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Department of Artificial Intelligence and Machine
Database Management Systems (CD252IA)

Synopsis

TITLE : Heart ECG Categorization using TensorRT and MQTT		
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1. Introduction

This project focuses on real-time ECG signal categorization using **TensorRT** and **MQTT** communication between multiple **Raspberry Pi publishers** and a **Jetson Nano subscriber**. The Raspberry Pis simulate heartbeat data from the **MIT-BIH Arrhythmia** and **PTB Diagnostic ECG datasets** and transmit it to the Jetson Nano via MQTT. Initially, **Mosquitto** was used for local communication, later upgraded to **HiveMQ** for cross-network connectivity. The Jetson Nano uses a **TensorRT-optimized deep learning model** for heartbeat classification, storing structured data in **PostgreSQL** and unstructured data in **MongoDB**, and sends alerts back to the respective Raspberry Pi when anomalies are detected.

2. Existing System

The current ECG monitoring systems have several limitations as listed below:

- Mostly rely on **manual or cloud-based analysis**, causing high latency.
- **Single centralized server** for processing, lacking real-time edge computation.
- Limited or **no two-way communication** between devices.
- Dependence on **internet connectivity** for continuous monitoring.
- Use of **only one database type**, making data handling less efficient.

3. Proposed System

The proposed system introduces a **real-time, distributed ECG categorization framework** using **TensorRT** and **MQTT** to overcome the limitations of traditional monitoring systems.

- Multiple **Raspberry Pi devices** act as publishers, simulating ECG signals and sending data to a **Jetson Nano subscriber** via MQTT.
- **TensorRT-optimized deep learning model** on Jetson Nano ensures **fast and accurate heartbeat classification** at the edge.
- **Two-way communication** allows Jetson Nano to send anomaly alerts back to the respective Raspberry Pi in real time.
- **HiveMQ** broker enables **cross-network connectivity**, improving scalability and remote access.

- **PostgreSQL** handles structured data (patient info, timestamps, session details), while **MongoDB** stores unstructured data (ECG waveform logs, inference results).
- Reduces **latency**, increases **reliability**, and ensures **efficient data management** using a hybrid database system.

4. Relational Database Structure

The system uses **PostgreSQL** as the primary RDBMS for structured data. The schema is designed to efficiently store patient details, session information, and ECG heartbeat data.

Key Entities:

- **Patient** (Patient_ID, Name, Age, Gender, Contact, Medical_History)
- **Session** (Session_ID, Patient_ID, Session_Date, Duration)
- **Heartbeat** (Heartbeat_ID, Session_ID, Timestamp, Heart_Rate, Prediction)
- **Doctor** (Doctor_ID, Name, Specialization, Availability) *(optional if linking for consultation)*

Relational Model:

- **One-to-many** between Patient → Session
- **One-to-many** between Session → Heartbeat
- **Optional One-to-many** between Doctor → Patient (if including consultations)

5. RDBMS and NoSQL Integration

While **PostgreSQL** stores structured data such as **patient details, sessions, and heartbeat measurements**, the system also employs **MongoDB** for unstructured and high-frequency data, including:

- Raw ECG waveform segments and time-series logs.
- Model inference results and prediction metadata.
- MQTT message logs for system monitoring, recovery, and audit purposes.

This integration allows efficient handling of both **structured medical data** and **high-volume, unstructured ECG and system data**, ensuring real-time monitoring and scalable database management.

6. Societal Concern

While this system improves real-time ECG monitoring, it may raise societal concerns such as **data privacy risks**, since sensitive patient information could be misused if not properly secured. There is also a possibility of **false alarms or missed detections**, which could affect patient safety. Users might develop an **over-reliance on automated monitoring**, potentially neglecting professional medical advice. Additionally, accessibility could be limited in areas with **poor internet connectivity or lack of devices**, restricting the system’s benefits.