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Advanced Denoising and Meta-Learning Techniques for Enhancing Smart Health Monitoring Using Wearable Sensors

Minyechil Alehegn Tefera, Amare Mulatie Dehnaw, Yibeltal Chanie Manie, Cheng-Kai Yao, Shegaw Demessie Bogale and Peng-Chun Peng *

Department of Electro-Optical Engineering, National Taipei University of Technology, Taipei 10608, Taiwan; t110659401@ntut.edu.tw (M.A.T.); amare.mulatie@ntut.edu.tw (A.M.D.); yibeltal_chanie@mail.ntut.edu.tw (Y.C.M.); t109658093@ntut.org.tw (C.-K.Y.); t112659403@ntut.edu.tw (S.D.B.)
* Correspondence: pcpeng@ntut.edu.tw; Tel.: +886-2-2771-2171 (ext. 4671)

Abstract: This study introduces a novel meta-learning method to enhance diabetes detection using wearable sensor systems in smart health applications. Wearable sensor technology often needs to operate accurately across a wide range of users, each characterized by unique physiological and behavioral patterns. However, the specific data for a particular application or user group might be scarce. Moreover, collecting extensive training data from wearable sensor experiments is challenging, time-consuming, and expensive. In these cases, meta-learning can be particularly useful. This model can quickly adapt to the nuances of new users or specific applications with minimal data. Therefore, to solve the need for a huge amount of training data and to enable the application of artificial intelligence (AI) in data-scarce scenarios, a meta-learning method is proposed. This meta-learning model has been implemented to forecast diabetes, resolve cross-talk issues, and accurately detect R peaks from overlapping electrocardiogram (ECG) signals affected by movement artifacts, poor electrode contact, electrical interference, or muscle activity. Motion artifacts from body movements, external conditions such as temperature, humidity, and electromagnetic interference, and the inherent quality and calibration of the sensor can all contribute to noise. Contact quality between the sensor and the skin, signal processing errors, power supply variations, user-generated interference from activities like talking or exercising, and the materials used in the wearable device also play significant roles in the overall noise in wearable sensor data and can significantly distort the true signal, leading to erroneous interpretations and potential diagnostic errors. Furthermore, discrete wavelet transform (DWT) was also implemented to improve the quality of the data and enhance the performance of the proposed model. The demonstrated results confirmed that with only a limited amount of target data, the proposed meta-learning and DWT denoising method can adapt more quickly and improve the detection of diabetes compared to the traditional method. Therefore, the proposed system is cost-effective, flexible, faster, and adaptable, reduces the need for training data, and can enhance the accuracy of chronic disease detection such as diabetes for smart health systems.

Keywords: wearable sensors; smart healthcare systems; artificial intelligence; Internet of Medical Things (IoMT); meta-learning; machine learning; diabetes; IoT-enabled healthcare services

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1. Introduction

Wearable sensors are interesting attention with great potential for biomedical applications and healthcare monitoring systems especially for chronic disease monitoring such as diabetes, cancer, heart diseases, and others [1]. Currently, usually used wearable devices include the detection of several biochemical and physical information, such as heart rate, blood glucose, and others [1–3]. Diabetes is a chronic condition characterized by abnormal blood glucose levels due to either ineffective utilization or insufficient production of insulin [4,5]. It requires continuous monitoring because neglecting to do so can lead to the development of more complex health issues [5]. Also, poorly managed diabetes can

lead to chronic damage to various organs including the kidneys, heart, and blood vessels. Furthermore, it increases the risk of serious conditions such as hypertension, stroke, and cardiovascular disease [3–5]. Furthermore, this unhealthy condition diminishes families, individuals, and national resources if left untreated. Therefore, there is a need for continuous monitoring, early prediction, and detection of chronic diseases such as diabetes, cancer, and others to avoid complications and save lives [4].

Moreover, the emergence of smart-computing sensors, such as smartphones, smartwatches, and other wearables, along with advancements in healthcare technology, has made it ever more convenient to continuously and remotely monitor patients' health statuses in both home and hospital settings [1]. Deploying artificial intelligence (AI) such as deep learning and machine learning algorithms in smart healthcare systems and the Internet of Medical Things (IoMT) infrastructure can further improve performance in terms of decision-making, data analysis, and achieving various constraints. Moreover, accurate detection of the r-peak plays a pivotal role in every aspect of electrocardiogram (ECG) application. However, current r-peak predictors face challenges such as long computational times, limited adaptability, and increased detection errors. These issues arise due to the non-stationarity of noise and the complex QRS morphology, which includes a downward deflection after the primary waves (Q), an upward deflection following the Q waves (R), and a downward deflection after the R wave (S). Factors like skin contact quality, signal processing errors, power supply fluctuations, user activities, and the materials of the wearable device can impact the accuracy of wearable sensor data detection. To address these issues, the combined meta-learning and DWT denoising technique are proposed.

In recent years, various conventional deep learning and machine learning techniques [2–11] have been developed to classify and detect r-peaks, and predict chronic diseases such as diabetes, cancer, and others. However, these methods face significant challenges. One of the primary issues is long computational time, which refers to the extensive processing duration required for model training and inference, often making real-time applications impractical. Fast learning problems, also known as convergence issues, occur when models struggle to efficiently reach optimal performance, resulting in prolonged training periods and suboptimal results. Existing methods also exhibit limited adaptability and flexibility, meaning they often fail to generalize well to new, unseen data or adapt to variations in input data [9]. This limitation can lead to higher prediction errors, reducing the reliability of these models in practical scenarios. A cohort study, detailed in [10], utilized ECG and glucose level sensors in conjunction with IGRNet for predicting diabetes. The study reported promising results, achieving an accuracy rate of 78.1% and an AUC (area under the curve) of 77.7%. Additionally, the model demonstrated efficient performance with a testing time of 101.2 s, highlighting its potential utility in real-time clinical applications. Moreover, traditional machine learning models may achieve accuracy rates ranging from 68% to 74% in diabetes prediction on the Pima Indian dataset (PID) but often fall short when dealing with imbalanced datasets or noisy data [11]. The highest accuracy achieved so far was 95.1% using a combined CNN-LSTM model [11]. To address these issues, the recent deep learning method was proposed for handling complex data processing and imbalanced data compared to traditional machine learning [9,11]. Nevertheless, achieving improved predictive accuracy and improving the generalization performance of using deep learning methods entails a large amount of training data and training time. However, collecting sufficient amounts of wearable sensor data is complex, time-consuming, and costly. Moreover, real-time data collection for chronic diseases such as diabetes, cancer, cardiovascular diseases, and others is not only time-consuming and tedious but also resource-intensive due to the constant need for continuous or frequent monitoring across various sensors and devices [12–17]. Therefore, to address the problem of requiring a huge amount of training data and to enable the application of AI in data-scarce scenarios, a meta-learning approach is proposed. This approach reduces the total data required for training by allowing AI to adapt from experience or previous knowledge. The presence of noise in wearable sensor data significantly compromises the performance of

the proposed meta-learning model. To address this issue, employing denoising techniques emerges as a viable solution, enhancing the model's accuracy and reliability.

Moreover, effective and powerful techniques for denoising signals are significant for wearable sensors, devices, and others [18,19]. Recently, Various denoising and noise algorithms have been proposed, such as independent component analysis (ICA), adaptive filters, adaptive Fourier decomposition, empirical mode decomposition (EMD), median filter, Savitzky–Golay filter, moving average filter, Kalman filters, Bayesian filter framework, wavelet technique, clustering of morphological features, and neural networks [19,20]. However, DWT denoising stands out as equally effective, and superior, compared to these proposed techniques [19,20]. Therefore, the DWT denoising algorithm is implemented in the proposed system.

In this study, meta-learning and DWT are proposed and demonstrated for diabetes prediction systems, to increase adaptability and learnability, and improve prediction accuracy. The proposed method can reduce the amount of wearable biomedical sensor data needed to train predictive models in the target domain of interest needed for training by leveraging prior knowledge or experiences. Therefore, meta-learning and DWT denoising techniques are applied to enhance the prediction accuracy of smart health systems. The experimental results verify that the proposed technique enhanced the prediction accuracy. The study seeks to make the following contributions:

- The proposed meta-learning method is appropriate to empower AI, since biomedical wearable sensor data collection is expensive, challenging, or inadequate.
- An advanced multi-level denoising technique has been implemented and demonstrated for smoothing the noise signals and improving the performance of the proposed meta-learning model.
- The proposed meta-learning system significantly improves disease detection accuracy and efficiency while enabling adaptation to new data and learning from limited samples. It streamlines the training of predictive models for health wearables, enhancing efficiency and adaptability to new health tasks or patient conditions by leveraging diverse source datasets.
- After conducting comprehensive experiments and comparative analyses, meta-learning demonstrated significant outperformance compared to traditional methods without pre-training. This leads to a marked improvement in diabetes detection performance in healthcare monitoring systems.

Further, the remaining parts of this study are described as follows. Section 2 explains the methodology of this paper and provides a comprehensive explanation of the techniques and procedures employed in the study. Section 3 presents the results and discussion, detailing the findings from the research. Section 4 describes the results, discussion, and comparative analysis. Finally, Section 5, describes the conclusion part of the study.

2. Methodology

2.1. Data Collection

This section details the datasets employed in predicting diabetes, which involves utilizing data collected from multiple sensors. In this research, wearable sensor-based health training datasets are utilized and obtained from open-source platforms available on the Internet [7,21]. These datasets were selected based on their relevance and quality to ensure the robustness and accuracy of our analysis. The diabetes type 1 non-invasive activity monitoring (D1NAMO) multi-sensor dataset used in this article is described in detail in [7,21]. This dataset contains four kinds of sensor information: ECG sensor, glucose measurements, breathing sensor data, and accelerometer (ACC) signals. It also includes pictures annotated with food information, but we are only focusing on the data from the two sensors, the ECG sensor and glucose measurements, for this study because ECG and glucose levels are critical parameters in the diagnosis and management of various health conditions such as diabetes and were collected using standardized protocols, ensuring consistency and reliability. Glucose levels are a direct measure of glycemic control, while ECG data

can provide insights into cardiovascular health, which is often affected by diabetes. By analyzing both, we aimed to develop a more comprehensive predictive model for diabetes. Moreover, integrating cardiac and metabolic health data allows for a more holistic approach to diabetes prediction. Since cardiovascular health is closely linked to diabetes, combining ECG and glucose data can improve the accuracy of the predictive model. The data come from patients in non-clinical settings, gathered using three Zephyr BioHarness wearable devices [7,21]. The multimodal sensor dataset involves information from 29 patients, with 20 of them being healthy individuals and 9 diagnosed with diabetes. However, the data collected from public sources for all real-world applications are not sufficient for training the model and predicting chronic diseases such as diabetes. Therefore, to address this issue and enable artificial intelligence in scenarios with limited data, a meta-learning method is proposed.

Signal Processing

The process involves cleaning and transforming raw signal data to remove noise and artifacts, thereby making the signals more suitable for analysis. First, the raw ECG signals are cleaned using DWT denoising techniques to eliminate noise and unwanted signals. Next, important features such as heart rate variability (HRV), QT interval, and other ECG morphology metrics are extracted based on their relevance. Simultaneously, glucose level signal data are processed and smoothed using averaging methods. Finally, a meta-learning technique is employed to predict diabetes and glucose levels. Below, the details of the proposed meta-learning model and DWT are discussed.

2.2. Proposed Discrete Wavelet Transform (DWT)

The DWT is a powerful method for denoising ECG and other sensor signals, playing a crucial role in enhancing the accuracy and reliability of recorded data. This is essential for the precise monitoring of physiological parameters, early detection of health anomalies, and overall improvement in user experience in various healthcare applications. Advanced denoising techniques not only mitigate the impact of noise and artifacts but also ensure the integrity of wearable sensor data, facilitating accurate diagnostics, better patient outcomes, and broader adoption of wearable technology in both clinical and non-clinical settings [19,22]. Noises represent unwanted signals in data acquisition that need to be removed to process signals efficiently, especially in critical situations where the accuracy and clarity of the signal are paramount [22].

Previous studies have employed a variety of signal processing techniques, including the fast Fourier transform (FFT) and moving average filter, to address and mitigate noise in different types of signals such as electrocardiograms (ECG), fiber Bragg grating (FBG) signals, and others. These methods have been pivotal in enhancing the quality and clarity of the captured data by transforming the signals into a frequency domain where noise can be more easily identified and filtered out, as well as by smoothing the signal to reduce random variations. By leveraging these techniques, researchers have been able to significantly improve the accuracy and reliability of signal analysis, thereby advancing the effectiveness of monitoring and diagnostic systems across a wide range of applications. These advancements underscore the ongoing importance of developing robust noise reduction strategies to enhance signal fidelity in both clinical and technological contexts [22,23]. However, the coarse scale of the Fourier transform posed limitations in effectively removing noise, although it can be utilized to reduce noise in wearable sensor signals such as ECG sensors, glucose sensors, and others. Consequently, in this study, DWT is proposed for the proposed system. The wavelet transformation of an input signal x(t) is stated as follows [19]:

$$W a, b = \int_{-\infty}^{\infty} x(t) \left(\frac{1}{\sqrt{a}} \right) \gamma * \left(\frac{t - b}{a} \right) dt \quad (1)$$

where t is time, Wα,b is the wavelet transformation of x(t), α is the dilation parameter, b is the location parameter, $\gamma *$ (t) is the complex conjugate of the wavelet function.

In order to define the DWT, the following assumptions are made.

Moreover, the detailed process of DWT is described below [18]. In DWT, critical information is extracted from the sensor signal, and noise is removed from the data. The wavelet transforms separate signals into low and high frequencies to preserve the original data. It accomplishes this by extending and translating the basic wavelet, resulting in several wavelet coefficients. High-pass filters capture the high-frequency details of the signals, while low-pass filters capture the low-frequency information. the nosed signal can be defined as follows [18]:

$$\mathrm{Sn} = \mathrm{Xn} + \mathrm{Yn} \tag{2}$$

where n is signal length, S is the noised signal, X is the important signal, and z is the unimportant (noisy) signal. When the noise in the signal is random and discrete, the resulting wavelet coefficients are relatively low after applying the DWT. The low-frequency and high-frequency wavelet coefficients are then filtered using a preset threshold. The remaining coefficients are transformed back using the inverse DWT to reconstruct the original signal. The steps of the DWT noise reduction process are as follows:

1. Collect the original noisy data.
2. Apply the wavelet transform to the data.
3. Set the level of decomposition for wavelet decomposition.
4. Perform threshold processing.
5. Reconstruct the signal.
6. Finally, the noise in the signal is reduced.

Moreover, selecting the correct threshold in wavelet denoising is crucial. If the threshold is too low or too high, the signal cannot be accurately estimated. The threshold λ can be expressed as follows [18]:

$$\lambda = \varepsilon \times \sigma \tag{3}$$

where ε represents the control coefficient and σ represents the mean square error. Furthermore, given the availability of different threshold functions, such as hard-threshold and soft-threshold denoising types, we can select the most appropriate function. The wavelet coefficient (c) is a function of time in terms of the oscillations [18]. Soft and hard thresholding is used in wavelet denoising, defined by Equations (4) and (5), respectively [18,23].

$$\mathrm{c}\lambda = \begin{cases} \mathrm{sign}(|\mathrm{c}| - \lambda), \; if \; |\mathrm{c}| \geq \lambda \\ 0, if \;\; |\mathrm{c}| < \lambda \end{cases} \tag{4}$$

$$c\lambda = |x| = \begin{cases} \mathrm{c} \, , \; if \; |\mathrm{c}| \geq \lambda \\ 0, if \;\; |\mathrm{c}| < \lambda \end{cases} \tag{5}$$

where c represents the wavelet coefficient and λ is the threshold.

In the soft threshold de-noising method, when the wavelet coefficient $|\mathrm{c}| < \lambda$, the noise can be reset to zero, while when $|\mathrm{c}| \geq \lambda$, the $|\mathrm{c}|$ is subtracted by λ. In the hard threshold denoising technique, when $|\mathrm{c}| < \lambda$, the noise can be reset to zero, and when $|\mathrm{c}| \geq \lambda$, the wavelet coefficient retains c [18,23].

Shown in Figure 1a are the noise data before applying DWT, and Figure 1b presents the noise of the sensing signal, which is filtered and looks clear in different levels or stages. As shown in the figure, as the number of levels increases in the DWT denoising technique, the effectiveness of noise removal also increases, resulting in a clearer and more refined sensor signal. Conversely, reducing the number of levels may lead to less effective noise reduction and a signal that retains more noise artifacts. Indeed, they typically achieve a good, clear signal after applying DWT denoising at stage 4 or stage 5, or stage or level or layer 5, striking a balance between noise reduction and signal preservation.

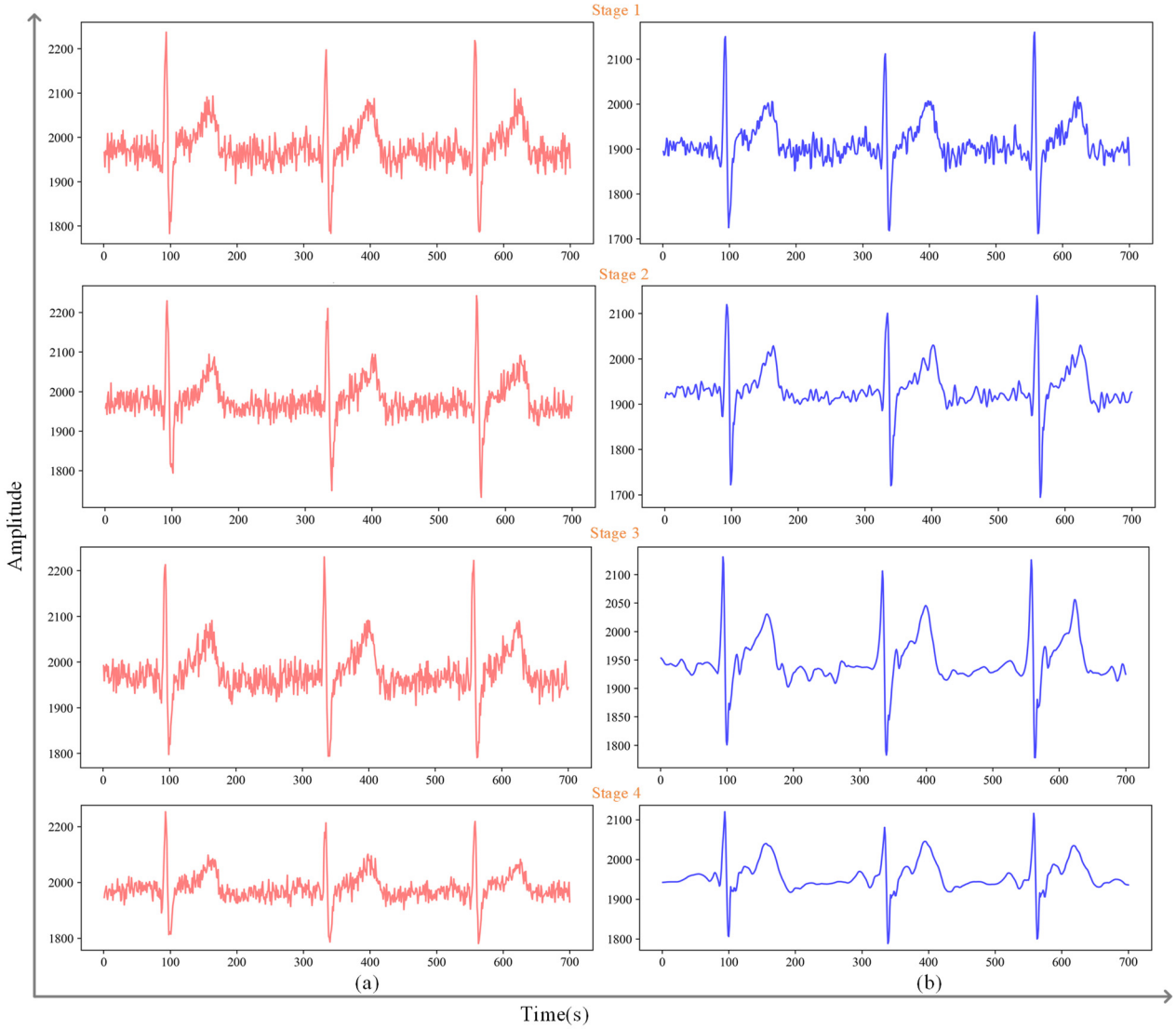

Figure 1. Proposed discrete wavelet transform (DWT) multi-level denoising (**a**) before applying the denoising technique, (**b**) after applying the denoising technique.

2.3. Proposed Meta-Learning Model

This section provides a detailed explanation of the proposed meta-learning model, as illustrated in Figure 2. A remarkable trait of human intelligence is its capacity to use existing knowledge efficiently to speed up the learning of new tasks. To emulate this human-like skill within artificial agents, researchers have introduced and extensively studied the concept of meta-learning. This approach holds promise for pioneering learning and adaptation within situations where only a few or limited data are available [16,17]. Like human learning methods, a model possesses the ability to acquire new tasks by leveraging experience gained from familiar and related ones [12–16]. The meta-learning technique can swiftly learn a new task from a limited amount of data in the target domain [12,16,17]. Using meta-learning shows great potential to decrease the amount of biomedical data needed to train predictive models in the target domain of interest [12,16]. Deep learning methods have enabled us to effectively process unlabeled data such as sensor data, medical images, medical health text records, audio, and others [24–27]. However, improving performance with deep learning requires extensive data. Moreover, meta-learning, as proposed, has the potential to transform machine learning by helping models learn and adjust to new tasks and environments quickly and efficiently, by reducing the huge amounts of training data and learning from past experiences similar to human beings.

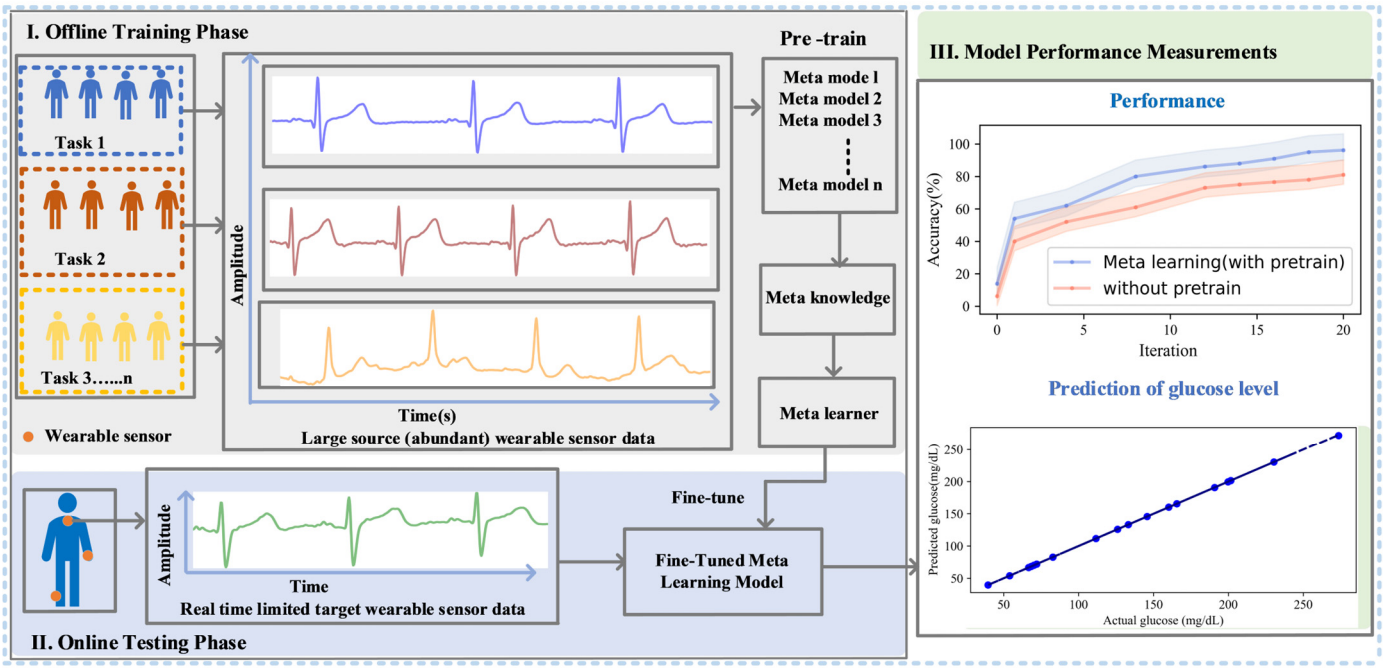

Figure 2. The scheme and implementation framework of the proposed system.

As shown, Figure 2 demonstrates the overall schematic and implementation framwork of the proposed method. As shown in the figure, the large data or source data with different patients (different ECG and glucose sensors signals) as diverse tasks, such as task 1, task 2, and task n, provides for the pre-train model, such as meta-model 1, meta-model 2. . . meta-model n, for knowledge transfer. In addition, the proposed system can support different related wearable sensors such as pressure sensors, glucose sensors, motion sensors, and others. Moreover, meta-learning has significant potential to decrease the quantity of biomedical data required for training predictive models in the specific target domain and using related data as source data for pre-training [12,16,17]. Meta-learning offers a solution for chronic diseases, where acquiring extensive training data and implementing AI can be challenging. By leveraging data sets from other related diseases, institutes, or cell types, a model can be pre-trained to be ready for learning new tasks even before encountering data in the target domain [12]. After completing the pre-training phase, the model acquires the ability to learn and extract features from the data to make meta knowledge. The model's weight is fine-tuned to optimize a particular objective such as iteration steps (k), learning rate, and others. The learning rate, threshold, and iteration steps (k) of the proposed model are set to 0.001, 02, and 24, respectively. After completing all the steps of pre-training stages, the knowledge gained from the pre-trained model is shared for the fine-tuning process on a few examples. Following the fine-tuning stage, the fine-tuned proposed model is tested using new unseen test data. Finally, a fine-tuned meta-learning model can forecast diabetes and glucose levels. The evaluation of both the proposed prediction model and denoising model was conducted on a computer system specifically configured with an Intel(R) Core (TM) i5-8500T processor (Taipei, Taiwan), which operates at a clock speed of 2.10 GHz, ensuring robust processing capabilities. This setup was further enhanced with 8GB of RAM, providing adequate memory resources to efficiently manage the computational load required for executing the model, thus guaranteeing a smooth and effective performance evaluation process. The development of the model was achieved through the utilization of the Keras library alongside the TensorFlow framework, employing Python version 3.10 for the programming tasks. To check the performance of the proposed meta-learning model, performance evaluation metrics such as accuracy and metrics for measuring errors such as mean square error (MSE), mean absolute error (MAE), and root MSE (RMSE), are used

for diabetes prediction and glucose level prediction, respectively, and are computed in Equations (2) and (3) [10,16,28–33], as follows:

$$\text{Acuracy} = 100 * \left(\frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \right) \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_{pred} - X_{ac})^2}{n}} \tag{7}$$

where TP represents true positive, TN represents true negative, FP represents false positive, FN represents false negative, *Ypred* represents estimated values, *Xac* represents truth or actual values, and *n* is the number of total test data.

Figure 2 illustrates the overall schematic and implementation framework of the proposed method, which is divided into three main phases: offline model training, online model testing, and model performance evaluation. In the offline training phase, the model is trained using preprocessed and normalized source input datasets from different tasks such as task 1, task 2. . .task n to ensure effective learning. Then, these different signals are given to pre-train models (model 1, model 2. . .model n) for pre-trained purposes. Then, the pre-trained model as previous knowledge is given to the meta-learner for fine-tuning purposes. Then, the online testing phase involves validating the well-trained model in real-time scenarios, crucial for assessing practical applicability. The fine-tuned meta-learning model uses the target data and the previous knowledge as input. The final phase, model performance evaluation, involves assessing the proposed meta-learning model's accuracy, efficiency, and robustness. This process includes calculating various evaluation metrics, implementing cross-validation techniques to ensure consistency, and continuously monitoring the model's performance. It also encompasses hyperparameter tuning to optimize the model, error analysis to understand its limitations, and comparing the model's performance against baselines or previous versions. The three phases of the proposed system are described in detail as follows: offline training phase: The denoised and preprocessed datasets from different tasks (task 1, task 2, . . ., task n). Normalize the data to ensure consistency across tasks. Then, use the prepared and denoised data to train pre-train models (model 1, model 2, . . ., model n). Once passed through the pre-training phase, the model learns and extracts features from the data and makes the meta-knowledge. This meta-knowledge serves as the foundation for the meta-learner, encapsulating task-specific knowledge. Then, use the pre-trained models as prior knowledge and feed them into a meta-learner. After completing pre-training, the knowledge gained from the pre-trained model is transferred for the fine-tuning process on target data by passing to the second phase. In the second phase, online testing phase: the meta-learner fine-tunes these models using additional small target data to generalize across tasks effectively. The final phase, model performance evaluation: indicates the finetuned meta-learning model results in diabetes prediction and glucose level measurement using measurement metrics of accuracy and error measurements by checking the actual and the predicted glucose level. Additionally, the model is validated on separate, unseen datasets to ensure it generalizes well to real-world data. Overall, this comprehensive evaluation ensures that the model maintains high accuracy and reliability.

3. Results and Discussion

This section provides an in-depth analysis of the findings derived from rigorous testing of innovative meta-learning techniques in conjunction with DWT de-noising methodologies, specifically tailored for advanced smart healthcare systems. These cutting-edge approaches have been applied to critical predictive tasks, such as the accurate forecasting of diabetes onset and the precise monitoring of glucose levels. The comprehensive evaluation demonstrates the potential of these novel techniques to significantly enhance the predictive capabilities of smart healthcare systems, thereby contributing to more effective and timely medical interventions for managing chronic conditions like diabetes. Figure 3 demonstrates the performance assessment of the proposed method concerning the impact

of changing the iterations (k) steps. As shown in the figure, the RMSE and MSE of the proposed meta-learning model are decreased when the iterations (k) steps increase and vice versa.

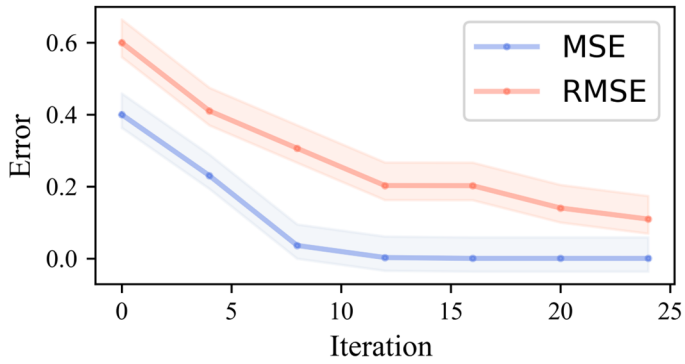

Figure 3. Proposed technique performance based on RMSE and MSE according to various iterations (k) steps.

Furthermore, to evaluate the effectiveness of the proposed approach, this study compared the performance outcomes between models without pre-train and with pre-train meta-learning, to indicate the effect of pre-training, and the proposed meta-learning method is the state of art. Figure 4 shows the estimation error results in terms of the MAE depending on the number of iteration (k) steps in meta-learning and without pre-train. The meta-learning exhibits a notable trend of significantly reducing the MAE within just a few iterations (k) of steps compared with without pre-train. Therefore, these results indicate that the proposed meta-learning system rapidly adapts to the target's limited data by learning from previous experience and show the possibility of achieving better performance using both small limited data and few iterations.

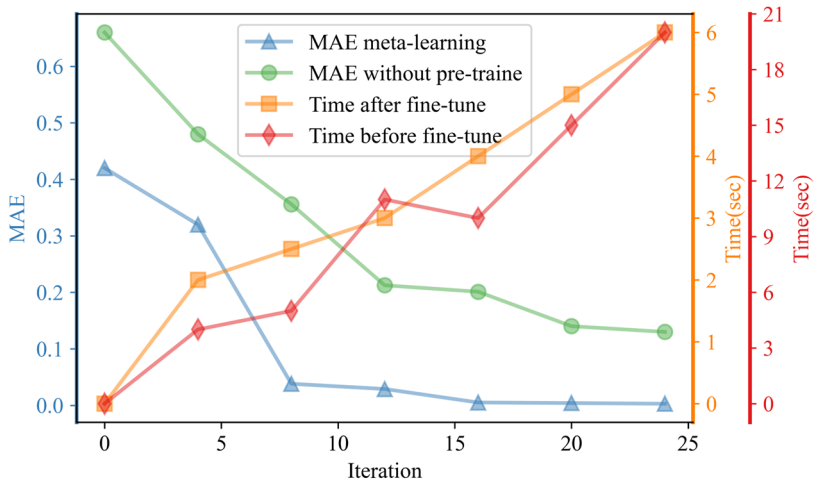

Figure 4. Comparison of performance of meta-learning, without pre-train, after fine-tune, and before fine-tune in terms of MAE and time.

In addition, as illustrated in the figure, the fine-tuned meta-learning approach shows respectable progress and tends to decline compared to without pre-train. Nevertheless, the non-pre-trained model necessitates substantial investments in collecting extensive training data, computational resources, human effort, and time to achieve optimal performance, whereas the pre-trained meta-learning model is an economical, swift, and resource-lean solution tailored for the IoMT or smart healthcare application using wearable sensor systems.

Moreover, by considering cost or time efficiency, comprehensive comparisons are conducted on the computational time to evaluate the performance of the proposed method.

As illustrated in the accompanying figure, the computational time, both before and after the fine-tuning process, exhibited a significant increase in direct proportion to the rising number of iterations (K) steps. This trend underscores a clear and direct correlation between the number of iterative steps and the total time required for computation, highlighting the importance of optimizing the number of iterations to balance computational cost and performance efficiency. However, after the fine-tuning process is applied, there is a marked reduction in computational time, with a time value of 6 s and iteration of 24, when compared to the duration required before fine-tuning with a time of 20 s at the iteration of 24. This significant decrease in computational time post-fine-tuning demonstrates the efficiency improvements gained through the fine-tuning adjustments, thereby underscoring the importance of this step in optimizing the model's performance and operational efficiency. The meta-learning model proposed in this study achieved a low MAE of 0.00297 and validates notable achieved computational efficiency by completing tasks in less computational time and with fewer iterations (k) steps.

Figure 5 shows the predicted glucose level by the proposed model result versus the actual glucose level. As shown in the figure, the x-axis indicates the actual glucose level whereas the y-axis indicates the predicted glucose level. The effectiveness of the proposed model is visually evident through the circles or points that closely align with the blue fitting line. The predicted and actual values are closely clustered around the ideal line, indicating the proposed method's accuracy. With a testing error represented by an RMSE of 0.010798, the proposed model achieves highly accurate predictions. Hence, the result indicates that the proposed meta-learning model would have a better prediction accuracy using only a small amount of data and low computational time. Based on the numerical analysis, the fine-tuned meta-learning improves the accuracy of glucose level prediction by 93.5631% compared with the traditional model without the pre-train model.

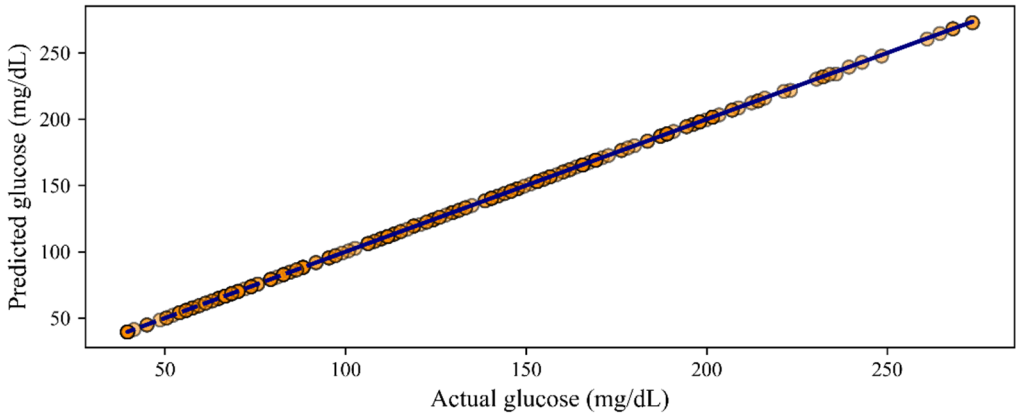

Figure 5. Predicted vs actual glucose level using the proposed method.

Moreover, the model has been evaluated using receiver operating characteristics (ROC). As shown in Figure 6, the ROC curve represents the performance of meta-learning and without pre-train models. The y-axis represents the rate of true positives, whereas the x-axis shows the rate of false positives. The area under the curve (AUC) summarizes the ROC curve, serving as an indicator of model capacity to distinguish between different classes. A higher AUC value signifies superior model performance. Based on the demonstrated experimental result using meta-learning, the model reached an AUC of 0.99 or 99%, significantly outperforming the model without pre-training, which scored an AUC of 0.94 or 94%.

Figure 7 demonstrates the detected r-peaks of the ECG signal. As demonstrated in the figure, the proposed method effectively detected the r-peaks, even when the r-peaks overlapped due to different reasons such as movement artifacts, poor electrode contact, electrical interference from nearby devices, or muscle activity. Shown in the figure are the detected r-peaks, QRS complex, and ECG signals. Hence, when the r-peaks of ECG

signals are overlapped, the model under consideration accurately measures the r-peaks of ECG signals.

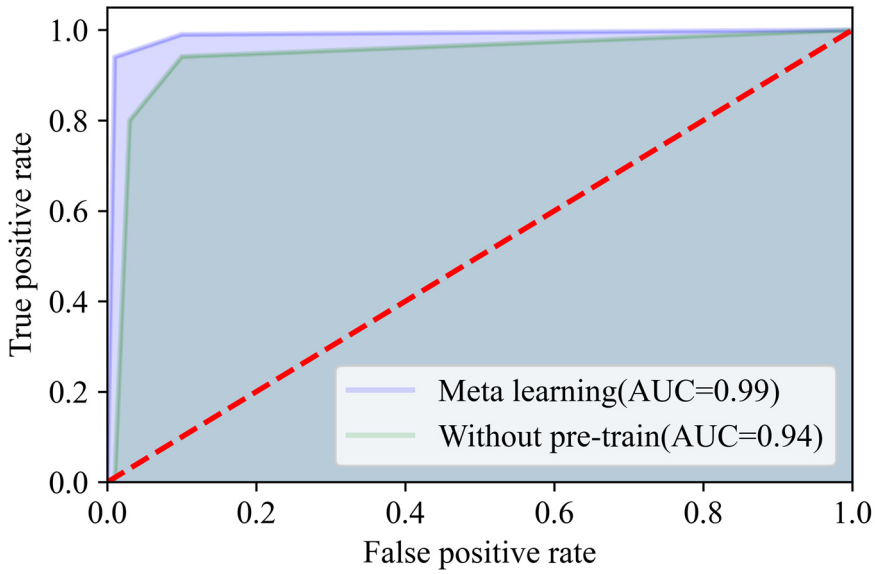

Figure 6. ROC curve of the proposed model.

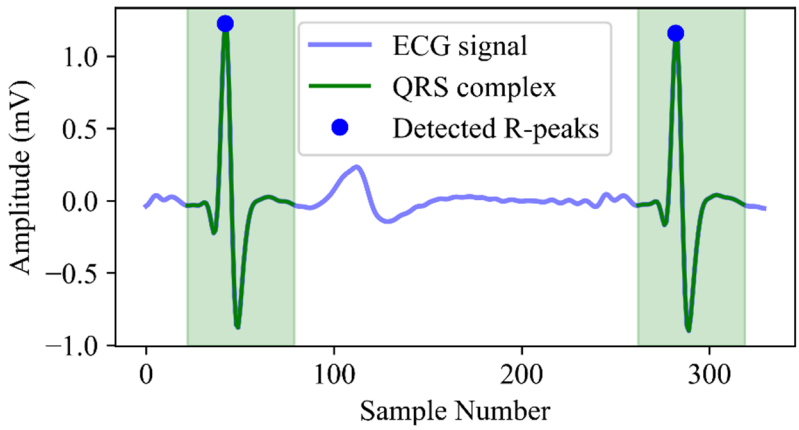

Figure 7. Detected r-peaks using the proposed method.

Moreover, the performance of the proposed meta-learning technique was also validated by comparing it with DWT denoising, without using DWT denoising, and without the pre-train model, based on accuracy evaluation metrics. Figure 8 shows the prediction results of meta-learning with DWT denoising, meta-learning without DWT denoising, and without pre-trained in terms of accuracy. The evaluation is based on accuracy metrics, providing a comprehensive analysis of how DWT denoising and pre-training influence the performance of meta-learning models. The results highlight the effectiveness of integrating DWT denoising in enhancing prediction accuracy, demonstrating a significant improvement over models that forgo this step. Additionally, the comparison underscores the importance of pre-training in the meta-learning framework, revealing its impact on achieving higher accuracy levels. The meta-learning model with the DWT denoising technique achieved an accuracy of 96.2%, outperforming both the model without DWT denoising, which achieved 85%, and the model without pre-training, which achieved 81% accuracy. The result indicates that DWT denoising and pre-training both play crucial roles in enhancing the accuracy of the meta-learning model. Based on the comprehensive numerical analysis, the proposed meta-learning diabetes detection model significantly enhances accuracy by 18.765% compared to a model without pre-training. This substantial

improvement in accuracy highlights the effectiveness of incorporating DWT denoising techniques and meta-learning techniques, demonstrating the superior performance of the pre-trained model.

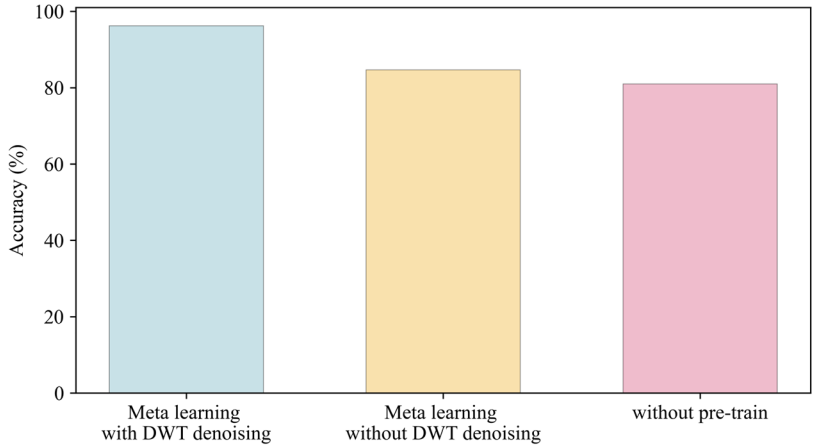

Figure 8. Performance of different models.

4. Performance Comparison Analysis

Moreover, a comparison of the performance is presented for the proposed meta-learning and DWT with other diabetes detection and glucose level monitoring approaches using different wearable sensors and machine learning techniques, as described in Table 1. Various techniques for chronic diseases such as diabetes prediction and glucose level detection have been proposed in previous studies [10,34–37], highlighting the importance of these areas in healthcare. In the comparison, previously studied work that focuses on wearable sensors is considered for chronic disease prediction such as diabetes, and glucose level prediction.

Table 1. Comparison table of the proposed method and previously studied approach for diabetes prediction.

Method and Reference	Accuracy
IGRNet [10]	78.1%
DNN [34]	94.53
Exponential GPR and CNN [35]	94%
Logistic Regression [36]	92.2%
SVM [37]	89%
Without pre-train (in this paper)	81%
Meta-learning without DWT denoising (in this paper)	85%
Meta-learning with DWT denoising (Proposed)	**96.2%**

Based on the result shown in Table 1, diabetes prediction techniques such as IGRNet, deep neural network (DNN), exponential GPR and conventional neural network (CNN), and logistic regression (LR) have lower performances because they either did not consider the denoising technique to improve data quality and improve the model performance or did not consider fast-learning algorithms.

As shown in Table 1, the proposed meta-learning model integrated with the DWT denoising technique achieves higher accuracy compared to others. Thus, the demonstrated result proves the proposed model has the capacity to accurately predict diabetes, improve sensing accuracy, predict r-peaks, and monitor glucose levels in smart healthcare systems. The performance of our proposed meta-learning model in conjunction with DWT data denoising techniques shows an accuracy of 96.2%, an RMSE of 0.010798, and an AUC of 99%. The accuracy of the model without pre-training is 81%, and the accuracy without DWT is 80%. Hence, the RMSE of our meta-learning model with DWT is lower, and the

accuracy and AUC are higher than those of the models without pre-training and without DWT. Hence, our proposed model not only outperforms the baseline models but also surpasses the performance of previously studied techniques. Therefore, the proposed model achieves better performance for diabetes detection in smart healthcare systems.

5. Conclusions

In this study, meta-learning and denoising approaches were proposed for diabetes prediction and glucose level prediction for smart health systems using wearable sensors of ECG and glucose sensors with HRV parameters. Wearable sensor technology often needs to operate accurately across a wide range of individual users who each have unique physiological and behavioral patterns. However, the specific data for a particular application or user group might be scarce. In these cases, meta-learning can be particularly useful. These models can then quickly adapt to the nuances of new users or specific applications with minimal data. This approach helps overcome the hurdle of limited target data, enhancing the performance and personalization of wearable sensor technologies.

Moreover, it is time-consuming and complex to collect sufficient training data with real wearable sensor experiments; meta-learning promises to reduce the amount of biomedical wearable sensor training data needed to train the predictive models in the target domain by learning from previous knowledge or experience. Therefore, the proposed method is suitable for scenarios where a sufficient amount of wearable sensor training data collection is challenging, expensive, or limited. Moreover, the proposed meta-learning approach addresses certain challenges, such as the need for sufficient training data, expensive operational costs, and other problems associated with traditional approaches in smart health systems. The experimental results demonstrate that the proposed meta-learning method boosted the prediction results in smart health systems. Furthermore, based on the results of the numerical analysis, the proposed fine-tuned meta-learning method achieved higher prediction results with an accuracy of 96.2% and AUC of 99%, and reduced detection error of diabetes with a lower RMSE of 0.010798 than without pre-train method with only a small amount of target data and less iteration using the same environment. Therefore, the proposed system is cost-effective, flexible, adaptable, and faster for the Internet of Medical Things (IoMT) or smart healthcare system applications using wearable sensors or devices.

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