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A Survey on Affective Computing for Psychological Emotion Recognition

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Abstract— **Human emotions are precious and it directly exposes the mental wellbeing of human beings. Understanding the real emotion of people creates clues for many decisions making in critical situations. With recent enhancements in the field of artificial intelligence and machine learning, affective computing becomes an interesting area of researches that adopts the emotional behavior of humans and improves the learning impacts that are closely related to behavioral phycology. Evaluation of machine learning algorithms improves the prediction quality, but the problem arises at a decision making that is closely related to each other. The problem of single and multiple modality issues arises during the final emotion identification that makes the decision resilient. The proposed study focused on a broad survey about different techniques used to detect human behavior and real emotion by considering the data analysis tools and platforms. The proposed study takes affective computing as an initiate, considers the physiological data and their relation in the detection of emotions. The study also considers the recent techniques in comparison like deep learning algorithms, machine learning, and toolsets related to that. To find the compact algorithm that works well in decision making, also helpful in creating a novel idea for emotion recognition even better the proposed study is formulated.**

Keywords— Affective computing, Emotion recognition, Machine learning, Psychology analysis, Deep learning

I. INTRODUCTION

With the advances in recent technology, the human-computer interface is quite improved and the determination of human emotion through unique physiological data and behavioural expressions are improved. [11] Detection of human behaviour, recognition, and interpretation of the exact emotion need robust features to accurately predict. Human emotion is not limited to physiological signals, nowadays the interactions in the webpages, blogs, and social media updates are also helpful in the keen analysis of human emotion. Affective computing is an interesting field of study that gets lots of attention towards the field of emotion recognition, phycology, and mental health studies [23].

Each Individual around the world expresses their opinions uniquely including the method of showing eye contact, using gestures, facial expressions, and landmark variations that determine their unique mood. [19] Few peoples convey silence and no facial expressions are identified, in such cases deep physiological signals help determine the real emotions of the humans. In the field of human-computer interface (HCI) the system intends to learn the way of improving the understanding between the human interactions with the computer in terms of handling the devices effectively. HCI is the initiative for the evaluation of a user-friendly approach for interactive device access. The general architecture of the human emotion detection framework is shown below. Computers are said to be very dissimilar from the perspective of emotions. [26] These feelings have humiliation in science; scientific principles are formed based on intellectual thought, logical judgments, perceptive arguments, testable starting and ending states, and repeatable experiments. But human feelings are a strange thing, which gets in the way of, and the pleasure of detection that leads to the development of science. Many scientific observations have been caused out of fear. Affective computing deals with the deep quality of emotions identified by computers. This technique is done using the iterative learning process performed by the computer. [26] Affective computing is the process of developing the system and device that recognize, read, interpret and simulate human effects. It is the new way of bringing the human emotions in a most systematic way of evaluation together we call emotional-AI to make people's emotional understanding better. Affective computing senses the emotional state of people through input sensors, microphones, cameras, and other software logic inputs.

II. BACKGROUND

A. Emotion Recognition systems

[1] One of the fast response a person show their emotion is through facial expressions. Facial emotion recognition acts as one of the powerful techniques to communicate real feelings during the interaction. [2] The success of human-computer interaction depends on the effectiveness of the communication signal that is derived from the input. For analysing such input the source of the data collection module is nothing but the real-time sensors, camera, body gestures, audio data, and facial expressions. Numerous systems are available to extract the emotion of humans. [1] data collected by these sources are significantly used in data mining operations to acquire market analysis, post-surgical emotion recognition even more.

B. Physiological signals

Every human emotion is characterized by two dimensions of understanding, the first one is arousal and the second one is valence. Arousal denotes the intensity of emotion while valence qualifies positivity or negativity of emotion felt by

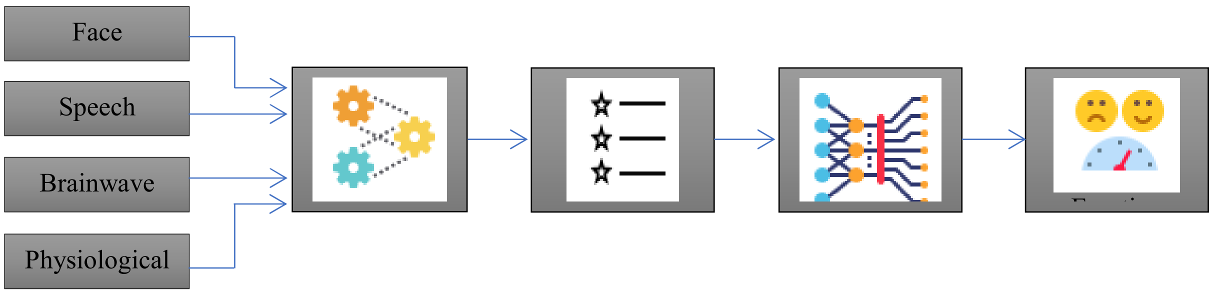

Fig. 1. *The general architecture of emotion detection system*

someone in nature. The autonomic nervous system (ANS) is responsible for controlling human body functions

such as heart rate, respiration, digestion, arousal, etc. These signals of the human body are extracted using ECG, EEG sensors that are used to detect the real change happening with the human body [1].

C. Electroencephalography (EEG) Signals

With the advancement of sensor technology and the internet of things, the remote monitoring of EEG signals is feasible. The goal of the system is to derive the emotion from the received physiological data. The sequence of physiological data and the continuous monitoring of the same helpful in detecting the emotion of the humans effectively. [2] Presented a robust model using recurrent neural networks algorithm with publicly available datasets on EEG signal recordings and face expression data. Both the spatial and temporal domains are used to improve the model discriminant ability. [3] Proposed a multi-modal collaborative emotion recognition system using the EEG data. [34] Deep learning algorithms are used to evaluate the obtained results. [4] multi-source target interpretation model is developed using the EEG data. The existing number of volunteers is considered as the training set. Using the existing data, the new person's emotion is being identified. The first level of approach uses single-source prediction, and the second level of approach uses transfer mapping of the extracted features from the training data. The cumulative system integrates the source models to recognize the real emotion of the subsequent sessions. [5] Interprets the emotion of the humans through DEAP (the dataset for emotional analysis using physiological data) dataset. [33] The proposed algorithm extracts the unique features from the EEG signal and classifies emotions using machine learning models. The correlated weights with the training data and the test data are used for making the decisions.

D. Heart rate signals

Heart rate is closely related to emotion. Simply for discussion the first change that occurs in the body when a person gets emotional changes is through heart rate only. Any kind of negative emotion affects the heart rate immediately. [8] An objective analysis of emotion is one of the complex tasks. A new approach is discussed to categorize the emotional objective as sadness, anger, pleasure; happiness, etc. using the healthy ECG recorded data the

proposed test model correlates the pattern on normal and abnormal categories.[9] Kalman filter-based ECG signal

filtering is developed to extract the real peaks of the signals. ECG signals are normally pattern verified through R-R intervals.

E. Facial Expressions

[6] Multi-feature fusion is the technique of combining N number of unique features to form the feature mapping for making pattern recognition. The proposed system in [6] uses EEG signals and facial expressions that fuse to identify the real emotion (positive, negative, neutral) using the recorded data as the training set. The system uses a real-time dynamic dataset. [7] The proposed system classifies the major depressive disorders (MDD) that lead to frequent changes in the mood which considers as a unique sign and symptom. The proposed system uses a convolution neural network (CNN) based automatic face expression, detection model. The face consists of unique landmarks, that show the real emotion using expressions such as moving an eye-brow, highlighting the chins, smiling, opening the eyes broader, etc. Each feature extraction model is used to identify the potential information that persists with the input. Such framework is also applicable for psychological changes detection too.

F. Speech and Gestures

People with frequent changes in emotion release various gesture outputs and speech tone variations detected by many systems. [11] Using CNN models the speech patterns of a normal person and abnormal person are detected and trained. The real-time collection of audio signal data is formulated with deep data augmentation and data normalization. Currently, the audio data is used for sentiment analysis also. The emotion analysis is the next level of sentiment analysis in which the classification of emotion varies and not simply like positive, negative and neutral emotion, etc. [14] Mel Frequency Cepstrum Coefficient (MFCC) features were the unique form of tone extraction process from speech signals to detect the underlying emotion of the speech data. Each audio data holds a unique pattern that keeps on repeating with the particular state. The presented system extracts seven different emotions using the pre-recorded emotion database of the Berlin database of emotional speech (Emo-DB). Understanding the human real emotion is a complex task. [15] Multi-modality speech recognition is done using the audio data and the text data that is correlated with it. The neural network model is applied to extract the hidden representation of modalities. The attention mechanism is used to combine the given information. Only some part of the speech data is considered as the modality. [16] A noise-reduced model was used for the detection of emotion using the small audio clips collected from smartphones. Mel-frequency cepstral coefficient (MFCC) algorithms to extract features. Various emotional states are identified using the training data of happiness, sadness, surprise, disgust, fear, etc. these are N number of stages available in the detection of emotion from the audio clips. [17] Provides an idea of a language-independent speech sentiment recognition system. The proposed system uses the Mel spectrogram method to detect the pattern variations accurately.

G. Text Data

Due to the increased usage of the internet, people are expressing their thoughts and feelings in the form of text. This text data acts as one of the cues for the human emotion detection analysis. Social media, microblogs contain enormous data on emotion that act as the bags of words used for training the existing model.[32] Methods such as (NLP) natural language processor, text mining, opinion mining, and sentiment analysis frameworks are used to analyze the real emotion of humans. A simple text comment posted by the user is simply categorized as negative, positive, and neutral sentiment based on N-gram models. [33] Unlimited datasets available on the internet nowadays provide a new path for innovating prediction frameworks. The text data act as one of the strongest modes of expressing the emotion regardless of facial expression, audio, and physiological data.

H. Emotion Models

Emotion models are the primary thing required to understand the concept of emotion detection. The emotion models (EM) consist of various emotional states that occur with humans. Various emotional models are in practice. [32] The study discusses the dimensional emotional model called DiEMs and Discrete emotional model called DEM etc. discrete emotional model represents the emotions placed in the different categories. The basic emotions that fall under the discrete emotion models are happiness, sadness, anger, disgust, surprise, and fear. Also, the combination of these emotions produces other emotions too like, guilt, shame, pride, etc. These emotions are also responsible for generating complex emotions that are initiated from basic emotions.

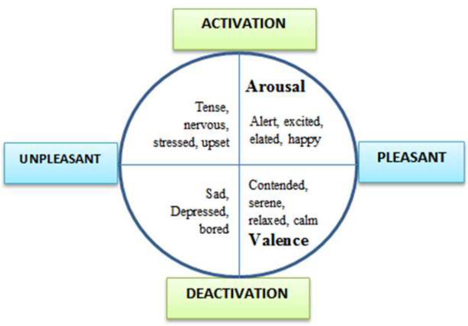

Fig. 2. *Wheel of Emotional states*

Dimensional emotion models (DiEMs) [32] are freedom of exposing type, where the expressed emotion interrelates to each other and denote the peculiar type of emotion that falls on the spatial space. Uni-dimensional and multi-dimensional emotions come under this category. [12] As stated in the article, the innermost real emotion arises from the primary emotions represented in the Dimensional emotion model. Fig.2 shows the wheels of emotional categories represented in the DiEMs system.

I. Datasets collection

Datasets act as an important factor for analyzing new data available in real-time. Some of the emotion recognition datasets are listed in TABLE I. EEG, heart rate, text data, speech, and audio data act as the crucial form of inputs available for the emotion detection framework. [18] CK+ database is one of the standard image databases utilized for an automatic face expression detection framework. It is used widely in many test-bed algorithms for training purposes.

TABLE I. PUBLICLY AVAILABLE DATASET

S No.	Behavior cue	Dataset name
1	EEG Signals	DEAP Dataset, MAHNOB-HCI Dataset, Ascertain, AMIGOS
2	Heart Rate	UCI Machine learning repository, MIT-BIH, DEAP,
3	Face Detection	CASIA - face detection dataset, JAFFEE, Japanese female expressions datasets, AffectNet, EmoTic, K-EmoCon, Google Facial Expression (GFE) dataset
4	Speech & Gesture	Affective Norms for English Words (ANEW), SUSAS, (Speech under simulated actual stress, MAD dataset, MSR daily dataset, Live android speech recorder data
5	Text data	Twitter comments dataset, Amazon customer reviews, COVID sentiment dataset, etc.

Affect-Net is one of the largest facial image datasets available in recent years. These datasets consist of 1250 emotion-related points in different languages that hold the facial landmarks data. Ascertain is a kind of EEG data signals and ECG data signals collected by inducing the patients to audio-visual simulation to grab the real peak changes occurring concerning the changes in the brain waves and heart waves during high stimulus points. EXOTIC is a context-based image dataset available with 26 discrete categories of positive, negative, and neutral emotions. Google Expression dataset is one of the largest collections of datasets evaluated to help the researchers on induced face expressions, emotion recognition, and sentiment analysis. K-EmoCon is the multi-modal multi-perspective dataset collected with 16 paired data of physiological sensors extract the data from volunteers. AMIGOS This dataset act as multi-modal research information used for affective computing, personality assessment, mood swings of the individuals or groups. This dataset is considered robust data with neurophysiological signals collected from volunteers.

III. Emotion recognition approaches using affective computing

[30] Affective computing is the process of learning the input cues and interpreting the emotion through an autonomous system built using the existing emotion data. The emergence of affective computing is applicable in all areas to imitate the real emotion felt by the user for betterment. Observation is the process in affective computing that holds numerous unique key points of expression. [26] The basic emotions classified by the emotion detection systems in previous works are sad, happy, fear, contempt, anger, and disgust, etc.

IV. Applications of affective computing

Sensing the real feeling of the individual helps many industries to enhance them in terms of improving the quality of their products and providing customer satisfaction, improving the diagnostic procedure in medical therapy, or improving the learning pattern in the education industry, etc. [27] The capturing information is processed to extract useful information and facts. Some of the potential applications are discussed here.

[29] E-learning is one of the major fields of interest with affective computing used to modify the presentation, content topic, and teaching pattern depending on the emotional feedback from the learners. Robotic systems are used to provide an enhanced response by learning the emotional behaviour of the users. They execute appropriate applications and gadgets based on the emotional mode of the consumers.

Social monitoring is one of the impacted fields utilizing the affective computing framework to provide safety to the society by monitoring the driver's emotions, sending warnings to the emails, triggering the vulnerable hints available with the systems through internet notifications, etc. [30] Medical and psychological domains have a large impact on affective computing in terms of changing the diagnostic procedures on treating autism peoples, providing a variety of therapy for mentally non-stabilized patients, etc. Affective computing applied to the field of communication and social interaction domain to extract the real emotion fetched by the participants in the social practices.

V. Computing Tools

A. SAM

SAM This is the traditional method of exploring emotion using the assessment scale. The SAM scale is used to range the emotion into three categories such as expression as valence, arousal, and dominance. It acts as a well-known method of self-assessment that ranges from high to low, where the highest range of 9 examples acts as the positive emotion or valence active state. The low range in the slider act as a highly negative state, and the value 5 act as a neutral state.

B. Acumen

Acumen is a tool used to extract facial expressions and gesture data. The open-source tool is used to directly read the gestures available in the facial expressions by utilizing the large collection of facial expressions in the source Kit. It consists of a spectrogram panel that is used to analyze the patterns [19].

C. Attention Meter

Attention Meter is developed using Python and OpenCV that holds the model for extracting the real-time facial expression routines. The unique frameworks present in it enable the face landmarks to get identified better.

D. EDAExplorer

EDA Explorer is one of the affective computing tools used to visualize and analysis of electrodermal activity data (EDR). The noise-removed data contains the EDR signals with 95% accuracy. The EDA Explorer is used with internet tools itself.

E. PhysioBoard

Physio Board is the toolkit available to explore the real-time physiological data and their corresponding emotions etc. The toolkit is available as an application installed with Mobile devices, IPDs, computers, and websites too.

VI. Affective computing algorithms

With the emerging growth of machine learning and deep learning algorithms with various open-source modules available with GitHub, Kaggle, Google pages, etc, the affective computing framework is kept on improving. [26] Deduction and classification of human emotion is a complex task. Segmenting the emotion as positive, negative, and neutral is the traditional approach held in many research works. [30] The recent research works implemented the deep emotions using the machine learning algorithms such as (SVM) Support vector machines, (KNN) K-Nearest neighbor, Hidden Markov Models (HMM), Artificial neural networks (ANN), Random Forest (RF), and Decision trees (DT), etc.

A. Support Vector Machines (SVM)

Problems observed by Support vector machines solve classification difficulties better. The standard model works apart from the dimensionality criteria. Creating a hyper lane between the randomly spread data to classify them into multi-scale perspectives is applicable. The SVM distinguishes the training vector with the test vector precisely and converges the relativity data that are close to each other into graphical visualization. Emotion recognition using SVM based classification is discussed in [22], [25], [27]. Using the pictures of facial affects (POFA) Dataset, leaving the central portion of the face, extracting large feature points SVM classification is done to predict emotions such as Happy, Sad, Afraid, Angry, Surprised and Disgust, etc. SVM seems more memory efficient and relatively provides a better response in handling high dimensional feature points.

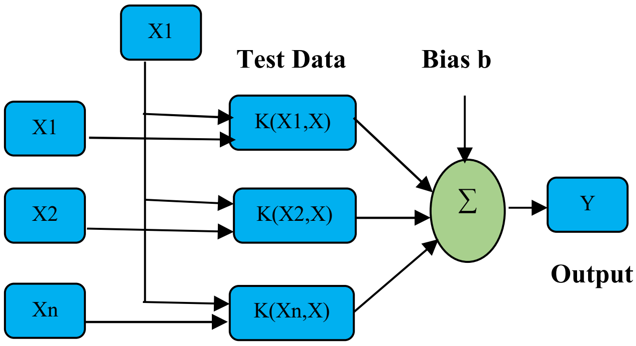

Fig. 3. *SVM algorithm general architecture*

B. *Gaussian Naïve Bayes (GNB)*

Gaussian Naïve Bayes algorithm is a kind of Naïve Bayes model that uses Gaussian normal distribution framework to handle the continuous data. It is purely based on the Bayes theorem for simple and high functionality needs. [31] Here three scenarios of analysis are done. The experiment is based on short videos recorded in real-time, long videos of facial expression, and a combination of both videos. Both using visual and physiological modalities are analyzed with the Gaussian Naïve Bayes model. GNB follows the measurement of mean and standard deviation values from the samples. The generative approach tends to extract the class-conditional distribution results of the input data under test. Hence the prediction of emotion using both modalities is evaluated well. It works on the principle of the likelihood of occurrence of present output that depends on the previous outcome.

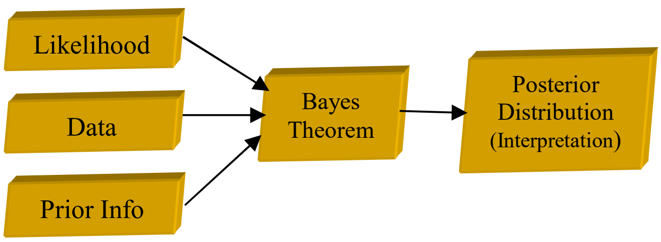

Fig. 4. *Gaussian Bayes model*

C. *Deep Belief Network (DBN)*

A generative graphical model with multiple layers of hidden units is used to recognize, cluster, and generate a sequence of understanding networks. [29] Each hidden layer holds unique feature information about the input samples. Restricted Boltzmann machines fall under the unsupervised learning category of deep belief networks. DBNs are symmetric and induced more in collaborating filter techniques, feature extraction in pattern recognition, recurrent mechanisms, etc. Deep belief networks are often slow in processing but still act as a standard model for complex data predictions. It often uses a neural network model with customized hidden nodes. The weighted bias generated from the hidden nodes is feed-backed to make the model adaptive.

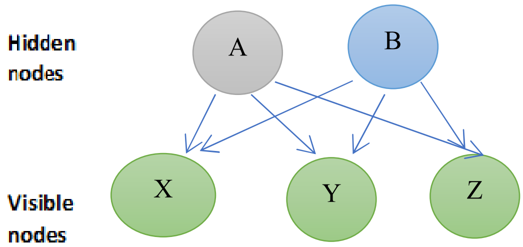

Fig. 5. *Deep belief network model*

D. *Fusion of Deep learning models*

Keeping the benefits of machine learning algorithms such as SVM, KNN, HMM, and ANN as mentioned in [30], and some of the deep learning models such as deep belief network [29], Deep learning convolution neural network [13], Deep learning neural networks [1] are discussed in the presented study, the prime challenges in the existing works are related to similarity issues in decision making. Single modality and multiple modality kinds of scores that occur in the decision-making process affect the accuracy. Further, the study motivated to develop a robust model using artificial intelligence (AI) tools, collaborated with deep learning models for emotion recognition with better results. The future work focuses on creating a novel ensemble system using a Deep convolution neural network with a CatBoost algorithm for making the decision model more robust. Boost is the prior version of the gradient boosted model that was highlighted for handling ranking problems. The tuning of layers in the deep learning model depends on the real-time training input and hence the system should be developed as an adaptive network to make such changes. The adaptive algorithm enables the system to iteratively repeat the learning pattern of datasets to improvise the levels of prediction. Robust Ensemble layers of Deep-AI model (REDA) for emotion recognition further focus on improving the quantitative measures with adaptive feature comparing the existing implementations.

VII. Discussions

From TABLE II, it is clear that many machine learning algorithms took part in the evaluation of emotion detection from various perspectives. [25] the system discusses the Cross-modal SVM algorithm and they achieved the accuracy of 90% as maximum from the compared works. SVM dominates in a maximum of the existing works since the reliability of the algorithm is good in complex data processing. It is an interesting area of research to study and discuss the emotion recognition frameworks. Based on many scholarly articles collected, with internet sources, the concept of affective computing is broadly explained here. The presented study list down the various techniques used for affective computing, applications of affective computing, and numerous datasets available for affective computing TABLE II. The toolsets that are available for open source are discussed here. With the emerging growth of artificial intelligence and people's involvement in opinion forecasting, medical wellbeing, and social security the emotional intelligence or emotional AI become an interesting area of research. It is also evident from the study that Deep learning models are not taking part very much in the Real-time emotion prediction that perhaps given the way for creating a robust model in further explorations.

VIII. CONCLUSION

Affective computing is an interesting area of research to read, observe and interpret human emotions in real-time. using various input features extracted from the data such as facial expression, face landmarks, text data, Physiological data, EEG brainwave data, ECG heart wave data, and acoustics data the peak highlights of emotions are extracted. Human emotions are not the same at all times. Affective computing helps numerous fields to read and interpret the real emotion using various machine learning algorithms discussed in SECTION III. In the aspect of real emotion extraction, the true inner feeling of the human at various situations affective computing framework plays an intelligent role shortly. The study covers the overall idea and information required to initiate the design work for

TABLE II. SUMMARY OF FEW DESIGN APPROACHES USED FOR AFFECTIVE COMPUTING

Sl.no.	Ref.	Algorithms Discussed	Dataset Type	Tools Used	Quantitative Measures
1	[21]	maps, SVM	Acoustic Data	SMILE	UAR:79.5%
2	[22]	3-NN,5-NN, SVM	ECG data	Audi	Accuracy:79.48%
3	[23]	Binary Classifier	Facial Expressions	Affect-Net	Accuracy:68%
4	[25]	Cross-Modal SVM	Text data	TEL	Accuracy:90% Precision:74% F1Score:73% Recall:73%
5	[26]	Auto-ML	Images, Handworks	Fire-Base, Auto-ML	Accuracy:80.6%
6	[27]	SVM	Facial Expressions	LFW, FDDB, and YFD	Accuracy:89%
7	[28]	C-Attenuation, Baseline network	Text data	CS-online file transfer	F1Score:73%, F2Score:84% Accuracy:76%
8	[29]	DBN, CD, RBM	Text data	Text Semantics	Accuracy:67%
9	[30]	SVM	Face landmarks	SAM	Accuracy:89.5%
10	[31]	Gaussian Naïve Bayes	AMIGOS	Affective annotation, SAM	F1Score:72.5%

Affective computing in psychology. Further based on TABLE II. Discussion, many machine learning algorithms such as SVM, NLP, NB, KNN play a great role in prediction. The system should be further improved by indulging Deep-AI models that consist of ensemble architecture of Deep convolution neural network with CatBoost model stacked together to form a robust prediction technique with the iterative updating process. The Robust Ensemble Deep AI (REDA) architecture needs to be compared in terms of achieving accuracy, intelligent and efficient prediction with less complexity.

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