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REAL TIME EMPLOYEE EMOTION DETECTION SYSTEM WITH ML

Ch. Chakradhara Rao[1], B. Raja Ram Mohan[2], B. Jalandhar[3], A. Teja Surya[4]
Raghu Engineering College
Dakamarri (V), Bheemunipatnam (M), Visakhapatnam – 531162
chakradhararao.ch@raghuenggcollege.in, 219981a0527@raghuenggcollege.in
319981a0517@raghuenggcollege.in ,419981a0501@raghuenggcollege.in

Abstract
At this time, the safety and well-being of workers is the top priority in the workplace. because it will reduce an employee's efficiency and effectiveness on the job, thereby diminishing their value to the team. In conclusion, autonomous Utilizing machine learning for the purpose of analyzing facial expressions is a fascinating and thriving field of study throughout the past few decades. Using machine learning, the Real time Employee Emotion Detection System (RtEED) can instantly determine how an employee is feeling. The RtEED technology enables management to monitor worker morale and relay any detected emotions to the appropriate staff member. As a result, workers will be able to make more informed decisions, focus more intently on their tasks at hand, improve their overall health, and increase their productivity. The FER-2013 dataset was used to teach the A model built upon machine learning techniques. Every worker A webcam will be integrated as a feature that can to seize or record their current expressions. Using the image that was captured, the RtEED system can detect and categorise six distinct emotions, including joy, sorrow, surprise, fear, disgust, and rage. The outcomes confirm that the objectives were successfully completed.
Keywords: Emotion detection, Convolution Neural Network, Machine Learning, Support Vector Machine

Introduction

AI and ML technologies have found applications in diverse fields, ranging from healthcare to e-commerce to logistics and supply chain, as well as agriculture. AI is used in just about every part of business today. So, business leaders need to make the most out of this technology. Methods of ML are leveraged lot in problems that involve recognizing patterns and putting them into groups. Especially since the 1970s, these methods have been used to recognize facial expressions and emotions and to measure brain waves (EEG), [1].

With the rise of the Internet of Things (IoT) and its application in creating "smart" environments such as hospitals, homes, cities, and businesses, facial expression analysis has also gained traction. Recognizing an individual's emotional state, either through their facial expressions or their words, is known as emotion recognition.

These feelings include fear, hate, disgust, anger, surprise, sadness, happiness, apathy, etc. These feelings are not very strong. So, figuring out how people feel is not only hard but also important. Face language is a highly effective, innate, and instantaneous means for people to communicate their feelings and preferences. In some situations, like when a patient is in the hospital, employees are not allowed to show how they feel. So, having a system that can recognize human emotions is important, and it helps people communicate well and get good results.

It has been shown that figuring out how someone feels from a picture or video is hard and takes a trained eye. In the past, an organization didn't care much about how its employees felt. But in recent years, there has been a lot of research into how emotions affect the work, the employer, and the success of the organization. Positive emotions from all employees always lead to the success of the organization, because emotions directly affect many factors, such as a range of aspects, including customer service, employee retention, and capital investment.

It's hard to see the differences in facial muscles because even small differences always lead to different kinds of expressions. Since emotions always depend on what's going on around them, the way the same person shows them or how other people show the same emotion is always different.

Literature Work

"Communication without Words ", As Human-Computer Interaction (HCI) improves, facial emotion recognition is becoming one of the most important applications. It is used in many fields, but it is still hard and problematic in many situations. This survey looks at the activities that lead to an expression and the architecture needed to recognize that expression, along with the problems that come with it. It also talks about how to classify facial expressions and the problems that come with them. Faces and emotions are the same all over the world The Journal of Personality and Social Psychology conducted a study to investigate whether there are universal facial expressions of emotion. While previous research showed that people in literate cultures linked the same emotions to the same facial expressions, these findings did not necessarily indicate that some facial expressions of emotion are universal. This is because the cultures that were compared had all been exposed to similar mass media presentations of facial expressions, which could have taught individuals to recognize the unique facial expressions of other cultures. To address this issue, researchers collected data from individuals in a preliterate culture in New Guinea, who had little contact with literate cultures. Specifically, 342 participants from the Fore language and culture group were asked to choose the face that showed the emotion that went with a story. The results of this study support the hypothesis that people from different cultures, including preliterate cultures, connect as identical emotions with identical facial expressions or actions. The study cites 30 references and is available in the PsycINFO Database Entry (c) 2016 APA, with all rights reserved.

This was the goal of "Image Analysis by Krawtchouk Moments," which was published in IEEE Transactions on Image Processing. The article presents the discrete Krawtchouk polynomials as the basis for a novel family of orthogonal moments. These moments are distinct from each other and avoid the repetition of information. Because the weighted Due to the discrete nature of Krawtchouk polynomials, the moments may be easily obtained without resorting to numerical approximation, making them well-suited for the analysis of two-dimensional pictures. In contrast to other orthogonal moments, the Krawtchouk moments can pinpoint specific characteristics inside a picture. The article explains how to calculate the moments using the recursive and symmetric properties, and presents a reconstructed image using Krawtchouk moments to test the theory. The results of the test are compared with those obtained using the appearance of ideas from Zernike, pseudo-Zernike, Legendre, and Tchebyscheff. Geometric moment invariants are combined linearly to create Krawtchouk moment invariants, and an object recognition experiment demonstrates that these invariants perform better than Hu's moment invariants, even when there is noise."

An automatic region-based method for recognizing facial expressions" was the title of the study. This work looks at how a point distribution model can be used to find important parts of a face, like the eyes, mouth, and brows. It also looks at how facial features can be extracted and facial expressions can be put into A multi-scale and multi-orientation Gabor filter bank is utilized to categorize seven groups of facial expressions, namely anger, fear, surprise, happiness, disgust, neutral, and sadness that is made Facial features are extracted at specific points to prevent the inclusion of duplicate information certain locations of a face's most important features (fiducial points). When figuring out where the fiducial points are, a region-based approach is used. Different-sized regions are used to give some flexibility and avoid artifacts caused by the wrong automatic discovery of these points. The classification of extracted feature vectors is performed using an Artificial Neural Network that employs both forward and backward propagation. The method is tested by dividing the world into 7 different areas, and the feature vector is taken from 20 fiducial points.

"A Way to Figure Out Feelings Based on Facial Action Units" It shows a reliable way to link The automatic recognition of Facial Action Units (AUs) is applied to associate six primary emotions can go wrong because of lighting problems, tracking problems, and objects in the way. So, traditional Rule-based approaches that map AUs to emotions are highly susceptible to errors, including false positives and missed detections of AUs. Using a learned statistical relationship and a good matching technique, we map a selected set of AUs is linked to the six fundamental emotions The connections between AUs and emotions are saved as template literals made up of the most distinguishing AUs for each emotion. A concept called "discriminative power" is used to figure out the template strings. The Longest Common Subsequence (LCS) distance, a method for roughly matching strings, is used to figure out how close a test string of AUs is to the template strings and, by extension, figure out what emotions are behind them. LCS is good at dealing with real-world problems like wrong AU detection and helps cut down on wrong predictions. Different databases like CK+, ISL, FACS, JAFFE, Mindreading, and many real-world video frames are used to test the proposed method. We compare how well our methods work with rule-based methods and find that the findings from benchmark databases and real-world datasets align, indicating clear improvements.

Methodology

The entire project is of 3 modules Building models, evaluating their performance and finding employee emotion.

a) Building Models

The FER-2013 dataset is used to build models. The dataset consists of grayscale facial images that are 48x48 pixels in size. The faces have been registered automatically so that the face is more or less in the middle of each image and takes up about the same amount of space. Models such as Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Artificial Neural Networks (ANN) are trained using the dataset.

Convolution Neural Network:

To analyze structured data arrays, such as photographs, Convolutional Neural Networks (CNNs) are a subset of deep learning neural networks. CNNs have become the standard for many computer vision tasks such as image classification and have also been successful in text classification for natural language processing. While similar to ordinary neural networks, CNNs are specifically designed to handle image inputs, allowing for certain image-specific properties to be encoded into the architecture. This design leads to greater efficiency and reduced parameters in the network. The neurons in CNNs are arranged in three dimensions: width, height, and depth. Input, Convolution, Pooling, and Fully Connected Layers are the four fundamental building blocks of a conventional CNN. The fully connected layer connects neurons in one layer to those in another layer using it utilizes weights, biases, and neurons to classify images into distinct categories, a process that is accomplished through training.
In this work 2Dconvolution is used, entire 10 layers are used among them 4 convolution layers with different kernel sizes, There were 3 puddle layers, 1 level layer, and 2 packed layers. In practise, the cost function of choice is the categorical cross entropy.

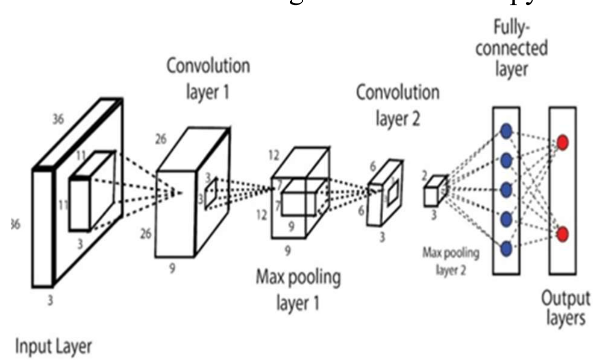

Figure 1: CNN Architecture

i. Support Vector Machine

One of the most widely used Supervised Learning techniques, When used for Regression, Support Vector Machine (SVM) is also quite useful.SVM algorithm is primarily used in Machine Learning, particularly for classification tasks. Its aim is to find the best decision boundary, or optimal line, that separates the data points into distinct classes. A hyper plane is used to define this optimal boundary. The SVM algorithm selects the extreme points and vectors that are used to construct the hyper plane. The term "Support Vector Machine" comes from the fact that the method is named after the "support vectors," which refer to the extreme instances. The SVM algorithm is designed to classify new data points accurately and efficiently in the future. When there are many features to consider, SVMs excel. It still performs well even if there are more characteristics than samples. Custom hyper planes constructed with the kernel method can also be used for classifying non-linear data. The model's ability to maximise margin makes it a powerful tool for resolving difficulties of prediction.

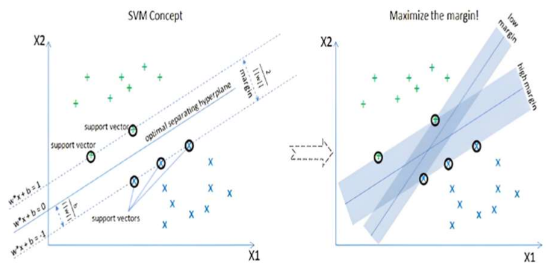

Figure 2: SVM

i. Artificial Neural Network

The human brain is a highly complex network of interconnected neural circuits that work together to process information and generate responses. Artificial Neural Networks (ANNs) emulate this structure and consist of input, hidden, and output layers of nodes. Each node, or artificial neuron, has a weight and threshold that determine its response to input from other nodes. If the output of a node exceeds the threshold value, it becomes activated and transmits data to the next layer of the network. If this condition is not met, no information is forwarded to the subsequent network layer.

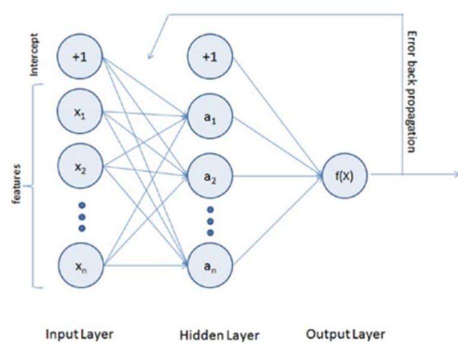

Figure 3: Artificial Neural Network

a) Model Evaluation

If the problem taken in Machine Learning is Classification problem then one metric can be used to assess the quality of a model is "**accuracy".** Accuracy is percentage of all observations that are correctly classified by the model.

It is calculated as:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Sample\ Size}$$

By comparing the accuracies of all three models CNN model attain higher accuracy. CNN model classifies the employee emotion better than other two models.

b) Displaying Employee emotion

Many methods exist for recognizing human emotions and expressions, with a focus on accuracy. These studies often employ six (Neutral, Happy, Anxiety, Anger, Surprise, and Sad) fundamental expression identification from foreign-origin databases.

i. Results And Discussion

Happy

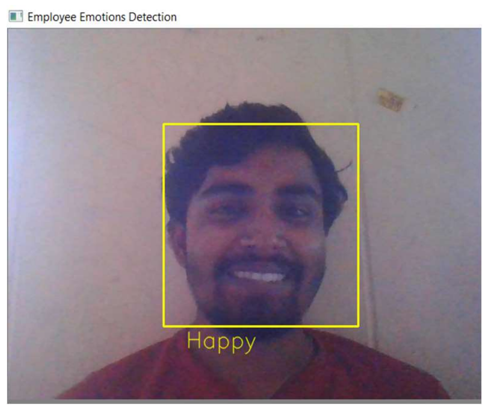

Figure 4: Displaying Happy emotion

Angry

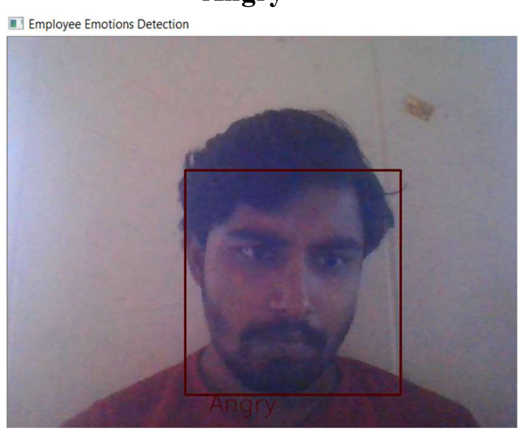

Figure 5: Displaying Angry emotion

Neutral

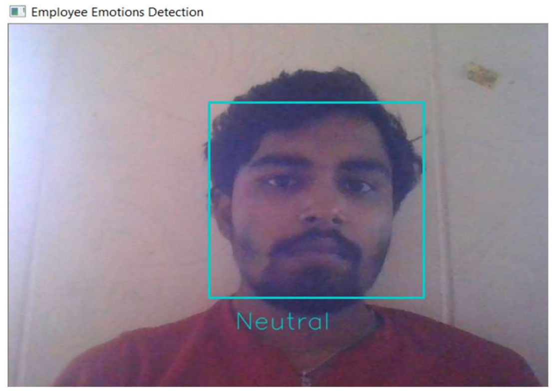

Figure 6: Displaying Neutral emotion

Sad

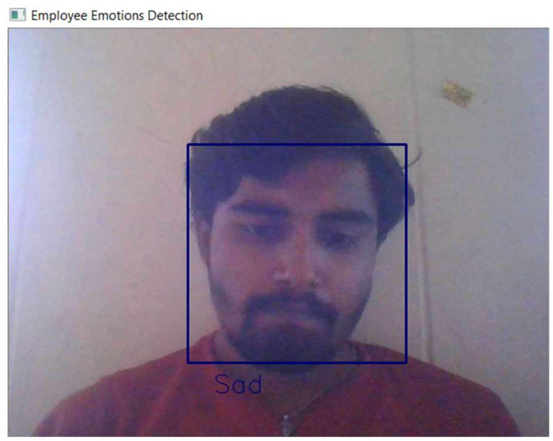

Figure 7: Displaying Sad emotion

Figure 4 displays employee showing sign of happiness by using of algorithms which analyze curvature of the lips, the position of the eyebrows, and the creases around the eye. Figure 5 displays employee exhibits anger; this is analyzed by algorithm based on the position of the eyebrows, the mouth, and the eyes. Figure 6 displays employee is in neutral mood by analyzing the position the angle of the mouth, the shape of the lips, and the placement of the eyebrows. Figure 7 displays employee is showing signs of sadness by detecting changes in the curvature of the lips, position of the eyebrows, and creases around the eyes that are associated with sadness.

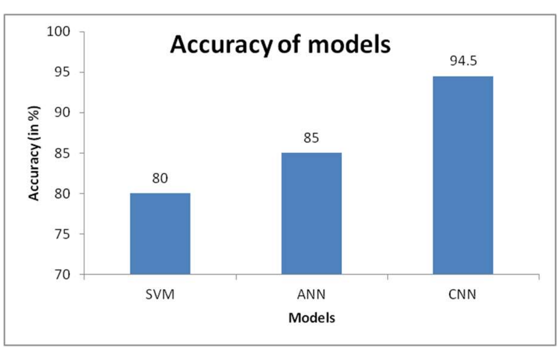

Table 1: Table of accuracy for 3 models

Model	Accuracy
SVM	80%
ANN	85%
CNN	94.5%

Conclusion

Identifying how an employee feels is an important part of many businesses' success and growth these days. In this paper, the RtEED system is proposed as a way to use machine learning algorithms to figure out how an employee feels in real time. The RtEED system shows how well it works by recording a webcam image in real time for a set amount of time, cropping the image, and correctly figuring out how an employee feels. To enable the employer to make more informed decisions about their employees' quality of life.

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References

1. Aya Hassouneh, A.M.Mutawa, M.Murugappan, “Development of a Real-Time Emotion Recognition System Using Facial Expressions and EEG based on machine learning and deep neural network methods,” Elsevier, Vol. 20 (2020)
2. B. Fasel, J. Luettin, “Automatic facial expression analysis: a survey. In: Pattern Recognition,” vol. 36 pp. 259–275 (2003)
3. Y. Yacoob, L.S. Davis, “Recognizing human facial expression from long imagesequences using optical flow. In: IEEE Transactions on Pattern Analysis and Machine Intelligence,” pp. 636–642 (1996)
4. I. Essa, A. Pentland, “Coding, analysis, interpretation, and recognition of facialexpressions,” IEEE Transactions on Pattern Analysis and Machine Intelligence pp. 757–763 (1997)
5. J. Hoey, J.J. Little, “Value directed learning of gestures and facial displays,” IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2004)
6. M. Yeasin, B. Bullot, R. Sharma, “From facial expression to level of interests: aspatio-temporal approach,” IEEE Conference on Computer Vision andPattern Recognition (CVPR) (2004)
7. G. Donato, M. Bartlett, J. Hager, P. Ekman, T. Sejnowski, “Classifying facialactions. In: IEEE Transactions on Pattern Analysis and Machine Intelligence,” pp. 974–989 (1999)

8. M. Turk, A.P. Pentland, “Face recognition using eigenfaces,” IEEE Conferenceon Computer Vision and Pattern Recognition (CVPR) (1991)
9. J.N. Bassili, “Emotion recognition: the role of facial movement and the relativeimportance of upper and lower area of the face,” Journal of Personality andSocial Psychology vol.37 (1979)
10. G. Zhao, M. Pietikäinen, “Dynamic texture recognition using local binarypatterns with an application to facial expressions,” IEEE Transactions on PatternAnalysis and Machine Intelligence pp. 915–928 (2007)