

Quantum –Driven Insights: A Medical Expert System for Insomnia Prediction Secured by Quantum Cryptography

Ayshwarya P^{1*}, K. Sujith²

¹ Department of Computer Science, Annai College of Arts & Science, Kumbakonam, India

² Department of Computer Science, Bharathidasan University, India

*Corresponding author: ayshwaryapcs@gmail.com

doi: <https://doi.org/10.21467/proceedings.173.15>

ABSTRACT

Quantum computing is protected by quantum cryptography, it offers a novel medical expert system for predicting sleeplessness. In order to increase predicted accuracy and address the substantial negative effects of insomnia on health, it uses sophisticated quantum machine learning algorithms to evaluate a variety of patient data, including lifestyle, psychological profiles, and sleep habits. It highlights how the system outperforms conventional techniques in terms of accuracy and efficiency, enabling the early identification of at-risk patients and facilitating individualized treatment plans. Future developments in medical diagnostics and individualized care are made possible by the research, which highlights the revolutionary potential of quantum technology in the treatment of insomnia and other healthcare applications.

Keywords: Insomnia, quantum computing, machine learning

1 Introduction

Insomnia, a widespread and debilitating sleep disorder, has emerged as a significant public health challenge due to its profound impact on physical health, cognitive performance, and emotional well-being. Early detection and management are critical in mitigating its long-term effects [1, 2]. However, traditional predictive approaches often struggle to process the intricate and multifaceted datasets required for accurate insomnia diagnosis and forecasting. This gap underscores the need for innovative, high-performance solutions capable of delivering precise predictions while safeguarding sensitive patient information. This paper introduces a novel approach—Quantum-Driven Insights: A Medical Expert System for Insomnia Prediction Secured by Quantum Cryptography [3]. At the heart of this system lies the transformative power of quantum computing, which enhances the efficiency and accuracy of analysing complex medical datasets. By leveraging quantum-driven algorithms, the system identifies subtle patterns and relationships within patient data, enabling reliable insomnia prediction. To address the paramount concern of data security in healthcare, the system incorporates quantum cryptography, a state-of-the-art technology that provides unparalleled security for data transmission and storage. By combining the predictive capabilities of quantum computing with the robust security framework of quantum cryptography, this expert system represents a ground-breaking fusion of technology and healthcare [4-6].

2 Quantum Algorithm for Insomnia Prediction

Algorithm: Insomnia Prediction Using Quantum Machine Learning & Quantum Cryptography Input

$D = \{d_1, d_2, \dots, d_n\}$ $D = \{d_1, d_2, \dots, d_n\}$: patterns, lifestyle factors, psychological profiles, medical history.



Output

Insomnia Risk Prediction PriskP_{risk}Prisk

Personalized Treatment Recommendations

Step 1: Data Collection and Reprocessing

Collect patient data DDD (sleep, lifestyle, psychological factors).

Normalize the data to ensure uniformity.

Handle missing or inconsistent data via imputation.

Perform feature selection to reduce dimensionality.

$D = \text{select_features}(D)$
 $D' = \text{select_features}(D)$

Step 2: Quantum Data Encoding

Encode the preprocessed patient data D' into quantum states.

$Q = \text{encode_to_quantum}(D')$

$Q = \text{encode_to_quantum}(D')$

Use amplitude encoding or other quantum encoding techniques.

Step 3: Quantum Model Selection

Select the appropriate quantum machine learning model:

If binary classification, use Quantum Support Vector Machine (QSVM).

For complex personalized analysis, use Quantum Neural Network (QNN).

Step 4: Model Training

1. Build quantum circuits to represent the problem.

$C = \text{construct_quantum_circuit}(Q)$

2. Train the model using quantum optimization algorithms Variational Quantum Eigensolver

$M = \text{train_quantum_model}(C, \text{training_data})$

$M = \text{train_quantum_model}(C, \text{training_data})$

Step 5: Insomnia Risk Prediction

For new patients, encode their data into quantum states.

$Q_{new} = \text{encode_to_quantum}(D_{new})$

Input the encoded data into the trained model to predict insomnia risk.

$P_{risk} = \text{predict_insomnia}(M, Q_{new})$

$P_{risk} = \text{predict_insomnia}(M, Q_{new})$

Classify the risk based on a predefined threshold:

$M = \text{If } P_{risk} > \text{threshold}_{risk} \rightarrow \text{classify as high-risk; otherwise, low-risk.}$

Step 6: Personalized Treatment Recommendations

For high-risk patients, analyze the data to determine factors influencing insomnia.

$F_{key} = \text{analyze_factors}(D_{new})$

Generate treatment recommendations based on key factors.

$T = \text{generate_treatment}(F_{key})$

$T = \text{generate_treatment}(F_{key})$

Step 7: Security via Quantum Cryptography

Secure communication between the system and patients using Quantum Key Distribution

$(QKD). \text{secure_communication}(QKD)$

$(QKD). \text{secure_communication}(QKD)$

Encrypt sensitive patient data with quantum-resistant encryption.

$\text{Encrypt}(D_{new})$

Step 8: Model Evaluation and Continuous Learning

Evaluate model performance (accuracy, precision, recall, F1-score).

$\text{evaluate}(M, \text{test_data})$

2.1 Quantum-Driven Insomnia Treatment System

Input Layer:

Box: Patient Data $D = \{d_1, d_2, \dots, d_n\}$ Sleep Patterns

Lifestyle Factors

Psychological Profiles

Medical History

Step 1: Data Collection and Preprocessing:

· Process Flow:

Collect Data → **Normalize Data** → **Handle Missing Data (Imputation)** → **Feature Selection**

$D' = \text{select_features}(D)$

Step 2: Quantum Data Encoding:

· Box: **Encode Data into Quantum States**

Update Model $M = \text{update_model}(M, D_{\text{new}})$
 $= \text{update_model}(M, D_{\text{new}})$

Techniques: Amplitude Encoding

Step 3: Quantum Model Selection:

· Decision Point:

Binary Classification

▪ **Yes** → Quantum Support Vector Machine (QSVM)

▪ **No** → Quantum Neural Network (QNN)

· Output: **Selected Model MMM**

Step 4: Model Training:

Process Flow:

Build Quantum Circuit

$C = \text{construct_quantum_circuit}(Q)$

$\text{\text{construct_quantum_circuit}}(Q) \rightarrow C = \text{construct_quantum_circuit}(Q) \rightarrow$

Train Model $M = \text{train_quantum_model}(C, \text{training_data})$

$\text{\text{train_quantum_model}}(C,$

$\text{\text{training_data}}) M = \text{train_quantum_model}(C, \text{training_data})$

Train Model $M = \text{train_quantum_model}(C, \text{training_data})$

$M = \text{\text{train_quantum_model}}(C,$

$\text{\text{training_data}}) M = \text{train_quantum_model}(C, \text{training_data})$

$M = \text{\text{train_quantum_model}}(C,$

$\text{\text{training_data}}) M = \text{train_quantum_model}(C, \text{training_data})$

Step 5: Insomnia Risk Prediction:

· Process Flow:

Encode New Patient Data $Q_{\text{new}} = \text{encode_to_quantum}(D_{\text{new}}) Q_{\text{\text{new}}}$
 $\text{\text{encode_to_quantum}}(D_{\text{\text{new}}}) Q_{\text{new}} = \text{encode_to_quantum}(D_{\text{new}}) \rightarrow$

Predict Risk $P_{\text{risk}} = \text{predict_insomnia}(M, Q_{\text{new}}) P_{\text{\text{risk}}} = \text{\text{predict_insomnia}}(M, Q_{\text{\text{new}}})$
 $P_{\text{risk}} = \text{predict_insomnia}(M, Q_{\text{new}})$

Decision Point: $P_{\text{risk}} > \text{threshold} ? P_{\text{\text{risk}}} > \text{threshold} ? P_{\text{risk}} > \text{threshold} \cdot \text{Yes} \rightarrow \text{High-Risk}$

No $\rightarrow \text{Low-Risk}$

Step 7: Security via Quantum Cryptography:

Box: Secure Communication

Quantum Key Distribution (QKD)

Encrypt Data $\text{encrypt}(D_{\text{new}}) \text{\text{encrypt}}(D_{\text{\text{new}}}) \text{encrypt}(D_{\text{new}})$

Step 8: Model Evaluation and Continuous Learning

Process Flow:

Evaluate Model $\text{evaluate}(M, \text{test_data}) \text{\text{evaluate}}(M,$

$\text{\text{test_data}}) \text{evaluate}(M, \text{test_data})$

Table 1: *Algorithm Table*

Component	Technology/Algorithm	Purpose	Details
Data Collection & Preprocessing	Classical Data Processing	Collect and prepare patient data for analysis.	Includes demographic, sleep, lifestyle, and psychological data normalization and encoding.
Feature Selection	Quantum Principal Component Analysis (QPCA)	Dimensionality reduction to focus on key predictive features.	Identifies significant features from high dimensional datasets.
Prediction Model	Quantum Support Vector Machine (QSVM)	Classify patient data into "insomnia" or "non-insomnia" categories.	Uses quantum feature mapping and kernel methods to improve prediction accuracy.
	Quantum Neural Network (QNN)	Handle complex nonlinear relationships in the data.	Quantum circuits simulate neural network behavior for enhanced predictive modeling.
	Variational Quantum Classifier (VQC)	Hybrid quantum classical classification of patient data.	Parameterized quantum circuits optimize predictions.
Optimization	Hybrid Quantum Classical Algorithms	Optimize model parameters for maximum accuracy and efficiency.	Combines quantum evaluation (e.g., QAOA) with classical refinement (e.g., gradient descent).
	Quantum Annealing	Optimize hyperparameters and find global minima in cost functions.	Suitable for improving predictive performance.
Data Security	BB84 Protocol	Secure generation and sharing of encryption keys.	Ensures data confidentiality by detecting eavesdropping during key distribution.
	E91 Protocol	Entanglement-based quantum cryptography for enhanced security.	Protects sensitive patient data using entangled quantum states.
Workflow Integration	Hybrid Quantum Classical Workflow	Coordinate quantum prediction and cryptographic operations.	Ensures seamless interaction between prediction models and secure communication protocols.

3 Implementation & Results

The proposed medical expert system for predicting insomnia was implemented using a hybrid classical-quantum computational architecture. This design leverages the unique capabilities of

quantum computing to process large and complex datasets efficiently, while classical systems handle tasks requiring lower computational overhead.

3.1 Results

To evaluate the system's performance, a dataset comprising 10,000 anonymized patient records was used. The dataset was split into training (80%) and testing (20%) subsets.

Table 2: Performance Comparison of the Proposed Quantum System

Metric	Metric	Metric	Metric
Accuracy	Accuracy	Accuracy	Accuracy
Precision	Precision	Precision	Precision
Recall	Recall	Recall	Recall
F1 Score	F1 Score	F1 Score	F1 Score
Computation Time*	Computation Time*	Computation Time*	Computation Time*

4 Conclusions

The use of quantum machine learning algorithms significantly improves the accuracy and efficiency of predicting insomnia by processing complex and multidimensional patient data, outperforming traditional methods. The integration of quantum cryptography ensures the secure handling of sensitive patient data, a critical aspect in modern healthcare systems. The system's ability to identify individuals at risk of insomnia earlier facilitates timely interventions and the design of personalized treatment strategies, improving patient outcomes. Applicability of quantum technologies, paving the way for advancements in other areas of medical diagnostics and personalized care.

5 Declarations

5.1 Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5.2 Acknowledgements

The author thanks The Gandhigram Rural Institute- Deemed to be University, Gandhigram for supporting this work.

References

- [1] Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., & Lloyd, S. (2017). Quantum machine learning. *Nature*, 549(7671), 195-202.
- [2] Rebentrost, P., Mohseni, M., & Lloyd, S. (2014). Quantum support vector machine for big data classification. *Physical review letters*, 113(13), 130503.
- [3] Wiebe, N., Kapoor, A., & Svore, K. M. (2015). Quantum nearest-neighbor algorithms for machine learning. *Quantum information and computation*, 15 (3-4), 318-358, <https://doi.org/10.48550/arXiv.1401.2142>.
- [4] Matondo-Mvula, N., & Elleithy, K. (2023, September). Advances in Quantum Medical Image Analysis Using Machine Learning: Current Status and Future Directions. In *2023 IEEE International Conference on Quantum Computing and Engineering (QCE)* (Vol. 1, pp. 367-377). IEEE, doi: 10.1109/QCE57702.2023.00049.
- [5] Moll, N., Barkoutsos, P., Bishop, L. S., Chow, J. M., Cross, A., Egger, D. J.... & Temme, K. (2018). Quantum optimization using variational algorithms on near-term quantum devices. *Quantum Science and Technology*, 3(3), 030503, DOI: 10.1088/2058-9565/aab822.
- [6] Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., et. al., C. S. (2018). Opportunities and obstacles for deep learning in biology and medicine. *Journal of the royal society interface*, 15(141), 20170387.
- [7] Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*, 521(7553), 452-459, <https://doi.org/10.1038/nature14541>.