem [28]. This refers to the difficulty in obtaining sufficient data when starting up a recommender system, which hinders the ability of the recommender system to give reliable recommendations. To tackle this problem, collaborative filtering recommendations are withheld until a predefined number of users and votes are available. When item-based collaborative filtering is implemented, user profiles will be extracted from the database, filtered based on the relevant emotion detected, and combined with movie rating information. Pearson correlation is used to identify movies with similar ratings, and a prediction score is calculated using a weighted technique. The movies with the highest prediction scores will then be recommended to the user. Another problem that both collaborative filtering and content-based filtering techniques for recommendation face is the "user cold start" problem. This is where systems are unable to recommend relevant items to the users due to the unavailability of adequate information about them. To address this, the study initially tries to associate different genres of movies with emotions. Since users' preferences are subjective, this system attempts to get explicit feedback from the users when they register to the system about the genres of movies they prefer to watch based on their emotions. This provides the framework for the system to initially recommend movies for the individual users, and the recommendation system would then continuously develop, taking explicit feedback on the movies recommended by the system.
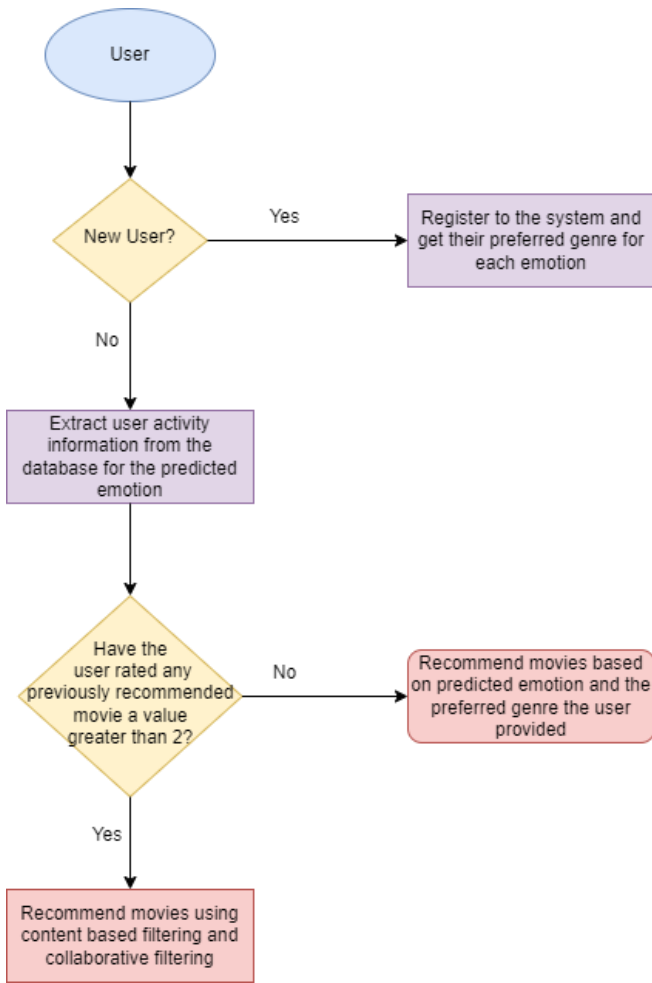
Fig. 2 Proposed methodology for the recommendation system

IV. RESULTS

As explained in the methodology section, several models were fitted for both emotion recognition using facial expressions and for emotion recognition using text classification. The following table summarizes the results for all the pre-trained models used in this study for emotion recognition using facial expressions.

TABLE 1

SUMMARIZED RESULTS OF THE TRAINED MODELS FOR EMOTION RECOGNITION USING FACIAL EXPRESSIONS

	Train Accuracy	Test Accuracy	F1 Scores			
			Anger	Fear	Happy	Sad
Inception	0.8258	0.7046	0.61	0.55	0.90	0.62
VGG	0.6754	0.6954	0.62	0.51	0.90	0.62
MobileNet	0.7681	0.7094	0.62	0.49	0.91	**0.65**
ResNet50	0.7609	**0.7300**	**0.66**	**0.56**	**0.92**	0.64

When comparing the F1 scores and the accuracies in Table 1, it is evident that among the four models used in this study, the ResNet50 model performs best for emotion recognition using facial expressions. Therefore, going further in this study, the ResNet50 model was utilized to classify facial expressions based on emotions.

This study also explored several machine-learning techniques for classifying text based on emotions. When observing the accuracies and the F1 scores in Table 2, it is evident that the Multinomial Naïve Bayes model performs best in classifying the text. However, the highest accuracy of the best classical machine learning model was 72%. Therefore, in an attempt to increase the accuracy, several deep learning models were trained, and a clear improvement in the accuracies was observed, as shown in Table 3.

TABLE 2

TABLE OF SUMMARIZED RESULTS FOR THE CLASSICAL MACHINE LEARNING MODELS.

	Test Accuracy	F1 scores			
		Anger	Fear	Happy	Sad
Multinomial Naïve Bayes with BoW features	0.72	0.70	0.76	0.72	0.70
Multinomial Naïve Bayes with TFIDF features	0.72	0.71	0.76	0.72	0.70
Support Vector Machine with BoW features	0.70	0.67	0.73	0.72	0.67
Support Vector Machine with TFIDF features	0.70	0.66	0.75	0.72	0.68
Random Forest with BoW features	0.70	0.65	0.75	0.72	0.68
Random Forest with TFIDF features	0.69	0.67	0.72	0.70	0.68

TABLE 3

SUMMARIZED RESULTS FOR THE DEEP LEARNING MODELS

	Train Accuracy	Test Accuracy	F1 scores			
			Anger	Fear	Happy	Sad
LSTM	0.8237	0.7521	0.69	0.75	0.72	0.67
Bi-LSTM	0.9512	0.708	0.69	0.75	0.70	0.69
BERT	0.7869	0.7700	0.72	0.77	**0.87**	0.70
CNN with BERT embeddings	0.8195	**0.7799**	**0.76**	**0.79**	0.84	**0.73**

Upon analyzing the summarized results of the different models, it is clear that the CNN model integrated with BERT embeddings outperforms the others. The findings indicate that this model displays strong performance across all classes, with the highest accuracy achieved in identifying the "happy" emotion class. Consequently, for the purpose of emotion recognition using text classification, the CNN model with BERT embeddings were selected as the best model in this study.

V. DISCUSSION

The best-performing model for this study was the ResNet50 model, with an accuracy of 73%. Several studies have been conducted on the FER2013 dataset to identify emotions using pre-trained models. When compared with the previous studies, it is evident that the selected model in this study performs sufficiently well in the classification. When analyzing the results of the selected model, it was evident that the model performed very well in identifying the "happy" emotion class, moderate performance in identifying the "sad" and "anger" emotion classes, with the lowest performance observed for the "fear" class. To further elaborate, some images which were classified incorrectly are presented below:
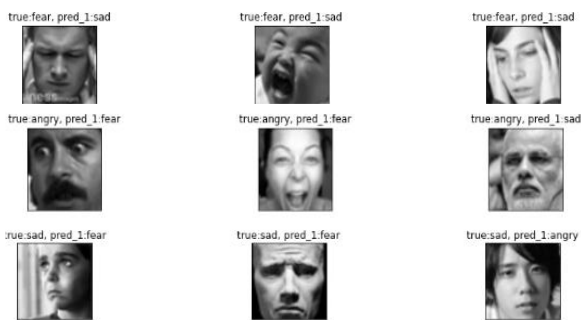

Fig. 3 Comparison of the misclassified images with the predicted emotion and the actual emotion

When analyzing these images, it is evident that even though they were wrongly classified, the emotion predicted could also be accepted for some of the images. This affirms that some of the misclassified images are ambiguous in nature and are difficult to differentiate. Therefore, the performance of the model can be considered sufficient. This observation further points out that using facial expressions alone would not be sufficient to identify the user's emotions efficiently. Consequently, incorporating a text analysis can make the emotion recognition model more efficient.

When considering the text analysis for emotion recognition, keeping in line with [29], this study also found that deep learning models outperformed classical machine learning models for the ISEAR dataset. All the deep learning models trained showed improved performance when compared to classical machine learning models. However, the model that showed the best accuracy in this study is the CNN model with BERT embedding. Compared with the previous studies, it is evident that the selected model, the BERT+CNN model, shows sufficient performance accuracy in identifying emotions within a text. Therefore, combining the model chosen for detecting emotions from facial expressions and the model selected for detecting emotions from the text could yield precise outcomes for identifying the emotions of the user of the recommendation system.

After emotion recognition, the next step of the study was to propose a recommendation system that incorporates the identified emotion when recommending movies. The model proposed by this study filters the information about the user's activity and then recommends movies by employing content-based and item-based collaborative techniques. Since the proposed recommendation system is built from scratch without any information about the user ratings for the movies,

it cannot be evaluated to check if the system performs well at the onset of using the system. After a considerable number of recommendations are made by the system, the precision metric can be used to evaluate the model's performance. According to the study by Ho et al. (n.d.), this precision value can be defined as the ratio between the number of well-recommended items and the total number of recommendations. This would measure how close the recommendations made by the user are to the users' actual preferences. It should also be noted that the quality of the recommendations made would improve based on the feedback given by the users.

After the research was completed, specific areas were identified for potential future research related to this study. One area that could be explored in the future is to explore more intricate methods for identifying small changes in facial expressions using more advanced computer vision techniques that can identify subtle changes in facial expressions. In addition, the emotion recognition model using facial expressions could also be improved by incorporating a dataset that represents greater cultural diversity so that the model can be better trained to recognize and interpret facial expressions across different cultures. Future studies could also explore the possibility of incorporating physiological data such as heart rate variability and skin conductance in a less intrusive manner to provide more insights into the user's emotions. Incorporating physiological data could possibly increase the effectiveness of the system. Another direction for future work could involve expanding the recommendation system to include demographic filtering, such as age and gender, for movie recommendations. This could lead to more personalized and accurate recommendations for individual users based on their demographic characteristics. Furthermore, the data obtained from the recommendation system could provide insights into the movie preferences of users based on demographic factors such as age and gender, which could be utilized for further research in this field.

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