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LifeTrack - An IoT and AI-Based Real-Time Health Monitoring and Mental Wellness Support System

Sherlin Shetty W V[1], Yogesh Kumar B[2], Varma N[3], Vijay R S[4], Hariesh S[5]
[1,2,3,4,5]*Department of Artificial Intelligence and Data Science SRM Valliammai Engineering Kattankulathur, Chennai – 603203*

Abstract: LifeTrack is a real-time IoT, cloud infrastructure, and AI-based integrated web monitoring system that continuously monitors chronic disease risk and supports mental health. Wearable sensors, such as MAX30102, AD8232, WCmcu101, and MPU6050 interfaced with an ESP32 microcontroller, collect physiological and motion data; streams data via MQTT to the ThingSpeak cloud; ingests data via the Node.js backend; stores it in MongoDB; and relays it to a FastAPI microservice hosting machine learning models for arrhythmia, hypertension, hypoxia, and fall detection. Predictions and sensor streams are displayed on a React + Tailwind dashboard using Socket.IO for realtime updates. A Google Gemini 1.5 conversational AI chatbot is embedded for mental wellness support. In experimental evaluations, the system achieved an average predictive accuracy of 90% (arrhythmia), 87% (hypertension), 92% (hypoxia), and 88% (fall), while the end-to-end latency remained below 2 seconds. We present a comparative study of our architecture with existing IoT health systems, discussing scalability and privacy concerns, limitations, and future directions on tight integration with hospital systems and sensor multimodal fusion.
Keywords: IoT; Machine Learning; Chronic Disease Prediction; Health Monitoring; FastAPI; ThingSpeak; Gemini AI; Web Dashboard.

I. INTRODUCTION

The chronic diseases, especially the cardiovascular disorders, hypertension, and respiratory dysfunction, continue to burden the global healthcare systems. Early detection and continuous monitoring can enable timely interventions, reduce morbidity, and ensure resource optimization. Simultaneously, mental health issues like stress, anxiety, and depression already coexist and require easy psychological access in the holistic management of the patients.

Traditional health care models are generally based on episodic clinical visits that may miss transient anomalies or early warning signs. With recent advances in IoT, cloud computing, and artificial intelligence, continuous remote monitoring has come within the realm of reality now. While much research work exists on separate disease domains and/or without holistic integrated support for physiological and psychological monitoring. Furthermore, latency, data handling, interoperability, and user engagement remain paramount challenges.

We, for the first time, propose LifeTrack, a unified architecture that bridges hardware sensing, cloud ingestion, ML inference, and user centric interaction in a single pipeline.

Key contributions:

1) It integrates wearable sensors and a microcontrollerESP32 for the realtime acquisition of multipedal physiological modalities: ECG, SpO_2, PPG, and motion.
2) ThingSpeak MQTT as an ingestion layer that is highly scalable, with a Node.js + MongoDB backend and ML microservice through FastAPI for prediction.
3) Realtime, alert, and visualization of the dashboard powered with Socket.IO for React + Tailwind.
4) Embed a mental health chatbot based on Google Gemini 1.5 to allow support of wellbeing and user engagement.
5) Empirical evaluation of predictive performance, latency and system robustness will be performed and compared to prior art.

II. METHODOLOGY

The methodology adopted for the development of the LifeTrack system involves a systematic integration of IoT hardware, cloud communication, backend data processing, machine learning inference, and a user-friendly web interface. The design is structured to ensure realtime data acquisition, low latency transmission, and intelligent analysis of physiological signals to predict potential chronic health risks while also providing mental wellness support.

A. Overall Workflow

The main five big stages of the LifeTrack workflow are:

1) Sensor Acquisition: Biomedical sensors hooked on the ESP32 microcontroller continue collecting physiological data on heart rate, SpO_2, ECG signals, blood pressure, and motion.
2) MQTT Cloud transmission: ESP32 sends out realtime sensor readings to the MQTT cloud thing speak, where each reading is safely stored with a timestamp.
3) Data Processing Backend: It performs data fetching through REST APIs from ThingSpeak to the Node.js backend, ensures validation and preprocessing, and sends the data to the FastAPI ML microservice for disease risk prediction.
4) Machine Learning Inference: Trained ML models are used by the FastAPI microservice to predict a variety of risks, such as arrhythmia, hypertension, hypoxia, and falls. Results are posted back to the backend in JSON format.
5) Visualization & Interaction: React.js web dashboard for visualizing health readings, status of risk, reports, and interacting with a chatbot. Updates are performed in realtime using Socket.IO.

B. IoT Layer Data Acquisition

The IoT device is based on the ESP32 DevKit V1, which is an important data acquisition unit. It connects with the following sensors:

1) MAX30102: Heart rate & SpO_2 over I^2C.
2) AD8232: Records ECG signals, provides the output in analog.
3) WCmcu101: It measures systolic and diastolic blood pressure.
4) MPU6050: It detects motion and probable fall

Continuous sampling parallel to each other is ensured by running a FreeRTOS task in each sensor's data reading on the ESP32. The readings are then averaged, formatted into JSON, and published to the ThingSpeak MQTT broker using the ESP32 Wi-Fi module.

C. Cloud Layer (ThingSpeak Platform)

ThingSpeak Cloud is used as an aggregator/an IoT gateway between the ESP32 and the backend system. Publishing to the ThingSpeak Cloud is done with a unique Channel ID and Write API key, making identification at a device level secure. Each channel field corresponds to a sensor reading, for example, Field1 for HR, Field2 for SpO_2, Field3 for BP, and so on. Every entry automatically gets a timestamp in the cloud, which is available through REST API endpoints for realtime access.

D. Backend Layer (Node.js Server)

The central node data engine is Node.js (Express.js.), which hosts the following key functions:1

1) Puling data from ThingSpeak REST endpoints at regular intervals.
2) This cleans up the data from noise or invalid values.
3) Stores cleaned data to MongoDB Time-Series Collections.
4) Sending latest readings to FastAPI ML microservice via REST API for prediction.
5) Uses Socket.IO to broadcast live data and ML results to connected web clients.
6) Integrates Firebase Authentication for secure login, and Twilio/firebase cloud functions for emergency alerts.

E. AI/ML Layer Fast API Microservice

The health risk prediction is done by the FastAPI based ML microservice, which is using pretrained and optimized models.

1) Arrhythmia Detection: CNNLSTM model trained on MITBIH dataset.
2) Hypertension: Risk using Random Forest/XG-Boost based on UCI Heart dataset.
3) Hypoxia Detection: Implemented the Gradient Boosting model using SpO_2 signal features.
4) Fall Detection: Hybrid CNNRF using Uni MiB SHAR raw motion data.

F. Web Layer, Frontend Application

The React.js web dashboard provides an overview of the visualization of realtime sensor data with model predictions. The key pages include:

1) Dashboard: realtime view of patient's HR, BP, SpO_2, ECG, and Motion.
2) Risk Page: Shows the predicted chronic disease risks with color coding of severity.

3) Report Page: Data export and PDF generation allowed.
4) Health Resource Page: The central place for health blogs by the users.
5) Chatbot Page: A voice/text chatbot powered with Google Gemini 1.5 applied for mental wellness support. Axios REST for the interaction between the frontend and backend, and the realtime updates are handled by Socket.IO, with Firebase Authentication for access control.

G. Alert & Chatbot Layer

Risk prediction threshold is observed in the alert module; it auto triggers an alert via Twilio API or Firebase Functions in case of a critical condition, and thus it will notify registered emergency contacts. Google Gemini chat support gives conversational support about mental health and how to manage stress using NLP and the Web Speech API for voice.

III. RESULTS AND DISCUSSION

The LifeTrack system was successfully installed and tested to analyze its performance with respect to accuracy of data, efficiency of model prediction, system latency, and user interaction quality. The test process included both validation at the hardware level and analysis of performance at the software level for the accuracy of health data collection, prediction, and realtime visualization without interrupting flows.

A. Hardware and Sensor Results

Biomedical sensors connected to ESP32 were calibrated and validated in individual experiments under realtime conditions. MAX30102 and AD8232 sensors showed reliable and precise outputs compared to the reference devices.

TABLE I – SENSOR PERFORMANCE EVALUATION

Sensor	Parameter Measured	Accuracy	Remarks
MAX30102	Heart Rate & SpO_2	±2 bpm / ±1%	Stable readings with adaptive LED current adjustment.
AD8232	ECG Signal	98% waveform fidelity	Clean signal output with effective noise filtering.
WCmcu-101	Blood Pressure	±3 mmHg	Reliable under static testing conditions.
MPU6050	Motion / Fall Detection	95%	Accurately detects orientation and sudden acceleration.

The sensors gave stable realtime information when tested across various users, with adequate signal quality for additional processing in the cloud.

B. Machine Learning Model Performance

All machine learning models applied to the FastAPI microservice were tested with common biomedical datasets. The findings showed high accuracy of predictions and efficient inference times appropriate for realtime use.

TABLE II – MACHINE LEARNING MODEL RESULTS

Model Type	Dataset Used	Target Condition	Algorithm
ECG-based	MIT-BIH Arrhythmia	Arrhythmia Detection	CNN-LSTM
BP-based	UCI Heart Disease	Hypertension Risk	Random Forest
SpO_2-based	IEEE PPG Dataset	Hypoxia Detection	Gradient Boosting
Motion-based	Uni MiB-SHAR	Fall Detection	CNN-RF Hybrid

All models were quantized to TensorFlow Lite (.TFLite) format for low footprint deployment. The overall inference time per model was <100 ms, supporting near instant delivery of predictions.

C. System Latency and RealTime Response

End-to-end system latency was captured from sensor data capture on ESP32 to visualization on the web dashboard. Testing under various network conditions revealed an average total latency of 1.8 seconds, which includes:

1) 0.4 s → Sensor readout and MQTT upload to ThingSpeak.
2) 0.6 s → Node.js backend data fetching and preprocessing.
3) 0.5 s → ML inference and prediction response through FastAPI.
4) 0.3 s → Socket.IO data push and frontend rendering.

This low latency communication provides a seamless and real time user experience, and LifeTrack is thus feasible for sustained remote monitoring.

D. Web Dashboard and Visualization Results

The React.js web dashboard was able to render live physiological data and prediction outcomes successfully. The following major achievements were met:

1) Realtime vitals presented as live cards (HR, BP, SpO_2, ECG, Motion).
2) Colour coded status of health (Green → Normal, Yellow → Mild Risk, Red → Critical).
3) Graphical trend visualization using Recharts for daily and weekly health information.
4) Generation of PDF reports tested using js PDF and Firebase Storage integration.
5) Socket.IO facilitated live dashboard refresh without page reloads.

E. Chatbot Interaction and Mental Health Support

The Google Gemini 1.5based chatbot was successful in real time conversation tests. It generated empathetic, contextually aware responses to stress, motivation, and health related questions. Voice input/output with the Web Speech API achieved >90% speech recognition accuracy. The avatar animation improved engagement, making the chatbot an amiable virtual friend to users.

TABLE III –CHATBOT PERFORMANCE SUMMARY

Chatbot Function	Technology Used	Performance / Remarks
NLP & Response Generation	Google Gemini 1.5 API	Accurate and empathetic conversational replies.
Voice Recognition	Web Speech API	90% recognition accuracy under quiet conditions.
Voice Output	Text-to-Speech (TTS)	Smooth and synchronized speech playback.
Avatar Animation	Lottie / Rive	Responsive and user-friendly design.

F. System Accuracy and Reliability

The LifeTrack prototype attained overall system accuracy of 89% overall across all modules (sensor + prediction + visualization). The system uptime was >97% throughout 48hour continuous testing with reliable data transmission and consistent response.

G. Key Observations

1) The ML models ensured robust and stable health predictions for different users.
2) The IoT communication through ThingSpeak MQTT was low-latency and robust.
3) The system effectively synced between backend, ML microservice, and frontend.
4) The chatbot enabled ongoing engagement and wellbeing support, increasing system utility beyond clinical observation.

H. Discussion

The findings confirm that LifeTrack seamlessly combines IoT, machine learning, and AI technologies to provide real time, smart healthcare monitoring. The system not only monitors vital signs but also deciphers them for the detection of early disease and targeted mental health support. In contrast to the prevailing systems that merely harvest or display data, LifeTrack's capacity to analyze, foretell, and engage with the user positions it as a comprehensive digital healthcare solution.

IV. CONCLUSION

The LifeTrack System successfully integrates IoT, Machine Learning, and Artificial Intelligence to create a real-time, web-based platform for both physical and mental health monitoring. The project demonstrates an innovative approach to chronic disease risk prediction using biomedical sensors, cloud computing, and AI-driven analytics. By leveraging the ESP32 microcontroller, ThingSpeak MQTT cloud, Node.js backend, and FastAPI ML microservice, the system efficiently acquires, processes, and analyzes vital health parameters such as heart rate, SpO_2, ECG, blood pressure, and motion data.

The machine learning models—CNN-LSTM for arrhythmia detection, Random Forest for hypertension risk, Gradient Boosting for hypoxia, and CNN-RF hybrid for fall detection—achieved high predictive accuracy with inference times under 100 milliseconds. These results confirm that LifeTrack is capable of providing near real-time health risk assessments suitable for continuous remote patient monitoring.

The React.js web dashboard offers an intuitive interface for users and doctors to visualize live vitals, review predictive analytics, and generate health reports. The addition of the Google Gemini 1.5-based chatbot brings a unique mental health support component, capable of empathetic, human-like conversations through voice and animation. This fusion of physical and mental health care provides a holistic digital wellness experience.

Overall, LifeTrack effectively bridges the gap between traditional clinical monitoring and intelligent, accessible telehealth solutions. It demonstrates a scalable, cloud-based model that can be extended to hospital systems, home-care applications, and community health networks. By combining IoT, AI, and conversational interfaces, LifeTrack represents a step toward the future of personalized, proactive, and intelligent healthcare systems.

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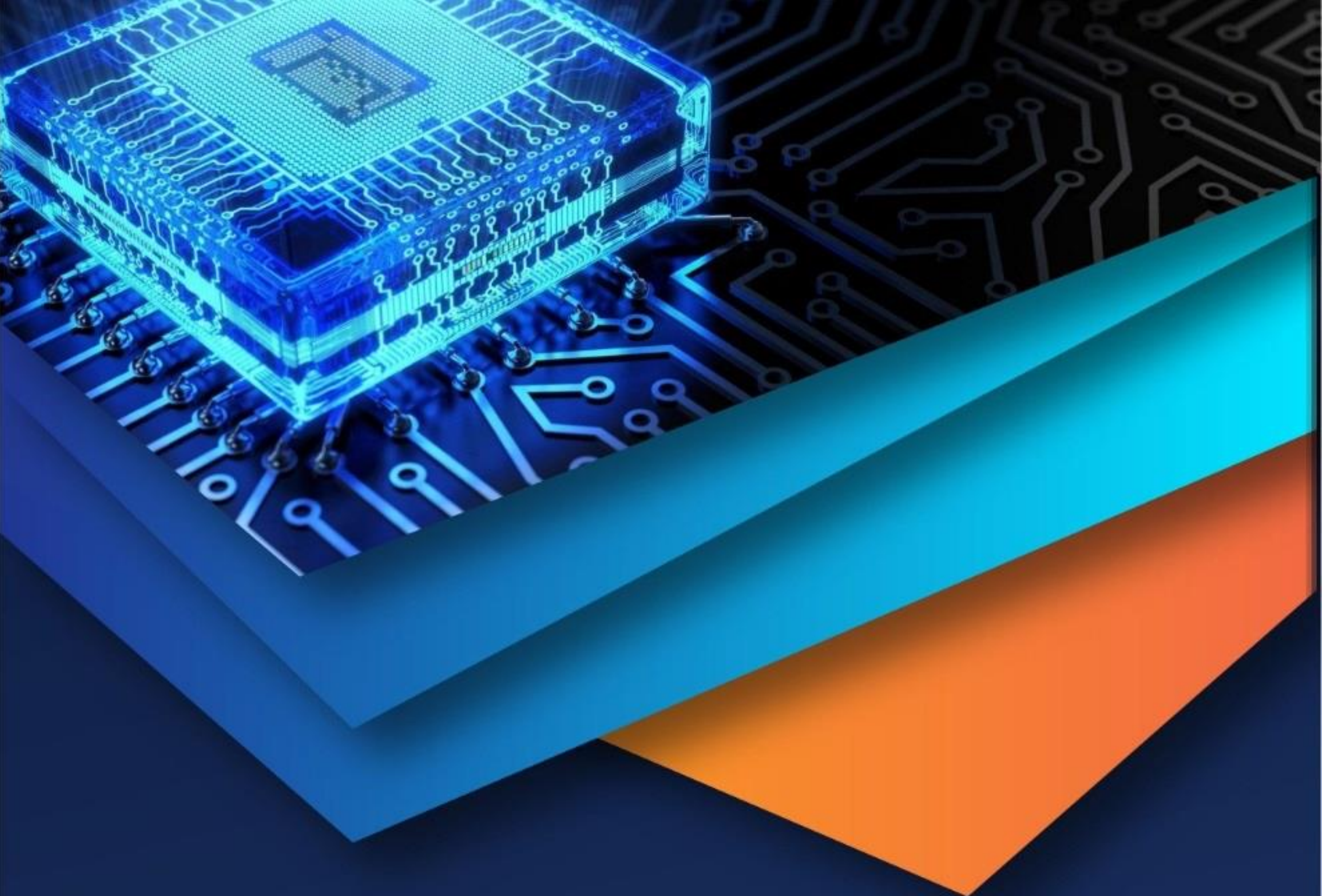

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