

IoT-Based Early Detection of Chronic Diseases Using Machine Learning

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Mubarak Jibril Yeldu¹, Anas Muhammad Gulumbe¹

¹Department of Computer Science, Abdullahi Fodio University of Science and Technology Aliero, Nigeria

 MJY [0009-0000-9158-5267](https://orcid.org/0009-0000-9158-5267)

Correspondence: Mubarak Jibril Yeldu, mubarakjibril59@gmail.com

Abstract

Chronic diseases, including cardiovascular disease, diabetes, chronic respiratory disease, and cancer, remain major causes of morbidity and premature mortality worldwide. The increasing availability of Internet of Things (IoT) devices, wearable sensors, smart phones, and remote monitoring platforms provides an opportunity to shift chronic disease management from periodic hospital-based assessment toward continuous, data-driven health monitoring. This seminar paper examines the application of IoT and machine learning (ML) for the early detection of chronic diseases. The paper reviews recent literature on IoT-enabled physiological sensing, wearable health technologies, machine learning algorithms, digital biomarkers, edge computing, explainable artificial intelligence, and privacy-preserving learning. Recent evidence shows that IoT devices can continuously collect physiological and behavioral indicators such as heart rate, blood pressure, blood oxygen saturation, glucose level, body temperature, sleep characteristics, physical activity, and electrocardiographic signals. Machine learning algorithms can subsequently transform these data into risk scores, anomaly alerts, and predictive information that may support earlier clinical intervention. The paper proposes a layered IoT-ML framework consisting of sensing, communication, preprocessing, intelligent analytics, risk assessment, and clinical decision-support layers. Particular attention is given to supervised learning, deep learning, anomaly detection, edge intelligence, federated learning, and explainable AI. The review also identifies important challenges involving data quality, interoperability, cyber security, privacy, model bias, computational limitations, clinical validation, and regulatory compliance. The paper concludes that IoT-based machine learning has considerable potential for proactive chronic disease detection, but successful clinical adoption requires reliable sensing, representative datasets, transparent algorithms, privacy-preserving architectures, and rigorous real-world validation.

Keywords: Internet of Things, Machine Learning, Chronic Diseases, Wearable Sensors, Early Disease Detection

1. INTRODUCTION

Chronic diseases, also referred to as non communicable diseases (NCDs), represent one of the most persistent challenges facing contemporary healthcare systems. Cardiovascular diseases, cancers, chronic respiratory diseases, and diabetes are responsible for a substantial proportion of global deaths, with a particularly heavy burden in low- and middle-income countries. The World Health Organization reported that NCDs accounted for at least 43 million deaths in 2021, representing approximately 75% of non-pandemic-related deaths globally. Cardiovascular diseases, cancers, chronic respiratory diseases, and diabetes constitute the dominant categories of premature NCD mortality.

Traditional approaches to chronic disease detection depend largely on periodic clinical consultations, laboratory investigations, medical imaging, and patient-reported symptoms. Although these approaches remain essential, they may provide only occasional observations of a patient's health status. A patient may therefore appear clinically stable during a hospital visit while experiencing abnormal physiological changes between appointments. This limitation has encouraged researchers to investigate continuous and remote health-monitoring technologies capable of detecting subtle changes before they develop into clinically significant conditions.

The Internet of Things (IoT) provides an important technological foundation for this transition. IoT-enabled healthcare connects wearable sensors, smart phones, medical devices, communication networks, edge platforms, and cloud services to collect and process health information continuously. Recent systematic research demonstrates that IoT and mobile sensing technologies are increasingly being applied to chronic diseases such as cardiovascular disease, diabetes, cancer, and chronic respiratory diseases (Liu & Wang, 2025).

The development of wearable sensing has further expanded the possibilities of IoT-based healthcare. Smart watches, fitness trackers, wearable electrocardiogram devices, continuous glucose monitors, pulse oximeters, and other biosensors can generate physiological and behavioral information at relatively high temporal resolution. Recent research identifies wearable sensing as an important source of continuous information for personalized healthcare and machine-learning-based analysis (Xiao et al., 2024).

However, collecting large quantities of health data alone does not guarantee early disease detection. IoT systems can generate continuous streams of heterogeneous, noisy, incomplete, and highly individualized data. Machine learning provides the analytical capability required to identify relationships and patterns within these data. Supervised algorithms can learn relationships between physiological characteristics and known disease outcomes, while unsupervised and deep learning techniques can identify abnormal patterns that may indicate emerging health risks. Recent reviews show increasing integration of machine learning with wearable devices for real-time health monitoring and personalized healthcare (Saad et al., 2024; Xiao et al., 2024).

Recent research has also expanded beyond conventional centralized machine learning. Edge AI allows selected analytical operations to occur close to the data source, reducing communication delays and dependence on cloud processing. Federated learning provides another important direction because models can be trained across distributed healthcare devices or institutions without requiring all raw patient data to be transferred to a central repository. Recent research identifies federated learning as a promising approach for privacy-preserving smart healthcare, although issues involving data heterogeneity, security, communication costs, and model bias remain significant (Kanauzia et al., 2026; Li et al., 2025).

Consequently, integrating IoT and machine learning offers an opportunity to develop proactive healthcare systems in which physiological information is continuously acquired, analyzed, and transformed into early

warnings. Such systems could help identify elevated disease risk, support remote patient monitoring, facilitate personalized intervention, and reduce dependence on delayed symptom-based diagnosis. Nevertheless, the clinical usefulness of these technologies depends on sensor reliability, algorithmic accuracy, interpretability, privacy, fairness, interoperability, and validation under real-world conditions.

2. LITERATURE REVIEW

2.1 IoT in Healthcare and Chronic Disease Monitoring

The Internet of Things has transformed healthcare by enabling physical objects to collect, communicate, and exchange health-related information. In an IoT healthcare environment, sensors may be attached to the body, integrated into wearable devices, embedded within medical equipment, or connected to smart phones. The resulting data can be transmitted through Bluetooth, Wi-Fi, cellular networks, 5G, or other communication technologies to edge or cloud platforms.

IoT-based health monitoring is particularly relevant to chronic disease management because chronic conditions generally require long-term observation rather than isolated measurements. A systematic review by (Gaya and Danladi 2024) describes IoT health monitoring as an emerging approach involving sensors, connected devices, artificial intelligence, and communication technologies for continuous healthcare monitoring. For chronic disease detection, an IoT platform may monitor heart rate, heart-rate variability, blood pressure, oxygen saturation, glucose concentration, respiratory rate, body temperature, sleep patterns, activity levels, weight, and other indicators. These measurements can be combined with demographic, behavioral, and historical medical information to construct a more comprehensive representation of an individual's health status.

2.2 Machine Learning for Early Disease Detection

Machine learning is a major component of intelligent healthcare systems because it can identify patterns that may be difficult to detect through manual observation. Depending on the application, classification algorithms can categorize patients according to disease status or risk level, regression models can estimate continuous health indicators, and anomaly-detection algorithms can identify deviations from an individual's normal physiological state.

Common algorithms include logistic regression, decision trees, random forests, support vector machines, k-nearest neighbors, gradient boosting, artificial neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Deep learning models are particularly useful for complex time-series and signal-processing tasks involving ECG, activity, respiratory, and other physiological data. (Xiao et al. 2024) reported that both supervised and unsupervised learning have become important approaches for extracting useful information from high-dimensional wearable-sensor datasets. Their review emphasizes the potential of machine learning to improve the accuracy, reliability, and interpretation of wearable health information.

A broader systematic review of digital phenotypes and digital biomarkers also demonstrates growing use of machine learning with passive data collected from wearable devices and smart phones. Such continuously collected information can support disease screening, identification, and prediction because it captures changes over time rather than relying solely on occasional clinical measurements (Sameh et al., 2025)

2.3 IoT and Cardiovascular Disease Detection

Cardiovascular diseases represent one of the most important application areas for IoT-based machine learning. Wearable devices can collect heart rate, ECG signals, physical activity, blood oxygen saturation,

sleep information, and other cardiovascular indicators. Machine learning can analyze these signals to identify abnormal rhythms and patterns associated with cardiovascular risk.

Recent research on AI-driven real-time cardiovascular monitoring emphasizes the potential of wearable devices for continuous cardiovascular signal collection and early detection. At the same time, the research identifies practical challenges involving signal quality, large data volumes, rapid physiological fluctuations, and the need for reliable clinical decision-making. Wearable cardiovascular sensors are also becoming increasingly sophisticated. (Xie et al. 2025) describe recent progress toward real-time, personalized, non-invasive cardiovascular monitoring and early-warning capabilities using advanced wearable sensing technologies.

2.4 IoT and Diabetes Detection

Diabetes is another important target for IoT-based healthcare. Continuous glucose monitoring devices can provide frequent glucose measurements that can be analyzed together with physical activity, dietary behavior, sleep, heart rate, and other contextual information.

Machine learning can identify patterns associated with abnormal glucose regulation and potentially estimate future glucose changes. Rather than relying exclusively on occasional blood glucose measurements, an IoT-based approach can provide longitudinal information that reflects the patient's daily physiological condition.

Recent reviews of AI-powered wearable sensors identify diabetes among the major chronic conditions being investigated through AI-enabled continuous monitoring. Such systems increasingly combine sensor data with machine learning, edge computing, and personalized analytics.

2.5 IoT and Chronic Respiratory Disease

Chronic respiratory diseases can also benefit from continuous IoT-based monitoring. Wearable and connected devices can collect respiratory rate, oxygen saturation, physical activity, heart rate, and environmental information. These variables may be analyzed to detect deterioration or identify patterns associated with respiratory problems.

The combination of multiple physiological variables can be particularly valuable because disease progression may not be represented by a single measurement. Machine learning can combine temporal and multimodal information to estimate individual risk and generate alerts when abnormal patterns emerge.

Liu and (Wang, 2025) identify chronic respiratory diseases as one of the major chronic disease areas in which IoT mobile sensing and machine-learning approaches are being investigated.

2.6 Wearable Sensors and Digital Biomarkers

Digital biomarkers represent measurable physiological, behavioral, or biological characteristics collected through digital technologies. Wearable devices and smart phones are increasingly being used to generate such information continuously.

The advantage of digital biomarkers is that they can provide longitudinal observations of an individual rather than isolated clinical measurements. Changes in sleep, mobility, heart rate, activity patterns, or other physiological characteristics may provide early indications of changes in health status.

(Sameh et al. 2025) found that passive non-invasive signals from wearable devices and smart phones are increasingly used with machine learning to screen, identify, and predict health-related outcomes.

This development is important to early chronic disease detection because disease-related changes may initially appear as small deviations from an individual's normal physiological pattern. Machine learning

can potentially identify these deviations before obvious symptoms become apparent.

2.7 Deep Learning in IoT-Based Healthcare

Deep learning extends conventional machine learning by using multilayer neural networks to learn complex representations from large datasets. In IoT healthcare, deep learning is particularly relevant to physiological time series, ECG signals, images, speech, activity recognition, and multimodal health data.

A systematic literature review by (Amiri et al. 2024) examined deep learning applications in IoT-based biomedical and medical informatics and demonstrated the growing role of deep neural networks in intelligent healthcare applications.

CNNs can be applied to transformed physiological signals or biomedical images, while recurrent and temporal architectures can model sequential data. More recent systems also investigate transformer-based architectures and multimodal models. Nevertheless, complex models require substantial computational resources and may be difficult for clinicians to interpret.

2.8 Edge Computing and Real-Time Detection

Cloud computing provides substantial computational and storage capacity, but sending every physiological measurement to a remote cloud server can introduce communication delays, increase bandwidth requirements, and create additional privacy risks. Edge computing addresses this limitation by processing some data closer to where they are generated. For example, a wearable gateway or smart phone can perform data filtering, feature extraction, anomaly detection, or preliminary prediction before transmitting selected information to a cloud platform. For early disease detection, edge intelligence can enable faster alerts. This is particularly important when abnormal physiological conditions require rapid attention. However, edge devices have limited processing power, memory, battery capacity, and storage. Therefore, lightweight machine-learning models and efficient feature-processing methods are important research requirements.

2.9 Explainable AI and Clinical Trust

High prediction accuracy alone is insufficient for many healthcare applications. Healthcare professionals need to understand why a model has classified a patient as high risk. Explainable artificial intelligence (XAI) attempts to address this problem by providing interpretable information about model decisions.

For example, an XAI system may identify changes in heart rate variability, oxygen saturation, glucose levels, or activity patterns as important factors contributing to a risk prediction. This information can assist clinicians in assessing whether an automated prediction is clinically reasonable.

(Radanliev 2025) emphasizes the importance of transparency, accountability, privacy, and bias mitigation in AI systems for wearable healthcare. Therefore, explain ability should be considered an integral component of IoT-based disease-detection systems rather than an optional feature.

2.10 Federated Learning and Privacy-Preserving Healthcare

Health information is highly sensitive, making privacy a major consideration in IoT-based healthcare. Centralizing large quantities of patient data creates security and governance challenges. Federated learning offers an alternative by allowing machine-learning models to be trained across distributed devices or institutions while keeping raw data locally.

Recent systematic research indicates that federated learning is becoming an important approach for smart healthcare because it can support collaborative model development without requiring centralized storage of all patient information (Kumar et al., 2024; Kanauzia et al., 2026).

However, federated learning does not eliminate security risks. Model updates may still be vulnerable to inference attacks, poisoning, or other threats. Communication overhead, heterogeneous datasets, unequal computational resources, and differences among patient populations also create implementation challenges.

2.11 Summary of Recent Literature

Author/Year	Research Focus	Main Contribution	Identified Gap
Gaya and Danladi (2024)	IoT health monitoring	Reviewed IoT-enabled healthcare monitoring	Greater need for intelligent predictive systems
Amiri et al. (2024)	Deep learning and IoT medical informatics	Examined deep learning applications in IoT healthcare	Computational and implementation challenges
Saad et al. (2024)	ML and wearable devices	Reviewed ML applications in wearable healthcare	Data quality, privacy and generalization
Xiao et al. (2024)	ML for wearable sensors	Examined supervised and unsupervised learning for wearable data	Interpretability and reliability
Sameh et al. (2025)	Digital biomarkers	Reviewed ML using passive wearable/smartphone data	Need for stronger validation and standardization
Liu and Wang (2025)	Chronic disease monitoring	Reviewed IoT and ML for major chronic diseases	Interoperability and clinical implementation
Radanliev (2025)	AI ethics and wearable devices	Examined privacy, transparency and accountability	Need for responsible AI frameworks
Li et al. (2025)	Federated learning in healthcare	Identified FL opportunities and implementation limitations	Bias, generalization and communication costs
Xie et al. (2025)	Cardiovascular wearables	Reviewed advanced cardiovascular sensing	Real-world reliability and clinical translation
Kanauzia et al. (2026)	Federated learning in digital healthcare	Reviewed privacy-preserving FL approaches	Security and privacy remain unresolved

3. PROPOSED IOT-BASED EARLY DETECTION FRAMEWORK

This paper proposes a conceptual architecture that integrates IoT sensing and machine learning for continuous chronic disease risk assessment.

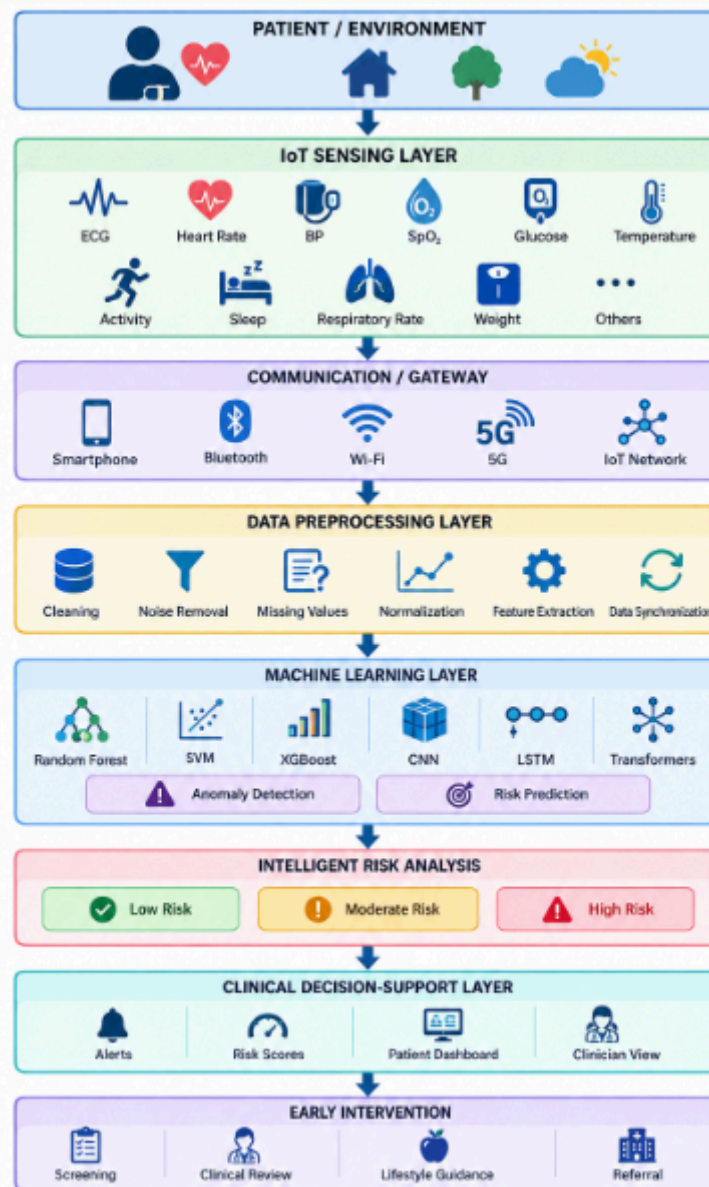


Figure 1. Proposed IoT-Based Chronic Disease Early Detection Architecture

Description

The IoT sensing layer collects physiological and behavioral information from connected sensors. The communication layer transfers measurements to a smart phone, gateway, edge device, or cloud platform. Preprocessing removes noise, handles missing values, synchronizes measurements, and prepares the information for machine learning.

The machine-learning layer analyzes the processed information. Depending on the disease and dataset, different algorithms may be selected. The resulting predictions are transformed into risk categories. A clinical decision-support layer then communicates relevant alerts to patients or healthcare professionals. Importantly, the system is intended to support clinical assessment rather than replace healthcare professionals.

4. PROPOSED METHODOLOGY

The proposed study can be implemented using a machine-learning experimental methodology consisting of the following stages.

4.1 Data Acquisition

Health data can be obtained from publicly available healthcare datasets and, where ethically approved,

IoT-enabled wearable sensors. Data may include ECG, heart rate, blood pressure, glucose, oxygen saturation, respiratory rate, physical activity, sleep, and demographic information.

4.2 Data Preprocessing

Raw sensor data may contain missing observations, motion artifacts, measurement errors, duplicated records, and inconsistent sampling frequencies. The preprocessing stage should therefore involve:

- i. Missing-value treatment
- ii. Noise filtering
- iii. Outlier detection
- iv. Signal normalization
- v. Data synchronization
- vi. Feature extraction
- vii. Class balancing where required

4.3 Feature Engineering

Relevant features can be extracted from physiological time-series data. For example, ECG data may generate heart-rate and rhythm-related features, while activity data may provide step count, movement intensity, and activity duration. Combining multiple data types can provide a richer representation of patient health.

4.4 Machine Learning Model Development

Several machine-learning algorithms can be evaluated, including:

- i. Logistic Regression
- ii. Decision Tree
- iii. Random Forest
- iv. Support Vector Machine
- v. Gradient Boosting/XGBoost
- vi. Artificial Neural Network
- vii. CNN
- viii. LSTM

4.5 Model Evaluation

The models should be evaluated using clinically meaningful metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2(Precision \times Recall)}{Precision + Recall}$$

5. EXPECTED SYSTEM OPERATION

The proposed system operates continuously. First, IoT sensors acquire physiological information from the

patient. The collected measurements are transferred to an edge gateway or cloud platform. The preprocessing module cleans and organizes the data before extracting relevant features.

The machine-learning model then compares the patient's current and historical patterns with learned disease-related patterns. If the system identifies a potentially abnormal pattern, it calculates a risk score. A low-risk condition can continue under routine monitoring, while a moderate-risk condition may generate a recommendation for additional assessment. A high-risk prediction can generate an alert for clinical review.

The approach is particularly valuable because it emphasizes change over time rather than relying exclusively on individual measurements. A patient's normal baseline can be learned and subsequent deviations can be monitored. This may improve personalized risk assessment compared with applying identical thresholds to every patient.

6. BENEFITS OF IOT-BASED MACHINE LEARNING FOR CHRONIC DISEASE DETECTION

6.1 Continuous Monitoring

IoT devices enable health measurements to be collected outside conventional healthcare facilities. This creates opportunities for monitoring patients during normal daily activities.

6.2 Earlier Identification of Risk

Machine learning can identify patterns that may indicate increasing disease risk before severe symptoms occur. This supports a preventive rather than purely reactive healthcare model.

6.3 Personalized Healthcare

Machine-learning models can incorporate individual patient histories, allowing risk predictions to be tailored to the patient's physiological characteristics and behavioral patterns.

6.4 Remote Patient Monitoring

Patients living far from healthcare facilities can potentially be monitored remotely, reducing unnecessary hospital visits and supporting healthcare delivery in underserved communities.

6.5 Improved Clinical Decision Support

IoT systems can transform large volumes of physiological information into summarized risk scores and alerts, helping healthcare professionals focus attention on patients requiring additional assessment.

7. CHALLENGES AND LIMITATIONS

7.1 Data Quality

Sensor measurements may be affected by motion, poor sensor placement, device calibration, environmental interference, and battery limitations. Poor-quality data can significantly reduce machine-learning performance.

7.2 Privacy and Security

IoT healthcare systems process sensitive personal information. Unauthorized access, insecure communication, malicious devices, and compromised cloud infrastructure can expose patient data.

7.3 Algorithmic Bias

A machine-learning model trained using data from a limited population may perform poorly when applied to individuals from different demographic, geographic, or clinical populations. This is particularly important for systems intended for deployment across diverse populations.

7.4 Interoperability

Healthcare environments frequently contain devices from different manufacturers using different data formats and communication protocols. Lack of interoperability can make it difficult to combine information from multiple sources.

7.5 Explain ability

Complex deep-learning models may produce accurate predictions without providing easily understandable explanations. This can reduce clinician confidence and make clinical adoption more difficult.

7.6 Computational and Energy Constraints

Wearable devices typically have limited battery capacity and computational resources. Continuous machine-learning processing can increase energy consumption.

7.7 False Alarms

A highly sensitive system may produce numerous false-positive alerts. Excessive alerts can lead to alert fatigue among patients and healthcare professionals.

7.8 Clinical Validation

High accuracy on a laboratory dataset does not automatically demonstrate clinical usefulness. Models need prospective and real-world validation before being considered suitable for clinical deployment. A recent systematic review of machine-learning-based remote monitoring studies found substantial methodological and bias concerns across the existing evidence base, emphasizing the importance of stronger validation practices.

8. FUTURE RESEARCH DIRECTIONS

Future research should move toward multimodal IoT-ML systems capable of integrating physiological, behavioral, environmental, and clinical information. Combining ECG, glucose, activity, sleep, blood pressure, environmental exposure, and electronic health information may produce more comprehensive disease-risk models than relying on a single sensor.

Another important direction is the development of edge-based machine learning. Lightweight models could perform initial analysis directly on smart phones, wearable devices, or gateways, thereby reducing latency and communication requirements.

Federated learning is also expected to become increasingly important. Recent research in wearable and digital healthcare emphasizes decentralized learning as a pathway toward privacy-preserving health analytics, although security, communication efficiency, bias, and heterogeneous data remain open research problems.

Explainable AI should also be incorporated into future systems. Instead of presenting only a prediction such as "high risk," an intelligent system should indicate the major physiological or behavioral factors responsible for the prediction.

Furthermore, future studies should investigate personalized baseline modeling, where each patient's normal physiological state is learned over time. Such approaches could potentially identify small but clinically meaningful deviations before conventional disease thresholds are reached.

Finally, research should prioritize prospective clinical studies, standardized datasets, interoperability standards, cyber security, regulatory compliance, and evaluation across different populations. These factors will determine whether promising research prototypes can become reliable healthcare systems.

9. CONTRIBUTION TO KNOWLEDGE

This seminar paper contributes to the field in five main ways:

- i. Integration of Technologies: It brings together IoT sensing, machine learning, edge computing, explainable AI, and privacy-preserving learning within a unified chronic disease detection perspective.
- ii. Early Detection Perspective: It emphasizes continuous risk assessment rather than waiting for severe symptoms or periodic clinical examinations.
- iii. Multimodal Architecture: The proposed framework supports the combination of multiple physiological and behavioral measurements.
- iv. Trustworthy Healthcare: Privacy, explain ability, fairness, security, and clinical validation are incorporated as fundamental design considerations.
- v. Research Direction: The research identifies research opportunities involving personalized models, federated learning, edge AI, multimodal sensing, and real-world clinical validation.

10. CONCLUSION

IoT-based machine learning represents an important direction for transforming chronic disease management from periodic assessment toward continuous and proactive healthcare. Wearable sensors and connected medical devices can continuously collect physiological and behavioral information, while machine-learning algorithms can analyze these data to identify abnormal patterns and estimate disease risk. Current research demonstrates considerable progress in wearable sensing, digital biomarkers, deep learning, edge intelligence, explainable AI, and federated learning.

The proposed framework demonstrates how IoT sensors, communication networks, data preprocessing, machine-learning analytics, risk assessment, and clinical decision support can operate as an integrated system. Such a system could assist in identifying early warning signals associated with cardiovascular disease, diabetes, chronic respiratory disease, and other chronic conditions.

Despite its potential, technological capability alone is insufficient for clinical adoption. Sensor reliability, data quality, privacy, cyber security, algorithmic bias, interpretability, interoperability, computational limitations, and clinical validation must be addressed systematically. Future research should therefore focus on trustworthy, personalized, privacy-preserving, explainable, and clinically validated IoT–ML systems. With appropriate validation and responsible deployment, IoT-based machine learning could become an important component of preventive healthcare and early chronic disease management.

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