Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.777998

ACQCNNET: AFFECTIVE COMPUTING APPROACH FOR RECOGNITION OF VISUAL EMOTIONS BASED ON QUANTUM CONVOLUTIONAL NEURAL NETWORK

Ezzat Abdulaziz Mansour[1*]
[1*]Information Science Department, Faculty of Arts and Humanities, King Abdulaziz University, Jeddah, Saudi Arabia E-mail: emansour@kau.edu.sa

***Corresponding Author:** Ezzat Abdulaziz Mansour
*Information Science Department, Faculty of Arts and Humanities, King Abdulaziz University, Jeddah, Saudi Arabia E-mail: emansour@kau.edu.sa

Abstract
Affective computing is presently one of the large amount dynamic research domains which include speech descriptors, Facial affect detection, multimodal system and Emotion classification. Affective computing is a multidisciplinary knowledge, such as psychology, cognitive and computer sciences. In this article, describe the overview of affective computing emotion theories, state of art of key technologies, projects, research challenges, emotion feature extraction, algorithms and applications. This paper analyzes the various emotions of humans such as happy, sad, anger, surprise and neutral emotions based on Warsaw set of facial emotional dataset. This research work comprises of two phases. The first phase contains the preprocessing of given image data. The preprocessing is comprised of grey scale conversion, histogram equalization, face detection algorithm and image cropping & resizing. The second stage is classification of emotions is based on Quantum Convolutional neural network. Our proposed work attain the recognition accuracy is 95%. The performance measures of the research work have been evaluated. The performance measures are recall, precision, and confusion matrix.
Keywords: Emotion classification, Automated Face Analysis, Deep learning, Quantum Computing

1. INTRODUCTION

Affective Computing is the vibrant investigation fields of computing paradigm. The primary objective of this field is to detect and recognize emotional information by using sensors. In the affective computing, sensors embrace the major part of the system. This system is used to confine the relevant information and to take out the pattern from the gathered data. In order to predict the required pattern of the gathered facts so many technologies like data mining, machine learning, deep learning methods, algorithms and techniques are incorporated.[3] The term emotion is defined as a strong feeling such as love, anger, fear, happiness or excitement. Conventionally the emotion and feelings with responses and reactions are denoted specifically only for human beings. At present in the technical era it becomes a significant quality that is to be possessed by the machines with artificial intelligence, because only emotions will help the machines to interpret the commands. It will enhance the quality communication between machines and its users as well.[2]

The human computer interaction is expected to be prominent and successful for an exquisite communication and processing. It would be more obtainable and rational if the machine interprets the emotional state of human beings and adapt their behaviour to them. In order to attain this, affective computing is one of the best solutions. The affective signal can capture facial lexis, body posture, speech & gestures. The goal of affective computing is to enable people to communicate their emotions and have a cognitive based understanding [8].
Quantum learning is one of the most emerging fields of Quantum machine learning which is used to solve real world problem. In the current scenario, classification of visual emotions is a still exigent task. In recent years, many researchers developed numerous algorithms based on machine and deep learning approach. In this paper, presents a QCNN which is used for the classification of visual emotions from face images. The planned architecture consists of two phases such as preprocessing along with classification. Each phase incorporated with quantum and classical components. Additionally, to facilitate find the effectiveness of the anticipated model compared with modern models. The key part of this research work is summarized as follows

- A new Quantum based Convolutional Neural Networks is proposed.
- The Proposed QCNN is applied for classification of various emotions
- Real time datasets are used to evaluate the proposed model with routine measures.

This paper is structured as follows. Section 2 describes emotion theories and their classification. Section 3 describes automated face analysis and feature extraction approach. Basic notations of quantum computing are briefly described in section 4. Section 5 describes the proposed methodology of the Emotion classification. Section 6 illustrates the results and discussion of the proposed system. Finally, the conclusion of the paper will be made in section 7.

2. EMOTION THEORIES

Emotion is a fundamental mode of non-verbal adaptation among people. Emotions in humans are complex in various aspects such as natural, emotional, societal and civilizing. Emotion recognition is categorized into two ways such as facial features and speech descriptors. In this paper, our proposed methodology is based on facial features. In general, the emotion is categorized into following forms: Primary emotions, Secondary emotions and mixed emotions. The basic emotions are annoyance, dislike, bravery, misery, expectancy and acceptance.[10]

Primary emotion is mainly focus on physiological reactions of human and animals. In this emotion, sensors are measuring changes of emotion in terms of physiological aspects to detect the facial expression and posture. Primary emotions are crucial for survival, functionality adaptive, innate and universal, distinct affective states and hardwired in our brains. Secondary emotions are fueled by primary emotion. Mixed emotions are conflicting feelings or behavior. The table 1 summarizes the important sets of basic emotions.[9]

Table 1- Basic Emotions

Type	Basic Emotions
Primary Emotions	Anger: irritability, Frustration, bitterness, Humiliation Fear : Anxiety, panic, nervous, apprehensive, overwhelmed Sadness: Grief, neglect, guilt, regret, anxiety Disgust: disdain, distaste, disappointment Surprise: eager, amazed, shocked, and perplexed. Anticipation, trust and joy
Secondary Emotions	Guilt, fervor, gloominess, pride, vulnerability, regret, jealously, frustration, shame, confusion and optimism
Mixed Emotions	joyful - cheerless, optimistic-unenthusiastic, lovely-disagreeable

3. AUTOMATED FACE ANALYSIS

Automated Face Analysis seeks to detect one or more measurement of the supervised learning system. In affective computing, measurement is categorized into three approaches such as message-based, sign-based and dimensional measurement. Message based measurement describes the implication of emotion.[7] The common examples of the system includes agonize, attention, playfulness and sympathy. In sign based measurement deals with the relationship between signs and emotion, based on experimental or observational approach. The common method of sign-based measurement is Facial Action Coding System (FACS). This system is automatically extracts the action units, action descriptors and movements of the facial system. Dimension measurement predicts the similarities of emotion and signs. AFA need several steps that include face detection and feature extraction.[10]

3.1 Feature Extraction

Feature extraction is a form of “dimensionality reduction” techniques that accurately depicts the useful pattern of the face image database. In other words, “Feature extraction refers to the selection of the vital uniqueness of an image”. For identification of automated face analysis, many parameters like shape, color, edge, appearance, motion and morphology can be performed. In this proposed work, numerous types of features have been used. The most common skin texture of automated facial analysis is Geometric features, Appearance features, motion features and Data reduction & data selection features.

3.1.1 Geometric Features

This kind of features is focused on facial landmarks of the image. Landmarks refer to eyes or brows. Geometric features can be described as connecting face mesh, fiducial points of facial image and face component shape model. Generally, geometric features alone are sufficient feature for the automated face analysis. Some of the other features were incorporated with the geometric for better classification of emotion recognition.[4]

3.1.2 Appearance Features

This feature represents the changes in the skin texture such as wrinkling and deepening of facial furrows and pouching of the skin. The common methods of these features are Gabor wavelets, SIFT and HOG.[1]

3.1.3 Motion features

This feature mainly focuses on video sequence of objects. From the each video frame, facial recognition is classified with various emotions. The common methods for motion features are Motion History Images based on optical flow and Local binary pattern.

3.1.4 Data reduction and selection

This is another method for feature extraction. In this approach features have high "Dimensionality Reduction" which means that deriving new features from old one. Generally this is done by data transformation. Data transformation is the method of converting the data from one format to another format. The common methods of data reductions are PCA, LDA, LLE, Locality preserving projections, AdaBoost, kernel LDA.[5]

4. BASIC NOTATIONS OF QUANTUM COMPUTING

4.1 Qubits

In quantum computing, Qubits is basic unit of data and the states of a quantum particle. The random states are based on superposition principle. The Qubits values are 0 and 1. In the analogical approach Qubits consist of two ways such as distinct states or basis states. Each states represented into two notations (Dirac notation and Hilbert space notation).

4.2 Quantum Convolutional Filters

This section describes the procedure of QCNN architecture based on Variation Quantum Circuit (VQC). VQC are adjustable parameters to solve optimization problem. The main objective of this approach is categorized into three possible notations such as data encoding layer, Variation layer and Quantum Measurement Layer. The data encoding layer is used to encode the input vectors into quantum state. The input vectors of the quantum state with a dimension of n*n. The variation layer is used to transformation of classical rates into quantum state. This variation layer consists of two parts such as entanglement part and rotation part. The entanglement part defines the group of CNOT gates. The rotation part is updated the optimization of parameterized parameters. Quantum Measurement Layer is irreversible process, where data is augmented into transformed layer.

4.3 Quantum Gates

Quantum gates are used to perform the qubit gate operations. The basic idea of these operations to predict the target gate. In general, Quantum gates can be represented into three types such as Hadamard gate, Rotation gates and CNOT gate. The Hadamard gate provides the super position principles of two states. This gate can be represented equation 1.

$$H_g = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \qquad (1)$$

Rotation gates can be optimized with the Bloch sphere, where each rotation is used to train the features from the quantum gates. The general equation of the rotation gates represent in equation 2.

$$RG_m\ (\Theta) = \begin{pmatrix} cos\frac{\theta}{2} & -sin\frac{\Theta}{2} \\ sin\frac{\varphi}{2} & cos\frac{\varphi}{2} \end{pmatrix} \qquad (2)$$

CNOT gate is performed with two-qubit state for alters the features from the Quantum circuit.

5. PROPOSED METHODOLOGY

In this proposed system, emotional recognition can be performed by two stages. The first stage is concentrates on preprocessing techniques. The preprocessing is comprised of grey scale conversion, histogram equalization, face detection algorithm and image cropping & resizing. The second stage is extracted the facial features from the convolutional neural network for categorization of various emotions. Figure 1 shows the proposed architecture.

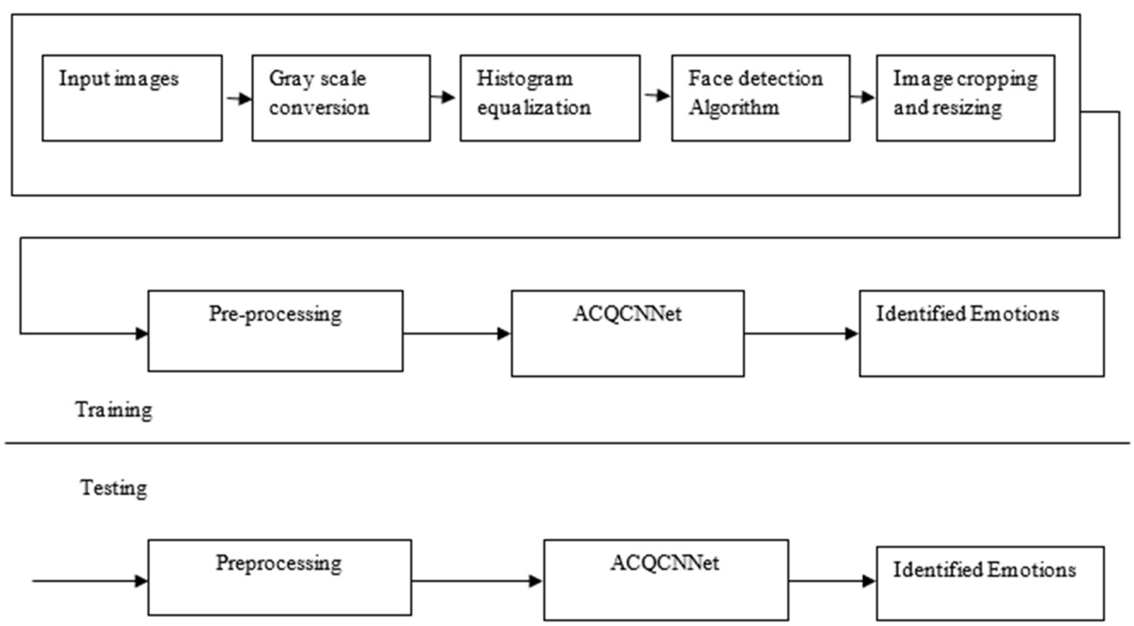

Figure 1 System Architecture

5.1 Emotion Image Database

In this proposed work, Warsaw set of emotional facial expression dataset has been considered to develop the proposed emotion recognition system. This dataset contains 210 top-notch pictures of 30 people. The dataset contains the following emotions: happy, fear, disgust, anger, sadness and surprise. The sample dataset is shown in figure 2.

Figure 2 – Sample Warsaw dataset

5.2 QC-CNN Structure

The typical structure of convolutional neural network (CNN) consists of three main components they are convolutional layer, a pooled layer and fully connected layer. The convolutional layer applies an activation function to perform non linear feature extraction on images. The extracted feature are then integrated in the fully connected layer, which uses soft max function to generated probability for each type of label , enabling the prediction of the images label. Prior to obtaining the final predicted value and the factual value using a loss function .This process ultimately determines the arrangement performance of the model .In this work Adam optimizer is utilized to revise and analyze the network parameters, which impact both model preparation and output . These optimizations techniques aim to estimated or arrive at the optimal value necessary to minimize loss function. The pooling layers are flattened into quantum circuit. This proposed structure contains two fully connected layers which are used to modify the quantum layer input sizes into number of classes. This layer interprets how the classes learned and merging information and also generates class probabilities of each class. The building block diagram of QCNN architecture is revealed in figure 3.

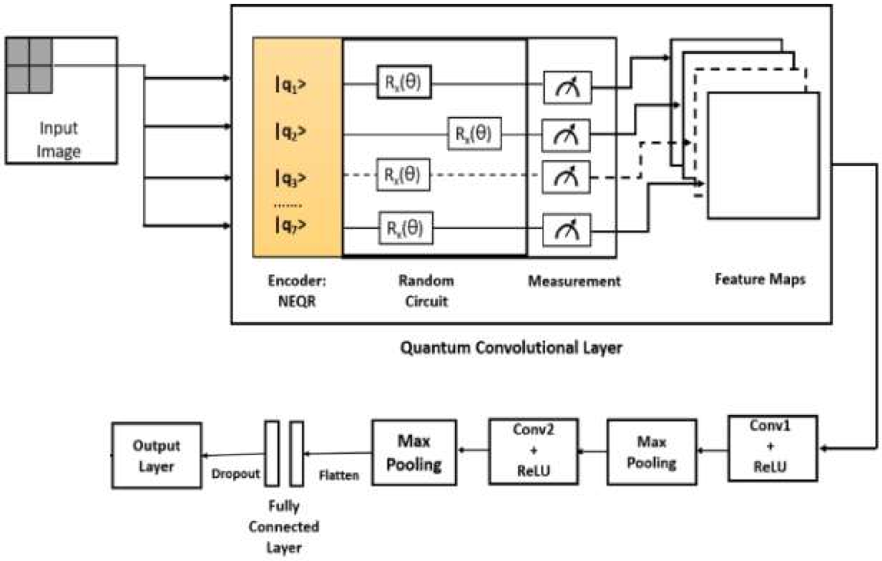

Figure 3 – QCNN architecture

5.3 Proposed Algorithm

The classification of emotion recognition is completely performed into two stages such as training and testing. In training phase, characteristics of facial features were extracted. Next, testing stage each facial feature was classified with different emotions. The categorization of various emotions with the help of pre-trained in ACQCNNet approach. The classification of various emotions is completed by using the below proposed algorithm and schematic illustration of proposed method is shown in the figure 4.

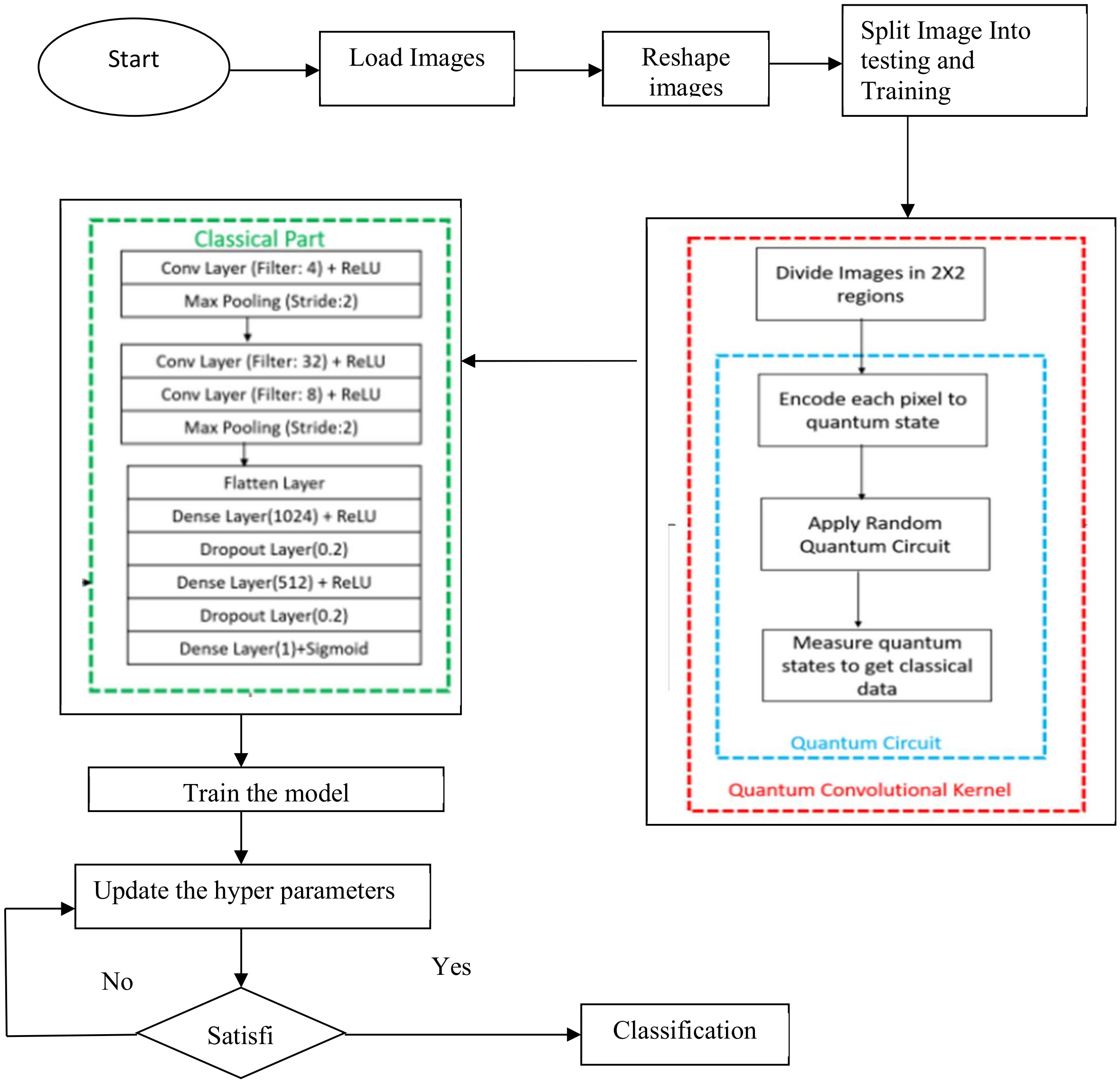

Figure 4 Schematic Diagram of Proposed Work

Begin: ACQCNNet
Input: Data set, Samples S, Batch Size

Steps

i. Separate the dataset into Training set, Test set, and Validation set
ii. Load and preprocess the test data.
iii. Prepare the data using the ACQCNNet Model.
iv. Accumulate the features after training the network.
v. Apply Support Vector Machine algorithm for classification
vi. End

Output: classify Emotions, Accuracy, precision, recall

End

6. Result and Discussion

The CNN were implemented using the ACQCNNet framework. In our experiment we apply our approach to Warsaw Set of emotional Facial expression images. This work test environment for conducting experiments is MATLAB 2020a**.** The hardware requirements of the proposed system are Intel core i7 with GPU processor. Emotion labeling shows in the table 2. The maximum epochs for training are assigned to 100 and the maximum iterations were assigned to 100. In the proposed work, accuracy, confusion matrix, precision and recall metrics are performed. For categorization of dataset, cross-validation was performed to enhance the results of performance of metrics. The main objective of cross-validation technique is to maximize the productivity of our samples. This research work, k-fold cross-validation methods are used to categorize the dataset. If k=2, the data is resample into validation set 1 and validation set 2. In validation set1, training is 65% and 35%. Validation set 2; training is 80% and 20%. The proposed work attains 95% of accuracy on 200 iterations with 100 epochs. The classified emotions are angry, happy, neutral, sad and surprise. The proposed accuracy is compared with traditional approach which is represented table 3.

Table 2 Labeling Emotions

Emotions	**Files**	**Labels**
Surprise	50	1
Angry	50	2
Sad	50	3
Happy	50	4
Neutral	50	5

Table 3 Comparison results of Accuracy

Methods	**Accuracy rate (%)**
SVM	78
KNN	82
LBP	79
LBP+KNN	78
LBP+SVM	80
CNN	88

Proposed work	95

The comparison results are state that, the proposed algorithm is suitable for emotion classification when compared to the existing algorithms and methods. Table 4 and figure 3 describe the performance metrics table and accuracy chart.

Table 4 Performance Metrics

Emotion	**Validation set 1**		**Validation set 2**	
	Recall	**Precision**	**Recall**	**Precision**
Angry	1	1	0.8	1
Happy	1	0.5	0.7	0.25
Neutral	0.50	0.8	1	0.5
Sad	0.45	1	0.25	1
Surprise	0.67	1	0.8	1

Methods	**Accuracy rate (%)**
SVM	78
KNN	82
LBP	79
LBP+KNN	78
LBP+SVM	80
CNN	88
ADQCNNet	95

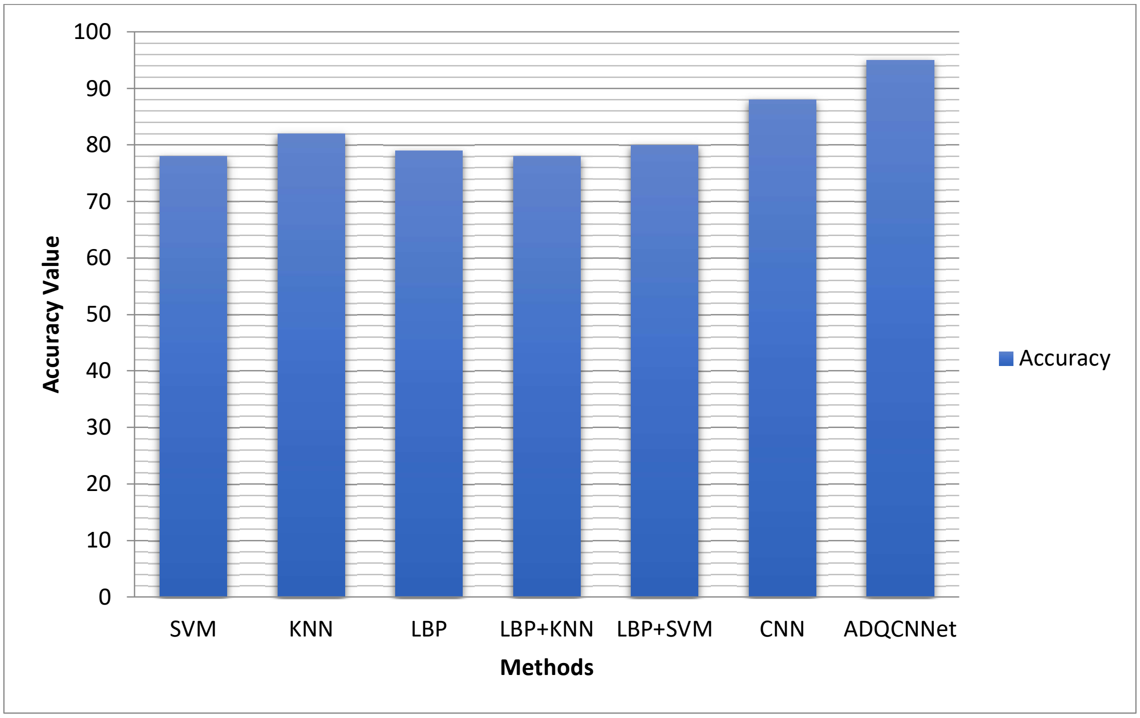

Figure 3 – Results of Accuracy

7. Conclusion

Affective computing is one of the most active research topics which are mainly focused on many applications like AU Detection, Facial analysis and Emotion recognition. This book chapter attempted to provide an overview of recent developments of emotion theories and Feature extraction were summarized. It also presents the details about the recognition of emotions based on proposed approach. In this work, ACQCN Net architecture has been discussed and classifies different emotions using Warsaw data Set. Further, the experimental findings have been shown our proposed algorithm attain the recognition accuracy is 95%. Finally, performance measures were analyzed and compare with existing algorithms.

8. References

1. Z. Yin, M. Zhao, Y. Wang, J. Yang, , and J. Zhang, “Recognition of emotions using multimodal physiological signals and an ensemble deep learning model,” Computer methods and programs in biomedicine, vol. 140, pp. 93–110, 2017.
2. E. Cambria, D. Das, S. Bandyopadhyay, and A. Feraco, “Affective computing and sentiment analysis,” A practical guide to sentiment analysis, vol. 1, pp. 1–10, 2017
3. C. A. Corneanu, M. O. Simon, J. F. Cohn, and S. E. Guerrero,(2016) “Survey on rgb, 3d, thermal, and multimodal approaches for facial expression recognition: History, trends, and affect-related applications,” IEEE transactions on pattern analysis and machine intelligence, vol. 38, no. 8, pp. 1548–1568.
4. D. Li, R. Rzepka, M. Ptaszynski, and K. Araki,(2019) “A novel machine learning-based sentiment analysis method for chinese social media considering chinese slang lexicon and emoticons.” AffCon@ AAAI, vol. x, p. 2328.

5. K. Chakraborty, S. Bhatia, S. Bhattacharyya, J. Platos, R. Bag, and A. E. Hassanien,(2020) “Sentiment analysis of covid-19 tweets by deep learning classifiers—a study to show how popularity is affecting accuracy in social media,” Applied Soft Computing, vol. 97, p. 106754.
6. L. Chen, W. Su, Y. Feng, M. Wu, J. She, and K. Hirota,(2020) “Two-layer fuzzy multiple random forest for speech emotion recognition in humanrobot interaction,” Information Sciences, vol. 509, pp. 150–163.
7. Z. Zhao, Y. Zhao, Z. Bao, Z. Z. H. Wang, and C. Li,(2018) “Deep spectrum feature representations for speech emotion recognition,” Proceedings of the Joint Workshop of the 4th Workshop on Affective Social Multimedia Computing and first Multi-Modal Affective Computing of Large-Scale Multimedia Data, vol. x, pp. 27–33.
8. R. Santhoshkumar and M. K. Geetha, “Human emotion recognition using body expressive feature,” Microservices in Big Data Analytics, vol. x, pp. 141–149, 2020.
9. X. Jiang, Y. Zong, W. Zheng, C. Tang, W. Xia, C. Lu, and J. Liu, (2020) “Dfew: A large-scale database for recognizing dynamic facial expressions in the wild,” Proceedings of the 28th ACM international conference on multimedia, vol. x, pp. 2881–2889.
10. Hari Kishan Kondaveeti and Mogili Vishal Goud, \"Emotion Detection using Deep Facial Features\", 2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI), December 2020
11. C. Bentéjac, A. Csörgő, G. Martínez-Muñoz, “A comparative analysis of gradient boosting algorithms”, Artificial Intelligence Review, vol. 54, no. 3, pp.1937-67, 2021.
12. G. N. Ahmad, S. Ullah, A. Algethami, H. Fatima, and S. M. H. Akhter, “Comparative Study of Optimum Medical Diagnosis of Human Heart Disease Using Machine Learning Technique with and Without Sequential Feature Selection,” *IEEE Access*, vol. 10, pp. 23808–23828, 2022, doi: 10.1109/ACCESS.2022.3153047.
13. Y. Kumar *et al.*, “Heart Failure Detection Using Quantum-Enhanced Machine Learning and Traditional Machine Learning Techniques for Internet of Artificially Intelligent Medical Things,” *Wirel. Commun. Mob. Comput.*, vol. 2021, 2021, doi: 10.1155/2021/1616725.
14. S. Arunachalam and R. de Wolf, Guest column: A survey of quantum learning theory, ACM SIGACT News, vol. 48, no. 2, pp. 41–67, 2017.