Analysis of Disease Diagnosis and Monitoring Methods Based on Wearable Devices

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Abstract. With the rapid advancement of sensor technology, artificial intelligence, and the Internet of Things (IoT), wearable devices have demonstrated tremendous potential in healthcare, providing revolutionary tools for early disease diagnosis, continuous monitoring, and personalized management. This review focuses on wearable technology applications in four major chronic diseases: heart disease, Parkinson's disease, diabetes, and depression. The article first outlines key physiological and behavioral parameters collected by wearables, such as heart rate variability, gait patterns, blood glucose levels, and sleep quality, then systematically analyzes core diagnostic and monitoring methodologies for these conditions. It summarizes critical biomarker identification strategies, mainstream data analysis algorithms, clinical validation outcomes, and practical advancements in disease prediction, condition assessment, and rehabilitation management. Future wearable technologies hold significant potential to deliver continuous, objective, real-time, and accurate health data, while also addressing challenges related to data privacy, user compliance, and regulatory approval. Through multi-modal data integration and the development of advanced AI algorithms, chronic diseases can achieve enhanced treatment and management, ultimately improving patient outcomes and quality of life.

Keywords: Wearable Devices, Sensor Technology, Heart Disease, Parkinson'Disease, Diabetes.

1. Introduction

With the deep integration of sensor technology and artificial intelligence, wearable devices are evolving from health monitoring tools to core platforms for disease diagnosis and management in healthcare. These devices enable non-invasive, continuous collection of multidimensional physiological and behavioral data--including electrocardiograms, accelerometer readings, blood glucose trends, and skin conductance responses--providing revolutionary solutions for early warning, real-time monitoring, and personalized interventions in chronic diseases. The four major global chronic diseases--heart disease, Parkinson's disease, diabetes, and depression--are characterized by prolonged courses, subtle symptoms, and requiring long-term management. Traditional diagnostic methods relying on intermittent clinical examinations suffer from limitations such as subjective assessments, extensive monitoring blind spots, and difficulty capturing dynamic changes. Wearable-based intelligent diagnostic technologies, by acquiring real-time physiological data in authentic scenarios and leveraging machine learning algorithms to identify disease signatures, aim to transcend the temporal-spatial constraints of conventional medicine. This transformation from "passive treatment" to "proactive health management" holds significant implications for enhancing diagnostic efficiency and reducing healthcare costs.

The diagnosis of heart disease primarily relies on intelligent monitoring systems powered by IoT and cloud platforms. For instance, the Bi-LSTM model developed by the Nancy team integrates a fuzzy inference system to process multi-source data including electrocardiogram (ECG), blood pressure, and blood glucose levels. Through real-time analysis via cloud platforms, this system achieved 98.86% accuracy and 98.9% specificity in a clinical data test involving 100,000 cases [1]. While this system highlights the advantages of deep learning in processing time-series data, challenges remain in deploying edge computing to reduce latency.

The Atri research team's Parkinson's disease investigation focuses on motion symptom recognition in unsupervised environments. Using Verily smartwatches to collect daily inertial sensor data (including accelerometer and gyroscope readings), they employ human-machine activity recognition algorithms to extract "walking-like events" and develop one-dimensional CNN models for gait pattern analysis. In a study involving 7 PD patients and 4 healthy individuals, the single-event classification accuracy reached nearly 90% within 5 seconds, while the majority vote accuracy for daily event recognition achieved 100% [2], demonstrating the feasibility of PD detection in unsupervised scenarios.

The research team compared the performance of single-sensor and multi-sensor systems, finding that the triple-sensor combination of glucose, ECG, and accelerometer with the XGBoost algorithm achieved the highest accuracy rate of 98.2%, representing a 4-5% improvement over single-sensor configurations [3]. The study demonstrated that the multi-sensor fusion strategy significantly enhanced diabetes prediction accuracy. Additionally, the researchers optimized the feature extraction window and confirmed that respiratory data contributed minimally to prediction accuracy, providing a foundation for lightweight device design.

The Shui research team collected six-hour daily physiological data through wristband devices, including pulse waveforms, cutaneous conductance, and acceleration measurements. By extracting static statistical features and dynamic autocorrelation coefficients, they applied random forest modeling for depression detection. Results demonstrated 90% classification accuracy across the full six-hour dataset and maintained 80.1% accuracy when analyzing 30-minute segments [4],confirming the clinical potential of short-term monitoring. The study highlighted that dynamic features exhibit stronger discriminative power than static metrics, underscoring the value of temporal dynamics in psychiatric assessment.

This review examines the current research status of wearable devices for four major chronic diseases: cardiovascular disease, Parkinson's disease, diabetes mellitus, and depression. It systematically reviews the latest advancements in wearable technology applications across these conditions, analyzing sensor selection strategies including electrocardiography, accelerometer, photoplethysmography, and skin conductance monitoring. The study compares feature engineering methodologies--such as time-domain, frequency-domain, and nonlinear dynamic feature extraction--with machine learning models like XGBoost, CNN, Bi-LSTM, and random forest. The paper evaluates wearable technologies' practical effectiveness in critical clinical scenarios: early screening/diagnosis, continuous symptom monitoring, and treatment efficacy assessment. It also objectively examines existing limitations and challenges in these technological implementations.

2. Methods and Applications of Wearable Device Prediction Identification and Disease Prediction

2.1. Wearable Devices and Heart Disease

As a critical data acquisition component, IoT technology plays an essential role in enabling countless real-time applications that facilitate individual interactions. Meanwhile, the massive data generated by IoT devices poses significant challenges for healthcare systems in data processing, storage, and management. Consequently, AI-related algorithms have become increasingly vital for IoT applications. Predictive analytics in healthcare employ diverse techniques ranging from traditional linear models to advanced AI and machine learning algorithms [5]. The "central hub" of IoT--cloud computing--possesses near-infinite storage and computational capabilities to manage received data [6]. For instance, integrating IoT with wearable devices for heart disease diagnosis involves collecting physiological indicators related to cardiac health from wearable devices (e.g., smartwatches, blood pressure monitors, ECG devices) including blood pressure (BP), heart rate, blood glucose levels, respiratory rate, oxygen saturation, cholesterol levels, activity data, electrocardiograms (ECG), electromyography (EMG), and electroencephalograms (EEG). These data are transmitted via Bluetooth or Zigbee to gateway devices, where pre-processing and predictive analysis are performed using a system algorithm combining FIS and Bilstm with hospital cloud clinical databases. The final results are then delivered to hospitals and other medical facilities. This process is illustrated in Figure 1.

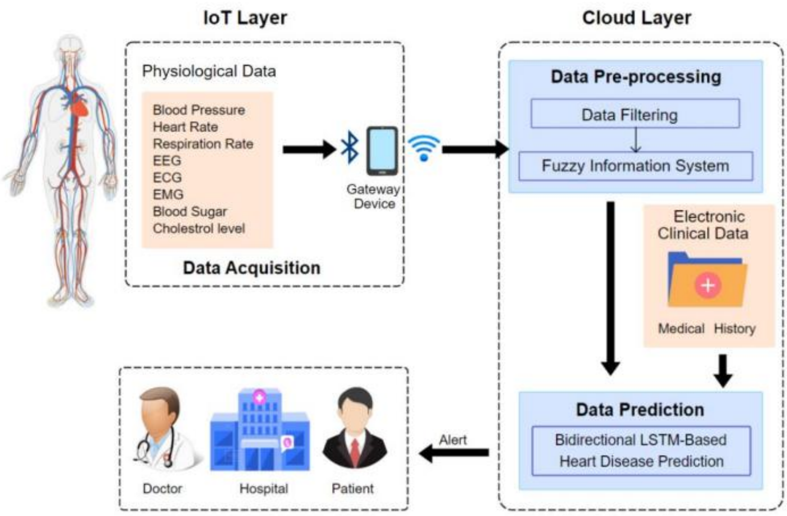

Fig 1. Heart disease prediction implementation framework [1]

2.1.1 Bi-LSTM Algorithm

LSTM is an artificial intelligence algorithm specifically designed to process sequential data (such as traffic flow data and industrial equipment operation data) by leveraging cyclic transmission in hidden states. Its core capability lies in processing new data while retaining historical information and filtering out irrelevant interference when receiving a continuous sequence of time-ordered data. However, the limitation of the LSTM algorithm is its ability to process only past content rather than future data. To overcome this, a bidirectional recurrent neural $X = (x1, x2, x3 \ldots xn) -> hi = (-> h1, -> h2, -> h3 \ldots -> hn) < -ht = (< -h1, < -h2, < -h3 \ldots < -hn) -> hi < -hty = (y1, y2, y3 \ldots yn)$network was proposed, consisting of two independent LSTM hidden layers with opposite directions and equivalent outputs. This approach enables the output layer to utilize both past and future information. In Bi-LSTM, the input sequence vector is computed as in the forward direction and as in the reverse direction. The final output yt is jointly generated by and, resulting in the final output sequence [1]. Figure 2 shows a simplified diagram of this architecture.

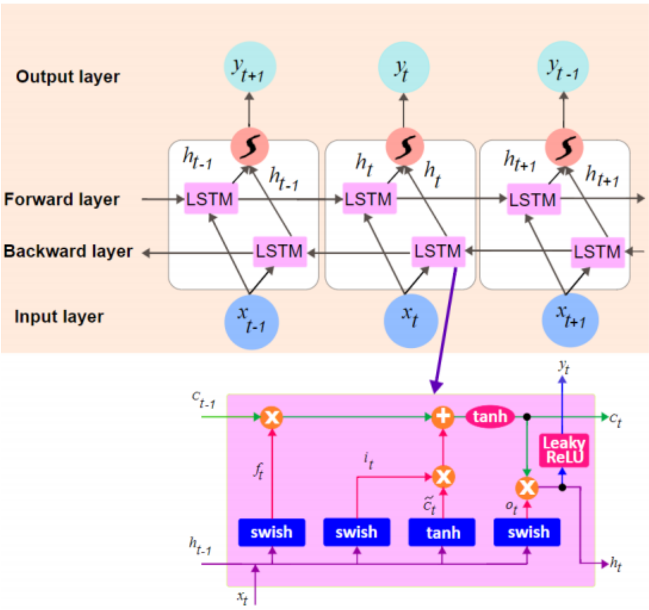

Fig 2. Single LSTM cell and Bi-LSTM of the proposed model [1]

2.1.2 Fis System

The FIS system is an algorithmic framework designed to perform fuzzing and defuzzing operations. The term "fuzzy" refers to ambiguous or indeterminate concepts, with the fuzzy system being developed in response to the necessity of modeling inherently vague real-world events [7]. It first fuzzes the received data before performing defuzzing, ultimately yielding precise risk classification outcomes (such as "High Risk" or "Normal"). The system consists of four core components: Knowledge Base, Fuzzifier, Fuzzy Inference Engine, and Defuzzifier.

The Knowledge Base serves as the "brain" of the FIS system, consisting of two components: the database and rule base. The database stores fuzzy-related data such as membership functions, while the rulebase contains rules that provide the basis for inference processes. Fzzifier primarily performs the "fuzzification" process, converting clear input data (such as maximum heart rate, ECG, blood pressure) into fuzzy sets (simply defined as defining ranges: low, normal, high) using the fuzzy data from the database in the Knowledge Base, thereby adapting to fuzzy logic processing. The Fuzzy Inference Engine receives the fuzzified dataset from Fzzifier and performs logical inference operations based on the Knowledge Base. The Defuzzifier, operating in reverse, performs "defuzzification" by converting the fuzzy results obtained through inference into clear outputs according to the rulebase in the database (low membership function ranges: 40/90-70/100; normal: 70/110-80/120; high: 90/130 and above). Figure 3 shows structural diagram.

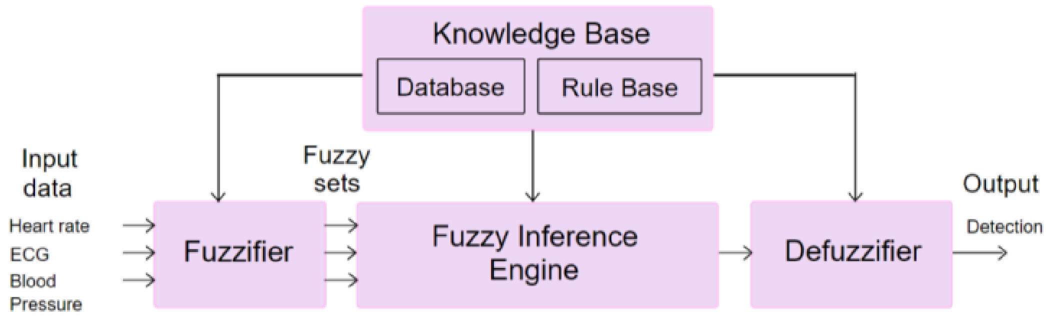

Fig 3. FIS for heart disease risk prediction [1]

2.1.3 Data Comparison Between FIS-LSTM and Other Algorithms

In this experiment, fis-lstm was also compared with the lstm model and flstm in the middle for the accuracy, precision, recall rate, specificity and fl score. As can be seen from Table 1, fis-lstm proposed in this experiment has a data of more than 98%, which is the highest among the three experiments.

Table 1. Comparing performance measures of the proposed system.

Performance Metrics	**LSTM**	**FLSTM**	Fis-Bi-lstm
Accuracy (%)	95.07%	98.04 %	98.86 %
Precision (%)	95.07 %	98.03 %	98.90%
Recall (%)	95.06 %	98.04%	98.81%
Specificity(%)	95.07%	98.03%	98.90%
F1 Score (%)	95.07%	98.03 %	98.86%

2.2. Wearable Devices and Parkinson's Disease

The research team first equipped free-living experimenters with wristband sensors containing triaxial accelerometers and gyroscopes. The collected data undergoes preprocessing through windowing and downsampling, then flows into a detection module utilizing rule-based signal processing technology. This system identifies dynamic activities from accelerometer data, filters out walking events using positive/negative gate mechanisms, and finally processes the information through machine learning classification blocks. Figure 4 shows a schematic diagram of this system.

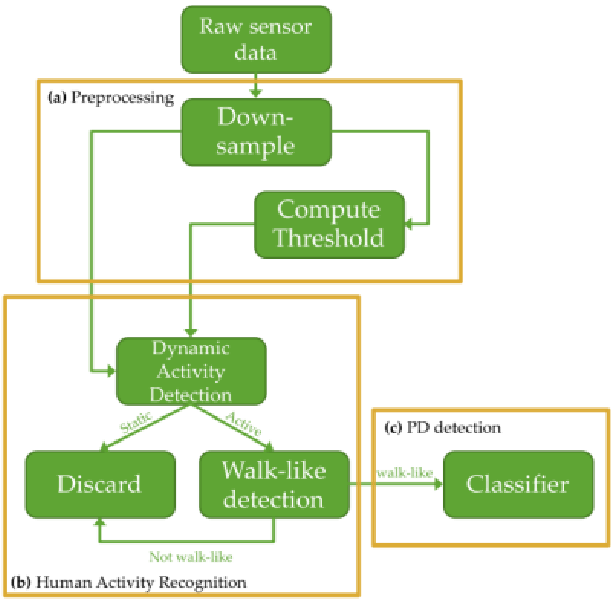

Fig 4. Identification implementation framework

Convolutional Neural Networks (CNNs) serve as a tool for automatically learning "walking pattern event" data captured by wearable sensors to distinguish between patients and healthy controls. As a deep learning model, CNNs excel at processing grid-structured data such as image pixel grids and time-series continuous data points. Their core principles include mechanisms like local receptive fields, weight sharing, and pooling, which efficiently extract local features from data and progressively construct global features, ultimately enabling tasks such as classification or regression.

A convolutional neural network consists of four core components: convolutional layers, activation functions, pooling layers, dropout layers, and fully connected layers. The convolutional layers extract local features through sliding kernels, while activation functions introduce nonlinearity to enable the network to model complex relationships. The pooling layer reduces image dimensions through dimensionality reduction, preserving critical information and enhancing model robustness (resilience to interference). During training, dropout layers randomly discard neurons to prevent over-reliance on specific features, thereby improving generalization. The fully connected layer processes extracted features into global representations and outputs final predictions. Notably, the convolutional network architecture in this study comprises four layers, each employing 5-point kernels with a stride of 2 and no pooling operation, as illustrated in Figure 5.

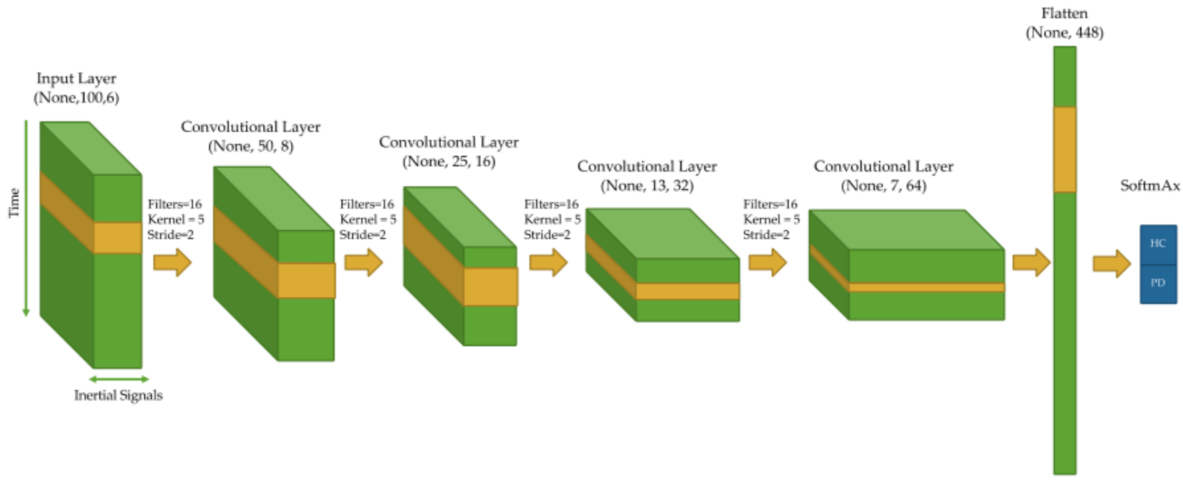

Fig 5. Structure diagram of convolutional neural network in this experiment

Table 2. Accuracy of various machine learning algorithms

Method	Healthy Control Mean Accuracy	Parkinson's Disease Mean Accuracy
CNN	99%	90%
Logistic Regression	99%	64%
Random Forest	99%	85%
Gradient-Boosted Trees	99%	72%
Elastic Net	100%	86%

As can be seen from the Table 2 above, the convolutional neural network has a very high accuracy rate compared with other machine learning algorithms when predicting Parkinson's disease through "type walking" behavior.

2.3. Wearable Devices and Diabetes

At present, most wearable devices for diabetes prediction are single sensors, and there is little research on multi-sensors. They proposed to use multi-sensors (including ECG, ACC, respiratory sensor and glucose sensor) to predict the engine combined with artificial intelligence algorithm to predict diabetes, and compared and studied them with single sensors.

In this experiment, physiological data related to diabetes collected by various sensors are fed into a machine learning framework. The algorithms within the framework process and analyze each data point through windowing measures, then input these feature-rich datasets into a supervised machine learning ensemble. The system selects the most suitable algorithm based on the accuracy of sensor data and computational complexity. The final output is transmitted to the second system, the -- Multi-Sensor Prediction Engine, for cross-sensor prediction [3]. The multi-sensor prediction model integrates feature data from different sensors and evaluates diabetes prediction accuracy across configurations with 2, 3, and 4 sensors. Features are then passed to corresponding algorithm models based on their performance in the machine learning framework. This process is illustrated in Figure 6.

2.3.1 Xgboost Algorithm

In this experiment, the XGBoost algorithm was employed for prediction tasks. It achieved a peak accuracy of 93.5% in single-sensor prediction comparisons using control variables, outperforming GBoost even with identical sensor configurations as shown in Table 3. As an evolutionary version of gradient boosting (which builds new models by fitting residuals from previous iterations), XGBoost introduces regularization and parallel optimization mechanisms. Its core mechanism involves iterative model training: each iteration refits the residual gradient from the previous model to generate new predictions, ultimately integrating all model outputs through weighted aggregation. The system successfully fused data from glucose sensors, ECG sensors, and ACC sensors, capturing both individual dataset characteristics and interrelationships among these three types of sensors. This integrated approach demonstrated high prediction accuracy, as evidenced in Table 3.

2.3.2 Experimental Results

After conducting extensive experiments and comparative analyses, the research team concluded that the XGBoost algorithm was the most suitable machine learning model for prediction. The optimal configuration comprised ECG, ACC, and glucose sensors, which demonstrated 4% to 5% higher accuracy than single-sensor setups (the four-sensor setup required more time than the previously mentioned three-sensor configuration).

The relevant data are shown in Table 3.

Table 3. Comparison of accuracy of three and four groups of sensors

Sensor	Algorithm	Accuracy in %	False positive	False negative
Glucose+ECG+ ACC	XGBoost	98.2%	1.07%	2.77%
Glucose+ECG+ Breathing	XGBoost	96.1%	2.22%	4.88%
Glucose+ACC+ Breathing	XGBoost	97.0%	1.60%	5.54%
ECG+ACC+ Breathing	XGBoost	97.0%	2.31%	3.88%
Glucose+ECG+ ACC+ Breathing	XGBoost	98.2%	1.24%	2.99%

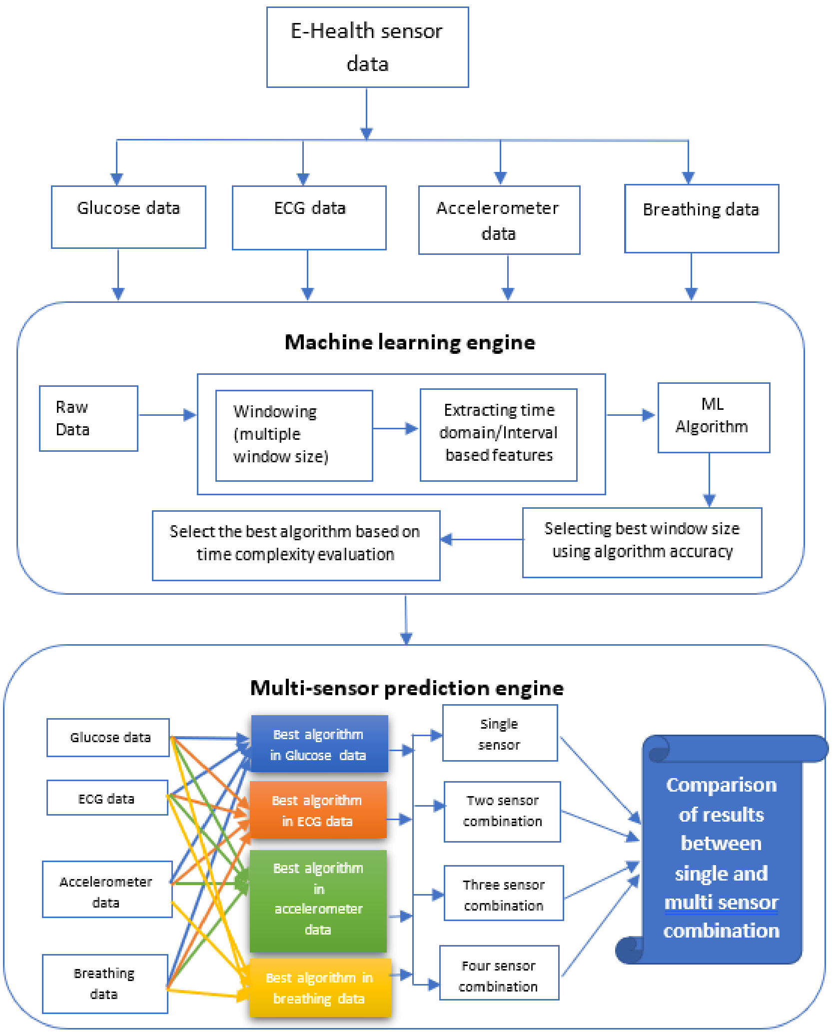

Fig 6. Implementation framework

2.4. Wearable Devices and Depression Identification

Currently, most medical institutions diagnose depression by having patients answer questions from a computerized diagnostic questionnaire. This approach lacks objectivity, as patients may intentionally select preferred answers to 'confirm' their diagnosis, potentially causing unnecessary harm to both healthcare providers and individuals. Therefore, updating diagnostic methods has become an urgent priority. In recent years, researchers worldwide have introduced technological innovations in depression diagnosis and assessment to improve mental health services. Specifically, obtaining objective quantitative data from patients is crucial for enhancing diagnostic accuracy [8].

The research team recruited 58 participants and equipped each with wrist-worn sensors to collect four static physiological parameters: acceleration, pulse wave amplitude, skin conductance, and their statistical measures (mean, variance, skewness, kurtosis). Additionally, they employed an Autoregressive Integrated Model (AR) [9] to derive dynamic features from these parameters. The combined static and dynamic data were then fed into a classification model for recognition, with results presented in Figure 7. Notably, among the machine learning models (support vector machine, random forest, k-nearest neighbor, linear discriminant analysis), the random forest algorithm demonstrated exceptional performance--achieving 90% accuracy (1.7) across all 6-hour measurement periods when both dynamic and static features were considered(Table 4), establishing it as the optimal algorithm for this study.

Table 4. Accuracy of models used in the experiment

model	Five minutes	Thirty minutes	2h	6h	random
radio frequency	76.0(3.5)	80.1(3.2)	84.7(2.5)	90.0(1.7)	49.7(5.1)
SVM	67.4(4.4)	67.0(4.0)	73.2(3.5)	74.1(2.2)	49.2(4.5)
Leu	64.6(5.1)	69.2(4.7)	77.0(3.4)	81.5(2.3)	52.1(3.7)
nearest neighbor	60.8(4.9)	64.6(5.5)	71.6(3.7)	76.1(2.0)	53.4(2.6)

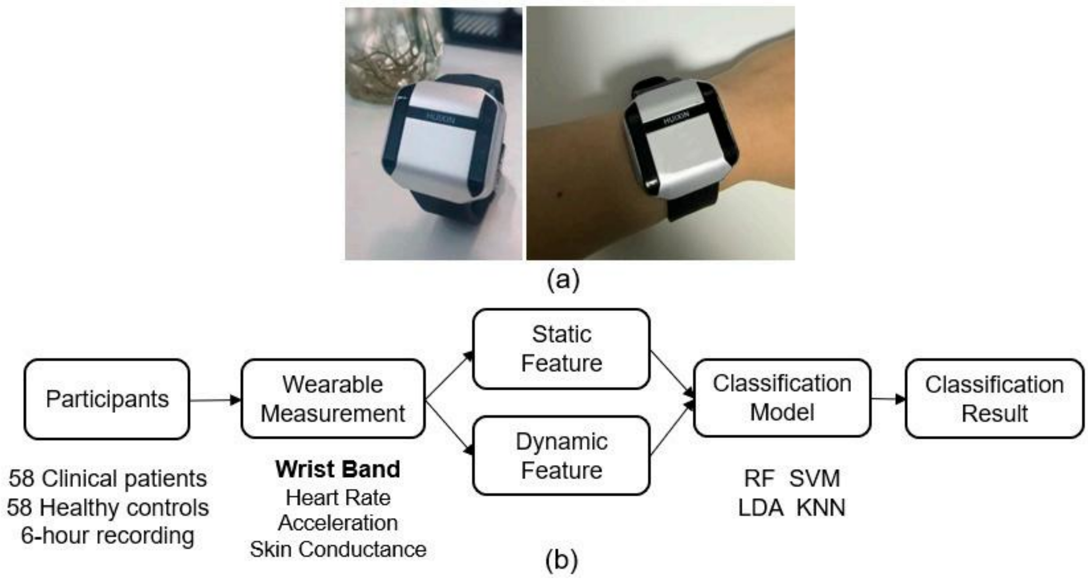

Fig 7. Depression identification wristband diagram and its implementation framework (Part a in the figure is the shape of the experimental device, and part B is the experimental framework of the experiment)

Random Forest is an ensemble learning algorithm that constructs multiple decision trees using the Bootstrap sampling method. These trees are built from random samples and random feature subsets, with predictions synthesized through majority voting (for classification) or averaging (for regression) to enhance predictive performance. In this study, it was employed to classify Parkinson's disease patients and healthy individuals using six hours of multimodal physiological data (including heart rate, skin conductance, and static/dynamic acceleration features). The algorithm demonstrated high accuracy in this application.

2.5. Presentation and Characteristics of Each Method

In conclusion, machine learning algorithms play a very important role in the process of disease prediction and identification. The prediction accuracy of machine learning algorithms is not less than 90%. The paper summarizes the accuracy and innovation points of each method, as shown in Table 5.

Table 5. Performance comparison and innovation points of different methods

disease	optimal algorithm	precision	innovation point
heart disease	FIS--Bi-LSTM	98.86%	Using fis system, fuzzy-defuzzification is used to transform the data into concrete The classification results are obtained. The application of bi-lstm algorithm not only solves the problem of knn algorithm The "forgetting problem" also solves the problem that traditional lstm can only transmit data in a single way
diabetes mellitus	XGBoost	98.2%	Multiple sensors are used to receive data and the most appropriate machine learning algorithm is selected The prediction results can be combined with multiple data for prediction
agitans paralysis	1D-CNN	90.0%	Local motion feature extraction
depression	random forest	90.0%	The voting mechanism of random forest algorithm was used to identify whether the behavior was depression This makes the results more objective and more evidence-based

3. Challenges and Future Trends

Current sensors lack sufficient accuracy and anti-interference capabilities in complex environments. For instance, diabetes respiratory sensors exhibit low precision, while skin conductance data in depression research requires extensive artifact elimination. Additionally, long-term wear compliance remains suboptimal, as multi-sensor combinations in Parkinson's disease studies significantly reduce patients' walking duration. To address these challenges, we propose adopting novel flexible electronic skin sensors for non-invasive multimodal integration. These devices enable simultaneous monitoring of biochemical indicators (e.g., blood glucose) and physiological signals (e.g., ECG, EMG), replacing invasive equipment. Combined with self-powered miniaturization design, they utilize kinetic or thermoelectric energy harvesting technologies along with MEMS processes to manufacture millimeter-scale sensors. This approach enhances accuracy, comfort, compliance, while improving battery life and wearability.

Current data processing, integration, and compatibility face challenges in cross-device interoperability. For instance, reliance on single-vendor equipment and the absence of standardized data fusion frameworks for heterogeneous sensors remain critical issues. Feature engineering heavily depends on manual design--while traditional machine learning requires human-designed temporal features, deep learning models suffer from interpretability limitations. To address this, we propose adopting multi-task joint learning to build unified models for simultaneous prediction of chronic diseases such as diabetes and heart disease. By sharing feature extraction layers, we enhance analytical efficiency and potential compatibility. Additionally, introducing explainability-enhancing mechanisms like Transformer-based attention modules allows visualization of deep learning model decision-making processes, highlighting key physiological segments to improve clinical credibility and interpretability.

Current data privacy and security risks stem from inadequate protection mechanisms. For instance, raw physiological data is directly transmitted to cloud platforms without implementing end-to-end encryption or anonymization. To address this, we recommend adopting privacy-preserving computing frameworks like federated learning, combined with differential privacy-based noise injection mechanisms for data aggregation [10]. Additionally, deploying blockchain-based evidence storage and traceability systems, along with patient-led access logs and dynamic permission management, will systematically strengthen data sovereignty safeguards and enable transparent audit capabilities.

Current models demonstrate insufficient generalization capabilities compared to real-world applications, primarily due to limitations in their adaptability. For instance, small-scale datasets targeting specific populations often fail to capture real-world diversity, while performance discrepancies between laboratory-controlled and open-world environments remain unverified. To address this, we propose implementing multi-task collaborative learning with shared features to develop more universal representations. By integrating digital twin early warning systems, we can establish personalized disease progression models with dynamically adjustable alert thresholds. Furthermore, rigorous external validation using diverse real-world datasets will significantly enhance the model's adaptability and reliability.

4. Conclusion

This study provides a comprehensive review of wearable technology solutions and their application limitations in monitoring four major chronic diseases: heart disease, Parkinson's disease, diabetes, and depression. The findings indicate that different conditions require specific monitoring strategies: cardiac diagnosis necessitates multi-source analysis combining electrocardiogram (ECG) and photoplethysmography (PPG) signals; Parkinson's disease motor dysfunction monitoring relies on gait dynamics analysis through inertial sensors (accelerometer/gyroscope); diabetes management requires integration of three modal data streams--blood glucose levels, electrocardiograms, and accelerometer readings; while depression assessment demands comprehensive analysis combining skin conductance signals with pulse wave dynamics characteristics.

In terms of technical implementation, research has demonstrated that temporal analysis methods--particularly bidirectional long-short-term memory networks--achieve over 90% accuracy in deciphering periodic physiological patterns associated with heart disease and depression. Spatial feature extraction algorithms have achieved 100% daily accuracy in gait recognition for Parkinson's disease patients during free movement. Multi-sensor data fusion significantly boosted diabetes diagnosis accuracy from 93.5% to 98.2% when using single sensors, validating the complementary value of heterogeneous data sources. Meanwhile, dynamic temporal features outperformed traditional static metrics by 12% in depression assessment accuracy, highlighting the critical role of physiological signal temporal variations in mental health monitoring.

These findings provide crucial insights for advancing wearable medical devices: By optimizing sensor configurations and refining multimodal data analysis methods, we can significantly improve the accuracy of chronic disease monitoring. Future research should focus on developing more sensitive sensing technologies and establishing standardized data analysis protocols, thereby providing reliable technical support for early detection, personalized interventions, and long-term management of chronic conditions.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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