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Enhancing emotional response detection in virtual reality with quantum support vector machine learning

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ABSTRACT

Accurate and efficient emotion classification is essential for virtual reality (VR) affective computing, as it allows systems to tailor gameplay, difficulty, and feedback to improve user engagement and support therapeutic outcomes. However, the high-dimensional and multimodal nature of the physiological signals used in these emotion classification models often poses significant challenges for traditional machine learning methods. This study explores the use of quantum support vector machines (QSVM) to improve efficiency and accuracy in classifying emotions within a VR Pong game featuring three conditions (slow-paced, fast-paced, and lag-induced). Physiological signals, including electrocardiogram (ECG), galvanic skin response (GSR), and electromyogram (EMG), were analyzed along with self-reported emotions from the Self-Assessment Manikin (SAM). Traditional SVMs and QSVMs were compared for their ability to classify arousal and valence from the collected physiological signals and self-reported emotions. A QSVM model using circular entanglement achieved 0.693 precision and a 0.923 F1 score for arousal with five features, surpassing the SVM's 0.648 precision and 0.44 F1 (using nine features). For valence, QSVM achieved 0.637 accuracy and a 0.95 F1 score with five features, exceeding the SVM 0.603 accuracy and 0.31 F1 (with eight features). Our findings demonstrate that QSVMs efficiently handle high-dimensional physiological data while improving classification performance with fewer features. Although physical movement can affect physiological signals, our results indicate that QSVMs remain promising for improving emotion classification in VR and may enable more effective real-time adaptation in immersive environments.

1. Introduction

Humans communicate and express emotions through various modalities, including speech, facial expressions, physiological signals, and body gestures [1]. These forms of expression are critical for everyday decision making, learning, and social interactions [2–4]. As technology becomes increasingly integrated into daily life, emotional responses can significantly influence interactions with modern systems [5]. Affective Computing (AC), introduced by [6], aims to develop systems capable of recognizing and responding to human emotions [7]. This field has gathered considerable attention across multiple disciplines, driving research in computer science, psychology, and cognitive science to strengthen user experiences with technologies [3,7]. The applications of AC range from analyzing how emotional states affect the usability of the software [8] and interpreting user sentiments on social media [9] to creating personalized therapeutic tools such as music therapy [10].

Traditionally, AC studies have used two-dimensional (2D) non-immersive stimuli, such as images, audio, and video clips, to induce emotional states [1,11,12]. Although these methods have advanced our understanding of emotional responses, they often lack the immersive realism needed to capture complex emotional reactions [13]. Recent studies increasingly use virtual reality (VR), which provides realistic and interactive simulations for more natural and intense emotional experiences [1]. For example, VR has been applied to study anxiety about public speaking [14], paranoia [15], and cognitive load using EEG and additional physiological measures [16,17]. VR-based emotion recognition has also been integrated into real-time gaming, where physiological feedback can adjust difficulty based on player stress and engagement [18,19].

AC also relies extensively on machine learning (ML) techniques to detect and classify emotions, often using physiological signals as input to model emotional states, predict user responses, or adapt interactive systems in real time [1]. Popular ML approaches in this domain include k-nearest neighbors (kNN) [1], Decision Trees (DT) [20], and Neural Networks (NN) [21]. In addition, support vector machines (SVMs) have proven especially effective handling high-dimensional feature spaces

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for emotion recognition [22–27]. However, SVMs can encounter difficulties with large-scale data due to the curse of dimensionality and the need for substantial training sets [28].

Recent quantum machine learning research has demonstrated the potential of quantum support vector machines (QSVMs) in handling complex and high-dimensional datasets. QSVMs have been applied in fields such as medical diagnosis [29,30], genomic data analysis [31], and financial modeling [32], where they have shown advantages in managing noisy and computationally demanding problems. However, their use in AC and immersive VR environments remains largely unexplored. Existing research in VR-based emotion recognition primarily relies on classical machine learning approaches [1,33], leaving a gap in understanding how quantum methods could improve classification accuracy and computational efficiency under potential real-time constraints. QSVMs take advantage of quantum mechanical principles such as superposition and entanglement to process high-dimensional data more effectively [31,34,35] and have already demonstrated success in materials science and healthcare diagnostics [28,36,37]. Despite these advantages, quantum hardware is still evolving, with qubit limitations and noise susceptibility posing challenges for large-scale deployment [38,39].

This study investigates the use of QSVMs for emotion classification in VR-based AC and compares their performance with traditional SVMs to achieve improved classification accuracy. The work is structured around two primary objectives:

1. Assess the capability of QSVMs to classify affective states from physiological signals in a VR Pong game under varied pacing conditions (fast, slow, and lag-induced).
2. Compare the classification performance of QSVMs and classical SVMs, emphasizing accuracy and feature efficiency for potential real-time adaptation in VR.

To help visualize the VR setup and data flow, the graphical abstract provides an overview of the virtual environment, methodology, physiological sensors, and a comparison of QSVM and SVM results. The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature, covering studies in AC, machine learning, and QSVM applications. Section 3 outlines the methodology, including details of data collection, pre-processing, and model training. Section 4 presents the results of the comparative analysis, while Section 5 discusses key findings and broader implications. Finally, Section 6 concludes the study, addressing limitations and offering directions for future research.

2. Literature review

Recent advances in AC have increasingly used VR and physiological signals to improve emotion recognition research. This section reviews how VR-based physiological data can improve our understanding of user affect, outlines the computational challenges traditional SVMs face with high-dimensional data, and discusses how QSVMs offer improved efficiency and real-time processing capabilities.

2.1. Physiological data in VR for emotion recognition

Recent research in VR-based AC uses physiological signals to obtain objective measures of user emotional states [1,19]. These signals, often captured through wearable or minimally intrusive sensors, facilitate continuous user assessment in immersive environments [40–42]. Among the main modalities are heart rate variability (HRV), derived from electrocardiography (ECG) and associated with stress and arousal [43,44]; Galvanic Skin Response (GSR), also called electrodermal activity, reflecting changes in skin conductivity caused by sweat gland activity [18,45]; Electroencephalography (EEG), which measures electrical activity in the brain to indicate cognitive workload and emotional states [16,17]; and electromyography (EMG), which detects muscle activity relevant to subtle facial expressions or voluntary actions [46,47].

Integrating multiple physiological signals has been shown to improve the ability to classify emotional states and enable real-time adaptation of the VR environment [48,49]. For example, in VR gaming or rehabilitation, real-time physiological feedback can adjust difficulty based on user stress levels or engagement [18,33]. Therapeutic interventions for conditions such as autism or anxiety have used HRV and GSR to monitor ongoing emotional states [33], and educational VR systems can tailor the complexity of the lesson to the cognitive loads of the students [19]. Despite these benefits, issues such as noisy data and the high cost of specialized hardware continue to limit large-scale implementation, emphasizing the need for more efficient data processing [50,51].

2.2. SVMs and QSVMs in emotion classification

SVMs are widely used for classifying emotional states using physiological signals, typically within the framework of the Circumplex Model of Affect, which defines emotions in terms of arousal (high vs. low activation) and valence (positive vs. negative experience) [2,18,52]. Multiple studies have demonstrated that SVM-based classifiers applied to physiological signals can effectively differentiate emotional states. For example, GSR has been used to distinguish stress from relaxation, and HRV and ECG have been used to predict arousal and valence in real time [18,53]. SVMs have also been effective in identifying EMG-based affective expressions [47,54]. However, as VR applications increasingly incorporate several sensors (e.g., GSR, HRV, EEG, EMG), the resulting data become high dimensional, creating potential computational challenges for SVMs [55,56]. In addition, complex kernel tuning and extended cross-validation can hinder near-real-time emotion feedback [57], a critical requirement for immersive VR systems that instantly adapt to user affect.

QSVMs offer a promising solution for handling high-dimensional data by leveraging quantum bits (qubits), which utilize superposition and entanglement to process information more efficiently than classical systems [34,35,58]. This advantage enables quantum parallelism, which can significantly reduce training times for large or complex physiological data sets [59,60]. Furthermore, quantum feature maps allow for more refined decision boundaries, improving the classification accuracy in high-dimensional spaces [56]. These capabilities have led QSVMs to outperform classical SVMs in various domains, such as medical diagnostics, where they have demonstrated superior classification performance and faster convergence rates [29,30,61].

Beyond healthcare, QSVMs have shown versatility in fields such as genomics, financial modeling, and big data classification [32,62]. In particular, [35] demonstrated that QSVMs can be implemented on a quantum computer with logarithmic complexity in both vector size and training sample count, achieving an exponential speed-up through efficient inversion of the kernel matrix. Furthermore, recent work has applied a hybrid quantum–classical framework for image classification using quantum kernels and amplitude encoding [63], illustrating that quantum approaches can reduce computational complexity while achieving competitive performance in visual data processing. Despite these advances, QSVMs have yet to be fully explored for VR-based emotion recognition, where multimodal physiological signals introduce additional challenges. As quantum hardware continues to evolve, QSVMs may offer a viable approach to managing the high data throughput and real-time processing demands of immersive VR environments. This work compares QSVM and classical SVM methods for classifying arousal and valence in VR-based physiological signals, providing insights into the feasibility of quantum machine learning for AC applications.

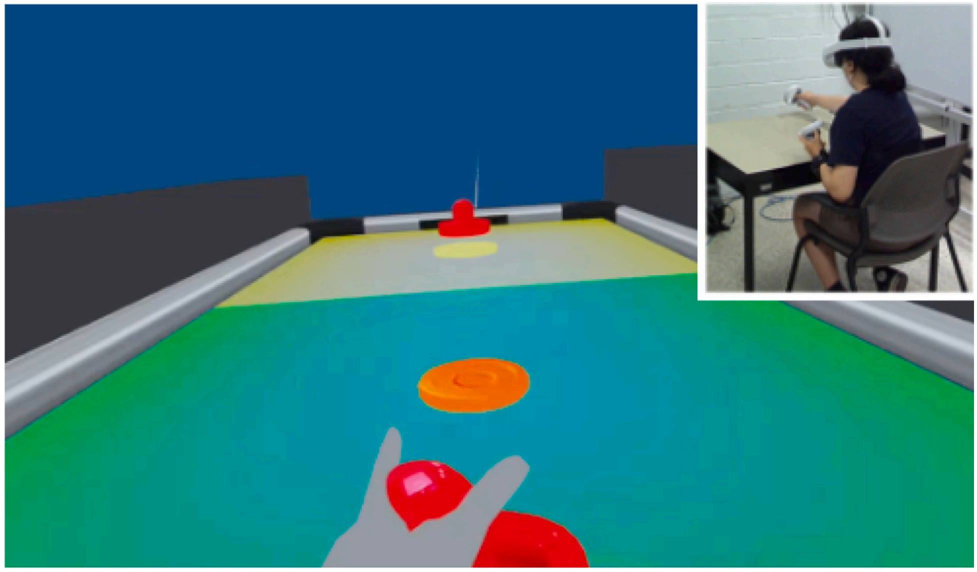

Fig. 1. A user's perspective (main image) and a third-person viewpoint (inset) of the VR Pong gameplay environment.

3. Materials and methods

In this study, a VR Pong game was used as an experimental platform to investigate the effects of variations in game play on user affect. Previous research has manipulated game speed and artificial latencies to induce distinct emotional responses. For example, [64] simulated frustration by partially ignoring user input to induce lag, while [65] showed that unbalanced pacing in a VR rhythm game can lead to boredom or frustration, with optimal flow achieved when speed matches player skill. Similarly, [66] demonstrated that the modification of task parameters such as speed and competition levels could improve motivation and emotional engagement in VR-based rehabilitation. Building on this body of work, a prior investigation [67–69] established that VR game play variations evoke distinct emotional responses, as evidenced by changes in heart rate and nonspecific skin conductance responses. This manuscript extends that research by revisiting the VR Pong setup, analyzing how physiological signals and self-reports (e.g., SAM) reflect user emotions, and evaluating SVM and QSVM classification approaches for detecting VR-induced affective states.

A total of 30 participants (14 women, 16 men), aged 18–62 years (mean = 27, SD = 8.72), participated in an IRB-approved protocol (IRB #2021-0808). Recruitment occurred through flyers, direct communication, and referrals. Most of the participants were moderately familiar with VR, although one reported no experience and two had a high degree of familiarity.

3.1. Virtual reality Pong game

A custom virtual environment (VE) was developed in Unity, adapting the Air Hockey Game Kit from the Unity Asset Store[1] to support the Oculus HMD functionality and VR-specific features. Mouse-and-keyboard controls were replaced with hand- and controller-tracking for more immersive interaction, and head-tracking was added for smoother movement. Unity's physics engine was used to model realistic object dynamics and collisions. Fig. 1 shows a screenshot of the VR environment, illustrating the Pong single-player setup where participants compete against a computer-controlled opponent.

3.1.1. Game variations

Three distinct VE versions were created to elicit different emotional responses: fast-paced, slow-paced, and lag-induced gameplay. A supplementary video is provided to demonstrate these three game versions from the player's perspective.

- **Fast-paced**: The puck speed was tripled to deliver a highly responsive, fluid experience. The virtual mallet was programmed to instantly mirror hand and controller movements (i.e., zero latency), and the game difficulty was set to its highest level, producing a challenging computer opponent.
- **Slow-paced**: This version was designed to evoke boredom by reducing the puck speed to one-third of its default, coupled with the lowest difficulty setting, resulting in a minimally challenging opponent and a more relaxed experience.
- **Lag-induced**: This version intentionally introduced sporadic frame-rate drops and periodic freezes (every 30 s) by fixing the mallet's position, creating a less responsive, more unpredictable environment. Difficulty was set to a regular level.

3.2. Data collection

This section describes the instruments and procedures used to collect both subjective and objective data. Participants completed the Self-Assessment Manikin (SAM) survey to report their emotional states, while physiological signals (ECG, GSR, and EMG) were recorded using BIOPAC Systems hardware. In addition, the overall experimental design, including participant screening and the VR Pong game setup, is outlined.

3.2.1. Self-Assessment Manikin

The SAM uses a nine-point scale for each dimension, where 1 represents displeasure or low activation and 9 represents pleasure or high activation [70]. In the present study, the valence scale ranges from displeasure (1) to pleasure (9), while the arousal scale ranges from calmness (1) to high activation (9).

3.2.2. Physiological measures

Physiological data (GSR, ECG, EMG) were recorded using BIOPAC Systems, Inc. hardware, and audio data were collected through a MAONO dynamic microphone (MAONO Technology Co.) during post-gameplay open-ended questions. For GSR measurements, the volar

[1] Air hockey game kit. https://assetstore.unity.com/packages/templates/systems/air-hockey-game-kit-18249#releases, accessed 2024-12-22.

Table 1
Extracted physiological features. Abbreviations: Root mean square of successive differences (RMSSD), standard deviation of successive NN intervals (SDSD), proportion of adjacent R-R intervals that differ by more than 50 ms (pNN50), sympathetic activity index (SAI), parasympathetic activity index (PAI), respiratory sinus arrhythmia (RSA), heart rate (HR), skin conductance level (SCL), number of non-specific skin conductance responses (NS-SCR), root mean square (RMS).

Electrocardiogram	Galvanic skin response	Electromyogram	Audio
RMSSD (ms)	Max SCL (μS)	Avg. RMS (mV)	Avg. pitch (Hz)
SDSD (ms)	Min SCL (μS)	Std. RMS (mV)	Std. pitch (Hz)
pNN50 (%)	Avg. SCL (μS)	Median frequency (Hz)	Avg. energy (W)
Power in very low freq (ms^2)	NS-SCRs (peaks/min)	Mean freq (Hz)	Max energy (W)
Power in low freq (ms^2)	Avg. NS-SCR height (μS)	Peak frequency (Hz)	Std. energy (W)
Power in high freq (ms^2)	–	Mean power (mV^2)	Avg. zero crossing (Hz)
Power in very high freq (ms^2)	–	Total power (mV^2)	Max zero crossing (Hz)
SAI	–	–	Std. zero crossing (Hz)
PAI	–	–	–
SAI–PAI	–	–	–
RSA (ms)	–	–	–
Avg. HR (bpm)	–	–	–
Min HR (bpm)	–	–	–
Max HR (bpm)	–	–	–
Std HR (bpm)	–	–	–

surfaces of the non-dominant index and middle fingers were rinsed with water before electrode gel was applied. Electrodes were then taped to these fingertips to maintain stable contact. For ECG readings, the chest area was lightly abraded, cleaned with alcohol, and dried. Gel was applied to each ECG sensor, which was placed according to the standard Einthoven 3-lead arrangement. EMG electrodes were positioned over the flexor digitorum superficialis (FDS) and extensor carpi radialis longus (ECRL) muscle bodies, following recommendations by [71,72]. Each site was similarly abraded, cleaned, and dried before electrode placement. A reference electrode was placed on the elbow.

Data from GSR, ECG, and EMG were processed using Biopac AcqKnowledge. Predefined functions handled EMG feature extraction, while GSR and ECG protocols followed earlier methods described in [67,68]. Additionally, audio data (participant responses) were processed in MATLAB (R2022b, MathWorks Inc.) with *audioFeatureExtractor* to obtain pitch, zero-crossing rate, and short-term energy. Table 1 lists all features derived from the physiological signals. Further preprocessing involved removing outliers beyond ± 1.5 times the interquartile range and applying a max–min normalization step.

3.3. Experimental design

A counterbalanced, within-subjects design was employed. Prospective participants were first selected using the Patient Health Questionnaire-9 (PHQ-9) [73], excluding individuals who scored above five to reduce the likelihood of mild depression. Additional exclusion criteria were age under 18, susceptibility to motion sickness, significant visual impairment or reliance on glasses, history of seizures, and hand impairment.

3.4. Study procedure

Upon arriving at the laboratory, the participants reviewed and signed a consent form, completed a demographic survey, and were fitted with GSR, ECG and EMG sensors. A five-minute baseline was recorded, followed by a two-minute VR Pong practice session. Participants remained seated throughout to minimize motion artifacts, holding a single controller in their dominant hand. The first experimental session used one of three randomly assigned Pong variants (slow-paced, fast-paced, or lag-induced), each lasting five minutes.

At the end of each session, while still immersed in the VR environment and wearing the headset, the participants answered open-ended questions (Table 2) verbally. A MAONO microphone captured these responses in real time along with other physiological signals. The participants then removed the headset and completed the SAM survey.

A two-minute break was provided before starting the next session and this sequence was repeated until all three variants of the game were completed. The participants then completed an exit questionnaire on their experiences, perceived emotions, and preferences for the game. Finally, the sensors were removed and the participants received $15 compensation. The entire experiment lasted approximately 75 min.

Table 2
Open-ended questions asked after each gameplay session.

(1) Please describe how you are feeling right now.
(2) How was the pace of this game?
(3) Would you play this game version if it were available to you at home?
(4) How would you describe this game to your friends and family?
(5) What feedback would you give a game designer to improve this game?

3.5. Data analysis

This section provides an overview of the framework used to process the collected data, including cleaning, normalization, and preparation of physiological signals for classification.

3.5.1. Traditional support vector machine analysis

Python was used to perform the SVM-based classification of arousal and valence. In line with standard AC practices, the original 9-point SAM ratings were shifted to a range of −4 to +4 (with the origin at (0,0)) for more intuitive 2D plotting. Because 0 is now the midpoint of this shifted scale, we used 0 as the threshold for binarization: responses ≤ 0 were labeled "low" and responses > 0 were labeled "high" [74]. Although this method simplifies analysis and aligns with discrete classification tasks, it also reduces the granularity of the original scale [74]. Missing values were imputed using k-nearest neighbors (kNN), which locates the k most similar samples in feature space and averages them to fill the missing entry. To address potential class imbalance, we report both accuracy and F1-scores.

The data set was divided into 80% for training and 20% for testing, the training subset being used to adjust model parameters and the testing subset providing an unbiased performance estimate. Principal Component Analysis (PCA) then reduced the dimensionality by extracting the 10 principal components that account for the greatest variance. Formally, for a data matrix X, the covariance matrix $C = \frac{1}{N} X^T X$ was calculated, and its eigenvectors defined the principal components.

Linear, polynomial, and sigmoid SVM kernels were evaluated. The linear kernel decision function is

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i \langle x_i, x \rangle + b.$$

For a polynomial kernel of degree d,

$$K(x, x') = \left(c + \langle x, x' \rangle\right)^d,$$

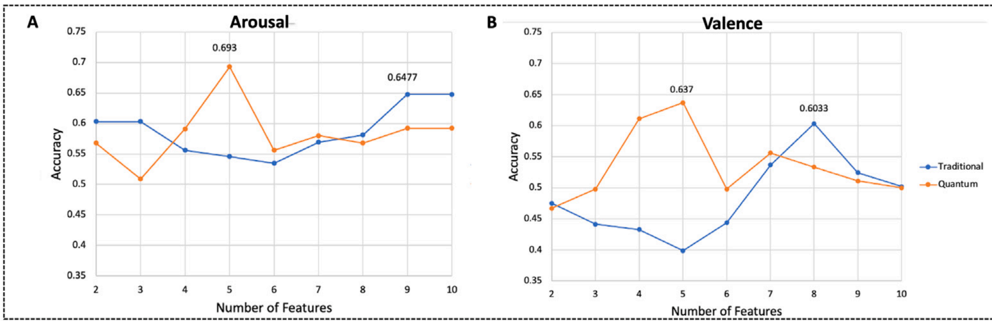

Fig. 2. Comparative analysis of feature utilization and prediction accuracy between Traditional SVM and QSVM.

and the sigmoid kernel is

$$K(x, x') = \tanh\big(a\langle x, x'\rangle + r\big).$$

Each kernel influences the formation of the SVM decision boundary in the feature space. A 5-fold cross-validation scheme assessed each model's performance, implemented in Python's machine learning libraries.

3.5.2. Quantum support vector machine analysis

An analogous procedure was followed for the Quantum SVM (QSVM), using the ZZ feature map to encode classical data into quantum states [75]. For a data vector $x = (x_1, x_2, \ldots, x_n)$, the ZZ feature map applies parameterized rotations and controlled-Z gates to transform the n-qubit state $|0\rangle^n$ into $|\phi(x)\rangle = U_{zz}(x)|0\rangle^n$. Circular, linear, and fully entangled configurations were explored, iterating from 1 to 10 layers. PCA was again used to select the top 10 features, which were then encoded into the QSVM via Qiskit. A 5-fold cross-validation scheme evaluated performance, paralleling the approach used for traditional SVMs.

4. Results

Prior analyses [67,68,76] showed that fast-paced, slow-paced, and lag-induced versions of the VR Pong game elicited significantly different emotional states. Self-reported measures indicated positive arousal and valence for the fast-paced condition (2.9 ± 1.0 arousal, 1.8 ± 1.3 valence), positive arousal but negative valence for the slow-paced condition (0.6 ± 2.2 arousal, -2.1 ± 1.8 valence), and both negative arousal and negative valence for the lag-induced condition (-0.4 ± 2.2 arousal, -0.3 ± 2.1 valence). These findings confirm that variations in game speed and responsiveness can influence players' emotional experiences. Among the 20 physiological variables examined, average heart rate and non-specific skin conductance responses (NS-SCR) showed significant differences across conditions, illustrating that changes to gameplay parameters can affect emotional responses.

4.1. Principal component analysis

The PCA identified the top ten features with the highest variance, including key HRV indicators such as VLF power, HF power, pNN50, SDSD, and RMSSD. EMG measures like FDS Total Power, Mean Power, Avg RMS, and ECRL Mean Power also showed substantial variability, indicating muscle-group responsiveness to emotional states.

4.2. Comparison of traditional and quantum SVM analysis

This subsection presents a direct comparison of the performance of classical SVM and QSVM models on both arousal and valence classification tasks. The metrics and evaluation criteria are summarized, followed by a detailed description of the results for each classifier, highlighting strengths and potential limitations observed under different feature configurations.

4.2.1. Arousal detection accuracy

In the traditional SVM analysis with five-fold cross-validation, the linear kernel achieved its highest accuracy of 0.648, with an F1 score of 0.44, using nine features. This result demonstrates the linear kernel's effectiveness in handling high-dimensional data for emotion recognition. However, a QSVM employing circular entanglement surpassed the traditional SVM, obtaining an accuracy of 0.693 and an F1 score of 0.923 with only the top five features for arousal prediction (Fig. 2a). Fig. 3 provides a detailed comparison, illustrating (a) the linear SVM feature map, (b) the QSVM circular entanglement map, and the respective confusion matrices (c, d) for both models.

4.2.2. Valence detection accuracy

For the valence dataset, a comparative analysis was conducted between the traditional SVM with a polynomial kernel and the QSVM with circular entanglement. The traditional SVM achieved an accuracy of 0.6033, along with an F1 score of 0.31, using eight features. In contrast, the QSVM outperformed the traditional model, reaching an accuracy of 0.637 and an F1 score of 0.95 with only the top five features (Fig. 2b). This result highlights the efficiency of QSVM with circular entanglement, which offers more accurate valence predictions, both in accuracy and F1, while requiring fewer features. Fig. 4 provides a detailed comparison, illustrating (a) the feature map for the polynomial SVM, (b) the circular entanglement feature map for the QSVM, and their respective confusion matrices in (c) and (d).

5. Discussion

This study demonstrates that QSVMs can surpass classical SVMs in both classification accuracy and feature efficiency to detect valence and arousal in VR-based AC. Specifically, QSVMs achieved a maximum accuracy of 0.693 with an F1 score of 0.923 for arousal and 0.637 accuracy with a 0.95 F1 score for valence, using fewer input features than classical SVMs. These results align with the principles of quantum superposition and entanglement, which allow a more detailed exploration of high-dimensional feature spaces [77,78]. From a practical point of view, reducing the number of features is particularly useful for large-scale physiological datasets, where resource-intensive computations can impede the scalability of classical models [79,80].

Such performance gains echo broader research on quantum-driven algorithms for real-time computing. Recent studies suggest that quantum-based methods can handle data complexity more effectively than their classical counterparts, potentially lowering both training time and feature load [62,81]. This capacity to maintain higher accuracy with fewer variables is especially compelling in VR contexts, which generate multimodal, high volume datasets (e.g. physiological) [82,83].

Moreover, these findings align with ongoing trends in immersive technology, where continuous monitoring of emotional states supports adaptive gameplay, exposure therapy, and personalized learning [33,84]. Although traditional machine learning models (e.g. SVMs and deep neural networks) have demonstrated strong performance in static tasks,

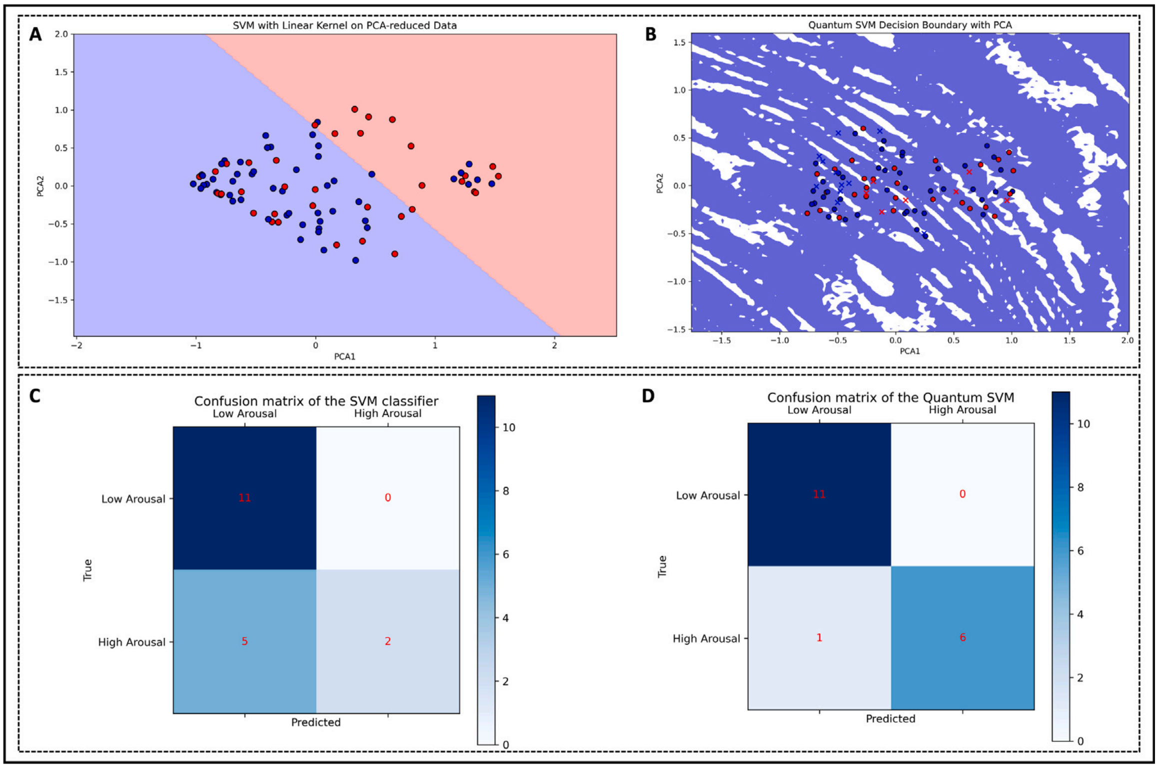

Fig. 3. Detailed representations of SVM and QSVM methodologies for the arousal data set. (a) Feature map of the traditional SVM with a linear kernel. (b) The circular entanglement feature map for the QSVM. (c) Confusion matrix for the traditional SVM. (d) Confusion matrix for the QSVM.

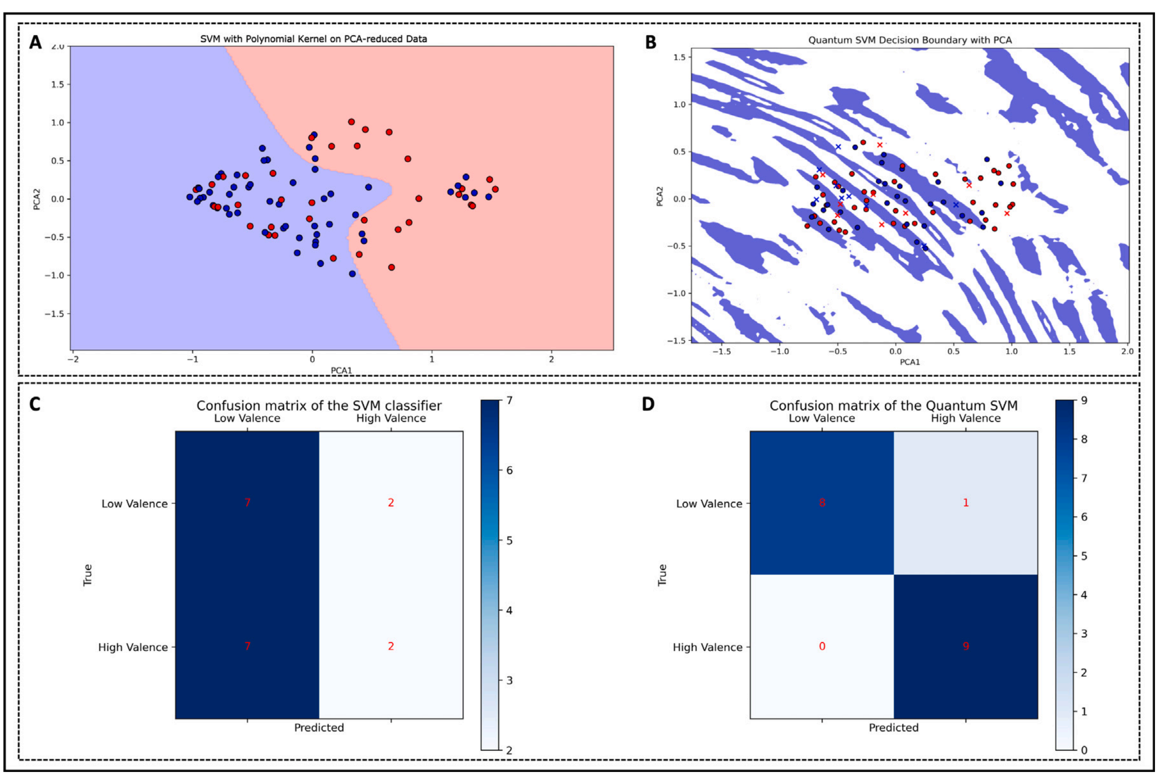

Fig. 4. Detailed representations of SVM and QSVM methodologies for the valence data set. (a) Feature map of the traditional SVM with a polynomial kernel, illustrating feature integration and processing. (b) The circular entanglement feature map for the QSVM. (c) Confusion matrix for the traditional SVM. (d) Confusion matrix for the QSVM.

quantum approaches may offer advantages in dynamic VR environments that require near-instant updates [17]. As quantum hardware continues to advance, QSVM pipelines could enable faster feedback loops, enhancing user experiences in applications based on precise real-time emotion detection [39].

Recent research has explored multi-stage data processing strategies for emotion detection, focusing on how specialized feature extraction and advanced models can improve reliability in immersive environments. For example, [85] proposed a capsule-based knowledge distillation pipeline to compress EEG networks for AC, demonstrating that careful model design and training can enhance efficiency without compromising accuracy. Integrating modalities such as EEG or facial EMG helps capture subtle cognitive changes and facial expressions that can be missed by signals such as GSR and HRV [46,86]. Although processing these diverse data streams increases feature dimensionality, quantum-based approaches such as QSVMs may offer a scalable solution for integrating multiple signals in real time. Ultimately, combining robust processing pipelines with quantum-enhanced methods may enable future VR systems to provide more adaptive feedback based on a richer set of physiological signals.

6. Conclusion

Although QSVMs demonstrated improved accuracy and feature efficiency compared to classical SVMs for valence and arousal detection in VR-based AC, several limitations remain. In particular, the experimental design used different pacing (fast-paced, slow-paced, lag-induced) to induce varying emotional states, which inevitably introduces a confounding between physical activity and affect. Recent studies indicate that physical movements alone can significantly affect physiological signals and can be misinterpreted as changes in emotional state [87]. Consequently, it is challenging to unravel how much of our classifier performance arises from genuine emotional changes versus variations in physical exertion or motor activity. Future experiments should consider integrating motion-tracking sensors (e.g. accelerometers, IMUs) to quantify movement and rigorously separate its effects from physiological markers of affect.

Second, relying on descriptive statistics from entire five-minute sessions restricts generalization to real-time contexts, where short-window or second-by-second analyses often drive adaptive VR experiences [84]. Investigations that segment physiological data into finer intervals could clarify whether the advantages of QSVM persist under rapid updates. Moreover, current quantum hardware frequently suffers from limited qubits and noise, constraining QSVM scalability [38,39]. Progress in quantum feature maps and kernel strategies will help mitigate these issues [77,78], along with incorporating additional modalities such as EEG or facial EMG [62,88]. Future work may also evaluate QSVMs in more diverse VR settings, such as multiplayer social platforms or clinical exposure therapies, and compare them against alternative machine learning models (e.g., deep neural networks) under real-time constraints.

Despite these challenges, our study confirms the potential of QSVMs to process high-dimensional physiological signals in immersive VR environments. By achieving higher accuracy with fewer features, QSVMs offer more efficient pipelines for user-focused adaptive VR applications. Importantly, our primary focus was on comparing QSVM and SVM methods for AC, rather than trying to separate motor activity from emotional responses. Looking ahead, our next steps include evaluating QSVM on larger, publicly available AC datasets (e.g., DEAP [74], DREAMER [89], and AMIGOS [90]) to assess performance across diverse populations and signal modalities. Furthermore, future work will integrate additional physiological signals such as EEG along with motion tracking data (e.g., IMU) to better disentangle the effects of physical activity from emotional responses, thus advancing both practical applications and the potential for real-time emotion recognition systems in VR.

CRediT authorship contribution statement

Allison Bayro: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Heejin Jeong:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2025.104196.

Data availability

Data will be made available on request.

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