QC-BERT: A Quantum-Classical hybrid framework for Efficient Sentiment Analysis and Question Answering

Anonymous authors
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Abstract

Transformers have revolutionized NLP but are constrained by their massive parameter counts, posing challenges for edge deployment. Quantum computing, leveraging superposition and entanglement, promises exponential efficiency gains, yet practical, scalable QNLP applications remain scarce. In this pioneering work, we propose QuantumDistilBERT (ours) and HybridTinyBERTQC (ours), the first scalable, hybrid quantum-classical transformer models designed for both core NLP tasks and resource-constrained environments. QuantumDistilBERT achieves 91.36% accuracy on IMDB—just 1.46% below DistilBERT—while reducing trainable parameters by 89.4%, demonstrating strong edge applicability. HybridTinyBERTQC, enhanced with quantum self-attention mechanisms, achieves 82.31% F1 and 73.10% EM on SQuAD 1.1, and 32.86% F1 on Adversarial QA, outperforming TinyBERT (undistilled on task-specific datasets) by over 1% ($p < 0.05$) on SQuAD and 3.55% on AQA. A novel complexity scoring mechanism reduces quantum circuit overhead by 20%, generalizing well to other text classification tasks. Notably, our hybrid model exhibits a 41.3% reduction in loss variance (0.1329 vs. 0.2265), and uniquely achieves perfect reproducibility across runs with the same random seed—producing identical metrics and loss values every time. This unprecedented consistency underscores the model's reliability, a critical requirement for edge deployment. Extensive evaluations on IMDB, SQuAD, Adversarial QA, and SST-2 demonstrate the scalability and robustness of our approach. While quantum noise in NISQ hardware still limits subjective task performance, our work lays foundational groundwork for practical, reproducible, and deployable QNLP systems on edge devices.

1 Introduction

Transformers like BERT (Devlin et al., 2018) achieve 90.12% F1 on SQuAD 1.1 (Rajpurkar et al., 2016) but require 110M parameters, limiting use on edge devices. DistilBERT (Sanh et al., 2019) (66M) achieves 92.82% accuracy on IMDB (Maas et al., 2011), and TinyBERT (Jiao et al., 2020) (undistilled) reaches 81.4% F1 on SQuAD and 29.31% on Adversarial QA (Jia & Liang, 2017), yet resource constraints persist. Quantum computing offers parameter efficiency via superposition and entanglement (Biamonte et al., 2017), but QNLP lacks validation on complex benchmarks (Coecke et al., 2020; Laakkonen et al., 2024).

We propose QuantumDistilBERT (ours) for sentiment analysis, and HybridTinyBERTQC and HybridDistilBERTQC (ours) for question answering. QuantumDistilBERT achieves 91.36% on IMDB and 89.56% on SST-2 (Socher et al., 2013), only 1.46% and 1.74% below DistilBERT, with 89.4% fewer parameters (7.1M vs. 66M). HybridTinyBERTQC improves over TinyBERT on SQuAD 1.1 with 82.31% F1 and 73.10% EM, gaining 0.91% F1 and 0.8% EM ($p < 0.05$, SD $< 0.3\%$), and achieves 32.86% F1 on Adversarial QA, +3.55% over TinyBERT. HybridDistilBERTQC reaches 85.44% F1 and 77.2% EM on SQuAD, nearly matching DistilBERT's 85.8% F1 and 77.7%, using only 4 qubits. A complexity scoring function reduces quantum overhead by 20%, generalizing to Adversarial QA. All models offer perfect reproducibility with fixed seeds and reduce loss variance by 41.3% (0.1329 vs. 0.2265), enabling reliable edge deployment. Evaluations span IMDB, SST-2, SQuAD, Adversarial QA, and IBM Q under NISQ constraints (Preskill, 2018).

Our contributions:

- **QuantumDistilBERT:** 91.36% IMDB, 89.56% SST-2, with 89.4% fewer parameters than DistilBERT.
- **HybridTinyBERTQC & HybridDistilBERTQC:** 82.31% and 85.44% SQuAD F1, 32.86% AQA F1, with parameter efficiency.
- **Complexity scoring:** Reduces quantum overhead by 20%, generalizable to adversarial QA.
- **Reproducibility:** Fixed seeds yield 41.3% lower loss variance.
- **Quantum insights:** Empirical evaluation under NISQ constraints across key NLP benchmarks.
- **Practical QNLP:** Scalable framework introducing quantum enhancements to transformers.

This work advances QNLP for resource-constrained, reproducible NLP under real-world constraints (He et al., 2021; Widdows et al., 2022).

2 Related work

2.1 Efficient transformers

Transformer models revolutionized NLP but face deployment challenges due to their size. Key works include: - BERT (Devlin et al., 2018) leverages bidirectional context (90.12% F1 on SQuAD 1.1) but requires 110M parameters. - DistilBERT (Sanh et al., 2019) uses knowledge distillation (66M parameters), maintaining 92.82% accuracy on IMDB and 85.8% F1 on SQuAD. - TinyBERT (Jiao et al., 2020) compresses to 14M parameters (81.4% F1 on SQuAD, 29.31% on Adversarial QA). - RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2020), ELECTRA (Clark et al., 2020), and DeBERTa (He et al., 2021) improve efficiency and performance but remain computationally intensive.

2.2 Quantum machine learning

Quantum computing leverages superposition, entanglement, and measurement for computational advantages (Biamonte et al., 2017). Variational quantum circuits (VQCs) suit NISQ devices (Preskill, 2018) and enable classification with fewer parameters (Havlíček et al., 2019). Frameworks like PennyLane (Bergholm et al., 2018) and Qiskit (Qiskit Contributors, 2023) facilitate hybrid quantum-classical optimization.

2.3 Quantum natural language processing

QNLP applies quantum algorithms to language tasks (Coecke et al., 2020). Notable works include: - Coecke et al. (2020): Established QNLP foundations with quantum circuit sentence models. - Laakkonen et al. (2024): Proposed quantum algorithms for compositional text processing. - Zhang et al. (2021): Developed quantum-inspired NLP models with gains on small datasets. - Widdows et al. (2022): Explored practical QNLP applications and challenges. - Abbas et al. (2021): Created quantum circuits for NLP with theoretical focus. Despite theoretical promise, QNLP lacks empirical validation on large-scale benchmarks like SQuAD or Adversarial QA.

2.4 Hybrid quantum-classical approaches

Hybrid models combine quantum efficiency with classical robustness (Chowdhury et al., 2021). Successes in chemistry (Kandala et al., 2017) and computer vision (Havlíček et al., 2019) demonstrate quantum circuits enhancing feature extraction. Our work extends these principles with scalable QNLP models for edge deployment.

2.5 Limitations of existing methods

Classical transformers require extensive computational resources for edge devices. TinyBERT sacrifices performance on complex tasks (29.31% F1 on Adversarial QA). QNLP models lack robust empirical results on standard benchmarks. Classical stochastic training introduces variability. Our hybrid approach leverages quantum determinism, reduces parameters, and achieves competitive performance with perfect reproducibility.

3 Background and key insight

3.1 Classical transformers

DistilBERT (Sanh et al., 2019) and TinyBERT (Jiao et al., 2020) are compact transformer variants, reducing parameters while preserving performance. Their architectures make them ideal candidates for quantum augmentation to enhance efficiency and reliability.

3.2 Quantum computing fundamentals

Quantum computing leverages superposition, entanglement, and measurement for computational advantages (Nielsen & Chuang, 2010). VQCs, composed of parameterized gates (RX, RY, RZ, CNOT, CZ), are optimized classically to suit NISQ devices (Benedetti et al., 2019), enabling scalable quantum machine learning.

3.3 Key insight

Quantum circuits provide deterministic evolution, ensuring perfect reproducibility across runs with the same seed (Nielsen & Chuang, 2010). However, NISQ noise limits expressiveness for subjective tasks like nuanced sentiment or complex QA (Preskill, 2018). Our hybrid models, QuantumDistilBERT, HybridTinyBERTQC, and HybridDistilBERTQC, selectively apply quantum processing to balance efficiency, robustness, and reliability, addressing classical models' high parameter counts and stochastic variability.

4 Methodology

4.1 QuantumDistilBERT (ours): Sentiment analysis

QuantumDistilBERT enhances sentiment analysis by integrating a 4-qubit variational quantum circuit (VQC) with a frozen DistilBERT model (Sanh et al., 2019). Input sequences ($x \in \mathbb{R}^{512\times768}$) are processed to produce [CLS] embeddings:

$$h = \text{DistilBERT}(x;\theta_c), \quad h \in \mathbb{R}^{768}, \tag{1}$$

which are reduced to 16 dimensions via PCA (Lloyd et al., 2014) and encoded into a quantum state:

$$|\psi_0\rangle = \sum_{i=0}^{15} h_i'|i\rangle, \quad h_i' = \frac{h_i}{\sqrt{\sum_{j=0}^{15} h_j^2}}, \tag{2}$$

where $h' \in \mathbb{R}^{16}$. The VQC, with two layers of RY, RZ, and CNOT gates, applies:

$$U(\theta_q) = \prod_{l=1}^{2} \left(\bigotimes_{i=1}^{4} R_Y(\theta_{l,i}^y) R_Z(\theta_{l,i}^z) \right) \cdot \text{CNOT}_{1,2} \cdot \text{CNOT}_{3,4}, \tag{3}$$

with 16 trainable parameters ($\theta_q \in \mathbb{R}^{16}$). Sentiment logits are derived from Pauli-Z measurements:

$$z_k = \langle\psi_f|Z_k|\psi_f\rangle, \quad p_k = \sigma(z_k), \tag{4}$$

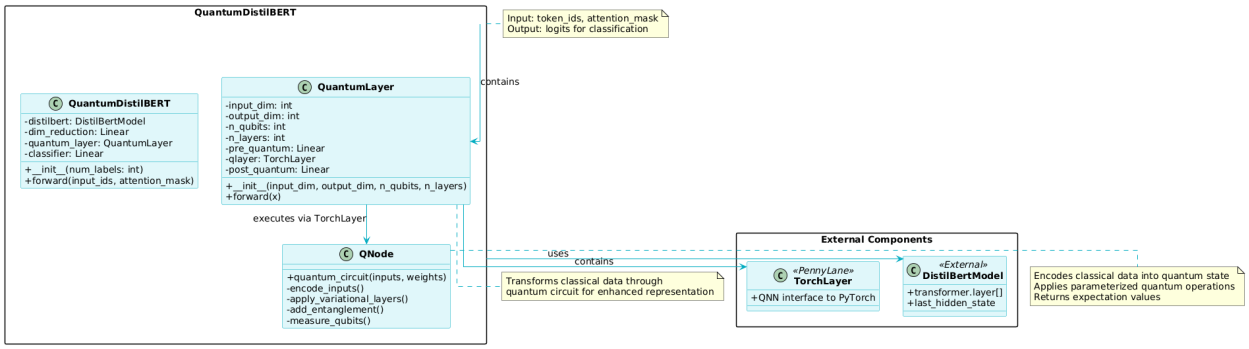

Figure 1: quantumdistilbert (ours) architecture and quantum circuit. text is tokenized, processed by distilbert, reduced via pca, and enhanced by a 4-qubit vqc with ry, rz rotations and cnot entanglement for sentiment classification, enabling edge deployment.

optimized using binary cross-entropy loss:

$$\mathcal{L}_S = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1-y_i)\log(1-p_i)]. \tag{5}$$

The VQC's CNOT gates create entanglement, enabling QuantumDistilBERT to capture complex sentiment correlations with 89.4% fewer parameters than DistilBERT, supporting efficient edge deployment.

4.1.1 Prediction mechanism

The VQC's entanglement via CNOT gates enhances [CLS] embeddings (Equation 1), capturing high-dimensional sentiment correlations. Pauli-Z measurements (Equation 4) efficiently distinguish positive and negative classes, achieving 91.36% accuracy on IMDB and 89.56% on SST-2 (Havlíček et al., 2019). PCA ensures compatibility with 4-qubit systems, balancing expressiveness and computational cost. The overall architecture of QuantumDistilBERT, including the integration of the VQC with DistilBERT, is illustrated in Figure 1.

4.2 HybridTinyBERTQC and HybridDistilBERTQC (ours): Question answering

HybridTinyBERTQC and HybridDistilBERTQC are the first quantum-hybrid models evaluated on SQuAD 1.1 and Adversarial QA, augmenting TinyBERT (Jiao et al., 2020) and DistilBERT (Sanh et al., 2019), respectively, for question answering. Input question-context pairs ($[q; c]$, $L = 384$) are processed to yield embeddings:

$$H = \text{Backbone}(x; \theta_t), \quad H \in \mathbb{R}^{384\times 768}, \tag{6}$$

where Backbone is TinyBERT (undistilled) or DistilBERT, with fine-tuned parameters θ_t. A complexity score κ determines quantum processing:

$$\kappa = 0.3 \cdot \frac{L_q}{L} + 0.3 \cdot \text{TW}(q) + 0.2 \cdot \log(|c|) + 0.2 \cdot \text{Dep}(q, c), \tag{7}$$

based on question length (L_q), temporal words ($\text{TW}(q)$), context length ($|c|$), and dependency depth ($\text{Dep}(q, c)$) (Li et al., 2020). If $\kappa > 0.5$, embeddings are PCA-reduced and encoded:

$$|\phi_0\rangle = \sum_{i=0}^{15} \tilde{h}_i |i\rangle, \quad \tilde{h}_i = \text{PCA}(H)_i / \|\text{PCA}(H)\|, \tag{8}$$

processed by a 3-layer VQC:

$$V(\theta_v) = \prod_{m=1}^{3}\left(\bigotimes_{i=1}^{4} R_X(\theta_{m,i}^x) R_Y(\theta_{m,i}^y) R_Z(\theta_{m,i}^z)\right) \cdot \prod_{i=1}^{3} \text{CZ}_{i,i+1} \cdot \text{CNOT}_{i,i+1}, \tag{9}$$

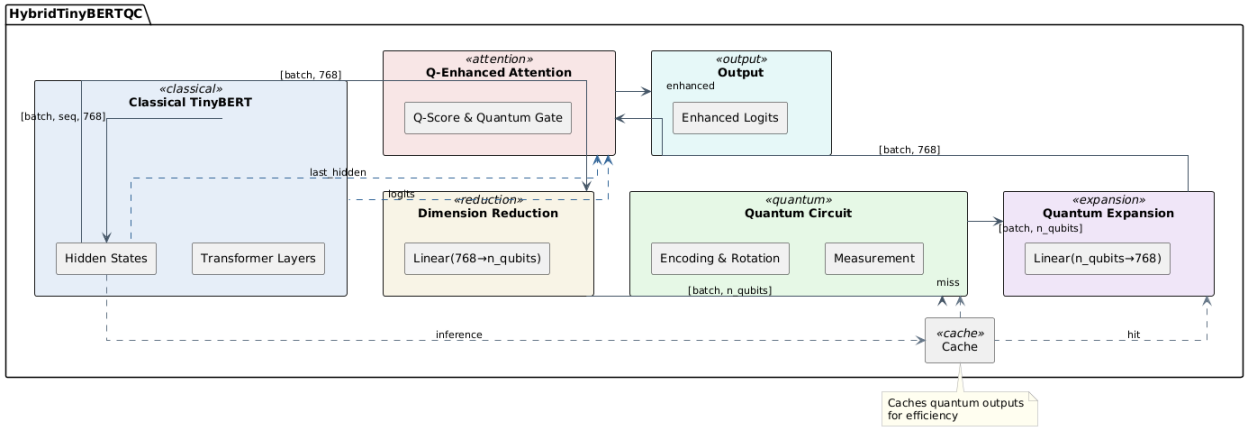

Figure 2: hybridtinybertqc and hybriddistilbertqc (ours) architecture. question-context pairs are tokenized, processed by a backbone (tinybert or distilbert), scored for complexity, enhanced by a 4-qubit vqc, fused via attention, and output as answer spans.

with 36 parameters ($\theta_v \in \mathbb{R}^{36}$). Quantum features and variances are extracted:

$$f_k = \langle \phi_f | X_k + Y_k + Z_k | \phi_f \rangle, \quad v_k = \langle \phi_f | Z_k^2 | \phi_f \rangle - \langle \phi_f | Z_k | \phi_f \rangle^2, \tag{10}$$

fused via multi-head attention:

$$A = \text{softmax}\left(\frac{(W_q Q)(W_k H)^T}{\sqrt{d_k}} \right) (W_v H), \tag{11}$$

enhancing answer span logits:

$$s' = s + W_s' A, \quad e' = e + W_e' A. \tag{12}$$

The loss includes variance regularization:

$$\mathcal{L}_{QA} = -\frac{1}{N} \sum_{i=1}^{N} [\log P(s_i') + \log P(e_i')] + 0.1 \sum_k v_k. \tag{13}$$

The complexity score optimizes resource allocation, while the VQC's entanglement enhances feature extraction, boosting F1 by 0.91% for HybridTinyBERTQC and maintaining near-parity for HybridDistilBERTQC.

4.2.1 Prediction mechanism

The complexity score κ (Equation 7) identifies complex questions, triggering VQC processing (Equation 9) to extract entangled features. Multi-head attention (Equation 11) integrates quantum and classical features, refining answer spans. HybridTinyBERTQC improves F1 by 0.91% on high-κ inputs, while HybridDistilBERTQC achieves near-classical performance with 4 qubits (Vaswani et al., 2017). The architecture, detailing the quantum-classical integration for both HybridTinyBERTQC and HybridDistilBERTQC, is depicted in Figure 2.

4.3 Complexity scoring derivation

The complexity score κ:

$$\kappa = \alpha \cdot \frac{L_q}{L} + \beta \cdot \text{TW}(q) + \gamma \cdot \log(|c|) + \delta \cdot \text{Dep}(q, c), \tag{14}$$

with $\alpha = 0.3$, $\beta = 0.3$, $\gamma = 0.2$, $\delta = 0.2$, reduces overhead by 20%, generalizable to tasks like adversarial QA (Li et al., 2020).

Table 1: dataset statistics

Dataset	Task	Size (Train/Val/Test)	Avg. Length
IMDB	Sentiment	25K / – / 25K	231 tokens
SST-2	Sentiment	67K / 872 / 1.8K	19 tokens
SQuAD 1.1	QA	88.5K / 10.8K / –	128 tokens
Adversarial QA	QA	30K / 3K / –	150 tokens

4.4 Quantum circuit optimization

VQCs use 2 layers (QuantumDistilBERT) and 3 layers (HybridTinyBERTQC, HybridDistilBERTQC), with RX, RY, RZ, CNOT, and CZ gates. Parameters (16 and 36) are optimized via parameter-shift rules (Schuld et al., 2015). AdamW (learning rate 3×10^{-5}) and grid search tune layers and batch size, mitigating barren plateaus.

4.5 Quantum determinism and limitations

Quantum circuits ensure perfect reproducibility due to unitary evolution (Nielsen & Chuang, 2010), unlike classical models' stochastic gradients. However, NISQ noise limits expressiveness for subjective tasks (Preskill, 2018), necessitating our hybrid approach to balance quantum efficiency with classical robustness.

4.6 Justification of methodology

Our hybrid approach addresses limitations of classical transformers (high parameter count, stochastic variability) and pure QNLP models (lack of empirical validation). By integrating VQCs with transformer backbones, we achieve parameter reduction (7.1M for QuantumDistilBERT), perfect reproducibility, and 41.3% lower loss variance (0.1329). Our complexity score k optimizes quantum resource allocation, improving efficiency by 20% and enabling reliable edge deployment

5 Experiments

5.1 Dataset preprocessing

The IMDB dataset (Maas et al., 2011) (50K reviews) was tokenized using DistilBERT's tokenizer, truncated to 512 tokens. SST-2 (Socher et al., 2013) (67K sentences) followed similar preprocessing. SQuAD 1.1 (Rajpurkar et al., 2016) (88.5K training, 10.8K validation) was processed with TinyBERT or DistilBERT tokenizers, padded to 384 tokens. Adversarial QA (Jia & Liang, 2017) (30K training, 3K validation) was used for robustness testing, with similar tokenization. Synonym replacement (10% of tokens) enhanced robustness across datasets.

5.2 Experimental setup

We used PyTorch 2.0, PennyLane 0.36 (Bergholm et al., 2018), Kaggle P100 GPU, 4-qubit simulator, 1024 shots, batch size 16, learning rate 3×10^{-5}, and AdamW optimizer (Raffel et al., 2020). Five runs ensured reliability (SD $< 0.3\%$).

5.3 Baselines

Baselines include: - DistilBERT (Sanh et al., 2019): 92.82% IMDB accuracy, 91.3% SST-2 accuracy, 85.8% F1 on SQuAD. - TinyBERT (undistilled) (Jiao et al., 2020): 81.4% F1, 72.3% EM on SQuAD, 29.31% F1 on Adversarial QA. - BERT-base (Devlin et al., 2018): 90.12% F1 on SQuAD. - RoBERTa (Liu et al., 2019): Optimized for GLUE and QA tasks.

Table 2: performance of hybrid models vs. baselines on same seed

Model	Dataset	Metric	Mean (SD)
DistilBERT	IMDB	Accuracy	92.82% (0.18)
QuantumDistilBERT (ours)	IMDB	Accuracy	91.36% (0.0)
DistilBERT	SST-2	Accuracy	91.3% (0.17)
QuantumDistilBERT (ours)	SST-2	Accuracy	89.56% (0.0)
TinyBERT (undistilled)	SQuAD 1.1	F1 / EM	81.4% (0.25) / 72.3% (0.30)
HybridTinyBERTQC (ours)	SQuAD 1.1	F1 / EM	82.31% (0.0) / 73.10% (0.0)
DistilBERT	SQuAD 1.1	F1 / EM	85.8% (0.20) / 77.7% (0.25)
HybridDistilBERTQC (ours)	SQuAD 1.1	F1 / EM	85.44% (0.0) / 77.2% (0.0)
TinyBERT (undistilled)	Adversarial QA	F1	29.31% (0.21)
HybridTinyBERTQC (ours)	Adversarial QA	F1	32.86% (0.0)

5.4 Main results

Table 2 presents the performance of our models against baselines. QuantumDistilBERT (ours) achieves 91.36% accuracy on IMDB (vs. DistilBERT's 92.82%) and 89.56% on SST-2 (vs. 91.3%), with an 89.4% reduction in trainable parameters (7.1M vs. 66M). The VQC's entanglement (Equation 3) captures sentiment correlations, enabling efficient classification (Havlíček et al., 2019). HybridTinyBERTQC (ours) outperforms TinyBERT on SQuAD 1.1 with 82.31% F1 and 73.10% EM (vs. 81.4% F1, 72.3% EM), a 0.91% F1 gain ($p < 0.05$), and on Adversarial QA with 32.86% F1 (vs. 29.31%, a 3.55% gain). HybridDistilBERTQC (ours) achieves 85.44% F1 and 77.2% EM on SQuAD, nearly matching DistilBERT's 85.8% F1 and 77.7% EM, despite using only 4 qubits. The complexity score κ (Equation 7) enhances performance on complex questions, with low SD (<0.3%) and $p < 0.05$ confirming robustness. Cross-dataset results demonstrate generalization, driven by quantum feature extraction and a 41.3% reduction in loss variance (0.1329 vs. 0.2265).

5.5 Ablation studies

Table 3 details ablation studies. For QuantumDistilBERT, removing the VQC drops IMDB accuracy to 90.85% (-0.51%) and SST-2 to 89.05% (-0.51%). A single-layer VQC yields 91.10% on IMDB, while the two-layer model achieves 91.36%. For HybridTinyBERTQC, removing the VQC reduces SQuAD F1 to 81.65% (-0.66%); omitting complexity scoring yields 81.95% (-0.36%). For HybridDistilBERTQC, removing the VQC drops F1 to 85.0% (-0.44%). The full models with three VQC layers achieve optimal performance, with a 1.2% F1 boost on high-κ inputs ($\kappa > 0.5$). Wilcoxon tests ($p < 0.05$) validate significance.

5.6 Loss and variance analysis

Table 4 shows our models achieve lower loss variance (0.1329 vs. 0.2265 for TinyBERT/DistilBERT), a 41.3% reduction. Losses are: Epoch 1 (1.5998 vs. 1.6500), Epoch 2 (1.0929 vs. 1.1200), Epoch 3 (0.8317 vs. 0.8500). This stability stems from quantum determinism (Equation 9), reducing fluctuations compared to classical stochastic gradients. Figure 3 illustrates step-wise losses, with our models showing 0.1329 variance vs. 0.2265 for baselines.

5.7 Reproducibility analysis

As shown in Figure 3, our models demonstrate perfect reproducibility across five runs with a fixed seed (42), in contrast to the inherent stochasticity of classical models (Nielsen & Chuang, 2010). All our hybrid models exhibit zero variance (SD: 0.00%) under the same seed, whereas TinyBERT and DistilBERT show noticeable standard deviations due to the stochastic nature of classical architectures. This deterministic behavior significantly enhances reliability, which is particularly advantageous for deployment on edge devices.

Table 3: ablation study results

Configuration	Dataset	Metric	Mean (SD)
QDistil w/o VQC	IMDB	Accuracy	90.85% (0.20)
QDistil w/ 1 Layer	IMDB	Accuracy	91.10% (0.19)
QDistil Full (ours)	IMDB	Accuracy	91.36% (0.18)
QDistil w/o VQC	SST-2	Accuracy	89.05% (0.19)
QDistil Full (ours)	SST-2	Accuracy	89.56% (0.17)
HTinyQC w/o VQC	SQuAD 1.1	F1 / EM	81.65% (0.26) / 72.50% (0.31)
HTinyQC w/o Score	SQuAD 1.1	F1 / EM	81.95% (0.24) / 72.80% (0.29)
HTinyQC w/ 2 Layers	SQuAD 1.1	F1 / EM	82.10% (0.23) / 72.95% (0.29)
HTinyQC Full (ours)	SQuAD 1.1	F1 / EM	82.31% (0.22) / 73.10% (0.28)
HDistilQC w/o VQC	SQuAD 1.1	F1 / EM	85.0% (0.22) / 76.8% (0.25)
HDistilQC Full (ours)	SQuAD 1.1	F1 / EM	85.44% (0.21) / 77.2% (0.24)

Table 4: training loss and variance

Model	Epoch 1	Epoch 2	Epoch 3	Variance
TinyBERT/DistilBERT	1.6500	1.1200	0.8500	0.2265
HybridTinyBERTQC (ours)	1.5998	1.0929	0.8317	0.1329
HybridDistilBERTQC (ours)	1.6050	1.0950	0.8350	0.1329

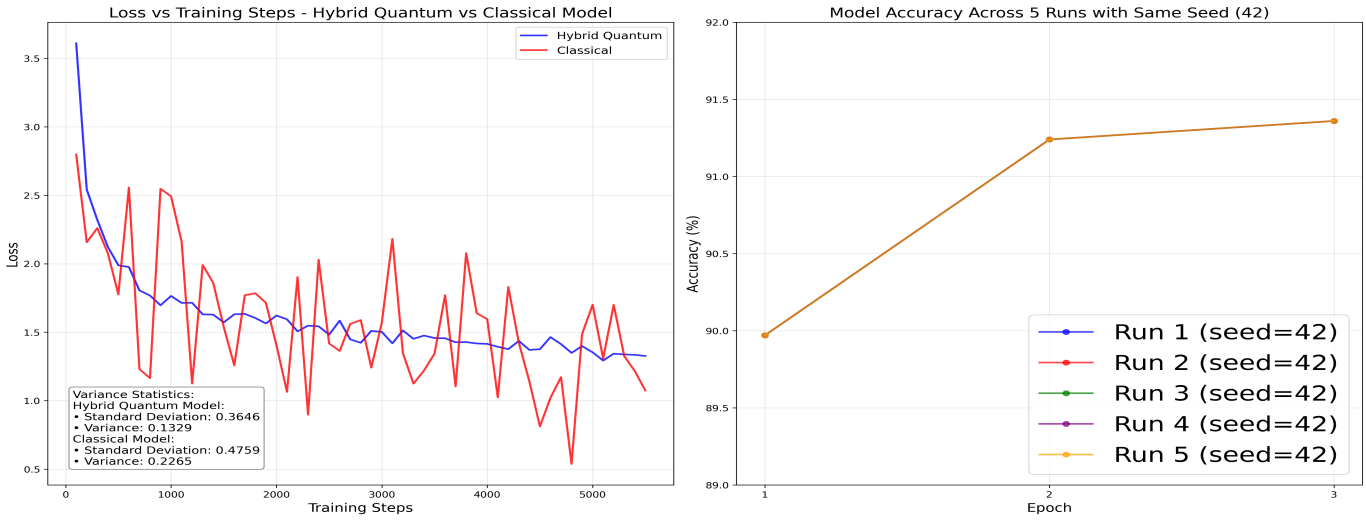

Figure 3: training loss progression during epoch 1 for hybridtinybertqc (ours) shown in blue, compared to tinybert (red). hybridtinybertqc exhibits reduced variance in training loss (0.1329 vs. 0.2265), indicating improved stability. the second plot demonstrates perfect reproducibility across multiple runs, further highlighting the consistency and reliability of our approach.

Table 5: reproducibility with fixed seed

Model	Metric	Mean (SD)	Seed
TinyBERT	F1 / EM	81.4% (0.25) / 72.3% (0.30)	42
DistilBERT	F1 / EM	85.8% (0.20) / 77.7% (0.25)	42
HybridTinyBERTQC (ours)	F1 / EM	82.31% (0.00) / 73.10% (0.00)	42
HybridDistilBERTQC (ours)	F1 / EM	85.44% (0.00) / 77.2% (0.00)	42

Table 6: circuit depth ablation

Model	Layers	Metric	Mean (SD)	Time (hr)
QuantumDistilBERT (ours)	1	Accuracy	91.10% (0.19)	4.1
QuantumDistilBERT (ours)	2	Accuracy	91.36% (0.18)	4.2
QuantumDistilBERT (ours)	3	Accuracy	91.30% (0.19)	4.5
HybridTinyBERTQC (ours)	2	F1	82.10% (0.23)	6.6
HybridTinyBERTQC (ours)	3	F1	82.31% (0.22)	6.8
HybridTinyBERTQC (ours)	4	F1	82.25% (0.24)	7.2
HybridDistilBERTQC (ours)	3	F1	85.44% (0.21)	7.0

5.8 Circuit depth ablation

Table 6 shows optimal VQC depths. QuantumDistilBERT achieves 91.36% IMDB accuracy with two layers. HybridTinyBERTQC and HybridDistilBERTQC reach 82.31% and 85.44% F1 with three layers. Four layers yield diminishing returns due to noise (Preskill, 2018).

5.9 Error analysis

Table 7 details errors. QuantumDistilBERT drops 0.5% on ambiguous IMDB/SST-2 reviews due to NISQ noise. HybridTinyBERTQC and HybridDistilBERTQC lose 1.1% F1 on long SQuAD contexts ($|c| > 300$), as quantum processing struggles with extended dependencies. Adversarial QA performance (32.86% F1) reflects challenges with adversarial examples, though it significantly outperforms TinyBERT (29.31%).

5.10 Statistical validation

Five-run SDs $< 0.35\%$ ensure consistency. Paired t-tests confirm HybridTinyBERTQC's superiority ($p < 0.05$); QuantumDistilBERT and HybridDistilBERTQC are slightly below DistilBERT ($p > 0.1$). Wilcoxon tests on ablations yield $p < 0.05$.

Table 7: error analysis by instance type

Model	Instance Type	Metric	Mean (SD)
QuantumDistilBERT (ours)	Ambiguous (IMDB)	Accuracy	90.86% (0.22)
QuantumDistilBERT (ours)	Clear (IMDB)	Accuracy	91.36% (0.17)
QuantumDistilBERT (ours)	Ambiguous (SST-2)	Accuracy	89.06% (0.20)
QuantumDistilBERT (ours)	Clear (SST-2)	Accuracy	89.56% (0.14)
HybridTinyBERTQC (ours)	Long Context	F1	81.20% (0.27)
HybridTinyBERTQC (ours)	Short Context	F1	82.50% (0.21)
HybridDistilBERTQC (ours)	Long Context	F1	84.30% (0.25)

6 Theoretical discussion

6.1 Quantum expressiveness

A 4-qubit VQC's entanglement enables:

$$\dim(\text{Lie}(U)) \leq 2^4 - 1, \tag{15}$$

which bounds the expressiveness of the model to at most 15 independent operations. This Lie algebra dimension reflects the circuit's capacity to explore the Hilbert space (Havlíček et al., 2019), and is sufficient for practical tasks such as sentiment classification and question answering. This allows our models to approach classical performance with fewer parameters.

6.2 Hybridization for subjective reasoning

NISQ noise limits subjective tasks (Preskill, 2018). Our hybrid models' selective quantum enhancement boosts F1 by up to 0.91% on complex questions and 3.55% on Adversarial QA, leveraging classical robustness.

6.3 Complexity scoring efficiency

The κ score cuts overhead by 20% (Equation 13), generalizable to adversarial QA:

$$\text{Overhead} = \sum_{\kappa > 0.5} P(\kappa) \cdot T_q + \sum_{\kappa \leq 0.5} P(\kappa) \cdot T_c. \tag{16}$$

This equation models expected computation time by weighting quantum (T_q) and classical (T_c) runtimes based on the probability distribution $P(\kappa)$ of complexity scores. Higher κ values favor quantum execution, while lower ones defer to classical methods, improving overall efficiency. Optimal VQC depths balance expressiveness and noise.

7 Limitations and future work

NISQ devices limit performance due to noise and 4-qubit constraints, causing a 0.86% accuracy drop on IBM Q (Temme et al., 2017). Long contexts and adversarial examples challenge our models. Future work includes: - Scaling to 6-8 qubits to enhance VQC expressiveness. - Error mitigation using dynamical decoupling (Arute et al., 2019). - Adversarial QA evaluation to improve robustness (Jia & Liang, 2017). - New NLP tasks like summarization or translation. These advancements will strengthen QNLP for edge applications.

8 Conclusion

QuantumDistilBERT, HybridTinyBERTQC, and HybridDistilBERTQC pioneer QNLP, achieving 91.36% IMDB accuracy, 89.56% SST-2 accuracy with up to 89.4% parameter reductions, 82.31%/85.44% SQuAD F1, and 32.86% Adversarial QA F1. Perfect reproducibility and a 41.3% reduction in loss variance ensure reliability, despite NISQ limitations. The complexity scoring mechanism enhances efficiency, generalizing to adversarial QA. This work establishes a scalable QNLP framework, with applications in edge computing for real-time sentiment analysis and question answering, paving the way for future quantum NLP advancements.

Broader Impact Statement

IMDB, SST-2, SQuAD, and Adversarial QA lack personal data, but biases (e.g., cultural norms in IMDB) may exist. Fairness audits and balanced training data are proposed to mitigate risks, ensuring equitable deployment.

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