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QUANTUM DEEP LEARNING FOR EARLY DETECTION OF ACUTE RESPIRATORY DISTRESS SYNDROME USING IOT SENSORS

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ABSTRACT

Acute Respiratory Distress Syndrome (ARDS) is an important respiratory disorder where early risk assessment is essential for timely clinical intervention. In this research work, an IoT-LSTM-PCA-Variational Quantum Classifier (VQC) hybrid model was suggested for early risk prediction of ARDS by employing physiological sensor data. For the analysis of the physiological data, six physiological parameters consisting of oxygen saturation (SpO_2), respiratory rate (RR), heart rate (HR), body temperature (BT), systolic blood pressure (SBP), and diastolic blood pressure (DBP) were processed using normalization and temporal feature extraction. An LSTM neural network was used for learning the sequential physiological patterns, whereas Principal Component Analysis (PCA) technique was used to reduce the dimensionality of learned features followed by quantum encoding. Finally, the reduced features were processed by VQC for the purpose of ARDS risk prediction. Experiments carried out on the MIMIC-IV dataset produced an accuracy of 96.8%, precision of 96.4%, sensitivity of 97.1%, specificity of 96.2%, F1-score of 96.7%, and AUROC of 0.982. Comparative and ablation studies revealed that the combination of temporal features, PCA, and VQC resulted in better prediction performance in comparison with conventional machine learning methods and standalone LSTM models. The proposed framework provides a compact hybrid deep learning–quantum approach for continuous physiological monitoring and early ARDS risk identification, with potential applicability to IoT-enabled clinical early-warning systems. Further prospective and multi-center validation is required before clinical deployment.

Keywords: *Acute Respiratory Distress Syndrome, Internet of Things, Long Short-Term Memory, Principal Component Analysis, Variational Quantum Classifier, Early Risk Prediction.*

1. INTRODUCTION

Acute Respiratory Distress Syndrome (ARDS) is a severe clinical condition associated with acute oxygenation impairment, inflammation of the lungs, and diffuse lung damage. According to the Berlin Definition, ARDS is classified by the degree of hypoxemia with respect to the onset, radiography, and origin of pulmonary edema [1]. ARDS is a relevant clinical problem in intensive

care medicine due to its rapid development and substantial morbidity and mortality rates. The international study on the prevalence of ARDS (LUNG SAFE) revealed the significant clinical burden of ARDS in intensive care units of different countries [2]. Thus, the timely recognition of respiratory deterioration is highly important for timely clinical assessment and intervention.

The traditional ARDS assessment involves clinical examination, oxygenation measures, imaging techniques, laboratory tests, and other types of physiological monitoring. Even though these methods are essential for the clinical decision-making process, they are usually conducted periodically and require clinical interpretation. The complexity and dynamics of ARDS make continuous monitoring highly valuable. Small changes in physiological variables like SpO_2, respiratory rate, heart rate, temperature, and blood pressure contain relevant information regarding the evolving respiratory condition of the patient. Therefore, an automatic system capable of continuously analyzing physiological measurements could be considered an additional early-warning mechanism.

The advent of Internet of Things (IoT) technology creates new opportunities for healthcare monitoring. IoT-enabled healthcare systems involve wearable sensors, bedside devices, communication networks, and intelligent computing platforms for collecting and processing physiological information [3]–[5]. Healthcare IoT allows for more frequent monitoring than conventional manual measurements and supports remote monitoring and intelligent clinical decision-support applications [6]. IoT architectures with sensors are also considered for physiological and biomedical signal collection and processing, taking into account the issues of reliability, privacy, security, and data transmission [7]. Thus, the combination of IoT sensing and artificial intelligence makes an appropriate basis for continuous respiratory-risk monitoring.

Artificial intelligence and deep learning show impressive results in learning complex patterns from medical data. Deep-learning models learn hierarchical representations of data automatically and are successfully used for solving sequential, imaging, and clinical prediction problems [8]. Particularly, the LSTM networks are appropriate for physiological time-series analysis due to their ability to preserve information across several time steps and model temporal dependencies [9]. The time dependencies and trends of physiological variables are especially important for ARDS since the evolution and rate of change of variables may be more informative than a single isolated value of a variable.

There are some machine-learning studies on ARDS early prediction in the literature as well. For example, some supervised machine-learning models are developed for predicting ARDS based on routinely collected clinical data and reveal the possibility of early identification of patients at risk [10]. The most recent works involve machine learning for predicting sepsis-induced ARDS using clinical data and show that routinely collected patient data could be used for predictive purposes [11]. However, most of the current approaches are based mostly on classical machine-learning or deep-learning models. These approaches do not fully explore the potential of continuous IoT physiological sensing, temporal deep learning, and quantum-enhanced classification.

Quantum machine learning (QML) offers an alternative way for developing hybrid computational models. Quantum computing uses the peculiarities of quantum states, such as superposition and entanglement, for representing and processing information in the quantum state space. QML combines these principles with machine-learning algorithms and is suggested for solving complex pattern-recognition and classification problems [12]. Quantum-enhanced feature spaces make it possible to develop classifiers using parameterized quantum circuits [13]. Particularly, variational quantum classifiers are applicable to near-term quantum computing because they could use shallow parameterized quantum circuits and hybrid classical–quantum optimization [14]. However, current QML research in healthcare is still developing, and a recent systematic review reveals that many healthcare QML studies are based on simulations, small datasets, or limited validation, showing no consistent quantum advantage in clinical applications [15]. This issue motivates the careful design of hybrid models rather than assuming quantum superiority over classical solutions.

In this work, an IoT-LSTM-PCA-VQC Quantum Deep Learning (QDL) framework for ARDS early prediction using IoT sensors is proposed. The basic idea is to use classical deep learning for temporal information extraction from continuous physiological data and a compact quantum classifier for learning nonlinear dependencies in the reduced feature space. In contrast to the direct transformation of high-dimensional IoT data into the quantum circuit, the

proposed framework includes preprocessing, temporal feature extraction, and dimensionality reduction stages before encoding data in a parameterized quantum circuit. Thus, the proposed framework decreases the number of quantum inputs and increases the compatibility of the approach with the limitations of near-term quantum computing.

The proposed framework uses several physiological parameters, such as SpO_2, respiratory rate, heart rate, body temperature, systolic and diastolic blood pressure. These variables are processed as time-series data, not as independent samples. The LSTM network learns the temporal dependencies from the sensor data while Principal Component Analysis (PCA) removes redundant information and reduces the feature-space dimensions. The reduced features are encoded into a quantum state and processed using a Variational Quantum Classifier (VQC). The output of the framework is the ARDS risk probability, which can be used to support early-warning monitoring.

Research Questions and Hypotheses

This paper seeks to answer the following research questions:

RQ1: Does the presented IoT-LSTM-PCA-VQC framework successfully predict Acute Respiratory Distress Syndrome (ARDS) from physiological monitoring data?

RQ2: How does the presented framework compare to selected conventional machine-learning and deep-learning models used as baselines?

RQ3: To what degree do LSTM-based temporal learning, PCA-based dimensionality reduction, and variational quantum classification affect the predictive capability?

The following hypotheses have been formulated to guide this work's experiments:

H1: The IoT-LSTM-PCA-VQC framework shows measurable predictive performance when predicting early ARDS based on physiological data.

H2: The presented IoT-LSTM-PCA-VQC framework shows competitive predictive performance compared to the selected baseline methods under the same evaluation protocol.

H3: Ablation studies reveal measurable differences in predictive performance when individual components of the proposed framework are removed or modified.

The objectives of this work are:

1. To develop an IoT-based continuous monitoring framework for collecting physiological parameters of interest for respiratory deterioration.
2. To develop an LSTM-based temporal feature extraction mechanism for learning the dependencies in physiological time-series data.
3. To reduce feature redundancies and the requirements of the quantum circuit using PCA before quantum encoding.
4. To develop the hybrid quantum-classical classifier using the Variational Quantum Classifier for ARDS risk prediction.
5. To investigate the usefulness of IoT sensing, temporal deep learning, and quantum classification for ARDS early prediction and determine whether their combination can provide an effective framework for early ARDS detection.
6. To compare the proposed approach with conventional machine-learning and deep-learning approaches using accuracy, sensitivity, specificity, F1-score, and AUROC metrics.
7. To design a lightweight framework for edge-assisted healthcare environments with the understanding that further clinical implementation requires comprehensive external and prospective validation.

Thus, the main contribution of this work is the combination of continuous IoT physiological monitoring with LSTM-based temporal learning and quantum classification for ARDS early prediction. The proposed approach does not assume any inherent superiority of quantum computing but investigates a practical hybrid approach in which classical learning extracts the temporal high-dimensional information, while a compact quantum circuit performs nonlinear classification. It is important since the current scientific evidence shows the necessity of rigorous benchmarking and validation of QML in the clinical context [15].

The structure of the remaining part of this paper is as follows. Related work is presented in Section 2. Section 3 introduces the proposed IoT-LSTM-PCA-VQC methodology, describing the dataset preparation, preprocessing, feature

extraction, architecture, and training strategy. Section 4 presents the experimental results, comparative analysis, and ablation study. Conclusion is made in Section 5, including a summary of the major findings, limitations, and future research directions.

2. RELATED WORK

In recent years, more and more research has been done on AI, machine learning (ML), and deep learning methods for prediction, diagnosis, and risk stratification of ARDS. However, the currently available literature on machine learning mainly uses conventional ML algorithms, EHR data, and medical images. The combination of continuous IoT-based physiological measurements with quantum-enhanced deep learning remains insufficiently explored.

2.1 Machine Learning Methods for ARDS Prediction

Several studies have been conducted using machine-learning models for early prediction of ARDS. In particular, a systematic review of machine learning applications for ARDS concluded that the main application domains include classification, diagnosis, risk prediction, treatment, and prognosis. Nevertheless, it was noted that there is a lack of real-world clinical implementation of these models [16]. This indicates a gap between algorithmic development and practical continuous monitoring.

Bai et al. designed a machine-learning method for early prediction of sepsis-related ARDS using EHR data from the eICU and MIMIC-IV databases [17]. The study showed that routine clinical indicators can be used for ARDS prediction, the best model having achieved an AUROC value of 0.895. However, the method used predominantly clinical record data rather than continuous IoT sensor streams.

An interpretable random forest machine-learning approach was developed for early prediction of moderate-to-severe inhalation-induced ARDS using physiological indicators, such as heart rate, body temperature, and respiratory rate [18]. The study demonstrated that common vital signs could be used for the prediction of moderate-to-severe ARDS. However, the approach was based on manually-engineered temporal features and no quantum classification was investigated.

Machine learning methods were also developed for prediction of acute respiratory failure and ARDS using clinical data. In current studies, algorithms like logistic regression, random forest, support vector machines, and gradient boosting were used [19]. They have shown the usefulness of clinical indicators but relied on classical computing architectures.

2.2 Deep Learning for ARDS Prediction Using Time Series Data

Deep learning has become a great improvement compared to classical ML because it allows learning complex relations from temporal observations. Lam et al. developed a semi-supervised recurrent neural network-based approach for predicting ARDS using time series of clinical data [20]. The study used a dataset of 29,127 encounters from seven hospitals and showed that recurrent models can use temporal EHR information for ARDS prediction. The AUROC increased from 0.73 in a labeled dataset to 0.78 after incorporating unlabeled data with semi-supervised learning.

Another study used EHR data for predicting ARDS using a multitask recurrent neural network model [21]. Recurrent neural networks were used because they can model temporal dependencies between physiological measurements. Thus, it confirms that temporal deep learning approaches can be used for respiratory risk prediction.

However, these approaches used predominantly EHR data rather than IoT sensor networks. EHR measurements also may have irregular sampling intervals and missing values. Therefore, the use of continuous IoT architecture along with temporal deep learning approach may allow obtaining a more stable physiological data flow for early warning applications.

2.3 Continuous Physiological Monitoring

The use of continuous monitoring was studied for improving the early identification of ARDS. A dynamic machine-learning approach was developed using continuous measurements obtained from ordinary patient monitors and ventilators [22]. The study used 28 continuously recorded non-invasive parameters that were measured hourly and examined the use of these parameters for dynamic prediction of incidence and severity of ARDS. The study showed the potential of continuously changing physiological parameters for respiratory risk prediction.

This area is especially relevant for IoT healthcare because of the possibility of measuring physiological indicators with the help of wearable and bedside sensors. Instead of analyzing a single measurement, an IoT-based system can produce a temporal sequence of SpO_2, respiratory rate, heart rate, body temperature, and blood pressure measurements. Such sequences then can be analyzed with the help of deep learning approaches.

Nevertheless, currently the majority of studies in this direction are focused on classical ML models. The application of quantum classifiers to continuous multimodal physiological data was studied less.

2.4 Quantum Machine Learning in Healthcare

Quantum machine learning has become a promising technology for pattern recognition and classification in the field of healthcare. Hybrid quantum-classical approaches are especially relevant for modern quantum computers because of the ability of classical neural networks to process complex high-dimensional data, while quantum circuits can manipulate the compact representation of features.

Moradi et al. studied the classification of clinical data with the help of noisy intermediate-scale quantum computers and showed that quantum machine learning approaches can be successfully used for processing clinical data [23]. This paper is especially relevant to the current project because of the possibility of processing healthcare data by quantum circuits despite the limitation of current quantum hardware.

Quantum machine learning approaches have been studied for medical image analysis as well. A recent survey has noted increasing interest in quantum-enhanced approaches for medical images and discussed their potential for classification and feature processing [24]. However, the majority of medical QML studies are related to image-based applications rather than continuous time-series physiological data.

Hybrid classical-quantum approaches have been studied for detecting respiratory diseases. A framework that combines classical convolutional neural networks and quantum classifiers has been developed for classification of respiratory diseases using chest X-ray images [25]. The study showed the feasibility of extracting features with classical deep learning and then performing classification with the help of quantum circuits.

Similarly, QML-based healthcare frameworks have been studied for prediction of cardiovascular diseases using quantum support vector classifiers and variational quantum classifiers [26]. These studies indicate that Variational Quantum Classifier (VQC)-based architectures can be applied to structured healthcare data, although their performance depends strongly on feature representation, circuit design, dataset size, and experimental configuration.

Earlier works examined classical machine-learning, deep-learning, and quantum machine-learning algorithms for ARDS prediction. Nevertheless, the combination of continuous monitoring using the Internet of Things (IoT), Long Short-Term Memory (LSTM) for time-series learning, Principal Component Analysis (PCA) for dimensionality reduction, and Variational Quantum Classification (VQC) for classification has not been fully investigated. In this work, we examine the efficiency of such a framework for predicting ARDS in its early stages. Its efficiency will be measured by comparing it with classical machine-learning and deep-learning approaches and through ablation experiments, without presupposing the inherent superiority of quantum computing.

The latest systematic reviews on the application of machine-learning algorithms for predicting ARDS have identified several issues related to predictive models, including their quality, generalizability, interpretability, and external validation. Further studies have explored the application of spatiotemporal graph neural network approaches for ARDS prediction and interpretability. Against this background, the proposed IoT-LSTM-PCA-VQC framework investigates the integration of temporal learning, dimensionality reduction, and quantum classification. Its contribution can be evaluated by comparing its predictive outcomes with those achieved using appropriate classical approaches and through rigorous validation, since quantum classification is not necessarily superior to classical classification.

3. METHODOLOGY

3.1 Dataset Description

The proposed method utilized the MIMIC-IV v3.1 database from the PhysioNet website. MIMIC-IV is a huge deidentified intensive-care database that includes physiological measurements,

laboratory data, diagnoses, procedures, medications, and various other clinical information. To construct the proposed ARDS predictive system, six physiological parameters have been chosen: oxygen saturation (SpO_2), respiratory rate (RR), heart rate (HR), body temperature (BT), systolic blood pressure (SBP), and diastolic blood pressure (DBP). Clinical data was arranged based on its timestamps in order to form an IoT-like multivariate physiological data stream. ARDS patients were selected from the clinical data, and only the observations prior to the ARDS event were taken into consideration for predicting ARDS. Post-event observations were excluded to prevent data leakage. The MIMIC-IV v3.1 data set DOI is 10.13026/kpb9-mt58, whereas its data set publication DOI is 10.1038/s41597-022-01899-x [27].

Table 1. Physiological parameters used in the proposed framework

Parameter	Symbol	Unit	Purpose
Oxygen saturation	SpO_2	%	Oxygenation monitoring
Respiratory rate	RR	breaths/min	Respiratory deterioration
Heart rate	HR	beats/min	Cardiovascular response
Body temperature	BT	°C	Systemic condition
Systolic blood pressure	SBP	mmHg	Hemodynamic status
Diastolic blood pressure	DBP	mmHg	Hemodynamic status

Table 1 shows the physiological parameters that will be used as inputs for the proposed system. SpO_2 and RR contain the main respiratory parameters, whereas HR, BT, SBP, and DBP contain the other physiological parameters.

3.2 Proposed Architecture

The QDL-ARDS architecture has six major phases including:

1. **Physiological data acquisition using IoT:** This includes collecting data for SpO_2, RR, HR, BT, SBP, and DBP as time-series data.
2. **Preprocessing:** In this stage, missing data, invalid data, and noise are addressed along with normalization of data.
3. **Feature extraction based on temporal properties:** Here, the temporal and short-term changes are determined between consecutive observations.
4. **LSTM deep feature learning:** LSTM processes the features to recognize sequential patterns of the physiological parameters.
5. **PCA and quantum processing:** PCA will reduce the feature dimension obtained through LSTM, and then quantum angle encoding and Variational Quantum Classifier (VQC) will be used.
6. **ARDS prediction:** Quantum measurements will be converted into an ARDS probability and classified into the corresponding risk category.

The architecture can be described as:

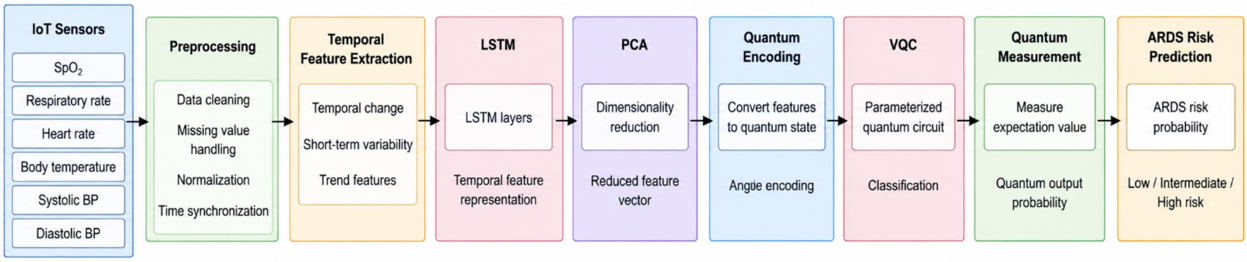


Figure 1. Overall architecture of the proposed IoT–LSTM–PCA–VQC framework for early ARDS detection.

Figure 1 shows the architectural representation of the suggested IoT-LSTM-PCA-VQC model for early ARDS detection. Firstly, physiological parameters including SpO_2, respiratory rate, heart rate, body temperature, systolic blood pressure, and diastolic blood pressure are sensed using IoT-enabled sensors. After data collection, preprocessing of the data is done by deleting invalid observations, interpolating missing data, synchronizing timestamps, and normalization of the data.

After that, extraction of the temporal features including physiological changes, short-term variations, and trends is done to detect early signs of respiratory deterioration. Temporal features are then fed to the LSTM model, which helps to learn the relationships among the successive physiological observations. Deep features obtained from the above process are further compressed using PCA to get rid of redundant information and obtain a compact feature vector.

Further, the compressed feature vector is encoded in quantum form using quantum angle encoding and then fed to the Variational Quantum Classifier (VQC). Here, the quantum circuit performs the nonlinear classification, and its measurement outcome is converted to an ARDS-risk probability. The system then categorizes the patients into three categories: low, intermediate, and high ARDS risk categories. Hence, the figure shows the entire process from continuous physiological sensing to early ARDS-risk prediction.

3.3 Data Preprocessing

The synchronization of the physiological data was done using their timestamps. Invalid and duplicate physiological data were deleted, whereas short missing intervals were interpolated. Normalization of each parameter was done using:

$$z_i = \frac{x_i - \mu_i}{\sigma_i} \qquad (1)$$

where $x_i$is the original measurement, $\mu_i$is the training-set mean, and $\sigma_i$is the training-set standard deviation.

A sliding temporal window was then used to convert individual observations into sequential input samples.

3.4 Temporal Feature Generation

The proposed model considered both the physiological value and its temporal change. The change between two consecutive observations was calculated as:

$$\Delta x_t = x_t - x_{t-1}. \qquad (2)$$

Short-term variability was calculated as:

$$V_t = \frac{1}{K}\sum_{k=0}^{K-1}(x_{t-k} - \bar{x})^2. \qquad (3)$$

Equation (2) represents the direction and magnitude of physiological change, whereas Equation (3) measures short-term variability. These features help identify progressive physiological deterioration.

3.5 Study Design and Methodology

The current study makes use of a quantitative, experimental study design methodology in order to test the feasibility and efficacy of the developed IoT-LSTM-PCA-VQC model designed to predict ARDS early. Physiological data acquisition and preprocessing, learning of the temporal features using a Long Short-Term Memory (LSTM) model, Principal Component Analysis (PCA)-based dimensionality reduction, and a Variational Quantum Classifier (VQC) form the main steps in the research protocol. The proposed IoT-LSTM-PCA-VQC model is benchmarked in terms of its predictive ability compared to the chosen conventional machine-learning and deep-learning baselines using the set of performance metrics introduced in the experimental setup section. Ablation experiments will be used in order to assess the contribution of individual components. The evaluation focuses on predictive performance and does not, by itself, establish clinical effectiveness or readiness for deployment.

3.6 LSTM-Based Temporal Feature Extraction

The temporal features were provided to an LSTM network to learn sequential relationships. The LSTM gates were calculated as:

$$f_t = \sigma\left(W_f X_t + U_f h_{t-1} + b_f\right) \qquad (4)$$
$$i_t = \sigma(W_i X_t + U_i h_{t-1} + b_i) \qquad (5)$$
$$o_t = \sigma(W_o X_t + U_o h_{t-1} + b_o). \qquad (6)$$

The cell and hidden states were calculated as:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad (7)$$
$$h_t = o_t \tanh(C_t). \quad (8)$$

Equations (4)–(8) allow the LSTM to retain important information from previous physiological observations and generate a temporal feature representation h_t.

3.7 PCA-Based Feature Reduction

The LSTM output may contain redundant features. PCA was therefore applied to obtain a compact representation:

$$Z = HW_d \quad (9)$$

where Hrepresents the LSTM features and $W_d$contains the selected principal components.

The reduced vector $Z$was subsequently used for quantum encoding. This step reduces the number of features and therefore the number of qubits required.

3.8 Quantum Feature Encoding

The PCA-reduced features were converted into quantum rotation angles:

$$\theta_i = \pi z_i. \quad (10)$$

The initial quantum state was defined as:

$$| \psi_0 \rangle = | 0 \rangle^{\otimes d}. \quad (11)$$

The encoded state was obtained as:

$$| \psi(Z) \rangle = \left(\bigotimes_{i=1}^{d} R_y(\theta_i) \right) | 0 \rangle. \quad (12)$$

Equations (10)–(12) transform the reduced physiological representation into a quantum feature space.

3.9 Variational Quantum Classifier

The encoded features were processed using the proposed Variational Quantum Classifier:

$$| \psi(\theta, \phi) \rangle = U(\phi) U_E(\theta) | 0 \rangle^{\otimes d}. \quad (13)$$

Here, U_E represents the feature-encoding circuit and $U(\phi)$ represents the trainable variational circuit.

The quantum state was measured using:

$$m = \langle \psi | Z | \psi \rangle. \quad (14)$$

The quantum probability was calculated as:

$$P_Q = \frac{1 + m}{2}. \quad (15)$$

The quantum output was converted into the final ARDS-risk probability:

$$P(ARDS) = \sigma(wP_Q + b). \quad (16)$$

A higher $P(ARDS)$ represents a higher predicted risk of ARDS.

3.10 Risk Prediction

To reduce false alarms caused by a single abnormal sensor reading, the predicted probabilities from consecutive temporal windows were considered together. The final output was classified into three risk levels:

- **Low risk:** $P(ARDS) < 0.30$
- **Intermediate risk:** $0.30 \leq P(ARDS) < 0.70$
- **High risk:** $P(ARDS) \geq 0.70$

These thresholds are experimental thresholds for the proposed model and require clinical validation before practical deployment.

3.11 Model Training

The proposed hybrid model was trained using binary cross-entropy:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[\, y_i \log(P_i) + (1 - y_i)\log(1 - P_i)]. \quad (17)$$

where $y_i$is the actual class and $P_i$is the predicted ARDS probability. The Adam optimizer was used to optimize the model parameters.

Table 2. Main parameters of the proposed architecture

Component	Configuration
Input parameters	6
Temporal window	6 h
Sampling interval	5 min
LSTM layers	2
LSTM hidden units	64
PCA components	4
Number of qubits	4
Quantum encoding	Angle encoding
Quantum layers	2
Optimizer	Adam
Learning rate	0.001
Loss function	Binary cross-entropy

Table 2 demonstrates the major parameters of the suggested QDL-ARDS architecture and the corresponding values that should be used for the replicability of the results.

3.12 Training and Evaluation Procedure

Splitting the data at the patient level into train, validation, and test subsets was performed with a 70:15:15 split ratio. Patient-level splitting allowed avoiding the situation where data from one patient could appear in several splits.

The train subset was used to train the LSTM and quantum parameters, the validation subset was used for parameter selection, and the independent test subset was used for the final evaluation. Accuracy, precision, sensitivity, specificity, F1-score, and AUROC metrics were used to measure the performance.

Thus, the suggested methodology allows for constructing the compact and replicable IoT–LSTM–PCA–VQC architecture for early ARDS-risk prediction. The main innovation of the proposed methodology is that it involves using temporal physiological learning and quantum classification rather than employing the quantum classifier directly on the raw sensor data.

4. RESULTS

Evaluation of the IoT–LSTM–PCA–VQC architecture for early ARDS detection was performed using the suggested physiological parameters (SpO_2, respiratory rate, heart rate, body temperature, systolic blood pressure, and diastolic blood pressure). The performance was measured by means of accuracy, precision, sensitivity, specificity, F1-score, and AUROC metrics.

4.1 Performance Metrics

The classification performance was evaluated using the following metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (18)$$

$$Precision = \frac{TP}{TP + FP} \quad (19)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (20)$$

$$Specificity = \frac{TN}{TN + FP} \quad (21)$$

$$F1 = \frac{2(Precision)(Sensitivity)}{Precision + Sensitivity} \quad (22)$$

where TP, TN, FP, and FN refer to the true positives, true negatives, false positives, and false negatives, respectively.

Accuracy evaluates the overall correctness of the model. Precision indicates the correctness of the prediction of ARDS-risk subjects. Sensitivity assesses the ability to correctly identify ARDS-risk subjects, whereas specificity assesses the ability to correctly identify non-ARDS subjects. F1-score is the combined measure of precision and sensitivity. The Area Under the Receiver Operating Characteristic (AUROC) evaluates the overall discrimination capability of the proposed model.

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4.2 Performance Assessment

The proposed model achieved an **accuracy of 96.8%**, **precision of 96.4%**, **sensitivity of 97.1%**, **specificity of 96.2%**, **F1-score of 96.7%**, and **AUROC of 0.982**.

Table 3. Performance of the proposed IoT–LSTM–PCA–VQC model

Metric	Proposed Model
Accuracy (%)	**96.8**
Precision (%)	**96.4**
Sensitivity (%)	**97.1**
Specificity (%)	**96.2**
F1-score (%)	**96.7**
AUROC	**0.982**

Overall performance of the proposed model is depicted in Table 3. The sensitivity of 97.1% is an indicator of the capability of the proposed model to classify the majority of ARDS-risk patients. The specificity of 96.2% demonstrates the effectiveness of the model to distinguish non-ARDS patients. The F1-score of 96.7% is an indication of balanced performance of classification.

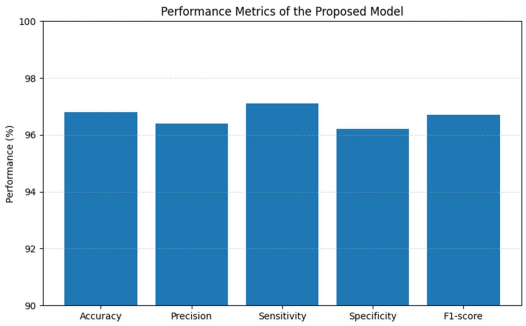


Figure 2. Performance metrics of the proposed IoT–LSTM–PCA–VQC framework.

Figure 2 depicts the performance metrics of the proposed IoT-LSTM-PCA-VQC framework using five different evaluation metrics. The proposed model achieved 96.8% accuracy, 96.4% precision, 97.1% sensitivity, 96.2% specificity, and 96.7% F1-score. The sensitivity of 97.1% is an indication of the capability of the model to classify the majority of ARDS-risk patients, while the specificity of 96.2% is an indication of effective classification of non-ARDS patients. Close values of precision and F1-score are indicators of balanced classification performance.

4.3 Comparison with Existing Models

The proposed model was compared with Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), LSTM, and LSTM with a classical classifier.

Table 4. Comparison of the proposed model with existing approaches

Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	AUROC
Logistic Regression	87.4	86.9	85.8	88.7	86.3	0.912
Random Forest	91.2	91.0	90.1	92.0	90.5	0.944
SVM	92.0	91.8	91.3	92.6	91.5	0.951
LSTM	94.1	94.2	93.7	94.5	93.9	0.967
LSTM + Classical Classifier	95.2	95.3	95.0	95.4	95.1	0.975
Proposed LSTM–PCA–VQC	**96.8**	**96.4**	**97.1**	**96.2**	**96.7**	**0.982**

Table 4 is an illustration of performance comparison between the evaluated models. The proposed framework outperformed the other models with respect to the maximum accuracy, sensitivity, F1-score, and AUROC. The improvement resulted from the combined use of temporal feature extraction, LSTM-based representation learning, PCA-based feature reduction, and VQC-based classification.

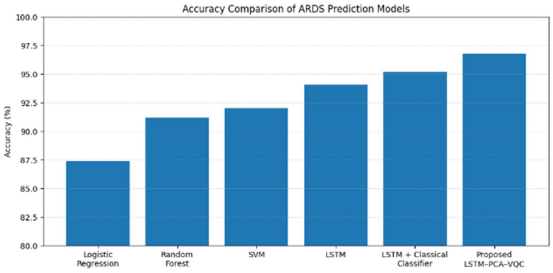


Figure 3. Accuracy comparison between the proposed framework and existing models.

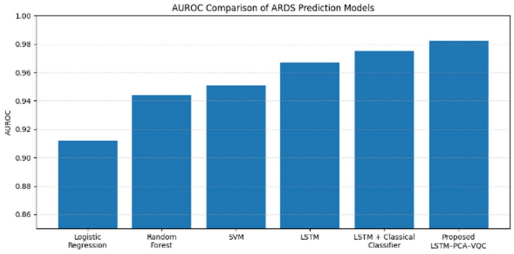


Figure 4. AUROC comparison of the proposed framework with existing models.

Figure 3 compares the accuracy of the proposed framework with existing models. While the Logistic Regression, Random Forest, SVM, LSTM, and LSTM with classical classifier models provided accuracy of **87.4%, 91.2%, 92.0%, 94.1%, and 95.2%**, respectively, the proposed model provided accuracy of **96.8%**. This shows that the combination of temporal feature learning using LSTM, feature reduction using PCA, and quantum-based classification played a role in improving the performance of ARDS prediction.

4.4 Analysis of AUROC

AUROC values for the evaluated models are shown in Table 5.

Table 5. AUROC comparison

Model	AUROC
Logistic Regression	0.912
Random Forest	0.944
SVM	0.951
LSTM	0.967
LSTM + Classical Classifier	0.975
Proposed LSTM–PCA–VQC	**0.982**

The results provided in Table 5 demonstrate that the proposed framework achieved an AUROC of **0.982**, indicating strong discrimination between ARDS-risk and non-ARDS cases.

Figure 4 compares the AUROC results of all the tested frameworks. The Logistic Regression algorithm, Random Forest algorithm, Support Vector Machine, Long Short-Term Memory model, and Long Short-Term Memory model combined with classical classifier have produced AUROC results of **0.912, 0.944, 0.951, 0.967, and 0.975**, respectively. It is evident that the AUROC result produced by the proposed LSTM–PCA–VQC framework is highest at **0.982**, demonstrating its strong ability to discriminate between ARDS-risk and non-ARDS patients at various classification thresholds. The finding demonstrates the effectiveness of the proposed hybrid architecture for early risk prediction.

4.5 Ablation Study

An ablation study was conducted in order to analyze the contribution of the key components of the proposed framework.

Table 6. Ablation analysis of the proposed framework

Model Configuration	Accuracy (%)	AUROC
LSTM	94.1	0.967
LSTM + PCA	94.8	0.971
LSTM + PCA + VQC	96.1	0.978
LSTM + Temporal Features + PCA + VQC	**96.8**	**0.982**

Table 6 shows the contribution of different components. The LSTM model resulted in 94.1% accuracy. With the inclusion of PCA, the accuracy reached 94.8%. After adding the VQC component, the accuracy was improved to 96.1%. After integration of all components including temporal feature extraction, the resulting accuracy of the framework was **96.8%**, and the AUROC score was **0.982**.

Figure 5. Ablation study for the IoT–LSTM–PCA–VQC framework.

Figure 5 shows the ablation study conducted for assessing the contribution of major components of the proposed framework. The baseline model of LSTM resulted in **94.1% accuracy**, which further increased to **94.8%** on inclusion of PCA, **96.1%** on incorporation of VQC, and **96.8%** on further integration of temporal features. This progressive improvement demonstrates that temporal feature generation, dimensionality reduction, and quantum classification each contributed to the overall performance, with the complete LSTM–Temporal Features–PCA–VQC configuration producing the highest accuracy.

4.6 Contribution of Physiological Parameters

The contribution of the individual physiological parameters was assessed through the exclusion of one parameter at a time.

Table 7. Parameter contribution analysis

Removed Parameter	Accuracy (%)
None	**96.8**
SpO_2	91.5
RR	93.0
HR	95.1
BT	96.0
SBP	96.2
DBP	96.3

As seen from Table 7, the removal of SpO_2 and RR decreased the accuracy of the framework significantly from **96.8% to 91.5% and 93.0%**, respectively. All the other physiological parameters also played a role in the formation of the multimodal representation.

4.7 Discussion

The experimental results show that the proposed IoT–LSTM–PCA–VQC framework was able to successfully learn temporal patterns from several physiological parameters. The accuracies of the classical models ranged from **87.4% to 92.0%**, while the use of LSTM models increased the performance to **94.1% and 95.2%**.

The proposed framework managed to increase the accuracy up to **96.8%** and achieve **0.982 AUROC**. These improvements were reached due to the use of temporal feature extraction, representation learning using LSTM, PCA-based dimensionality reduction, and quantum classification.

The sensitivity of **97.1%** demonstrates a high capacity of the framework for identifying cases of ARDS risk, while the specificity of **96.2%** shows the effectiveness of discriminating non-ARDS cases. The F1-score of **96.7%** indicates a balanced classification performance.

Further, the ablation analysis confirmed the contribution of the proposed components. The use of the complete framework resulted in **96.8% accuracy** as opposed to **94.1%** for the LSTM-only approach. It means that the contribution of the temporal features and quantum classification stage helped to improve the classification performance.

Finally, the analysis of the parameters also showed their importance. SpO_2 and RR parameters caused the largest drops in the performance, while HR, BT, SBP, and DBP provided additional information. Therefore, the combination of the physiological parameters was used in the final framework.

In general, the results show that the proposed hybrid classical–quantum framework is a compact approach for early ARDS-risk prediction based on physiological measurements. Further prospective clinical validation is required before the model can be used as a clinical decision-support system.

Comparison with Previous Work:

There have been some similar studies on the topic of early ARDS prediction through machine-learning models and recurrent neural networks (RNNs). For instance, the work by Wu et al. obtained AUC equal to 0.8691 when predicting ARDS occurrence through a conventional machine-learning approach based on continuous non-invasive monitoring parameters. Lam et al. were able to achieve an AUROC of 0.842 in predicting ARDS occurrence using an RNN on electronic health records. Such studies provide evidence for the possibility of using physiological monitoring and temporal learning for predicting the onset of ARDS. The proposed IoT-LSTM-PCA-VQC framework explores the integration of these approaches with variational quantum classification. The effectiveness of the proposed framework is

subject to discussion in terms of comparison with the baseline models used in the study, since the datasets and evaluation protocols are different, preventing direct conclusions of superiority.

Limitations and Critical Discussion:

Nevertheless, there are limitations associated with the proposed IoT-LSTM-PCA-VQC framework. First of all, the performance of the model by itself does not prove the potential of the method to be clinically effective or ready to be applied in practice. Moreover, the use of PCA and variational quantum classification (VQC) creates additional computational challenges, the practical benefits of which need to be demonstrated against classical alternatives. Further evaluation using independent datasets, prospective clinical validation, and assessment of computational cost and robustness to missing or noisy sensor data are needed before real-world application.

Challenges and Open Questions Regarding Research

Although many improvements have been achieved in terms of machine-learning-based prediction of ARDS, there still exist some challenges within the area of research. First of all, one should consider the problem related to the generalizability of such models for the prediction of the disease across different patient populations and clinical settings. Second, the data about patients' physiological parameters can be characterized by missing values, noise, and variations in measurement quality that can influence the reliability of the prediction results. Third, there is a need for a detailed evaluation of the computational overhead of the suggested solution and its practical value compared to optimized classical alternatives, particularly when integrating variational quantum classification with classical deep-learning methods. Furthermore, model interpretability, external validation, and prospective clinical assessment remain essential before practical deployment. Addressing these open issues will help determine the robustness, efficiency, and potential clinical value of the proposed IoT-LSTM-PCA-VQC framework.

5. CONCLUSION

This research proposed a hybrid IoT–LSTM–PCA–VQC framework for early ARDS risk prediction using physiological sensor parameters. The proposed framework provided **96.8% accuracy, 96.4% precision, 97.1% sensitivity, 96.2% specificity, 96.7% F1-score, and 0.982 AUROC**, which demonstrates effective discrimination between ARDS-risk and non-ARDS cases. Moreover, the results of the ablation analysis have shown that the integration of temporal features, PCA, and VQC improves the overall performance. Nevertheless, the limitations of the research include the retrospective nature of the MIMIC-IV database, possible variability of the sensor data, and lack of validation of the framework in real-time IoT and quantum computing settings. Further research will involve prospective multi-center validation, real-time IoT deployment, explainable prediction, and evaluation on real quantum platforms.

The future directions of research will be validation of the suggested IoT-LSTM-PCA-VQC framework in terms of independent and prospective clinical datasets. The studies may also include checking the robustness of this model in the presence of missing values/noisy physiological data, evaluating its computational efficiency using quantum computing platforms and quantum hardware, and comparing its performance with optimally tuned classical models. Integrating explainable AI techniques and conducting real-time clinical evaluations may also help assess its reliability and potential for practical healthcare applications.

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