CONTENT SUGGESTIONS THROUGH TRACKING OF HUMAN EMOTIONS

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **"CONTENT SUGGESTIONS THROUGH TRACKING OF HUMAN EMOTIONS"**, submitted by Md. Mazbaur Rashid, ID No: 192-15-2837 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 4th June, 2023.

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We hereby declare that, this project has been done by us under the supervision of **Shah Md. Tanvir Siddiquee, Assistant Professor, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

The amount of content that is available to consumers has expanded tremendously with the introduction of social media platforms and online content consumption. The vast volume of material, however, makes it difficult to find and suggest customized content that matches users' emotional inclinations. Additionally, a lot of research has been done on human emotion recognition. However, no research on content recommendation utilizing emotion is mentioned. This study offers a novel approach for content suggesting to overcome this problem. It demonstrates the use of CNN (Convolutional Neural Network) to identify facial expressions and recommend contents. Three models—a custom model developed using CNN and two transfer learning models, VGG16 and ResNet50—are employed and explained in this article. The proposed approaches are assessed using a customized dataset that was produced by combining FER2013, CK+48, and some images collected from online. The custom model performed well with higher accuracy, which is 98.05% with less epochs, as compared to VGG16 and ResNet50, whose frequent accuracy values are 97.22% and 82.36%. Last but not least, the model evaluation has been explored with content suggestions, which is the major goal of this work.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Emotions are states of mind. Generally, it is triggered by neurophysiological adjustments, it also can be variably connected to ideas, sensations, behavioral reactions and a level of pleasure or discomfort. There is presently no agreed-upon definition of such a topic in science but emotions and mood, temperament, personality, disposition, and creativity are frequently linked [1].

The inner esoteric fundamental condition of circumstances is described by a feeling. Emotion has a crucial role in many study domains, including psychology, health, biomedical engineering, and even neurology, and it has grown to be a massive research topic [2]. People are consumed by emotions every moment. Some people have difficulty keeping their emotions under control. As a result, they occasionally lose and are compelled to make tough choices.

The suicide mortality rate is the amount of suicide fatalities per 100,000 people annually. suicide rate in general (not age-adjusted). The suicide rate in Bangladesh for 2019 was 3.70, up 2.78% from 2018. The rate increased by 2.86% from 2017 to 2018, reaching 3.60. The suicide rate was 3.50 in 2017, a 2.94% rise from 2016, and 3.40 in 2015, a 0% increase from that year [3]. According to the report, out of the eight divisions in the nation, the Dhaka division has the highest rate of suicide among high school and college students (23.77%). [4]

The demand for technologies that can evaluate a potential customer's needs and select the best solution for those customers is growing drastically as a result of the quick expansion in the usage of smart technologies in society and the growth of the industry [5]. Besides, Digital content is expanding quickly these days, including music, films, games, news, and many other things. Filtering them out is also a difficult question.

Technology is a constant companion of people. The majority of individuals worldwide use technology. Everything has a technological component, even daily essentials like phones and computers. In addition, they favor these common technologies over all others. The camera on these phones or computers enables us to interpret facial data.

We aim to use technology to regulate these emotions so that the machine can recognize a person's feelings and respond appropriately with proper steps and decisions. Artificial intelligence is rapidly advancing and integrating with this technology also. We wish to utilize these benefits by making machines friend of humans.

This research will help machines to interact with humans as a friend. What could be better than this where a machine will understand human emotion and take steps? Another reason is, Google implemented their voice search but didn’t work with emotion. They can also use this as a "Search by emption tracking" system and take this era to the next level. Google can use it on "YouTube", the most popular platform. Also, many other organizations may take advantage of it. Here an example can be: if a device found a person is sad then it will suggest funny content.

To make the research work fine, we proposed a CNN (Convolutional Neural Networks) model. We created this model unilaterally and obtained higher accuracy. A type of Artificial Neural Network (ANN) utilized in image processing or recognition is the CNN (Convolutional Neural Network). It is designed specifically to examine image pixel data. The most beneficial aspect of CNNs is that they allow ANNs to have fewer parameters.[6]

1.2 Motivation

1. Enhanced content suggestions accuracy: The accuracy of content suggestions can be increased by using Convolutional Neural Networks (CNN) to detect and evaluate human emotions. CNNs are highly suited for catching emotional and

delivering more accurate suggestions since they have successfully extracted and understood complicated patterns from visual data.

2. Customized user experience: By recognizing and responding to different emotional states, emotion monitoring with CNNs can offer a more tailored user experience. As a result, users may receive more pertinent and customized content recommendations, which will increase their pleasure and engagement with the platform or service.
3. Improved comprehension of emotional reactions: The study's subject enables a clearer comprehension of the connection between emotions and content choices in people. Researchers may advance the subject of affective computing by using CNNs to evaluate emotion-related data and obtain insights into the nuanced link between emotions and the kinds of information people are likely to find engaging.
4. An innovative approach to content recommendation: A novel and innovative strategy is to use CNNs to propose material based on emotions. Researchers can advance the state-of-the-art in content recommendation systems by using CNN architectures and approaches for emotion monitoring.
5. Enhance user experience and satisfaction: User pleasure and engagement may be increased by the capacity to make content recommendations based on observed human emotions. The algorithm can produce a more engaging and rewarding user experience by recommending emotionally compelling material, building a stronger bond between users and the platform.

1.3 Rationale of the study

Users are overloaded in the current digital environment with numerous content options. To aid consumers in navigating this deluge of information, personalized content recommendation algorithms have becoming more important. The work intends to increase the customization of content suggestions based on users' emotional states by adding emotion monitoring using CNNs, boosting their experience of content discovery and consumption.

The performance of Convolutional Neural Networks (CNNs) in a variety of areas, including as image recognition and natural language processing, has been astounding. The work makes use of CNNs' capacity to monitor and examine emotional information from several modalities, including facial expressions. Therefore, we want to capitalize on this and create something beneficial.

1.4 Research Questions

This effort will address a number of content recommendation issues. Our main objective is to create an effective system that can recognize human emotion and offer content. A list of solid questions that will be addressed at the end of the study is required to direct the effort. Through our efforts, we want to uncover some answers to certain questions we have. It's them,

1. How can emotion analysis using convolutional neural networks (CNNs) be done effectively?
2. What is the connection between a person's emotions and preferred contents, and how can CNNs simulate this connection?
3. How much can CNN-based emotion tracking enhance the accuracy and applicability of content recommendations over conventional recommendation algorithms?
4. Which modalities, such as facial expressions, physiological signals, and textual data, offer the most trustworthy and illuminating indications for CNNs to use when monitoring human emotions?
5. What can be done to improve the efficacy of CNN-based emotion tracking models in predicting content choices based on emotional states?
6. What are the accuracy and personalisation criteria for recommendations using the CNN-based emotion tracking approach?
7. What are the privacy issues and ethical ramifications of utilizing CNNs to track human emotions in order to recommend contents, and how can they be resolved?

1.5 Expected Output

Artificial intelligence, or AI, is remarkably adept at mimicking human intellect and carrying out jobs that were previously exclusive for our species. The potential of AI is expanding daily, defying our preconceived conceptions of what is feasible. Once this research has been completed, we will be able to create a system that can track human emotions and generate content recommendations based on the data gathered. So, the following are potential outcomes:

1. The study is anticipated to lead to the creation of a framework that successfully monitors and evaluates human emotions using CNNs.
2. The development of a sizable and varied dataset that links human emotions.
3. A CNN model that is optimized for content suggestion based on monitored human emotions should result from the research. The model should be able to anticipate content preferences with accuracy and offer tailored suggestions that take into account users' emotional states.
4. The creation of assessment criteria to gauge the effectiveness of the CNN-based content recommendation system is one of the intended results.
5. It is anticipated that the study will produce new information and conclusions about how human emotions and content preferences interact.
6. The study will aim to improve the state-of-the-art in recommendation systems and make a contribution to the field of emotion-based content recommendations.

1.6 Report Layout

Deep learning has substantially impacted the development and progress of artificial intelligence, as described. Through this, it is also described how the usage of user emotional profiles may assist filter out a wide range of contents.

Some background work with a related area has been discussed in the second chapter. While many authors have experimented with emotion detection, they have not used emotion monitoring to manage contents. Additionally, some context was given to enable others who are not experts comprehend our works.

The research methodology portion of the report includes a detailed description of the whole procedure, from gathering data to creating algorithms. This section delves into extensive detail on everything.

In chapter four, we have outlined the findings of our experiment. Additionally described the live preview and the algorithm's or model's performance, including information on factors like accuracy loss and confidence in detection and many more.

Impact on Society, Impact on Environment, Ethical Aspects, and Sustainability Plan will be covered in Chapter five. It refers to the effects of the work and if it will be positive in certain ways. Such inquiries have been addressed and described.

Chapter six of the report, which summarizes what we accomplished, what we discovered, and the direction of our future work, served as the conclusion.

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries/Terminologies

The intricate psychological and physiological condition that develops in reaction to inputs that affects people's ideas, actions, and subjective experiences. Among other things, emotions include joy, sorrow, rage, fear, surprise, and disgust. Deep learning neural networks are created specifically for the analysis of visual data, such as images or videos. Convolutional neural networks (CNNs) are particularly suited for tasks like image identification, object detection, and now emotion recognition because they employ convolutional layers to extract spatial data hierarchically. When gathering, keeping, and using data on users' emotions, there are ethical considerations and privacy issues to take into account. Emotion tracking research should take informed permission, data anonymization, transparency, and user privacy protection into consideration. The basis for comprehending the fundamental ideas and elements pertinent to the study issue is provided by the preliminary terminology. They create a common vocabulary and framework for talking about recommendation systems, emotion recognition, and related fields of study.

For facial emotion recognition, the FER 2013 dataset was used by the majority of the authors. Yet, it is difficult to get decent accuracy with this. Whatever, collaborative filtering, content-based filtering, and hybrid models that mix the two have all been studied in previous research as different methods for tailored content suggestion. To create suggestions, these methods, however, heavily rely on user activity data like clicks, searches, and likes. Although these techniques have proven somewhat effective, they do not account for users' emotional moods or demographic details, which can have a big impact on the kinds of information they enjoy.

By making recommendations that are more individualized and pertinent to users' emotional states. Emotion monitoring has the potential to improve content suggestion systems. To overcome these issues and create reliable systems that can precisely detect users' emotions and offer pertinent recommendations, further study is nonetheless required. We tried to provide a solution to overcome this issue and this paper motivates us in this case.

2.2 Related Works

In the present instance, face identification, feature extraction, and emotion classification were the three key procedures presented by A. Jaiswal et al. For the purpose of extracting emotions from photographs, they have suggested a deep learning architecture based on convolutional neural networks (CNN). The FERC-2013 and JAFFE datasets were employed in this analysis, and the accuracy obtained from each was 70.14% and 98.65%, respectively. 100 epochs of labor were required to get the greatest precision. For the 2 aforementioned datasets, they used 2 different models [7].

Utilizing the FER2013 Dataset was the work of Kusuma Negara et al. They have put out a standalone-based modified Convolutional Neural Network (CNN) that is based on the Visual Geometry Group – 16 (VGG-16) classification model that was pre-trained on the ImageNet dataset and optimized for emotion classification. With 69.40% accuracy, the suggested method performs better than the majority of outcomes from standalone models [8].

M. Kalpana et al. used deep learning techniques to assist in the recognition of emotions. The pre-trained networks utilized include Resnet50, vgg19, Inception V3, and Mobile Net, with the newly added layers being trainable to update the weights. The experiment's average success rate in identifying emotions was 96% when utilizing the CK+ database, and it achieved the maximum accuracy of 98.5% while using the inceptionV3 model [9].

By employing complex characteristics of the Xception algorithm, Jung Hwan et al. suggested a facial image threshing (FIT) machine that improves the FER system performance for autonomous cars. It involves a significant amount of removing unnecessary facial photographs, obtaining facial images, locating lost face data, and merging original data. With the FER 2013 dataset, the recommended method's final FER results improved validation accuracy by 16.95% in comparison to the conventional approach [10].

FERC, a cutting-edge method for recognizing facial emotions using convolutional neural networks (CNN), was introduced by Ninand Mehendale et al. Due to the special 24-digit long EV feature matrix, it operates in orientations (less than 30°) other than vertical. utilizing FERC and an EV of length 24 values, which outperformed Alexnet, VGG, GoogleNet, and Resnet, it was feasible to appropriately highlight the emotion with 96% accuracy utilizing supervisory data from the stored database of 10,000 photos (154 people). Caltech faces, CMU, NIST, expanded Cohn-Kanade expression, and more than 750K photos were used to thoroughly test FERC [11].

Ninaus et al. evaluated the emotional involvement of adult participants executing either a numerical task based on a game or a non-game-based counterpart using both automatic facial emotion recognition and subjective assessments. They were able to determine, with classification accuracy well above chance level, whether a participant was working on a game-based or non-game-based task using a machine learning approach. The average with a 95% quantile of 55.85% classification accuracy demonstrated that the emotionally engaging aspect of games enhances learning [12].

In order to anticipate and recognize facial emotions in real-time, Lutifah Zahara et al. suggested a system that employs the Convolution Neural Network (CNN) method together with the OpenCV library, TensorFlow, and Keras. The three main operations of the system are face detection, facial feature extraction, and facial emotion categorization. The prediction accuracy for facial emotions was 65.97% in research using the CNN technique and Facial Emotion Recognition (FER-2013). Overall, the system's attempt to predict seven human facial expressions from the Raspberry Pi-based FER-2013 dataset was successful [13].

Manoj et.al conducted Literary works which are used to explore emotion detection through various techniques such as 'Viola Jones Face Detection', 'Zernike moments', 'DCT transform' or 'LBP'. Another technique uses convolutional neural organizations for facial emotion recognition. Computer vision has paved the way for emotion detection through inspecting human faces through various algorithms and techniques. There are several different methods for detecting emotions, including FERC, hybrid CNN-LSTM, action units with MLP, and k-NN, although they can all result in decreased accuracy [14].

In a study conducted by Shivam Gupta et al. facial expressions of emotion were fully automatically recognized using machine learning and computer vision techniques. The emotion labels have been updated and confirmed, and every sequence in the datasets has a target expression that is completely FACS coded. Facial landmarks are used to identify faces, and the datasets are trained using machine learning technology (Support Vector Machine) before being divided into eight mood categories. The best outcomes were provided by support vector machines, which had an accuracy of almost 94.1%. This machine learning-based system for emotion identification may be changed into a deep learning system by using convolutional neural networks, which have many layers and the potential to reach substantially greater accuracy [15].

2.3 Comparative Analysis and Summary

Many authors have worked on emotion detection, with different approaches. It is still being worked on. However, suggesting content through emotion detection did not seem to work as well as we are doing. Moreover, by creating a new model, we were able to achieve better performance than the pre-trained models as well as existing works.

Through this work, it will be possible to filter out a wide range of content and present it to people.

2.4 Scope of the Problem

Numerous studies have been done on the issue of facial emotion recognition. This has been under development for a while. The authors have also displayed a number of pieces on topic. Its dataset is continually being improved as well. We began this research, nevertheless, as a means of incorporating emotion into the content as well. The problem's scope includes creating precise methods for sensing facial emotions, integrating such methods with content recommendation system, and customizing content recommendations depending on identified emotional states. Through the use of facial expressions for better suggestions, the emphasis is on improving user experience, engagement, and relevancy of content.

2.5 Challenges

The main difficulty in this study is in gathering precise, useful datasets to work with and in accurately executing the algorithm. Processing the datasets, we have obtained has also been problematic. We had to create algorithms and resize every image to the same size. Another issue we further triggered was the procedure of recommending contents.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

3.1.1 Research Subject

The identification of emotions has long been studied. This has drawn the attention of several study teams and continues to do so. However, none of this includes content recommendations. Therefore, recommending content based on human emotions will be an emphasis.

3.1.2 Instrumentation

The term "instrumentation" refers to the apparatus, procedures, and strategies for gathering data that are employed in research. Considerable instrumentation aspects include the following:

1. Emotion tracking sensors: Make use of a variety of sensors and gadgets to record information about users' emotional states. This can be done via cameras in devices
2. Convolutional Neural Networks (CNNs): Use convolutional neural networks (CNNs) as the main tool for processing and interpreting data connected to emotions. To identify and categorize emotions from facial expressions and fine-tune CNN models.
3. Content recommendation system: Integrate CNN's emotion monitoring skills into a system for recommending content. In order to provide users with individualized content recommendations based on their emotional states, this system should employ the recorded emotions as input.
4. Datasets: Collect and arrange datasets that include emotional annotations and associated content choices. The CNN models and content recommendation system

will be trained on and evaluated using these datasets. The datasets consist of labeled images.

5. Evaluation data: Establish assessment measures to gauge the functionality and success of the CNN-based content recommendation system. Accuracy, performance, testing with data are a few examples of these measurements.
6. Data analysis tools: Process and analyze the gathered data using software platforms and statistical analysis tools. This involve using machine learning algorithms, feature extraction techniques, data preparation techniques, and statistical tests to assess the study hypotheses most of which we have used.
7. Software and other tools: The Anaconda program and Google Collaboratory, an IDE that makes it easy to develop and run Python code, were utilized in the implementation process. These tools are used for the training and testing phases. Other python packages that we utilized include Numpy, Pandas, Scikit-Learn, Matplotlib, OS, and Open-CV etc.

3.2 Data Collection Procedure/Dataset Utilized

In order to increase Accuracy, we built our own dataset. We integrated the FER 2013 [16] and CK+48 [17] datasets with some online image data. After that, we analyzed our data to make sure it was accurate all around. Following preprocessing, we simply extract the features from, make a list of the emotions that will serve as directory names, and then train our algorithm to be able to identify the classes.

3.3 Statistical Analysis

As with the FER 2013 dataset, we intended to maintain every category. We have worked with 7 types of emotions that contain several images that represent each type.

Angry: Anger is defined by facial expressions including furrowed brows, clenched lips, and dropped eyebrows. It frequently brings up sentiments of annoyance, wrath, or exasperation. This class includes 735 images.

Disgust: We have 521 images here. A wrinkled nose, a curled upper lip, and squinting eyes are characteristics of the disgust emotion. It frequently causes nausea, aversion, or feelings of disgust.

Fear: The facial expressions of dread include an open mouth, expanded eyes, and elevated eyebrows. It frequently brings on feelings of dread, worry, or horror. The class contains 712 images.

Happy: The cheerful mood is indicated by physical characteristics including a lifted upper lip, upturned cheeks, and crow's feet around the eyes. It frequently evokes sentiments of happiness, pleasure, or contentment. Here we have 809 images.

Sad: The sad emotion is marked by facial expressions including slack jaw, downturned lips, and drooping eyebrows. It frequently brings up emotions of sadness, grief, or dissatisfaction. This class has 812 images

Surprise: Raised eyebrows, expanded eyes, and an open mouth are characteristics of the surprise emotion. It frequently conjures up emotions of surprise, shock, or disbelief. The class includes 667 images.

Neutral: Lack of overt facial manifestations of emotion characterizes the neutral feeling. It is frequently linked to a lack of emotional reactivity or a calm, detached mood. This has 716 images.

In total the image count for the dataset is 4972.

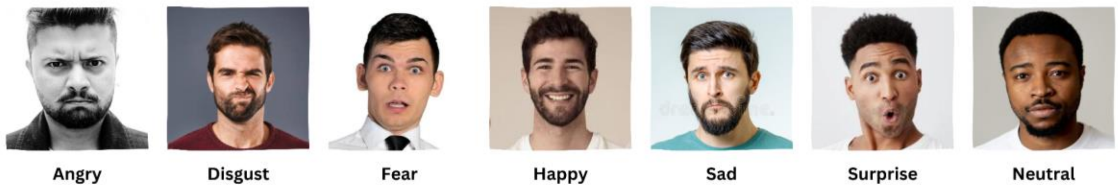


Figure 3.3.1: Dataset

TABLE 3.3.1: DATA (IMAGES) COUNTS FOR ALL THE 7 MENTIONED CLASSES

Name	**Amount**	**Total**
Angry	735	4972
Disgust	521	
Fear	712	
Happy	809	
Sad	812	
Surprise	667	
Neutral	716	

3.4 Proposed Methodology/Applied Mechanism

CNN is used to classify the dataset. This is because deep learning has become a potent machine learning method that integrates several layers of features or data representation and produces state-of-the-art outcomes. The classification, segmentation, and object recognition of images are just a few of the application fields where deep learning applications have excelled. Recently, the effectiveness of fine-grained image classification, which seeks to distinguish subordinate-level categories, has increased [18].

All other models were outperformed by our unique model. Hence, we decided with this model.

We'll employ user face data in our work. By using a facial scan, we will gather information and face data. In order to find patterns and connections between particular emotional reactions and other forms of content, the information acquired through these approaches is then processed using our CNN model. Based on each user's particular emotional profile, this information is utilized to provide customized suggestions for them. Here's an example: If a device detects that a person is depressed, it will recommend humorous content.

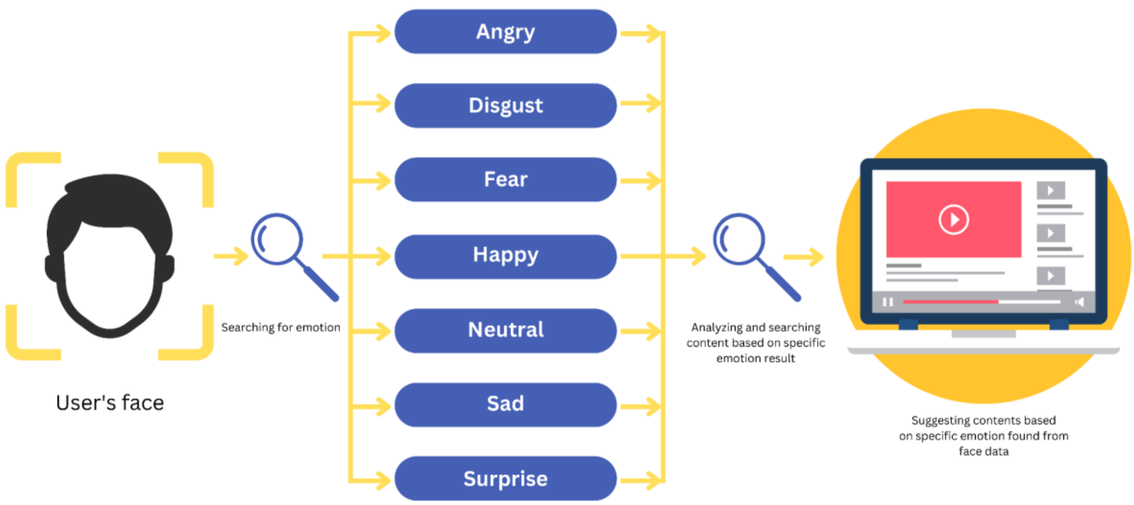


Figure 3.4.1: Method of finding emotion through facial expressions and suggesting content.

To evaluate this model's ability to recognize facial expression or emotion, the camera will capture a video, and each frame that is produced from the clip will be tested with the Model. The following figure shows the general procedure for detecting emotion from frames using the model.

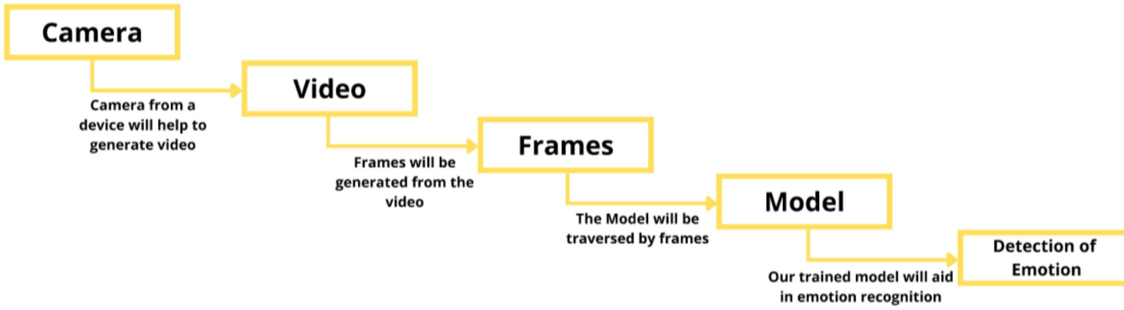


Figure 3.4.2: The method of interpreting frames for emotion using the model

A process should be adhered to and maintained for better works.

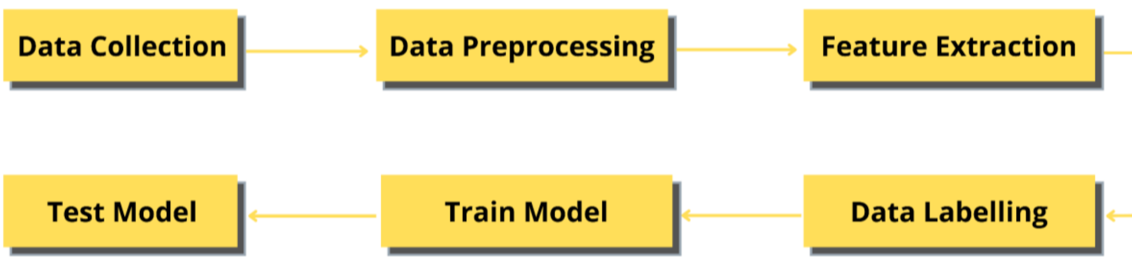


Figure 3.4.3: Workflow Diagram

3.4.1 Data Processing

Seven classes—Angry, Disgust, Fear, Glad, Sad, Surprise, and Neutral—have been used in our research. We have separated them all into several folders based on each class in order to keep them organized. Although the size of the FER 2013 and CK+48 dataset's image size was 48 by 48, but since we collected data from different sources with different sizes, we had to convert all the images to 48 by 48 size to make the machine easy to learn. That's how we have processed our data.

3.4.2 Dealing with Objects

We've already described the dataset of emotion in broad terms. Each image in the system is put into a directory or folder, and each item is identified by the name of the directory or folder. To find them (emotion), a list of similar things that were automatically extracted from the directory names has been created, as shown in table below.

TABLE 3.4.2.1: CORRESPONDENT LABELS OF DIFFERENT CLASSES

Labels	**Classes**
0	Angry
1	Disgust
2	Fear
3	Happy
4	Sad
5	Surprise
6	Neutral

3.4.3 Splitting the Dataset

4972 images from 7 classifications make up the dataset. For better training, these images were divided into batches, with each batch including 32 images. 25% of the dataset was used for testing, while the remaining 75% was used to train the machine. For better analysis, the data set is shuffled over multiple times.

3.4.4 Data Normalization

The process of normalization is frequently used to prepare data for machine learning. The purpose of normalization is to convert the values of the dataset's numeric columns to a standard scale without losing information or distorting the ranges of values [19]. For simpler measurement, images inside the datasets are shrunk and scaled by dividing each pixel by 255. In a description, the pixel values might range from 0 to 255. Each number represents a color code. By using the image as-is and feeding it through a Deep Neural Network, the computation of high numerical values may become more challenging. By standardizing the numbers to fall between 0 and 1, we can reduce this.

3.4.5 Data Augmentation

The process of artificially deriving new data from previously collected training data is known as data augmentation. Methods include cropping, cushioning, flipping, rotating, and resizing. It strengthens the model's performance and addresses problems like overfitting and a lack of data. Recent research has shown that data augmentation (DA) may significantly improve deep learning's (DL) performance through improved accuracy, stability, and reduced overfitting [20]. The images from the data set were rotated both horizontally and vertically using random flip. Moreover, we included random rotation with a scale of 0.2. So, it was feasible to consume anything with high accuracy.

3.4.6 Model

We first tested with VGG16 and ResNet50 to find the best model. A customized CNN model has been developed and it outperformed them in comparison.

3.4.6.1 VGG16

The deep convolutional neural network (CNN) architecture VGG16, sometimes referred to as the Visual Geometry Group 16, has grown significantly in prominence in the area of computer vision. The task of emotion recognition from images has seen extensive use of VGG16. Consequently, we tested this model using the dataset we produced. The dataset's images were scaled to 244 × 244 for improved learning in VGG16.

The VGG16 has 3 fully linked layers and 13 convolutional layers. The use of 3x3 convolutional filters, VGG16's defining feature, allows it to efficiently learn complicated patterns.

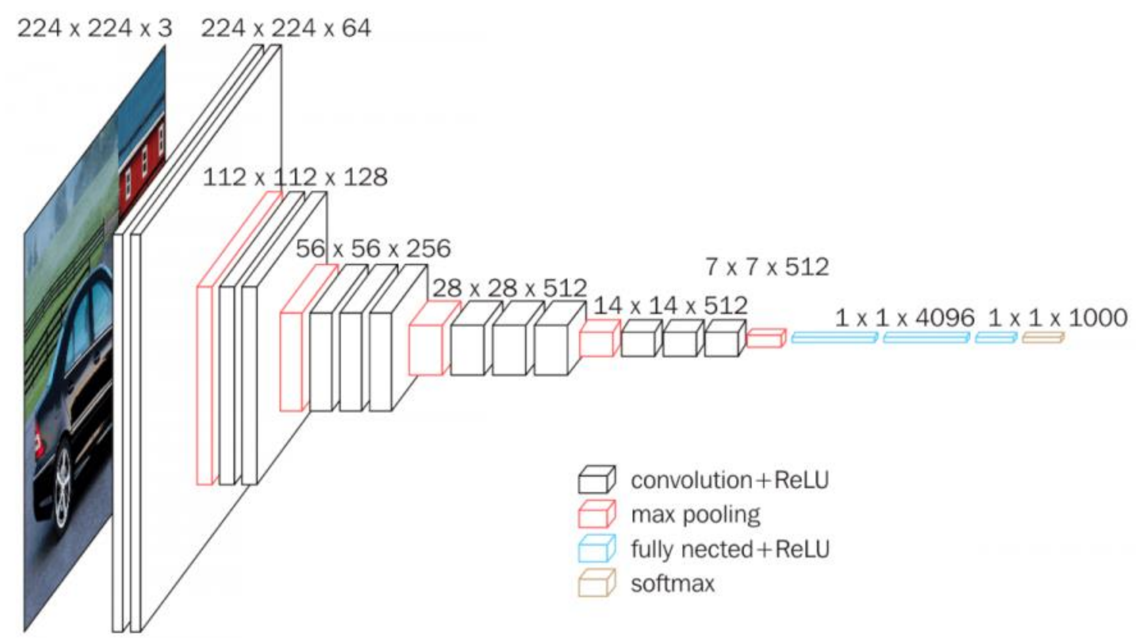


Figure 3.4.6.1.1: VGG16 Model Architecture

Convolutional layers are stacked on top of one another in a sequential sequence by the network to improve its depth. Max pooling layers are also included for down sampling. The VGG16 model has gained widespread use in computer vision applications.

TABLE 3.4.6.1.1: THE MODEL'S SUMMARY UTILIZING VGG16 AS A FEATURE EXTRACTOR

Layer (type)	**Output Shape**	**Param #**
vgg16 (Model)	(None, 7, 7, 512)	14714688
dense (Dense)	(None, 256)	6422784
dense_1 (Dense)	(None, 7)	1799

Total params: 21,139,271

Trainable params: 6,424,583

Non-trainable params: 14,714,688

Overview of the ideas CNN used the VGG16 basic model as its base, and we built our own fully connected layers on top of it.

3.4.6.2 ResNet50

A popular deep neural network design in computer vision is called ResNet-50. It is a member of the ResNet (Residual Network) model family, which is renowned for its capacity to efficiently train extraordinarily deep networks.

The design starts with an input layer that accepts an image with three RGB color channels and a resolution of 224x224 pixels. Convolutional layers that extract features from the input image are added after that. In order to condense the input's spatial dimensions, the first layer conducts a 7x7 convolution with a stride of 2 and is followed by a 3x3 max pooling layer with a stride of 2. Our images have been resized to the input shape the model required.

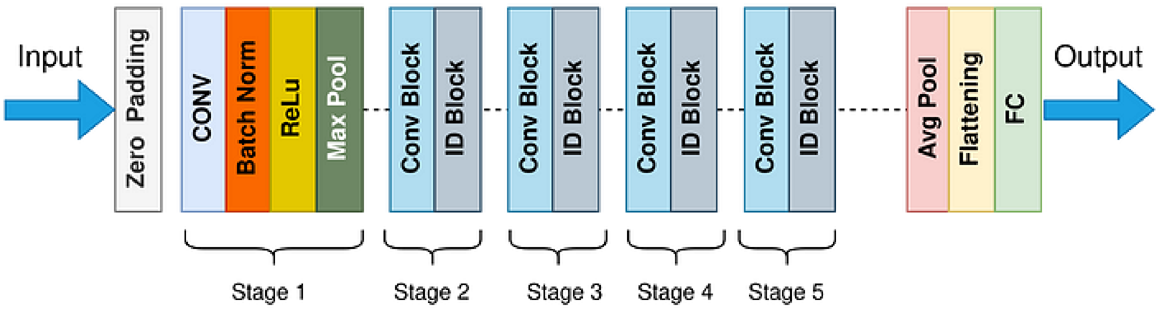


Figure 3.4.6.2.1: ResNet50 Model Architecture

The residual block is the main component of ResNet-50. Each residual block consists of a skip connection after three or more convolutional layers, on average. By skipping a few convolutional layers, the skip connection enables the input to flow directly to deeper layers. As a result, the network may learn residual mappings that account for variations between the block's input and output. By maintaining gradient information, skip connections solve the vanishing gradient problem and facilitate very deep network training.

ResNet-50 learns progressively complex characteristics and patterns from the input picture by stacking numerous residual blocks together. At the very end of the architecture are fully linked layers that use the acquired features to perform classification or regression tasks.

TABLE 3.4.6.2.1: THE MODEL'S SUMMARY UTILIZING RESNET50 AS A FEATURE EXTRACTOR

Layer (type)	**Output Shape**	**Param #**
resnet50 (Model)	(None, 7, 7, 2048)	23587712
dense (Dense)	(None, 256)	25690368
dense_1 (Dense)	(None, 7)	1799

Total params: 49,279,879

Trainable params: 25,692,167

Non-trainable params: 23,587,712

We have added our own fully connected at the top to the ResNet50 base model, similar to VGG16.

3.4.6.3 Custom Model

Our most recent deep learning study revealed that CNN is the most effective approach for computer vision (CV), therefore we utilized it to train our model. The dataset is trained using different CNN multilayers or convolutional neural networks. Four convolutional layers followed by a Maxpooling layer, a flatten layer, and two dense layers make up the network with the greatest performance. as in the figure.

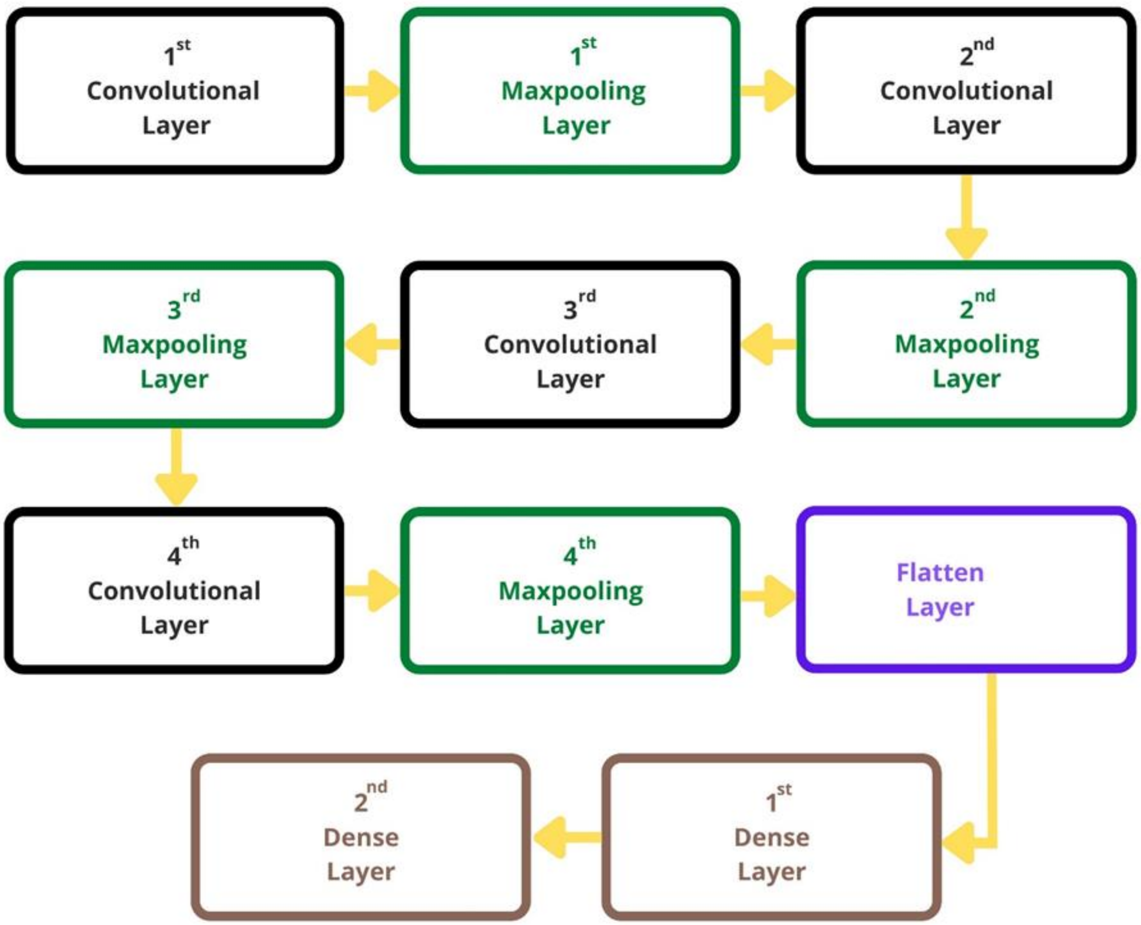


Figure 3.4.6.3.1: Custom Model Architecture

Each convolutional layer's kernel size was 3x3. On different levels, we used various filters. Starting with 32 filters, we progressed to 64, 128 and eventually 256 filters. After each convolutional layer, we used a Maxpooling layer with a pool size of (2x2). We also have used the same padding size in each convolutional layer and default strides of (1, 1).

We utilized a flatten layer to adjust the dimension of the input coming from the convolutional layer, and then we sent it into the dense layer. We employed a single dense layer with 128 hidden units and the same "relu" activation function. The ReLU function equation is (1),

$$ReLU(X) = MAX(0, X) \qquad (1)$$

In a deep neural network, ReLU is typically employed as an activation function for the hidden layers [21]. If the input is negative, this function will return 0; otherwise, it will leave the input as-is.

The output layer was similarly simulated using a dense layer that had four hidden units. We used the "sigmoid" (2) activation function in this layer.

$$S\,(x) = \frac{1}{1 + e^{-x}} = \frac{e^{x}}{e^{x}+1} = 1 - S\,(-x) \qquad (2)$$

A sigmoid function is a real function that is bounded, differentiable, defined for all real input values, has exactly one inflection point, a non-negative derivative at every point, and is bounded and differentiable. Both the term "sigmoid function" and the term "sigmoid curve" refer to the same thing [22].

The "adam" (3) optimizer was used for optimization. Because the Adam optimizer outperforms other optimization algorithms in terms of outcomes, computation time, and tuning parameter requirements [23]. Adam is suggested as the default optimizer for the majority of applications as a result of all of this.

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt[1]{\hat{v_t}}+\varepsilon}\hat{m_t} \qquad (3)$$

By θ(t+1) and θt, respectively, the weights at time t+1 and t are represented. A modest positive constant ε is utilized to avoid division by zero mistake. η controls the learning rate or step size. The starting value of mt is 0, and it stands for the combined gradients at time t. vt, which is likewise initially 0, represents the squared sum of the preceding gradients. The bias-corrected weight parameters ($\hat{m}$)t and ($\hat{v}$)t, rather than the standard weight parameters (mt and vt), are employed.

In order to get the precise loss, we employed the Cross-entropy (4) loss function. Our method uses categorical cross entropy (4) as the loss function, and our investigation showed that it outperforms all other loss functions.

$$L_i = \sum_j \; t_{i,j} \, log \, (p_{i,j}) \qquad (4)$$

The model's output scalar value is called log (pi,j), the loss parameter is called Li, and the target parameter is called ti,j.

3.4.7 Suggesting Contents

Since we worked on research that will suggest content to people based on emotions, we have made the system in such a way that it will suggest some specific randomly selected content to people based on that found emotion from the model.
The following table provides examples.

TABLE 3.4.7.1: CONTENT SUGGESTION BASED ON DETECTED EMOTION

Emotion	Content Type Suggestions
Happy	Comedy shows, motivational speeches, funny animal videos
Sad	Funny videos, drama movies, inspirational videos
Anger	Mindfulness and Meditation Videos, Positive Affirmation Podcasts, Physical Exercise and Fitness Content.

Fear	Guided Meditation, Positive Affirmations, Educational Resources
Disgust	Nature and Travel Photography, Inspirational and Uplifting Stories, Comedy and Humor
Surprise	Unboxing videos, magic shows, unexpected animal encounters
Neutral	Ghost stories, educational videos, sad songs

From the topics in the column “Content Type Suggestions”, the system will randomly choose one suggestion and start to show the content based on the specific emotion.

3.5 Implementation Requirements

We needed a decent system in order to execute this model throughout the entire procedure. Below are the system requirements:

- Hardware:
  - Processor: Core i5
  - Ram: 12 GB
  - GPU: Google Colaboratory Service Provided
- Software:
  - IDE: Jupyter Notebook
  - Language: Python 3.11.3
  - Libraries/Packages: Tensorflow, Matplotlib, Open-CV, Pandas, Keras etc

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The architecture of our model and other specifics has been discussed. It's time to assess the three models that have been presented. In this section, we'll test each model, analyze the results, and then choose one to use for additional testing, such as determining how well it predicts emotion and suggests content. We took 80% of the entire dataset to train the machine and 20% to test. So, from the total 4972 images from the whole dataset 3978 images were used for training the machine and on the other hand 994 images were taken for testing the machine.

4.2 Experimental Results & Analysis

We have evaluated the model with a learning curve and testing with random images to justify the prediction of the machine.

4.2.1 Learning Curve

A learning curve, also known as a training curve, is used in machine learning to compare the ideal value of a model's loss function for a training set to the same loss function evaluated on a validation data set with the same parameters as the ideal function. During training, learning curves can be plotted following each update. A training dataset and a holdout validation data set are used to assess the models.

4.2.1.1 VGG16 Model

We attempted to view the results in VGG16 with the epochs set to 50. It is clear from the learning curve that the pace occasionally increased and occasionally dropped. it led to overfitting. The model exhibited 95.10% test accuracy and 97.22% training accuracy.

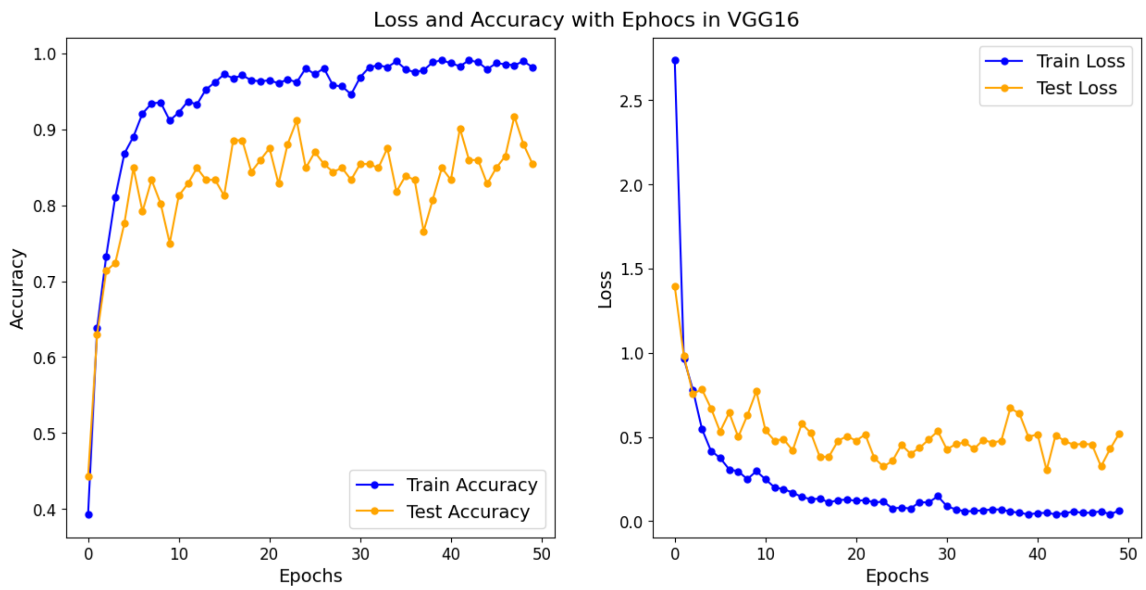


Figure 4.2.1.1.1: Learning curve for VGG16 model

4.2.1.2 ResNet50 Model

Similar to VGG16, when the epochs were 50, this example also yields the same outcome, as seen in the accompanying illustration. The model demonstrated 82.36% training accuracy and 79.20% test accuracy.

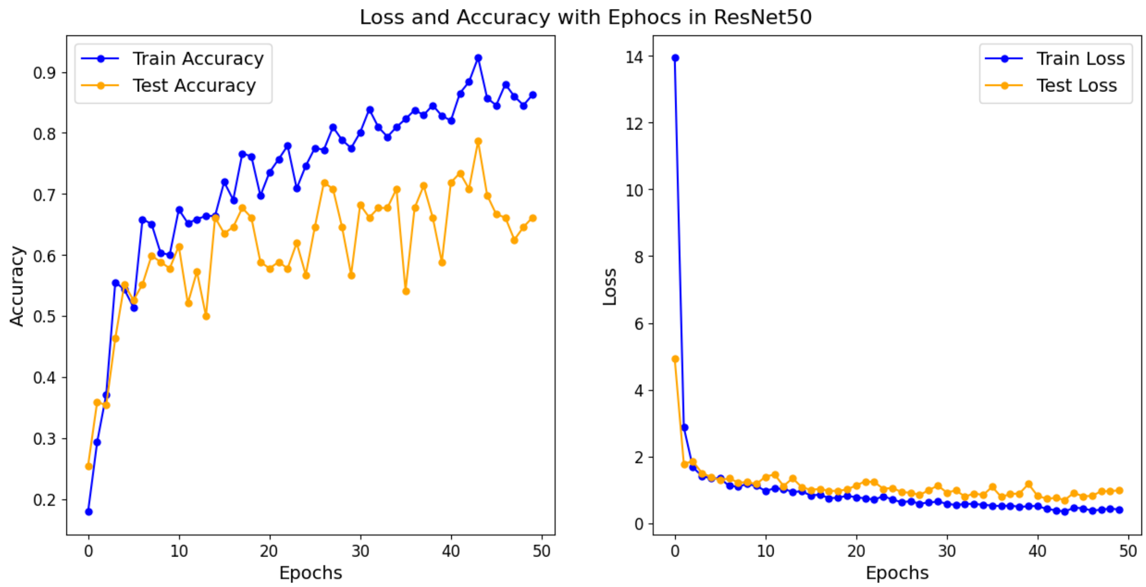


Figure 4.2.1.2.1: Learning curve for ResNet50 model

4.2.1.3 Custom Model

Finally, we have conducted comparable tests on our custom-built model. We lowered the number of epochs to 15, and it worked well since we discovered that after 15 epochs, the accuracy stays constant.

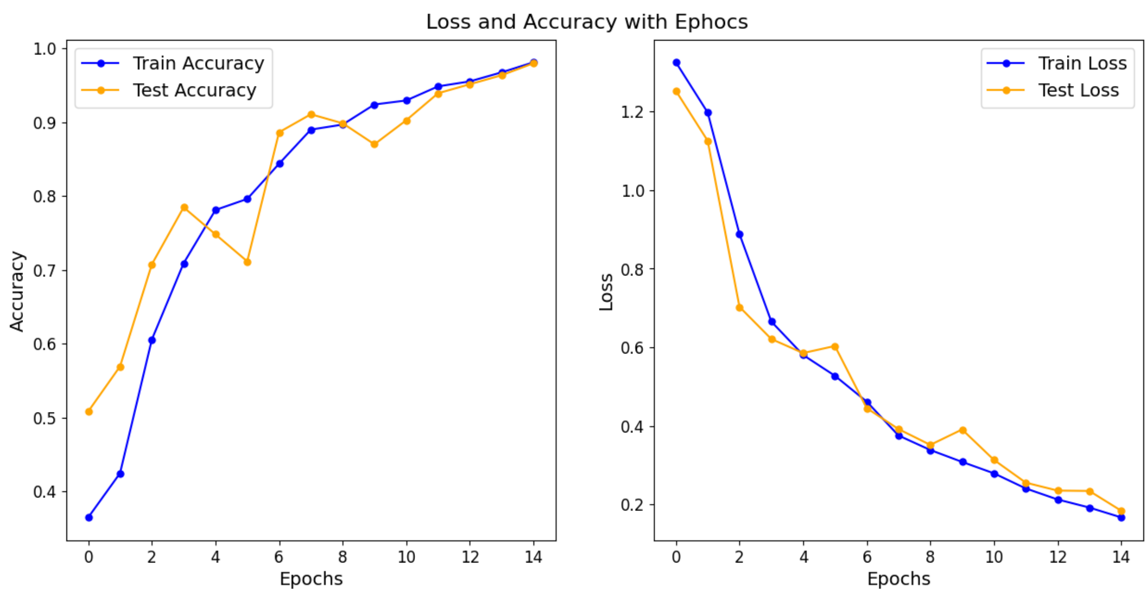


Figure 4.2.1.3.1: Learning curve for custom model

This learning curve demonstrates that neither underfitting nor overfitting issues exist with our model. Over time, the model stabilized and gained accuracy. As the custom model performed well, we evaluated the rest with this well performed model.

4.2.2 Prediction

As the custom model performed well, we have tested the model with some random images to check if it can detect the emotion correctly and suggest content.

The model's prediction accuracy was evaluated with a set of random images for testing. 12 images were used to evaluate the model's input, and the model correctly predicted the results. In the following figure, the outcome is displayed together with the Actual Label, Predicted Label, and the confidence.

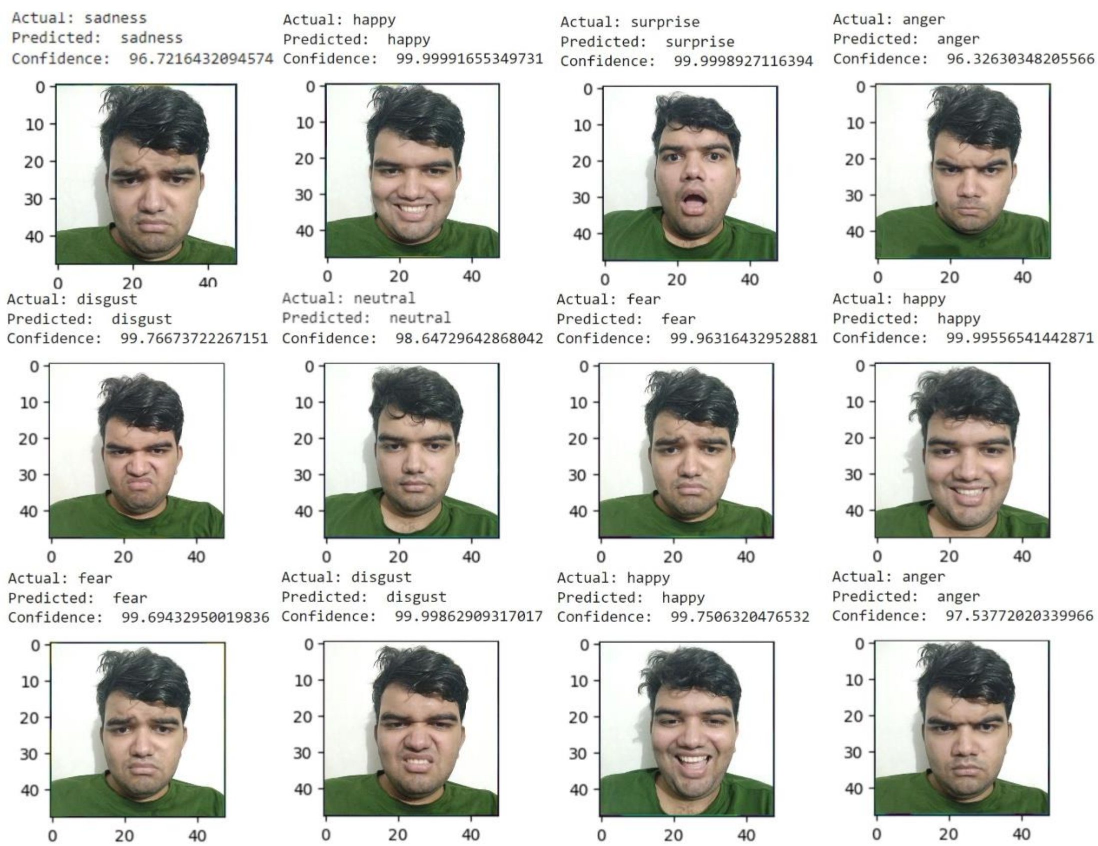
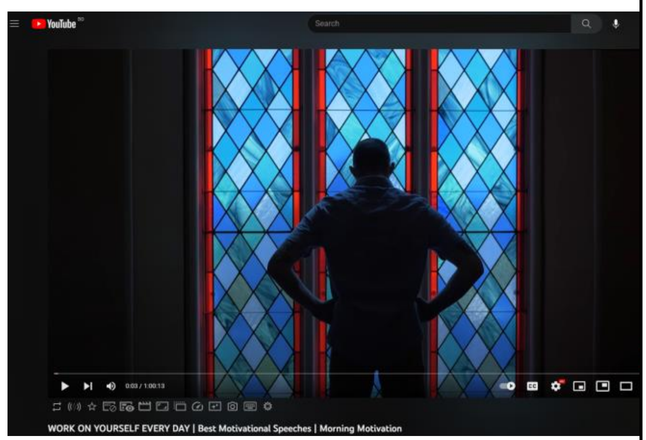


Figure 4.2.2.1: Prediction Result

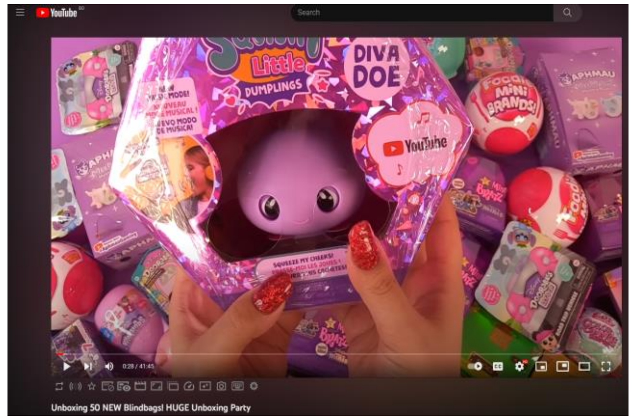
4.2.3 Suggesting Contents

The system is tested by recommending and playing content in accordance with the predictions of the model. On the basis of the forecast outcome, YouTube initially picked to play content. Based on the type of emotion that is anticipated, a content subject is chosen at random from the Content Type Suggestions column in table below.

TABLE 4.2.3.1: SUGGESTING LIVE CONTENT BASED ON EMOTION

Emotion	**Selected Type of Content by the system**	**Displayed Content**
Happy	Motivational speeches	
Sad	Inspirational videos	

Anger	Physical Exercise and Fitness Content	
Fear	Guided meditation	
Disgust	Nature and Travel Photography	

Surprise	Unboxing videos	
Neutral	Educational videos	

For choosing random topics from the Content Type Suggestions column, random (random()) function is used which helps to select random topics from an array created by users.

To play videos on YouTube, ‘pywhatkit’ library is used which is mostly used for YouTube automation [24]. It is able to play any videos on YouTube just using some commands. For an example whenever it gets a topic to play like ‘Educational Video’, it will automatically play that type of video on youtube

4.3 Discussion

We ran all further tests using the custom model because it outperformed the two previously mentioned models and saw that the system could properly recommend content.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

By boosting user experiences, supporting mental health, building empathy, enabling personalized marketing, enhancing education and treatment, and resolving privacy and ethical issues, the work has the potential to have a beneficial influence on society.

1. **Personalized User Experience:** Online platforms and applications may improve the user experience by offering customized content catered to users' emotional states by employing facial expression monitoring and content suggestion algorithms.
2. **Mental Health and Well-being:** Our mental health and well-being are greatly influenced by our emotions. Finding people who could be going through emotional discomfort or having mental health problems might be made easier with the capacity to detect and recognize facial emotions and can be entertained by recommended content.
3. **Emotional Awareness and Empathy:** The use of face expression tracking can help society become more emotionally aware and empathic. Users who engage with content that speaks to their emotional states may grow to comprehend both their own and other people's emotions more fully.
4. **Customized Marketing and Advertising:** Marketing and advertising tactics can be strongly impacted by suggestions for emotional content. Advertisers may increase the success of their campaigns and better the overall customer experience by customizing their commercials and promotional content to fit the emotional states of the target audience.
5. **Educational and Therapeutic Applications:** In educational and therapeutic contexts, the use of emotions tracking and content recommendation algorithms might be beneficial. In order to improve learning results, educational platforms can modify how their content is delivered based on how emotionally engaged

their users are. To customize interventions or therapies and offer support to people with mental health issues like anxiety or depression, therapeutic applications might use emotional monitoring.

5.2 Impact on Environment

By encouraging energy efficiency, lowering information overload, influencing sustainable behaviors, and encouraging digitalization, this research has the potential to indirectly affect the environment and create a more environmentally conscious digital ecosystem.

5.3 Ethical Aspects

There are various ethical issues with CNN-based facial emotion recognition. First and foremost, privacy issues arise with the usage of face recognition technologies. The right to privacy and individual autonomy must be respected. It is essential to get participants' agreement after fully educating them about how their facial data will be collected, stored, and used. It is crucial to preserve privacy through secure data management, anonymization, and data protection procedures. Algorithms for content recommendation and facial expression monitoring must take into account the possibility of biased results or discriminating consequences. Algorithm design, training data selection, and algorithmic decision-making procedures should all be done with care to ensure justice and equity. Users should have access to their data, be able to change their settings, and be able to choose not to have their facial expressions tracked. We propose using a search button with user consent to utilize their facial output as an emotion and search for material in order to keep the ethical elements.

5.4 Sustainability Plan

The system has to be trained with new data in order to continue operating successfully. To enable the system to learn on its own, steps need be done. In addition, steps should be taken to guarantee the algorithm's accuracy. To assist discover and handle any new ethical or sustainability issues, make the system constantly monitored and improved. The system may be improved and continued adherence to moral and sustainable standards can be ensured by conducting regular audits, feedback loops, and user surveys.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Our primary goal was to develop a system that could recommend content by identifying human emotions. Many people have dealt with emotions, but no one has used them to propose contents. The two top models from transfer learning were chosen by us, and we also developed a model on our own. The custom model performed well once we compared the models. Finally, we tested the new model by making some emotion predictions and content suggestions.

6.2 Conclusions

A fascinating and creative strategy that has the potential to alter the way we consume content is content suggestion by tracking human emotion. Personalized content that is more likely to connect with the user and elicit a positive emotional reaction may then be suggested using the data collected. Through this project, machines may tend to our feelings and support us through our misery.

Although this strategy undoubtedly raises privacy issues, it's vital to remember that people already provide a ton of sensitive data online. Also, people will have a manual control while providing their personal data for tracking emotion. For many people, it could also be a reasonable trade-off if this data can be utilized to improve their experience consuming content. To guarantee that users' privacy is protected, it is crucial that the right protections and moral standards are established in place.

The potential advantages of content recommendation based on the analysis of human emotion are substantial, and they include better user engagement, more content consumption, and more successful content marketing. It will be interesting to observe how this strategy develops and gets incorporated into our daily lives as technology advances.

6.3 Implication for Further Study

We have constructed the dataset with previously stored datasets and image. For better detection, Different data or images are needed for improved detection. There are many distinct ethnic groups in the globe. The dataset and the algorithm must be able to recognize as many different types of human faces as possible in order to detect emotion.
Additionally, efforts must be made to increase accuracy as much as the model is capable of.

We have used a random selection of contents from a predetermined range in our work, but we will switch to a machine learning algorithm in the future because various age groups have varying preferences for content, so gender and age will also be taken into account. In order to train the machine, we will create a dataset of people's ages, genders, and emotions. Based on this dataset, the machine will first recognize age, gender, and emotion from faces before predicting the result of suggested contents and display it.

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APPENDIX

Appendix A: Related Issue

While working on this project, we ran into a few problems. mostly in the gathering and processing of data. Images of various sizes must be processed and converted to the same size. Additionally, while we built the model, we regularly experimented with different parameters in an effort to improve accuracy. To work with the model, we had to learn about CNN and models and many more.

CONTENT SUGGESTIONS THROUGH TRACKING OF HUMAN EMOTIONS

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