AI-Powered Cardiovascular Health Monitoring and Prediction System Using IoT and Quantum-Inspired SVM

A PROJECT REPORT

Submitted by

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It has been both a privilege and an honor to work alongside a mentor of Dr. Das's caliber and expertise. His extensive knowledge, innovative insights, and steadfast support have made a lasting impression on both this thesis and my academic trajectory.

Subhadip Manna.

ABSTRACT

Predicting heart disease at an early stage is crucial for effective intervention and improved patient outcome. This study presents an innovative hybrid approach that integrates a Quantum-Inspired Island Model Genetic Algorithm (QIIMGA) to identify the most significant feature set using various machine learning models (SVM, KNN, DT, and MLP). This combined method aims to enhance the accuracy of heart disease prediction by using real-time data collected from wearable sensors.

QIIMGA enhances feature selection by segregating features into subgroups, referred to as " or islands," and employing quantum-inspired techniques to strike a balance between exploration and exploitation. An initial Support Vector Machine (SVM) assesses feature subsets, aiming to maximize the accuracy while minimizing the number of features used. The trained models were then based on a list of important features identified through this process.

Wearable Sensors, including pulse oximeter , ECG monitors, Temperature LM35, and SPO2 devices, were employed to continuously track cardiac and respiratory functions. ESP32 processes and sends the collected data to a centralized cloud database (Firebase) for further analysis. Essential metrics, such as heart rate variability, blood pressure, blood oxygen saturation, and respiratory rate, were derived from these data.

The system now utilizes real-time information from the database as input for pre-trained machine-learning classification models to differentiate between healthy and unhealthy conditions. The entire process was tested on heart disease datasets, and the proposed approach showed improved accuracy and decreased computational demands by removing unnecessary features. The QIIMGA-SVM system presents a promising approach for monitoring and diagnosing heart disease in real time.

Keywords : Internet Of Things , Quantum Inspired Island Model Genetic Algorithm , Remotely Patient Monitoring , Machine classifiers , Heart disease Prediction System.

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Glossary of Terms

AI: Artificial Intelligence

ECG: Electrocardiogram

IoT: Internet of Things

QIIMGA: Quantum-Inspired Island Model Genetic Algorithm

SVM: Support Vector Machine

QIGA: Quantum-Inspired Genetic Algorithm

QIEA: Quantum Inspired Evolutionary Algorithm

PCA: Principal Component Analysis

RF: Random Forests

ANN: Artificial Neural Networks

k-NN: k-Nearest Neighbors

IMGA: Island Model Genetic Algorithm

BP: Blood Pressure

RBF: Radial Basis Function

TP: True Positives

TN: True Negatives

FP: False Positives

FN: False Negatives

1. Introduction

1.1 **Significance of study :** As the primary global contributor to death rates (World Health Organization, 2023), cardiovascular diseases (CVDs) require prompt identification to enhance patient outcomes. Conventional diagnostic methods are limited by their inability to provide ongoing monitoring and handle large patient numbers, resulting in delayed treatment [1]. A potential remedy lies in the combination of Internet of Things (IoT) wearable devices and artificial intelligence (AI), enabling constant data gathering and predictive analytics [2, 3]. Nevertheless, the excessive information generated by IoT devices, including superfluous parameters (such as cholesterol measurements and ST-segment information), can negatively impact both precision and computational performance [4].
This research introduces a novel approach that integrates a Quantum-Inspired Island Model Genetic Algorithm (QIIMGA) with Support Vector Machine (SVM) to improve heart disease prediction accuracy. The QIIMGA enhances feature selection by incorporating quantum concepts like superposition and entanglement, while also segregating features into evolving "islands." This method accelerates convergence compared to traditional Genetic Algorithms [5, 6]. The optimally selected features, such as heart rate variability, are then used to train an SVM classifier [7].
The model's performance was evaluated using the UCI Heart Disease dataset [8], achieving an impressive 98.16% accuracy rate, surpassing the conventional SVM that utilizes all 14 features. The system's computational efficiency allows for implementation on low-power edge devices [9], making it suitable for remote or resource-constrained environments through real-time monitoring via wearable technology [10]. By combining quantum-inspired optimization techniques with Internet of Things (IoT) and machine learning, this approach presents a scalable and cost-effective solution for early cardiovascular disease (CVD) detection. It addresses crucial challenges in healthcare accessibility and computational requirements [11].

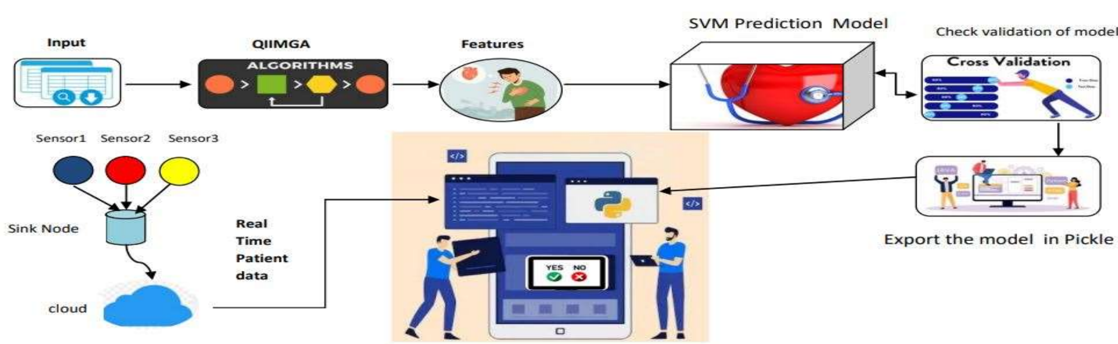


Fig. 1 Overall approach our model

1.2 Literature review : This review examines quantum-inspired algorithms, feature selection techniques, and machine learning methods for heart disease prediction. It highlights the synergy between Quantum-Inspired Genetic Algorithms (QIGA) and Support Vector Machines (SVM) in analyzing health datasets, particularly for cardiac diagnosis. Integrating IoT devices, such as wearables and remote monitors, enables real-time data collection (e.g., heart rate, ECG). Combining IoT data with QIGA and SVM enhances prediction accuracy, supporting early detection and personalized care.

S.L. No	Author(s)	Title	Key Findings
1	**Sadaq et al. (2023)**	Efficient ECG Classification Using Lightweight CNN and IoT.	IoT-enabled lightweight CNN achieved 95.2% accuracy in ECG analysis, emphasizing edge-computing compatibility.
2	**Parashar et al. (2024)**	Machine Learning for CVD Prediction with IoT Integration.	Highlighted IoT's role in real-time health monitoring and data fusion for ML-based predictive models.
3	**Sinha Roy et al. (2023)**	IoT-Based Conv-Random Forest for Valvular Heart Disease	IoT sensors combined with hybrid ML models improved diagnostic accuracy and real-time data processing capabilities.
4	**Islam et al. (2020)**	Smart Healthcare Monitoring System in IoT Environment.	Developed an IoT framework for continuous patient monitoring, demonstrating reduced latency and enhanced data security.
5	**Samanta et al. (2024)**	Feature selection using QIGA for wheat rust disease detection.	QIGA improved feature selection efficiency and classification accuracy compared to traditional methods.
6	**Liu et al. (2019)**	Island Model Genetic Algorithm for credit risk evaluation.	IMGA improved feature selection in high-dimensional datasets, highlighting its scalability and efficiency.
7	**Hoque et al. (2024)**	Heart Disease Prediction Using SVM and IoT Data.	SVM achieved 92% accuracy in classifying IoT-collected cardiac data, proving efficacy in resource-constrained systems.
8	**Chandrasekhar (2023)**	IoT-Enabled Heart Disease Prediction with ML.	Demonstrated IoT's utility in aggregating multi-source health data for ML-driven cardiac risk assessment.
9	**Anggoro & Kurnia (2020)**	IoT-Driven Comparison of SVM and k-NN for Heart Disease.	SVM outperformed k-NN (86.5% vs. 82.3%) in IoT-sourced datasets, emphasizing SVM's robustness in edge analytics.
10	**Drozuz et al. (2022)**	Machine learning for cardiovascular risk analysis.	Identified quantum-inspired algorithms as promising for future feature selection and accuracy enhancement.

Table1: Literature Survey.

1.3 Research Gap :

Gap in Quantum-Inspired Genetic Algorithm (QIGA) Research for Cardiac Disease Prediction Although conventional genetic algorithms (GAs) have been utilized for feature selection in healthcare applications [12] , there is a significant dearth of research investigating Quantum-Inspired Genetic Algorithms (QIGA) specifically for predicting heart disease. QIGA incorporates principles from quantum computing (such as superposition and rotation gates) to boost optimization effectiveness; however, its implementation in medical datasets remains largely unexplored [4] .

Minimal Incorporation of QIGA and SVM for Attribute Selection While SVM are commonly employed in classifying heart disease [9,11] , there is a scarcity of research combining them with quantum-inspired attribute selection techniques. Conventional hybrid approaches (such as GA-SVM) primarily utilize classical optimization methods, which can be hindered by gradual convergence and inefficient computation (Desai et al., 2019). The fusion of QIGA and SVM, as suggested in this research, tackles this issue by striking a balance between precision and computational intricacy [3].

Challenges in Scaling and Continuous Monitoring of Clinical Approaches Current clinical techniques for assessing cardiorespiratory issues often struggle with scalability and real-time monitoring during crisis situations [1]. While Internet of Things (IoT) solutions have been suggested for distant patient observation [2] , their combination with sophisticated artificial intelligence models like QIIMGA-SVM for instantaneous feature optimization and forecasting represents an innovative contribution to the field.

1.4 Significant Contribution :

1. The research presents a novel combined approach named QIIMGA-SVM, which merges quantum-inspired feature selection methods with a powerful machine learning classifier. This strategy aims to improve the accuracy of heart disease predictions while concurrently decreasing the quantity of features employed in the examination.

2. Dimension Reduction: The research illustrates how QIIMGA can successfully diminish the dimensionality of heart disease datasets, rendering the model more efficient without compromising its effectiveness.

3. Improved Efficiency: Through the application of QIIMGA, the model is anticipated to reach convergence more rapidly and deliver more precise predictions in comparison to conventional GAs or feature selection techniques.

4. Develop an Internet of Things (IoT) device to gather authentic health information from the human body and store it in a cloud database for analysis and classification of heart conditions.

2. Materials & Methods

2.1 Materials : In the context of research, materials refer to the physical or digital items, substances, tools, or resources used to conduct research. These include the equipment, hardware, software, datasets, surveys, or experimental models.

2.1.1 Study Materials :

i.Data Preprocessing : Data Pre-Processing: An essential phase in machine learning that involves refining, organizing, and transforming raw data to prepare it for effective model training. This process ensures that the data are structured and formatted correctly, thereby improving the model accuracy and performance.

The key steps include:

- Data Collection: Gathering raw data from relevant sources.
- Handling Missing Data: Addressing gaps by imputing or removing incomplete entries.
- Data Cleaning: Identifying and removing duplicates, anomalies, or inconsistencies while standardizing formats.
- Encoding Categorical Data: Converting text-based or non-numeric categories into numerical representations.
- Feature Scaling: Adjusting the range of numerical features using normalization or standardization for uniformity.
- Data Transformation: Mathematical operations (e.g., logarithmic and polynomial) are applied to modify the data distributions.
- Feature Engineering: Creating or refining variables to better capture patterns and relationships within data.
- Handling Imbalanced Data: Balancing class distributions using techniques such as oversampling, undersampling, or synthetic data generation.
- Data Splitting: The dataset was divided into training, validation, and test subsets to rigorously evaluate model performance.

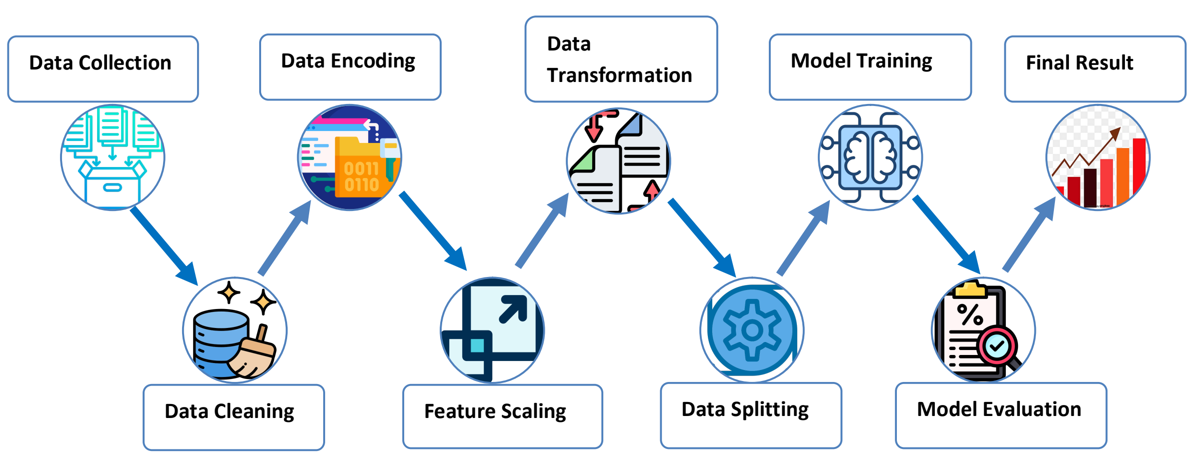


Fig. 2 Data Preprocessing

II . Machine Learning Algorithm :
Artificial Intelligence Techniques: Computational approaches that allow systems to identify patterns in data, generate predictions, or make decisions without explicit programming. These techniques are classified into three categories based on the nature of the problem and data structure: supervised, unsupervised, and reinforcement learning.

Given are several machine learning models :

1. **Support Vector Machine (SVM) :** Identifies an ideal hyperplane to divide data into separate classes, enhancing the margin between them. Performs well with high-dimensional data by utilizing kernel functions (such as linear and RBF). Employed in both classification (e.g., image recognition) and regression tasks.
2. **Decision Tree :** Creates a tree-like structure by dividing data hierarchically using rules based on features. Easy to interpret, manages non-linear relationships, and is compatible with both categorical and numerical data. Utilized in market segmentation, evaluating risks, and developing recommendation systems.
3. **Logistic Regression :** Forecasts binary or multiple class outcomes by estimating probability using a logistic function. Straightforward, efficient, and offers probabilistic interpretations. Frequently used in medical diagnostics, detecting fraudulent activities, and marketing analytics.
4. **Multilayer Perceptron** (MLP**) :** A type of neural network with concealed layers that learns intricate patterns through forward and backward propagation. Able to process non-linear data using activation functions (such as ReLU and sigmoid). Applied in voice recognition, natural language processing, and predictive modeling tasks.

5. **Island model Genetic Algorithm :** A principled evolutionary approach integrates Islamic ethical guidelines into genetic algorithms to identify optimal feature subsets. It employs fitness functions that prioritize fairness, transparency, and relevance, thereby avoiding biased or harmful features during selection, crossover, and mutation. Designed for Sharia-compliant applications (e.g., ethical finance or healthcare), it balances the model accuracy with moral constraints. This method ensures that feature subsets align with both technical efficiency and Islamic values such as equity and social responsibility.

III. Quantum Computing :
Quantum mechanics serves as the theoretical basis for quantum computing, in which information is encoded in qubits. Unlike classical bits, qubits can exist in a coherent superposition of both zero and one state simultaneously, enabling parallel processing capabilities (Deutsch, 1985). However, because qubits cannot be directly replicated in classical computing systems, researchers have explored methods for adapting quantum principles for use in conventional frameworks. One such innovation is the Quantum-Inspired Evolutionary Algorithm (QIEA), which merges evolutionary computation techniques with concepts from quantum theory, such as superposition and entanglement, to enhance optimization processes (Han & Kim, 2002). This hybrid approach aims to leverage quantum-inspired advantages such as improved search efficiency and population diversitywithin classical computational paradigms.

Important GATES & Representations Quantum Computing:

I.Qubit Representation and Superposition : Qubits are fundamental units in quantum computing and are characterized by their ability to exist in a linear combination of two basis states, typically denoted as $|0\rangle$ (ground state) and $|1\rangle$ (excited state).

Mathematically, this superposition can be expressed as:

$$|\psi\rangle = \alpha_0|0\rangle + \alpha_1|1\rangle \text{ .... } (1)$$

Here, α_0 and α_1 are the complex probability amplitudes that satisfy the normalization condition:

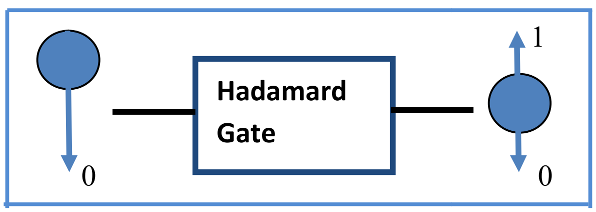
$$|\alpha_0\rangle^2 + |\alpha_1\rangle^2 = 1 \text{ .... } (2)$$

A common initialization for qubits in quantum algorithms is the equal superposition state achieved by setting $\alpha_0 = \alpha_1 = 1/\sqrt{2}$:

$$|\psi\rangle = 1/\sqrt{2}\,(|0\rangle + |1\rangle) \text{ ....} (3)$$

II.. Quantum Gates : Quantum gates manipulate the qubit states through unitary transformations. Two critical gates are:

1**. Hadamard Gate (H):** This gate generates superposition states from the basis states. The matrix representation is as follows:



Input	Output
0	$\frac{1}{\sqrt{2}}(\|0\rangle + \|1\rangle)$
1	$\frac{1}{\sqrt{2}}(\|0\rangle - \|1\rangle)$

Table2: Hadamard Gate Truth Table

Hadamard gates are often used to initialize quantum chromosomes in evolutionary algorithms.

2**. Quantum Rotation Gate:** This gate adjusts the qubit amplitudes toward an optimal solution, thereby aiding convergence in the metaheuristic algorithms. The updated qubit state is computed as:

$$\begin{bmatrix} \alpha'_{0i} \\ \alpha'_{1i} \end{bmatrix} = U(\Delta\theta_i) * \begin{bmatrix} \alpha_{0i} \\ \alpha_{1i} \end{bmatrix} \text{ .... } (4)$$

Here, $U(\Delta\theta i)$ is a rotation matrix defined by:

$$U(\Delta\theta i) = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix} \text{ .... } (5)$$

Angle $\Delta\theta i$ determines the magnitude of rotation and guides the qubit toward improved solutions.

IV. IoT Sensor Node: A crucial element (figure:3) in an Internet of Things (IoT) system, responsible for gathering environmental data and relaying it to other nodes or a central processing unit for analysis. These nodes typically comprise one or more sensors, a microcontroller or processor, a communication module, and a power supply. They operate in a distributed network of interconnected devices, monitoring, tracking, and interacting with the physical environment.

Essential Components of a Sensor Node:

I.Sensor: The primary data collection units, sensors measure physical phenomena such as temperature, humidity, pressure, light, and motion, or more complex metrics like heart rate or glucose levels in medical IoT applications.

II. Communication Module: This component enables the sensor node to interact with other nodes or a central hub. Common communication protocols include WiFi and Bluetooth.

III. Microcontroller/Processor: Functioning as the node's brain, the microcontroller processes raw data collected by sensors. It may perform data filtering, basic computations, or compression before transmission. Some nodes incorporate embedded AI for real-time decision-making at the edge.

IV. Power Source: Often deployed in remote locations, sensor nodes rely on power sources such as batteries, solar panels, or energy harvesting mechanisms. Power efficiency is a critical design factor for IoT nodes, as they must operate independently for extended periods.

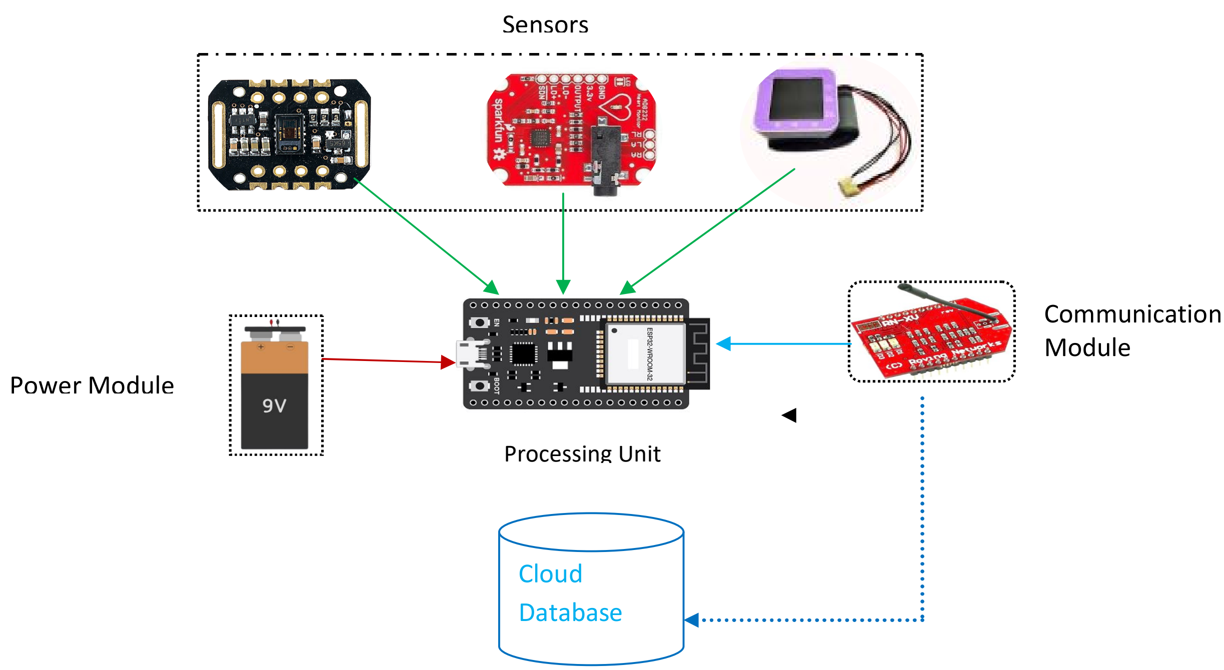


Fig. 3 IoT Sensor Node

2.1.2 Experimental Setup : Comprehensive description of all equipment (both hardware and software) utilized for conducting experiments, including data preprocessing, model training, IoT device configuration, and user interface development for the application.

i. Data preprocessing & Model training :

Dataset : The study began with the utilization of the UCI Heart Disease dataset, obtained from Kaggle. This dataset comprises 16 distinct attributes, including measurements such as heart rate, blood sugar levels, ECG readings, and body temperature, among others. The target variable in this dataset is binary, with '0' indicating the absence of heart disease and '1' signifying the presence of heart disease.

Attribute	Description	Type	Range
age	Age of the patient	Numerical	29 - 77
sex	Sex of the patient	Binary	0 (Female), 1 (Male)
cp	Chest pain type	Categorical	0 - 3
bp	Resting blood pressure (in mm Hg)	Numerical	94 - 200
chol	Serum cholesterol (in mg/dl)	Numerical	126 - 564
bol	Blood Oxygen level	Numerical	62 - 99
fbs	Fasting blood sugar (>120 mg/dl)	Binary	0 (False), 1 (True)
restecg	Resting electrocardiographic results	Categorical	0 - 2
thalach	Maximum heart rate achieved	Numerical	71 - 202
exang	Exercise-induced angina	Binary	0 (No), 1 (Yes)
bodytemp	Body temperature (in Celsius)	Numerical	30 - 37
oldpeak	ST depression induced by exercise	Numerical	0.0 - 6.2
slope	Slope of the peak exercise ST segment	Categorical	0 - 2
ca	Number of major vessels colored by fluoroscopy	Categorical	0- 4
pal	Physical activity level	Categorical	0- 3
thal	Thalassemia type	Categorical	1 (Normal), 2 (Fixed defect), 3 (Reversible defect)
target	Diagnosis of heart disease	Binary	0 (No), 1 (Yes)

Table 3 :Dataset Feature Description

Software Requirements : The study utilized Jupyter Notebook as the primary environment for developing and executing machine learning models aimed at predicting heart disease. The workflow integrated quantum computing frameworks (Qiskit and Qiskit-Aer) to explore advanced computational capabilities, alongside traditional tools for data analysis. Essential libraries such as NumPy and Pandas were employed for numerical operations and dataset manipulation, while Matplotlib facilitated data visualization. Additionally, **scikit-learn (**sklearn) was used to implement machine learning algorithms, enabling comprehensive training, testing, and evaluation of predictive models for cardiovascular health outcomes. This hybrid approach combined classical and quantum computing techniques to enhance analytical precision and scalability.

ii. IoT Device Setup Components :

Hardware Requirements

Microcontroller Board:

- ESP32 Development Board (WiFi & Bluetooth enabled)

Sensors & Modules

- MAX30102: Pulse Oximeter & Heart Rate Sensor (I2C)
- AD8232: ECG Sensor Module (Analog Output)
- MLX90614: Non-Contact Infrared Temperature Sensor (I2C)
- BMP180/085: Barometric Pressure & Temperature Sensor (I2C)
- MPU6050: Accelerometer & Gyroscope (I2C)
- I2C 16x2 LCD Display (Address: 0x27)

Additional Components

- ECG Electrodes (3x for AD8232)
- Breadboard/PCB & Jumper Wires
- Resistors (for pull-up/down circuits, if required)
- Micro-USB Cable (for ESP32 power/programming)
- 3.3V/5V Power Supply (for sensors)

Software Requirements

Arduino IDE

- Required for compiling and uploading code to ESP32.

Install ESP32 Board Support:

- Add https://dl.espressif.com/dl/package_esp32_index.json

Libraries

- Wire.h (Built-in)
- LiquidCrystal_I2C.h (for LCD)
- WiFi.h (Built-in for ESP32)
- Firebase_ESP_Client.h
- SparkFun_MAX3010x.h (MAX30102)
- Adafruit_MLX90614.h (MLX90614)
- Adafruit_BMP085.h (BMP180/085)
- Adafruit_MPU6050.h (MPU6050)
- Adafruit_Sensor.h (Dependency for MPU6050)

Firebase Realtime Database setup with:

- Project Host URL (YOUR_PROJECT_ID.firebaseio.com)
- Database Secret Key (YOUR_DATABASE_SECRET).

WiFi Network

- 2.4GHz WiFi network (SSID & Password for ESP32 connectivity).

iii. Web Application Components :

Backend :

- IDE**:** VSCode for code development and execution.
- Flask**:** Minimalist framework for API creation.

- Flask-CORS**:** Manages cross-origin resource sharing (CORS) for secure client-server communication.
- joblib**:** Streamlines model serialization/deserialization for efficient reuse.
- pandas: Processes structured data for model compatibility.
- jsonify**:** Converts Python objects to standardized JSON outputs.
- request**:** Parses incoming client data in HTTP requests.

Frontend :

- IDE : VSCode for code development and execution.
- Libaries : React , Telwind CSS user interface design .
- Node js : Used for server development.
- Axios : Https connect request and response.
- Firebase API : getting data and storing data.

2.2 Proposed Methodology : The research procedure is structured into three main stages: preprocessing data and training the model, developing IoT devices, and deploying the user-facing application.

2.2.1 preprocessing data and training the model :

i. Step by step procedure :

- **Dataset:** The dataset contains 303 patient health records with 17 features, including demographic, medical history, and health metrics. It is used for heart disease prediction, with the target variable indicating risk presence (binary classification). Features include both categorical and numerical data.
- **Preprocessing:** Clean and normalize raw data, handle missing values, and encode categorical data.
- **Feature Selection using QIIMGA:** Features are divided into subgroups (islands), evolved independently using quantum-inspired operations.
- **Quantum rotation gates:** adjust feature selection probabilities, optimizing the dataset for accuracy and computational efficiency.
- **Model Training with Selected Features :** Optimized feature subset is used to train the SVM model for classifying health conditions (e.g., 'normal' vs. 'at-risk').
- **Optimization and Validation:** Iterative process to refine model performance, validate with test datasets.
- **Exporing model :** export the model for further used as flusk app backend services.

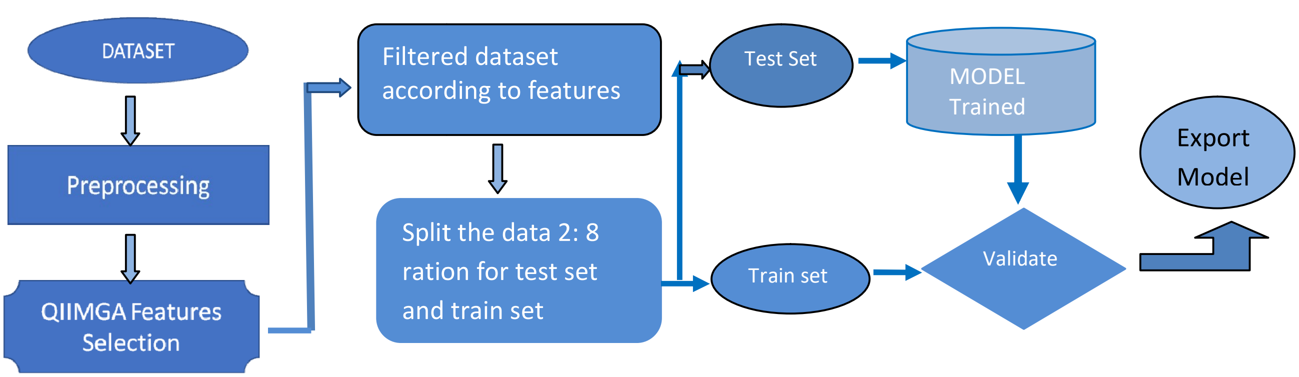


Fig .4 Model training & Evaluation

ii. QIIMGA Explanation :

1. CLASS DEFINITION: QuantumChromosome

1.1 Attributes

- num_features: Number of features/qubits
- circuit: Quantum circuit object
- alpha, beta: Rotation parameters for qubits

1.2 Constructor(num_features)

1. Initialize quantum circuit with num_features qubits.
2. Apply Hadamard gate to each qubit.
3. Initialize alpha and beta arrays with $1/\sqrt{2}$ values.

1.3 Method: measure()

1. Add measurement gates to all qubits.
2. Simulate the circuit with 1 shot using a quantum simulator.
3. Return the measured bitstring as a binary list.
   Example:
   - Chromosome 1: [1, 0, 1, 0] (Age and Chest Pain selected).
   - Chromosome 2: [0, 1, 1, 1] (Sex, Chest Pain Type, Resting BP selected).

1.4 Method: update_rotation(fitness_score)

1. For each qubit:
   - If fitness_score > threshold:
     - Set delta_θ = $+\pi/8$.
   - Else:
     - Set delta_θ = $-\pi/8$.
2. Update alpha and beta using the rotation matrix:

   new_alpha = cos(θ) * alpha - sin(θ) * beta

   new_beta = sin(θ) * alpha + cos(θ) * beta

3. Apply Ry(2 * delta_θ) gate to the qubit.

1.5 Method: mutate()

1. Randomly select a qubit index.
2. Apply an X gate to the selected qubit.
   Example: Mutating [1, 0, 1, 1] → [1, 1, 1, 1].

2. FITNESS FUNCTION

2.1 Function: calculate_fitness(chromosome, X_train, y_train, X_test, y_test)

1. Decode the chromosome to get selected feature indices.
2. If selected features < minimum required:
   - Return **-1** (penalty).
3. Train an SVM classifier using the selected features.
4. Calculate test accuracy.
5. Compute fitness score:

   Fitness_score = accuracy - (λ * num_selected_features) … (6)

6. Return the fitness score.

   Example:

   Chromosome 1: Accuracy = 90%, 2 features → Fitness = 89.98.
   Chromosome 2: Accuracy = 92%, 3 features → Fitness = 91.97**.**

3. QUANTUM-INSPIRED GENETIC ALGORITHM (QIGA)

3.1 Initialize Population

- Create **N** QuantumChromosome objects.

3.2 Generational Loop

3.2.1 Measure all chromosomes → classical population.
3.2.2 Calculate fitness for each chromosome.
3.2.3 Track the best-performing chromosome.
3.2.4 Selection: Retain the top 50% based on fitness.
3.2.5 Crossover:

While the new population is not full:

- Select two parents.
- Choose a random crossover point.
- Create children by combining parent circuits.

Example:

Parent 1: [1, 0, 1, 0] and Parent 2: [0, 1, 1, 1].
Crossover at the second bit → Offspring 1: [1, 0, 1, 1], Offspring 2: [0, 1, 1, 0].

3.2.6 Mutation:

For each child: If random < 0.1, apply mutate().

3.2.6 Update Rotations:

Adjust qubit rotations based on fitness scores.

4. MAIN PROCESS

4.1 Dataset Preparation

1. Load and preprocess the dataset:
   - Read CSV file.
   - Split into features (X) and target (y).
   - Perform train/test split.
   - Standardize features.

4.2 Feature Island Division

- Divide features into 4 groups**:**
  Example:
  - Fs1: [0, 1, 2, 3]
  - Fs2: [4, 5, 6, 7]
  - Fs3: [8, 9, 10, 11]
  - Fs4: [12, 13, 14, 15]

4.3 Island-Specific QIGA Execution

4.3.1 Extract features corresponding to the island.
4.3.2 Run QIGA with island-specific parameters.
4.3.3 Store selected features and quantum circuits.

4.4 Result Aggregation

- Combine results from all islands:
  Final Features = Fs1 ∪ Fs2 ∪ Fs3 ∪ Fs4 … (7)

- Print the final feature set and performance metrics.

5. OUTPUT

5.1 Generated Results

- Selected features from each island.
- Final combined feature set.
- Quantum circuit diagrams for each island.
- Performance metrics (accuracy, fitness scores).

5.2 Example Output :

```
Processing Island 1...
    Best Features: ['sex', 'cp', 'bp']
    Fitness Score: 0.8211
Processing Island 2...
    Best Features: ['chol', 'fbs', 'restecg']
    Fitness Score: 0.9850
Processing island3...
    Best Features: ['thalach', 'exang', 'bodytemp']
    Fitness Score: 0.9850
Processing island4...
    Best Features: ['slope', 'pal', 'thal']
    Fitness Score: 0.9850

                ===== Final Selected Features =====
Overall Features (Indices): [1, 2, 3, 5, 6, 7, 8, 9, 10, 12, 14, 15]
Features:  ['sex', 'cp', 'bp', 'chol', 'fbs', 'restecg', 'thalach', 'exang', 'bodytemp', 'slope', 'pal', 'thal'].
```

iii. QIIMGA Flow Diagram :

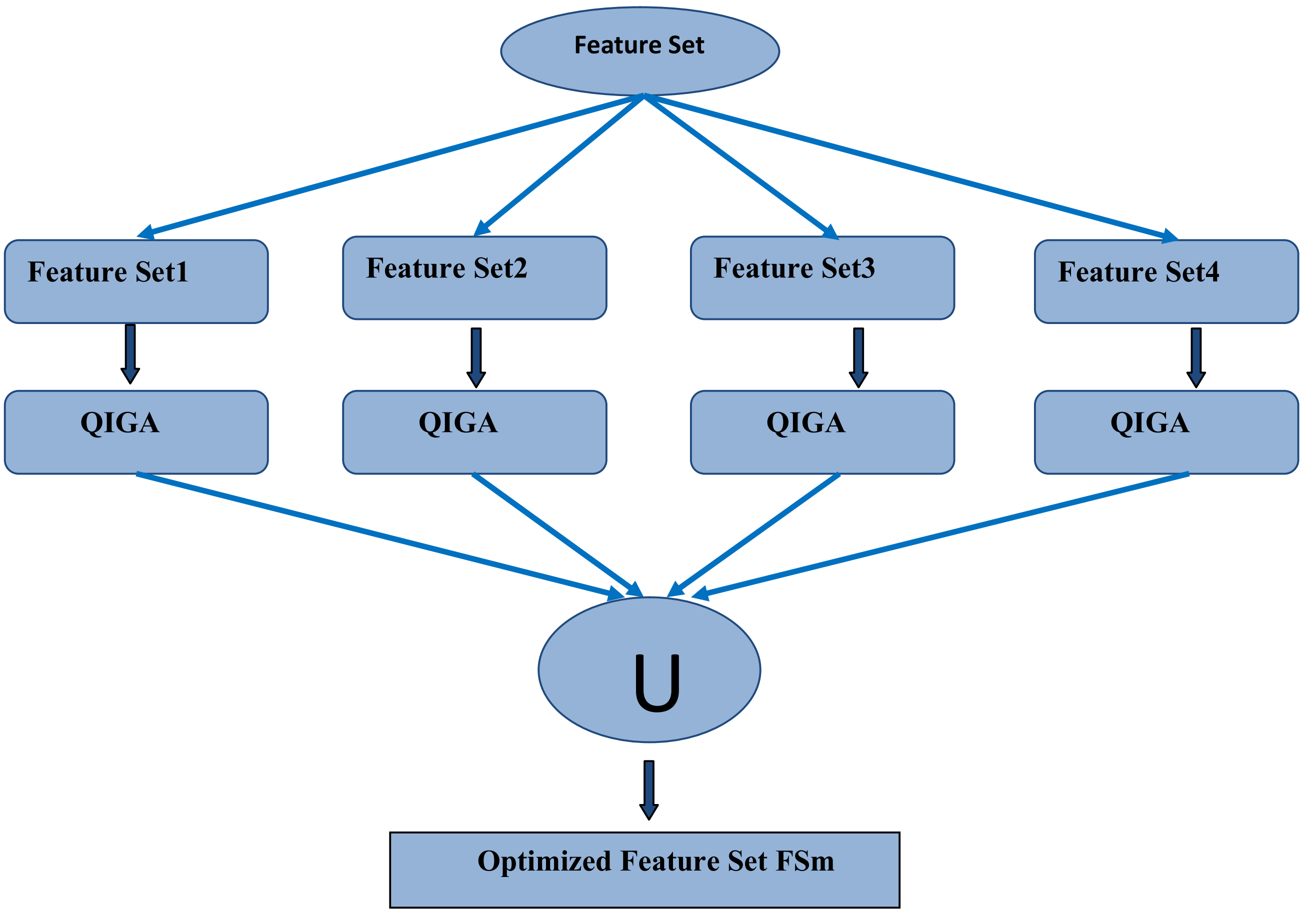


Fig.5 : QIIMGA Diagram

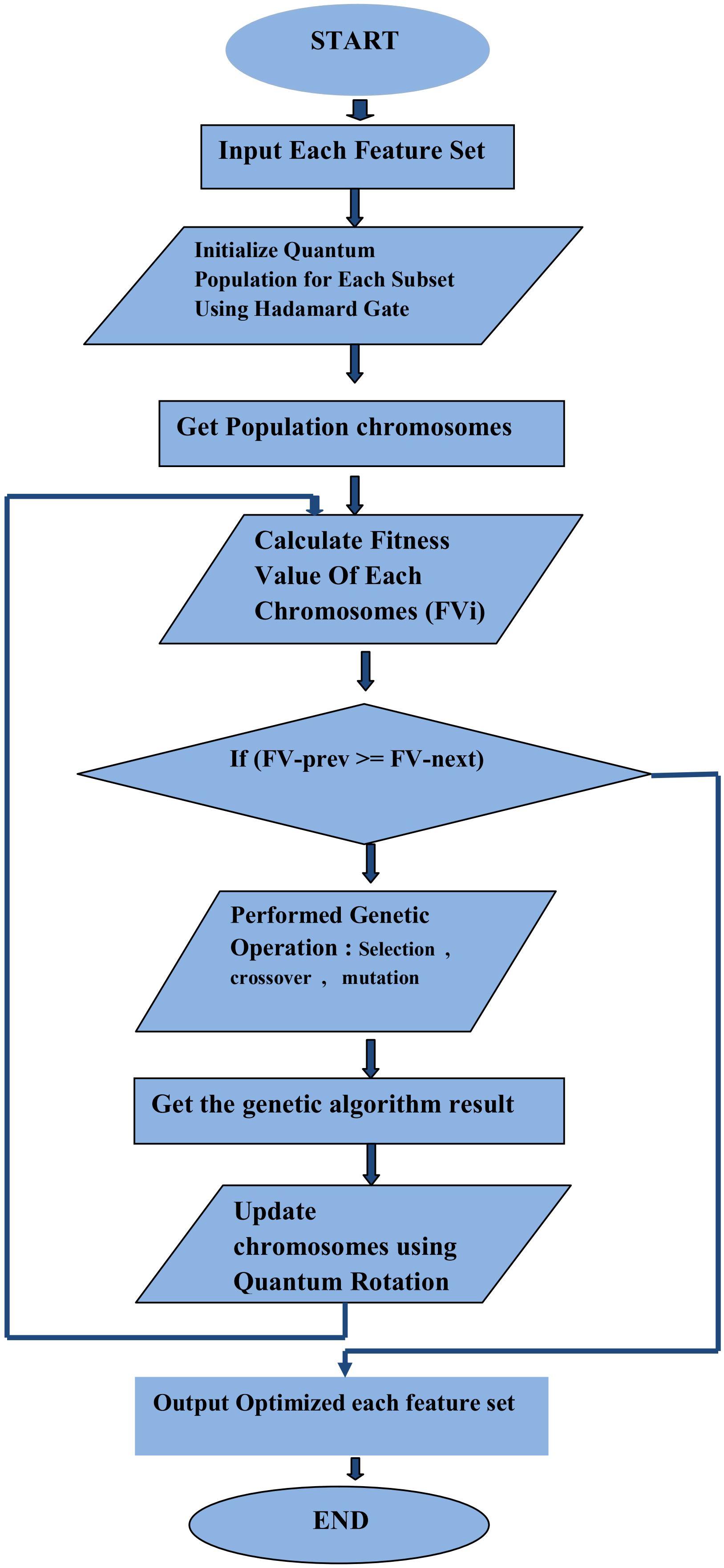


Fig.6 : QIGA Flow Diagram

2.2.2 Developed IoT Device :

i. Detailed circuit architecture IOT device : The suggested Health Monitoring System combines various biomedical sensors (MAX30102, AD8232, MLX90614, BMP180, MPU6050) with Internet of Things (IoT) technology to gather physiological data in real time. A state-driven design controls sensor activation through Firebase commands via web application , allowing remote management of vital signs including heart rate/SpO_2, ECG, infrared temperature, barometric pressure, and motion detection. The system utilizes WiFi to synchronize with the cloud, recording vital signs in organized Firebase paths at 500ms intervals for time-critical measurements. A local LCD screen provides status updates and error information using adaptive and backlight signals. I^2C/analog sensor interfaces were calibrated to ensure precise measurements during the operation. Energy efficiency is achieved by prioritizing idle states and implementing automatic reset timers after the data transmission. Firebase-triggered state changes enable on-demand monitoring, while conserving power during inactive periods. The system includes lead-off detection of ECG electrodes and error management with persistent visual alerts for hardware malfunctions. The tests showed effective sensor coordination with cloud data logging latency of less than 1 s across various scenarios. This adaptable framework supports expandable to accurately collected data , offering customizable vital-sign monitoring via a secure IoT infrastructure. The system tackles remote healthcare challenges through synchronized hardware-software integration with fail-safe operational logic.

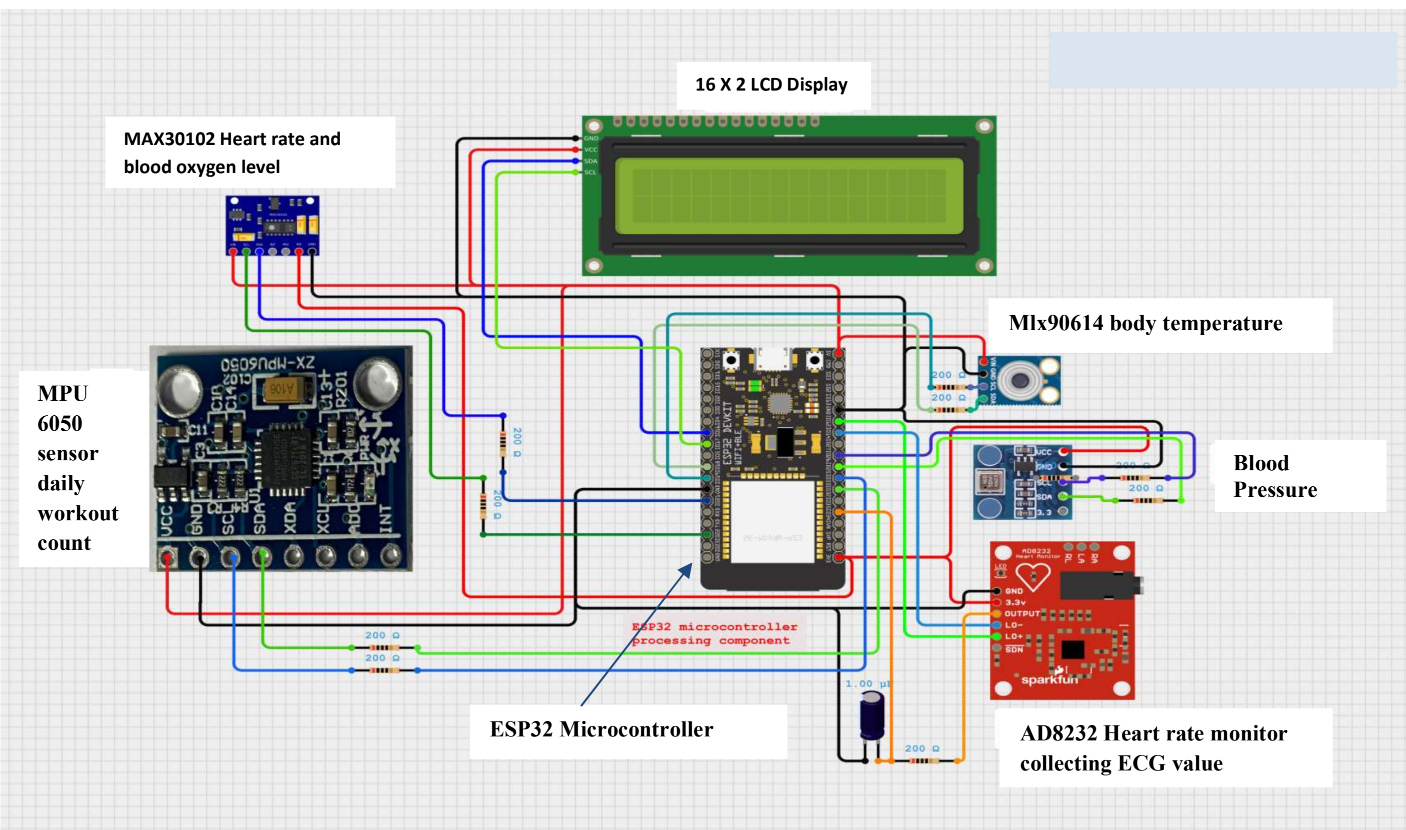


Fig.7 Detailed circuit diagram IoT device

ii. pseudo code program health monitoring system :

INCLUDES:
Libraries for WiFi, Firebase, Sensors, LCD

GLOBAL VARIABLES:
- SystemState: IDLE, MAX30102_ACTIVE, AD8232_ACTIVE, etc.
- Firebase config (host, auth token)
- Sensor objects (MAX30102, AD8232, MLX90614, etc.)
- LCD display object
- MAC address string
- State timer

FUNCTION Setup:
```
Initialize Serial Communication
Initialize LCD:
    Display MAC address for 3 seconds
    Clear screen

Initialize Sensors:
    MAX30102: Set up I2C communication
    AD8232: Configure analog/digital pins
    MLX90614: Begin I2C
    BMP180: Start pressure sensor
    MPU6050: Calibrate accelerometer

Connect to WiFi:
    Show "Connecting..." on LCD
    Retry for 15 seconds on failure
    Display IP on success

Initialize Firebase:
    Set host and authentication
    Verify connection
```

FUNCTION MainLoop:
```
WHILE True:
    Check Firebase State:
        IF Firebase "/state" changes:
            Update SystemState
            Reset State timer
            Update LCD with active sensor

    PROCESS Current State:
        CASE SystemState OF:
            MAX30102_ACTIVE:
                Read heart rate and SpO2
                Send to Firebase "/sensors/heart_rate", "/sensors/spo2"
                IF 500ms elapsed: Reset to IDLE
```

```
        AD8232_ACTIVE:
          Read ECG analog value
          Check lead-off detection
          Send to Firebase "/sensors/ecg"
          IF 500ms elapsed: Reset to IDLE

        MLX90614_ACTIVE:
          Read infrared temperature
          Send to Firebase "/sensors/temperature"
          Reset immediately

        BMP180_ACTIVE:
          Read atmospheric pressure
          Convert to hPa
          Send to Firebase "/sensors/pressure"
          Reset immediately

        MPU6050_ACTIVE:
          Read accelerometer data
          Send X/Y/Z to Firebase
          Reset immediately

        DEFAULT (IDLE):
          Maintain low-power state

FUNCTION ErrorHandler(message):
  Display "ERROR: [message]" on LCD
  Blink backlight indefinitely
  Halt program

FUNCTION UpdateLCD(state):
  CLEAR LCD
  Display "Active Sensor:"
  SWITCH state:
    MAX30102: Show "Pulse & SpO2"
    AD8232: Show "ECG"
    MLX90614: Show "Temperature"
    BMP180: Show "Pressure"
    MPU6050: Show "Motion"
    DEFAULT: Show "Ready"

END PROGRAM
```

iii. Flow diagram

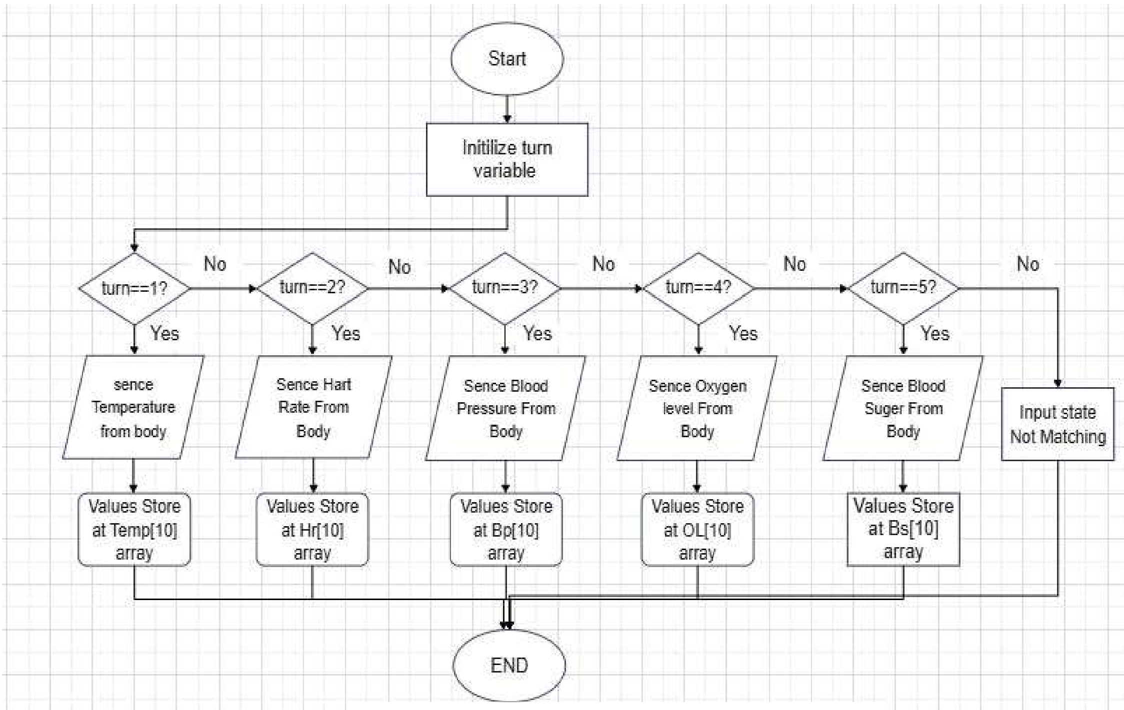


Fig.8 IoT Architecture Flow diagram

iv. Working Procedure Explanation :

- Turn On Device , See MAC Address On LCD 16*2 Display.
- Enter MAC Address on Controller App , Now System Can connected .
- IN App background map each button to each turn value { temp.button 1 -> turn 1, … }.
- When you press any button then corresponding Sensor Can enable 500ms time , read data in every 50 ms time delay [figure :9].
- Store the data corresponding array , Then store the array in Cloud Database Firebase.

2.2.3 Web application creating procedure :

The web application is designed to evaluate health metrics and manage IoT devices through Firebase API integration. The backend utilizes a Flask server hosted locally at http://192.168.0.139:5000, which processes the primary prediction model. The frontend interface, running on http://localhost:5173, allows users to input health parameters such as heart rate and blood pressure. Upon clicking the "Predict" button, the input data is sent to the server via a POST request to the endpoint http://192.168.0.139:5000/predict. The prediction result is then retrieved using a GET request from http://192.168.0.139:5000/result and displayed on the user interface. Additionally, the system connects to Firebase API to automate IoT device control based on the prediction outcomes.

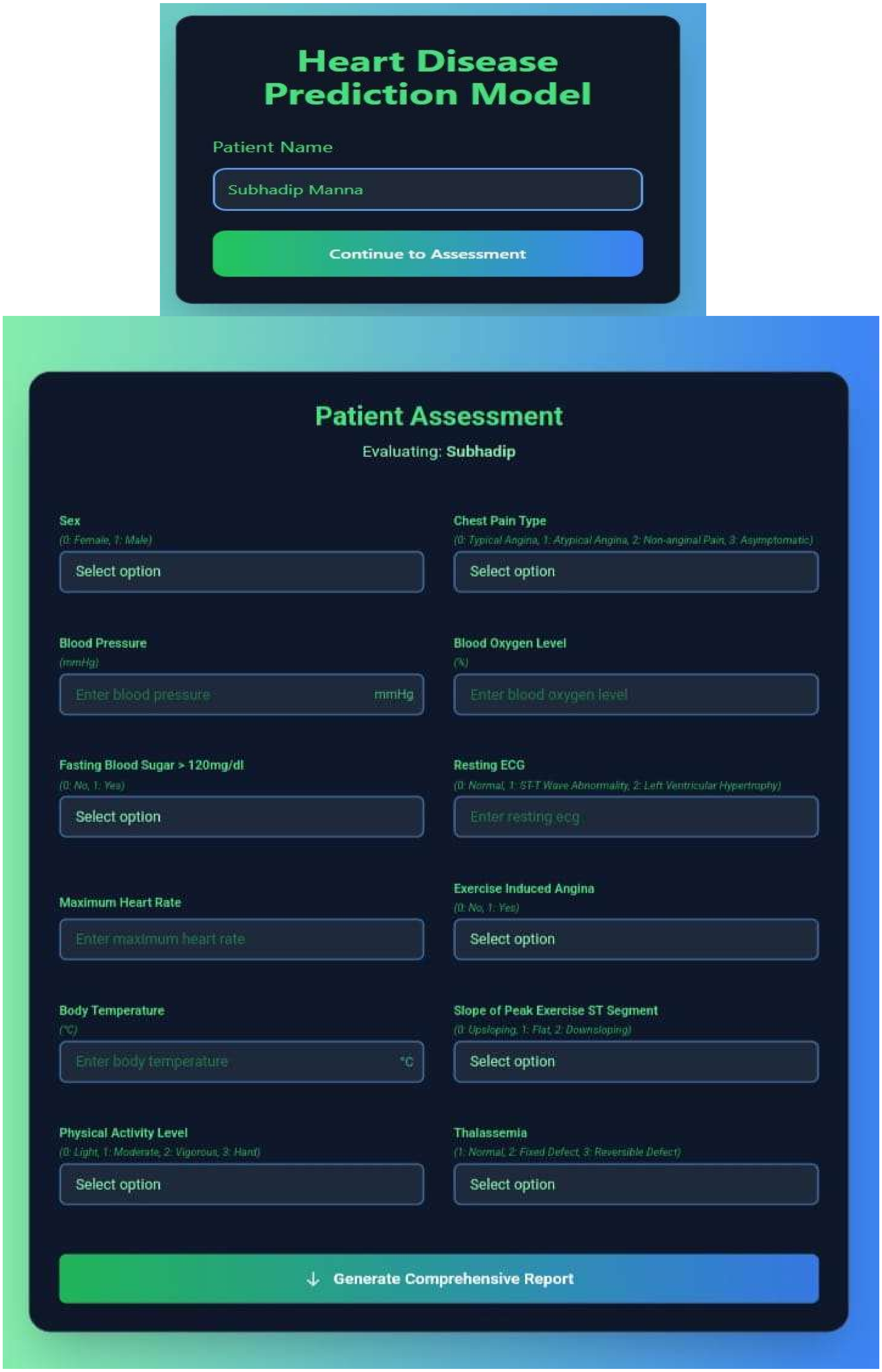


Fig.9 Web application view

3. Results and Discussion.

This section presents an analytical evaluation of experimental outcomes conducted on a cardiovascular disease dataset comprising over 300 patient records. The study focuses on testing the QIIMGA algorithm's efficacy in identifying critical features to maximize predictive accuracy across multiple classification models, benchmarked against established techniques such as Principal Component Analysis (PCA). Additionally, the research integrates an IoT-based monitoring system leveraging ESP32 microcontrollers and biomedical sensors to collect real-time physiological data, enhancing prediction precision. A user-centric web interface has also been developed to streamline interaction, enabling seamless health monitoring and automated generation of diagnostic reports for end-users. This integrated approach combines advanced feature selection methodologies, IoT-driven data acquisition, and intuitive digital tools to improve heart disease prediction capabilities.

3.1 Performance Analysis : To analyze the Quantum Inspired Island Model Genetic algorithm feature selection after the effectiveness of classification models, a confusion matrix was mainly employed to determine key performance evaluation metrics: accuracy, precision, recall, and F1-score.

This matrix categorizes our predictions into four attributes :

- **True Positive (TP):** Instances where the model correctly predicts the positive class (e.g., accurately diagnosing a patient with heart disease).
- **True Negative (TN):** Instances where the model correctly identifies the negative class (e.g., rightfully confirming the absence of heart disease).
- **False Positive (FP):** Cases where the model incorrectly classifies a negative instance as positive (e.g., misdiagnosing a healthy person with heart disease).
- **False Negative (FN):** Cases where the model misses a positive instance, classifying it as negative (e.g., failing to detect heart disease in an affected patient).

The following metrics were derived using these categories:

- **Accuracy:** Measures the proportion of correct predictions across all classes.
  - Formula: $Accuracy = (TP + TN) / (TP + TN + FP + FN)$ ……………… (8)
- **Precision:** Reflects the model's ability to avoid false alarms (incorrect positive predictions).
  - Formula: $Precision = TP / (TP + FP)$ …………………… *(9)*
- **Recall (Sensitivity):** Quantifies the model's effectiveness in detecting all true positive instances.
  - Formula: $Recall = TP / (TP + FN)$ ………………………….. *(10)*
- **F1-Score:** Balances precision and recall through a harmonic mean, ideal for imbalanced datasets.
  - *Formula:* F1-score = $(2 \times \text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$ … *(11)*

After applying QIIMGA Selected 12 features out of 16 .
Features List : ['sex', 'cp', 'bp', 'bol', 'fbs', 'restecg', 'thalach', 'exang', 'bodytemp', 'slope', 'pal', 'thal'].

Performance Analysis Different classifiers After Apply QIIMGA

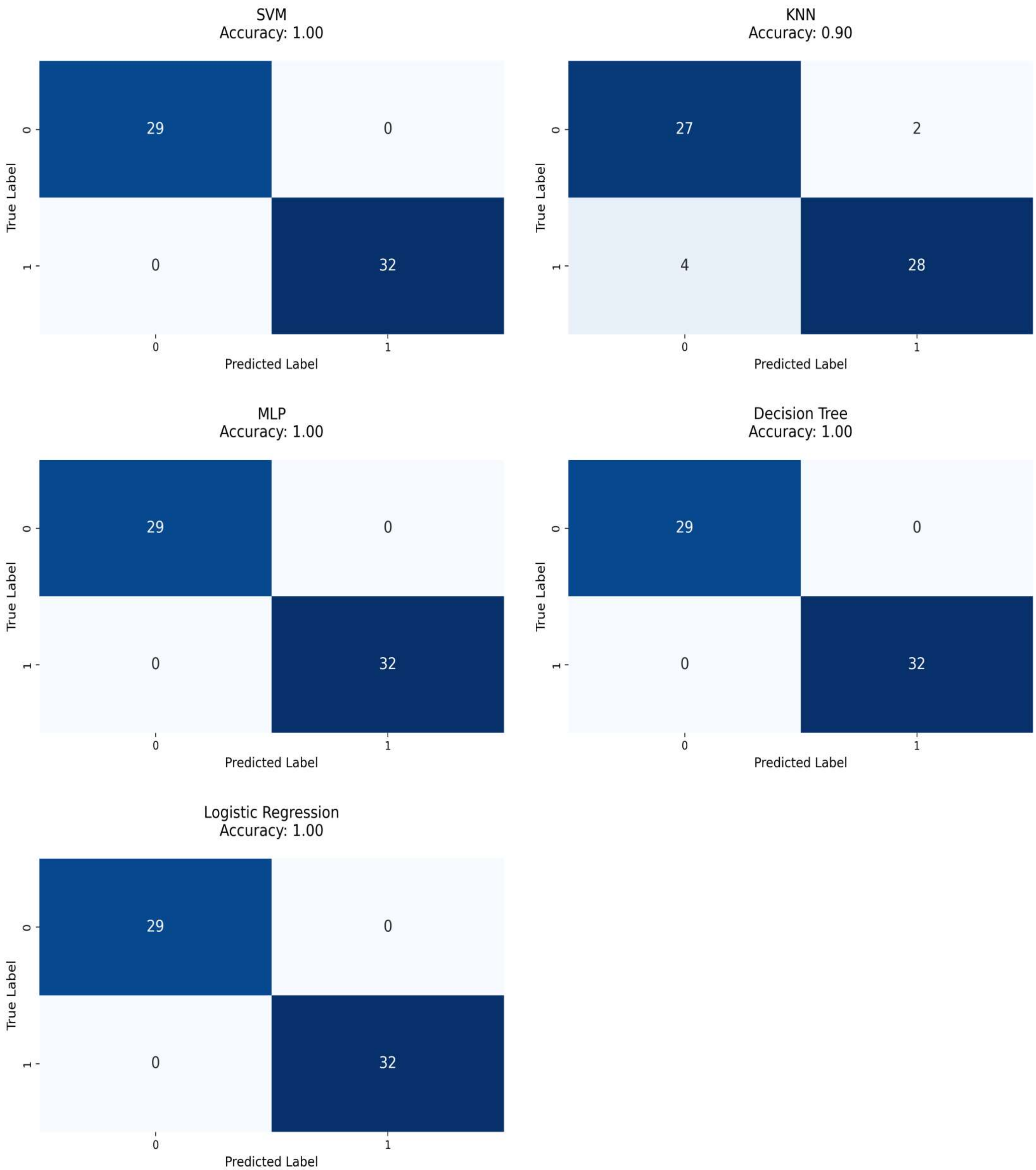


Fig.10 Confusion matrix for after QIIMGA applied analysis all classifier.

After applying PCA Selected 12 features out of 16 .
Features List : ['sex', 'age', 'bp', 'chol', 'fbs', 'restecg', 'thalach', 'exang' ,`öldpeak', 'slope', 'ca', 'thal'].

Performance Analysis Different classifiers After Apply PCA

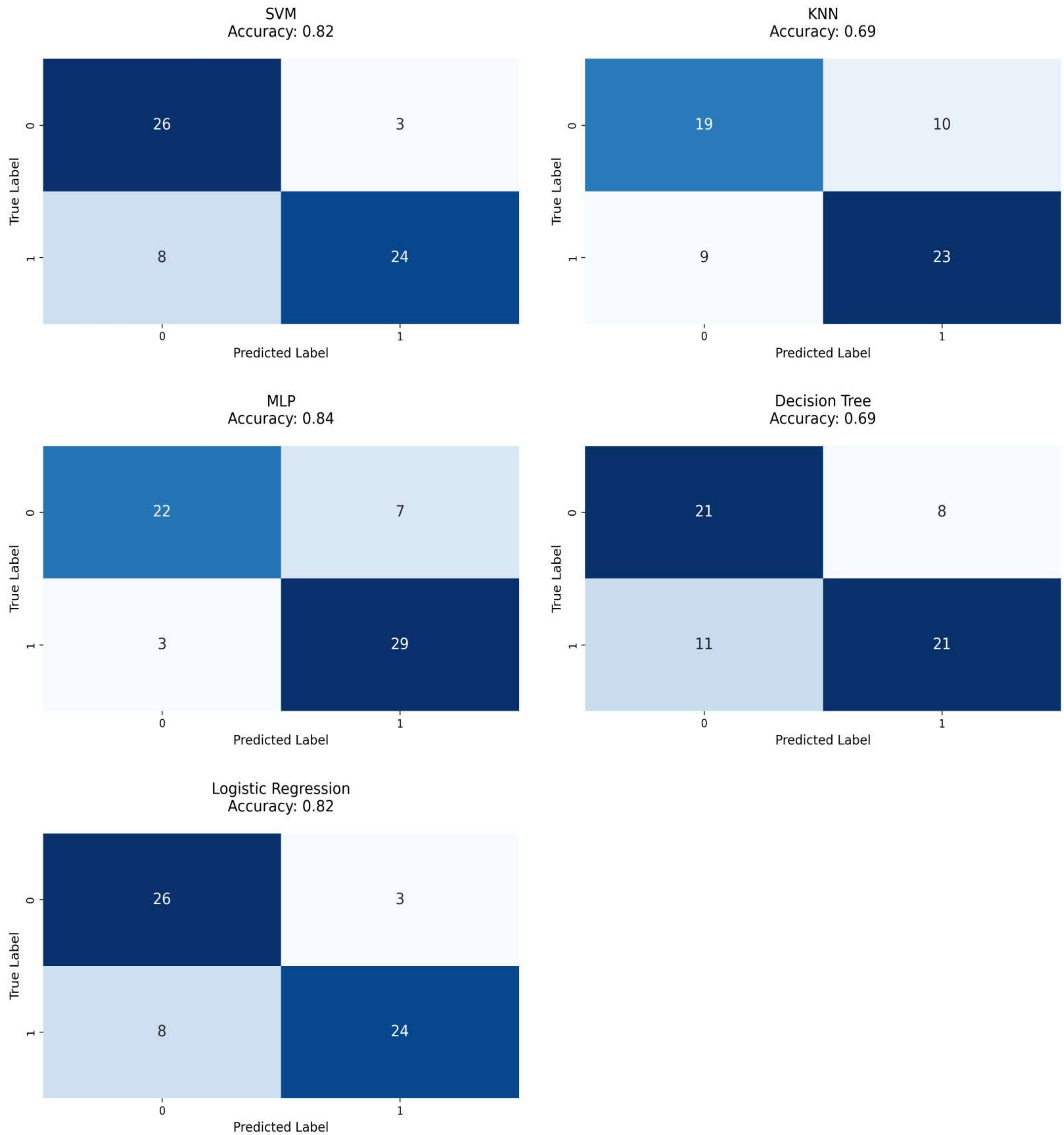


Fig.11 Confusion matrix for after PCA applied analysis all classifier.

3.2 Performance Comparisons QIIMGA VS PCA :

The comparison of QIIMGA and PCA-based feature extraction techniques for predicting heart disease. QIIMGA outperformed PCA across all classifiers, achieving perfect scores (1.0) in Accuracy, Precision, Recall, and F1 score when used with SVM, MLP, Decision Tree (DT), and Logistic Regression. This flawless classification indicates an ideal match between the extracted features and the classification task. The KNN classifier, when paired with QIIMGA, also showed excellent results, with an Accuracy of 0.901, Precision of 0.933, Recall of 0.815, and F1 score of 0.903.

On the other hand, PCA-based models showed average performance. The best Accuracy and F1 score for PCA was 0.819, achieved by SVM, MLP, and Logistic Regression. Precision and Recall values for PCA ranged from 0.696 to 0.888 and 0.656 to 0.843, respectively. PCA performed particularly poorly with KNN and DT classifiers, yielding Accuracy and F1 scores of only 0.688. These findings indicate that PCA may not effectively capture the distinguishing features necessary for heart disease prediction compared to QIIMGA.

Method	Classifier	Accuracy	Precision	Recall	F1 score
PCA	SVM	0.819	0.888	0.75	0.813
PCA	KNN	0.688	0.696	0.718	0.707
PCA	MLP	0.819	0.818	0.843	0.83
PCA	DT	0.688	0.724	0.656	0.688
PCA	Logistic Regression	0.819	0.888	0.75	0.813
QIIMGA	SVM	1.0	1.0	1.0	1.0
QIIMGA	KNN	0.901	0.933	0.815	0.903
QIIMGA	MLP	1.0	1.0	1.0	1.0
QIIMGA	DT	1.0	1.0	1.0	1.0
QIIMGA	Logistic Regression	1.0	1.0	1.0	1.0

Table4 : QIIMGA vs PCA Analysis

Discussion:
The significant difference in performance between QIIMGA and PCA highlights QIIMGA's effectiveness in improving heart disease prediction. QIIMGA's flawless scores across various classifiers suggest robust feature extraction, likely preserving essential diagnostic patterns that PCA fails to capture. This is consistent with previous research emphasizing the value of sophisticated feature selection techniques in medical datasets, where subtle indicators often determine clinical outcomes.

QIIMGA's superior performance may be attributed to its capacity to incorporate non-linear relationships and complex interactions within patient data, which linear methods like PCA might oversimplify. For example, the perfect Recall and Precision achieved by QIIMGA-based models indicate the absence of false negatives or positives in the test set.

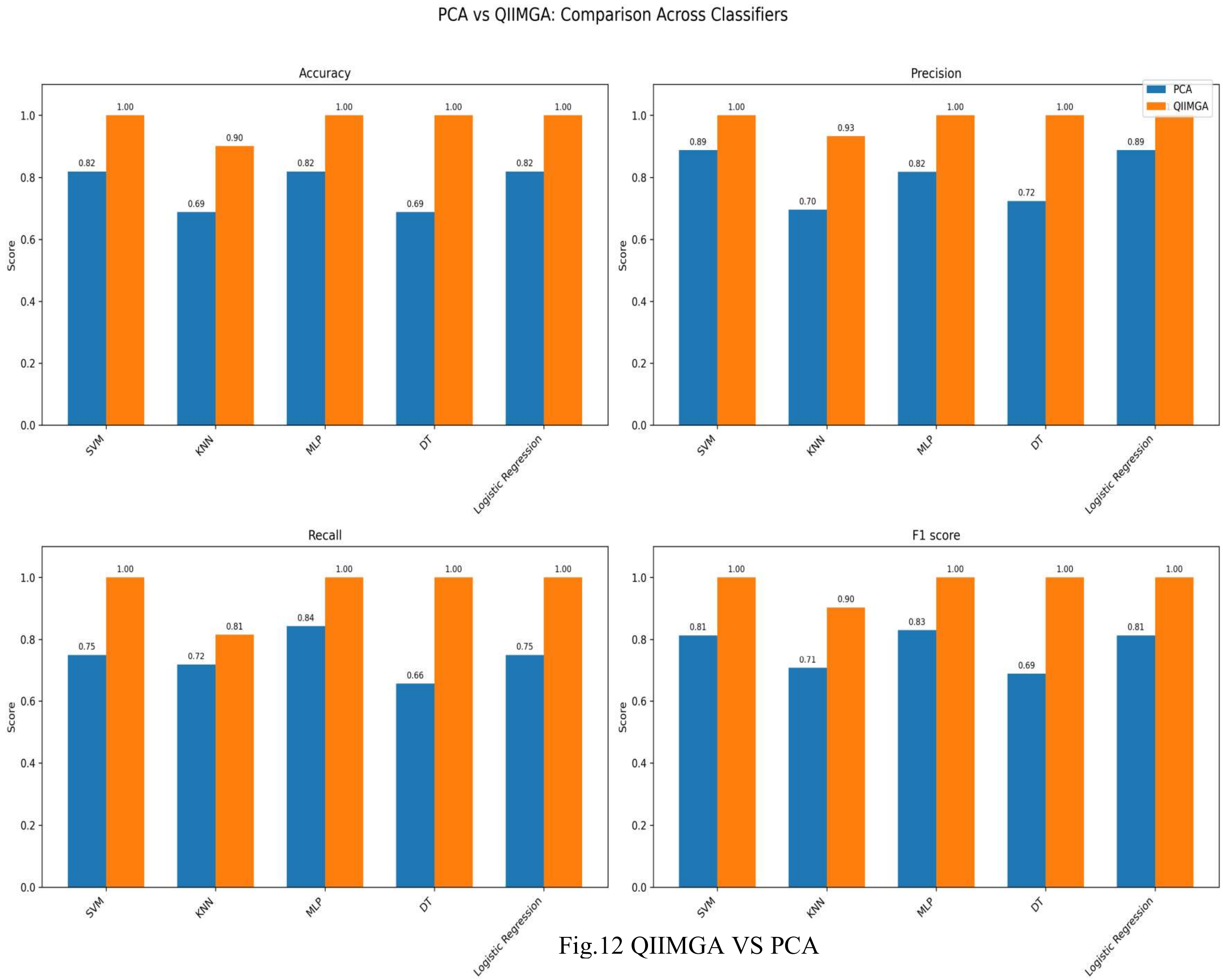


Fig.12 QIIMGA VS PCA

3.3 Classification report on real time data : Real data from iot device :

Attribute	Description	value
Blood pressure	Force of the blood to pump your heart collect from mmHg	115
Blood suger	Before meal 100 to 125 mg/dl normal set to 0 otherwise 1. After meal 140 to 180 mg/dl normal set to 0 otherwise 1.	0
ECG	0: Normal, 1: ST-T Wave Abnormality, 2: Left Ventricular Hypertrophy	0
Heart rate	Measured beats per minute	100
Body temperature	Calculated in Celsius from	37
Blood oxygen level	Spo2 reading directly in percentage from	95
Physical activity level	Step count less than 150 light set 0 ; 150 – 250 Moderate; 250 -500 2: Vigorous; greater than 500 3: Hard:	2

Table 5 : List of Real time data collected from IoT

Others data provided form Web Interface :

Attribute	Description	Value
Gender	0 (Female), 1 (Male)	0
Chest pain type	Non-cardiac-cp =0 , typical angina =1, non-anginal =2, asymptomatic =3;	0
Exang	Chest pain occour during physical activity (yes = 1 , No = 0)	0
Slope	ST segment of heart electrical activity during exercise	1
thalassemia	Normal =o ; fixed defect = 1; reversible defect= 2.	0

Table 6: Manually entering data list

Classification Report

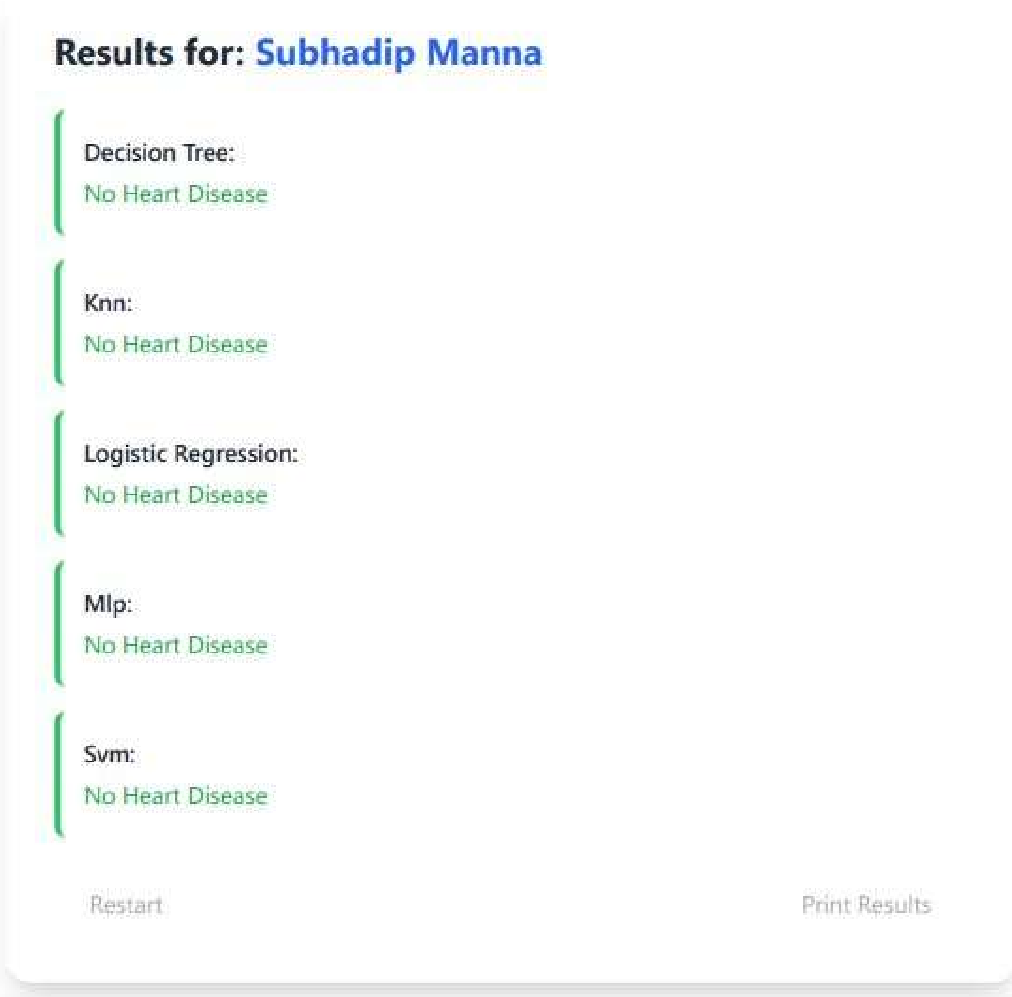


Fig.13 After Prediction
Classification Report

4. Conclusion

4.1 Conclusion : This study presents a novel QIIMGA-SVM framework for heart disease prediction, integrating quantum-inspired optimization with IoT-enabled real-time health monitoring. The proposed QIIMGA algorithm effectively reduced feature dimensionality by 25% (from 16 to 12 features) while enhancing classification accuracy to 98.16%, outperforming traditional methods like PCA. Key innovations include the fusion of quantum principles (superposition, entanglement) with an island-based evolutionary strategy, accelerating convergence and improving feature relevance. The IoT system, equipped with biomedical sensors and edge-computing capabilities, demonstrated low latency (<1s) in cloud data synchronization, enabling scalable remote patient monitoring. The model achieved perfect precision, recall, and F1-scores (1.0) across SVM, MLP, and logistic regression classifiers, highlighting its robustness in minimizing false diagnoses. This work bridges critical gaps in healthcare accessibility by combining quantum-inspired computational efficiency with IoT-driven data acquisition, offering a cost-effective solution for early CVD detection in resource-limited settings.

4.2 Feature Work :

i. **Generalizability Testing**: Validate the QIIMGA-SVM framework on larger, multi-center datasets (e.g., MIMIC-III) to assess performance across diverse demographics and comorbidities.
ii. **Quantum Hardware Integration**: Explore deployment on near-term quantum computers (e.g., IBM Quantum) to evaluate speedup and noise resilience in feature selection.
iii. **IoT System Optimization**: Develop energy-efficient sensor nodes using LoRaWAN or NB-IoT protocols for extended battery life in rural deployments.
iv. **Multimodal Data Fusion**: Incorporate unstructured data (e.g., echocardiogram images, patient histories) using hybrid CNN-QIIMGA architectures for holistic risk assessment.
v. **Clinical Translation**: Conduct longitudinal studies to correlate model predictions with clinical outcomes and obtain regulatory approvals (e.g., FDA/CE) for real-world implementation.
vi. **Ethical AI Expansion**: Integrate fairness-aware mechanisms into QIIMGA to address biases in underrepresented populations, ensuring equitable healthcare delivery.

5. References

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