Chapter 13
Employing Machine Learning for Multi-perspective Emotional Health Analysis

Monika Mangla, Rakhi Akhare, Sanjivani Deokar, and Vaishali Mehta

Contents

13.1 Introduction ................................................................. 199
13.2 Emotional Health Analysis ............................................... 201
13.3 Comparative Analysis of Various Perspectives ...................... 207
13.4 Case Studies .................................................................. 208
13.5 Conclusion and Future Work ............................................. 209
References ......................................................................... 209

13.1 Introduction

In this era of digital revolution, people are surrounded by smart devices and gadgets. Revolution in the field of IoT (Internet of Things) and IoE (Internet of Everything) has further resulted in gaining control of human life. Although these devices were earlier designed to be controlled by humans, but in recent few years, it has been observed that humans are getting driven by these devices. However, this excessive usage of technology in human life has resulted in several concerning issues related to health. Generally, the human health is perceived to be the state of the physical health ignoring the state of mental health. This ignorant attitude toward mental health is supported by the lack of research in this field. However, during the past few years, researchers are focusing on studying and understanding the emotional health of patients. There is no universal agreement on the definition of emotion. However, emotion may be defined in relation to a list of predefined descriptors such as anger, happiness, and sadness.

Here, it is worth mentioning that the emotional health of ordinary people is also equally concerning and thus must be focused upon (Tivantansakul & Ohkura, 2014). Now, it must be realized that society is in dire need of developing systems that aid
people to get rid of mental stress and negative emotions (Ambarkar & Akhare, 2020). Various researchers have devised different strategies to improve emotional health of patients by providing effective, intelligent, and attractive healthcare systems.

All these proposed systems understand that the most crucial part of emotional health management is analysis and recognition of real-time emotions which is capable of understanding user emotions in minimum time, so that appropriate corrective therapies could be activated or suggested. Recognition of emotional health is a challenging part as it involves recognition of facial expressions, speech, text, or biological signals for enhanced accuracy (Tivatansakul & Ohkura, 2014). According to a popular psychological theory, emotion may be defined as a complex psychological state that involves three distinct components: a subjective experience, a physiological response, and a behavioral or expressive response. Hence, it is evident that analyzing emotional health is extremely challenging. Despite the involved complexities, researchers have been attempting to devise efficient approaches owing to its widespread application in several areas. Some of these application examples are social media analysis, measuring satisfaction level of customers, chatbots integration, sophisticated robot communication, call center performance monitoring, etc. Emotional health analysis is also referred as affective computing as it measures the affect (emotions) (Hakak, Mohd, Kirmani, & Mohd, 2017). The authors of this chapter aim to present the employment of machine learning (ML) in analysis of emotional health. The chapter has been organized as follows:

The introduction has been presented in Sect. 13.1. The basics of emotional health analysis have been presented in Sect. 13.2. Section 13.2 also discusses all principle perspectives of emotional health analysis. Comparative study of these different perspectives have been presented in Sect. 13.3. Section 13.4 presents some promising case studies. Section 13.5 is dedicated to conclusion and future directions of research in the domain.

**Fig. 13.1** Principle components of Emotional Health Analysis
13.2 Emotional Health Analysis

As stated earlier, emotional health analysis comprises analyzing speech, text, and behavior of the concerned which has been illustrated in Fig. 13.1. Various researchers have applied distinct approaches to analyze different components of emotional health. Among several approaches, Artificial Intelligence (AI) has established itself as a promising and efficient tool (Ramalingam, Pandian, Jaiswal, & Bhatia, 2018).

AI employs various techniques to analyze facial expressions, body movements, speech, and textual information in order to analyze emotional health of a human. For all these components of emotional health, there exists a challenge to identify which data should be used for feature extraction and how to overcome the evolution or change in these components. Some additional challenges involve selection of emotion indicators for speech, extraction of contextual data, labeling of emotions, and selection of machine learning classifier. There have been several computational approaches to implement an emotional classifier. These classifiers have been broadly classified into lexicon based approach and the machine learning approach as shown in Fig. 13.2.

Emotion lexicon contains textual units annotated with emotional labels and work on lexicons. ML approaches use different ML algorithms to train the system and map a function for emotion classification. Some promising approaches of machine learning are supervised learning, unsupervised learning, and semi-supervised learning as demonstrated in Fig. 13.2. The various components of emotional health analysis have been discussed in subsequent subsections.
13.2.1 Emotion Analysis Using Text Processing

Language is a vital method of communication to express various emotions like love, anger, anxiety etc. This subsection considers the human emotion expressed through text. Humans can easily interpret the textual message, but it remains a challenging task for computers to interpret and understand the text (Khan & Ejaz, 2016). To address this challenge, human–computer interaction (HCI) provides a big relief. Humans provide massive data on the Internet every second which is challenging to digitize. Various emotions like joy, happiness, anger, surprise, fear, and love are expressed by different kinds of words. Some words also belong to the territory category of emotions, thus obscuring the recognition (Mohanty & Suar, 2014). This categorization is used to perform sentiment analysis. According to Carrillo-de-Albornoz, Vidal, and Plaza (2018), subjects are classified into positive, negative, and neutral personalities (Mohanty & Suar, 2013). Broadly, the emotional analysis through text processing has been classified into two classes, viz. hard sensing and soft sensing (Khan & Ejaz, 2016). In hard sensing, brain signals, heart rate, etc. are analyzed. On the other hand, soft sensing detects emotions through emails, text messages, and social website interactions.

Text processing is a significant component of analyzing emotional health. Apart from monitoring a patient’s emotional health, it has also been applied to analyze satisfaction levels of customers and employees in big companies. For its implementation in analyzing emotional health of patients, the daily observations of a patient are documented in terms of degree of pain or any other discomfort experienced (Deng, Stoehr, & Denecke, 2014). This documented information is further processed in order to analyze the patient’s health that eventually supports and guides treatment process.

Natural language processing (NLP) and few other computational techniques are used to determine the emotions embedded in a text. This analysis of text is done at document level, sentence level, and finally word level (Hakak et al., 2017). At each level of analysis, the actions performed are NLP, feature selection, emotion identification, emotion classification, and evaluation in order. According to Goeuriot et al. (2012), subjective sentences from patients are used to perform polarity classification. Similarly, authors (Goeuriot et al., 2012) presented a medical lexicon containing user reviews about drugs and medication in the scale of 0 to 10 and thus performs polarity classification on subjective issues. In the same line, Bobicev, Sokolova, Jafer, and Schramm (2012) performed analysis of Twitter messages into positive, negative, or neutral. For the same, Bobicev et al. (2012) employed Naive Bayes, Decision trees, KNN, and SVM algorithms on different word bags.

Lim, Tucker, and Kumara (2017) proposed an unsupervised ML model that is competent to identify real-world latent infectious diseases by mining social media data. A latent infectious disease is a communicable disease that has not yet been formalized by national public health institutes like COVID-19 (Lim et al., 2017). In such latent infectious diseases, symptoms are unknown. Lim et al. (2017) have presented a study to discover latent infectious disease through social media messages where users share their experience about symptoms, body pain locations etc. For discovering symptoms of latent disease, the suggested approach uses unsupervised
sentiment analysis and social media content pertaining to the same disease. For instance, a social post like “I had a headache the past 2 days, feeling better now because drugs” expresses positive feelings as the handler has gotten rid of the headache. However, if a message does not express body part of feeling, it cannot be classified as an indicator of symptoms. An example of such message is “I hate experiencing mean friendship.”

Ji, Chun, Wei, and Geller (2015) also study Twitter about diseases’ outbreak. It has been realized that it is important to understand and analyze the public sentiments during outbreaks of Ebola in Africa and measles on the West Coast of the USA. The same can also be realized during the recent pandemic outbreak of coronavirus in the whole world. Understanding the unparalleled demand for monitoring the social data is supported by developing a gauge that evaluates the measures of concern (MOC) using Twitter (Ji et al., 2015). Here, the tweets are classified into personal tweets and news tweets. The personal tweets are classified into negative or non-negative tweets. The classification of tweets into personal and non-personal tweets is a novel concept in Ji et al. (2015) as traditional Twitter sentiment analysis methods do not distinguish among personal and non-personal tweets. This classification model is demonstrated in Fig. 13.3.

Ji et al. (2015) have developed an intelligent system Epidemic Sentiment Monitoring System (ESMOS) which collects Twitter data related to public health. Thereafter, ESMOS classifies the data into different sentiment categories and calculates the degree of concern. ESMOS can also represent the intensity map using various visual tools which enables understanding the spatial distribution and concentration of public concerns. The data is classified into labeled classes using keyword spotting technique in (Shivhare & Saritha, 2014) where words like sad, angry, fearful, and surprised are used for classification. Another promising approach for this classification is machine learning where previously trained classifiers are used to identify which category the input text belongs to. The same can also be achieved using integration of techniques in hybrid methods which achieves enhanced accuracy. These approaches for tweets classification bear some limitations also. Some of these limitations are ambiguity in keywords, complex nature of emotions, incapability of recognizing sentences in the absence of keywords, lack of linguistic information, determination of emotion indicators, etc. Ramalingam et al. (2018)

**Fig. 13.3** Illustration of tweet classification model
have attempted to address these limitations by presenting a method that uses algorithms of Support Vector Machine and thus providing a better and accurate solution.

Bosubabu Sambana (2017) have proposed a method to assess the behavior of aspiring candidates for the recruitment process. It works by analyzing the candidate’s tweets in order to assess his emotions and polarity as entire tweets provide a large dataset, and thus extraction of personality traits becomes more effective and meaningful. Such a model is competent to predict the candidate’s behavior in the condition of work pressure and competition and thus helps the recruiting companies to hire the right person.

13.2.2 Emotion Analysis Using Speech Processing

Speech is an unparalleled mode of communication to express emotions among humans. Each speaker has its own voice quality which conveys vital information like emotion and attitude of the speaker. Also, this mode of communication is important as it is able to analyze emotions of the society comprising a large portion of uneducated people who are unable to express their emotions through text. Another motivation for research in the domain of emotion analysis through speech is its instantaneous and real nature. As a result, rigorous research is taking place in this direction for proper psychometric analysis of people in order to understand their psychological problems like bipolar disorders, severe depression, anxiety and schizophrenia etc. It also carries a vital significance in analyzing the emotional health of patients which aids the treatment process (Vij & Pruthi, 2018) (Mohanty, Pratihar, & Suar, 2015). Vij and Pruthi (2018) have developed a psychometric analyzer that analyzes the emotional health of patients based on medical history and recorded communication. Here, the emotional health is analyzed in terms of various components viz. intensity, emotions, polarity and subjectivity. Kerkeni et al. (2019) have defined the emotional health analysis through speech as a four step process. These four steps are as follows:

Collection of voice samples
Feature extraction
Feature selection
eClassification

This emotional health analysis through speech has also been accepted in automatic detection of dementia diseases (Mirheidari, Blackburn, & Walker, 2019). For the same, the health professional asks specific questions to the patient and then interprets the response. In order to interpret the speech, the audio file is processed using some diarization tool that identifies the speech portion and the speaker. Further the output of the diarization tool and the audio file is passed to Automatic Speech Recognition (ASR) system which generates a string of words spoken by each speaker (health professional and patient) (Mirheidari et al., 2019). These are further analyzed using natural language processing and other similar approaches to evaluate the emotional health of patients. Chen, Yang, Hao, Mao, and Hwang (2017) have
also developed a model for emotional health analysis leveraging the deep learning and ML algorithms.

Additionally, Davletcharova, Sugathan, Abraham, and James (2015) have interestingly established that emotions influence the heart rate and nervous system also. This principle is employed to assess the emotional state of a person through heart rate as speech is also influenced by transitions in heart rate. For instance, in case of a negative stimuli, the heart rate decelerates rapidly in comparison to positive stimuli. The task of emotional analysis through speech recognition has also been researched in (Nwe, Foo, & De Silva, 2003) where the authors used a discrete Hidden Markov Model (HMM) for the classification of emotions into six labeled classes. Here, authors have used a database of 60 emotional utterances from 12 speakers for training the model. This line of research has been carried forward by few other researchers by employing other promising approaches. The readers can refer to Davletcharova et al. (2015) for detailed analysis of the same.

13.2.3 Emotion Analysis Using Behavior Perception

Emotional health of a person can also be analyzed from his or her behavior in addition to text and speech. Unlike text and speech, the behavior of a person is the most authentic and natural perspective of expression of emotions and intentions. Hence, the behavior of a person should be closely monitored and analyzed in order to understand emotional state of a person. The behavior of a person is mainly demonstrated by his facial expression that mainly studies contraction and expression of facial muscles and eyes. These facial expressions are mainly analyzed through promising techniques of computer vision and image processing. As discussed, the emotions are detected by facial expressions interpreted through facial textures, facial muscles, eyes, and eyebrows. The generic model for behavioral analysis is as follows:

1. Finding of user’s face from vide frames
2. Extraction of facial features and its normalization to feature vectors
3. Classification of user emotions
4. Calculation of the intensity of each emotion (if required)

In general, it captures the image of patient through some camera. The captured image is processed to detect the face and feature extraction. It then uses the classifier which classifies the image into different emotion classes. This classifier has been pre-trained using a huge training dataset. The approaches for recognition of facial expressions have been broadly classified into geometric based approaches and appearance based approach.

The geometric-based approaches represent the human face is represented in the form of a feature vector that represents the human face in terms of its geometry. This geometry comprises of shapes, points, and locations of facial components like eyes, nose, eyebrows, and mouth and their distances. The downside of this geometric based approach is that it requires an accurate and reliable detection method
Another challenge for geometric-based approach is that the facial geometry of human is affected by the environment and climatic conditions. For instance, in case of extreme cold weather or some stinking odor, the face geometry changes even in the absence of any emotional transformation.

Appearance-based approaches work on the principle of extracting changes in face appearances and skin textures. There are numerous existing methods to extract changes in face appearance. One such method is Local Binary Patterns (LBP) which divides the image into a grid of rectangular regions. Each region is then encoded into curves, edges and other local features using comparison with neighboring pixels and center value. Thereafter, it constructs a 256 level histogram for each region which are later concatenated to form a global description of entire face (Tivatansakul & Ohkura, 2014). Similarly, there exists a Local Directional Pattern (LDP) method which employs edge detector to evaluate edge response in all eight directions. LDP is a robust method for appearance-based behavioral analysis as LDP uses edge responses which are stable in comparison to intensity based values for generation of binary patterns. Apart from LDP and LBP, there are few other methods in existence which can perform appearance-based behavioral analysis. Researchers have also proposed few Internet of Things (IoT)–based models for automated monitoring and assistance of patients in their homes (Enshaeifar et al., 2018). These kind of systems basically consists of sensors in order to sense vital body parameters. The sensed parameters are then forwarded to some back-end system that implements some analysis method (Bhardwaj, Khanna, Sharma, & Chhabra, 2019). Thereafter, user interface presents the clinical and technical alerts to health profession. With the help of this information, health professionals are capable to monitor the health of patients and accordingly suggest treatment around the clock. Enshaeifar et al. (2018) have employed such approach for maintaining the well-being of dementia affected patients by analyzing their behavior captured through installed camera and other sensing devices. The observed values are processed using data analytics and machine learning algorithms to generate notifications and recommendations to the patients thus providing timely and effective support thus preventing worsening of health.

Further, Ahn, Fox, and Jabon (2010) have proposed a model that analyzes facial expressions beyond categorized measurements. For the same, a computer is installed with a camera, tracking software and ML that enables selection of the most relevant facial features and improves the prediction model in a cost-effective manner. Ability to fit it beyond predefined categories achieves greater power and efficiency. Its working model has advocated its applications in various domains like predicting unsafe behavior of driver, monitoring operator fatigue and shopping experience etc. Similarly, Smirnov, Banger, Davis, Muraleedharan, and Ramachandran (2013) have also proposed a two stages framework for emotion recognition through facial feature extraction. These two steps in this framework are signal acquisition (through camera) and signal processing. In signal processing, the image is transformed to two dimensional array which is used for face detection and feature extraction. The extracted features are further classified into different emotions using various ML algorithms. Sapiński, Kamińska, Pelikant, and Anbarjafari (2019) have also
proposed a similar model to recognize human emotion using body movement based on body joints within the tracked Skelton.

13.3 Comparative Analysis of Various Perspectives

In the previous section, we have discussed various perspectives to analyze emotional health. Each of these perspectives has its own capabilities and limitations. Text processing is a better perspective as it requires less storage in comparison to its counterparts. In speech, the voice signals are processed to recognize and extract different emotions. On the contrary, video data processes audio, image, and text (sometimes) thus giving better results than other approaches. Although, video processing gives better results, its processing takes a lot of resources in terms of time and memory.

Apart from requirement of resources, these approaches perform best in some specific application scenarios. For instance, facial expression and speech can be employed in everyday life where user interacts in most natural way as it does not require any sensor (Tivatansakul & Ohkura, 2014). Moreover, facial expression overcome the barrier of cross-culture analysis as different languages and geographic regions have different dialects and voice quality, whereas facial expressions are universal to a certain extent. Facial expression processing also achieves consistent and higher accuracy in comparison to speech processing despite regional and language discrepancies. Moreover, the technological advancement has propelled the availability of image capturing devices in an affordable range, further enhancing the popularity of facial expressions perspective. However, mere facial expression processing is not sufficient in some scenarios. One such example is healthcare where it is mandatory to analyze biological signals in addition to facial expressions (Tivatansakul & Ohkura, 2014). The behavioral method obtains enhanced accuracy as mentioned earlier. However, it also has some challenges. The most critical challenge is its high computational complexity due to which it requires high computational time (Thacker & Makwana, 2019), requires high training time and thus not suitable for very large datasets. Another concerning issue is that behavioral method experiences difference based on gender, culture, geographical region and environmental conditions.

Similar to facial expressions processing, text processing also has some associated challenges. The foremost challenge of text processing is extraction of opinion from text understanding the context of words. Another major challenge for text processing is subjectivity detection as some text may be sensitive for some while others may feel quite neutral toward the same. Subjectivity detection for small message like Twitter data is further cumbersome due to lack of contextual information and requirement of suitable regularization to fill missing data. Context dependency is another major challenge for text processing as a particular word could have different subjectivity in a particular context (Chaturvedi, Cambria, Welsch, & Herrera, 2018). For instance, the adjective “long” have positive reflection in “long battery life” and negative in “long waiting time.”
Also, emotional health analysis through speech processing has some associated challenges. Noise robustness is a serious challenge specially in changing acoustic environments. Thus, recording of natural emotion is a challenging task as even the most popular recording protocols lacks recording elicited emotion (Ratna Kanth & Saraswathi, 2014). Another challenge is the possibility of multiple emotions in same utterance. The efficiency of speech processing is also affected as expression of a certain emotion by a person is also influenced by his or her background (culture, region, etc.). Resultantly, same emotion may be expressed differently by different speakers. Sometimes, a speaker a may undergo a particular emotional state for a prolonged period (days, weeks, or months). In such scenario, other emotions will not last long and thus it is not evident which emotion will be recognized by the recognizer among long-term or transient emotion.

13.4 Case Studies

Esturgó-Deu and Sala-Roca (2010) has implemented emotional analysis in order to analyze the behavior of students in primary education. On the same line, Wong, Wong, and Peng (2010) believed that the Emotional Intelligence (EI) have an impacts on the job outcome for each employee. Thus, authors Wong et al. (2010) in have implemented the approach to analyze effect of teacher’s EI on her job satisfaction. The analysis of emotional health is also implemented for evaluating emotional health of employees in workplace. The study of emotional health of employees is based on the principle that that organizations involve complex and competitive relationships. It is also required as the employees generally need to interact with some seniors and peers not of their choice which has a significant impact on their emotional health. The evaluation of employees at workplace is required as it helps to maintain his emotional status at optimum levels thus creating a healthy workplace environment for all others. On the other hand, if emotional health of an employee depletes, it results in his tendency to physically and psychologically withdraw from work by engaging him in some non-work related activities. This also results in a decrease in his performance as the employee experiences a downfall in self-efficacy and escalation in stress and tension.

Extending the research further, Sullivan (2018) have analyzed the group emotions in order to research the impact of sporting events. Similarly, Raman, Sambasivan, and Kumar (2016) have attempted to study the impact of emotional health on counterproductive work behavior (CWB) of government employees. It is observed that CWB instantly negatively impacts the customer’s association with the organization. Moreover, researchers showed that this CWB of employees may results into huge costs to organizations sometimes running into billions of dollars.


### 13.5 Conclusion and Future Work

In this chapter, authors have presented the various perspectives of emotional health analysis. Authors have also discussed the urgency to evaluate emotional health of humans by discussing the case studies related to students, employees, government officials, etc. Each perspective for emotional health analysis has its own constraints and challenges. For instance, performance of speech processing is greatly influenced by the dialect, region, and gender of the subject. Similarly, behavioral analysis is also influenced by gender and climatic conditions thus impacting the accuracy of model. Thus, each model has its own limitations.

In order to enhance the efficiency and accuracy of such system, it must take the research one step ahead by integrating multiple approaches. The research must also be extended in the direction of incorporating nature of stimulus for change in emotional status (Schirmer & Adolphs, 2017). For instance, the research must be carried out in the direction of dynamic stimulus like touch and vocalization that resulted in change in emotional state. It may also be taken further to study the location of touch on body or its cultural significance. Thus, it is concluded that visual, auditory and tactile senses offer specific strengths and challenges for emotional analysis. The research can be carried forward in this direction to improve the accuracy and efficiency of existing approaches for holistic and ecological emotional health analysis.

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