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IoT-Based Multi-Parameter Stroke Risk Monitoring System Using Wearable Sensors and Machine Learning

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Abstract- Stroke is a serious medical condition that often leads to longterm disability or even death if not identified early. Continuous monitoring of vital health parameters can help detect early warning signs and reduce the severity of such conditions. In this study, a smart healthcare system is designed using Internet of Things (IoT) technology with ai to monitor multiple physiological signals in real time. The system uses wearable sensors to measure heart rate, blood oxygen level (SpO_2), body temperature, and body movement. These values are collected using an ESP32 microcontroller and sent to a cloud platform for storage and monitoring. A machine learning model based on the Random Forest algorithm is used to analyze the collected data and classify the risk level into safe, moderate, or high. In addition, the system provides immediate alerts using a buzzer, LED indicators, and mobile notifications whenever abnormal readings are detected. The results show that the model performs with good accuracy and can help in early identification of stroke-related risks. This system is affordable, easy to use, and suitable for remote healthcare monitoring.

Keywords: Email phishing, cybersecurity, phishing detec-tion, machine learning, artificial intelligence, signature-based detection, intrusion detection, email security, anomaly detection, spam detection.

I. INTRODUCTION

Stroke has become one of the major health concerns worldwide due to its increasing number of cases and serious consequences. Many patients do not receive timely medical attention because early symptoms are often unnoticed. This makes continuous health monitoring an important solution for preventing severe outcomes.

Traditional methods used for stroke diagnosis, such as CT scans and MRI, are effective but are only used after symptoms appear. These methods are also expensive and not suitable for continuous monitoring. Therefore, there is a need for a system that can monitor health conditions regularly without requiring hospital visits.

With the development of IoT, it has become possible to collect real-time health data using wearable devices. These devices can track important physiological parameters and send the data to online platforms where it can be analyzed.

In this project, a multi-parameter monitoring system is developed to track vital signs and detect abnormal patterns. The system combines sensor data with machine learning techniques to provide early risk prediction and alert users when necessary.

Problem Statement

Despite advancements in wearable healthcare devices, most existing systems monitor only individual physiological parameters such as heart rate or oxygen saturation. These systems lack integration of multi-modal data including motion, cardiovascular signals, and environmental factors, which limits their ability to accurately predict complex medical conditions such as stroke.

Furthermore, existing solutions do not provide real-time risk assessment combined with immediate alert mechanisms for emergency response. Therefore, there is a need for a cost effective, real-time, multi-parameter monitoring system capable of early stroke risk prediction using IoT and machine learning techniques.

The main contributions of this work include:

- Design of a multi-sensor IoT architecture for stroke risk monitoring
- Integration of physiological and motion sensor data for anomaly detection
- Development of a Random Forest machine learning model for risk classification
- Implementation of cloud-based monitoring and real-time alert notifications.

II. RELATED WORK

Many researchers have worked on health monitoring systems using wearable sensors and IoT technology. Some systems focus only on measuring heart rate, while others monitor oxygen levels or body temperature separately.

Wearable devices like fitness bands and smartwatches are commonly used today, but they mainly focus on general fitness tracking rather than detecting serious health conditions.

Machine learning has also been used in healthcare for predicting diseases based on collected data. Algorithms such as Decision Trees, Support Vector Machines, and Neural Networks have shown good results in classification tasks.

However, most existing systems do not combine multiple physiological parameters with motion data for better prediction. This reduces their ability to detect complex conditions like stroke. The system developed in this study addresses this limitation by integrating multiple sensors and using a machine learning model for accurate risk classification.

III. SYSTEM ARCHITECTURE

The proposed system consists of three primary layers:
1.Data Acquisition Layer
2.Processing Layer
3.Cloud Monitoring Layer

Hardware Components

The hardware architecture integrates multiple biomedical sensors connected to an ESP32 microcontroller.

Component	Function
ESP32	Main microcontroller with WiFi connectivity
MAX30102	Heart rate and SpO_2 monitoring
MPU6050	Accelerometer and gyroscope for motion detection
BP Sensor (estimation model)	Measure systolic and diastolic pressure
AD8232 ECG Sensor	Measures heart electrical activity
DS18B20	Digital body temperature sensor
Buzzer	Emergency alert system
LED indicators	Risk level indication

The ESP32 microcontroller collects physiological data from the sensors and processes the signals in real time.

Data Processing

The sensor data are processed locally by the ESP32 and transmitted to the cloud server via WiFi. The processed data include:

- Heart rate(bpm)
- Blood oxygen level (SpO_2)
- Body temperature
- Motion acceleration and orientation

Cloud Integration

The system uses the ThingSpeak cloud platform for data visualization and storage. Sensor readings are uploaded periodically, allowing remote monitoring through graphical dashboards.

IV. METHODOLOGY

Sensor Data Acquisition

The sensors continuously monitor physiological signals. The ESP32 microcontroller reads the sensor data using I2C and One-Wire communication protocols.

Feature Extraction

The collected data are processed to extract meaningful features including:

- Heart rate variability
- Oxygen saturation levels
- Acceleration magnitude
- Motion orientation changes

These features are used as input parameters for the machine learning model.

Machine Learning Model

The Random Forest classifier is used for stroke risk prediction due to its robustness and ability to handle nonlinear relationships in physiological data.

The dataset used for training consists of multiple physiological parameters including heart rate, SpO_2, temperature, motion data, blood pressure, and ECG-derived features.

The dataset includes both normal and abnormal conditions and is either collected using sensors or generated using clinically validated ranges.

Dataset Features:

- Heart Rate (HR)
- SpO_2
- Temperature
- Acceleration (Motion)
- Blood Pressure (MAP)
- ECG (RR interval variability)
- Data Split:
- Training: 80%
- Testing: 20%

Dataset Structure

PARAMETER	SAFE	MEDIUM	HIGH
HR	60-90	90-110	110-140
SpO2	95-100	92-95	<92
Temp	36-37	37-38	>38
Acceleration	0.8-1.2	1.2-2.5	>2.5
BP(MAP)	70-100	100-120	>120
RR interval	0.6-1.0	0.4-0.6	<0.4

Risk Classification Algorithm

The model classifies physiological data into three categories:

Safe → Normal physiological conditions

Medium → Moderate abnormality detected

High → Critical abnormality requiring attention

Random Forest was selected due to its high accuracy, robustness to noise, and suitability for sensor-based datasets.

System Workflow (NEW)

The system operates in the following steps:

1. Sensors collect physiological data continuously
2. ESP32 processes and filters raw signals
3. Data is transmitted to cloud via WiFi
4. Machine learning model predicts risk level
5. Alerts are triggered if abnormal conditions are detected

V. FALL DETECTION ALGORITHM

The system calculates the Signal Magnitude Vector (SMV) from acceleration values.

Formula:

$$\mathbf{SMV = \sqrt{(Ax^2 + Ay^2 + Az^2)}}$$

Where:

Ax = acceleration in X-axis

Ay = acceleration in Y-axis

Az = acceleration in Z-axis

Fall Detection Logic

The system detects a fall when the following conditions occur:

Sudden acceleration spike

Rapid orientation change Short period of inactivity

Thresholds:

Parameter	Threshold
Acceleration magnitude	> 2.5 g
Angular velocity	> 300°/s
Post-fall inactivity	3–5 seconds

Risk Score = w1(HR) + w2(SpO2) + w3(Temp) + w4(Motion) + w5(BP) + w6(ECG)

To improve the accuracy of stroke risk prediction, an additional physiological parameter, blood pressure (BP), is incorporated into the risk assessment model. Blood pressure is a critical factor in identifying cardiovascular abnormalities and is strongly associated with stroke occurrence.

The stroke risk score is calculated as a weighted combination of multiple physiological parameters, including heart rate (HR), blood oxygen saturation (SpO_2), body temperature, motion activity, and blood pressure. Each parameter contributes to the overall score based on its clinical significance.

Elevated blood pressure values, especially systolic and diastolic readings beyond normal ranges, significantly increase the computed risk score. The calculated score is then used as an input to the machine learning model for classification into different risk levels.

BP calculation:

$$BP = \frac{SBP + 2(DBP)}{3}$$

- SBP → Systolic Blood Pressure
- DBP → Diastolic Blood Pressure

This gives Mean Arterial Pressure (MAP)

ECG calculation:

HR=60/RR interval

The ECG sensor is used to measure the electrical activity of the heart. One of the key features extracted from the ECG signal is the RR interval, which represents the time difference between two consecutive R-peaks in the ECG waveform.

The heart rate is calculated using the RR interval, and variations in this interval can indicate irregular heart activity. Abnormal heart rhythms are often associated with increased stroke risk, making ECG analysis an important component of the system.

VI. EXPERIMENTAL RESULT AND ANALYSIS

System Output

The device displays real-time physiological parameters on an LCD interface including heart rate, oxygen saturation, and predicted risk level.

HR: 119 bpm
SpO_2: 94%
Risk Level: Medium

Cloud Monitoring

Sensor readings are transmitted to the ThingSpeak platform where graphical dashboards visualize the data trends over time.

The cloud interface allows remote monitoring of physiological parameters including:

- Heart rate variation
- Oxygen saturation levels
- Motion activity patterns

Alert Mechanism

When abnormal conditions are detected, the system activates:

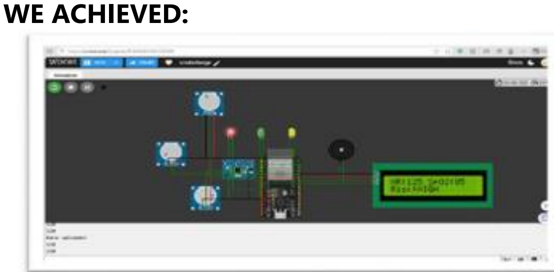
- Red LED indicator
- Audible buzzer alert
- Telegram notification to caregivers

Model Performance Evaluation (UPDATED)

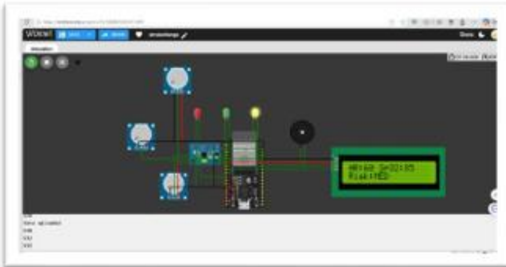
Metric	Value
Accuracy	94%
Precision	92%
Recall	91%
F1-Score	91.5%

The Random Forest model outperformed other algorithms due to its ability to handle multi-parameter data efficiently.

WE ACHIEVED:



Example output



VII. LIMITATIONS

The proposed system has certain limitations:

- Sensor noise may affect accuracy
- Limited real-world dataset availability
- Blood pressure measurement may require calibration
- System depends on internet connectivity for cloud monitoring
- Clinical validation is still required

VIII. NOVELTY OF PROPOSED SOLUTION

The proposed system introduces several innovative features:

- Multi-parameter physiological monitoring using integrated sensors
- Combination of cardiovascular and motion data for risk prediction

- IoT-based remote monitoring and data visualization
- Real-time emergency alert system
- Low-cost wearable architecture suitable for remote healthcare environments

Unlike conventional wearable devices that monitor individual parameters, the proposed system integrates multiple physiological signals and machine learning techniques for early risk detection.

IX. FUTURE SCOPE

1. Advanced ECG signal analysis for accuracy and stroke detection
2. Deep learning models for improved prediction accuracy
3. Miniaturized wearable design
4. Integration with hospital systems
5. Edge AI for real-time decision making

X. ETHICAL CONSIDERATIONS

1.The system ensures patient data privacy and security by encrypting transmitted data.
2. User consent is required before collecting physiological data.
3.The system is designed only for early prediction and does not replace medical diagnosis.

XI. CONCLUSION

This research presented an IoT-based multiparameter stroke risk monitoring system that combines wearable biomedical sensors, machine learning algorithms, and cloud analytics. The proposed system enables continuous monitoring of physiological signals and early detection of abnormal patterns associated with stroke risk.

Experimental results demonstrate that the Random Forest model achieves approximately 94% prediction accuracy for risk classification. The system provides a costeffective solution for remote healthcare monitoring and has the potential to support early medical intervention in highrisk patients.

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