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Transformation of Emotions to Emoticons

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Abstract: **There are many different ways to express and communicate our feelings. The two classified ways of communication are verbal and non - verbal. Facial expressions are a great way of communication involving the exchange of wordless intimations. It has enticed much research attention in the field of computer vision and Artificial intelligence nowadays, the automatic detection of emotions is employed by many applications in different fields like security informatics, e-learning, humour detection, targeted advertising, customer survey and feedback forms. Hence, there is a need for techniques to understand their sentiment and emotion. In this work, we provide a method to quantify the emotional association of basic emotions such as anger, fear, joy, and sadness for a set of emojis and will refer to a health prescription according to the emotional state of that person and will also refer to the web page which will provide information about what to do in that state of emotion in this paper, people will look into the detection of the faces in real time images using readily available APIs. Further after the detection of the faces, using HAAR Cascade, we can extract the features of the images and then process it. Followed by which the emotions are classified through SVM. These emotions are then transformed to their identical emoticons which will be later superimposed on the face.**

Keywords: **Artificial intelligence, Deep learning, Emotions, Emojis emotion detector, Emotional health prescription, Face detection Machine learning,**

I. INTRODUCTION

Over the last few decades lots of work has been done in face detection and recognition as it's the best way for person identification because it doesn't require human cooperation so that it became a hot topic in biometrics. Since lots of methods are introduced for detection and recognition which is considered as a milestone. Although these methods are used several times for the same purpose separately for limited number of datasets in past but there is no work found who provides overall performance evaluation of said methods altogether by testing them on tough datasets. Emotional aspects have a huge impact on Social intelligence like communication understanding, decision making and also helps in understanding behavioural aspects of humans. Emotions play a pivotal role during communication. Emotion recognition is carried out in diverse ways, it may be verbal or non-verbal .Voice (Audible) is verbal form of communication & Facial expression, action, body postures and gesture is non-verbal form of communication. [1] While communicating only 7% of the message is contributed by the verbal part as a whole, 38% by the vocal part and 55% of the speaker's message is contributed by facial expression. For that reason automated & real time facial expression would play an important role in human and machine interaction. Facial expression recognition would be useful from human facilities to clinical practices. Analysis of facial expression plays fundamental roles for applications which are based on emotion recognition like Human Computer Interaction (HCI), Social Robot, Animation, Alert System & Pain monitoring for patients. By looking at someone's facial expression, we can comprehend the other person's feelings. These non-verbal signs give more insights and meaning that is not provided by verbal communication. A major chunk of non-verbal communication involves the facial emotions exhibited by a person. Emotions represent the mental state along with the facial expressions, actions or any physical changes.

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They are associated with the current mood but differ from it, in a way that emotions are temporary feelings over an issue while mood is a generalized sentiment that usually lasts longer. Primarily there are seven different forms of emotions expressed by humans [2]. They include: Happiness, Sad, Anger, Surprise, Disgust, Fear and Neutral. All the other emotions are the inferences of these emotions. With the widespread application of computing and the development of technology, computer mediated communication (CMC) is infiltrating daily life to a greater and greater extent. It has many advantages, including enhancing the continuity of individual communication (Juhasz and Bradford, 2016), improving the quality of relationships (Pettigrew, 2009; Perry and Werner-Wilson, 2011), and strengthening emotional communication (Derks et al., 2008b). However, the lack of non-verbal cues such as facial expressions, intonation, and gestures in CMC can affect the transmission of information (Archer and Akert, 1977). To address this problem, communicators have devised new non-verbal cues, such as capitalization as a substitute for shouting, multiple exclamation points for excitement, and expression symbols for facial expressions (Harris and Paradice, 2007; Riordan and Kreuz, 2010). These expression symbols make up for the lack of non-verbal cues in CMC (Tossell et al., 2012; Negishi, 2014), and are very well-suited for social media communication (Barbieri et al., 2016c). As a result, emoji, which are a set of expression symbols, came into being. Emoji are used more and more frequently in network communication, and the way they are used is becoming more and more diversified as well. They not only have unique semantic and emotional features, but are also closely related to marketing, law, health care and many other areas. The research on emoji has become a hot topic in the academic field, and more and more scholars from the fields of computing, communication, marketing, behavioural science and so on are studying them. This paper reviews the details of the emotional and linguistic features of emoji, summarizes the results of research on emoji in different fields, and puts forward future research directions and this will tell the

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human emotions through emojis. In this paper, we will look into the detection of the faces in real time images using readily available APIs. Further after the detection of the faces, using HAAR Cascade, we can extract the features of the images and then process it. Followed by which the emotions are classified through SVM. These emotions are then transformed to their identical emoticons which will be later superimposed on the face.

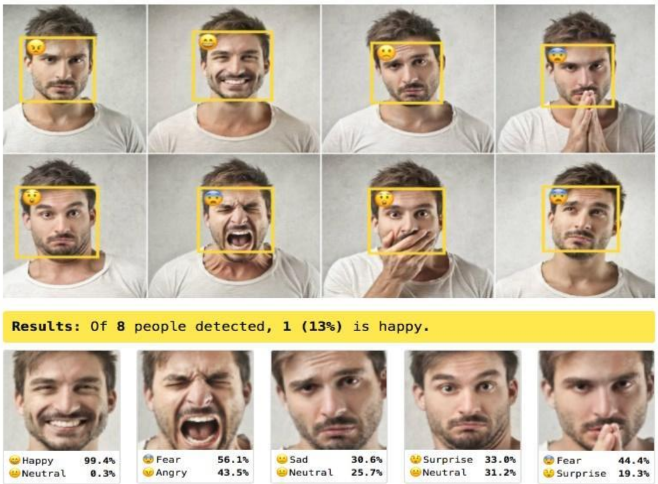

Figure 1. Different Emotional State

II. LITERATURE SURVEY

Multimodal User Interfaces and Emoji Entry Related to our approach, Filho et al. [3] augmented text chatting in mobile phones by adding automatically detected facial expression reactions using computer vision techniques, resulting in an emotion enhanced mobile chat. For using the user's face as input, Anand et al. [4] explored a use-case of an eBook reader application wherein the user performs certain facial expressions naturally to control the device. With respect to emoji entry, Pohl et al. [5] proposed a new zooming keyboard for emoji entry, Emoji Zoom, where users can see all emoji at once. Their technique, which was tested in a usability study against the Google keyboard, showed 18% faster emoji entry. Emoji and Emotion Communication The compactness of emojis reduces the effort of input to express not only emotions, but also serves to adjust message tone, increase message engagement, manage conversations and maintain social relationships [6]. Moreover, emojis do not have language barriers, making it possible for users across countries and cultural backgrounds to communicate [7]. In a study by Barbieri et al. They found that the overall semantics of the subset of the emojis they studied is preserved across US English, UK English, Spanish, and Italian. As validation of the usefulness of mapping emojis to emotions, preliminary investigations reported by Jaeger et al. [8] suggest that emoji may have potential as a method for direct measurement of emotional associations to foods and beverages.

Emoji (Mis-) interpretation Recently, Miller et al. [9] demonstrated how same emoji look differently across devices (iPhone, Android, Samsung) and is therefore differently interpreted across users. Even when participants were exposed to the same emoji rendering, they disagreed on whether the sentiment was positive, neutral, or negative around 25% of the time. In a related preliminary study,Tigwell et al. [10] found clear differences in emoji valence and arousal ratings between platform pairs due to differences in their design, as well as variations in ratings for emoji within a platform. In the context of our work, this highlights the need to account for multiple interpretations, where an emoji (as we show later) can be classified as belonging to one or more emotion categories and the sentiment classification of tweets, using both emoticons and bag-of-words as features. Ganesan et al. [11] presents a system for adding the graphical emoticons to text as an illustration of the written emotions. Several studies have analyzed emotional contagion through posts on Facebook and showed that the emotions in the posts of online friends influence the emotions expressed in newly generated content .Gruzd et al. [12] examined the spreading of emotional content on Twitter and found that the positive posts are retweeted more often than the negative ones. It would be interesting to examine how the presence of emojis in tweets affects the spread of emotions on Twitter, i.e., to relate our study to the field of emotional contagion [13].Emoji Associations. The first paper that thoroughly investigated the sentiment of emojis (Novak et al., 2015) proposed a sentiment ranking of 715 emojis on a corpus of 70,000 tweets. This work provides a basis for future research on the logographic usage of emojis in social media.[14]Zhou and Wang (2017) trained a natural language conversation model that accounts for the underlying emotion of utterances by exploiting the existence of emojis as a signal. Emoticons. Early studies focused on the use of emoticons in social media.[15] Davidov et al. (2010) adopted a fairly similar approach by handpicking smileys and hash tags as tweet labels and relying on a supervised method for sentiment analysis of tweets. Emoji Semantics. A prominent work on emojis is the Deep Emoji project (Campero et al., 2017) from MIT. It provided a model that recommends emojis given a natural language sentence as input. The deep learning model was trained on a collection of 1.2B tweets to learn the sentiment, emotions, and the use of sarcasm in short text. [16]Multi-pose FER systems are addressed as pose-invariant FER systems are robust in nature. has too many parameters and its performance is about 79%.. Mao, Q. Rao, Y. Yu, and M. Dong,have worked on "Hierarchical Bayesian Theme Models for Multipose Facial Expression Recognition.[17]Gede Putra Kusuma, Chin-Seng Chua have introduce a complete framework of multimodal 2D + 3D face recognition that utilizes the 2D and 3D facial information at the enrolment, image and score levels.[18]Jonathan Jonathan Andreas Pangestu Lim. This paper examines how human emotion, which is often expressed by face expression, could be recognized using computer vision. A number of algorithms and techniques have been reviewed, and at the end of this paper, a summary of recommendation for performing facial emotion recognition based on the reviews of the techniques/methods is given.[19]Computer Needs a model that could represent the human face, and thatmodel is later trained and then tested using positive and negative values. Moura and Ferreira-Lopes cited that one development made by Paul Viola and Michael Jones enabled

III. METHODOLOGY

The proposed approach aims to properly classify individuals' emotions through emoji. The performance of different ML-based methods is evaluated in terms of accurately diagnosing emotions on the basis of complete and selected features. A

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supervised learning-based method is adopted for classification data availability. The proposed approach aims to classify individuals based on their emotions and tell them which emotion out of classified seven they are feeling at that time. For getting the highest probability of correct emotion this project has been made by using some previously made datasets and training them with the help of an algorithm. The dataset of this project is broadly classified into seven categories named as:(happy, sad, surprised, angry, disgust, neutral, fearful)for each category it has different training sets to train particular emotion as well as there are test sets to test particular emotions.

A. PROPOSED SYSTEM

The idea of the proposed system is to employ an API that will detect the face after which the image can be processed using HAAR cascade for facial feature extraction. SVM Classifier is then used to categorize the emotions into its seven distinct types. Using the HAAR of Open CV package, the corresponding emojis of the emotions can get superimposed over the subjects' faces. In any camera module of any leading social networking apps, the use of APIs can reduce the processing time for face detection for which they have their in-built face detection algorithm which can detect the face smoothly and followed by which the emoticons can be implemented over the faces as filters.

BASIC STRUCTURE OF FACIAL EXPRESSION RECOGNITION

FACE DETECTION--->
FEATUREEXTRACTION----->
EXPRESSION RECOGNITION--------------->
FACIAL EXPRESSION CLASSIFICATION
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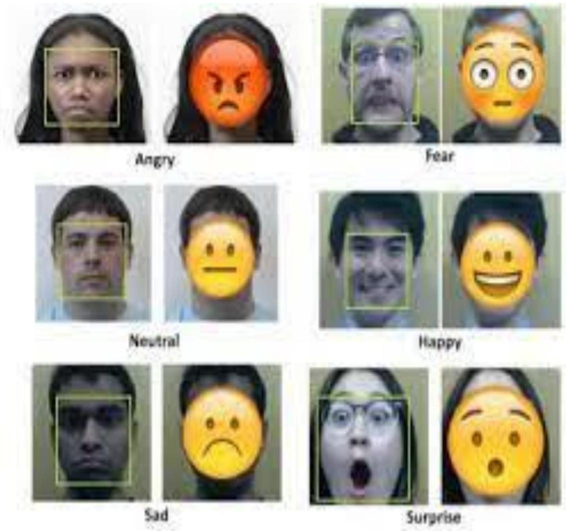

Figure 2. Emoticons as per Emotions

API IMPLEMENTATION: An API acts as an interface between an operating system, application and the user. The API design plays a significant role in its usage. An API is designed in such a way that it hides the background details of modules from the users who do not have the knowledge of complexity of the modules. Thus, API facilitates the user-friendly interface. A camera-based API can be used which automatically detects the face of the subject(s) regardless of the background and sends this image to the model for processing after which the emoji will be superimposed over the face.

HAAR CASCADE: The image that is supplied by the API is then provided to the HAAR cascade in which some dataset has been given for training the data. For the development of a working model, we will use datasets. HAAR-Like features have high accuracy to detect faces from different angles. It extracts the facial features from the face of the subject like eyes, eyebrows, and mouth expressions which we get through the API. These results are then delivered to the Support Vector Machines (SVM).

SUPPORT VECTOR MACHINE (SVM):

Support Vector Machine is a supervised machine learning algorithm that is used for classification as well as regression problems. The SVM is used in many pattern analysis tasks with support of a binary classifier that differentiates between the classifications of the expressions. It works by classifying data through the use of assessment of an optimal hyperplane which separates one class's data points from the other .The features of image that is given to the SVM after HAAR Classification, is then compared with the datasets which have been trained and then those images are categorized to the corresponding emotion variant. After this, the corresponding emoticon is superimposed over the image. The result is transferred back to the API that displays the corresponding new superimposed image with the emoticon.

DEEP CNN FOR EMOTION RECOGNITION:

To build our emotion recognition module, we used deep Convolutional Neural Networks (CNNs). Deep Learning Based approaches, particularly those using CNNs, have been very successful at image-related tasks in recent years, due to their ability to extract good representations from data .We chose to build our own recognition system instead of using available APIs (such as Microsoft's Emotion API10) because: (a) it allows us greater flexibility in inspecting the classification accuracies ourselves and determining why certain emotions are not correctly classified, (b) this project can ensure user privacy by running all predictions directly on the device, and (c) it is free.

DEEP LEARNING:

Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces.

For training the datasets different types of ML algorithms are used. To perform an experiment a standard database is required. The data can be perceived as primary or secondary. The primary dataset [20] takes longer time to be completed with collection. The facial expression database comprised of multi-ethnic subjects (Malaysian, Indians, Kuwaitis, Syrian, and Chinese). The database consists of facial expression video sequences of seven basic emotions. The collected data of facial images is in a controlled environment with 25°C ambient room temperature and high quality resolution . Our preliminary experimental work confirms that the proposed methodology is not affected by any background changes. Hence, the data are collected with different background scenes. [21]. These datasets are collected from the Kaggle website.

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IV. EXPERIMENTAL RESULTS

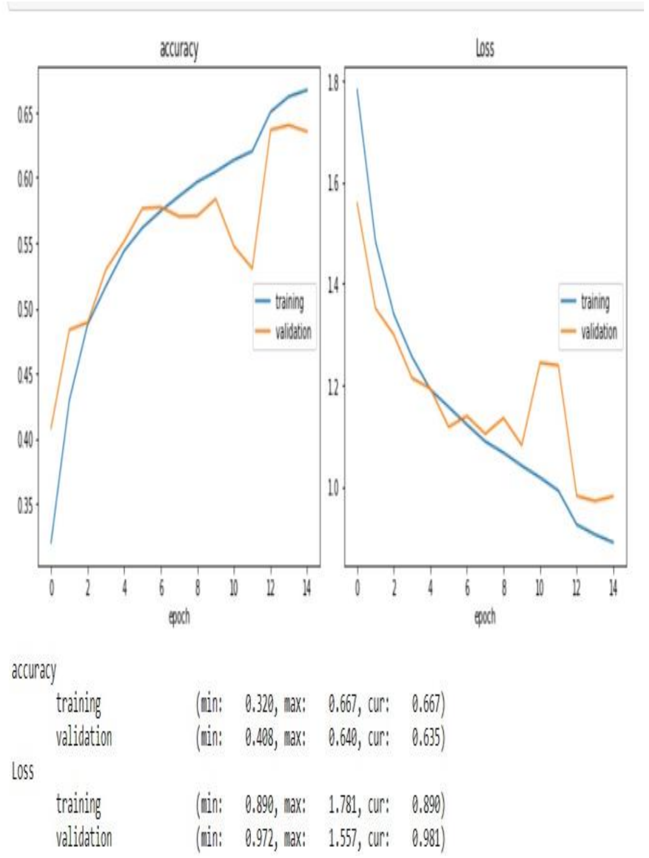

Figure 3. Accuracy Graph

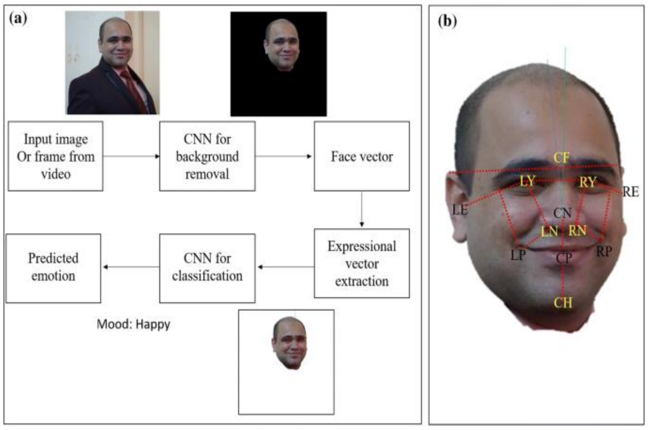

Figure 4. Flow line of Emotion Detection

V. CONCLUSION

In this paper, Computer Vision has been used for the recognition of facial emotion and converting those emotions into their corresponding emoticons. Object face is detected using any camera-based API. The Features of the expressions of the detected face will be extracted using HAAR cascade that will supply the feature extractions of the expressions depicted in the image for further classification into seven emotions by employing Support Vector Machines (SVM) that exhibits a good accuracy value as compared to the other existing algorithms. This proposed model can be used by the leading social networking handlers like Facebook, Instagram, Snapchat for their camera-based applications involving various effects , filters and can also be used in e- learning or zoom office meeting to detect the students or employee psychological emotions so that their work pressure can be reduced and also to get the reviews from them to stabilize and create an optimistic and good working and studying environment. There are many existing face-detecting neural networks that have good efficiency but their implementation may be difficult in some cases. Through our approach of using APIs instead of neural networks, we can make the implementation convenient.This paper also summarizes the developmental process, usage features, functional attributes, and fields of research related to emoji. Emoji developed from emoticons, and have both emotional and semantic functions. The use of emoji is influenced by and varies according to factors such as individual circumstances, culture, and platforms. Ambiguity and misunderstanding may occur in different situations and cultural backgrounds. From the perspective of many fields (communication, computing, behavioural science, marketing, and education), this paper comprehensively combs the research topics, methods and tools used in studies related to emoji, and face recognition using emoji to tell the emotions of the people.

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