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IOT BASED HEALTH CARE PREDICTION USING AI

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Abstract—Wearable health monitoring devices play a crucial role in the timely detection of medical emergencies, such as abnormal heart conditions and falls. But current systems primarily depend on cloud computing, which leads to delays, the need for reliable network connectivity, and privacy issues. To address these issues, this paper proposes an edge-intelligent wearable health monitoring system that can perform real-time health and safety monitoring by fusing multiple sensor readings and applying TinyML. Proposed system incorporates physiological and motion sensors such as heart rate, SpO_2 (oxygen saturation), body temperature and a triaxial accelerometer, interfaces to an ESP32 microcontroller. Rather than sending data to the cloud, the system leverages on-device analytics with TinyML models. This allows real-time detection of cardiac abnormalities and falls to occur on the device. The multi-sensor fusion and embedded machine learning enhance detection performance while minimizing energy and bandwidth costs. The edge computing approach allows for rapid response, improved security and privacy, and does not rely on a strong network connection. In case of a fall or other abnormal event, the device sends immediate notifications to family or health-care providers via wireless communication. The developed system offers a small, low-cost and scalable solution to continuous health monitoring, enabling safe and independent living for the elderly and patients who need continuous monitoring.

Keywords: Wearable-type sensors, IoT healthcare, real-time monitoring, fall detection, edge computing, Tiny ML, low-power systems, embedded system.

I. INTRODUCTION

Heart diseases are one of the major causes of death globally, and need to be monitored and detected at an early stage to avoid emergency medical conditions. Likewise, falls, particularly among the elderly, are a major cause of injuries and death if not timely detected. Conventional health care systems are predominantly based on regular clinic visits and in-hospital monitoring, which may not be timely enough. Moreover, cloud-based IoT systems for health monitoring are prone to issues like network latency, energy efficiency and privacy, and are hence less suited for continuous personal health monitoring in emergencies. The latest developments in IoT and wearable healthcare systems aim to overcome these challenges. For example, a cost-effective wearable IoT-based system was designed for cardiovascular disease monitoring with real-time monitoring of vital signs such as heart rate, blood pressure and oxygen saturation levels using mobile based alarms and alerts, enhancing access in resource-limited environments [1]. Likewise, AIoT cardiovascular monitoring systems use machine learning and big data analytics to provide early warning and home health care, improving preventive health care and risk factors [2]. Other systems have adopted smart biomedical systems with active regulation of physiological functions, such as thermoelectric-based circulation boosters to enhance blood circulation in remote areas, showing the benefits of integrated sensing and actuation in medical systems [3]. IoT-enabled smart bands for real-time monitoring of physiological signals, such as ECG, temperature and heart rate, with cloud-based emergency alert systems, have also been proposed, showcasing the critical role of real-time data transfer in cardiovascular monitoring [4]. Moreover, fog and cloud supported IoT-based healthcare systems have been proposed for scalable cardiac monitoring systems for remote patient monitoring and to provide better decision-making support for the doctors [5]. But despite these developments, current systems largely rely on cloud-based data processing, making them less responsive in real-time settings and adding network-reliance to the system. To address these shortcomings, there is an increasing demand for edge-intelligent wearable devices with on-device processing and decision-making capabilities. In this paper, we present an ESP32-based wearable health monitoring solution that employs multi-sensor fusion and TinyML to perform real time cardiac anomaly and fall detection on the device itself, providing low latency and privacy, while maintaining offline functionality and accuracy.

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II. LITERATURE REVIEW

The integration of IoT and AI in healthcare has significantly improved remote monitoring, particularly for cardiovascular diagnosis and fall detection in the elderly. Various studies have used sensors, machine learning, and deep learning to enhance detection accuracy and support independent living. For instance, Alharbi et al. developed a smart flooring system using RFID and achieved 99% accuracy with KNN, while Karar et al. highlighted wearable sensor-based systems and challenges like lack of standard datasets and real-time processing. Other works, such as those by K S and Kumar and Khan et al., demonstrated high accuracy (around 95–97.9%) using sensors and machine learning models like Random Forest and Naïve Bayes. Systems integrating emergency response features, such as GPS-enabled alerts and mobile notifications, further improve patient safety and timely intervention. Additional research emphasizes automation, activity recognition, and multi-sensor approaches for reliable monitoring, achieving accuracies above 90%. Despite these advancements, many systems rely on cloud or threshold-based methods, leading to delays and security concerns, highlighting the need for efficient TinyML-based solutions that enable real-time processing directly on wearable devices.

III. DATASET AND PREPROCESSING TECHNIQUES

The dataset used in the proposed system is generated from real-time wearable sensors, including heart rate, SpO_2, body temperature, and accelerometer data, capturing both normal activities and abnormal conditions such as falls and cardiac irregularities. Data is collected continuously in controlled and real-world scenarios to ensure proper model training and evaluation. Preprocessing techniques are applied to improve data quality, including noise removal using moving average filtering, normalization, and time-window segmentation. Feature extraction methods such as mean, variance, and acceleration magnitude are used to convert raw signals into meaningful inputs. Finally, sensor fusion combines physiological and motion data to enhance accuracy and support efficient real-time inference using Tiny ML.

IV. METHODOLOGY

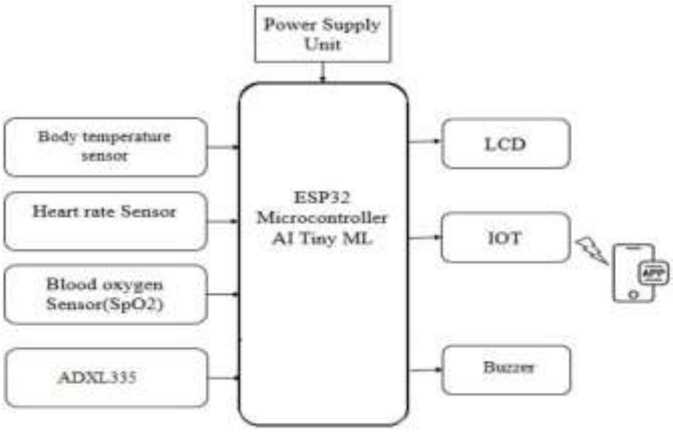

Fig. 1 System Architecture of IOT based health care prediction using AI

The system proposes a lightweight wearable health monitoring solution for real-time tracking of physiological parameters and activities. It uses sensors such as heart rate, SpO_2, temperature, and an accelerometer connected to an ESP32 microcontroller. Data is processed locally using Tiny ML, eliminating the need for cloud computing and ensuring low latency and privacy. Sensor fusion improves the detection of cardiac anomalies and fall events with higher accuracy. In emergencies, the system sends instant alerts via wireless communication, enabling quick response and supporting independent living.

A. System Architecture Design

The system is designed using a modular architecture centered around the ESP32 microcontroller with AI TinyML capabilities. Multiple health sensors are integrated to collect real-time physiological data. The ESP32 processes this data and communicates with output modules such as alert systems, IoT platforms, and buzzers for monitoring and response.

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B. Data Acquisition and Sensor Integration

The system collects real-time health parameters using various sensors, including a body temperature sensor, heart rate sensor, blood oxygen (SpO_2) sensor, and ADXL335 accelerometer. All sensors operate at 3.3V and continuously send data to the ESP32 through designated GPIO pins for further processing.

C. AI-Based Processing (TinyML on ESP32)

The ESP32 microcontroller processes the incoming sensor data using embedded AI (TinyML) models. These models analyze patterns in physiological signals to detect abnormalities such as irregular heart rate, low oxygen levels, or unusual body movements.

D. Health Monitoring and Analysis

The system evaluates multiple parameters such as body temperature, heart rate, oxygen saturation, and motion data. By combining these inputs, it identifies potential health risks like fever, fatigue, falls, or abnormal vital signs, ensuring continuous monitoring of the user's condition.

E. Alert and IoT Communication

When abnormal conditions are detected, the system generates alerts through a display indicator and buzzer. Simultaneously, data is transmitted to an IoT platform or mobile device for remote monitoring. This enables timely medical response and improves overall healthcare efficiency.

V. SYSTEM ARCHITECTURE

The system architecture of the proposed AI-based health monitoring system is designed to provide continuous and real-time tracking of vital health parameters. It consists of multiple interconnected modules that work together to collect physiological data, process it using embedded intelligence, analyze health conditions, and generate alerts. Each module plays a crucial role in ensuring accurate monitoring and timely response.

A. Sensor Input Module

The Sensor Input Module is responsible for collecting real-time physiological data from the user. It includes sensors such as body temperature sensor, heart rate sensor, blood oxygen (SpO_2) sensor, and the ADXL335 accelerometer. These sensors continuously measure vital parameters and send analog or digital signals to the ESP32 microcontroller for further processing.

B. Data Acquisition Module

The Data Acquisition Module gathers and organizes data received from all connected sensors. It ensures proper sampling, synchronization, and signal stability. The collected data is prepared in a structured format so that it can be efficiently processed by the embedded system.

C. ESP32 Processing Module (AI TinyML)

The ESP32 Processing Module acts as the core unit of the system. It processes incoming sensor data using embedded AI models (TinyML). The microcontroller analyzes patterns in real-time and performs intelligent decision-making to detect abnormalities such as irregular heart rate, abnormal temperature, low oxygen levels, or sudden movement.

D. Health Analysis Module

The Health Analysis Module evaluates the processed data to determine the user's health condition. It compares sensor readings with predefined thresholds and identifies abnormal patterns. Parameters such as motion (fall detection), heart rate variation, and oxygen saturation are analyzed to assess potential risks.

E. Alert Generation Module

The Alert Generation Module is responsible for triggering alerts when abnormal conditions are detected. It activates visual indicators, such as an alert display, and audible warnings using a buzzer. This ensures immediate awareness in case of emergencies.

F. IoT Communication Module

The IoT Communication Module enables remote monitoring by transmitting data to cloud platforms or mobile devices via Wi-Fi. It allows doctors or caregivers to access real-time health data and receive notifications, improving response time and decision-making.

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G. Monitoring and Storage Module

The Monitoring and Storage Module provides an interface for viewing health data and system status. It stores historical records of sensor readings and alerts for future analysis. This module ensures efficient data management and supports long-term health tracking.

VI. RESULTS

The proposed AI-based health monitoring system was tested using real-time sensor data. The ESP32 with TinyML efficiently monitored body temperature, heart rate, SpO_2, and motion. It accurately detected abnormal conditions such as irregular heart rate, low oxygen levels, and sudden movements. The system showed fast response and reliable real-time performance.

A. System Performance and Accuracy

The system achieved good accuracy under different conditions with minimal errors.

B. Detection Efficiency

It processed multiple sensor data quickly and detected abnormalities in real time.

C. User Experience and Reliability

The alert system worked effectively with buzzer and IoT notifications, ensuring stable and continuous operation.

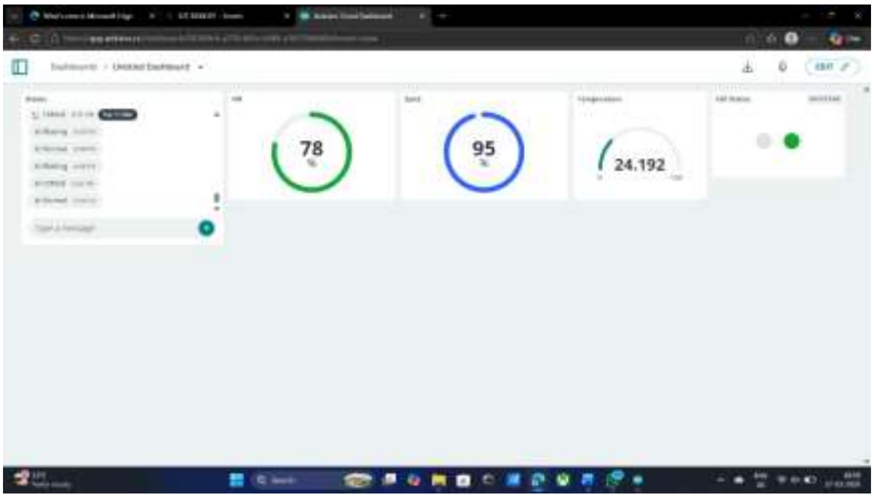

Fig. 2 Output Showing Abnormal Behaviour Detection

VII. COMPARATIVE ANALYSIS

The comparison highlights the difference between traditional health monitoring methods and the proposed AI-based system. Traditional systems require manual measurement of vital signs using separate devices, leading to delays and lack of continuous monitoring. In contrast, the proposed system provides automated, real-time monitoring using sensors and ESP32 with TinyML. It continuously tracks health parameters and detects abnormalities instantly, enabling faster response.

A. Existing System vs Proposed System

Traditional systems are manual and periodic, requiring human intervention to record data. They are reactive and may miss sudden health issues. The proposed system is automated and proactive, continuously monitoring vital signs and detecting abnormalities in real time, reducing human effort and improving efficiency.

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B. Feature Comparison

Existing systems offer basic measurement without intelligent analysis or alerts. The proposed system integrates multiple sensors, AI-based analysis, IoT connectivity, and real-time alert generation. This enhances accuracy, enables remote monitoring, and improves overall healthcare management.

VIII. CONCLUSION AND FUTURE SCOPE

The proposed AI-based health monitoring system using ESP32 and Tiny ML provides an efficient solution for real-time tracking of vital parameters. It successfully monitors body temperature, heart rate, SpO_2, and motion, and detects abnormal conditions with good accuracy. The system reduces manual effort, ensures continuous monitoring, and generates instant alerts during emergencies. Its modular design makes it reliable and suitable for real-world healthcare applications, improving patient safety through proactive monitoring.

A. Future Scope

The system can be further enhanced by integrating advanced AI models for improved accuracy and predictive analysis. Cloud integration can be used for large-scale data storage and remote monitoring. Mobile application support can provide real-time notifications and user-friendly access. Additional sensors and wearable integration can expand functionality, while improved analytics can help predict health risks before they occur.

REFERENCES

[1]. Bansal, A. K. Shukla and S. Bansal, "Machine Learning Methods for Predictive Analytics in Health Care," *2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART)*, MORADABAD, India (2021), pp. 258-262, doi: 10.1109/SMART52563.2021.9676233.

[2]. F. Yu, L. Cui, Y. Cao, F. Zhu, Y. Xu and N. Liu, "Feature-Guided Logical Perception Network for Health Risk Prediction," *2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Las Vegas, NV, USA (2022), pp. 1787-1790, doi: 10.1109/BIBM55620.2022.9995625.

[3]. Dipendra Pant; Kaban Koochakpour; Odd Sverre Westbye; Carolyn Clausen; Bennett L. Leventhal; Roman Koposov.(2024), "Visualizing Patient Trajectories and Disorder Co-occurrences in Child and Adolescent Mental Health," *2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Lisbon, Portugal, pp. 5531-5538, doi: 10.1109/BIBM62325.2024.10822472.

[4]. Fengli Zhu; Junfeng Wang; Chen Cheng; Chang Zhu; Siyu Yuan; Huoba Li"Design of AI in the Health and Elderly Care Service Platform in the Big Data Environment," *2023 IEEE International Conference on Paradigm Shift in Information Technologies with Innovative Applications in Global Scenario (ICPSITIAGS)*, Indore, India (2023), pp. 111-116, doi: 10.1109/ICPSITIAGS59213.2023.10527766.

[5]. R. Golchha, P. Khobragade and A. Talekar, "Design of an Efficient Model for Health Status Prediction Using LSTM, Transformer, and Bayesian Neural Networks," *2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET)*, Nagpur, India (2024), pp. 1-5, doi: 10.1109/ICICET59348.2024.10616353.

[6]. M. E. Hossain, A. Khan, M. A. Moni and S. Uddin, "Use of Electronic Health Data for Disease Prediction: A Comprehensive Literature Review," in *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 18, no. 2, pp. 745-758, 1 March-April (2021), doi: 10.1109/TCBB.2019.2937862.

[7]. S. Kamoji, S. Rozario, S. Almeida, S. Patil, S. Patankar and H. Pendhari, "Mental Health Prediction using Machine Learning Models and Large Language Model," *2024 Second International Conference on Inventive Computing and Informatics (ICICI)*, Bangalore, India (2024), pp. 185-190, doi: 10.1109/ICICI62254.2024.00040.

[8]. Kausthav Pratim Kalita; Sarat Kumar Chettri; Rup Kumar Deka"A Blockchain-based Model for Maternal Health Information Exchange and Prediction of Health Risks using Machine Learning," *2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, Bengaluru, India (2023), pp. 1184-1189, doi: 10.1109/IITCEE57236.2023.10090997.

[9]. Z. Lai, S. Ponmudi, H. Chen, S. -Y. Chan, M. J. Meaney and M. Z. L. Kee, "ML-Based Prediction of Prenatal Maternal Mental Health Risk before Pregnancy Using Multi-Ethnic Cohorts," *2025 Second International Conference on Artificial Intelligence for Medicine, Health and Care (AIxMHC)*, Taichung, Taiwan (2025), pp. 237-240, doi: 10.1109/AIxMHC65380.2025.00049.

[10]. Miguel Contreras; Brandon Silva; Benjamin Shickel; Sabyasachi Bandyopadhyay; Ziyuan Guan; Yuanfang Ren"Dynamic Delirium Prediction in the Intensive Care Unit using Machine Learning on Electronic Health Records," *2023 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI)*, Pittsburgh, PA, USA (2023), pp. 1-5, doi: 10.1109/BHI58575.2023.10313445.

