Qure

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1 Introduction

1.1 Overview

This project aimed to develop a non-invasive system for early cancer detection by analyzing the body's electrical properties using Quantum Machine Learning (QML). Inspired by the idea that the body emits measurable signals that can reveal early signs of disease, the system processes bioelectrical impedance data and compares it to healthy profiles using QML. The goal was to create a smart, accessible health monitoring tool that empowers individuals to take early action and supports the UN's Sustainable Development Goal 3: Good Health and Well-Being.

1.2 Objectives

- Use bioelectrical impedance to measure resistance and detect abnormal tissue properties.
- Provide users with an early warning system that recommends medical follow-up if needed.
- Offer a low-cost, non-invasive solution to improve early diagnosis, especially in underserved communities.

2 Scientific Background

2.1 Bioelectrical Impedance Analysis (BIA)

2.1.1 What is BIA?

Bioelectrical Impedance Analysis (BIA) measures the resistance (R) and reactance (Xc) of the body to a small electrical current. These measurements are influenced by the body's composition-specifically, the amount of water, fat, muscle, and tissue resistance.

2.1.2 How BIA works

When a small, safe electrical current is passed through the body, different tissues offer varying degrees of resistance. Fat tissue, for example, is a poor conductor, while muscle and water-rich tissues are better conductors. By measuring how much current is resisted and how much reactance occurs, we can infer body composition.

2.2 BIA in Cancer Detection

2.2.1 Cancerous tissue properties

Cancerous tissues often exhibit altered physical properties compared to healthy tissues. These changes include differences in water content, cellular structure, and blood flow. Tumor cells tend to have lower resistance because they are more hydrated and have a different cellular makeup.

2.2.2 Altered impedance in cancerous tissues

Since cancerous tissues are generally more conductive (lower resistance) than normal tissues, they show distinct impedance values. These deviations in resistance and reactance can serve as a marker for the presence of abnormal tissue, which is why BIA can be used as a non-invasive tool for detecting early signs of cancer.

2.3 Measuring and Interpreting Impedance Data

2.3.1 Impedance measurement

BIA measures the body's impedance (Z) using two main parameters: resistance (R) and reactance (Xc). The total impedance (Z) is calculated using the formula:

$$Z = \sqrt{R^2 + X_c^2} \tag{1}$$

where R is the resistance and Xc is the reactance of the body. These measurements are then compared to typical impedance values for healthy tissues.

2.3.2 Changes in impedance patterns

As cancerous cells grow, they alter the impedance profile in the affected area. BIA can detect these subtle changes, which are indicative of the presence of abnormal tissue. The key is that cancerous tissue generally has a lower resistance and a higher reactance than healthy tissue, which can be measured using specialized electrodes.

2.4 Application of BIA in Cancer Diagnosis

BIA offers a non-invasive, affordable, and quick method of assessing changes in tissue properties. Early detection through BIA could lead to more proactive monitoring and faster diagnosis, providing a valuable tool for healthcare providers to detect cancers at earlier stages.

3 Algorithms for diagnosis

In order to correctly assess whether or not the studied tissue might be cancerous, two different methods can be used: classical machine learning (CML) or quantum machine learning (QML).

3.1 Dataset selection

Most importantly, the dataset used to train these two models was taken from a study on electric bioimpedance sensing for the detection of head and neck squamous cell carcinoma. It contains 2,015 entries, each corresponding to a different tissue in one of 43 patients' bodies. Each entry thus contains 10 different measurements of reactance, each taken at a frequency of 10 to 100 kHz, and 10 different measurements of phase angle, each taken at a frequency of 10 to 100 kHz as well.

3.2 Classical Machine Learning

In this first approach, a random forest regressor is used, composed of 100 decision trees to ensure the highest possible precision for the model. The accuracy is calculated with an R^2 score, while the loss is calculated as a root mean squared error loss.

3.3 Quantum Machine Learning

In this second approach, data is first standardised using a standard scaler. Principal Component Analysis (PCA) is then used to reduce the dataset to 4 dimensions, by projecting data onto orthogonal axes of maximum variance. The aim is to keep only the most important features to reduce computational complexity for the quantum model.

After this, a feature map will be created, in which each parameter of the now 4 parameters of a given entry gets transformed into a qubit, and gets rotated using an operation similar to a Z-gate in a quantum circuit. Each qubit then gets entangled to the next one, so that the relationships between the parameters can be calculated and estimated appropriately.

An Ansatz is then created, which is a parametrized quantum circuit that can be used for variational algorithms of the sort. In it, qubits are rotated around the Z and Y axes, then a CNOT gate is performed for entangling layers. The outputs of that circuit are then passed through a Constrained Optimization By Linear Approximation optimizer (COBYLA) over 20 iterations, in order to find the optimal approach.

Finally, a variational quantum classifier (VQC) will be implemented in our quantum variational algorithm, taking in the feature map, the ansatz, and the optimizer. This classifier will take in single entries with complete parameters, and return a percentage representing the possibility of the tissue studied being cancerous or not.

3.4 Comparison: Classical ML vs. Quantum ML

When comparing any two classical and quantum ML models, here are the differences that can arise:

Classical ML	Quantum ML
Reliable and well-established	Emerging and experimental
Scalable and computationally efficient on classical hardware	Requires quantum simulation or access to quantum processors
Faster training and inference time, suitable for real-time deployment	Longer execution time due to complex quantum circuit simulations
Uses ensemble learning (e.g., random forests) for robustness and accuracy	Uses variational circuits optimized via hybrid classical-quantum algorithms
Handles structured/tabular data effectively with classical models	Potential to uncover complex hidden correlations using entanglement
Mature ecosystem and easy deployment in real-world pipelines	Promising for future advancements, but currently harder to integrate

4 Conclusion

4.1 Marketing Perspective

Every day, someone hears the words "you have cancer" too late. We built Qure to change that, because we believe early detection should be simple, affordable, and available to everyone, right from home. Aligned with SDG 3: Good Health and Well-Being, Qure fits seamlessly into users' lives, quietly working in the background to monitor health signals using a non-invasive, cost-effective body composition analysis. Unlike other apps, Qure doesn't replace doctors; it empowers users to detect potential cancer early, providing peace of mind at a fraction of the cost and from the comfort of their own homes. With Qure, users take a proactive step in their health journey, gaining an early advantage in the fight against cancer.

4.2 Future Directions

Looking ahead, we plan to refine our system by collaborating with hospitals to integrate real-world data from diverse patient datasets, improving the accuracy and reliability of our model. We will also focus on expanding the dataset to train the model further, ensuring better detection of cancerous tissues. Additionally, we aim to integrate Qure with popular fitness and health apps, allowing users to effortlessly monitor their health in the background. This integration, combined with our ongoing data expansion, will help ensure Qure becomes an increasingly effective tool for early cancer detection and a proactive health management solution.

4.3 Project Summary

In summary, Qure represents a breakthrough in affordable, early cancer detection. By combining body composition analysis with cutting-edge Quantum Machine Learning (QML), we've created a tool that can detect early signs of cancer without the need for expensive or invasive procedures. This project aligns with global healthcare needs by providing accessible technology that can reach underserved communities. As we continue to improve the system, collaborate with healthcare professionals, and expand our dataset, we aim to empower individuals worldwide to take charge of their health and detect potential cancer risks early, ultimately saving lives.