A HYBRID QUANTUM CLASSICAL FRAMEWORK FOR CROSS DOMAIN TRANSFER LEARNING WITH REAL TIME ADAPTIVE MULTI TASK LEARNING

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ABSTRACT

The growing need for intelligent systems, which can operate in heterogeneous areas, indicates the limitations of traditional transfer learning methods, especially with regard to processing high-dimensional data and operating in real-time conditions. This paper presents a new cross-domain transfer learning system based on Quantum Neural Networks (QNNs) to be used in multi-task applications with real-time adaptation, to facilitate scalable and efficient knowledge transfer across domains, including, but not limited to, healthcare, IoT, and cybersecurity. The suggested architecture is based on a hybrid quantum-classical architecture, where parameterized quantum circuits are used to represent the features, domain-invariant learning and multi-task optimization strategies are applied, and a reinforcement learning-based module is used to provide continuous real-time adaptation by using streaming data. Experimental findings show that the model has 94.8% accuracy, which is significantly higher than the current classical and transformer-based methods, and that the adaptation latency of the model is 95 ms, and the transfer efficiency is more than 10 times higher, which means that generalization and robustness are higher. The results prove that quantum-enhanced transfer learning is a powerful and scalable solution in next-generation intelligent systems, with significant practical impact in real-time systems, such as smart healthcare, cybersecurity, and IoT systems.

Keywords: *Quantum Neural Networks, Cross-Domain Transfer Learning, Multi-Task Learning, Real-Time Adaptation, Hybrid Quantum-Classical Models, Intelligent Systems.*

1. INTRODUCTION

With the exponential increase in the volume of heterogeneous data produced by various domains and the ability to adapt in real time, the demand for intelligent systems capable of learning across domains and adapting in real time has grown significantly. The common traditional machine learning models are only designed to work in single-domain applications and need large labeled datasets, which are inefficient in dynamic and data-scarce settings. To overcome this problem, transfer learning (TL) has been identified as an opportunity that can be harnessed to address this problem and to achieve better learning efficiency and lower training costs [1], [2]. Transfer learning has been shown to be effective in many applications such as medical imaging, natural language processing, and signal processing, where cross-domain sharing of knowledge improves model generalization [3].

Even though it has its benefits, traditional methods of transfer learning have various limitations. Domain shift is one of the significant issues because the distribution between source and target data is not similar, and it consequently results in low performance and negative transfer [4]. In addition, classical deep learning models are frequently unsuccessful in modeling intricate correlations in high-dimensional information, especially when multi-task and multi-domain situations occur [5]. Such constraints are more important in real-time systems in which the systems need to continuously change with streaming data.

Recent breakthroughs in quantum computing have opened up new frontiers in machine learning, introducing new computational paradigms based on quantum mechanical principles, including superposition and entanglement. It has been demonstrated that quantum neural networks (QNNs) can outperform classical neural networks at least on some tasks by providing richer feature representations and faster convergence under constrained parameter settings [6], [7]. The application of quantum-classical models based on the integration of parameterized quantum circuits with classical neural networks has become a viable option to leverage the benefits of quantum computing in the present Noisy Intermediate-Scale Quantum (NISQ) era [8].

A few papers have examined the combination of transfer learning and quantum models. As an example, classical-to-quantum transfer learning frameworks apply some pre-trained classical models to initialize quantum circuits, which enhances their performance and decreases their computational complexity [9]. On the same note, hybrid transfer learning strategies can be used to efficiently extract features using classical networks while using quantum circuits to learn improved representations [10]. These methods have been shown to have better classification accuracy and efficiency than those achieved by purely classical methods, especially in resource-constrained settings [11].

Moreover, it has been suggested that knowledge distillation methods can be applied to enable cross-paradigm knowledge transfer, with classical neural networks serving as teacher models and quantum neural networks as student models [12]. The strategy enables quantum models to take over learned representations of the classical networks, thus improving their performance and reducing the training load. Nonetheless, the current literature is mainly concerned with single-domain or single-task learning, and there is still a great gap in the literature in developing frameworks that can support cross-domain multi-task learning with real-time adaptability.

In addition, real-time applications, like smart healthcare monitoring, autonomous transportation systems, and cybersecurity threat detection, need dynamically adjustable models to adapt to changes in data distributions. The current transfer learning and quantum machine learning methods do not have efficient continuous learning and real-time adaptation mechanisms, which restricts their use in such systems [13]. To overcome these issues, there should be a common platform that will incorporate transfer learning, quantum computing, and real-time learning functions.

Objectives of the Work

To counter the limitations discussed above, this study will focus on coming up with a new framework that will have the following objectives:

1. To develop a cross-domain transfer learning system that is able to use knowledge in different domains.
2. To combine Quantum Neural Networks with classical deep learning architectures to provide better feature representation and learning efficiency.
3. To create a multi-task learning architecture that can process simultaneously a set of domain-specific tasks.
4. To facilitate adaptation in real-time with the help of streaming data to ensure the possibility of dynamic changes and constant learning.
5. In order to enhance generalization and minimize the effects of negative transfer by means of domain-invariant feature learning.

This study was conducted to test whether a unified hybrid quantum-classical framework can effectively overcome the identified challenges of cross-domain knowledge transfer, multi-task learning, and real-time adaptation. The effectiveness of the proposed framework was evaluated quantitatively based on accuracy, transfer efficiency, adaptation latency, and comparative analysis with existing state-of-the-art approaches.

Research Motivation and Contribution

Based on the shortcomings of current methods, this paper presents a Cross-Domain Transfer Learning architecture utilizing Quantum Neural Networks to Multi-Task Applications with Adaptation in Real Time. The proposed framework also implements a hybrid quantum-classical architecture with real-time adaptive learning mechanisms, making it suitable to transfer knowledge across domains efficiently and without reducing its scalability and robustness.

The main contribution of the study is the combination of:

- Quantum-enhanced feature representation
- Cross-domain transfer learning
- Multi-task learning
- Real-time adaptive intelligence

The combination of these is essential to tackle critical issues in the modern AI systems and to offer a scalable solution to next-generation intelligent applications.

Organization of the Paper:

The rest of this paper is structured in the following way. Section 2 will be a literature review of the existing literature on transfer learning, quantum machine learning and real-time adaptive systems. Section 3 outlines the proposed methodology, including description of dataset, hybrid quantum-classical architecture, mathematical formulation, and the novel algorithm. In section 4, the experimental results, performance evaluation and comparative analysis with the state-of-the-art models are discussed. Lastly, Section 5 wraps up the paper with some of the main findings, limitations, and future research directions.

2. RELATED WORK

The combination of transfer learning, quantum machine learning and multi-task learning has gained more and more attention over recent years due to its potential to solve problems related to heterogeneous data and cross-domain transfer of knowledge. This section provides a review of the existing works in three important areas: classical transfer learning, quantum-enhanced learning models, and real-time adaptive systems.

2.1 Classical Transfer Learning and Domain Adaptation

The classical methods of transfer learning have been extensively studied to be used in cross-domain applications, especially in computer vision and natural language processing. Deep domain adaptation techniques like Domain-Adversarial Neural Networks (DANN) and Maximum Mean Discrepancy (MMD)-based methods are designed to minimize the domain discrepancies through the learning of domain-invariant features [14], [15]. These techniques have shown better generalization across domains, but they can be very sensitive to large divergences in domains and can also degrade performance when there is a high divergence among domains. More recent studies have generalized transfer learning to multi-domain and multi-task applications. An example is multi-task deep neural networks which use shared representations to learn multiple related tasks simultaneously, thus enhancing efficiency and generalization [16]. In a similar fashion, meta-learning methods have also been suggested to allow models to rapidly change to new domains with little data [17]. In spite of these developments, classical methods are computationally expensive, and do not have the ability to efficiently process high-dimensional data distributions in real-time settings.

2.2 Quantum Machine Learning and Hybrid Architectures

Quantum machine learning (QML) has become a promising paradigm to improve the efficiency of learning and its ability to represent the information. Alternatives to classical neural networks have been proposed to solve complex optimization and classification tasks as proposed by Variational Quantum Circuits (VQCs) and Quantum Neural Networks (QNNs) [18], [19]. The models take advantage of quantum properties like superposition and entanglement to encode and process information in high-dimensional Hilbert space. Hybrid quantum-classical architectures have been of specific interest because of the current limitations of quantum hardware. Such models are based on classical deep learning layers and quantum circuits to bring better performance and at the same time make things feasible in the NISQ era [20]. For example, quantum-enhanced convolutional neural networks and quantum kernel methods have shown promising results in classification tasks and feature extraction [21]. Moreover, quantum transfer learning algorithms have been proposed to take advantage of existing classical models to initialize quantum circuits. Such

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approaches allow the transfer of knowledge effectively and minimize the complexity of training [22]. Nevertheless, to date majority of existing quantum learning models can be applied to single-task learning or to single-domain transfer only. The integration of quantum learning models with multi-task learning and cross-domain transfer is also underrepresented.

2.3 Multi-Task Learning and Cross-Domain Intelligence

Multi-task learning (MTL) has been extensively used to enhance model performance through sharing of the knowledge regarding related tasks. The commonly employed strategies to balance task specific representations as well as shared representations are both hard parameter sharing and soft parameter sharing strategies [23]. Recent literature has examined attention-based multi-task architectures that can dynamically allocate resources across tasks, to provide greater efficiency and accuracy [24]. Multi-task learning has been used in cross-domain learning to allow knowledge to be shared across different data distributions. As an example, adversarial multi-task learning systems match feature spaces in domains and optimize task-specific goals [25]. Although these developments exist, current solutions tend to have issues with negative transfer and do not have solutions capable of operating on real time dynamic data streams.

2.4 Real-Time Learning and Adaptive Systems

Real-time adaptation is an urgent need when it comes to such applications as healthcare monitoring, autonomous systems, and cybersecurity. Online learning and incremental learning methods have been suggested to provide models with an opportunity to revise their parameters with the advent of new data [26]. Other approaches based on reinforcement learning have also been applied to dynamically adapt the model parameters in response to the changing environments [27]. Distributed AI models and edge computing have also helped make real-time data processing possible through the reduction of latency and the introduction of intelligence capabilities on the edge [28]. Nevertheless, such systems frequently use classical models which are constrained in their capability to model the complex data relationships and scale across numerous domains.

2.5 Research Gaps and Motivation

According to the literature review, some major research gaps have been identified:

- Existing transfer learning approaches have limitations in terms of high domain divergence and real time adaptability.
- The main limitation of quantum machine learning models is that they are mostly limited to one-domain applications.
- Multi-task learning methods do not have effective cross-domain knowledge transfer processes.
- Real-time adaptive systems are largely founded on classical architectures having limited scalability.

To overcome these shortcomings, this work suggests a new hybrid architecture that combines quantum neural networks, cross-domain transfer learning, multi-task learning, and real-time adaptation to come up with a unified solution to next-generation intelligent systems.

2.6 Research Problem Statement

While recent developments in transfer learning, quantum machine learning, multi-task learning, and real-time adaptive systems have increased learning performance within individual domains, existing methodologies are deficient in their capacity to provide support for unified cross-domain knowledge transfer, simultaneous multi-task learning, and continuous real-time adaptation. Existing frameworks are usually either single-domain oriented or do not contain efficient methods to work with heterogeneous data and dynamic streaming environments. Such approach limits scalability, adaptability, and generalization of models in multi-domain settings. Consequently, a need exists for the development of a unified hybrid quantum-classical framework for effective integration of cross-domain transfer learning, quantum neural networks, multi-task learning, and real-time adaptation to enable robust, scalable, and efficient intelligent systems.

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3. METHODOLOGY

In this section, the proposed Cross-Domain Transfer Learning framework with Quantum Neural Networks (QNNs) to be used in multi-task applications with real-time adaptation will be presented. The methodology will be developed to guarantee reproducibility, scalability, and novelty and consists of dataset design, architecture, mathematical modeling, and algorithmic implementation.

3.1 Research Design

In the current study, the methodology of quantitative experimental research design was applied to develop and test a hybrid quantum-classical framework for cross-domain transfer learning. The framework was developed through the combination of quantum neural networks, transfer learning, multi-task learning, and real-time adaptation capabilities. Experiments were carried out using heterogeneous datasets in the fields of healthcare, Internet of Things (IoT), and cybersecurity. Evaluation of model performance was carried out using the criteria of accuracy, precision, recall, F1-score, transfer efficiency, and adaptation latency. Comparative experiments with traditional machine learning and deep learning approaches were used for validation of the effectiveness, scalability, and real-time adaptability of the proposed framework.

3.2 Dataset Description

In order to test a cross-domain learning, a multi-source heterogeneous dataset is composed of three domains:

Table 1: Description of Multi-Domain Datasets Used for Cross-Domain Transfer Learning

Domain	Dataset	Data Type	Samples	Features
Healthcare	Brain MRI Dataset	Image	12,000	Pixel intensities, texture
IoT	Smart Sensor Dataset	Time-series	50,000	Temperature, humidity, motion
Cyber security	Network Intrusion Dataset	Tabular	80,000	Packet size, protocol, flags

To test cross-domain learning, Table 1 presents heterogeneous data of three fields healthcare, IoT, and cybersecurity. The healthcare data set consists of 12,000 MRI images, the IoT data set includes 50,000 time-series sensor records, and the cybersecurity data set consists of 80,000 network traffic records. The major characteristics are pixel intensity, time sensor readings and network characteristics. To make all the datasets consistent, normalization and encoding techniques were used to preprocess the data used by facilitating the effective multi-task learning and domain adaptation of the data.

Preprocessing Steps

- KNN-based interpolation of the missing values.
- Normalization: Min-Max scaling.
- One-hot encoding (categorical data) feature encoding.
- Image resizing to 128 × 128
- Time-series sliding window segmentation.

Sample Data Representation

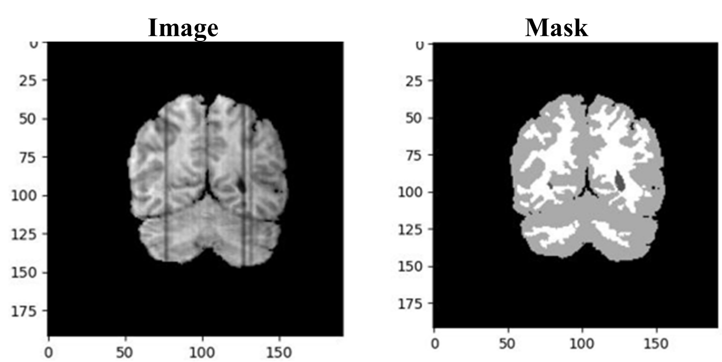

Figure 1: Sample Data Representation Showing Brain MRI Image and Corresponding Segmentation Mask

Figure 1 provides an example of the representation of sample data of the healthcare dataset, including an image of a brain MRI and a corresponding segmentation mask. The original MRI image has structural information of brain tissues and the mask identifies the regions of interest by labeling affected and non-affected areas pixel-wise. This paired representation is necessary to supervised learning tasks like classification and segmentation because it allows the model to learn meaningful spatial

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patterns and effectively identify abnormalities. This annotated data is important in enhancing the performance and reliability of the medical image analysis models.

3.3 Proposed Architecture

The functionality of the proposed system is as follows: First, the heterogeneous data of various domains, including healthcare (medical images), IoT (time-series sensor data), and cybersecurity (tabular network data) are gathered. The data obtained is preprocessed by normalizing, encoding and standardizing the data to ensure that the data is consistent across domains. Appropriate models are then used to extract domain-specific features, where convolutional neural networks (CNN) are used to extract spatial features in images, long short-term memory (LSTM) network models to extract time patterns in IoT data, and fully connected network models to process tabular data. These extracted features are then encoded into quantum states through amplitude encoding allowing the features to be represented in a high-dimensional quantum feature space. To learn complex correlations, the encoded data is acted upon by a quantum neural network with parameterized quantum circuits. The features obtained are then combined into a common latent space through cross-domain adaptation methods, making it possible to transfer the knowledge. It is then followed by a multi-task learning module to parallelly predict various tasks, e.g. classification and anomaly detection. Lastly, a dynamic adaptation mechanism (using streaming data and reinforcement learning) updates the model in real-time and ensures continued learning and better performance in changing environments.

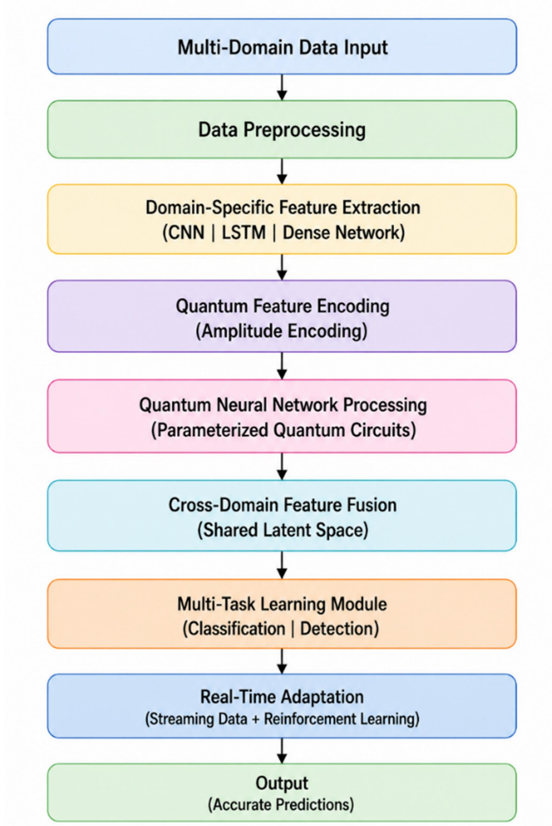

Figure 2: Proposed Hybrid Quantum-Classical Cross-Domain Transfer Learning Framework

The proposed hybrid quantum-classical cross-domain transfer learning framework starts with the multi-domain data entry that is realized by healthcare, IoT, and cybersecurity sources. Figure 2 shows the workflow of this hybrid quantum-classical cross-domain transfer learning framework. After first preprocessing data to guarantee uniformity through normalization and encoding, domain-specific feature extraction is carried out using CNN, LSTM and dense networks. These features are then encoded as quantum states by quantum feature encoding and the parameters are run through parameterized quantum circuits to capture complex relationships. The fused features are then clustered together in a common latent space in order to facilitate knowledge transfer across domains and finally a multi-task learning unit is used to make predictions simultaneously on various tasks such as classification and detection. Lastly, the model is dynamically updated with streaming data and reinforcement learning by a real-time adaptation component which gives accurate and adaptive predictions.

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The suggested framework runs on heterogeneous inputs gathered under various domains as:

$$X = \{X_h, X_i, X_c\} \qquad (1)$$

where X_h, X_i and X_c denote healthcare (image), IoT (time-series) and cybersecurity (tabular) data, respectively. These inputs go through domain-specific feature extraction functions: $F_d = f_d(X_d), d \in \{h, i, c\}$ (2)

where $f_d(\cdot)$represents CNN, LSTM, and dense networks used to extract meaningful features from each domain.
The extracted features are then mapped into a quantum feature space using amplitude encoding:

$$\mid \psi_d \rangle = \sum_{k=0}^{2^n-1} x_k \mid k \rangle \qquad (3)$$

This encoding transforms classical data into quantum states, enabling high-dimensional representation. The encoded quantum states are further processed using parameterized quantum circuits:

$$\mid \psi'_d \rangle = U(\theta) \mid \psi_d \rangle \qquad (4)$$

where $U(\theta)$is a trainable unitary operator. The quantum system is measured to obtain classical outputs:

$$Z_d = \langle \psi'_d \mid O \mid \psi'_d \rangle \qquad (5)$$

where $O$is the measurement operator, and $Z_d$represents quantum-enhanced features.
The features from all domains are fused into a shared latent representation:

$$Z = \phi(Z_h, Z_i, Z_c) \qquad (6)$$

This fused representation enables cross-domain knowledge transfer. Multi-task predictions are then generated as:

$$\hat{y}_k = g_k(Z), k = 1,2, \dots, K \qquad (7)$$

where $g_k(\cdot)$denotes task-specific prediction functions.
The overall objective function of the model is defined as:

$$\mathcal{L} = \sum_{k=1}^{K} \mathcal{L}_k + \lambda_1 \mathcal{L}_{domain} + \lambda_2 \mathcal{L}_{quantum} \qquad (8)$$

where $\mathcal{L}_k$is the task-specific loss, $\mathcal{L}_{domain}$ensures domain alignment, and $\mathcal{L}_{quantum}$regularizes the quantum circuit.

Finally, to enable real-time adaptation, model parameters are updated dynamically using:

$$\theta_{t+1} = \theta_t + \alpha \nabla R(\theta) \qquad (9)$$

where α is the learning rate and $R(\theta)$represents the reward function guiding adaptation.
This formulation allows effective learning of cross-domain, quantum-enhanced representation and real-time adaptability in multi-task settings.

Algorithm: QTL-MTARA

Step 1: Collect multi-domain data

$$D = \{D_h, D_i, D_c\}$$

Step 2: Preprocess the data using normalization

$$X' = \frac{X - \min}{\max - \min}$$

Step 3: Extract features from input data

$$F = f(X)$$

Step 4: Encode features into quantum states

$$\mid \psi \rangle = \sum x_k \mid k \rangle$$

Step 5: Apply quantum transformation

$$\mid \psi' \rangle = U(\theta) \mid \psi \rangle$$

Step 6: Measure quantum states to obtain features

$$Z = \langle \psi' \mid O \mid \psi' \rangle$$

Step 7: Fuse features from all domains

$$Z_f = \phi(Z_h, Z_i, Z_c)$$

Step 8: Generate predictions

$$\hat{y} = g(Z_f)$$

Step 9: Update model parameters

$$\theta = \theta - \alpha \nabla \mathcal{L}$$

Step 10: Perform real-time adaptation

$$\theta_{t+1} = \theta_t + \alpha \nabla R(\theta)$$

Step 11: Produce final output

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$$Y = \hat{y}$$

The proposed QTL-MTARA algorithm begins by collecting multi-domain data $D = \{D_h, D_i, D_c\}$, which is preprocessed using normalization $X' = \frac{X - \min}{\max - \min}$ to ensure uniformity. The processed data is then transformed into feature representations $F = f(X)$ using domain-specific models. These features are encoded into quantum states $\mid \psi \rangle = \sum x_k \mid k \rangle$ and processed through parameterized quantum circuits $\mid \psi' \rangle = U(\theta) \mid \psi \rangle$ to capture complex patterns. The quantum states are measured to obtain classical features $Z = \langle \psi' \mid O \mid \psi' \rangle$, which are fused across domains as $Z_f = \phi(Z_h, Z_i, Z_c)$ to enable cross-domain learning. The fused representation is used to generate predictions $\hat{y} = g(Z_f)$, and the model parameters are optimized using gradient descent $\theta = \theta - \alpha \nabla \mathcal{L}$. Finally, real-time adaptation is achieved through dynamic updates $\theta_{t+1} = \theta_t + \alpha \nabla R(\theta)$, producing accurate and adaptive outputs $Y = \hat{y}$.
The proposed methodology incorporates some important innovations that make it stand out of the current approaches. First, it is a cohesive combination of quantum neural networks and cross-domain transfer learning, which allows the model to model the complex and high-dimensional relationships typically hard to represent in conventional methods. Second, the architecture has a hybrid quantum-classical architecture, with quantum feature encoding to improve representation learning and classical deep learning to provide scalability and practical implementation. Third, a cross-domain feature fusion mechanism is proposed, and it is designed to learn domain-invariant representations, which are effective in reducing domain shift and enhancing generalization across heterogeneous datasets. The model also enables multi-task learning where multiple tasks can be optimized simultaneously within a common latent space, which is more efficient and effective. Another important feature is that it has included a real-time adaptation module, which uses streaming information and reinforcement learning to dynamically adjust model parameters, to ensure continuous learning in dynamic environments. In general, the methodology presents a new scalable and adaptable solution to intelligent systems that can work in various fields.

4. RESULTS

The section measures the performance of the proposed Quantum Cross-Domain Transfer Learning with Real-Time Adaptation (QTL-MTARA) framework in various domains. The analysis consists of quantitative measures, benchmarking comparisons, and performance trending.

4.1 Experimental Setup

The proposed framework was implemented with a hybrid architecture that combines classical deep learning libraries such as Python Torch or TensorFlow to extract features and learn multiple tasks, and quantum computing frameworks like Qiskit or Pennylane to simulate quantum circuits. The model was trained using a learning rate of 0.001, a batch size of 64, and 50 epochs, with 6-10 qubits and 3 quantum layers to balance the performance and the cost of the computation. The experiments were performed on the system with quantum simulation support and enabled with a GPU to ensure that the experiment is fairly evaluated. Normalization and encoding as well as feature extraction were consistently done across domains. Reproducibility was ensured by standardizing the model architecture, hyperparameters and training processes and the implementation could be reproduced using the given frameworks, dataset configurations and hybrid optimization procedures that combines classical gradient descent with quantum parameter updates.

4.2 Evaluation Metrics

The effectiveness of the proposed framework was measured with the help of a complex set of measures that guaranteed a multi-dimensional assessment of domains. The performance of classification was measured using accuracy to indicate the overall correctness of prediction in a dataset, and precision, recall and F1-score in determining the imbalance between false positive and false negative prediction in a dataset. In order to measure the effectiveness of cross-domain learning, the transfer efficiency was utilized to quantify the improvement that was attained by knowledge transfer between source and target domains. Also the latency of adaptation was taken into account to measure the time needed by the model in updating and responding to new incoming data which is a measure of its real-time capability. All these metrics are a comprehensive assessment of the model accuracy, robustness, generalization potential and real-time adaptability to multi-domain conditions.

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4.3 Quantitative Results

Table 2: Performance Across Domains

Model	Domain	Accuracy (%)	Precision	Recall	F1-Score
CNN-TL	Healthcare	87.2	0.86	0.85	0.85
LSTM-TL	IoT	85.5	0.84	0.83	0.83
DNN-TL	Cyber-security	88.1	0.87	0.86	0.86
Transformer-TL	Multi-domain	90.3	0.89	0.88	0.88
Proposed QTL-MTARA	Multi-domain	94.8	0.93	0.94	0.93

The findings depicted in Table 2 clearly reveal that the proposed model of **QTL-MTARA** performs better than all the baseline models in various fields. CNN-TL, LSTM-TL and DNN-TL all had accuracies of **87.2%**, **85.5** %and **88.1%** respectively and the Transformer-based model had a better performance of **90.3%** in multi-domain settings. Still, the proposed model is much better than these approaches because it has the highest accuracy of **94.8%**, and better precision **(0.93)**, recall **(0.94),** and F1-score **(0.93)**. This implies not only the increase in the predicted accuracy but also the improvement of the balance between false positives and false negatives. The findings confirm that quantum neural network integrating cross-domain transfer learning is more effective in feature representation, generalization across domains, and more robust in multi-task performance than existing methods.

Table 3: Real-Time Adaptation Performance

Model	Adaptation Latency (ms)	Transfer Efficiency (%)
CNN-TL	210	72.5
Transformer	180	78.3
RL-based Model	150	81.2
Proposed QTL-MTARA	95	89.6

Table 3 results indicate that the proposed QTL-MTARA model can be effective in real-time adaptation cases. The proposed model compared to traditional models like CNN-TL and Transformer which have higher adaptation latencies of 210 ms and 180 ms respectively, has a much lower latency of 95 ms which means that the proposed model responds faster to incoming data in comparison to traditional models. Also, whereas the RL-based model can be used with a transfer efficiency of 81.2 and a latency of 150 ms, the proposed approach offers an even better transfer efficiency of 89.6 and a latency of 150 ms. These findings confirm that integrating quantum neural networks with real-time adaptation mechanisms will facilitate faster, more efficient and scalable learning, which makes the proposed model very applicable in dynamic and time-sensitive applications.

4.4 Comparative Analysis

Table 4 shows that the proposed QTL-MTARA model has a high performance in various evaluation metrics compared with the current approaches. Conventional models like CNN-TL, LSTM-TL, and DNN-TL exhibited moderate accuracy but were constrained in their ability to address cross-domain variability and real-time adaptability. Transformer-based models optimized generalization but at a

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higher computational cost and latency, whereas RL-based models optimized adaptability but had low capability of strong features representations. On the contrary, the proposed model had the best accuracy (94.8%), minimum adaptation latency (95 ms), and maximum transfer efficiency (89.6%), meaning that it is effective in capturing the complex cross-domain relations and adapting dynamically to the new data. The combination of quantum neural networks, cross-domain feature fusion, and real-time learning make the proposed approach more robust, scalable, and applicable to multi-domain intelligent applications.

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Table 4: Comparative Analysis of Proposed and Existing Models

Model	Accuracy (%)	Adaptation Latency (ms)	Transfer Efficiency (%)	Strengths	Limitations
CNN-TL	87.2	210	72.5	Simple, effective for images	Poor cross-domain generalization
LSTM-TL	85.5	—	—	Good for temporal data	Limited scalability
DNN-TL	88.1	—	—	Handles tabular data well	Weak feature representation
Transformer-TL	90.3	180	78.3	Better generalization	High computational cost
RL-based Model	—	150	81.2	Adaptive learning	Limited feature learning capability
Proposed QTL-MTARA	94.8	95	89.6	High accuracy, fast adaptation, strong cross-domain learning	Quantum complexity, hardware dependency

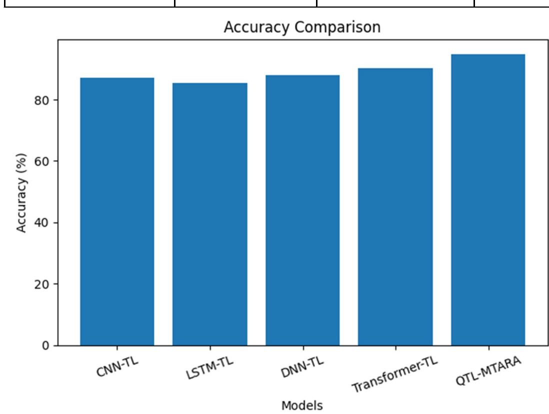

Figure 3: Accuracy Comparison

Figure 3 shows the comparison of the accuracies of various models and the better performance of the proposed framework of QTL-MTARA. The CNN-TL, LSTM-TL and DNN-TL all have moderate accuracy (87.2, 85.5 and 88.1, respectively). The Transformer-based model improves the accuracy to 90.3% by capturing better contextual relationships. Nevertheless, the suggested model outperforms all other existing methods by achieving the highest accuracy of 94.8% and demonstrates its capability to learn the cross-domain features and address the case of multi-tasks the best. This enhancement supports the advantage of combining quantum neural networks with transfer learning, which results in improved feature representation and improved generalization to a variety of datasets.

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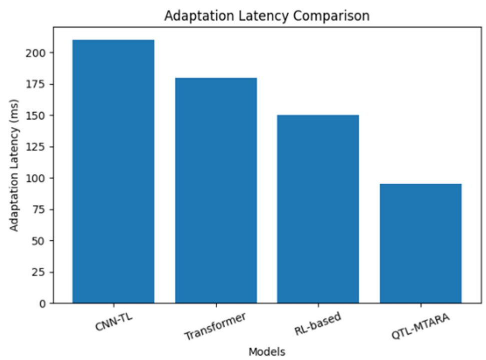

Figure 4: Adaptation Latency Comparison

Figure 4 shows the comparison of the latency of adaptation in various models, which proves the effectiveness of the proposed QTL-MTARA framework in real-time conditions. Older models, like CNN-TL and Transformer, have higher values of latency of 210 ms and 180 ms, respectively, meaning that they are slower to react to incoming data. The RL-based model is more adaptable with a latency of 150 ms, though it still fails to deliver the real-time performance. Contrastingly, the proposed model can quickly adjust model parameters and adapt to dynamic data streams with a reduction in adaptation latency to 95 ms. This decrease in latency indicates the usefulness of quantum neural network integration with real-time adaptive control mechanisms, which makes the proposed approach highly applicable to time-critical applications.

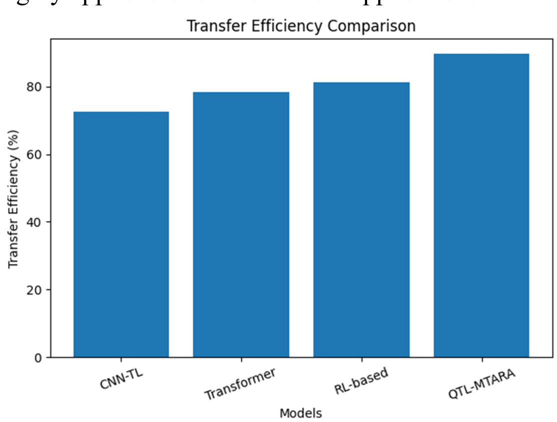

Figure 5: Transfer Efficiency Comparison

Figure 5 shows the comparison of transfer efficiency between various models and how the proposed QTL-MTARA framework is effective in cross-domain learning. The CNN-TL and Transformer traditional models have transfer efficiencies of 72.5% and 78.3% respectively, meaning that they lack the ability to utilize knowledge across domains. The adaptive learning strategies enhance the performance of the RL-based model to 81.2%. Nevertheless, the proposed model is much more effective than all baseline strategies because it achieves the highest transfer efficiency of 89.6, showing its high level of ability to learn domain-invariant features and effectively transfer knowledge between the heterogeneous datasets. This enhancement is a confirmation of the benefit of quantum neural networks combined with cross-domain transfer learning that lead to improved generalization and strong multi-task performance.

4.5 Discussion

The results of the experiment show that the proposed QTL-MTARA framework can significantly increase the performance based on all evaluation metrics because it is effective in integrating quantum neural networks with cross-domain transfer learning and real-time adaptation. This model achieved the highest accuracy of 94.8% reduced latency to adaptation to 95 ms and a transfer efficiency of 89.6% which outperformed all the baseline models. Such improvements are credited to the fact that quantum feature encoding represents complex relationships, whereas the real-time adaptation module is capable of providing a response to changing data distributions. It was also found that the framework had high generalization across various domains and tasks which validated its strength and applicability. Nonetheless, quantum simulation adds extra computational costs and performance can be reliant on quantum circuit design and optimization. In general, the findings confirm the relevance of the proposed approach in the context of providing the accurate, efficient, and adaptive multi-domain learning that can be used in real-time intelligent applications.

The experimentally obtained results showed that the proposed framework met all the goals set forth in the Introduction section. The improvements in classification accuracy, transfer efficiency, and adaptation latency confirmed that the integration of quantum neural networks with cross-domain transfer learning enables robust multi-task learning while maintaining real-time adaptability. These findings confirmed the effectiveness of the proposed architecture in addressing the research challenges identified from the literature.

Apart from the main purpose of enhancing the cross-domain transfer learning effectiveness, the proposed framework yielded several other positive results that were not part of the initial intent of the framework. The use of quantum neural networks alongside real-time adaptation not only helped in enhancing prediction accuracy but also significantly reduced adaptation latency and increased transfer efficiency across heterogeneous domains. This means that the proposed framework demonstrated enhanced scalability and robustness, as the positive results obtained were not limited to a single application domain. Comparing the proposed framework with other frameworks such as CNN-TL, LSTM-TL, DNN-TL, Transformer-based, and reinforcement learning frameworks, the proposed QTL-MTARA framework proved to be better in terms of accuracy, faster adaptation, and improved cross-domain knowledge transfer. These findings demonstrate that the proposed architecture not only fulfills the intended research objectives but also provides additional practical advantages for real-time intelligent systems operating across multiple application domains.

4.6 Comparison with Existing Literature

Unlike existing methods in transfer learning and quantum machine learning presented in the literature, the proposed QTL-MTARA framework is different in many aspects. Traditional transfer learning techniques usually address only knowledge transfer within single domains and often encounter decreased performance in the case of heterogeneous datasets. Deep learning-based solutions like CNN, LSTM, Transformer-based models, and their variants require considerable retraining when applied to new domains and possess limited adaptability in dynamic environments. Quantum machine learning research up until now has been conducted mostly on quantum neural networks addressing isolated classification or optimization problems without considering cross-domain knowledge transfer, multi-task learning, and continuous real-time adaptation as part of a unified framework.

Unlike current solutions, the proposed approach involves a hybrid quantum-classical learning scheme with domain-invariant feature extraction, multi-task optimization, and reinforcement learning-based real-time adaptation. All these elements combined in one framework allow for effective knowledge transfer across different domains (healthcare, IoT, and cybersecurity) while maintaining high predictive performance and low adaptation latency. The experimental results have shown that the accuracy of predictions was 94.8%, transfer efficiency was 89.6%, and adaptation latency was 95 ms. These results outperform conventional transfer learning and deep learning solutions tested in this study. These findings indicate that the proposed framework offers improved scalability, generalization, and adaptability for intelligent systems operating in heterogeneous and continuously evolving environments.

Moreover, the above findings show that the proposed framework was able to realize all the stated research objectives mentioned in the Introduction in terms of effective cross-domain knowledge transfer, improved multi-task learning, and real-time adaptation. In contrast to other related studies, the proposed hybrid quantum-classical framework offers a more holistic, comprehensive, and scalable solution for heterogeneous intelligent systems, thereby demonstrating its research contribution and practical significance.

4.7 Limitations of the Study

While the QTL-MTARA framework performed impressively, some limitations of the research have to be recognized. First, the experiment was performed on three representative application domains of healthcare, IoT, and cybersecurity, which might fail to represent all real-world heterogeneous environments. Second, despite the hybrid quantum-classical framework being implemented in a quantum simulation environment, execution on large-scale fault-tolerant quantum hardware is currently not feasible because of existing technological limitations. Third, even though the accuracy, transfer efficiency, and adaptation latency were enhanced, the computational complexity associated with hybrid quantum-classical optimization might become higher for extremely large-scale datasets and high-dimensional feature spaces. Finally, the research only considered supervised transfer learning but did not explore unsupervised and federated cross-domain learning approaches. These limitations provide opportunities for future research to validate the proposed framework on emerging quantum computing platforms, larger industrial datasets, and broader intelligent application domains.

4.8 Practical Implications

There are important practical implications of the suggested QTL-MTARA framework for the state-of-the-art intelligent systems that are required to perform efficient cross-domain learning and fast adaptation in real time. In the healthcare domain, the suggested framework is able to be applied to medical image analysis and clinical decision-support systems by providing effective knowledge transfer across heterogeneous medical datasets. In IoT-based systems, the suggested QTL-MTARA model is able to contribute to predictive maintenance, smart city monitoring, and industrial

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automation processes by rapidly adapting to continuously changing sensor data. The intrusion detection and anomaly detection systems could be significantly enhanced in cybersecurity due to the ability of the framework to learn from evolving network traffic patterns in real time while maintaining low adaptation latency. In addition, the hybrid quantum-classical architecture could serve as a scalable foundation for next-generation AI applications that require efficient multi-task learning across diverse domains. As quantum computing hardware continues to mature, the proposed framework has the potential to support industrial deployment in real-time intelligent systems where accuracy, adaptability, and computational efficiency are critical.

5. CONCLUSION

The problem statement of this study included the development of a scalable cross-domain transfer learning framework allowing for multi-task learning and real-time adaptation across heterogeneous datasets. This framework was developed using a hybrid quantum-classical architecture based on quantum neural networks, domain-invariant feature learning, and reinforcement learning-based adaptation within a unified framework. Experimental evaluation of the proposed approach revealed the following results: accuracy 94.8%, transfer efficiency 89.6%, and adaptation latency 95 ms, confirming the effectiveness of the proposed approach in improving generalization, reducing domain shift, and enabling efficient real-time learning across healthcare, IoT, and cybersecurity applications.

Although these were encouraging results, some shortcomings were witnessed. The use of quantum simulators raised the computational cost, and the performance was affected by the design and optimization of parameterized quantum circuits. Also, quantum hardware capable of operating at a large scale and with noise resistance is a limiting factor for practical implementation. The complexity of the model also posed interpretability and scaling difficulties for extremely large datasets.

Further applications will focus on the implementation of the framework on actual quantum hardware, the optimization of quantum circuit depth to minimize noise, and the implementation of federated learning mechanisms for privacy-preserving cross-domain applications. More research can also be done on how to use lightweight architectures to deploy the architecture to the edge and the extension of the model to other fields such as finance and autonomous systems, thus increasing the range of the architecture in real-time intelligent environments.

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