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EmoFlix: A Movie Recommendation System Based on Human Emotions Using Cascade Classifier and CNN

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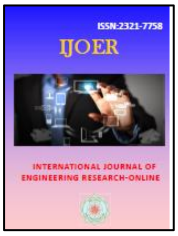

Abstract

In recent years, the entertainment industry has witnessed a significant rise in the demand for personalized recommendations. However, traditional movie recommendation systems often fail to capture the emotional aspect of viewers, which plays a vital role in their overall movie-watching experience. To bridge this gap, we present EmoFlix, an innovative movie recommendation system that leverages human emotions to provide tailored movie suggestions. EmoFlix utilizes a combination of cascade classifiers and convolutional neural networks (CNNs) to accurately detect and interpret facial expressions. The cascade classifier initially detects faces in input images or video frames, followed by the extraction of facial features. These features are then fed into a CNN-based model, which is trained to classify emotions such as happiness, sadness, anger, surprise, and more. Once the viewer's emotions are identified, EmoFlix employs a recommendation engine that incorporates collaborative filtering techniques and content-based filtering methods. The system compares the emotional profile of the user with a comprehensive movie database, considering factors such as genre, plot, director, and actor information, to generate personalized movie recommendations. To evaluate the effectiveness of EmoFlix, we conducted extensive experiments on a diverse dataset consisting of facial expression images and movie metadata. The results demonstrate the system's ability to accurately recognize human emotions and provide relevant movie recommendations, enhancing the overall movie-watching experience for users.

Keywords: Cascade Classifier, CNN, Emotion Recognition, Movie Recommendation, EmoFlix.

1. Introduction

In general, many people love movies and many of us usually spend our time watching movies. Movies help us as a stress buster and for entertainment purposes. Due to work stress or personal issues, people may get their mood swings. Many of us face mood swings very often due to many reasons such as stress, work pressure, and tension. To get relief and become normal, one of the best ways is watching movies. To bring them out of the mood swings the present work implements a model that suggests the movie based on the person's facial emotion [1]. Facial Emotions are detected based on the muscle movement under the skin. Based on certain theories muscle movement helps to detect the facial emotions of individuals. The current work recommends entities such as movies to the user based on individual facial emotions rather than past feedback or other patterns as it is the best way to understand one emotion.

Facial Emotion Recognition (FER) is done on real-time human images. FER plays a key role in many sectors such as Security, Biometrics, Law enforcement, and recommendation systems. It is also useful for multimedia lovers to recommend movies, music, and videos based on their facial emotions. It is difficult for many of us to identify facial emotions if we have Social Anxiety Disorder (SAD) [2]. Even if a facial emotion is neutral, people with SAD frequently read it negatively and may even turn away from unfavorable facial emotions altogether. Muscles under the skin are mainly responsible for facial emotions. There are several theories on the movement of the muscles under the skin to identify facial emotions.

There are mainly two types of emotions humans can make they are voluntary and involuntary emotions. Voluntary emotions are the emotions that come out without any force. Eyes, Eyebrows, and lips play an important factor in recognizing the facial emotions of a person [3]. Based on the facial emotions we can able to know what's going on in other's mind. Facial emotion also plays an important role as a sign of communication. As we know people who aren't able to talk when they are in a dangerous situation or many other situations during that time facial emotions play an important role and act as a sign language to communicate.

Below are a few features that are used to recognize emotion.

- Biting of Lips due to anxiety.
- Pursing of lips which is a sign of disapproval
- Covering the mouth
- Opening mouth (moving jaw down)
- Lifting of Eyebrows
- Widening of eyes
- Movement of Cheeks
- Based on the corners of the lips.

Facial emotion recognition is implemented in two stages. The first stage of the system is face object localization and the second stage is recognizing the emotion. Based on their emotions we recommend movies. For people with happy emotions, we recommend Thriller movies, for fear, we recommend Sports movies, for sad we recommend Drama movies, for disgust we recommend musical movies, For Anger we recommend family movies, for neutral we recommend Western movies, surprise we recommend Film-noir movies [4]. Here we are dealing with the Top 50 IMDB-rated movies as per emotion. The IMDB movies we recommend can be watched through the OTT platform. Whenever we are having mood swings and want to watch movies it is a big thing to go to the theatre as we must spend a lot of money on it. Not only about money, but it is also impossible to have a movie according to our emotions at the theatre. So, the best way to reduce costs and to watch movies based on our requirements is through the OTT platform.

Developing a movie recommendation system based on human facial emotions poses a unique challenge in accurately understanding and interpreting the emotions displayed by users. The system needs to accurately capture and analyze facial emotions in real-time, and translate them into meaningful emotional states to provide personalized movie recommendations. The challenge lies in accurately recognizing and classifying a wide range of facial emotions and associating them with appropriate movie genres, ensuring that the recommendations align with the user's emotional preferences.

The objective is to develop a movie recommendation system that accurately captures and interprets human facial emotions in real-time, leveraging this information to provide personalized movie suggestions that align with the user's emotional preferences. The system should ensure user privacy and data protection while continually improving the recommendation algorithm to enhance user engagement and satisfaction.

2. Literature Survey

This section explores the methods and recent related works of the facial emotion-based movie recommendation system.

Elias, T., et al. [5] proposed a model to recognise facial emotions using CNN, VGGNet, Inception, MobileNet, and DenseNet. All these experiments are trained and tested using the CK+ dataset. It attained an accuracy of 96%. Gupta et al. [2] proposed a model to recognize facial emotions using fuzzy and genetic algorithms. All these experiments are trained and evaluated using the Movie Lens 1M dataset. Shreya Agrawal et al. [3] proposed a model to recognize facial emotions using filtering techniques and SVM. All these experiments are carried out using three datasets. They are Movie Lens datasets. Here they worked on different datasets and made a comparative analysis. Ziyang Yu et al. [4] proposed a model to recognize facial emotions using content-based CNN and mood-based music recognition. This model can recognize facial emotions and can also propose music based on the facial emotion information. The facial micro-emotion recognition model implemented in this work uses the FER2013 dataset and it attained an accuracy of 62.1%.

Milad Mohammad Taghi Zahed et al. [5] anticipated a model to recognize facial emotion. The authors have used Gabor filters for face feature extraction and CNN for classification. The dataset used to implement this model is JAFFE and it attained an accuracy of 97%. Anuja Bokhare et al. [6] Here proposed a model based on Haar cascade and deep face technologies to detect facial emotions. After detecting the facial emotions, a video is suggested. The dataset here used to be FER 2013. Anmol Chauhan et al. [7] In this research work, they proposed a model using collaborative filtering and content-based filtering. It is used for movie recommendations to the user as per their interests. The dataset here used to be enormous.

P.Karthikeyan et al. [8] The work provided in summarised and briefly evaluated the techniques of the movie recommender algorithm. Brief descriptions of movie recommendation systems. Here, they have used a movie lens data set. N Pavitha et al. [9] Here the model is proposed by using naïve CNN which attained an accuracy of 89.15. Here, they have used three datasets which are tmdb_5000_movies.csv and tbmd_5000_credits.csv for movie recommendation and reviews.txt for sentiment analysis. SRS Reddy et al. [10] Content-based filtering is used to recommend movies using the facial emotions of the user. Here, we used the movie lens dataset.

Jennifer Golbeck et al. [11]. proposed a model to recognize facial emotions using CNN and suggested movies based on facial emotions. All these experiments are trained and evaluated using different datasets. Here they worked on different datasets and made a comparative analysis. H., Liu et al. [12] The model is proposed based on the LSTM recurrent neural network by using a movie lens dataset whose training accuracy is 96.27% and the testing accuracy is 95.89%. Haq et al. [13] suggested a model based

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on a segmentation mechanism after segmentation CNN is performed on it using the VGG Face dataset and KDE face dataset whose accuracy is 92%.

Mahadik et al. [14] Here they proposed a model for music recommendation using the facial emotions of the user by using the CK+ dataset whose accuracy is 75%. V, Mareeswari, et al. [15] This article demonstrates the project's focus on constructing an efficient music, video, movie, and tourism recommendation system that assesses user emotion using facial recognition techniques. The fundamental goal of the system is to recognize facial emotions and deliver music, video, and movie suggestions based on the user's mood. Shavak Chauhan et al. [16] This paper was completed by capturing the emotion of the user rather than hunting for individual films. CNN is implemented for facial recognition utilizing decision trees and boosting algorithms to achieve efficient results as compared to decision trees and boosting algorithms, as demonstrated. The data is pre-processed and then sent to the CNN model. The image is submitted as input to the recommender system, which can then provide a list of films. The user's face is treated as an input which is captured. Here they used the Face dataset whose accuracy is 62%.

Prateek Sharma et al. [17] In this case, the input is the user's face as caught by a camera. The main source of information for gaining vital information for input to acquire the outcomes is the facial emotion. CNN is the primary classification model employed. The primary principle here is guided learning. The training dataset is connected with labels in this case. The OpenCV library and VGG-16 are used to transform datasets into vectors. Karzan Wakil et al. [18] Here they proposed a system based on a hybrid approach that combines the CBF and CF systems with an emotion recognition algorithm. They recommend movies from 1 to 5 stars and the user can select according to their interest by using the movie lens dataset. Abhishek Mahata et al. [19] The proposed method is clever as well as secure because a user is validated at the time of login by matching his face to one stored at the time of registration. A fully dynamic interface, i.e. a website that recommends films to the user, is used to implement the system. Nisha Sharma et al. [20] Here they discussed different recommendation systems. They did a comparative analysis of those systems by using different datasets.

3.Proposed Methodology

3.1 Overview

In this paper, a movie recommendation system based on facial emotions is proposed to help people overcome mood swings. The work is carried out in three stages. The first human face is located using the Haar cascade classifier. Next, the located face part is fed to the Convolutional Neural Network(CNN) for classifying the type of emotion. Finally, a movie is recommended from the Internet Movie Database based on facial emotion. The proposed pipeline used for recommending movies based on facial emotion is shown in Figure 1.

3.2 Dataset

The proposed model is trained and evaluated using the datasets obtained from [21]. This dataset comprises seven facial emotions or mood swings which we can observe in many of us frequently they are Sad, Happy, Neutral, Anger, Disgust, Fear, and Surprise as shown in Figure 2.

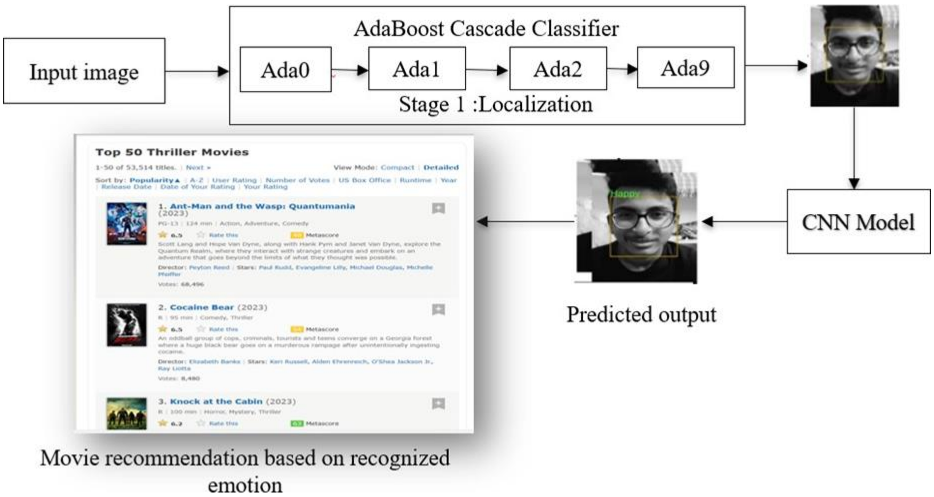

Figure 1: Proposed pipeline to recommend the movies based on facial emotion

Figure 2: Types of Emotions (7 Classes)

Table 1 shows the different classes of facial emotions and their corresponding movie genre.

Table 1: Human emotion and corresponding movie genre

Class	**Captured Emotion**	**Movie Genre**
1	Angry	Family
2	Disgust	Musical
3	Fear	Sport
4	Happy	Thriller
5	Neutral	Western
6	Sad	Drama
7	Surprise	Film-Noir

Facial emotion recognition, Facial expression recognition dataset, and a few custom samples. The dataset is split into two parts such as the Training and Testing dataset. It consists of 71K samples and is grouped into 7 classes. The dataset is divided into 80-20 ratios as shown in Table 2.

Table 2: Splitting of dataset [21]

Class Name	Number of Images	Training (80%)	Testing (20%)
Angry	9906	6935	2971
Disgust	1094	766	328
Fear	10242	7170	3072
Happy	17978	12612	5366
Neutral	12396	8677	3719
Sad	12154	8508	3646
Surprise	8004	5603	2401
Total	71767	50271	21503

IMDB, short for the Internet Movie Database, is an online database that contains information on the films. IMDB contains a vast collection of data related to movies and TV shows, including information on cast and crew, plot summaries, user ratings, and reviews. It also provides a platform for users to create their own watch lists, rate and review movies, and discuss films with other users. IMDB is a valuable resource for anyone interested in the film industry, from casual moviegoers to aspiring filmmakers. Its comprehensive database of information helps users make informed decisions about what to watch, and its user-generated content provides a community for movie enthusiasts to discuss and share their opinions.

3.3 Locating Face object:

This section describes the finding of the position of the face in the image. This section deals with the detection of driver faces. To detect the face of a driver, a Haar cascade classifier is trained with positive and negative samples. Positive samples mean the images that contain the face object. Negative samples mean that the images don't contain the face objects. To extract the features of the human face Haar kernels are used. The Haar kernels used for this experiment are shown in Figure 3. A total of 6000 Haar features are extracted. Instead of applying all 6000 features on a window, the features are grouped into different stages of the classifier and applied one by one. If a window fails at the first stage, discard it. We will not consider the remaining features on it. If it passes, apply the second stage of features and continue the process. The window that passes all stages is a face region. The final classifier is a weighted sum of these weak classifiers. It is called weak because it alone cannot classify the image, but together with others forms a strong classifier. Then, the image is moved into further steps i.e., the CNN model for emotion classification.

Figure 3: Haar kernels used to extract features

3.4 Emotion Recognition

Once the face is detected it undergoes Emotion recognition. For Express recognition, we are using the CNN model is shown in Figure 4. We are giving an input size of 48*48. Then the input undergoes into the convolutional layer for the feature map. The mapped features again go into the convolutional layer of kernel size 3*3. Then pooling is done on the mapped features to extract the required features from the mapped features. Then here we are using dropout to drop some of the unwanted features. Here the input size is reduced to 24*24. After that, it again undergoes a convolutional layer of kernel size 5*5 for feature mapping on the extracted image. It again continues and pooling, dropout is done on it. After that, it again undergoes a convolutional layer of kernel size 3*3 for feature mapping on the extracted image. It again continues and pooling, dropout is done on it. After that, it again undergoes a convolutional layer of kernel size 3*3 for feature mapping on the extracted image. It again continues and pooling, dropout is done on it. Then it goes to flatten. Here Flatten is used to convert 2D vector into 1D vector. Then goes to the fully connected layer. At last, the image is mapped to its emotion with the help of SoftMax. Here we are using the Relu Activation function. It is used to remove the negative values from an image by replacing them with zeros.

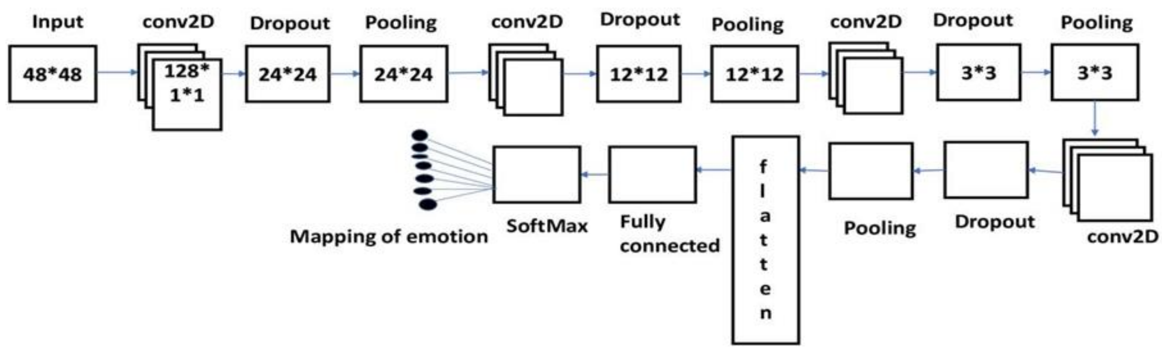

Figure 4: Proposed CNN for emotion recognition

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4. Results and Discussions

4.1 Experimental settings

The tests are run on Windows 10 Pro workstations using NVIDIA Quadro RTX 4000 graphics cards and Python 3.0 as a programming language. The desired data set is first gathered, and then its size is increased utilizing data augmentation techniques. The face object is located using a cascade classifier, and CNN is utilized to distinguish the exact type of emotion.

4.2 Model Training

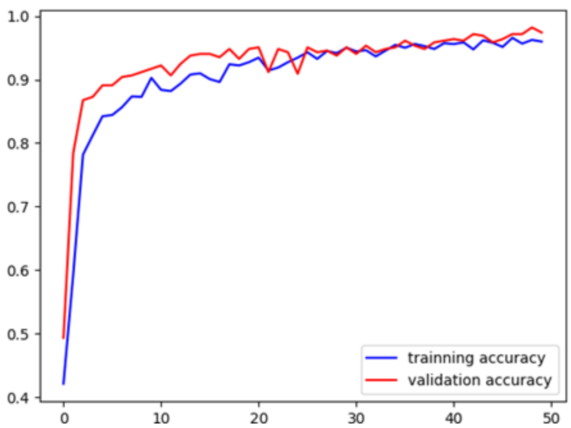
In this experiment cascade classifier is used to locate the human face object. CNN is used to recognize the type of emotion. The parameters used to train the cascade classifier is shown in Table 3. The parameters used to train the CNN are shown in Table 4. The model accuracy and loss charts are shown in Figure 5. The proposed model obtained 98 and 0.094 percent training accuracy and loss, respectively, and 97 and 0.021 percent validation accuracy and loss.

Table 3: Cascade classifier parameters

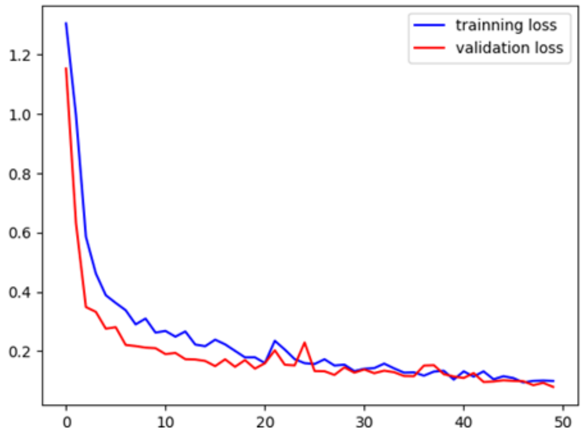
Input size	Positive samples	Negative Samples	Stages	Hit Rate
64 x 64	3000	6000	9	0.998

Table 4: CNN hyper parameters

Input size	Epochs	Batch size	Learning Rate	Optimizer	Classifier
64 x 64	25	64	0.001	Adam	Softmax



(a) Training and validation Accuracy



(b) Training and validation loss

Figure 5: Training and Loss Plots of Proposed CNN

4.3 Evaluation Metrics

In the context of binary classification, **true positive (TP)**, **false positive (FP)**, **true negative (TN)**, and **false negative (FN)** are used to describe the outcomes of a classification model by comparing its predictions with the actual ground truth.

4.3.1 Precision: Precision measures the proportion of correctly predicted positive emotion instances among all instances predicted as positive. It reflects the model's ability to avoid false positive predictions.

$$\text{Precision (Pre)} = \frac{TP}{TP + FP} \quad (1)$$

4.3.2 Recall: Recall, also known as sensitivity, measures the proportion of actual positive emotion instances that are correctly identified by the model. It indicates how well the model captures all relevant positive cases.

$$\text{Recall (Rec)} = \frac{TP}{TP + FN} \quad (2)$$

4.3.3 F1 Score: The F1 score is the harmonic mean of precision and recall, providing a balanced evaluation metric, especially useful when the class distribution is imbalanced.

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad (3)$$

4.3.4 Error Rate (1 − Accuracy): The error rate represents the proportion of incorrectly classified instances relative to the total number of instances.

$$\text{Error Rate } (E_{rate}) = \frac{FP + FN}{TP + TN + FP + FN} \quad (4)$$

4.3.5 Accuracy: Accuracy measures the proportion of correctly classified instances (both positive and negative) out of the total number of instances.

$$\text{Accuracy (Acc)} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

4.4 Testing

To test the model, OpenCV3 is used. Figure 7 depicts the emotion recognition results of the proposed approach. Figure 7(a) shows that the emotion recognized by the proposed model is anger, and it proposes family-oriented films as shown in Figure 7(b) to lessen the anger. Figure 7(c) indicates that the proposed model recognizes happiness as an emotion, and it suggests thriller films, as shown in Figure 7(d), to make people happier. Figure 7(e) shows that the emotion recognized by the proposed model is Neutral, and it proposes Western films as shown in Figure 7(f). Figure 7(g) shows that the emotion recognized by the proposed model is Sad, and it proposes drama films as shown in Figure 7(h). Figure 6 depicts the confusion matrix for predicted vs actual data.

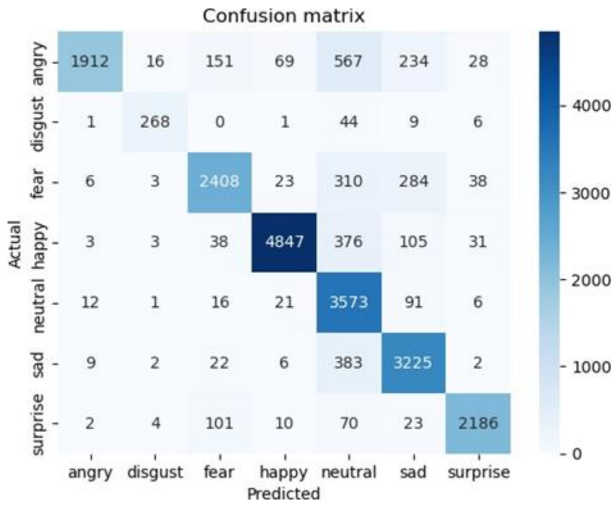


Figure 6: Confusion Matrix

Table 5: Comparative Analysis of Different Models on Dataset [21]

Model / Metric	Precision (Pre)	Recall (Rec)	Error Rate (Erate)	F1 Score (Fsco)	Accuracy (Acc)
Proposed Model	**98.21%**	**97.74%**	**2.26%**	**97.97%**	**98.13%**
Karthikeyan *et al.* [8]	96.86%	97.20%	2.80%	97.02%	97.50%
Pavitha *et al.* [9]	95.47%	94.59%	5.41%	95.02%	96.38%
Liu *et al.* [12]	94.97%	95.30%	4.70%	95.13%	94.99%
Mahadik *et al.* [14]	91.72%	90.59%	9.41%	91.15%	92.19%

Table 6: Comparative Analysis of Different Models on Dataset [22]

Model / Metric	Precision (Pre)	Recall (Rec)	Error Rate (Erate)	F1 Score (Fsco)	Accuracy (Acc)
Proposed Model	**97.12%**	**97.47%**	**2.53%**	**97.29%**	**97.89%**
Karthikeyan *et al.* [8]	95.68%	96.02%	3.98%	95.84%	96.57%
Pavitha *et al.* [9]	96.74%	95.95%	4.05%	96.34%	97.46%
Liu *et al.* [12]	95.79%	96.03%	3.97%	95.90%	96.12%
Mahadik *et al.* [14]	93.27%	91.95%	8.05%	92.60%	93.72%

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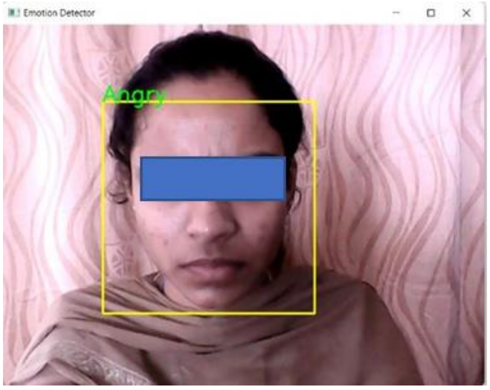
Here the Comparative Analysis of loss and accuracy with respect to the different models. Here we are dealing with the three different CNN models with different number of convolutional layers. Then we are comparing the loss and accuracy of each model and finding the best model.

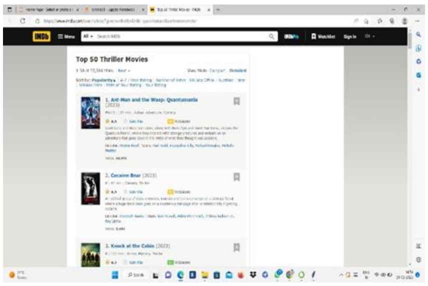
A confusion matrix is a table which is used to know the working of the categorization model. It contrasts the actual class labels of the test data with the anticipated class labels produced by the model.



(a)Angry emotion detected

(b) Movies suggested based on angry emotion

(c) Happy emotion detected



(d) Movies suggested based on happy emotion

(e) Neutral emotion detected

(f) Movies suggested based on neutral emotion

(g) Sad emotion detected

(h) Movies suggested based on sad emotion
Figure 7: Sample outcomes of the proposed model

Conclusions

Finally, the Movie Recommendation System Based on Human Emotions Using Cascade Classifier and Convolutional Neural Network (CNN) shows great promise in improving the user experience by personalizing movie suggestions. The system effectively captures subtle cues and translates them into meaningful recommendations by analyzing human emotions through facial expressions. Cascade Classifier implementation enables accurate and efficient facial expression detection, allowing for real-time emotion recognition. The addition of CNN improves the system's ability to learn and extract features from facial images, thereby improving the precision and reliability of emotion classification. This method has several significant advantages.

For starters, it makes movie recommendations more intuitive and user-friendly by leveraging the natural way humans express emotions. Second, by incorporating human emotions into the recommendation algorithm, the system can better match movie recommendations to the user's mood and preferences, resulting in a more engaging and satisfying viewing experience. Furthermore, the use of deep learning techniques, such as CNN, enables the system to adapt and evolve as more data is collected, resulting in increasingly accurate recommendations. The system's use of Cascade Classifier and CNN allows it to handle a wide range of facial expressions and emotions, making it versatile and adaptable to a wide range of users.

However, there are still opportunities for advancement. To improve the recommendation process and provide a more comprehensive understanding of the user's preferences, the system could benefit from incorporating contextual information such as user feedback and movie metadata. Addressing privacy concerns and ensuring data security should also be priorities to maintain user trust and regulatory compliance. Overall, the proposed EmoFlix has a lot of potential for revolutionizing personalized movie recommendations. The system creates a more empathetic and enjoyable movie-watching journey for users by leveraging human emotions as a vital input, increasing their overall satisfaction and engagement.

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