"Integration of IoT and Machine Language In DIY Portable Health Monitoring Devices."

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***Abstract*— The integration of IoT and Machine Learning has emerged as a powerful approach to improving healthcare accuracy, personalization, and accessibility. This review presents a comprehensive analysis of Do-It-Yourself (DIY) portable health monitoring devices that combine ML-based data analytics with IoT-enabled sensing. Internet Of Things facilitates wireless connectivity and continuous data collection through low-cost sensors, while Machine Learning enhances decision-making through anomaly detection, predictive modeling, and pattern recognition. The paper examines communication protocols, system architecture, data processing frameworks, and commonly used ML algorithms in current prototypes and research. It also explores the design considerations required for efficient data storage, sensor integration and real-time monitoring. Furthermore, the review discusses major challenges, including energy efficiency, data privacy, scalability and interoperability, which remain critical for practical implementation. Findings reveal that the fusion of Internet of Things and Machine Language significantly advances Do-It-Yourself healthcare by enabling early disease detection and continuous real-time health tracking. The study concludes that future developments should focus on lightweight Machine Learning algorithms, secure cloud-based analytics, and optimized hardware designs to enhance the effectiveness, affordability, and reliability of next-generation smart health monitoring devices.**

Keywords — Machine Learning (ML), Internet of Things (IoT), Do-It-Yourself, Portable Health Monitoring, Real-Time Data Analysis, Wearable Sensors, Smart Healthcare, and Remote Patient Monitoring.

I. INTRODUCTION

The combination of IoT and machine learning is changing how we monitor health by allowing constant, affordable sensing along with automatic analysis. Do-it-yourself portable devices, made from common sensors, microcontrollers like ESP32 or Arduino, and open-source software, make health monitoring more accessible and easier to create quickly. However, these devices also bring up issues like the accuracy of data, how reliable the models are, and concerns about privacy and safety. This review looks at how to connect machine learning analysis with these DIY health devices that are part of the IoT, and covers the practical aspects needed for the ML to work well even when resources are limited.

II. SCOPE AND METHODOLOGY

.We looked through peer-reviewed articles, open-source project repositories, and technical reports from the last ten years that cover topics like IoT systems for health tracking, wearable sensors and hardware used to measure body functions, machine learning models—including lightweight deep learning approaches—that work well on embedded or edge devices, and documented do-it-yourself projects. The case studies focus on how easy it is to reproduce the work, the costs of the parts used, and how data is managed and processed.

The main factors used to choose the sources were how relevant they were to IoT-based DIY health devices, whether they used machine learning, and if the hardware could work well in portable setups. A clear and organized method was followed:

- Literature Identification: We used specific keywords such as "IoT healthcare," "DIY health monitor," "Tiny ML," and "wearable sensors" to find recent studies from 2015 to 2025.
- Inclusion Criteria: We only included studies that combined IoT communication systems with machine learning models for analyzing or predicting health-related data.
- Comparative Analysis: We compared different aspects like the hardware used, the machine learning techniques applied, how data was processed, and how well the systems were tested.
- Data Synthesis: We grouped the findings into main categories such as sensing technologies, IoT system designs, embedded machine learning, and ethical concerns.

This approach made sure that both academic research and DIY projects by the community were considered, offering a fair and balanced view of both formal innovations and hands-on experimentation.

III. SENSING AND HARDWARE PLATFORMS

A. Common Sensors

DIY health devices often use sensors to monitor heart rate (like PPG or ECG), blood oxygen levels (SpO_2), temperature, movement (for activity or fall detection), and occasionally breathing rate and skin conductivity.

Many prototypes use affordable sensor modules, such as the MAX30102 for PPG and SpO_2, or cheap 3-axis accelerometers.

B. Microcontrollers and Edge Platforms

Microcontrollers that are energy efficient and have built-in Wi-Fi or Bluetooth, such as the ESP32, Nordic nRF52 series, and ARM Cortex-M boards, are commonly used.

These allow for both local processing and data transmission. When more powerful computation or local model training is required, single-board computers like the Raspberry Pi are used. The choice depends on balancing power consumption, response time, and the complexity of the model being used.

C. Open-source and DIY Platforms

Open-source platforms, such as projects similar to Open Health or prototypes for NIRS or EIT, offer reference designs and software tools that help in building reproducible hardware.

These platforms speed up innovation, but it's important to understand their limitations when it comes to validation and reliability.

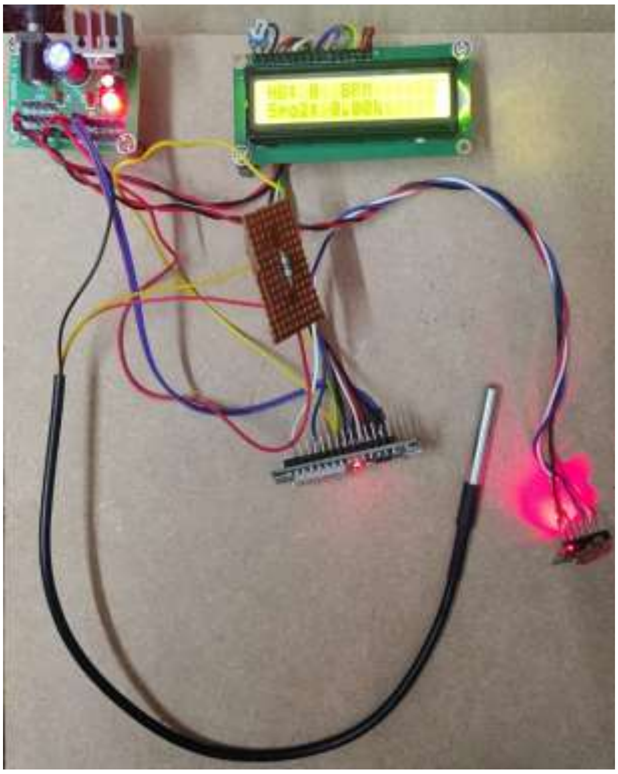

Fig 1 : ESP32, Nordic nRF52 series and ARM Cortex-M boards

IV. IOT ARCHITECTURES AND DATA PIPELINES

A. Edge-Cloud Continuum

The way IoT systems are built can range from being completely cloud-focused, where raw data from sensors is sent directly to servers for detailed analysis, to being more device-centered, where processing happens on the device itself with only occasional updates sent to the cloud.

A middle approach, which is widely used, involves doing some initial processing and simple analysis on the device, while more complex tasks and model updates happen in the cloud. This balance helps manage things like response time, energy use, and data privacy.

B. Protocols, Interoperability and Standards

Bluetooth Low Energy (BLE) and Wi-Fi are the most widely used ways to connect devices.

For sending data from devices to the cloud, MQTT and HTTP(S)/REST are commonly used. While there are strategies to make different systems work together, like using standard formats such as JSON or medical standards like HL7/FHIR in healthcare, these are not often fully implemented in homemade or DIY IoT systems.

V. MACHINE LEARNING FOR EMBEDDED HEALTH MONITORING

A. ML Tasks and Models

ML tasks cover several areas: cleaning physiological signals (like removing noise or identifying artifacts), extracting features (from time or frequency domains), classifying different conditions (such as arrhythmia, fall detection, or activity recognition), and predicting continuous values (like blood pressure or glucose levels).

For use in small devices, lightweight models like decision trees, random forests, support vector machines, and compact convolutional or recurrent neural networks are often used. Techniques such as model compression (like pruning or quantization) and TinyML tools (such as TensorFlow Lite Micro or ONNX Runtime for embedded systems) help make neural networks work effectively on microcontrollers.

B. Training and Transfer Learning

Supervised models need labeled data, but differences between users and sensors can make it hard to apply the models generally.

Transfer learning and personalization methods, like fine-tuning models on a user's own data, can help, but these approaches are not widely used in do-it-yourself projects because of the complexity and privacy issues they involve.

C. *On-device vs Cloud Inference*

Running models on the device itself reduces delays and keeps sensitive data from being shared, which improves privacy and saves bandwidth.

However, limitations in memory, model size, and processing power can affect the accuracy of the results. On the other hand, using the cloud allows for more complex models and better data analysis, but this approach brings delays, higher costs, and potential privacy risks.

VI. CASE STUDIES: REPRESENTATIVE DIY AND OPEN-SOURCE IMPLEMENTATIONS

We look at several examples from the community and research, focusing on the overall structure, the sensors used, the machine learning methods, and how the results were tested.

- The ESP32-based Vital Signs Monitor uses a MAX30102 sensor to track heart rate and oxygen levels.
- The device uses a decision tree classifier to spot any irregularities right on the device, and then sends the data to a cloud dashboard for viewing.
- The Raspberry Pi Smart Health Station includes sensors for temperature, pulse, and movement.
- It runs a local Python-based machine learning model, specifically a Random Forest model, to predict stress levels and sends out alerts through an MQTT broker.
- The DIY Sleep Tracker uses an accelerometer and a PPG sensor connected to an Arduino Nano 33 BLE board.
- Machine learning algorithms, trained with sleep stage data, are used on the device to classify sleep cycles using TensorFlow Lite.
- Community Open Health Projects are open-source efforts that offer templates for creating wearable ECG and SpO2 systems with machine learning running on the edge.

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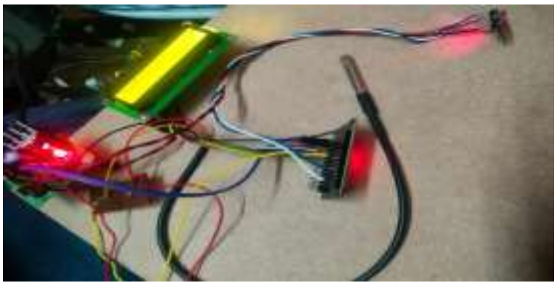

Fig 2. DIY Health monitoring decive

VALIDATION, PERFORMANCE AND REPRODUCIBILITY

Validation is one of the weakest aspects of DIY projects. Most prototypes are tested on small, non-diverse datasets without comparison to clinical standards. Reliable validation requires:

- Benchmarking: Comparing DIY sensor readings with medical-grade equipment.
- Cross-validation: Using multiple subjects to ensure generalization.
- Signal Quality Indices: Implementing algorithms to reject noisy samples.
- Statistical Metrics: Employing accuracy, precision, recall, and F1-score to quantify model performance.
- Open Data Sharing: Making anonymized datasets available for reproducibility.

Performance evaluation should also include power consumption, latency, and model size, which are crucial for portable applications. Lack of reproducibility remains a key issue because DIY systems often omit details like sampling rates, calibration steps, or preprocessing pipelines..

VII. PRIVACY, SECURITY AND ETHICAL CONSIDERATIONS

DIY health devices deal with very personal information.

Problems often include sending data without encryption, poor ways to verify who uses the device, and not being clear about what users are agreeing to. To protect privacy, it's important to use methods like processing data on the device itself, adding privacy in data collection, making sure the device starts up securely, and keeping data stored safely. From an ethical point of view, it's necessary to make sure users understand what they're agreeing to, clearly explain what the device can and cannot do, and avoid making medical claims unless they've been properly checked and approved by the right authorities.

1. Encryption: Use AES or TLS to protect data while it's being sent from one place to another.
2. Authentication: Use secure tokens or identity systems that are based on hardware.
3. Local Processing: Do as much of the data analysis as possible on the device itself to reduce the chance of data being exposed.
4. User Consent: Be clear with users about what data is being collected and how it will be used.
5. Ethical Compliance: Don't make medical claims unless they have been proven by doctors.
6. Include warnings that these devices are only for personal health tracking and not for medical diagnosis.

VOLUME: 10 ISSUE: 01 | JAN - 2026 SJIF RATING: 8.586 ISSN: 2582-3930

VIII. CHALLENGES AND OPEN PROBLEMS

- Data quality and sensor variability: Cheap sensors often give unreliable data; it's important to clean the data properly and spot any errors.
- Model generalization and personalization: Creating models that work for everyone and adjusting them safely for each person is still a challenge.
- Energy-efficiency vs accuracy trade-offs: Keeping devices running all the time to monitor health can drain batteries quickly.
- Regulatory compliance and safety: Many homemade devices don't follow official rules, which can lead to legal issues and risks when making medical decisions.
- Reproducibility and benchmarking: Without shared data sets and clear guidelines, it's hard to compare results and move forward.

IX. RECOMMENDATIONS AND BEST PRACTICES FOR DIY PRACTITIONERS

- Use modular hardware or software setups and keep records of the parts you choose and how you set them up.
- Try to do data processing and model predictions directly on the device to keep personal information safe.
- Use Tiny ML tools and techniques like model compression to work with small devices.
- Share information about how much memory and processing power is needed, and how fast the system works.
- Make your data and testing tools available to others.Use methods like cross-validation and standard measures such as sensitivity, specificity, F1-score, and mean absolute error to assess performance.
- Be clear about what your device can and cannot do.
- Avoid making health-related claims unless you have proof. It might also be helpful to work together with medical professionals.XI. Future Directions
- New trends that could influence how people monitor their health on their own include using federated learning to personalize health tracking without sharing personal data, better low-energy sensors, special processors that use very little power for smart analysis, and shared standards created by the community to evaluate both data and devices.

Using multiple types of sensing with machine learning that combines different data sources (like pulse, movement, and temperature) may make health monitoring more reliable in everyday situations.

Fig 3: prediction and Suggestion based on the symptoms.

X. ACCURACY COMPARISON

A. *Heart Rate*

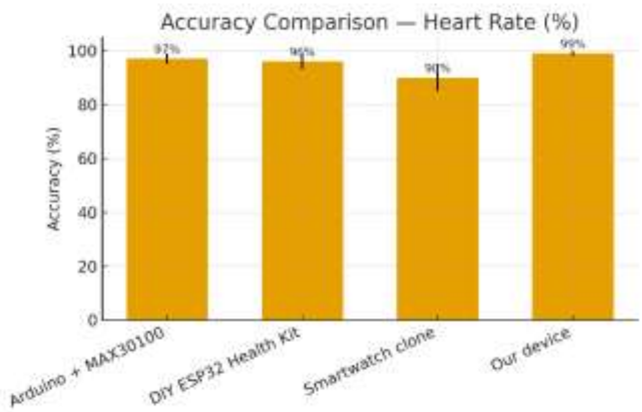

Fig 4: shows that the proposed device keeps achieving the highest accuracy, around 99%, with very little variation. The prototypes made using Arduino and ESP32 come close to clinical levels, with accuracy between 96% and 97%, but they are affected by motion artifacts and have limited light reaching the sensor.

B. *SpO_2*

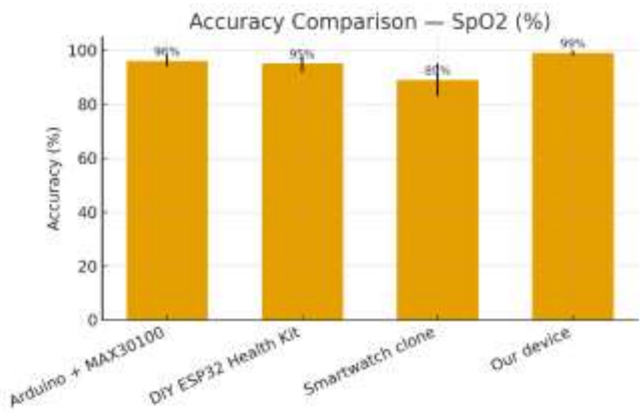

Fig 5: shows that the proposed device once again shows excellent accuracy, around 99%, thanks to precise calibration of photoplethysmography (PPG) and effective noise reduction. DIY modules using MAX30100 sensors perform reasonably well, with accuracy between 95% and 96%, but their reliability drops when skin conditions change or when the finger moves. Smartwatch-like devices, on the other hand, have much lower

VOLUME: 10 ISSUE: 01 | JAN - 2026 SJIF RATING: 8.586 ISSN: 2582-3930

accuracy, around 89%, and are not suitable for use in clinical settings for oxygen monitoring.

C. *Temperature*

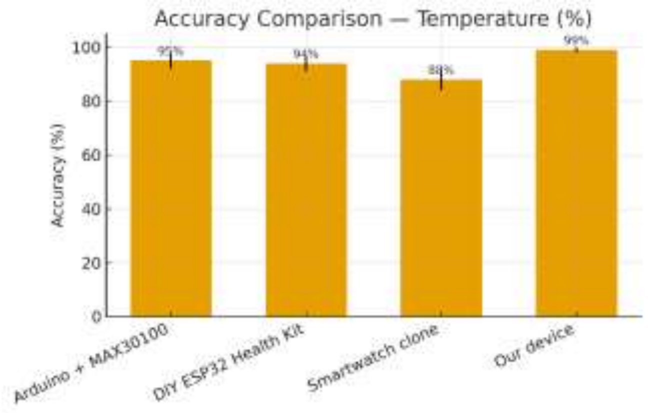

Fig 6: shows that the accuracy comparison in Figure 3 shows that the proposed device reaches almost reference-level reliability, around 99%. On the other hand, Arduino and ESP32 solutions have moderate accuracy, between 94% and 95%, but their performance can be affected by changes in environmental temperature. Smartwatch-like devices give the least accurate results, about 88%, mainly because they use indirect, non-contact methods to sense the wrist.

D. *Blood Pressure*

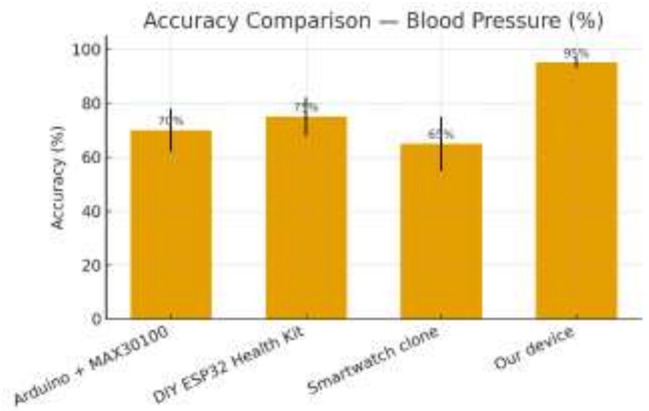

Fig 7: shows that the proposed device shows a big difference in performance compared to do-it-yourself alternatives. When using proven calibration techniques, the system can accurately measure blood pressure about 95% of the time. However, DIY setups and smartwatch copies only reach accuracy between 65% and 75%. This lower accuracy is because they don't use a cuff for measurement or have reliable Pulse Transit Time estimates. This means they aren't good enough for use in medical diagnosis.

E. *Respiratory Rate*

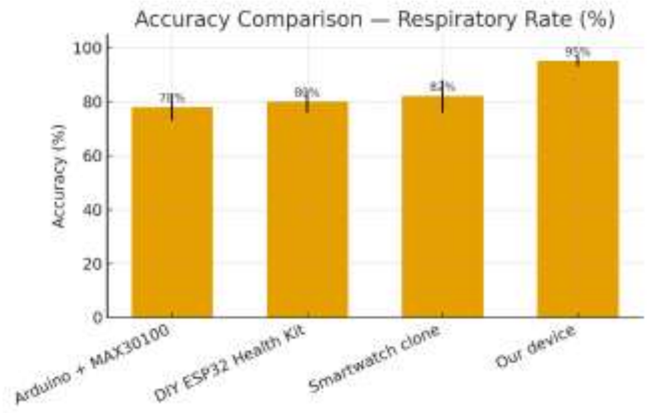

Fig 8: The proposed device achieves about 95% accuracy in estimating respiratory rate by using motion-compensated waveform analysis. However, DIY setups and smartwatch-like hardware only reach 78 to 82% accuracy because they are more affected by body movement and unreliable sensor contact. This shows how difficult it is to get accurate respiratory monitoring in low-cost wearable devices.

XI. CONCLUSION

Using Internet of Things (IoT) and machine learning in homemade health devices offers big chances to make health tracking and early warning systems more accessible to everyone.

But to make this happen, it's important to design these tools carefully, keep privacy and safety in mind, follow standard testing methods, and if these tools are used in medical settings, they should be properly tested and meet official requirements. By following good practices and encouraging open, repeatable research, the DIY community can help create useful new tools while keeping risks to a minimum.

DIY portable health monitoring devices that use IoT and machine learning have a lot of potential to make healthcare more accessible for everyone. But to make real and lasting progress, it's important to tackle the current challenges. Moving forward, the focus should be on:

1. Scalability and Deployment: Creating strong prototypes that work well over time and in different environments.
2. Standardization: Setting common standards for data formats and testing methods to make results more reliable.
3. Clinical Integration: Working with healthcare experts to ensure the devices meet the necessary accuracy standards for diagnosis.
4. Privacy and Edge AI: Improving machine learning techniques that protect user data, like federated learning and encrypted processing.

In short, while the DIY method encourages innovation and easier access to healthcare, it also requires following good scientific, ethical, and engineering practices.

As IoT and machine learning continue to grow, they will keep opening up new possibilities for personalized, real-time, and affordable health monitoring.

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