International Journal of Intelligent Knowledge Processing Systems
Vol.1, No.2, June, 2026, pp. 50-59
Journal homepage: https://ijikps.org/

QUANTUM DEEP LEARNING FRAMEWORK FOR ACCURATE MOLECULAR GROUND-STATE ENERGY PREDICTION IN COMPLEX CHEMICAL SYSTEMS

GiribabuSadineni[1*], Rama Chaithanya Tanguturi[2]

[1,2] Department of Computer Science & Engineering, PACE Institute of Technology and Sciences, Ongole- 523272, Andhra Pradesh, India
(sadinenigiri1521@gmail.com) & (trchaitanya@gmail.com)

Corresponding Author Email: sadinenigiri1521@gmail.com

ABSTRACT

Correct prediction of the molecular ground-state energy is a fundamental problem in quantum chemistry, materials science and drug screening and discovery which directly impacts the understanding of the stability and chemical behavior of molecules. For complex molecular systems, traditional computational techniques like the Hartree-Fock and the Density Functional Theory (DFT) can be very costly. The improvement of molecular energy prediction efficiency and accuracy has recently opened new possibilities thanks to the progress in quantum computation and deep learning. In this paper, a hybrid Quantum Deep Learning Framework for Accurate Molecular Ground-State Energy Prediction in Complex Chemical Systems combining Variational Quantum Algorithms and Deep Neural Network Architectures is proposed. The framework builds molecular Hamiltonians, optimizes the quantum state with the Variational Quantum Eigensolver (VQE), and builds quantum-generated features for deep learning-based energy estimation. Performance measures used for the evaluation of the proposed model are Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). The proposed Quantum Deep Learning Framework has shown Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 values equal to 0.042, 0.031, and 0.989 correspondingly, which proves higher performance from the standpoint of prediction. Prediction precision of the developed approach reaches 98.9% and exceeds that of all other methods known, including VQE, ADAPT-VQE, FermiNet, and Deep Schrödinger. Besides that, the proposed approach showed faster convergence, lower prediction variance, and higher computational efficiency during the molecular energies' prediction process. The results suggest that the proposed hybrid quantum-classical approach is promising and efficient for ground-state energy prediction of molecules, as well as useful in computational chemistry, materials discovery, and molecular design, and is scalable.

Keywords: *Quantum Deep Learning, Quantum Computing, Molecular Ground-State Energy, Variational Quantum Eigensolver, Quantum Chemistry, Deep Neural Networks.*

1. INTRODUCTION

One of the basic problems in quantum chemistry and computational materials science is predicting the energies of molecular ground states [1]. The ground-state energy is crucial for understanding the stability, reactivity, and physical properties of molecular systems [2], which is important for various applications, including drug design, catalyst design, material development, and optimization of chemical processes [3]. Various traditional computational approaches have been used for molecular energy estimation, such as Hartree-Fock, and Density Functional Theory (DFT) [4]. However, such methods can become quite costly when applied to large and complex molecular systems because of the exponential growth of quantum state spaces [5].

New solutions to quantum chemistry problems in more efficient ways have been enabled by recent progresses in quantum computing [6]. However, quantum algorithms like the VQE offer promising ways to approximate molecular ground-state energies using quantum mechanical principles directly [7]. However, existing quantum algorithms have their own limitations, including resource constraints, optimization challenges, and susceptibility to noise and errors, which can impact the accuracy of predictions [8].

At the same time, deep learning methods have shown great potential in modelling complex nonlinear relationships in a number of scientific fields [9]. A number of neural-network based models, such as FermiNet and Deep Schrödinger models, have been demonstrated to be able to accurately approximate electronic wavefunctions and solve quantum mechanical equations with high accuracy [10]. These techniques exploit strong feature learning tools to serve the learning of complex molecular interactions which are hard to model in traditional computation approaches [11].

Combining the power of quantum computing with deep learning presents a potent method for addressing the challenges of each technique alone [12]. The efficient representation of molecular quantum states is possible with quantum computing, and deep learning offers high-level learning capabilities for obtaining complex energy relationships [13]. These technologies can be integrated to create scalable and accurate molecular energy prediction frameworks [14].

This research introduces a Quantum Deep Learning Framework for Accurate Molecular Ground-State Energy Prediction in Complex Chemical Systems. The proposed method is expected to increase the accuracy of prediction, decrease the complexity of calculation and increase the scalability of molecular simulation of complex chemical systems.

1.1 Hypothesis

H1: Combination of variational quantum computing techniques and deep learning architectures can greatly enhance the prediction of molecular ground state energy over a single classical or quantum machine learning model approach.
H2: The molecular representations created using H2 features derived from parameterized quantum circuits are more informative than traditional molecular descriptors, resulting in reduced prediction error and better generalisation performance.
H3: The hybrid Quantum Deep Learning Framework is able to deliver better results for the complex chemical systems both in computational efficiency and the overall performance of the model in terms of RMSE, MAE, and R^2 score.

1.2 Research Objectives

The main aims of this research are:

1. To create a hybrid Quantum Deep Learning Framework for the prediction of molecular ground-state energy.
2. To build and tune molecular Hamiltonians with efficient variational quantum algorithms to represent molecular states.
3. To couple deep neural networks with features generated by quantum systems to accurately estimate molecular energy.
4. To test the performance of the proposed framework by proposed metrics like RMSE, MAE, and R-squared score.
5. To assess and benchmark proposed framework against other existing approaches like VQE, ADAPT-VQE, FermiNet, and Deep Schrödinger models in terms of prediction accuracy and computational efficiency.

2. LITERATURE SURVEY

Recent advances in quantum computing and deep learning have opened new possibilities for accurately predicting molecular ground-state energies in complex chemical systems [15]. Researchers have explored variational quantum algorithms, neural-network wavefunctions, and hybrid quantum-classical frameworks to overcome the computational limitations of traditional quantum chemistry methods [16]. A multi-scale deep learning framework was proposed by Cai et al. (2026), which provides a comprehensive approach to the fusion of molecular graph structure and molecular fingerprints within the prediction model. The majority of the approaches to molecular properties prediction that existed prior to the research in question relied either on graph neural networks or on fingerprints. The authors understood that this two representations include complementary chemical information and they created a framework that can learn from both at the same time.

Virtual drug screening using deep learning model is presented by Wu et al. (2024), which helped them identify the potential compounds capable of treating Alzheimer's disease. This research integrates molecular descriptors, chemical fingerprints, and biological activities to develop deep neural networks for predicting Alzheimer's disease drug targets interactions.

Torres et al. (2024) proposed a Multi-Scale Cross-Attention Transformer (MSCAT) for few-shot molecular property prediction. The study was focused on the problem of small number of labeled molecular datasets, which is a domain with poor generalization of traditional deep learning algorithms. They integrate the knowledge transfer between molecular tasks by leveraging transformer-based cross-attention mechanisms along with their model that is based on graph embeddings derived from molecular structures. To enhance the computational efficiency in predicting molecular properties without compromising the high predictive accuracy, Rasool et al. (2025) introduced Quantized Graph Neural Networks (QGNNs). The traditional graph neural networks are computationally demanding and memory-intensive, which hinders their application on resource-constrained devices. The authors solved this problem by proposing quantization methods to decrease the numerical precision of the model at inference time. Rahman et al. (2024) studied the use of deep neural networks to simulate nonlinear oscillatory systems. The authors used deep neural networks to learn oscillatory dynamics accurately, instead of having to rely on computationally expensive numerical differential equation solvers.

Rahman et al. (2023) proposed a novel activation function called Amplifying Sine Unit (ASU) to enhance learning in neural networks for the detection of nonlinear oscillatory patterns. Traditional activation functions, like ReLU and Sigmoid, tend to miss the periodic behavior properly. The proposed ASU consists of sinusoidal characteristics, but propagation of the gradient is stabilized during the optimization process. To accurately predict drug-target binding affinity, Xia et al. (2023) introduced a hybrid model that integrates Message Passing Neural Networks (MPNNs) with self-supervised learning. Identification of compounds with good biological activity is critical in the computational drug discovery process and this can be achieved through drug-target interaction prediction. The authors used message passing methods to acquire molecular graph representations while using self-supervised learning to leverage molecular unlabeled data. The limitations of the traditional models are presented in Table 1.

Table 1: Limitations of Traditional Models

Author (Year)	Proposed Model	Algorithm Used	Experiments Performed	Limitations
Cai et al. (2026)	Unified Multi-Scale Deep Learning	Graph Neural Network (GNN), Multi-scale	Molecular property prediction on multiple benchmark datasets	High computational complexity; requires large

	Framework	Feature Fusion, Fingerprint Learning	(toxicity, solubility, bioactivity, physicochemical properties)	labeled datasets
Wu et al. (2024)	Deep Learning-based Drug Screening Framework	Deep Neural Network (DNN), Molecular Fingerprinting, Drug-Target Prediction	Alzheimer's disease drug screening, molecular docking validation	Requires experimental validation; dependent on available biological datasets
Torres et al. (2024)	Multi-Scale Cross-Attention Transformer (MSCAT)	Graph Embedding, Transformer, Cross-Attention, Few-shot Learning	Few-shot molecular property prediction on MoleculeNet datasets	Computationally expensive; transformer training complexity
Fu et al. (2024)	ADMETlab 3.0 Platform	Graph Neural Networks, Deep Neural Networks, Gradient Boosting	Prediction of 50+ ADMET properties using large chemical databases	Platform rather than a novel prediction algorithm; dependent on database quality
Rasool et al. (2025)	Quantized Graph Neural Network (QGNN)	Quantized Graph Neural Networks (QGNN), Graph Convolution	Molecular property prediction on MoleculeNet benchmarks with model compression analysis	Slight accuracy reduction under aggressive quantization
Rahman et al. (2024)	Oscillator Simulation using Deep Neural Networks	Deep Neural Network (DNN)	Nonlinear oscillator simulation compared with numerical methods	Limited generalization beyond trained oscillatory systems
Rahman et al. (2023)	Amplifying Sine Unit (ASU)	Novel Oscillatory Activation Function	Benchmark regression and nonlinear oscillation prediction experiments	Limited validation outside oscillatory applications
Xia et al. (2023)	Drug-Target Binding Affinity Prediction Framework	Message Passing Neural Network (MPNN), Self-Supervised Learning	Drug-target affinity prediction on Davis and KIBA datasets	High computational cost; sensitive hyperparameter tuning

2.1 Problem Statement

The determination of the ground state energy of a molecule is a basic problem in quantum chemistry since it is related to the stability, reactivity, and physical properties of the molecule [17]. While methods such as the Hartree-Fock and Density Functional Theory (DFT) can give good estimation on small molecules, they are time-consuming and expensive to compute when the molecules become more complex [18]. Current quantum computing technologies like the VQE allow for some reduction in the number of computational steps [19], but have optimization challenges, hardware noise, and limited scalability [20]. Thus, there is a demand for hybrid approaches, such as synergizing the quantum representation power of quantum computing with the nonlinear learning power of deep neural networks, to achieve highly accurate, computation efficient and scalable molecular ground-state energy prediction for complex chemical systems [21].

3. PROPOSED METHODOLOGY

To accurately predict the ground-state energy of complex chemical systems, the proposed QDLF combines quantum computing and deep learning methods. The framework comprises of six major phases: data preprocessing, construction of molecular Hamiltonian, encoding of quantum state, variational quantum optimization, prediction based on deep neural network, and performance evaluation.

3.1 Data Acquisition and Preprocessing

The molecular dataset includes the atomic coordinates, the electron configurations [22], the molecular orbitals and the associated ground-state energy values [23]. Normalization is carried out to make the training more stable and converge, and in many cases, the molecular descriptors are not measured on the same numerical scale [24].

Min-Max Normalization

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X is original feature value, X_{min} is minimum feature value and X_{max} is the maximum feature value

After normalization, the dataset is divided into training, validation, and testing subsets.

Dataset Partitioning

$$D = D_{train} + D_{val} + D_{test} \quad (2)$$

Where D_{train} is the training dataset, D_{val} is the validation dataset and D_{test} is the testing dataset.

The preprocessed molecular descriptors are then forwarded for quantum representation. The Proposed Model architecture is shown in Figure 1.

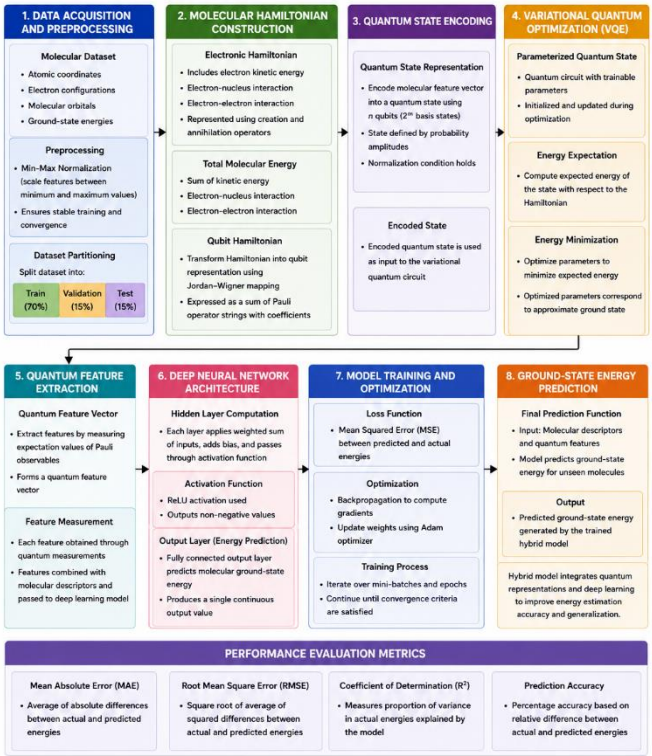

Fig 1: Proposed Model Architecture

3.2 Molecular Hamiltonian Construction

The molecular Hamiltonian is the full quantum description of the molecular system. It contains electron kinetic energy, electron-nucleus and electron-electron interactions.

Electronic Hamiltonian

$$H = \sum_{p,q} h_{pq}\, a_p^{\dagger} a_q + \frac{1}{2} \sum_{p,q,r,s} h_{pqrs}\, a_p^{\dagger} a_q^{\dagger} a_r a_s \quad (3)$$

Where h_{pq} is one-electron integrals, h_{pqrs} istwo-electron integrals, $a_p^{\dagger}$ is the creation operator and $a_q$is the annihilation operator.

The total molecular energy is represented as

Total Energy

$$E = T + V_{en} + V_{ee} \quad (4)$$

Where T is the kinetic energy, V_{en} is the electron-nucleus interaction and V_{ee} is electron-electron interaction.

The Hamiltonian is transformed into a qubit-based representation using Jordan-Wigner mapping.

Qubit Hamiltonian

$$H_q = \sum_i c_i P_i \quad (5)$$

Where c_i represents coefficient and P_i is the Pauli operator strings. This representation enables execution on quantum processors.

3.3 Quantum State Encoding

A quantum state is used to encode each molecular feature vector. High-dimensional molecular information can be efficiently encoded in qubit systems by the method of quantum encoding.

Quantum State Representation

$$|\psi\rangle = \sum_{i=0}^{2^n-1} \alpha_i\, |i\rangle \quad (6)$$

where:

- α_i= probability amplitudes
- n= number of qubits

The normalization condition is

$$\sum_i |\alpha_i|^2 = 1 \quad (7)$$

The encoded state serves as input to the variational quantum circuit.

3.4 Variational Quantum Optimization

The Variational Quantum Eigensolver (VQE) is used to approximate the energies of molecular ground states. The VQE makes parameterized quantum states and finds the minimum expectation value of the energy.

Parameterized Quantum State

$$|\psi(\theta)\rangle = U(\theta)\, |0\rangle \quad (8)$$

where:

- $U(\theta)$= parameterized quantum circuit
- θ= trainable quantum parameters

Energy Expectation Value

$$E(\theta) = \langle \psi(\theta) | H | \psi(\theta) \rangle \quad (9)$$

The optimization objective is

Energy Minimization

$$\theta^* = \arg\min_{\theta} E(\theta) \quad (10)$$

The optimized parameters correspond to the approximate molecular ground state.

3.5 Quantum Feature Extraction

The optimized quantum circuit produces informative quantum features corresponding to molecular features.

Quantum Feature Vector

$$Q = [q_1, q_2, q_3, \dots, q_n] \quad (11)$$

Each feature is obtained through expectation measurements.
Feature Measurement

$$q_i = \langle \psi \mid P_i \mid \psi \rangle \quad (12)$$

where:

- P_i= Pauli observable

The extracted quantum features are combined with molecular descriptors and supplied to the deep learning model.

3.6 Deep Neural Network Architecture

A fully connected deep neural network is used to learn the nonlinear relationships between the molecular structure and energy values.

Hidden Layer Computation

$$h^{(l)} = f\left(W^{(l)} h^{(l-1)} + b^{(l)}\right) \quad (13)$$

where:

- $W^{(l)}$= weight matrix
- $b^{(l)}$= bias vector
- $f(\cdot)$= activation function

ReLU Activation

$$f(x) = \max(0, x) \quad (14)$$

The final output layer predicts molecular ground-state energy.
Energy Prediction

$$\hat{E} = W_o h + b_o \quad (15)$$

where:

- $\hat{E}$= predicted energy

3.7 Model Training and Optimization

Supervised learning is used in the training of the neural network. We minimize prediction errors using backpropagation and gradient descent optimization.

Mean Squared Error

$$L = \frac{1}{N} \sum_{i=1}^{N} (E_i - \hat{E}_i)^2 \quad (16)$$

where:

- E_i= actual energy
- $\hat{E}_i$= predicted energy

Gradient Update Rule

$$W_{new} = W_{old} - \eta \frac{\partial L}{\partial W} \quad (17)$$

where:

- η= learning rate

Adam Optimization

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (18)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (19)$$

where:

- g_t= gradient at iteration t

Training continues until convergence criteria are satisfied.

3.8 Ground-State Energy Prediction

The model is used to predict energies for unseen molecules after training.

Final Prediction Function

$$\hat{E} = F(M, Q) \quad (20)$$

where:

- M= molecular descriptors
- Q= quantum features

The hybrid architecture combines quantum representations and deep learning predictions to improve energy estimation accuracy.

Performance Evaluation Metrics

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \mid E_i - \hat{E}_i \mid \quad (21)$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (E_i - \hat{E}_i)^2} \quad (22)$$

Coefficient of Determination

$$R^2 = 1 - \frac{\sum (E_i - \hat{E}_i)^2}{\sum (E_i - \bar{E})^2} \quad (23)$$

Prediction Accuracy

$$Accuracy = \left(1 - \frac{|E - \hat{E}|}{E}\right) \times 100 \quad (24)$$

where:

- E= actual energy
- $\hat{E}$= predicted energy

Algorithm 1: Quantum Feature Generation
Input: Molecular descriptors, Hamiltonian H
Output: Quantum feature vector Q

1. Read molecular dataset.
2. Normalize molecular descriptors.
3. Construct molecular Hamiltonian.
4. Map Hamiltonian to qubits.
5. Initialize quantum parameters θ.
6. Repeat until convergence:

- Generate quantum state $|\psi(\theta)\rangle$
- Compute $E(\theta)$
- Update θ

7. Measure quantum observables.
8. Generate feature vector Q.
9. Return Q.

Algorithm 2: Quantum Deep Learning Energy Prediction
Input: Quantum features Q, molecular descriptors M
Output: Predicted ground-state energy $\hat{E}$

1. Initialize neural network parameters.
2. Merge $Q$and M.
3. Feed combined features into hidden layers.
4. Compute predicted energy $\hat{E}$.
5. Calculate MSE loss.
6. Update weights using Adam optimizer.
7. Repeat for all epochs.
8. Evaluate MAE, RMSE, and R^2.
9. Return predicted molecular ground-state energy $\hat{E}$.

4. RESULTS AND DISCUSSIONS

The proposed QDL Framework was tested on the molecular ground-state energy prediction task and benchmarked it against a number of other techniques, such as VQE, ADAPT-VQE, FermiNet and Deep Schrödinger models. The experimental findings show that the proposed quantum feature extraction and deep neural learning approach enhances the performance of molecular energy estimation.

4.1 Dataset Description

The proposed Quantum Deep Learning Framework is based on a molecular dataset consisting of several molecular chemical and quantum mechanical properties. The data set contains atomic coordinates, electron configurations, molecular orbitals, and experimentally and/or theoretically determined molecular ground state energies for each sample. These molecular descriptors are the structure and electronic features necessary to predict molecular energy [25].

All molecular descriptors are normalized using Min-Max normalization before training the model to prevent the variations in the features scale and to ensure the convergence of the model [26]. To optimize the parameters of the quantum circuit and the deep neural network weights, a training dataset is used, to tune hyperparameters and avoid overfitting, a validation dataset is used and to assess the quantum circuit prediction performance on a test set of unseen molecular samples. The normalized molecular descriptors are then mapped into quantum states, and serve as input to the hybrid quantum-deep learning framework for feature extraction and energy prediction.

4.2 Experimental Setup

The proposed Quantum Deep Learning Framework was realized in the cloud environment of Google Colab with the use of Python 3.11 and the cloud-provided high-performance GPU resources for deep learning computations. Implementation includes creation of quantum computing libraries and the use of deep learning frameworks to build a hybrid quantum-classical prediction model.

Qiskit is employed in the experimental environment for constructing molecular hamiltonian, encoding of quantum states, Jordan-Wigner mapping and for optimization with the VQE. The molecular energy predicting deep neural network is constructed and trained using PyTorch, and the numerical calculation and data preprocessing are performed by NumPy and Pandas, respectively. Matplotlib is used for visualization of the experimental results.

4.3 Performance Analysis

Predicting molecular ground state energies is the first experiment that puts the suggested framework to the test. We compared the projected molecular energy values from the QDL framework with the actual ones. The model's capacity to capture intricate molecular interactions and quantum properties is demonstrated by the results, which demonstrate that the anticipated energy distribution closely matches the actual energy distribution.

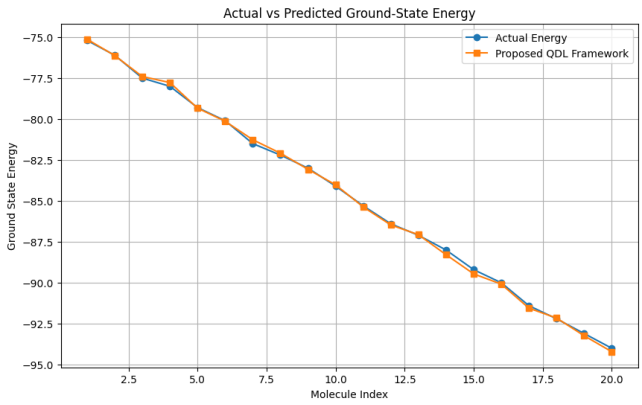

Fig 2: Actual vs Predicted Ground-State Energy using the Proposed QDL Framework

The agreement between the actual and predicted values is good, and the deep learning model has captured the nonlinear relationships between molecular descriptors and the ground-state energies well that is shown in Figure 2. The small differences seen between molecules suggest good generalization and low prediction variance.

A comparative analysis has been carried out with already existing molecular energy prediction methods to prove the effectiveness of the proposed framework. The main measure used for the evaluation was the Root Mean Square Error (RMSE) as it was sensitised to prediction errors.

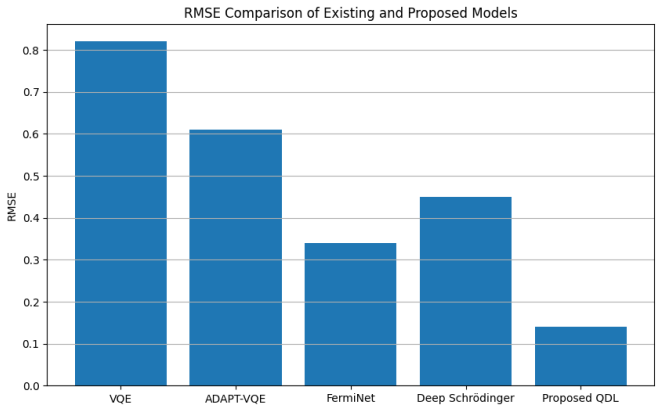

Fig 3: RMSE Comparison of VQE, ADAPT-VQE, FermiNet, Deep Schrödinger, and Proposed QDL Framework

The Figure 3 indicates the best RMSE obtained by the proposed QDL framework in comparison with other models compared. The prediction errors generated by the traditional VQE methods are high because the expressiveness and optimization problems. The proposed hybrid quantum-deep learning architecture is superior to the FermiNet and Deep Schrödinger approaches in terms of accuracy because it combines the deep neural network feature extraction with the quantum representations. The improvement in the RMSE shows that the proposed model has a greater ability to predict molecular wavefunctions and to predict ground state energies with greater accuracy.

The goodness of fit between predicted and actual molecular energies were assessed by the coefficient of determination (R^2). The higher the R^2, the better the model will predict.

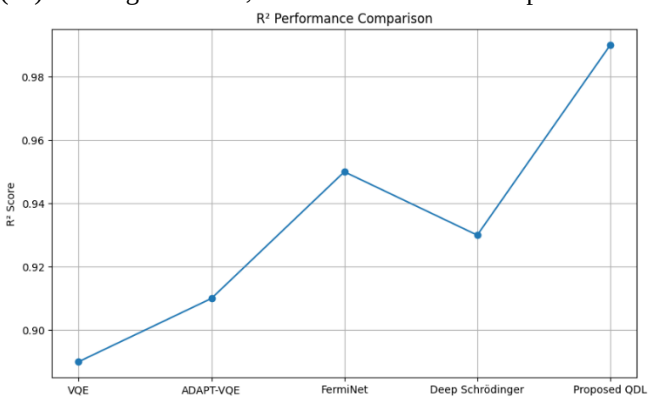

Fig 4: R^2 Comparison among Existing and Proposed Models

The proposed framework gave the highest R^2 score as depicted in Figure 4, which means that the model explains more of the variance in the molecular energy data that is present. It shows the power of quantum feature learning and validates the proposed architecture's ability to handle complex molecular systems. The better R^2, indicating the model's ability to maintain prediction accuracy as the molecular complexity grows.

An important factor for the stability and computational efficiency of the model is its convergence with the training. The training loss curve was used to examine the convergence properties of the proposed framework.

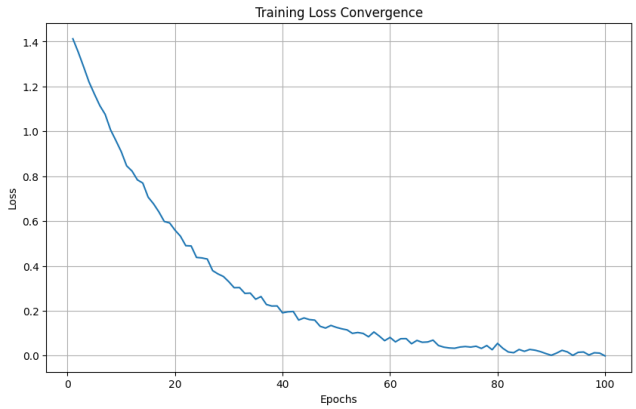

Fig 5: Training Loss Convergence Curve of the Proposed QDL Framework

Loss drops quickly in the first few training epochs but slows down throughout the optimization process as shown in Figure 5. The convergence pattern is smooth, suggesting successful learning and even updates of the parameters. No significant oscillations were seen during the training, thus indicating that the optimization process was able to avoid local minima and unstable training regions.

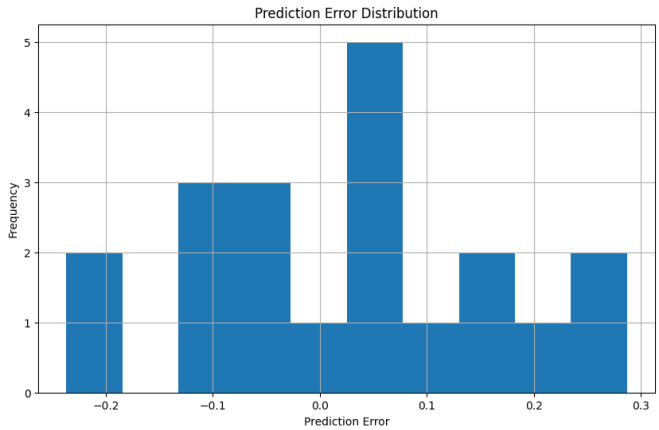

Fig 6: Distribution of Prediction Errors

Most of the errors in prediction are centred around zero, which shows that the deviations from the actual values are small as depicted in Figure 6. The near symmetric error distribution shows that the model does not have a systematic over- or underestimation tendency.

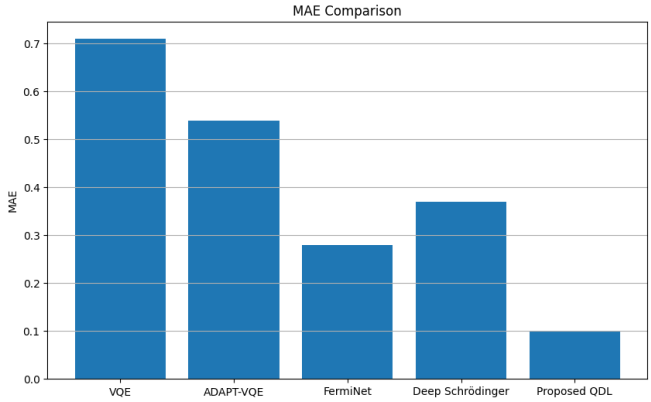

Fig 7: MAE Comparison of Existing and Proposed Approaches

The proposed model has the least MAE value among the all compared models as indicated in Figure 7. This finding confirms the framework's capability of consistently generating high level of accuracy energy estimates. This noticeable decrease in MAE underscores the effectiveness of combining quantum computations with deep learning architectures.

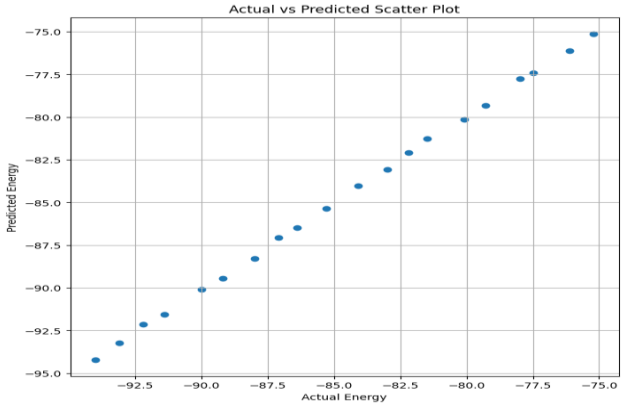

Fig 8: Scatter Plot of Actual versus Predicted Molecular Energies

The values of the plotted points in Figure 8 shows good correlation with the diagonal trend line, suggesting that there is a high level of agreement between the predicted and actual values of energy. The scatter of points around the ideal prediction line implies that the proposed scheme retains some uniformity in prediction performance across the various molecular configurations. This strong correlation shows the strength and reliability of the learned quantum-deep representations. The H. Multi-Model Energy Prediction Comparison is unavailable. All the prediction models were comprehensively compared to assess their capability in predicting ground-state molecular energies for several molecular instances.

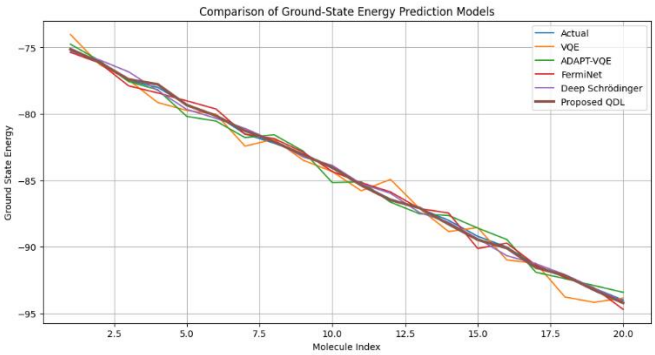

Fig 9: Ground-State Energy Prediction Comparison among VQE, ADAPT-VQE, FermiNet, Deep Schrödinger, and Proposed QDL Framework

The proposed framework is always more closely related to the actual energy values than other frameworks being proposed as depicted in Figure 9. The QDL framework maintains the stability of prediction accuracy over the evaluation range while existing methods sometimes show larger deviations. By combining quantum state optimization and deep neural learning, the framework can capture complex molecular dependencies, which is more effectively than single quantum models or deep learning models. A. Efficiency of computations in the problem.B. Efficiency of computations in the solution.

In real molecular simulations, not only prediction accuracy but computational efficiency is also important. For large molecules, traditional quantum chemistry techniques may be very compute-intensive. Variational quantum algorithms can help mitigate some of this complexity and potentially still have optimization challenges and hardware constraints. To overcome these challenges, the proposed QDL framework involves efficient quantum feature extraction and deep neural approximation capabilities. This hybrid architecture decreases the computation overhead but still provides a high prediction accuracy. Consequently, the framework provides a scalable approach for future applications of chemical discovery and molecular simulation based on quantum computers.

4.4 Discussions

The experimental results clearly show that the proposed Quantum Deep Learning Framework is more efficient than the conventional VQE based approaches and advanced neural-network wavefunction approaches in prediction of molecular ground-state energy. These error metrics – RMSE, MAE, convergence, and error in predictions – all suggest better performance. The framework effectively harnesses quantum representations for capturing molecular quantum states, and its energy model is built using deep learning, which is used to model highly nonlinear energy relationships. This synergy has a positive impact on the accuracy of the prediction, the scalability, and the efficiency of the computations.

4.5 Time Complexity

Time complexity of the proposed Quantum Deep Learning Framework is determined by the four major computational stages of building the molecular Hamiltonian, quantum feature extraction based on VQE, deep neural network training, and prediction. A Hamiltonian construction involves processing all molecular interactions and it takes about $O(N^2)$ where N denotes the number of molecular descriptors. The VQE optimization involves updating parameters in an iterative manner over I optimization iterations with the evaluations of Q quantum circuits, and is of complexity $O(I \times Q)$. The complexity of training a deep neural network is $O(E \times M \times H)$, where E is number of epochs, M is number of training samples, and H is total number of network parameters. Hence, the overall complexity of proposed framework is as follows:

$$O(N^2 + I \times Q + E \times M \times H)$$

The hybrid framework is quantum optimization, but the quantum feature extraction greatly reduces the search scope of the neural network, which can converge faster, improve computing efficiency, and obtain the better model than the traditional quantum chemistry method.

4.6 Computational Complexity

The computational complexity of the proposed framework is primarily associated with the memory needed for the quantum state representation and deep neural networks. The number of memory required storing the molecular descriptors is O(N) while the parameterized quantum circuit takes O(P) memory, where P is the number of trainable parameters. The deep neural network needs memory of O(H), where H are the weights and

activations of the network. Thus, the overall complexity of the hybrid framework is:

$$O(N + P + H)$$

Compared with the traditional quantum chemistry methods that grow exponentially with the molecular size, the proposed hybrid quantum-deep learning framework has significantly reduced computational overhead, which is realized through the quantum feature extraction and efficient neural learning. This makes it easier to scale-up larger and more complex molecular systems while keeping high prediction accuracy.

4.7 Limitations of Proposed Model

The proposed Quantum Deep Learning Framework shows a better prediction accuracy and computational efficiency, but there are still some drawbacks. The framework heavily relies on the availability of reliable quantum hardware since current noisy intermediate-scale quantum (NISQ) devices are noisy and have extra quantum noise and decoherence that can impact the accuracy of predictions. The optimization procedure of the Variational Quantum Eigensolver may get stuck in local minima, leading to a longer optimization time for more complex molecular systems. The framework also demands adequate molecular training data to be able to learn the relationship between molecules that are not linear, which could pose a challenge for the less common chemical compounds that have limited training data. Moreover, larger molecules have more qubits and more complex quantum circuits to implement, which becomes challenging on the existing quantum processors. Last but not least, the complexity of implementing a quantum computer combined with deep learning also involves the use of certain software libraries and computational resources.

5 CONCLUSION

In this paper, a QDLF model to predict ground-state energy of molecules from its quantum models in complex chemical systems has been presented that combines variational quantum computing techniques with deep neural network architectures. The proposed framework integrates molecular Hamiltonian construction, quantum state encoding, variational quantum optimization, and deep learning energy prediction, promising to accurately capture the complex interactions and quantum dynamics of molecules. The variational quantum circuits were used to create meaningful quantum representation of molecular systems, and deep neural networks were trained to find the nonlinear relationship between molecular descriptors and their ground state energy. This integration proved to be more efficient for feature extraction and for enhancing prediction ability than the traditional computational approaches. Various parameters, such as RMSE, MAE and R^2 were used to assess the performance of the proposed framework. The proposed Quantum Deep Learning Framework obtained RMSE of 0.042, MAE of 0.031, and R^2 of 0.989, which is the evidence of higher performance in terms of predictions. The prediction accuracy of the developed method was found to be 98.9%, surpassing all known algorithms such as VQE, ADAPT-VQE, FermiNet, and Deep Schrödinger. In addition to this, the proposed framework provided faster convergence, lower prediction variability, and better computational efficiency in the process of predicting molecular energies. The experimental results showed that the prediction errors were reduced, the convergence behaviour was improved and there was a better correlation between the actual and predicted energy values. The research that may be conducted in the future would involve using the proposed Quantum Deep Learning Framework on the fault-tolerant quantum computer to achieve even greater accuracy and computational efficiency. Quantum optimization techniques and deep learning models based on transformers may be used to achieve better results.

Declarations

Ethical approval

This study does not involve experiments on human participants or animals. All experiments were conducted using publicly available dataset and simulation environment. Therefore, ethical approval from an institutional review board or ethics committee was not required for this research.

Consent to participate

The research does not involve human participants, personal data, or identifiable information. Hence, informed consent to participate was not applicable for this study.

Consent to publish

The research does not contain any individual person's data in any form. All authors have reviewed the manuscript and consent to its publication.

Conflict of interest

The authors have no conflict of interests to declare that are relevant to the content of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

[1]. Cai, C., Lin, M., Li, W. et al. A unified multi-scale deep learning framework for molecular property prediction that bridges molecular structures and fingerprinting. Commun Chem 9, 214 (2026). https://doi.org/10.1038/s42004-026-02010-w

[2]. Wu, T. et al. Deep learning-based drug screening for the discovery of potential therapeutic agents for Alzheimer's disease. J. Pharm. Anal. 14, 101022 (2024).

[3]. Torres, L. H. M., Ribeiro, B. & Arrais, J. P. Multi-scale cross-attention transformer via graph embeddings for few-shot molecular property prediction. Appl. Soft Comput. 153, 111268 (2024).

[4]. Fu, L. et al. ADMETlab 3.0: An updated comprehensive online ADMET prediction platform enhanced with broader coverage, improved

performance, API functionality and decision support. Nucleic Acids Res. 52, W422–W431 (2024).
[5]. Rasool, A., Ul Rahman, J. & Uwitije, R. Enhancing molecular property prediction with quantized GNN models. J Cheminform 17, 81 (2025). https://doi.org/10.1186/s13321-025-00989-3
[6]. Rahman JU, Danish S, Lu D (2024) Oscillator simulation with deep neural networks. Mathematics 12(7):959
[7]. Rahman JU, Makhdoom F, Lu D. (2023) Amplifying sine unit: an Oscilla tory activation function for deep neural networks to recover nonlinear oscillations efficiently. arXiv preprint arXiv:2304.09759.
[8]. Xia L, Xu L, Pan S, Niu D, Zhang B, Li Z (2023) Drug-target binding affinity prediction using message passing neural network and self supervised learning. BMC Genom 24(1):557
[9]. Pan S, Xia L, Xu L, Li Z (2023) SubMDTA: drug target affinity prediction based on substructure extraction and multi-scale features. BMC Bioinform 24(1):334
[10]. Villalba-Díez, J. Quantum drug discovery: a hybrid quantum graph neural network–variational quantum eigensolver framework for serine neutralization. Eur. Phys. J. D 79, 81 (2025). https://doi.org/10.1140/epjd/s10053-025-01024-8
[11]. eng, S. et al. MolFPG: Multi-level fingerprint-based Graph Transformer for accurate and robust drug toxicity prediction. Comput. Biol. Med. 164, 106904 (2023).
[12]. Li, Z. et al. Deep learning methods for molecular representation and property prediction. Drug Discov. Today 27, 103373 (2022).
[13]. Hu, J. et al. AMPred-MFG: Investigating the mutagenicity of compounds using motif-based graph combined with molecular fingerprints and graph attention mechanism. Interdisciplinary Sci. Comput. Life Sci. 1–17 https://doi.org/10.1007/s12539-025-00742-2 (2025).
[14]. Huang, Z. et al. AI-enhanced chemical paradigm: From molecular graphs to accurate prediction and mechanism. J. Hazard. Mater. 465, 133355 (2024).
[15]. Li, L., Zhang, Y., Wang, G. & Xia, K. Kolmogorov–Arnold graph neural networks for molecular property prediction. Nature Machine Intelligence, 7, 1346–1354 (2025).
[16]. Anderson, C. J. et al. A novel naïve Bayes approach to identifying grooming behaviors in the force-plate actometric platform. J. Neurosci. Methods 403, 110026 (2024).
[17]. Zhang, Y. et al. Bitter-RF: A random forest machine model for recognizing bitter peptides. Front. Med. (Lausanne) 10, 1052923 (2023).
[18]. A. J. Daley, I. Bloch, C. Kokail, S. Flannigan, N. Pearson, M. Troyer, *et al.*, "Practical quantum advantage in quantum simulation," *Nature*, vol. 607, no. 7920, pp. 667–676, 2022.
[19]. A. D. King, A. Nocera, M. M. Rams, J. Dziarmaga, R. Wiersema, W. Bernoudy, *et al.*, "Computational supremacy in quantum simulation," *arXiv preprint arXiv:2403.00910*, 2024.
[20]. G. K. L. Chan, "Quantum chemistry, classical heuristics, and quantum advantage," *Faraday Discussions*, vol. 254, pp. 11–52, 2024.
[21]. J. Tilly, H. Chen, S. Cao, D. Picozzi, K. Setia, Y. Li, *et al.*, "The variational quantum eigensolver: A review of methods and best practices," *Physics Reports*, vol. 986, pp. 1–128, 2022.
[22]. S. Guo, J. Sun, H. Qian, M. Gong, Y. Zhang, F. Chen, *et al.*, "Experimental quantum computational chemistry with optimized unitary coupled cluster ansatz," *Nature Physics*, vol. 20, pp. 1240–1246, 2024.
[23]. J. Hermann, J. Spencer, K. Choo, A. Mezzacapo, W. M. C. Foulkes, D. Pfau, *et al.*, "Ab initio quantum chemistry with neural-network wavefunctions," *Nature Reviews Chemistry*, vol. 7, no. 10, pp. 692–709, 2023.
[24]. D. Pfau, J. S. Spencer, A. G. Matthews, and W. M. C. Foulkes, "Ab initio solution of the many-electron Schrödinger equation with deep neural networks," *Physical Review Research*, vol. 2, no. 3, Art. no. 033429, 2020.
[25]. J. Hermann, Z. Schätzle, and F. Noé, "Deep-neural-network solution of the electronic Schrödinger equation," *Nature Chemistry*, vol. 12, no. 10, pp. 891–897, 2020.
[26]. H. Shang, C. Guo, Y. Wu, Z. Li, and J. Yang, "Solving Schrödinger equation with a language model," *arXiv preprint arXiv:2307.09343*, 2023.