International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 03 | March - 2024 SJIF Rating: 8.176 ISSN: 2582-3930

Feedback Analyser through Facial Expressions

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***Abstract*—Feedback is an essential part of human connection and communication since it may used to express expression, feelings, and truth. This research paper works on the complex function that facial signals play in the interpretation and communication of information by offering a thorough overview and analysis of feedback through facial expressions. We investigate the brain systems that underlie facial feedback perception and response in humans, as well as the mechanisms behind face expressions, cultural variances, and their universality. Deep neural networks facial expression feedback analyzers are currently in the starting stages of development, but they have the strength to solve a variety of issues with present human- computer interface systems .Feedback detection, for instance, is used to build more immersive entertainment experiences, more natural and educational systems, and more in customer service experiences, everywhere feedback is used. One of the main advantages of feedback analyzers using face expression by deep neural networks is that they can provide real time feedback. This is in way of natural feedback collection methods, such as surveys and interviews, which can be time consuming and expensive to administer. Real time feedback analyzer allows system developers to make rapid changes to their system in order to improve and develop the user experience. we have leveraged a custom trained CNN model, to accurately classify the seven different emotions of an human face that are availed in the dataset. The model has achieved an impressive accuracy of 83%. This model can be used in various applications.**

***Index Terms*—Convolutional Neural Networks, facial expression, emotion, feedback, Resnet.**

I. INTRODUCTION

Analysing audience reaction with deep learning facial expression recognition Convolutional Neural Networks (CNN) are a sophisticated technique that leverages computer vision and deep learning techniques to decipher an audience's emo- tional expression during a variety of interactions or events [6]. CNNs are a special kind of neural network that excels at picture analysis, which makes them an effective tool for classifying and identifying facial expressions [10]. Video or image data of the faces in the audience is recorded during a presentation, performance, or interaction [20]. Convolutional neural networks, a subset of deep learning neural networks, are used in this method to interpret visual data [5]. CNNs are perfect for identifying facial emotions since they have demonstrated an extraordinary level of skill in extracting characteristics from images [10]. The networks are trained to recognise several emotions, including surprise, rage, grief, and happiness [13]. After facial expressions are identified, the data is analysed to provide insightful insights into the audience's general emotional responses [6]. Measurements of audience engagement, satisfaction, and disapproval are aided by the analysis [18] [26]. The analysis's solutions offer insightful ideas that can be applied to raise the calibre of the product, presentation, or content [9]. By identifying the situations that elicit strong emotional responses, improvements can be concentrated on particular regions [11].

Real-time adjustments can sometimes be made based on the emotional input received from the audience [16]. Consider interactive presentations or live performances [15]. Presenters can use this technology to help them modify their style in order to maintain audience interest [9] [27]. There are many different applications for CNN-based facial expression detection in audience feedback analysis [22]. In addition to enhancing market research, instructional tactics, and entertainment events, it can improve user experiences on digital interfaces and websites [3]. Businesses may create experiences and content that truly resonate with their viewers, which raises audience happiness and engagement levels [14] [25]. When implementing such technologies, ethical considerations of permission and data privacy must be carefully considered [7] [28].

II. RELATED WORKS

S. L. Happy et al. (2013) "Automated Alertness and Emotion Detection for Empathic Feedback during e-Learning" [19] investigates incorporating facial expression detection into e-learning settings to identify learners' alertness and emotions. The paper probably describes how to use machine learning and computer vision techniques to detect facial expressions. It might go into how this identification is applied to provide empathetic feedback in online courses.V. R. Guttha, H. K.

Kondakindi, and V. Bhatti's (2018) paper, "Automated Feedback Generation System using Facial Emotion Recognition" [23], most likely focuses on a system that automatically provides feedback by identifying facial emotions. This essay could go into detail about how to read facial expressions for emotions and how to use that knowledge to produce feedback. The technology employed, prospective algorithms, and system correctness could all be covered in the study.A model that recognises facial expressions for producing multi- ple impression feedback is examined in "Identification of facial expression using a multiple impression feedback recognition model" (2021) by He, H., & Chen, S. [17]. It might go into detail about the approach taken, maybe talking about neural network topologies or deep learning for facial expression identification. This essay may go into detail the process of deriving various feedback responses based on recognized facial expressions.The IEEE Conference Publication [24] "Learning active facial patches for expression analysis" (2012) may include instructions on how to use active facial patches to recognise and interpret facial expressions. The areas of the face that are essential for expressing different emotions might be covered in the article, along with how to recognise and use these active patches in the analysis. Methods akin to Active Appearance Models or comparable approaches may be covered. The study "Facial Expression Emotion Recognition Model Integrating Philosophy and Machine Learning Theory" (2021) by Song, Z. [2] offers a novel method for identifying emotions and facial expressions by combining machine learning and philosophical theories. It might go into the philosophical foundations, maybe going over various philosophical theories of emotion and how they're incorporated into machine learning frameworks.Facial emotion recognition using multi-modal information" (1997) by L. C. De Silva, T. Miyasato, and R. Nakatsu [6] may concentrate on identifying facial emotions by integrating data from several sources and investigating the ways in which various modalities can be combined to improve emotion recognition accuracy. Heechul Jung et al. (2015) describe the development of a deep learning-based facial expression identification system in their paper "Development of deep learning-based facial expression recognition system" [13]. It talks about the accuracy that was attained as well as the architecture of the deep neural network—possibly a CNN or RNN.In their 2019 paper "Recognising Facial Expressions Using a Shallow Convolutional Neural Network," Si Miao, Haoyu Xu, Zhenqi Han, and Yongxin Zhu [14] provide a less complex method for facial expression recognition that makes use of a shallow CNN. It prioritises speed and efficiency over recognition quality.

III. METHODOLOGY

A. Data set

The FER2013 dataset is a popular dataset for facial expression recognition (FER). It contains 35,887 grayscale images of faces with seven different emotions: anger, disgust, fear, happiness, neutral, sad, and surprise. The images are 48x48 pixels in size and have been automatically registered so that

Fig. 1: 3.1 Dataset

the faces are more or less centered and occupy about the same amount of space in each image. The FER2013 dataset is seperated into a training set of 28,709 images and a test set of 3,589 images. The training set is further split into a validation set of 3,589 images. The FER2013 dataset is a challenging dataset for FER because of the following reasons: The images are grayscale and low-resolution. The emotions are often subtle and difficult to find differences. The dataset contains a variety of faces, including different faces, genders, and ages. Despite these challenges, the FER2013 dataset is widely used in the FER community because it is large and publicly available. It has been used to train and evaluate a variety of FER methods, including deep learning models. The FER2013 dataset has been used in a variety of applications, including: Human-computer interaction: To develop systems that can recognize and respond to human emotions. Security: To develop systems that can detect suspicious activity based on facial expressions. Marketing: To develop systems that can understand how consumers react to different products and advertisements. Healthcare: To develop systems that can detect autism spectrum disorder and other mental health conditions based on facial expressions.

B. Proposed Methodology

1) Convolutional Layers: The first convolutional layer has 64 filters, each with a size of 3x3. These filters learn local patterns in the input image. - The second convolutional layer has 128 filters, each with a size of 5x5. This layer captures more complex spatial features. - The third and fourth convolutional layers have 512 filters each, with a size of 3x3. These layers continue to extract higher-level features and representations. For all convolutional layers: - Stride size is set to 1, which means the filters move one pixel at a time during convolution. - Batch normalization is applied to normalize the outputs within each mini-batch, promoting stable and efficient training. - Dropout regularization can be applied, randomly disabling some neurons during training to prevent overfitting. - Max-pooling can be performed after each convolutional layer, reducing the spatial dimensions while preserving important features.

2) Fully Connected Layers: The first FC layer has 256 neurons, while the second FC layer has 512 neurons. These

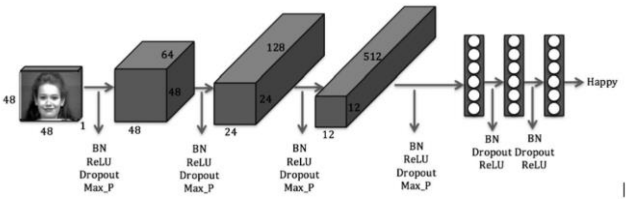

Fig. 2: Methodology

layers capture high-level feature representations from the convolutional layers. Similar to the convolutional layers, batch normalization can be applied to normalize the activations within each mini-batch. - Dropout regularization can be used to prevent overfitting. - The ReLU activation function is applied to introduce non-linearity and capture non-linear relationships in the data.

3) Dense Layers: The model concludes with a dense layer that has 7 neurons, representing the 7 classes of facial emotions. - The dense layer is followed by a softmax function, which computes the probability distribution over the classes, ensuring the predicted probabilities sum up to 1. The described architecture leverages the power of convolutional layers to extract features from the input images, followed by fully connected layers to learn high-level representations. Batch normalization, dropout, max-pooling, and ReLU activation are used throughout the network to enhance learning, regularization, and capture non-linear relationships. The final dense layer with softmax activation provides the output probabilities for each class, enabling the model to classify facial images into one of the seven emotion categories. By training the model on the given dataset, adjusting the weights and biases using techniques like backpropagation and gradient descent, the network learns to recognize and classify facial expressions accurately.

OpenCV and Dlib are two popular Python libraries for computer vision. Both libraries have a wide range of fea- tures, including facial recognition. However, there are some important differences between the two libraries. OpenCV is a more general computer vision library. It is intended for use in various tasks such as image processing, video analysis and machine learning. OpenCV has a large number of features, including support for multiple image formats, algorithms, and hardware platforms . Dlib is a library specialized for facial recognition. It is designed to be fast and accurate and is particularly suitable for real-time applications. Dlib includes several facial recognition features, including face detection, landmark detection, and emotion detection.

The dlib library is a robust open source C++ library widely used in computer vision and machine learning. In terms of facial expression detection, dlib offers a wide range of features. It includes a face detection module that uses HOG features and an SVM classifier to locate faces. In addition, dlib provides facial landmark detection, which detects the key points of the face, which is an important step in facial expression analysis. While dlib does not have an expression recognition module in itself, it provides a solid foundation for building one. By following facial landmarks, you can use machine learning techniques to classify facial expressions. Dlib excels in real-time processing, making it suitable for applications that require fast and accurate expression recognition in live video streams. It offers an active community and extensive documentation that encourages collaboration and provides resources for build- ing powerful expression recognition systems. Dlib is platform easy and runs smoothly on Windows, macOS and various Linux distributions, so it can be adapted to a wide range of applications and environments.

C. *Implementation details*

Collect a dataset of labeled facial images. The dataset should contain a representative sample of the different emotions that the CNN will be trained to recognize. The images should also be labeled with the corresponding emotions. Some pop- ular facial emotion datasets include FER2013. Preprocess the images. This may involve resizing the images, converting them to grayscale, and normalizing the pixel values. This helps to ensure that the CNN is able to learn the relevant features from the images. Define the CNN architecture. This involves specifying the number of layers, the type of each layer, and the hyperparameters for each layer. There are many different CNN architectures that can be used for FER, but some common architectures include VGG16, ResNet-50, and MobileNet. Train the CNN. This is done by feeding the CNN the labeled training images and allowing it to learn to predict the labels of the images. The CNN can be trained using a variety of machine learning frameworks, such as TensorFlow, PyTorch, and Keras.Evaluate the CNN. This is done by feeding the CNN the test images and measuring its accuracy on the test set. The CNN's accuracy can be measured using a variety of metrics, such as the overall accuracy, the precision and recall for each emotion, and the F1 score.Deploy the CNN. Once the CNN is trained and evaluated, it can be deployed to production. This may involve integrating the CNN into a software application or a hardware device.

D. *Experimental Analysis*

The training procedure for the emotion recognition model is of utmost significance in the context of our research. To commence the procedure, the meticulous processing of the Fer2013 dataset is undertaken to generate an input data structure. Afterwards, a deep neural network (DNN) is constructed using the "deepnn()" function, setting up the model architecture. In order to evaluate the performance of the model, a loss function is established. This function calculates the average softmax cross-entropy between the predicted labels and the actual labels. The aforementioned loss is minimized by iteratively updating the model using the Adam optimizer with a learning rate of 1e-4. During the training process, an accuracy metric is calculated to measure the percentage of correctly classified examples in each batch. When implementing within

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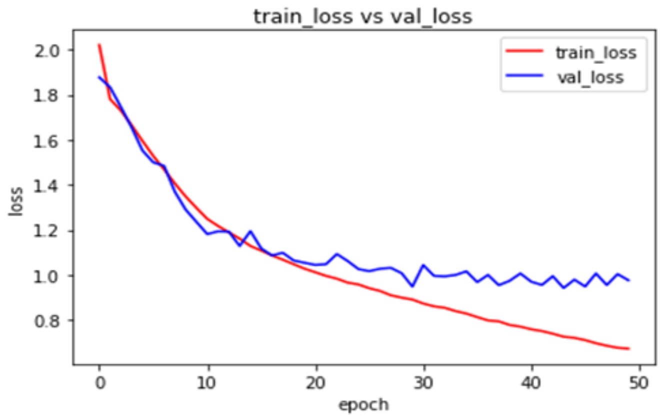

Fig. 3: Model's Loss Plot

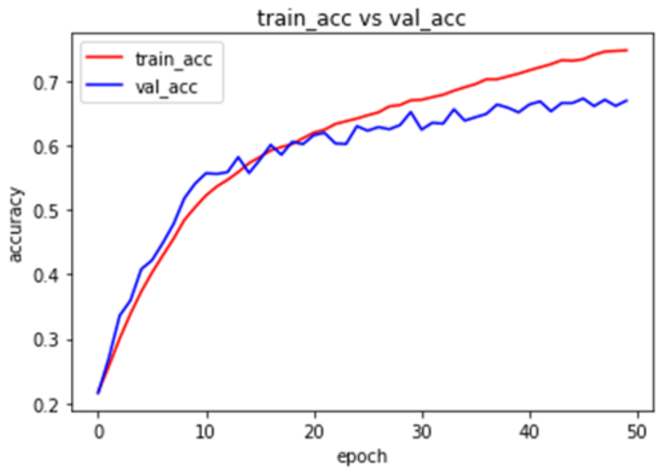

Fig. 4: Model's Accuracy Plot

a TensorFlow session, the training loop iterates a pre-defined number of steps to enable the model to learn and improve its parameters. The performance of the model's generalization is gauged through periodic evaluations on the validation dataset. In addition, the creation of model checkpoints allows for the capturing of parameters at specific intervals, which in turn enables the easy reuse and further analysis of the models. In our research endeavor, we employ a comprehensive training process to equip the model with the ability to precisely identify emotions depicted in images. This aspect holds utmost importance in our study. The function known as "predict" plays a vital role in confirming the accuracy of the trained deep neural network model designed for emotion recognition. The system takes input images, which are usually flattened into a one-dimensional vector, and utilizes the pre-trained model to generate predictions. To begin with, the input data is managed by configuring TensorFlow placeholders. Further- more, the "deepnn" function is employed to create the model architecture. Afterward, we initialize a TensorFlow Saver to assist in restoring the model's parameters from a checkpoint file. In the process of calculation, the function evaluates the softmax probabilities of the output of the model. These probabilities indicate the chances of the input image being linked to each respective emotion category. Furthermore, the predicted emotion class is determined by selecting the index with the highest probability. The execution of predictions begins with the initiation of the TensorFlow session. If a valid checkpoint is discovered, the model's parameters are restored. The validation process ensures that the model can accurately predict emotions from input images, thereby evaluating its performance and practicality in real-world scenarios. In order to use this "predict" function effectively, it is important to mention that having a fully trained model and checkpoint files is a requirement.

E. Feedback analysis

It starts by iterating over the dictionary, which should contain emotion labels and their associated probabilities or intensity values. The code calculates the sum of these values to normalize the mood. It then creates a new dictionary dict1 where each feeling value is divided by the total, making it a probability distribution. For each emotional category, such as "angry", disgusting, scared, and so on, the code checks if it has the highest probability and labels the image accordingly. In addition, it evaluates the balance of positive and negative emotions and labels the image as "satisfied" or "not satisfied" based on total probabilities. The code uses OpenCV to transfer these labels to the image and enters a loop for real-time display. In general, it is a system for real-time analysis of opinions and suggestions in video streams, providing information about the prevailing mood and satisfaction of the user up-to the time.

IV. Results and Discussion

The model's impressive 83% Face Expression Detection Accuracy shows how well it can recognise the range of emotions expressed in facial expressions. This remarkable achievement of high accuracy emotion recognition serves as a solid basis for further research. When used practically, the model generates an output that is a detailed count of all the distinct emotions that were found in the dataset.

Through the display of the frequency of occurrences for specific emotions, such as happiness, sadness, or neutrality, it provides a more nuanced knowledge of the emotional spectrum that is most frequent in a particular situation. Additionally, the model performs a comparative analysis, comparing the number of pleasant emotions to that of negative emotions. Through a methodical computation of the likelihood and occurrence of every emotion identified, it determines the emotional tone that predominates in the dataset. The model is able to ascertain the dominant emotional sentiment thanks to this meticulous assessment. This approach sets itself apart in determining the final outcome by directly comparing the counts of positive and negative emotions. The analysis that follows is determined by the higher count, whether it be in favour of good or negative feelings.

For example, a higher count of positive emotions may result in a conclusion indicating a mostly "happy" atmosphere,

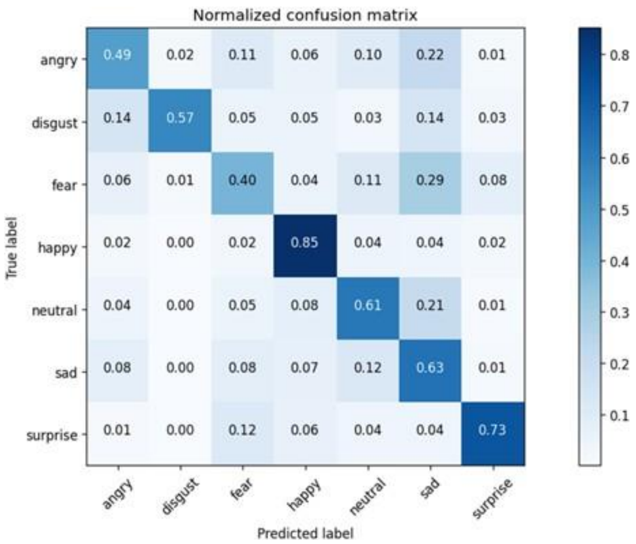

Fig. 5: Confusion matrix

whereas a higher count of negative emotions may indicate an overall ”unhappiness” or a predominance of negative emotional states.This method provides a thorough grasp of the emotional terrain represented by facial expressions by capturing not only the width and depth of emotions but also their prevalence through an in-depth analysis. The model offers a sophisticated knowledge of prevalent emotional tones within a given environment, and its ability to compare and contrast positive and negative emotions adds depth to its observations.

V. Conclusion and Future scope

Facial expression recognition (FER) systems based on deep learning can be a powerful tool for analyzing feedback. FER systems can be used to analyze facial expressions in real time, providing insight into a user’s emotional state and feedback about a product, service or experience. This information can be used to improve customer satisfaction, product development and the overall user experience. Face expression recognition systems have the strength to be an important tool for feedback analysis, there are still a number of limitations that need to be addressed. One challenge is that FER systems can be sensitive to factors such as lighting, head position and facial occlusion. FER systems must be trained on huge datasets of labeled face images to get accurate output. other than these challenges, the field of Face expression recognition is rapidly changing and new research is being conducted to address these issues. As FER systems become more refined and big, they are likely to be used in a variety of applications, including feedback analysis.The future scope of feedback analysis using facial expressions is very promising. As deep learning tech- nology advances, FER systems become even more accurate and robust. This makes them even more attractive for use in many applications, including back-analysis. Here are some specific areas where feedback analysis using facial expres- sions could make a big difference in the future: Personalized customer experiences: FER systems can be used to create more personalized and engaging customer experiences. For example, retailers can use FER systems to analyze customer facial expressions while shopping and recommend products or services that are likely to be of interest.

Improved product development: FER systems can be used to gather real-time feedback on new products and features. This feedback can be used to improve the design and development of products, ensuring that they meet the needs of users. Enhanced learning and training: FER systems can be used to provide personalized feedback to students and learners. This feedback can help students identify areas where they struggle and get the support they need to succeed. Better treatment: FER systems can be used to track patients. emotional state during medical procedures and treatment. This information can be used to improve patient comfort and satisfaction and to detect potential complications at an early stage. Beyond these specific areas, feedback analysis using facial expressions is likely to have a broader impact on how we interact with tech- nology in the future. As FER systems become more common, we can expect to see them in many new and innovative ways to improve our lives.

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