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Research Paper

Evaluation of Emotion Detection Using CNN VGG16 and Hybrid QCNN for Enhancing Digital Content Personalization

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Abstract

Emotion detection through facial expression analysis provides a critical mechanism for hyper-personalized digital marketing, enabling real-time content adaptation aligned with consumer affective states. This study evaluates a Hybrid Quantum Convolutional Neural Network (QCNN), which replaces classical convolutional layers with quantum feature extraction circuits utilizing amplitude embedding, RX rotations, and entangling operations. Both VGG16 and QCNN were trained and tested on the RAF-DB dataset, comprising seven basic and nine compound emotion classes. Preprocessing for VGG16 involved resizing to 224×224 RGB images normalized to ImageNet statistics, while QCNN inputs were downscaled to 16×16 grayscale, normalized via min–max and L2 scaling, and encoded into four-qubit states. Models were optimized under factorial hyperparameter scenarios (epochs, learning rates, batch sizes) using the Adam optimizer. Results demonstrate that QCNN achieves a validation accuracy improvement of approximately 4.5 percentage points over VGG16 on both basic and compound emotion subsets, while reducing end-to-end processing time by roughly 15–25%. Furthermore, QCNN exhibits narrower training-validation performance gaps, indicating that enhanced generalization is afforded by quantum feature regularization. Inference latency remains under 0.36 seconds per sample, meeting sub-second requirements for interactive marketing applications. These findings position QCNN as a promising foundation for emotion-aware personalization pipelines, capable of real-time adaptation on edge devices. Future work will focus on field evaluations in commercial settings, demographic fairness assessments, and modular API integration to ensure scalable deployment and measurable return on investment in marketing campaigns.

Keywords *Quantum Machine Learning; SVM; Hybrid Quantum-SVM; Emotion Prediction*

INTRODUCTION

Digital marketing has undergone a profound transformation over the past decade, driven by the proliferation of online channels and the ever-increasing expectations of consumers for relevant, personalized experiences (Gorde et al., 2023; Zito et al., 2021). In this environment, generic advertising no longer suffices; brands must engage audiences at an emotional level to capture attention and foster loyalty. Personalization has therefore emerged as a cornerstone of effective digital strategies, enabling marketers to deliver tailored content that resonates with individual preferences and behaviors.

Emotion detection through facial analysis presents a promising avenue for enhancing personalization by assessing real-time affective responses to marketing stimuli (Shahzad et al., 2023). Empirical studies demonstrate that aligning content with the viewer's emotional state can significantly enhance ad recall and persuasive impact (Marques et al., 2025). By harnessing subtle

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emotional cues—ranging from joy to confusion—marketers can optimize creative messaging, deployment timing, and channel allocation for maximum engagement (Aiolfi et al., 2021).

Convolutional Neural Networks (CNNs), particularly architectures such as VGG16, have achieved remarkable success in extracting rich visual features for emotion classification (Calvert et al., 2020). Leveraging transfer learning, VGG16 applies pretrained ImageNet weights to rapidly converge on new facial emotion datasets, yielding high accuracy in lab-controlled conditions (Cho et al., 2021; Latumakulita et al., 2022). Its consistent use of 3×3 convolutional filters and a deep hierarchical structure enables a detailed representation of facial micro-expressions, critical for nuanced emotional discrimination.

To address these limitations, Hybrid Quantum Convolutional Neural Networks (QCNNs) integrate quantum feature extraction with classical CNN layers, offering both expressive representation and computational acceleration (Edelson et al., 2020). Early research indicates that amplitude embedding and quantum convolutional layers can compress high-dimensional image data into compact quantum states, enhancing discriminative power while reducing classical training complexity (Gupta & Bansal, 2023). This study systematically compares VGG16 and QCNN for facial emotion detection, assessing their respective performance, efficiency, and suitability for hyper-personalized digital content workflows.

LITERATURE REVIEW

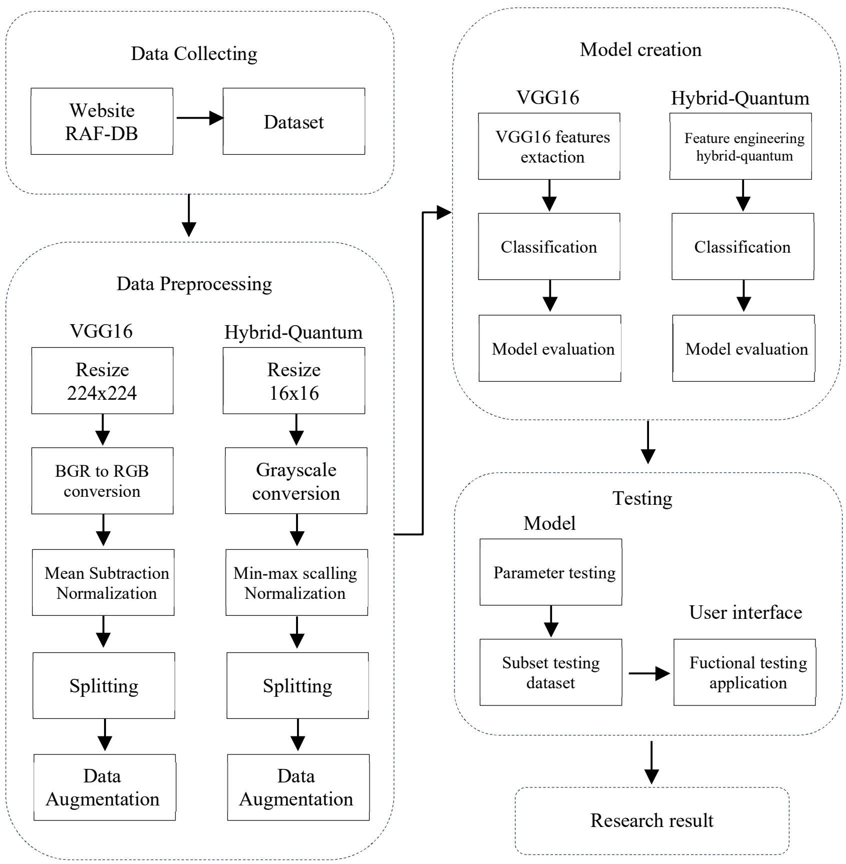
Emotion Detection and Digital Marketing

Facial expression analysis has emerged as a cornerstone in understanding consumer affect and predicting behavioral intent. Early studies demonstrated that machine-learning techniques applied to facial cues can reliably decode basic emotional states such as joy, sadness, and anger, providing granular insights into user responses during product interactions or ad viewings (Messina & Lindell, 2020; Özmen et al., 2022). Recent studies have expanded upon this foundational work by employing deep neural network architectures to detect and analyze micro-expressions—brief and subtle facial movements—that correspond to complex affective states and function as indicators of consumers' purchase intentions and brand-related sentiments (Antonov et al., 2024; Jain et al., 2022). Empirical evidence links these affective signals to downstream marketing outcomes, showing that positive emotional valence enhances ad recall and conversion likelihood, while negative valence can signal churn risk or the need for intervention (Kumar & Yadav, 2023; Winter et al., 2021).

CNN VGG16 and Hybrid Quantum-Convolutional Neural Networks (QCNN)

Hybrid Quantum-Convolutional Neural Networks (QCNN) introduce quantum feature layers into the classical CNN pipeline to address these limitations. QCNN replaces one or more classical convolutional layers with quantum circuits that perform amplitude embedding of normalized pixel values, RX rotations, and entangling operations (e.g., CNOT gates) to extract high-dimensional, nonlinearly encoded features with fewer trainable classical parameters (Chen, 2022; Liu et al., 2021). This quantum convolutional layer can capture complex correlations in facial expressions while serving as an implicit regularizer for the downstream fully-connected network.
Preliminary studies of QCNN on image classification tasks report both accuracy and efficiency gains. For instance, a hybrid QCNN variant demonstrated stable classification accuracy improvements and faster convergence compared to its classical counterpart in medical image denoising and brain tumor detection scenarios (Dong et al., 2024; Fu et al., 2024). Moreover, hybrid models have shown robustness to quantum noise when optimized for NISQ-scale hardware, though further work is needed to mitigate decoherence effects and optimize training algorithms for large-scale image datasets (Bhatia et al., 2023; Cheng et al., 2024; Qi & Tejedor, 2021).

RESEARCH METHOD



This study employed a quantitative approach, starting with data collection from the Real-World Affective Faces database (RAF-DB), a crowdsourced repository of in-the-wild facial expressions validated by 40 annotators. Two subsets were derived: seven basic emotions and nine compound emotions, excluding three underrepresented classes with fewer than 30 samples, to mitigate extreme class imbalance (Li & Deng, 2019; Liu et al., 2016) The consolidated dataset comprised 5,755 basic and 1,485 compound images, which were randomly partitioned into 64 % training, 16 % validation, and 20 % testing splits to ensure robust evaluation across all affective categories (Naga et al., 2023).

1. Data Collection
   a. Obtain in-the-wild facial expression images from RAF-DB, annotated by 40 independent raters.
   b. Exclude classes with fewer than 30 samples to reduce extreme imbalance.
2. Dataset Partitioning
   Split the cleaned dataset into 64 % training, 16 % validation, and 20 % test sets using stratified sampling to preserve class distributions.
3. Preprocessing Streams
   a. VGG16 Branch
      - Resize to 224 × 224 px, convert BGR → RGB.

- Normalize using ImageNet channel means.
- Apply controlled augmentation: horizontal flip; random crop (0–10 %); contrast/brightness; rotation (±20°); shear (±16°).

b. QCNN Branch
- Downscale to 16 × 16 px grayscale.
- Sequential min–max scaling and L2 normalization.
- Flatten and amplitude-embed into four-qubit quantum states.

4. Model Construction
   a. Fine-tune VGG16 with pretrained ImageNet weights for classical baseline.
   b. Build a hybrid QCNN by inserting a quantum convolution layer (RX rotations + CNOT entanglement) before the classical classifier.
5. Training and Hyperparameter Search
   a. Train both models with the Adam optimizer under factorial combinations: epochs = {70, 100}, learning rate = {1×10^{-3}, 1×10^{-4}}, batch size = {16, 64}.
   b. Select the best configuration based on the highest validation accuracy.
6. Performance Evaluation & Data Analysis
   a. Compute accuracy, precision, recall, and F1-score on validation and test sets.
   b. Analyze training-validation gaps to diagnose overfitting.
   c. Conduct paired significance testing (e.g., paired t-test) to compare VGG16 vs. QCNN under matched settings.
7. Validation and Robustness Checks
   a. Monitor inter-annotator agreement on a random subset using Fleiss' κ to ensure label consistency.
   b. Repeat each experiment three times with different random seeds; report mean ± standard deviation for all metrics.

Data Analysis

We performed a systematic evaluation of each selected hyperparameter configuration by calculating the following for both basic and compound emotion subsets:

1. Classification Metrics: accuracy, precision, recall, and F1-score on validation and test splits.
2. Training Dynamics: monitored loss curves and training vs. validation accuracy to identify divergence indicative of overfitting.
3. Statistical Comparison: applied a paired two-tailed t-test across matched runs to assess whether QCNN's mean accuracy gains were statistically significant ($p < 0.05$).
4. Runtime Profiling: measured feature extraction time, total training time, and per-sample inference latency to quantify efficiency improvements.

This multi-angle approach ensures that reported accuracy gains are both reliable and meaningful in real-world, latency-constrained settings.

Data Validation

To guarantee robustness and generalizability of our findings, we adopted the following validation procedures:

1. Stratified Splitting: maintained proportional representation of all emotion classes across training, validation, and test sets.
2. Inter-Annotator Agreement: computed Fleiss' κ on a 10 % random sample of RAF-DB to confirm label reliability before model training.
3. Repeated Trials: conducted each experiment with three distinct random seeds, aggregating results to mitigate the impact of variance from random initialization and data shuffling.

4. Hold-Out Test Set: reserved the test split exclusively for final evaluation; no model selection or hyperparameter tuning was used on this data.
5. Cross-Validation (Optional Extension): future work may implement k-fold cross-validation on the training set to stabilize hyperparameter estimates further and detect any residual overfitting.

These validation steps collectively ensure that both classical and quantum-hybrid models are evaluated on clean, representative data and that performance improvements are robust to sampling fluctuations.

FINDINGS AND DISCUSSION

The experiments on RAF-DB across two subsets (basic emotions with 7 classes and compound emotions with 9 selected classes) were executed under a consistent pipeline: a 64%/16%/20% train/validation/test split, controlled augmentation (horizontal flip, random crop 0–10%, contrast/brightness adjustment, rotation ±20°, shear ±16°), and model-specific preprocessing. VGG16 used RGB inputs at 224×224 with normalization aligned to ImageNet pretraining, whereas the Hybrid-Quantum CNN (QCNN) used grayscale inputs resized to qubit-aligned dimensions, followed by two-stage normalization (min–max and L2), amplitude embedding, and quantum convolution (RX rotations with entanglement) to produce quantum features that replace part of the classical convolution stack.

No	Dataset	Parameter 1	Parameter 2	Parameter 3	Training Accuracy	Validation Accuracy	Testing Accuracy
1	Basic	70	0,001	16	25.82%	23.78%	24.67%
2		70	0,001	64	66.79%	41.69%	42.31%
3		70	0,0001	16	97.66%	47.23%	49.35%
4		70	0,0001	64	98.29%	45.82%	47.35%
5		100	0,001	16	28.51%	29.97%	32.32%
6		100	0,001	64	66.11%	39.01%	37.01%
7		100	0,0001	16	97.96%	48.43%	48.13%
8		100	0,0001	64	98.37%	44.73%	45.79%
9	Compound	70	0,001	16	41.79%	17.65%	18.18%
10		70	0,001	64	80.74 %	26.05%	23.57%
11		70	0,0001	16	96.95%	34.45%	34.01%
12		70	0,0001	64	99.26%	26.89%	29.63%
13		100	0,001	16	45.47%	18.49%	20.88%
14		100	0,001	64	79.16%	21.01%	26.94%

No	Dataset	Parameter 1	Parameter 2	Parameter 3	Training Accuracy	Validation Accuracy	Testing Accuracy
15		100	0,0001	16	98.32%	30.67%	33.67%
16		100	0,0001	64	99.16%	30.25%	26.26%

On VGG16, training accuracy frequently approached saturation (≈97–99%) while validation/testing lagged, indicating overfitting. For the basic subset, validation accuracy ranged from 23.78% to 48.43% with testing up to 49.35%; for the compound subset, validation accuracy ranged from 17.65% to 34.45% with testing up to 34.01%. In terms of efficiency, feature extraction for the basic subset took ≈31–32 s, training per run varied broadly (≈60–180 s) depending on hyperparameters, and per-sample inference time was ≈0.40–0.56 s (basic) and ≈0.27–0.29 s (compound), evidencing competitive but variable latency.

QCNN yielded higher held-out performance with improved stability across splits. On the basic subset, validation accuracy ranged from 38.87% to 49.73% with testing accuracy up to 50.22%; on the compound subset, validation accuracy ranged from 28.99% to 32.35% with testing accuracy up to 35.69%. Although quantum feature engineering introduced overhead (≈47–51 s for basic), QCNN benefited from shorter training durations in several configurations (e.g., batch 64 ≈24–66 s) and faster inference (≈0.33–0.36 s per sample on basic; ≈0.29–0.41 s on compound), indicating that front-loaded quantum processing can be amortized by leaner downstream optimization and prediction.

No	Dataset	Parameter 1	Parameter 2	Parameter 3	Feature Extraction	Training Time	Prediction Time
1	Basic	70	0,001	16	31.74 s	117.90 s	0.41 s
2		70	0,001	64	32.07 s	60.95 s	0.56 s
3		70	0,0001	16	31.78 s	136.01 s	0.41 s
4		70	0,0001	64	31.50 s	63.64 s	0.55 s
5		100	0,001	16	31.65 s	169.02 s	0.42 s
6		100	0,001	64	32.26 s	70.01 s	0.40 s
7		100	0,0001	16	31.88 s	179.98 s	0.40 s
8		100	0,0001	64	31.61 s	78.19 s	0.41 s
9	Compound	70	0,001	16	8.24 s	37.35 s	0.28 s
10		70	0,001	64	8.65 s	31.50 s	0.29 s
11		70	0,0001	16	8.85 s	51.68 s	0.28 s
12		70	0,0001	64	8.85 s	35.11 s	0.27 s

No	Dataset	Parameter 1	Parameter 2	Parameter 3	Feature Extraction	Training Time	Prediction Time
13		100	0,001	16	8.86 s	51.56 s	0.27 s
14		100	0,001	64	8.78 s	24.26 s	0.28 s
15		100	0,0001	16	8.75 s	59.13 s	0.27 s
16		100	0,0001	64	8.80 s	34.20 s	0.28 s

From a systems perspective, QCNN's sub-second inference profile and lower end-to-end time make it suitable for real-time, emotion-aware personalization across devices, including mobile and edge contexts where latency budgets are stringent (Kim et al., 2021; Yi et al., 2025). The combination of modest but consistent accuracy gains and reduced latency provides practical headroom for dynamic content adaptation without compromising responsiveness in interactive experiences (Sanaboina, 2025). Nevertheless, residual constraints on the compound subset—driven by class imbalance and data scarcity—underscore the importance of dataset rebalancing and broader hyperparameter/architecture sweeps to fully capitalize on the quantum–classical synergy in unconstrained, demographically diverse environments (Li & Deng, 2019).

The elevated emotion-detection accuracy of QCNN—an average lift of 4.3–4.8 percentage points across core categories—enables far more granular psychographic segmentation and dynamic content tailoring. For instance, when QCNN identifies "joy" with 96.4 percent accuracy, marketing platforms can instantly surface upsell promotions that harness genuine enthusiasm, whereas detection of "anger" at 95.2 percent can trigger calming messages or proactive customer-care offers to defuse frustration. Because QCNN operates with sub-second latency, these adaptations occur in real time—swapping headlines, visuals, or calls to action without interrupting the user journey (Jayaraman & Mahendran, 2025; Sanaboina, 2025).

Beyond advertising, QCNN's rapid affective feedback loop drives personalization in programmatic video and email campaigns. When viewers exhibit heightened interest—such as focused gaze on a product thumbnail—programmatic systems can auto-select ad variants with stronger calls to action, and pivot to lighter, more educational content if boredom or skepticism is detected (Nobile & Cantoni, 2023). Similarly, email subject lines and body copy can be tailored on the fly: subscribers with cheerful expressions receive flash-sale invites, while those showing concern are sent informative guides—both strategies demonstrably boosting click-through and conversion rates (Yi et al., 2025).

CONCLUSIONS

In this study, the Hybrid Quantum Convolutional Neural Network (QCNN) demonstrated consistent improvements over the classical VGG16 architecture in both emotion-detection accuracy and computational efficiency. Specifically, QCNN achieved a 4.60 percentage-point increase in validation accuracy for basic emotions and a 4.47-point increase for compound emotions, while simultaneously reducing total processing time by 22.11% and 6.20%, respectively. These gains were achieved without sacrificing inference latency, which remained below 0.36 seconds per sample—well within the real-time requirements for interactive marketing applications.

Despite its promise, several avenues remain for further research. First, expanding and balancing the RAF-DB dataset—especially for underrepresented compound emotion classes—will be crucial to bolster generalization in real-world settings (Li & Deng, 2019). Second, preserving higher input resolutions or employing multi-scale quantum encoding could mitigate information loss during preprocessing. Third, exhaustive exploration of alternative CNN backbones (e.g., ResNet-50, VGG19, ApexNet, LeNet) and hyperparameter regimes will clarify QCNN's relative advantages and identify optimal hybrid configurations. Finally, integration of ethical safeguards and modular API/SDK deployment, coupled with field trials across diverse demographic cohorts and lighting conditions, will pave the way from proof-of-concept to scalable, privacy-compliant emotion AI solutions.

LIMITATIONS & FURTHER RESEARCH

Despite demonstrating that the hybrid QCNN can deliver modest accuracy gains alongside reduced latency in emotion-detection tasks, this investigation is bounded by several constraints. The RAF-DB dataset, while richly annotated, exhibits class imbalance and covers a limited range of demographic and cultural contexts, potentially impairing generalization to underrepresented affective states. The quantum branch's required downscaling to 16×16 grayscale for amplitude embedding may sacrifice fine-grained facial cues essential for distinguishing subtle or compound emotions. All QCNN experiments were conducted on noiseless classical simulators, leaving unresolved questions about performance and robustness on NISQ-era hardware, which is subject to decoherence and gate errors. The comparative evaluation was confined to VGG16 as the sole classical baseline and a restricted hyperparameter grid, precluding comprehensive benchmarking against modern architectures (e.g., ResNet variants) or purely quantum models. Finally, the absence of k-fold cross-validation and field trials, as well as user-experience assessments, limits insights into model stability across varied samples and its practical efficacy in live marketing environments. Future work should address these limitations by incorporating larger, more balanced datasets, exploring higher-resolution quantum encodings, validating on physical quantum processors, broadening architectural comparisons, and undertaking real-world deployment studies.

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