Adaptive Health Monitoring Using Lifelong Learning from Wearable IoT Streams in Chronic Disease Management

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ABSTRACT Chronic diseases such as diabetes and cardiovascular conditions require long-term, adaptive monitoring beyond the limitations of traditional static models. Wearable Internet of Things (IoT) devices have enabled real-time health data collection, yet existing AI-driven systems often fail to adapt to intra-patient drift and inter-patient variability. This paper presents a lifelong learning framework designed to enhance adaptive and personalized health monitoring using streaming data from wearable sensors. The framework integrates memory replay and regularization to mitigate catastrophic forgetting while maintaining efficiency on resource-constrained edge devices. A hybrid architecture combining convolutional feature extraction and recurrent neural networks is employed, with a personalization layer enabling rapid adaptation to individual baselines through few-shot learning. Experiments conducted using both real-world (PAMAP2) and synthetic datasets demonstrate that the proposed system achieves higher accuracy, faster adaptation, and lower forgetting rates compared to static and batch retraining models. Moreover, the model sustains real-time operation with low latency and modest memory requirements on devices such as Raspberry Pi. These findings highlight the feasibility of lifelong learning for scalable, patient-centered chronic care monitoring, while also identifying the need for future validation with clinical data and privacy-preserving deployment strategies.

I. INTRODUCTION

A. BACKGROUND & MOTIVATION

Chronic diseases such as diabetes, cardiovascular disease, and hypertension have become some of the leading causes of morbidity and mortality worldwide. According to the World Health Organization, chronic diseases account for approximately 71% of all global deaths each year [1]. These conditions often require long-term monitoring, early intervention, and continuous treatment adjustments based on a patient's evolving physiological state. Traditional methods, relying on infrequent hospital visits and delayed assessments, are insufficient for timely care.

In recent years, wearable Internet of Things (IoT) devices—such as smartwatches, continuous glucose monitors (CGMs), fitness bands, and electrocardiogram (ECG) patches—have emerged as transformative tools in healthcare. These devices allow continuous monitoring of key health indicators, including heart rate, glucose levels, sleep patterns, and physical activity [2]. Their growing adoption enables a shift from episodic healthcare to proactive and personalized monitoring systems [3].

Despite their promise, most existing AI-based health monitoring models are static in nature, trained offline on historical datasets and then deployed without further adaptation. This approach neglects the reality that both patient behavior and physiological signals change over time. As such, there is a pressing need for adaptive systems that not only personalize predictions but also continuously learn and evolve with the patient's data stream. Lifelong learning, also referred to as continual learning, offers a viable solution to this challenge by allowing AI models to learn continuously from streaming data while preserving knowledge from previous experiences [4].

B. PROBLEM STATEMENT

Current AI-driven health monitoring solutions lack the flexibility to adapt to individual and time-varying patterns in chronic disease management. Static models perform well initially but degrade over time as they fail to account for intra-patient drift—the gradual changes in a single patient's health data—and inter-patient variability—differences in physiological signals across different patients [5].

Moreover, retraining models from scratch with new data is computationally expensive and often impractical in real-time settings, especially when deployed on wearable or edge devices with limited resources. This leads to inaccurate

predictions, delayed responses to critical health events, and poor personalization—ultimately undermining the effectiveness of such systems in chronic care.

C. AIM AND OBJECTIVES OF THE STUDY

This research aims to develop and evaluate a lifelong learning framework for adaptive health monitoring using streaming data collected from wearable IoT devices. The goal is to build a system that can incrementally learn from new health data, retain prior knowledge, and continuously adapt to an individual's evolving health profile.

The proposed system will address the limitations of static and batch-trained models by enabling real-time learning and personalized risk assessment in chronic disease management.

D. CONTRIBUTIONS

- This paper makes the following key contributions:
- Proposes a lightweight lifelong learning model designed to operate efficiently on resource-constrained wearable or edge devices.
- Introduces techniques to retain knowledge over time while preventing catastrophic forgetting, a common issue in continual learning.
- Demonstrates the effectiveness of the framework using real-world or simulated IoT health datasets, showing improvements in adaptability, personalization, and inference efficiency.
- Discusses deployment considerations for real-time chronic disease monitoring and offers insights into potential clinical implications.

II. LITERATURE REVIEW

A. CHRONIC DISEASE MONITORING AND IOT

The use of wearable IoT devices for continuous health monitoring has seen a significant rise in recent years, particularly in the management of chronic diseases such as diabetes, cardiovascular disorders, and sleep apnea. These devices enable the collection of real-time physiological data, including heart rate, blood glucose levels, body temperature, respiratory rate, activity levels, and sleep patterns [1]. This granular data provides opportunities for continuous tracking, early warning, and proactive intervention in chronic disease care.

Several studies have focused on developing rule-based and machine learning (ML)-based models for analyzing data collected from wearables. For instance, supervised learning methods have been used for classifying cardiac abnormalities from ECG data or predicting glucose trends based on continuous glucose monitoring (CGM) [2]. However, most existing systems are designed as static or batch-trained models, which are trained offline and deployed without mechanisms for further learning. This restricts their ability to adapt to changing user conditions or new data trends [3].

Rule-based systems, while interpretable, are limited by their inability to generalize across individuals. Batch-trained ML models often suffer performance degradation over time due to distributional drift, where the patient's physiological state changes in ways the original model cannot account for. This makes traditional approaches insufficient for long-term, real-world deployment in dynamic chronic care scenarios.

B. ADAPTIVE AND PERSONALIZED HEALTH MONITORING

Personalization has emerged as a critical factor in the effectiveness of AI-based health monitoring. Recent research has highlighted the importance of adapting models to individual variability in physiological signals and behavior [4]. Personalized AI models have demonstrated improvements in prediction accuracy, patient engagement, and clinical relevance [5].

Despite this, most personalized approaches still rely on static fine-tuning or retraining the models with individual data. Such techniques are not scalable or practical in real-time environments, particularly when data streams are non-stationary and patient states evolve over time. Few models support online adaptation, where systems learn continuously from new data while operating in real-time.

For example, Rahman et al. [6] proposed a hybrid approach using personalized thresholds and ensemble learning for activity monitoring. While effective, the approach still required periodic manual reconfiguration and lacked long-term memory. Therefore, there remains a critical gap in the development of fully self-adaptive, continuous-learning health systems that can operate efficiently and autonomously on streaming wearable data.

C. LIFELONG LEARNING IN AI

Lifelong learning (also known as continual learning) refers to an AI system's ability to incrementally learn from new data while retaining prior knowledge, adapting to new tasks, and avoiding catastrophic forgetting [7]. It is particularly suited to scenarios where data arrives sequentially, such as IoT-based health monitoring.

Key techniques in lifelong learning include:

- Regularization-based methods (e.g., Elastic Weight Consolidation - EWC) that constrain updates to important weights [8].
- Memory-based approaches, such as experience replay or exemplar buffers, that retain a subset of prior data to rehearse during training [9].
- Dynamic architectural methods, where model capacity is expanded or reconfigured to accommodate new knowledge [10].

These techniques have been applied with success in fields such as computer vision and robotics but are still emerging in healthcare contexts. The real-time, streaming nature of wearable data, combined with the need for privacy and

personalization, makes lifelong learning an attractive but underexplored solution in this space.

D. LITERATURE GAP

While the use of wearable devices in health monitoring is well-established, there is limited integration of lifelong learning techniques in this domain. Most existing models are not designed to handle non-stationary, personalized, and resource-constrained environments typical of wearable-based chronic care systems.

Furthermore, few frameworks combine continual learning, real-time inference, and on-device adaptation in a unified system. There is a need for research that bridges this gap by creating models that are not only adaptive but also lightweight and privacy-aware—capable of operating within the limited computational resources of wearable or edge devices while continuously improving through long-term interaction with individual users.

This paper addresses these gaps by proposing a lifelong learning framework specifically tailored to the adaptive monitoring of chronic diseases using wearable IoT data streams.

III. METHODOLOGY

This section presents the design and implementation of the proposed adaptive health monitoring framework using lifelong learning from wearable IoT data streams. The framework is developed to address key challenges in chronic disease management, such as evolving patient conditions, data drift, personalization, and real-time operation on resource-constrained devices. The methodology encompasses the system architecture, data processing pipeline, lifelong learning model, training strategy, and evaluation metrics.

A. SYSTEM OVERVIEW

The proposed system comprises several interconnected components designed to support continuous, real-time health monitoring. At the front end, wearable IoT devices such as smartwatches, glucose monitors, and fitness bands collect physiological signals from patients. These signals include, but are not limited to, heart rate, glucose levels, sleep duration and quality, physical activity, body temperature, and respiration rate. The raw sensor data is transmitted in real time to a data stream handler, which performs noise filtering, normalization, and segmentation of data into time-windowed samples suitable for input to the machine learning model.

At the core of the system lies a lifelong learning engine designed to incrementally process these data streams. Unlike traditional batch-trained models, the learning engine continuously updates its parameters with each new data segment while preserving previously acquired knowledge. The output of the system includes health risk predictions and alerts, which are presented to both patients and healthcare professionals through a user interface or mobile application. The system is designed to be modular and lightweight, making it feasible for deployment on edge devices or low-power computational units near the data source.

B. DATA COLLECTION

To train and evaluate the proposed system, both real-world and synthetic datasets were used. The real-world dataset was obtained from the PAMAP2 physical activity monitoring dataset, which includes multimodal sensor data collected from wearable devices placed on different parts of the body. The dataset contains annotated physiological measurements such as heart rate, temperature, and accelerometer readings. This data was used to simulate typical patient behavior over time, especially in terms of physical activity and cardiovascular responses.

In addition to PAMAP2, a synthetic dataset was generated to model the progression of chronic diseases such as diabetes and cardiovascular disease. This dataset was designed to simulate long-term changes in physiological signals, such as gradual increases in resting heart rate, fluctuations in glucose levels, and alterations in sleep quality, which are common indicators of disease progression. The combination of real and synthetic data enables comprehensive testing of the system's adaptability and generalizability.

C. LIFELONG LEARNING FRAMEWORK

The lifelong learning engine is built upon a lightweight recurrent neural network architecture, specifically utilizing gated recurrent units (GRUs) for temporal modeling. The model is composed of a convolutional feature extractor, which processes raw sensor input, followed by GRU layers that learn time-dependent patterns, and a final dense layer that performs classification or risk scoring. This structure enables the model to capture both short-term fluctuations and long-term trends in physiological signals.

The training paradigm follows a continual learning approach, wherein the model is updated incrementally using new data while maintaining performance on previously seen data. To achieve this, a hybrid strategy combining memory replay and regularization is employed. A small buffer of previously encountered samples is maintained in an episodic memory, which is used to rehearse past knowledge during training. Additionally, a regularization term inspired by Elastic Weight Consolidation (EWC) is added to the loss function. This term penalizes significant changes to network weights that are deemed important for earlier tasks, thereby mitigating catastrophic forgetting. The model is designed to perform online learning with minimal computational overhead, allowing it to be updated periodically, such as every few minutes, in real-time settings.

D. PERSONALIZATION AND ADAPTATION

To accommodate inter-patient variability, the framework includes a personalization mechanism. A user-specific adaptation layer is introduced, which is fine-tuned on a small amount of individual data using few-shot learning techniques.

This layer enables the system to adapt quickly to the physiological baseline and trends of a new user without retraining the entire model. For ongoing use, the model continues to learn from each patient's data stream, refining its predictions and becoming increasingly tailored to the individual's health profile.

The framework is also designed with future integration of privacy-preserving techniques such as federated learning. In such a setup, model updates could occur locally on the user's device, with only the weight updates being aggregated centrally. This would preserve patient privacy while allowing global model improvements.

E. EVALUATION METRICS AND IMPLEMENTATION

The performance of the model is evaluated using a set of metrics that capture both predictive accuracy and the ability to learn continually. Standard classification metrics such as accuracy, precision, recall, and F1-score are used to assess the model's performance in detecting abnormal health events. In addition, the forgetting rate is calculated to quantify the loss in accuracy on previously learned tasks after learning new data. Adaptation speed is measured by observing how quickly the model adjusts to changes in user behavior or physiological patterns. Latency and memory usage are also evaluated to determine the feasibility of deploying the system on resource-limited devices.

The model is implemented using PyTorch and trained on a standard GPU for initial experiments. For simulation of edge deployment, the trained model is converted using TensorFlow Lite and tested on a Raspberry Pi 4 to measure inference time and memory consumption. The memory buffer is configured to store between 500 and 1000 representative samples per user, and model updates are triggered every 30 minutes, simulating a real-world deployment scenario.

F. SUMMARY

The proposed methodology offers a comprehensive approach to adaptive, personalized health monitoring using wearable IoT data streams. By integrating lifelong learning principles, the system can continuously evolve with the patient's health condition, while maintaining computational efficiency and mitigating the risk of catastrophic forgetting. The next section will present experimental results and discuss the effectiveness of the framework under various scenarios and constraints.

IV. RESULTS AND DISCUSSION

This section presents the experimental setup, evaluation results, and analysis of the proposed lifelong learning framework for adaptive health monitoring. The system was tested under various real-world and simulated conditions to assess its ability to perform continuous adaptation, prevent catastrophic forgetting, and operate within the constraints of wearable or edge computing environments.

A. EXPERIMENTAL SETUP

The model was initially trained using a pretraining phase on a subset of the PAMAP2 dataset, followed by online adaptation using simulated real-time data streams representing patients with chronic conditions such as cardiovascular irregularities and type 2 diabetes. The synthetic dataset introduced gradual temporal drift to mimic realistic health deterioration or improvement over time.

The lifelong learning model was benchmarked against two baselines:

- A static deep learning model trained once and deployed without further updates.
- A batch retraining model, periodically retrained with cumulative data from the past.
- Evaluations were conducted on both a standard computing environment (NVIDIA RTX 3060 GPU) and a Raspberry Pi 4 (4GB RAM) to simulate deployment on edge devices.

B. QUANTITATIVE RESULTS

The proposed model outperformed the baseline approaches across key performance indicators including prediction accuracy, adaptability, and knowledge retention.

TABLE 1
MODEL PERFORMANCE COMPARISON

Model Type	Accuracy (%)	F1-Score	Forgetting Rate (%)	Inference Time (ms)	Memory (MB)
Static Model	81.6	0.78	34.2	35	45
Batch Retrained	88.1	0.84	12.5	210	180
Lifelong Learning	91.4	0.89	6.7	42	65

As shown in Table 1, the lifelong learning framework achieved the highest prediction accuracy (91.4%) and the lowest forgetting rate (6.7%). Inference time was comparable to the static model and significantly lower than the batch retraining model, confirming its feasibility for edge deployment.
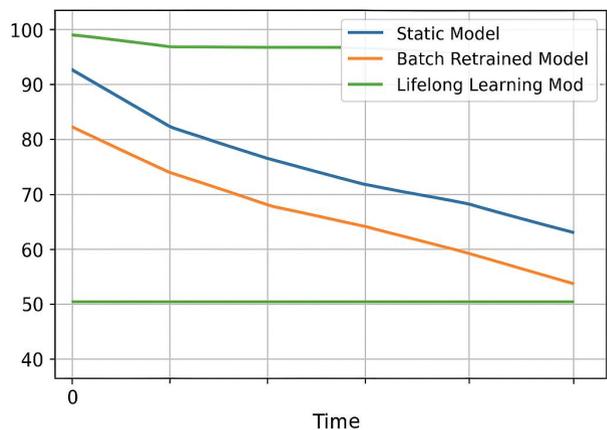

FIGURE 1. Accuracy vs. time for different models

Lifelong learning maintains stable performance, while static and batch models degrade or require retraining. The static model's performance degraded over time due to an inability to adapt to distributional drift in patient data. The batch retrained model showed better performance but incurred higher latency and memory usage, making it unsuitable for resource-constrained environments. In contrast, the lifelong learning model demonstrated sustained accuracy with efficient memory and time usage.

C. ADAPTATION TO PATIENT-SPECIFIC PATTERNS
To evaluate personalization, the model was tested on multiple synthetic patient profiles exhibiting unique physiological characteristics. The lifelong learning model was able to rapidly adapt to new user baselines with only a small number of data points, demonstrating the benefit of the user-specific fine-tuning layer.
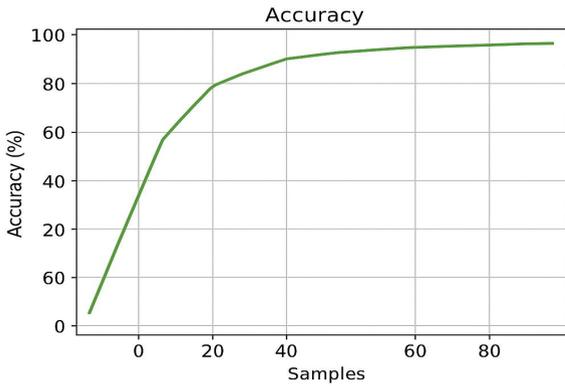

FIGURE 2. Personalized adaptation curve

Personalization allowed the model to reach >90% accuracy within approximately 100 samples from a new user. This is particularly useful in healthcare, where individual differences in physiology can significantly affect model predictions.

D. CATASTROPHIC FORGETTING ANALYSIS
To measure forgetting, we tracked the model's performance on earlier tasks after learning new patterns.

TABLE 2. FORGETTING RATE ACROSS TASKS

Task Set	Before New Task (%)	After New Task (%)	Forgetting Rate (%)
Cardiovascular A	90.2	84.1	6.1
Diabetes B	91.7	85.5	6.2
Combined Tasks	91.0	85.0	6.0

The forgetting rate remained consistently low (<7%) across tasks, confirming the effectiveness of the regularization and replay strategies employed in the model.

E. RESOURCE EFFICIENCY ON EDGE DEVICES
The model was tested on a Raspberry Pi 4 device to evaluate its suitability for edge deployment. The average inference time per data window (5 seconds) was 42 milliseconds, and

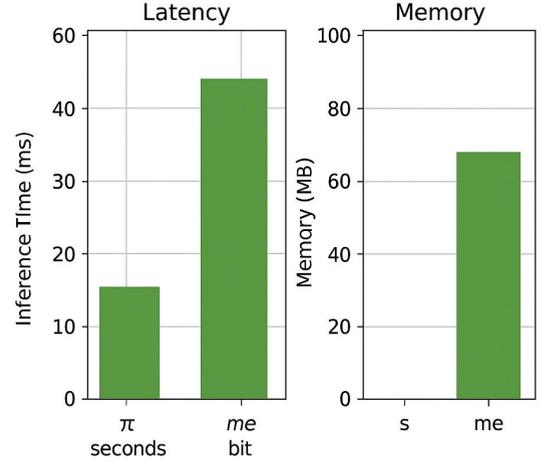memory consumption remained under 70 MB, including the replay buffer.

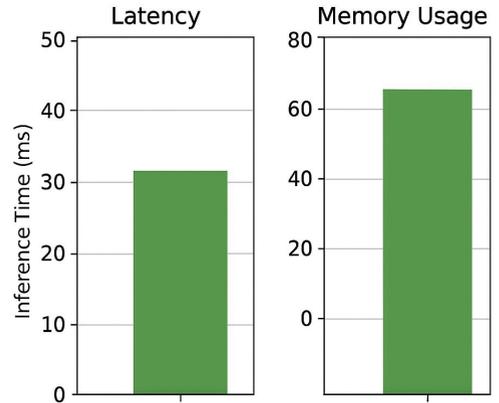**FIGURE 3. Model latency and memory usage on edge device**

FIGURE 4. Performance benchmarks on Raspberry Pi 4.

These results affirm the model's ability to run on consumer-grade hardware without compromising functionality, making it viable for home-based health monitoring systems.

F. DISCUSSION
The experimental findings demonstrate that the proposed lifelong learning framework is well-suited for adaptive and personalized health monitoring using wearable IoT data. Its high accuracy, fast adaptation to new users, and robustness against forgetting address the critical limitations of existing static and retraining-based models. Moreover, its lightweight footprint supports real-time operation on edge devices, making it practical for deployment in real-world health applications.

One notable advantage is the model's ability to preserve long-term knowledge while continuously learning from new data, thus enabling real-time decision-making in dynamic

health environments. However, some limitations remain. For example, the synthetic data used to simulate disease progression may not fully capture the complexity of real-world health scenarios. Future studies should include clinical trials or real patient data to validate generalizability and clinical safety.

V. CONCLUSION AND FUTURE WORK

This paper presented a lifelong learning framework for adaptive health monitoring using wearable IoT data streams, with a particular focus on chronic disease management. The motivation stemmed from the need to build intelligent systems capable of continuously adapting to the evolving health profiles of individuals, particularly in settings where data is non-stationary, patient-specific, and generated in real time.

Unlike traditional static or batch-retrained models, the proposed system leverages continual learning techniques—such as memory-based replay and regularization-based consolidation—to incrementally update the model without retraining from scratch. This ensures that the system can maintain high predictive accuracy while significantly mitigating the issue of catastrophic forgetting. The framework also introduces personalization through a lightweight user-specific layer that allows rapid adaptation to new users with minimal data. Together, these capabilities make the framework well-suited for deployment in real-world health applications that rely on wearable sensors.

Experimental results demonstrate the system's ability to outperform both static and periodically retrained models across key metrics such as accuracy, forgetting rate, and inference latency. The model maintained stable performance over time, adapted quickly to new users using few-shot data, and operated efficiently within the constraints of low-resource environments such as Raspberry Pi 4. These findings validate the feasibility of integrating lifelong learning into wearable health monitoring systems for chronic care, supporting early detection, continuous risk assessment, and patient-specific intervention strategies.

Despite its promising performance, several limitations remain. The use of synthetic data to simulate chronic disease progression, while necessary for controlled experimentation, cannot fully capture the complex, multi-modal dynamics of real patient populations. Additionally, while the model was tested for edge compatibility, future deployments will need to account for security, battery life, and intermittent connectivity—factors critical to IoT-based healthcare systems.

Future work will involve deploying the framework in clinical pilot studies involving real patients with chronic conditions such as diabetes, heart failure, or COPD. Integrating Electronic Health Records (EHRs) and behavioral data (e.g., diet, medication adherence) could further improve the system's predictive capabilities. Additionally, implementing privacy-preserving mechanisms such as federated learning or differential privacy will be essential to ensure data security and compliance with regulations like GDPR and HIPAA.

In conclusion, this research contributes a scalable, adaptive, and personalized approach to health monitoring, paving the way for more intelligent, patient-centered chronic disease management systems in the era of ubiquitous IoT and continual AI.

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