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RESEARCH ARTICLE

Emotion Quantification Using Variational Quantum State Fidelity Estimation

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ABSTRACT Sentiment analysis has been instrumental in developing artificial intelligence when applied to various domains. However, most sentiments and emotions are temporal and often exist in a complex manner. Several emotions can be experienced at the same time. Instead of recognizing only categorical information about emotions, there is a need to understand and quantify the intensity of emotions. The proposed research intends to investigate a quantum-inspired approach for quantifying emotional intensities in runtime. The inspiration comes from manifesting human cognition and decision-making capabilities, which may adopt a brief explanation through quantum theory. Quantum state fidelity was used to characterize states and estimate emotion intensities rendered by subjects from the Amsterdam Dynamic Facial Expression Set (ADFES) dataset. The Quantum variational classifier technique was used to perform this experiment on the IBM Quantum Experience platform. The proposed method successfully quantifies the intensities of joy, sadness, contempt, anger, surprise, and fear emotions of labelled subjects from the ADFES dataset.

INDEX TERMS Emotion detection, sentiment analysis, quantification of emotions, quantum machine learning, quantum computation.

I. INTRODUCTION

The sentiment analysis intends to extract sentiments and opinions from data. This research domain is conjoined with real-time applications like behavior analysis and decision-making. It helps to gain insightful information from multiple modalities like text and visual data. Sentiment analysis has been instrumental in developing artificial intelligence when applied to other domains. Traditionally, sentiment analysis has been investigated as a classification problem. It is because sentiment analysis includes several operations that result in classifying an expression as positive or negative sentiment. A sentiment can be stated as a mindset influenced by emotions. Sentiment allows a person to convey emotions through expressions. Many research studies have acknowledged that most sentiments are conveyed through facial expressions followed by intonations and verbal expressions [1]. Fundamental research challenge with emotions is that they are temporal and are often displayed in a complicated manner.

Further, several emotions can be experienced at the same time. Instead of recognizing only categorical information about emotions, scientists are trying hard to quantify emotions [2], [3], [4]. Facial Action Coding Systems (FACS) have been long used to identify emotions based on facial activities resulting from facial muscle movements. There were forty-four action units suggested to model facial expressions [2], [3], [4]. The most fundamental challenge with existing FACS or other coding systems is that they are time-consuming and highly labor-intensive.

Further, they are prone to inter-rater variability due to differing experience-based assessments. Furthermore, such coding systems do not suggest any quantitative measure of

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change in expressions. Although FACS cannot quantify the intensity and degree of difference between emotional expressions, they can easily classify emotions [5]. Contemporary solutions to quantify emotions simply extend the results from expression category classifiers [6], [7]. Subsequently, researchers proposed the use of training data with continuous or discrete intensity labels [8], [9], [10]. The major limitation of treating expression quantification as a multi-class classification problem is that; it ignores the ordinal consistency of predicted intensities. Existing sentiment analysis and emotion quantification models rely on nature-inspired or neural structures to process data. Such setups comply with limited numerical constraints and are purely data-driven. This results in the low interpretability of those approaches.

The proposed research intends to investigate a quantum-inspired approach for quantifying emotional intensities in runtime. The inspiration comes from manifesting human cognition and decision-making capabilities, which may adopt a brief explanation through quantum theory. The rest of the paper is organized as follows: Section 2 apprise related work in emotion detection, section 3 covers the methodology and techniques used, section 4 details the preliminaries required to understand the quantum circuit, and section 5 explains the quantum circuit and state fidelity estimation process. The results and comparison of studies are made in section 6, and finally, section 7 concludes the findings and briefs about future directions for possible improvements.

II. RELATED WORK

Reputed datasets like Scopus, Google Scholar, Mendeley, Taylor and Francis, Association for Computing Machinery (ACM DL), Web of sciences, and IEEE Xplore were explored to find quality literature related to Emotion Detection and Sentiment Analysis. A few other datasets like the MDPI journal database, Hindawi, and Wiley were also referred to find relevant literature. Manuscripts published from 2005 to 2022 were considered for reviewing related studies. The databases mentioned above were manually searched to find relevant literature. The articles were selected using ‘‘Emotion Detection’’ OR ‘‘Sentiment Analysis’’ OR ‘‘Multimodal Techniques’’ OR ‘‘Modalities’’ OR ‘‘Quantum Sentiment Analysis’’ as search keywords. Mendeley was used to collect and screen research publications [11].

This section retrospects the studies on sentiment analysis and emotion detection using lexicon-based and machine learning-based approaches. Emotion detection utilizing contemporary Quantum techniques is getting popular, and some of the work strengthening this perspective is also discussed here.

A. LEXICON-BASED APPROACH

Normally, the lexicon-based approach uses bag-of-words to portray any information. Bag-of-words technique infers the overall sentiment polarity of the information. It generally depends on a sentiment dictionary, linguistic knowledge, and sentiment rules which do not require a large data corpus and training procedure. The different approaches to Lexicon-Based are:

1) CORPUS-BASED APPROACH

Initial representatives of this approach are [12] and [13]. They detected and validated constraints on semantic information from a corpus of adjectives and worked on computing associations between positive and negative semantics of a phrase. In continuation of their work, researchers further elaborated to include adverbs for identifying sentiments of texts [14] and identified clues of evaluations and opinions using the clustering method. These subsequent motivated researchers to focus on creating dictionaries like SentiWordNet [15] and MPQA [16] that judge the sentiment polarity of the text. The semantic orientation calculator (SO-CAL) method is used by [17] to focus on a lexicon-based approach and extract sentiment from text to build a dictionary to annotate semantic orientation and assigns a positive or negative label to a text. Based on the emotion lexicon, [18] calculated the orientation score in the sentence. Again, based on the lexicon, [19] assigned positive and negative sentiment strengths to the text in a sentence.

2) KNOWLEDGE-BASED APPROACH

Additionally, [20] reckoned novel models for representing words as vectors within vector space models. Phrase level sentiment estimation was presented by [21]. Matrix representation for adjectives and vector representation for nouns was employed by [22]. Bag-of-words representation was used by [23] to deem negations and intensities for sentiment analysis. Another novel model termed Tensor Fusion Network is proposed by [24]. They studied and compared state-of-the-art approaches for multimodal and unimodal sentiment analysis. A similar kind of model optimization was proposed by [25], stating factorization for multimodal learning. Sentiment and subjectivity opinions in YouTube videos were investigated in [26]. It also introduced MOSI dataset for intensity analysis. The problem of late fusion is addressed in [27], and also proposed MinCq program accounts ranking problem of the models. The sentiment classifier on emotions is predicted in [28] and uses fuzzy logic to interpret the degree of emotions in video and text sequences. The formulation of audiovisual segments is detected in work [29] which proposed abstraction models based on saliency for visual and aural representations. The lexicon-based approach is known for reliability and accessibility in contrast to classification accuracy obtained by machine learning approaches for sentiment analysis that are boiled down next.

B. MACHINE LEARNING-BASED APPROACH

Machine learning-based approaches use machine learning algorithms to build classifiers. An autoregressive method presented by [30] leverages AR and AE for modelling purposes. They also introduced a transduction model that replaces recurrent layers. Sentiment classification is performed in [31] and used a Support Vector Machine (SVM) for classification on word embedding. [32] represented textual documents by word tuples and extracted phrases for sentiment analysis. The sentiment of sentences is determined by [33] using bag-of-words and built supervised sentiment classifier for Twitter corpus [34] applied various machine learning algorithms on IMDB for classifying movie reviews. The work carried out in [35] used machine learning techniques to find sentiments within images, and [36] built a novel image prediction algorithm while [37] presented techniques to analyze YouTube comments. [38] Improved code-switched emotion detection model and proposed dual-channel encoder. Construction of an emotion recognition system based on EEG is done in [39]. Semantic text analysis for human emotion detection is proposed in [40]. The strategy to combine Lexica with different label spaces using the Multiview Variational Autoencoder (VAE) was proposed in [41]. The evaluation of MUSEC's effectiveness in sentiment analysis and composition is efficiently done in [42] on MDPI data. [43] introduced approach for sentiment classification. It is meta-level features based. Machine learning-based techniques rely on feature extraction for computations, increasing complexity even though advancements are enormous in their usability.

From the above discussion, sentiment analysis and emotion detection have seen good syllogistic progress in recent years using both lexicon-based and machine learning-based approaches. Both have limitations in their respective horizons as lexicon-based largely ignores semantic representations, crucially focusing on sentiment knowledge. Meanwhile, machine learning does not capture sentiment information but concentrates on feature extraction for building robust classifiers. These shortcomings paved the way for the acceleration of quantum-based approaches, and some of the excellent work done by quantum researchers is outlined next.

C. GRAPH-THEORETIC BASED APPROACH

The study in [44] introduces a graph-based Lexical sentiment analysis (LSA) framework to compute scores in the lexical-affective graph (LAG). The paper proposes a graph-based model to investigate electronic site reviews [45]. The research [46] proposes a transparent DNN model for the sentiment classifier. Acknowledge-specific parser for efficient generalization and extraction of multiword expressions amid English text is proposed [47]. A graph-based approach for text summarization is presented in [48]. A well-organized polarity assignment algorithm for sentiment analysis based on graph-based keywords is proposed in [49].

D. QUANTUM MACHINE LEARNING-BASED APPROACH

Renowned researchers have started to shift their central work attention to Quantum Machine Learning to unravel the shortcomings of these approaches. The non-classical correlation of multimodal fusion was examined by [50] using Quantum techniques and tested several texts and in-age-based associations. The study [51] proposes a tensor product-based model to represent an image as a non-separable composite system. The work done by [52] designed a compositional model for different languages to evaluate the multilingual dataset. The work in [53] aimed to overcome the semantic gap between other modalities. The paper [54] provides a semiotic interpretation of entanglement for information retrieval. [55] uses quantum machine learning to extract meaningful sentimental information from large datasets. The speaker's emotion was recognized in [56] using Quantum Neural Networks. An innovative study of learning emotions through music is conducted in [57]. Emotion recognition using quantum probability theory is explained in [58]. The hate and non-hate semantic relations within speeches are done in [59] using notions of quantum geometry. [60] Proposed quantum-motivated fusion strategy to predict sentiment. The development of the quantum question order model for improving human judgments is performed in [61]. Interpretation of human decision-making and response time is made in [62]. A probabilistic framework to describe human cognition is proposed in [63]. All these studies successfully divulge Quantum technologies in their conspicuous experiments related to emotion detection but more to come on this approach to tackle some challenging problems like the one we intend to promulgate through our work on emotion detection quantification.

III. MATERIALS AND METHODS

The adopted methodology offers an amalgamation of quantum machine learning concepts with existing sentiment analysis methods. The experiment intends to augment the existing emotion identification and sentiment analysis methods. Though existing methods can identify emotions, they cannot estimate the intensity of emotions. Facial expression recognition is one of the primary applications of pattern classification [64].

The most suitable mathematical model for the identification of sentiments is graph theory. Graph theory may best encode the human face and can be used to identify facial expressions. Quantum computing has recently tried to address the problem of graph classification for emotions like happy or sad using facial expressions [65]. The proposed research primarily intends to quantify the intensities related to happy and sad emotions using a quantum computer. This research intends to address the future scope of [65] by including a variational algorithm. The proposed variational algorithm established the intensity of the identified emotions with the help of quantum circuits. The proposed quantum circuit is inspired by the work in [66] but is different in encoding the states. The variational state fidelity estimation, illustrated in [67], was adopted to find the closeness of states and to estimate the intensity of various emotions. Leveraging the quantum ability to characterize states helped to achieve better outcomes of the intensities of emotions than it would have been possible with classical Machine Learning algorithms [68], [69]. The experiment was performed using the Quantum Computing Software Development Framework-QISKIT, an open-source initiative by IBM. The overall end-to-end procedure is explained as under.

Amsterdam Dynamic Facial Expression Set (ADFES) was used to develop graphs using facial landmarks. ADFES offers

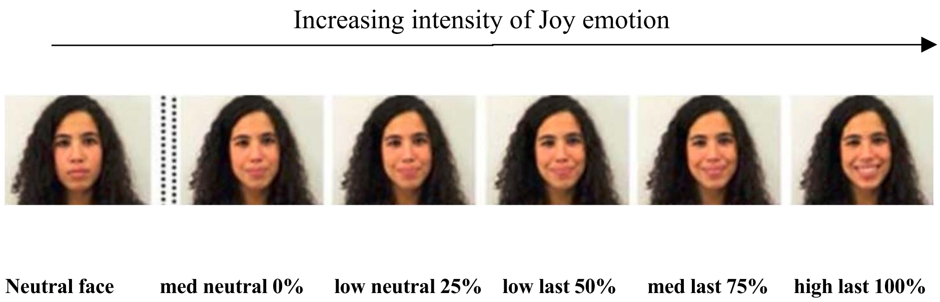

FIGURE 1. A sample image of Joy emotion with varying intensity from the ADFES dataset.

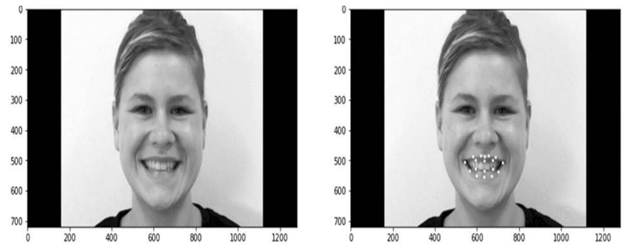

FIGURE 2. Dlib library degenerated facial landmarks of one of the subjects of the ADFES dataset.

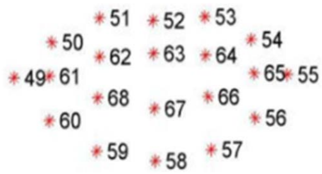

FIGURE 3. The 20 landmark coordinate points of mouth region degenerated through Dlib library.

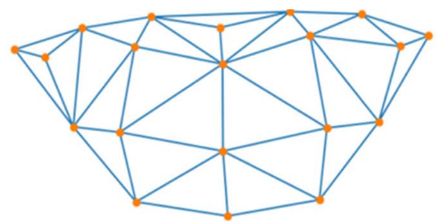

FIGURE 4. Graph formed with 20 landmarks of the mouth region.

annotated faces displaying five basic emotions. Images of joy, sadness, surprise, contempt, anger, and disgust. The ADFES database has images with variable intensities of each emotion. The intensities range from 0% to 100% of emotion with an increment of 25% to 100%. These are labelled as highlast, highneutral, lowlast, lowneutral, medlast, and medneutral. Sample images from ADFES are shown in Figure 1. Facial landmarks were identified on the given set of images. The 68 facial landmarks were identified using the Dlib library, which uses regression trees for face detection [70]. The database lacks Intermediate intensity of emotions in between the ones specified here. Figure 2 shows a detected face on the image from the ADFES dataset.

IV. PRELIMINARIES

This section illustrates a few steps to be used in the experiment, such as the generation of landmarks, angle estimation of the subjects of different emotions, and intensity estimation algorithm. A generalized Quantum Machine Learning Architecture is also explained and required for building the quantum circuit.

A. GENERATION OF LANDMARKS

The 20 landmark coordinate points associated with the mouth region were considered, and a graph was formed from these points, as depicted in Figure 3 and Figure 4.

Mathematically, G=(Vg, Eg) is a simple graph where Vg is the vertices, and Eg is the set of edges in G. The adoption of this method of angle computation is critical as we use the angle encoding technique to encode quantum states. As seen from the two figures, landmarks 49, 50, and 60 denote the left side of the mouth, whereas landmarks 54, 55, and 56 denote the right side of the mouth. The left and right sides directly correlate, and both sides are critical to consider for emotional significance. It then becomes valuable to record any slight change; thus, we emphasize the angle estimation method for this purpose. The change in angle is directly proportionate to the intensity of that emotion to be high or low. The next subsection gives detailed steps of the angle estimation process we worked on to find angles between the coordinates.

B. ANGLE ESTIMATION

We used the Dot Product Formula for Vectors to find the angle of the landmarks. The Dlib library generates the x and y coordinates of each associated landmark. The graph in Figure 4, G=(Vg, Eg) is formed from the mouth region. It has coordinate points from 49 to 68 as vertices Vg and the set of connected vertices as edges Eg. Apropos to the labelled intensities of emotion within the ADFES dataset, a machine could be trained to estimate angles for high last, high neutral, low last, low neutral, med last and med neutral emotions. Any emotional intensity lying in between the annotated emotional values could be easily calculated using the dot product process explained in the subsequent section.

TABLE 1. **The maximum and minimum angles of all the subjects of joy, sad, contempt, anger, surprise, disgust and fear emotions.**

	Percentage Intensity of the emotion	Maximum Left angle	Maximum Right angle	Minimum Left angle	Minimum Right angle	State Vector of the emotion
joyhighlast	100	40.19	40.86	11	11.52	SV 1
joymedlast	75	26.7	29.83	4.46	5.26	SV 2
joylowlast	50	14.46	16.06	5.11	4.39	SV 3
joylowneutral	25	11.41	13.32	4.12	4.74	SV 4
joymedneutral	25	11.3	11.3	2.84	3.71	SV 5
joyhighneutral	25	10.71	11.6	1.18	1.46	SV 6
sadhighlast	100	11.41	12.21	2.01	2.04	SV 1
sadmedlast	75	13.02	13.4	1.23	2.18	SV 2
sadlowlast	50	12.1	13.74	0.06	1.63	SV 3
sadlowneutral	25	11.98	11.6	1.96	1.87	SV 4
sadmedneutral	25	13.16	11.7	2.01	3.15	SV 5
sadhighneutral	25	13.45	13.17	3.27	1.77	SV 6
contempthighlast	100	12.1	12.51	3.94	3.88	SV 1
contemptmedlast	75	14.14	14.42	0.26	0.01	SV 2
contemptlowlast	50	11.1	13.24	2.99	2.76	SV 3
contemptlowneutral	25	13.81	13.17	3.46	3.36	SV 4
contemptmedneutral	25	10.8	11.64	4.36	3.27	SV 5
contempthighneutral	25	11.4	13.27	3.01	3.01	SV 6
angerhighlast	100	17.21	16.85	1.72	1.49	SV 1
angermedlast	75	14.07	13.36	0.1	0.1	SV 2
angerlowlast	50	14.46	12.99	2.76	1.38	SV 3
angerlowneutral	25	13.5	14.68	0.1	1.55	SV 4
angermedneutral	25	14.95	16.05	3.36	1.77	SV 5
angerhighneutral	25	12.48	13.48	3.5	3.09	SV 6
surprisehighlast	100	40.98	40.74	16.51	16.77	SV 1
surprisemedlast	75	41.86	41.3	10.24	10.35	SV 2
surpriselowlast	50	35.72	39.14	4.02	6.75	SV 3
surpriselowneutral	25	15.19	13.16	3.57	3.53	SV 4
surprisemedneutral	25	14.61	16.03	0.15	0.18	SV 5
surprisehighneutral	25	12.71	14.25	1.81	3.24	SV 6
disgusthighlast	100	25.6	28.05	3.57	1.78	SV 1
disgustmedlast	75	16.7	17.63	1.78	0.06	SV 2
disgustlowlast	50	13.31	12.52	0.1	1.97	SV 3
disgustlowneutral	25	56.22	58.35	0.1	2.1	SV 4
disgustmedneutral	25	11.86	12.55	0.1	0.22	SV 5
disgusthighneutral	25	13.89	14.03	1.97	1.97	SV 6
fearhighlast	100	31.13	28.98	5.71	7.35	SV 1
fearmedlast	75	27.05	28.34	7.56	8.97	SV 2
fearlowlast	50	25.16	26.19	2.62	3.35	SV 3
fearlowneutral	25	18.89	19.66	1.9	3.49	SV 4
fearmedneutral	25	18.45	18.7	1.78	1.73	SV 5
fearhighneutral	25	17.06	17.05	3.86	1.68	SV 6

Let a and b be two non-zero vectors in between coordinates. For example, a is the vector derived from the coordinates of landmark points 59 and 68, and b is the vector derived from the coordinates of landmark points 68 and 69. The dot product of vectors is defined as the product of the magnitudes of the vectors with the cosine of the angle between them [71]. To find the angle between two vectors using dot product, we used the equation as $a \cdot b = \|a\| \|b\| \cos\theta$, where $|a|$ is the magnitude (length) of vector a and $|b|$ is the magnitude (length) of vector b and θ is the included angle of the vectors.

C. INTENSITY ESTIMATION ALGORITHM

The maximum and minimum angle values of Joy, Sad, Contempt, Anger, Surprise, Disgust, and Fear are computed using the dot product technique. The subject angle values of all these emotions are shown in Table 1. The quantum circuit designed for this experiment was executed on a quantum computer, shown in section 3.4. The circuit uses the maximum and minimum angle values of the left and right sides of the mouth, as shown in the subsequent tables, to encode the qubits. The mechanism of the data encoding is also explained in the subsequent section. Each emotion intensity state vector is obtained from the circuit as denoted by a hypothetical value in the ‘‘state vector of the emotion’’ column of Table 1. Along with the angles of the emotions, the ‘‘percentage intensity of the emotion’’ column contains the percentage of the emotion, and it is expected that the test image would quantify in correlation to the specified percentage.

Next, the vectors of each test instance are obtained from the circuit by encoding the angles of that image. The state fidelity quantum function is then used to find the closeness between the state vectors obtained from the circuit for the test instance and the state vectors of the emotion from the tables above. The largest state fidelity value gives the maximally aligned intensity of the image that can be anyone from highlast, medlast, lowlast, lowneutral, medneutral, and highneutral intensities. Algorithm 1 finds the state vectors of each subject instance, which the state fidelity function uses to find the intensity's value. All the test instances tested in our experiment were taken from the ADFES dataset as it directly correlates with all the emotion intensities of the dataset. Therefore, it becomes more sense that the angles of the test instance of the dataset would inevitably contour among the maximum and minimum angles of the left and right sides of the mouth, as shown in Table 1 above.

Our program's state fidelity estimation process operates under a constraint that at any given state fidelity estimation, the test instance's angle has to be between the maximum and minimum angles of the emotion. If the angle is greater or smaller than the inclined emotion intensity, the cost function of the circuit adjusts the angles to estimate the state fidelity again. When the angle is greater, it's most likely that the state fidelity estimated from the quantum circuit after adjusting the angles via cost function would incline to the next lower emotion intensity with proper angles. On the contrary, if the angle is less than the inclined emotion intensity, the state fidelity estimated after adjustment of the angles would incline towards the next upper emotion intensity with proper angles.

The term t_instance used in the algorithm is the image whose intensity is to be estimated and emotion_intensity is the intensity from any of the highlast, highneutral, lowlast, lowneutral, medlast, medneutral emotions. The state fidelity gives the closeness or maximally aligned image of test_instance from these emotions. To calculate the intensity of the test_instance, percentage emotion brackets assumed for the emotions in their increasing order is as follows: joyhighlast - 75-100, joymedlast - 50-75, joylowlast - 25-50, joylowneutral - 0-25, joymedneutral - 0-25, joyhighneutral - 0-25. Likewise, for sad emotion, the percentage emotion bracket assumed is as follows: sadhighlast - 75-100, sadmedlast - 50-75, sadlowlast - 25-50, sadlowneutral - 0-25, sadmedneutral - 0-25, sadhighneutral - 0-25. The percentage emotion bracket and the angles of the established maximally aligned emotion are used for calculating the intensity of the test_instance.

D. GENERALIZED QUANTUM MACHINE LEARNING ARCHITECTURE

Quantum machine learning involves machine learning that runs on quantum computers. A typical quantum machine

Algorithm 1 Find the Intensity of the Subject Image

Require: Dlib library Facial Landmark degeneration of x and y coordinates representing the image
test_instance: SubjectI images loaded from ADFES dataset, Labels: associated Joy, Sad, contempt, anger, surprise, disgust and fear label
Output: intensity of the image
for all test_instance, label ε All_images, Labels do
procedure INTENSITY_ESTIMATION (image_instance):
for all emotion_intensity ε highlast, highneutral, lowlast, lowneutral, medlast, medneutral
procedure FINDANGLE (emotion_intensity)
returns angles from left and right sides of mouth coordinates as illustrated in angle estimation under preliminaries section
end procedure FINDANGLE
procedure QUANTUMCIRCUIT(max and min angles from FINDANGLE procedure)
Construction of QUANTUMCIRCUIT returns state vector of image as illustrated subsequently under quantum circuit section.
end procedure QUANTUMCIRCUIT
Estimation of State Fidelity between test_instance state vector and emotion_instensity state vector
end for
end procedure INTENSITY_ESTIMATION
end for

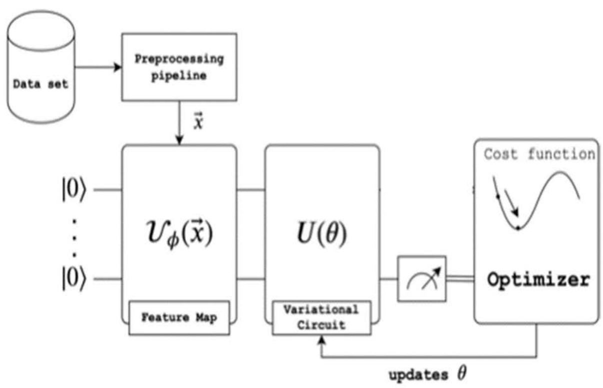

FIGURE 5. A generalized view of the parameterized quantum circuit.

learning model comprises two parts, a classical part for pre and post-processing data and a quantum part for harnessing the power of quantum mechanics to perform certain calculations easier. The architecture of the quantum machine learning model typically consists of a circuit, as shown in Figure 5. The feature map is the data encoding part that states the initial state of qubits of your experiment and is done by feature map schemes or data embedding. The next is the variational step which introduces the parameters in the circuit through variational techniques. Then the last part of the quantum formation is the measurement to predict the label for the machine learning task. The optimization of the model is performed through the classical cost function, which depends on a set of parameters. These parameters attain optimization through training and reduce the value of a loss function.

The classical data is encoded into a quantum state, and various techniques exist for data embedding into qubits [72]. Numerous methods of encoding data into quantum space have been suggested in the published literature [73], [74], [75]. Our experiment used the angle encoding technique to encode angles between landmarks into qubits. The quantum variational classifier uses a variational circuit to train the model with updated parameters. The classical cost function governs the optimization of these parameters. The classical cost function is the post-processing part and classifies the data. The variational forms on the qubits rotate with the parameterized angles obtained from the cost function. Different types of variational circuits are expressed in the paper [76]. This study also shows trivial and general operations that can be applied to qubits. In our experiment, we optimized the cost function to update the parameters or the angles that maximally aligned the intensities of the emotions of individual subjects for variational purposes. The COBYLA optimizer method is employed for the optimization of the quantum circuit.

Specific to our experiment, the cost function updates the angles of the test instance in case its angles are greater than the state fidelity of the emotion intensity returned from the circuit. During the second execution, the variational circuit again encodes the qubits with the updated angles and returns the state fidelity with the next maximum aligned state fidelity. This cycle gets repeated until the angles exist between the state fidelity of the returned emotion intensity. Finally, the intensity of the test instance is calculated as per Algorithm 1.

V. QUANTUM CIRCUIT

As stated antecedently, the deciding factor in our experiment is the calculation of the angle between the landmarks associated with the left and right sides of the mouth of the subject. This is influential since the angles encode the qubits for building the circuit. Angle encoding is essentially the basic form of encoding classical data into a quantum state [77]. The Qiskit library developed by IBM was used to execute the proposed technique. The state fidelity functionality of quantum we utilized computes the closeness of the encoded states. The variational algorithm updates the parameters to find the state fidelity with the changed angles. The preliminary section details the generation of landmarks, angle estimation, and intensity estimation using state fidelity and a generalized variational quantum circuit. All the information is required to construct a quantum circuit and extract results from the circuit.

The Quantum Circuit we created using IBM Quantum Composer is depicted in Figure 6 and explained hereby. To map the proposed technique within a quantum framework, a qubit with quantum state Rx (a π /2 +π /2)|0>= cos (a π/4 +π /4)|0> + sin(a π/ 4 +π/ 4)|1> was introduced, where a ∈ [−1, 1] is a scalar and Rx(t) = exp(−X /2) is a quantum operation corresponding to the rotation generated by the Pauli X operator [78]. The cases when a = −1 and a = 1 represent quantum states |0> and |1>, respectively, are equivalent to binary output in classical cases. The case

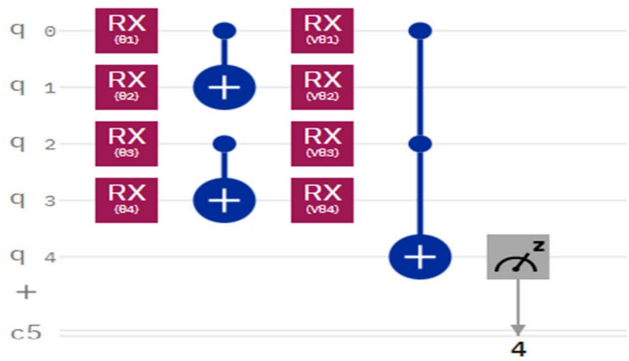

FIGURE 6. The constructed circuit on a quantum computer for our experiment purpose.

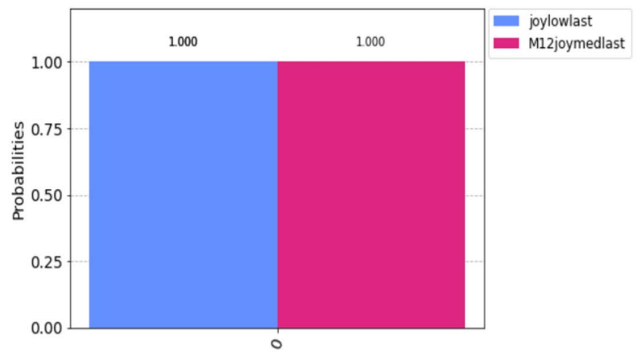

FIGURE 7. The histogram plot displaying the probability of emotion intensity of subject M12joymedlast aligned with joylowlast that underwent our quantum circuit.

a ∈ (−1, 1) represents the superposition of quantum states |0> and |1>. A parameterized unitary operator U(w) is created such that $|\psi\ (x: \theta)\rangle\ = U(w)|\psi(x)\rangle$. A parameterized unitary operator U(w) is created such that $|\psi\ (x: \theta,t)\rangle = U(w)|\psi(x,t)\rangle$ where wave function(x,t)⟩ represents the quantum state evolution of the circuit as parameterized theta gets updated along the x-axis at any given time t. The model circuit is constructed from gates that evolve the input state. The circuit is based on unitary operations and depends on adjustable external parameters. Given a prepared state $|\psi_i\rangle$, the model circuit, U(w), maps $|\psi_i\rangle$ to another vector $|\psi_i\rangle = U(w)|\psi_i\rangle$. In turn, U(w) consists of a series of unitary gates. As obvious in the circuit, the feature map is the encoding of the qubits, and the variational circuit has the updated parameters or angles followed by the measurement of the auxiliary qubit. For feature map purposes, six qubits are encoded with the angle encoding technique using Rx gate (rotation along with x-axis gate) with the angle obtained from the image of the subject, which can be in any of these six intensities of emotions - lowneutral, lowlast, medneutral, medlast, highneutral, highlast. As seen from the circuit, after the x-axis rotation gate, the first two qubits represent the left side of the mouth and are linearly entangled using cnot gates. Similarly, the last two qubits represent the right side of the mouth and are too linearly entangled using cnot gates. The leftmost and the rightmost qubits vary in accordance with each other. Because they represent two extreme sides of the mouth, that's why they are further entangled along with the auxiliary qubit using the toffoli gate for performing the measurement. For variational purposes, the parameters or angles are updated after the measurement with the classical cost function in place that updates the parameters. Then the variational quantum circuit gets executed with the updated parameters. The updated parameters or angles are calculated by finding the difference between the angles of the image with the angles of the most aligned image. The state vector of the aforesaid circuit is obtained using the Qiskit library's statevector function for each of the individual frames of the subject. The quantum state fidelity estimation F (ρ1, ρ2) is then performed between the facial expressions' encoded states, which compares and determines the closeness of the encoded states with respect to each of the intensities.

Mathematically, state fidelity is the trace of the square root product of the state vectors as given by Tr ($\sqrt{}$ ($\sqrt{}\rho 1\rho 2$) $\sqrt{}\rho 1$)2 where ρ1, ρ2 are the input state vectors or density matrix of the states obtained by encoding the angles of the individual images. This gives the intensity of the images that are most aligned with each other and thus quantification of the facial expression is established. The value of the intensities categorized by the most aligned images is shown in the result section.

VI. RESULTS

This section outlines a histogram plot of the most aligned intensity of the subject named M12. The subsequent tables thereby exhibit percentage values of each intensity as calculated by the quantum circuit. A sample result outcome and quantum circuit reciprocity with joymedlast emotion of M12 is discussed below.

Dot product step carries out the estimation of angles of this emotion intensity. The angles are then encoded onto our quantum circuit during test instance execution. The resemblance of the quantum circuit test instance run is plotted in the histogram, as shown in Figure 7. It forms the analogous of the quantum circuit. It shows the probabilistic view of states of the emotion intensity after encoding angles. The variational state fidelity estimation was used for the quantification of intensity. The program discovered that joymedlast intensity of subject M12 is maximally aligned to joylowlast rather than other available intensities in the ADFES dataset. Likewise, all the available intensities in the ADFES dataset such as lowneutral, lowlast, medneutral, medlast, highneutral, highlast for joy, sad, contempt, anger, surprise, disgust and fear emotions of all the subjects were examined with our program, and the turning point remained to be the estimation of the crescendo of the intensity values in between available intensities of the dataset for each of the subjects. Below we have represented all the images with the proposed intensities categorized by the maximally aligned intensity it falls into any of

TABLE 2. Proposed Average intensity values of images of joy emotion aligned with respective intensities.

Images aligned	Intensity	JHL	JHN	JML	JMN	JLL	JLN
Joy High Last	75-100	94.6	92.4	89.7	86.1	85.24	78.78
Joy Med Last	50-75	51.4	67.2	64.5	67.86	72.34	55
Joy Low Last	25-50	43.8	36.1	46.8	41.08	41.68	36.2
Joy High Neutral	0-25	16.3	14.9	12.8	21.43	24.37	18.34
Joy Med Neutral	0-25	24.0	18.4	13.1	20.81	15.9	16.13
Joy Low Neutral	0-25	22.0	20.8	25	23.08	16.46	22.92

TABLE 3. Proposed Average intensity values of images of sad emotion aligned with respective intensities.

Images aligned	Intensit y	SDH L	SDH N	SDM L	SDMN	SDL L	SDLN
Sadness High Last	75-100	97.85	78.4	86.2	93.33	86.4	96.06
Sadness Med Last	50-75	68.35	74.51	71.3	74.67	69.2	57.66
Sadness Low Last	25-50	28.37	38.4	50	42.8	41.6	38.36
Sadness High Neutral	0-25	18.58	21.5	22.9	13.45	20.1	17.36
Sadness Med Neutral	0-25	19.2	16.9	19.1	24.38	11.2	17.47
Sadness Low Neutral	0-25	15.96	22.74	17.6	24.43	17.2	19.87

the varying intensity of seven emotions via Table 2 through Table 8.

The experimentation resulted in the proposed intensities of the images along with aligned emotions and the tables represent average of intensity values aligned with particular emotion. For instance, the value of 92.4 in table 2 is the average of the intensity values of all the JHN (Joy High Neutral) images that are aligned to Joy High Last emotion. Similarly, 64.5 is the average of the intensity values of all the JML (Joy Mid Low) images that are aligned to Joy Med Last. This way of representation compactified the results in a coherent manner. Refer to Tables 9 and 10 for a better understanding of the abbreviations used in Tables 2 through 8. Combining both tables will denote the full form of the columns used in these tables.

A. COMPARISON OF PERFORMANCE

This sub-section aims to provide a comparative analysis of different classical studies performing quantification of emotions. Table 11 gives a detailed comparison of state-of-the-art approaches with the proposed framework. It can be seen that researchers used various techniques like EEG signals for the quantification of stress. Different classical machine learning algorithms were used, such as K- Nearest Neighbor (KNN), Linear discriminant analysis (LDA), Support Vector Machine (SVM) to achieve an accuracy of between 80 and 99 percent.

The classification strategies outperform each other in terms of F1 score, sensitivity and specificity factors. The proposed framework uses Quantum algorithm for performing the quantification of emotions. Six emotions; joy, sad, anger, contempt, fear and disgust were investigated using variational quantum state fidelity estimation and achieved an accuracy of 96 % for joy, sad, and anger emotions, whereas an accuracy of 88 % was attained for fear and disgust emotions. The overall 92 % accuracy was obtained through our process that utilized the quantum ability to find the closeness of the quantum states.

Moreover, EEG is the common modality among the studies. For instance, [85], [86] discussed the fusion of fNIRS

TABLE 4. Proposed Average intensity values of images of surprise emotion aligned with respective intensities.

Images aligned	Intensit y	SPHL	SPHN	SPML	SPMN	SPL L	SPLN
Surprise High Last	75-100	91.9	95	90.2	98.1	78.5	88.78
Surprise Med Last	50-75	53.7	75	59.6	62.77	75	73
Surprise Low Last	25-50	32.64	43.75	38.4	29.57	48.5	39
Surprise High Neutral	0-25	19.54	24	22.6	17.57	15.4	13.47
Surprise Med Neutral	0-25	13.65	11.57	10.5	23.57	16.1	19
Surprise Low Neutral	0-25	16.4	16.57	23.6	22.93	12.5	12.53

TABLE 5. Proposed Average intensity values of images of contempt emotion aligned with respective intensities.

Images aligned	Intensit y	CHL	CHN	CML	CMN	CL L	CLN
Contempt High Last	75-100	90.47	89.73	86.1	85.24	93.5	96.36
Contempt Med Last	50-75	67.47	68	71.5	73.36	59	54.73
Contempt Low Last	25-50	40.27	42.58	38.5	39.3	27.5	28.59
Contempt High Neutral	0-25	24.32	22.39	18.4	17	18.5	14.19
Contempt Med Neutral	0-25	18.84	14.84	17.7	21.81	18.5	23
Contempt Low Neutral	0-25	18.63	23.53	22.3	13.74	18.5	14

TABLE 6. Proposed average intensity values of images of anger emotion aligned with respective intensities.

Images aligned	Intensit y	AHL	AHN	AML	AMN	ALL	ALN
Anger High Last	75-100	93.4	86.47	89.1	81.61	88.53	96.5
Anger Med Last	50-75	73.3	67.21	54.5	66.86	57.64	71
Anger Low Last	25-50	37.53	44.53	47.4	36.64	28.64	31.4
Anger High Neutral	0-25	17.53	23.64	18.6	23.42	21	13.4
Anger Med Neutral	0-25	13.41	17.63	23.6	11.63	18.63	22
Anger Low Neutral	0-25	12.64	23	21.5	17.53	10.53	11.6

TABLE 7. Proposed average intensity values of images of fear emotion aligned with respective intensities.

Images aligned	Intensit y	FHL	FHN	FML	FMN	FLL	FLN
Fear High Last	75-100	95.53	92.32	94.42	96.32	97.43	98.53
Fear Med Last	50-75	69.32	64.53	59.64	73.42	53.53	66
Fear Low Last	25-50	43.83	36.19	37.3	38.63	48.64	39.53
Fear High Neutral	0-25	19.53	16.74	21.64	23.63	12.64	10.63
Fear Med Neutral	0-25	24	18.42	16.63	17	13.32	15.53
Fear Low Neutral	0-25	23.3	21.5	22	20.54	17.63	22.92

TABLE 8. Proposed average intensity values of images of disgust emotion aligned with respective intensities.

Images aligned	Intensity	DHL	DHN	DML	DMN	DLL	DLN
Disgust High Last	75-100	84.42	89.53	94.5	96	77.73	78.58
Disgust Med Last	50-75	64	66.74	69.5	68.5	71	69.52
Disgust Low Last	25-50	38.64	47	41.5	37.52	45.74	34.53
Disgust High Neutral	0-25	19.64	17.64	14	17.53	22	24.1
Disgust Med Neutral	0-25	20.52	15.52	16.6	22.53	21.63	18.64
Disgust Low Neutral	0-25	23.54	22	21.5	22.52	17.64	13.13

TABLE 9. Abbreviations of emotion prefix.

Emotion Prefix	Full Form
J	JOY
SD	SAD
SP	SURPRISE
C	CONTEMPT
A	ANGER
F	FEAR
D	DISGUST

TABLE 10. Abbreviations of intensity prefix.

Intensity Prefix	Full Form
HL	HIGH LAST
HN	HIGH NEUTRAL
ML	MID LAST
MN	MID NEUTRAL
LL	LOW LAST
LN	LOW N EUTRAL

and EEG for the detection of stress and reported accuracy of 95.1% and 97%, respectively, with fNIRS data fused along with EEG. Whereas our proposed quantum solution uses face expressions as the modality for detecting emotions. Using this type of modality succumbs few limitations and challenges as elaborated below:

- The step to find the angle is confounded for fear, disgust, and contempt emotions as it is not easy to differentiate the subjects with these emotions.
- The dataset consists of European folks, so the proposed solution of quantification could differ from other datasets.
- Similarly, the landmark generation procedure might exhibit varied results in the first place.
- The static images of the subjects extracted from the video stream are prone to errors while image extraction.

TABLE 11. Comparison of performance of proposed framework with other state-of-the-art studies.

State-of-the-art Studies	Technique Used	Classifier	Modality	Pros	Cons	Performance Metrics
[79]	Used Discrete Wavelet Transform (DWT) for extracting features from EEG signals.	KNN	EEG	Identified stress at multiple levels	It requires further analysis to quantify stress in to different levels	83.26 % accuracy
[80]	Linear discriminant analysis (LDA) was used to detect stress level	LDA	EEG ECG EMG GSR	Identified stress at multiple levels	It requires further analysis to quantify stress in to different levels	83.26 % accuracy
[81]	bi-directional Long Short-Term Memory (Bi-LSTM) Model was used to recognize human emotions	LSTM BGWO and Bi-LSTM	EEG	Contributed to enhance performance and accuracy of emotion recognition.	Difficulty in creating dataset due to high cost and human resources.	accuracy of 99.45% for valence, 96.87% for arousal and 99.68% for liking
[82]	Machine Learning framework involving electroencephalogram (EEG) signal analysis of stressed participants is proposed.	Proposed a ML frame-work	EEG	Proposed EEG-based ML framework has the potential to quantify stress objectively into multiple levels.	Quantification of stress levels can be improved.	94.6% accuracy
[83]	Investigated feasibility of exploiting Electroencephalography (EEG) signals for discriminating stress in arithmetic tasks.	SVM	EEG	Quantized stress levels.	Analyzation included arithmetic tasks only.	94 % accuracy
[84]	Performed quantification of physiological disparities in stress conditions	KNN	EEG ECG	Quantification of disparities achieved.	Quantitative analysis performed on limited EEG data	86 % accuracy
Proposed Framework	Used Quantum algorithm for quantification of emotions	Quantum State Fidelity	Facial Expression	Novel technique used in the studies of quantification of emotion detection	The results of disgust, fear and anger emotions can be improved	Overall 92 % accuracy

The varied results of landmark generation of disgust and contempt emotions give rise to errors, and inevitably, the angle determination gives improper outputs. The consequence is the incorrect computation of the intensity through the process. Thus, the root mean squared error calculated for our experiment came to be 17.37 and performed better than the study [87] where the root mean square error reported is 28.79 and 34.15 for ANN and SVM models respectively.

VII. CONCLUSION

In this work, we legitimately addressed the problem of finding intermediate intensities than available within the ADFES dataset of various emotions of subjects via quantum computation using a variational quantum state fidelity estimation algorithm. The key factor is that it is a novel method and has never been employed in studies of sentiment analysis and emotion detection before and it sensibly complements the quantum's ability to solve challenging problems like this.

We used static images to investigate emotion intensities in the present analysis, in the future, we aim to facilitate the feasibility of quantification estimation on the live video stream as well. Based on this open scope work, certain use cases can be explored that could promptly ease the emotion identification process utilizing quantum techniques. Lastly, the formation scheme of other quantum circuits can also be exploited for comparison purposes.

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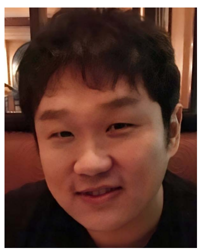

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