An Approach for the Transformation of Human Emotion and Energy-Field using Sound Therapy

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Abstract: The human emotions are very dynamic in nature, and get transformed from one mood to another rapidly. Emotion detector systems are available to identify the real-time emotions based on various external parameters like face expressions, lip movements, choice of words in speech and so on. Many applications were developed over and over again that are capable of providing solutions based on current emotions of an individual such as mood based music players. The humans are quite intelligent and smart enough to hide their actual emotion and represents themselves as per the environment, therefore they can fool others easily by expressing their fake expressions. The existing systems need high computation power and works upon probabilistic calculus models. On the other side of the coin, human biofield, energy around human body that reflects inner soul, is powerful enough to represent the actual psychology. It provides the visual verification and validation proofs regarding change in emotions. This research article shows a novel approach for determining the real-time human emotions, integrated with biofield analysis to overcome the mentioned issues. An algorithm is capable of expressing the true internal emotions of a person and classify the original and sarcastic emotions.

Keywords: Affective computing; Emotion detection; Human biofield, Sound therapy; Convolution Neural Network

1. Introduction

Affective computing deals with emotion detection as a key aspect that deals with psychology and cognitive science. It is capable of recognizing, interpretation, simulate and process human effects. Due to the interlinking of this technology with emotions, its accurate detection is the main focus and that attracted corporate sector to make huge profit**(Filippini, C., et al., 2020)**.In the past, under this domain, more emphasis is given on dedicated emotion (specific type of emotion detection) technology. The machine should interpret the emotional state of humans and adapt its behavior to them, giving an appropriate response for those emotions. While developing those systems are quite difficult that included information processing and interpretations simultaneously. These emotions can be expressed through various means like face expression, voice modulations, body gesture and others**(Affectiva 2016**). Other physical parameters like breath rate, heat rate, size of pupil etc. also varies in some emotion transformations. To gather such complex information, affective computing technologies require various sensors, computer vision techniques, audio devices to detect the emotional state of a user.Hence requires lot of computing power and high accuracy to respond back in a correct manner like recommendation system based on the mood of the user.

The computation of emotion recognition includes techniques of machine learning with other sub-modules like natural language processing, computer vision, speech recognition, and pattern analysis to extract the significant information. The human emotions are associated with surges in hormones and other neuropeptides, whereas in machines emotions it includes emotion speech i.e. algorithms, speech analysis and databases; secondly facial expression including body gestures and physiological monitoring. The emotions in machines is associated with abstract states meaning simulation of emotions in intelligent agents to improvise the human-computer interactions**(Garcia-Garcia, et al., 2017)**. Therefore, technologies are not capable enough to understand the real emotion of the humans, as those are not capable enough to calculate the real inside emotion (hormone level); thus can be forged easily.

The human biofield is an invisible electromagnetic layer of energy around every object (living and non-living). It possess the physiological and psychological characteristics of an individual. This energy field is associated with seven major chakras, also known as energy centers, which regulates wellbeing of a person. The strength of human biofield is quite low and beyond visible range of human eye, therefore one cannot see the energy field around**(Chhabra, et al., 2013)**. To make it visible different methods and technologies has been developed and its pattern analysis decodes about physical and mental health of a person. The visualization of these patterns contains different colorscodes based on their frequencies that helps in better understanding about the present condition. The improvisation of energy field can be done by practicing yoga, meditation and other alternative medicine methods. The biofield is very dynamic in nature that have capacity to change due to environmental factors, thoughts of person, easily get influence by the presence of negative energy, changes in hormone level and so on**(Chhabra, et al., 2018)**.

The guided medication techniques is apractice to reach a state of calmness and positives spiritually. The guided meditation is performed under the supervision of an expert or a guru and focus is on the instructed steps. The meditation is a process to remove the toxins or bad energy from the body as well as the Aura, thus direct towards the healing and replenishes negative emotions. The guided meditation includes dance, music and sound therapies. This research is focuses on the sound and music therapy, improve issues like respiration, lower blood pressure, and cognitive health while also reducing stress and muscle tension**(Guarneri, et al., 2015)**.

There are huge number of applications, present and future, and lot of research is going on in this domain (emotion detection). The business sector is highly attracted towards detecting emotions from a specific input to get hike in profit margin. This research article is focused on similar sector by merging affecting computing with biofield visualization for better, clear and detailed analysis of actual emotions of a consumer. The article focuses on some existing technologies, followed by proposed method of emotion detection and biofield analysis. The later sections includes the outcomes, conclusion and future scope of the work.

2. Literature Review

The emotions of a person can be identified from speech, text, face expressions, body gestures and body movements and from physiological states. Additionally, human biofield claims to detect the actual inner psychology of a person by analyzing the frequency or color intensity of biofield energy.While a person speaks, primary and secondary channels generates the information. The prime channel is interlinked with semantic and syntactic part, whereas subordinate channel is responsible for paralinguistic information of the speech. Hence to detect emotions from voice data, secondary channel information is main focus point**(Casale, et al., 2008)**. A lot many applications has been developed for emotion recognition via speech and still open for research. **Litman, et. al., 2003**developed the ITSPOKE intelligent tutoring system is a dialogue system that mentors a learner through a long physics qualitative question by describing each and every aspect of misconception. In order to identify the learner emotional state i.e. positive, neutral, and negative they utilize sound and prosodic features mined from learner speech. By using this technique they achieved 80.53% accuracy.

On the other hand, text data analysis is another method through which emotions can be analyzed. This domain is also known as sentiment analysis. Text analysis is a sub-field of natural language processing includes tokenization, parts-of-speech tagging, parsing, etc. This is one of the difficult method to analyze the emotions as it includes choice of words, tones, linguistic characteristics of text and many more. This technology needs high computing power and advance AI techniques**(Binali, et al., 2012)**.

Another method to detect the emotions is via body gestures and body movements that included hand movements, tapping of foot, eyes blinking, head movement etc. Although this field is novel but still lot of research has been done in this domain by integrating it with experimental psychology**(Mind tools, 2017)**. **D'Mello, et. al., 2008** designed AutoTutorsuccessfully addresses more refined emotional states i.e. confusion, boredom, frustration, flow and neutral. They observed emotions from body posture, conversational cues and facial features. For affective replies from a tutoring system they utilize some animated pedagogical agent having animated facial expression, sound and speech.

Woolf, B., Burleson, W., Arroyo, I., Dragon, T., Cooper, D., & Picard, R., 2009has taken five emotions i.e. self-confidence, frustration, boredom, motivation and fatigue into consideration. He utilized different heuristic rules for providing an effective response (changing voice and gesture, sympathetic response, graphs and hints, text messages) to learner's cognition state. He computed the degree of engagement in relation to overall impact on learner's learning and behavior.

Further, research by **Rosalind W. Picard. 2009**states that physiological reactions are also associated with emotions. The physiological information like blood pressure, pupil dilatation, breathe rate, heart rate etc. are linked with emotions but they are hard to determine and categorize with emotions. Based on dimensional approach, it is recommended to use classification techniques for better outcomes.

In addition to these techniques, another approach as mentioned in **Kadiri, S. R., &Alku, P. (2020)**elaborates emotion detection via facial expression analysis. Facial expression involves movements of lips, nose, eyebrows and other muscles that reveals ones emotions. The technologies works in combination of speech and crucial points on face to reveal the true emotions. Many researches has designed many different techniques to give accurate prediction of emotion detection and recognition.

Murthy, G. R. S., & Jadon, R. S. 2009&Becker, B. C., & Ortiz, E. G. 2008have taken six emotions i.e. Sad, Happy, Surprise, Disgust, Normal and Ambiguous into consideration. For emotion recognition they utilize Eigen faces. Their main inspiration was to use the dimensionality reduction technique (Principal Component Analysis) for a larger set of data. By using this technique they achieved 83% accuracy. However they utilize PCA, which incorporates its own drawback and makes this technique more expensive because computation of the covariance matrix is performed at the expense of efficiency mainly when abundant dataset are encompassed for training purpose.**Lien, C. C., Chang, Y. K., & Tien, C. C. 2006** have taken two approaches into consideration i.e. SVD (Singular Value Decomposition) and direct matching. Firstly, they transformed images into corresponding transitional expression matrices, then they perform a direct matching operation. These two approaches impose certain drawbacks i.e. a direct matching operation provides no or little precision for computing correlation coefficients therefore facial image conversion would result in producing asymmetrical output facial images.**Arumugam, D., &Purushothaman, S. 2011&Lu, H., Plataniotis, K. N.,&Venetsanopoulos, A. N. 2008**for feature extraction they integrate FLD (Fisher's Linear Discriminant) and SVD (Singular Value Decomposition) and for classifier they utilize Radial Basis Function. Mainly they focused on only three types of emotions i.e. Disgust, Happy and Anger. The major drawback of this approach is that they achieve low accuracy by utilizing this combination. The computation of naïve SVD is often going outside the skill of various machines.**Mao, X., &Li, Z. 2009, 2010**proposed an Emotion-Sensitive ITS named "*ALICE".* Alice utilizes emotion agent that is effectively capable of recognizing the emotions of the learner through text, speech and facial expression. They consulted human tutors to discuss all possible scenarios and developed rules. Thus 'ALICE' behaves closest to the human tutors, through the ongoing tutoring sessions.
There is another technique that is related to the reveal the psychological state of the person known as Human Biofield. It is an invisible and dynamic energy field around every living being linked with ones' physical and psychology. This energy field reveals the true state (physical and psychological) of an individual. Many researches has developed various devices and algorithms to visualize the human biofield that are further helpful for various applications like healthcare, sports management, affective computing and others. Some past studies states that the biofield structure changes with the change in state of mind i.e. positive or negative. The state of mind is further directly linked with ones' emotional condition. Hence, it is a good approach to include biofield analysis for the better understanding of emotional state of a human**(Chhabra, et al., 2019)**.

Zahran SK 2019, in his paper stated that, the human biofield as a human umbrella or atmosphere that represents human physical and psychological status and connect one to his/her surroundings. This umbrella contains information, and detect information too unconsciously, that help human adaptation to his/her environment. Bioenergy field radiates away from body, resonates and interacts with others- in a complex radiated communication system- to maintain coherence. Studying such Bioenergy field with its all components, may help scientist develop not only healing procedures, but also human psychical system, and how does it work.

The present research article includes both, the facial expression and biofield analysis, to showcase the transformation in emotions by sound therapy and its impact on the biofield of an individual.

3. Proposed Methodology

This section focuses on the detailed methodology of the identification of user's emotions along with its biofield. As stated in the previous sections, emotion recognition along with biofield's analysis can give much more accurate, detailed and tangible results. The experimentation was done on random population (working people, kids, and housewives etc.) to detect the different emotions (happy, sad, joy, anxiety, bored etc.) based on their day to day situations. The emotions of a person is detected via facial expression for the current research, which can be extended further by including body gestures, speech analysis and other parameters.

The architecture of the proposed methodology is based on three-layered architecture as demonstrated in figure 1, Capturing unit, Computing unit and Visualization unit. All these three units are connected to each other in a network and is Alexa enabled. In the very first unit or tier-1, a user is allowed to face the camera to detect the real time facial expressions and also an image to process it further for biofield analysis. Alexa will enable all the devices on receiving the voice command and act further as per the programming instructions. The acquisition of data is done in a dedicated environmental setup, designed for this experimentation.

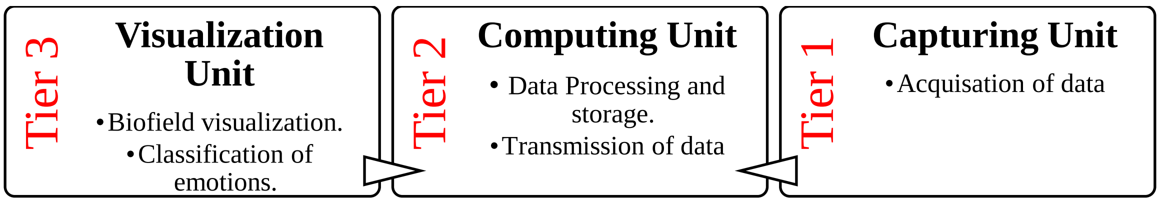

Figure 1. Three tier architecture

In the second unit, the data is processed for the computation of both, emotions and biofield, and further the processed data will be transferred for the cloud storage and analysis. The analysis of the emotions and biofield patterns will be done at cloud environment and stored for the future comparisons. Next, third stage, visualization of the analyzed data and final outcome of the overall computations will be displayed to the user, and accordingly, based on the current emotion state, a music will be enabled by Alexa, as sound therapy. The sound therapy plays a vital role in transforming moods in real time, hence, is included to transform the user's negative emotion to the positive one, therefore classified music, pre-programmed, will be enabled by Alexa as required.

The static experiment, as stated, setup is designed to lower the cost of computation, as shown in figure 3 below, along with dimensions. The dynamic environment requires lot many other constraints and calculations into consideration that will increase the computation cost.Therefore, initially, work has been carried forward in a static environment,which is also suitable for the computation of biofield as per the Aura Capture Visualizer (ACV) algorithm. The setup includes the color of background should be kept either pure white or pure black**(Chhabra, et al., 2019)**.

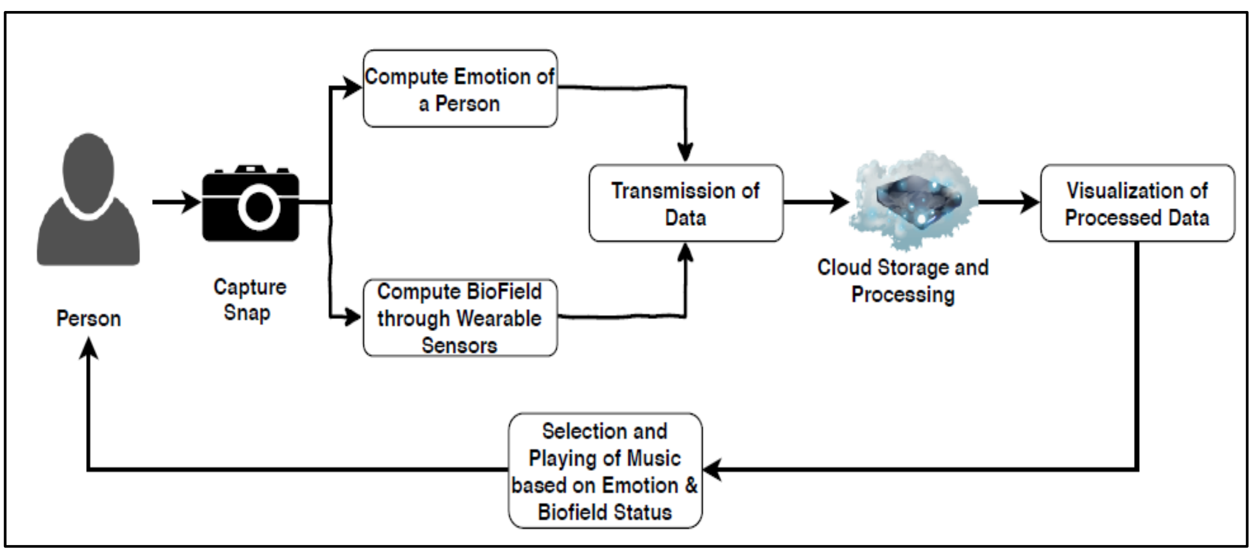

Figure 2 Experiment workflow diagram

In parallel to ACV process, emotion recognition model performs computations to detect the real time emotions via facial expressions. For this, convolution neural network (CNN) has been implemented with dataset taken from Kaggle. The combined results of both the processes has been analyzed and the emotions are classified into positive and negative. On obtaining result as negative emotion, a pre-selected playlist of different categories songs get streamed through media. After every ten minutes,facial expressions and aura of the user get reanalyzed, repeatedly, until the transformation is observed from negative emotion to the positive emotions**(Singh, et al., 2019).**

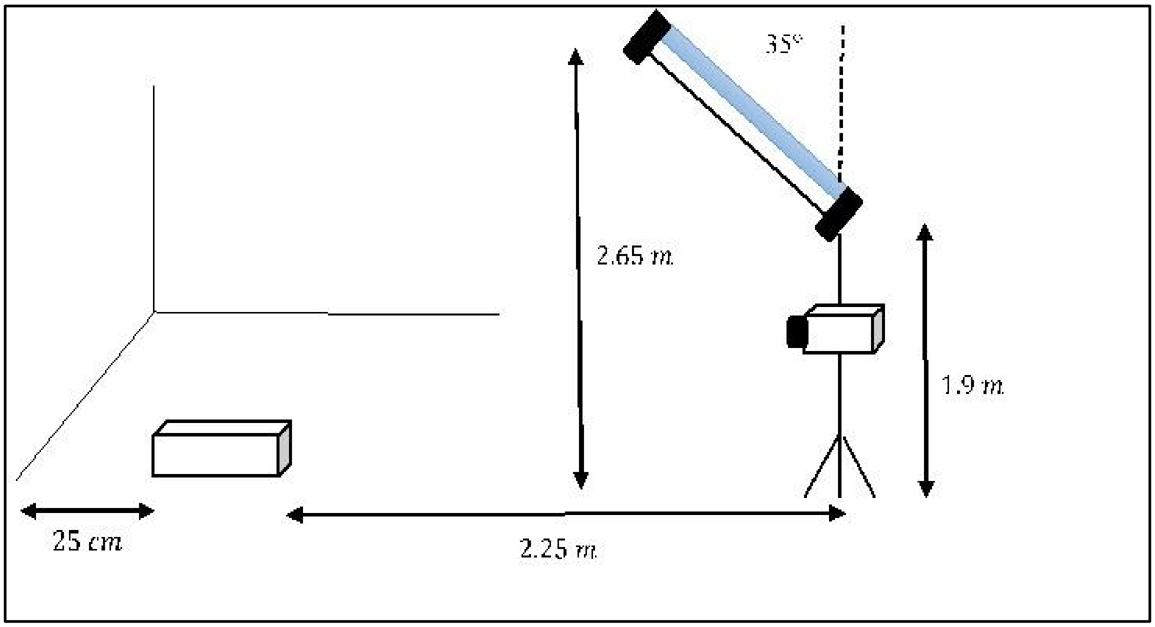

Figure 3 Static environmental setup

The emotions and the biofield of the user will be capture in parallel, and then transmitted to the cloud environment for its further processing and storage. The figure 2 presented above, shows the overall workflow of the experiment, biofield analysis is a new approach integrated with affective computing domain to improvise the results. The visualization of processed data is done on a screen or on a display unit. The classification of present emotion of the user will be done and accordingly pre-programmed sound therapy will be enabled to transform user's negative emotion to the positive one. The detailed algorithm for the mentioned process is described in figure 4.

Input: RGB image on an individual
Output: healed individual biofield using sound therapy

Begin

1. Capture the RGB image of an individual.
   $Vidcap = cv2.VideoCapture(0)$
   $Bgr\_img = Vidcap.read()[1]$
   $Gray\_image = cv2.cvtColor(Bgr\_img, cv2.COLOR\_BGR2GRAY)$
   $Rgb\_img = cv2.cvtColor(Bgr\_img, cv2.COLOR\_BGR2RGB)$

2. Identify $emotion\_text$ i.e. emotion and $human\_aura$ i.e. human Biofield of an individual.
   # emotion prediction
   $emotion\_prediction = emotion\_classifier.predict(gray\_face)$
   $emotion\_probability = np.max(emotion\_prediction)$
   $emotion\_label\_arg = np.argmax(emotion\_prediction)$
   $emotion\_text = emotion\_labels[emotion\_label\_arg]$
   # for Human Biofield visualization

```
    mcolor( ( i - 1 ) * 6 + j , :) = [ 0, 0, 35 ];
    mcolor( i * 6 + j, : ) = [ i * 10, 0, 0];
    mcolor( ( i + 1 ) * 6 + j, :) = [1, 0, 35 ];
    mcolor( ( i + 2 ) * 6 + j, : ) = [ i * 20, 0, i * 20 ];
    mcolor( ( i + 3 ) * 6 + j, : ) = [ i * 10, i * 5, i * 5 ];
    mcolor( ( i + 4 ) * 6 + j, : ) = [ i * 10, 0, i * 4 ];

      mcolor( (i-1) * 6 + j, : ) = [ 0, i * 10, 30 ];
      mcolor( i * 6 + j, : ) = [ 0, i * 10, 30 ];
      mcolor( ( i + 1 ) * 6 + j, : ) = [ 0, i * 10, 30 ];
      mcolor( ( i + 2 ) * 6 + j, : ) = [  i * 10, 0, 0 ];
      mcolor( ( i + 3 ) * 6 + j, : ) = [ i * 10, 0, 0 ];
      mcolor( ( i + 4) * 6 + j, : ) = [ i * 10, 0, 0 ];

      mcolor( ( i - 1) * 6 +j, : ) = [ 0, 0, i * 6 ];
      mcolor(  i * 6 + j, :) = [0, i * 6, i * 6 ];
      mcolor( ( i + 1 ) * 6 + j, :) = [0,i*6,0];
      mcolor( (  i + 2 ) * 6 + j, : ) = [  i * 6, i * 6 , 0 ];
      mcolor( ( i + 3 ) * 6 + j, : ) = [ i * 6 , 0, i * 6 ];
      mcolor( ( i + 4 ) * 6 + j, : ) = [ i * 6, 0, 0 ];

for n = 1:wid
for n1 = 1: hei
InputIMG( n, n1,1 ) = int16( ( InputIMG( n, n1, 1) + mcolor( grayIMG( n, n1) + 1, 1) ) / 1.2 );
InputIMG(n, n1, 2 ) = int16( ( InputIMG( n, n1, 2) + mcolor( grayIMG( n, n1) + 1, 2) ) / 1.2 );
InputIMG(n, n1, 3 ) = int16( ( InputIMG( n, n1, 3) + mcolor( grayIMG( n, n1) + 1, 3) ) / 1.2 );
    end
  end
```

3. Separate list of songs are created as per the emotions. i.e $playlist\_normal$, $playlist\_happy$, $playlist\_sad$, $playlist\_angry$, $playlist\_fear$, $playlist\_surprise$.

Figure 4 Propsoed algorithm

The input to the algorithm is received from the video capturing camera implanted in the static environment setup. At very initial step, image frames will be captured from the input video and then converted into grayscale image. From the captured images, emotions of the user will be evaluated using CNN based facial recognition unit that includes classification of expressions into different emotions like happy, sad, fear, normal and others. In parallel to this, ACV algorithm will identify the energy field around the seven chakras. The aura visualizer algorithm converts the RGB into visualized biofield image and also interpret the meaning of each color. Every human biofield color has its own meaning, hence negative emotions can easily be classified based on these color interpretations.

Based on both the outcomes, i.e. CNN module and ACV algorithm, proposed methodology will send a command to the sound/music streaming module to play the music based on the classified results. The pre-programmed lists of songs has been created as per the user's choice and recommended list will be played automatically to transform the negative emotion to the positive one. The whole experimental analysis was performed to conclude the efficacy of the proposed method, which included approx. 80 participants, with diverse demographics along with their consents. The present research performance is measured using the confusion matrix by calculating precision, recall and accuracy. A confusion matrix is a 2x2 matrix, shown in table-1, which is often used to describe the performance of a classification model, on a set of test data for which the true values are known.

Table 1 Confusion Matrix 2x2

True Positive **Criteria:** Noticeable impact if predicted accurately	**False Positive** **Criteria:** Noticeable impact if predicted accurately
False Negative **Criteria:** Un-Noticeable impact if not accurately predicted	**True Negative** **Criteria:** Un-Noticeable impact if not accurately predicted

It allows the visualize impact of the performance of the computing process, in the next section the complete results with visual graphs has been shown. For this purpose, polarities of emotion module, aura module and healing module are evaluated. Through confusion matrix, computation of precision, recall, and accuracy is performed. The Precision indicates the accurate prediction of positive cases, recall indicates the proportion of accurate prediction and accuracy indicates the accurate prediction of both positive and negative cases.

4. Results& Discussion

This section explains the overall outcomes of the experiment. The polarities of every module is calculated via following equations i, ii, iii, and those were used in finding values of confusion matrix.

$$Polarities_{Emotion} = \begin{cases} Prediction_{emotion} & \geq above\ 35\ \%\ \text{Noticeable Impact} \\ Prediction_{emotion} & \leq 35\ \%\ UnNoticeable\ \ Impact \end{cases} \quad \text{(i)}$$

$$Polarities_{Aura} = \begin{cases} Prediction_{emotion} & \geq above\ 35\ \%\ \text{Noticeable Impact} \\ Prediction_{emotion} & \leq 35\ \%\ UnNoticeable\ \ Impact \end{cases} \quad \text{(ii)}$$

$$Polarities_{Sound} = \begin{cases} Prediction_{emotion} & \geq above\ 35\ \%\ \text{Noticeable Impact} \\ Prediction_{emotion} & \leq 35\ \%\ UnNoticeableImpact \end{cases} \quad \text{(iii)}$$

Whereas to calculate the values for precision, recall and accuracy, equations iv, v, vi are required. Also, for the validation of the experiment, the feedback from the participants as control parameter and clinical examination (before and after sound therapy) as predictive model was performed. The whole process is iterative, therefore the total sample for the experiment is 716.

$$Precision_{predict} = True_{Positive} / True_{Positive} + False_{Positive} \quad \text{(iv)}$$

$$Recall_{predict} = True_{Positive} / True_{Positive} + False_{Negative} \quad \text{(v)}$$

$$Accuracy_{predict} = \frac{True_{\ Positive} + True_{\ Negative}}{True_{\ Positive} + False_{\ Positive} + True_{\ Nega\ tive} + False_{\ Negative}} \quad \text{(vi)}$$

On performing the complete experimentation, the predictive accuracy of emotion unit is 77% and recall is 75%, whereas accuracy of aura module is 79% and recall is 75% which is better as compare to the emotion module. After merging these modules, another experiment was performed that gives the accuracy of 83% and recall is 77% that is indicates the better outcome than other two. The visual results are shown in the figure 5 gives the representation of comparative study performed during the experiment.

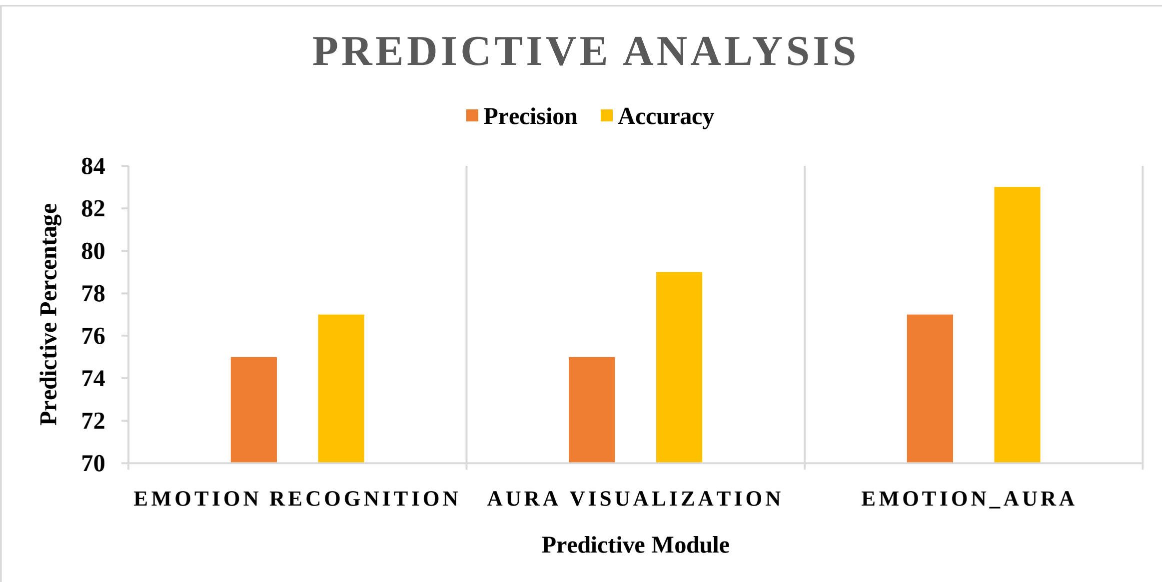

Figure 5 Comparative predictive analysis

Later, all the participants was allowed to give their feedback for this prediction and their level of satisfaction. The feedback analysis revealed that 83% of participants are strongly satisfied with the prediction. In the next step, sound therapy was given to those who are carrying negative emotions or were under stress or sad for the transformation. This was an iterative process and continued till the algorithm classified the change in emotion i.e. positive emotion class. Again, the feedback from those participants were taken, after healing and future recommendations and 87% of participants are satisfied with the healing process and future recommendation.

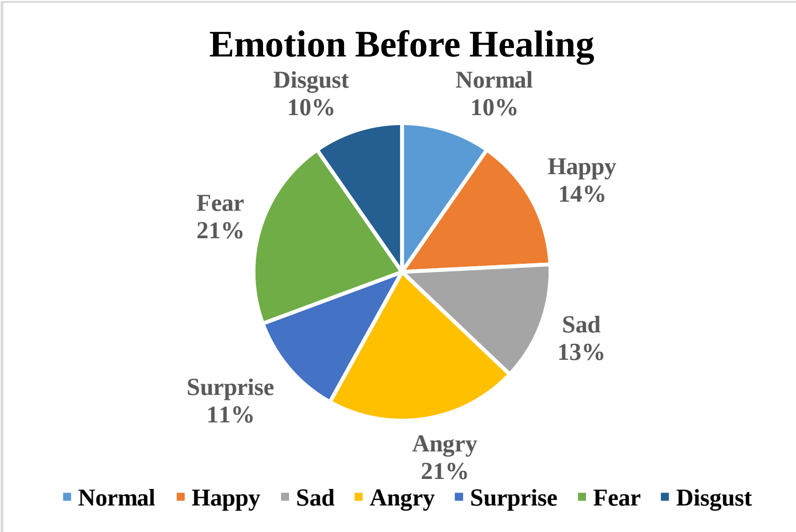

Figure 6 Emotion before healing process

Furthermore, sound therapy analysis was performed i.e. examination of emotions before therapy and after therapy. The results obtained was highly satisfied as positive emotions of the test cases found before healing was just 22%, whereas negative emotions was 78% as shown in the above figure 6.

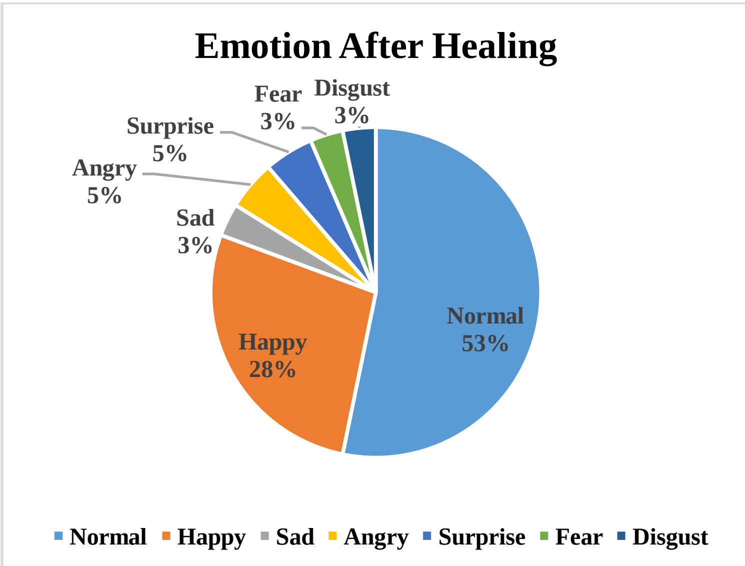

Figure 7 Emotions after healing

The iterative process of therapy continue to transform the negative emotion into positive ones. The preprogrammed and predefined playlists of music/sound was streamed on a media player. The transformed results obtained shows that new positive emotion population is now 83% whereas remaining 17% are still have negative emotions as shown in figure 7 and those where recommended to improve their lifestyle. Thus, the transformation in emotions are effective and can be improved via sound/music therapies and visible results can be observed by analyzing change in biofield colors.

Figure 8 Biofield before sound therapy

Figure 9 Biofield after sound therapy

The biofield visualization was obtained by the ACV algorithm, whereas emotion detection was obtained by the CNN emotion detection module. The biofield shows the actual psychology state of the person. From the figure 8, indicates more unbalance in biofield, high frequency of red colors (signifies negativity), and figure 9, indicates balances energy field after sound therapy, much green and related color frequencies (signifies positivity); clearly shows the change in biofield after sound therapy process. In figure 9, one can see the significant improvement in biofield after sound therapy, which indicates improvement in emotions from negative to positive.

5. Conclusion & Future Scope

The objective of this experiment was to check the effect of sound therapy on negative emotions and its transformation. In Complementary and Alternative Medicine (CAM) domain, this process is known as healing through sound therapy. To achieve the objective, machine learning and aura analysis was integrated to showcase the outcomes more effectively. The emotion recognition is performed via CNN based emotion recognition module and aura analysis is performed by a novel ACV algorithm. The accuracy of 83% is achieved by the amalgamation of these two domains along with strong satisfaction level of 87% of the participants after healing and future recommendations. Additionally, the effectiveness of sound therapy was analyzed, which was 22% positive, before the healing process, whereas it turns out to 83% after the healing process. Hence, the participant’s inner perceptions and feeling is altered through sound therapy that is clearly visible via change in biofield. Thus, conclusion can be made by this experiment that sound therapy have an effective impact on healing emotions.

Affective computing (Emotion AI) recognize human emotions and offer critical improvements for business. By understanding the customers better one can provide better services, also company can detect their employees’ emotional state and adjust their workload to keep them motivated. Along with voice analysis, facial expressions analysis and others, in this research article biofield is being introduced to enhance the understanding to human emotions in much better way. The future applications of this hybrid domain includes fraud detection, recommendation system, better customer services, healthcare analysis and informatics, lifestyle improvement, understand students’ during online teaching and many more**(Chhabra, et al., 2019)**. This will open up a gateway and bridge the gap between understanding human psychology and emotional status.

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