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Cross-Platform Interoperable Real-Time Wearable Sensor Data Analysis using Gated Capsule-Transformer Network for Clinical Diagnosis

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Abstract

Data heterogeneity, limited scalability and significant data imbalances are all problems and constraints faced by modern smart healthcare systems based on discrete wearable sensors (WS). These difficulties are responsible for a lot of misdiagnosis and delays in the analytical procedure. To address these key insights this paper proposes a new design is put forward for optimized healthcare operations through Cross-Platform Interoperability for Real-time Analytics and data management. The key of framework is a novel hybrid deep learning framework called Gated Capsule-Transformer Network (GCT-Net). The GCT-Net has a unique combination of the spatial-hierarchical feature mapping from capsule layers and the long-range temporal dependency modeling of customized transformer blocks. In the context of this framework, critical physiological data streams are dynamically prioritized by a Selective Meta-Heuristic Optimization (SMHO), and anomalies that are difficult to detect in the minority class and discrepancies among sensors are filtered by an Integrated Generative-Synthetic Data Balancing (IG-SDB) model. Evaluation results from experiments confirm that the the proposed framework leverages accuracy by 12.76%, precision by 12.95%, retains sensitivity by 11.3%.

Keywords: *Capsule Network, Data Analysis, Meta-Heuristic Optimization, Transformer Learning, Wearable Sensor*

1 Introduction

Wearable sensor (WS) data analysis plays a vital role in disease diagnosis in medical and healthcare applications. WS analyses the continuous physiological signals, features, and parameters that are collected from the patients [1]. The analyzed dataset produces reliable information for the disease detection and diagnosis services. WS data analysis enhances the overall precision and accuracy of the disease diagnosis process [2]. Data acquisition is performed in the analysis process, which combines the multimodal sensor data to form a robust dataset for

diagnostic services. Next to this is the signal pre-processing, which filters the noise and motion artifact from raw WS signals [3, 4]. In pre-processing, the denoising process is done via a filtering technique, which improves the precision of the disease diagnosis. A feature extraction approach is utilized in the analysis process to extract important features and patterns of the patients from the datasets [5, 6]. Heart rate, sleep cycle, temperature, blood pressure, and other behavioural patterns of the patients are collected via WS devices. These features are evaluated and examined to get spatial and temporal features for accurate disease detection and diagnosis processes [7].

WS data analysis faces certain challenges that cause complexity to the disease diagnosis process in medical systems. Some of the problems are unstable signal, energy consumption, missing data, environmental factors, and privacy concerns. These problems cause severe latency and error rate in the disease detection and diagnosis services in the medical field [8, 9]. WS contains noisy information, which provides poor datasets for the analysis process. This reduces the precision and accuracy rate of the disease diagnosis process [10]. Complex and continuous data require more energy resources to analyze and examine the important features and patterns for the analysis process. Missing data occurs due to motion and disconnected devices, which create a break in the dataset [11, 12]. Missing data creates failures in the monitoring and analysis services in medical applications. Environmental factors create poor signals and frequency, which provide poor datasets to the analysis process [13].

Achieving high precision in disease diagnosis using WS data is a complex task to perform in every healthcare application. WS data contain certain noisy signals, missing elements, and other complex dependencies [14]. Some of the problems that cause latency and complexity to the disease diagnosis using WS data are listed below. Environmental interferences, noisy data, physiological variability, and label errors [15]. Environmental interference is a problem that occurs due to huge buildings, weather conditions, and other natural scenarios. These issues minimize the precision and accuracy range of the diagnosis process [16]. Noisy data is a common problem that causes severe complexity and latency to the analysis and diagnosis services. It provides distorted signals and incorrect information as input for the diagnosis process [17]. Physiological variability occurs due to a change in the patterns of the collected information. Physiological signals vary across individuals, which leads to latency during the disease diagnosis

process. Inaccurate labelling causes certain issues that minimize the precision and accuracy of the disease detection process [18, 19]. The article's contributions are listed below:

- (i) The first contribution is the design of interoperable and scalable framework for uncertainty loss WS data analysis. The aim of this framework is to maximize the WS data utilization support for clinical diagnosis. This framework balances loss and uncertainty due to accumulated data fluctuations and discrete sequences.
- (ii) The second contribution is the inclusion of meta-heuristic optimization and balancing function to prioritize WS data for utilization and to reduce sensor dependencies. This collectively handles multi-modal WS data irrespective of the number of sequences, operational interval, and discrete inputs to maximize accuracy.
- (iii) A data-centric ablation study for cross-dataset (input) validation is performed to study the proposed framework's efficiency through associated parameters and influencing factors. This study emphasizes the significance of the parameter selection and internal functions of the proposed framework.
- (iv) A metric-dependent comparative study is presented to study the performance improvements achieved by the proposed framework against the existing methods. This study ensures if the proposed framework satisfies the objectives and satisfies its design goal.

2 Related Works

Nunes [20] proposed a new machine learning-based Huntington disease detection using wearable sensor data. This method is used to detect both lower and upper limb functions, which provide clinical aspects for an accurate disease detection process. The method increases the accuracy and effectiveness of the detection process. Zhong et al. [21] introduced a multi-modal deep learning framework for gait recognition. In this, wearable sensor data is used as input, which produces reliable information for the recognition process. Important characteristic and patterns of gait is collected via wearable sensor devices. The introduced method achieves high accuracy, F1-score, and reliability during the recognition process.

Schifino et al. [22] designed a smart watch sensor-based Parkinson's disease (PD) detection model. A property analysis technique is employed in the model to analyze the spatio-temporal features of the disease. The smart devices provide a continuous sequence of data that is

collected based on the activities of the patients. The model maximizes the reliability and accuracy of PD detection. Guo et al. [23] introduced a wearable sensor for a drug monitoring system in patients with PDs. The PD symptoms are assessed based on inertial measurement units (IMU), which minimizes the latency. The method increases the performance and intensity of the monitoring systems.

Poncelet et al. [24] developed a deep learning (DL) based cardiovascular disease diagnosis model using wearable sensors (WS). The author uses a convolutional neural network (CNN) algorithm to evaluate the ECG signals, which are collected by WS. It provides real-time non-invasive data, which improves the precision of the disease diagnosis process. Mostafavi et al. [25] proposed a new PD assessment model using a deep CNN with WS. A feature extraction technique is implemented in a CNN to extract reliable features and embedded patterns of PDs. It also classifies the actual types and classes of PD, which enhances the performance of the prediction process. The model achieves high accuracy and precision in the PD detection process.

Cotrone et al. [26] designed a new PD detection using non-invasive sensors. It is used for early disease detection based on dysphagia signs and characteristics. The commercial features of PD symptoms are identified and analyzed, which are extracted from the datasets. Experimental results show that the designed model increases the accuracy, F1-score, precision, and recall of the detection process. Louja et al. [27] developed a hybrid CNN-transformer architecture model for eye-rubbing monitoring with WS. The CNN algorithm evaluates the time-series sensor data, which are segmented based on spatial features. The developed model increases the sensitivity, specificity, accuracy, and feasibility of the monitoring systems.

Anjum et al. [28] introduced an allied data disparity technique (ADDT) based on WS data analysis for patient health monitoring systems. In this, a multi-instance ensemble perceptron learns to detect the reliable values for the analysis process. The introduced model increases the precision and reliability of the diagnosis services. Sathish et al. [29] proposed an intelligent decision-making system for Alzheimer's disease detection. Here, DL and WS technologies are utilized to detect the early stage of the disease. The behavioural patterns and characteristics of the patients are analyzed for early disease detection. The proposed method improves the accuracy and scalability of the monitoring systems.

Mila et al. [30] developed a machine learning (ML) model for infectious disease detection. In this, wearable sensors are used to collect patient details, which produce real-time

information for the detection process. The developed model improves the detection and precision of the disease detection process. Sar et al. [31] introduced a multi-modal DL framework for early PD detection. Physiological data and neurological data are used as input, which increases the precision of disease diagnosis. The framework improves the accuracy and reliability of the PD detection process.

Wallner et al. [32] designed a wearable disease detection system using GAN-based imputation. It is done to detect the early signs and symptoms of the disease, which reduces the error rate of the detection process. The designed method improves the robustness and reliability of the detection process. Douhani & Adhikari [33] developed a contagious disease detection model using WS. In this, a real-time monitoring system is employed, which is used to analyze the physiological parameters of the disease. The model improves the precision and accuracy of the contagious disease detection.

Oh et al. [34] proposed a supervised contrastive learning model for stress detection in healthcare applications. WSs are used here to collect or produce individual characteristics of stress patterns. The patterns are analyzed and evaluated to detect the exact cause of stress, which enhances the precision of the diagnosis services. Fynn et al. [35] proposed a non-invasive detection method for coronary artery disease. A wearable vest is used to get limited patterns and characteristics of the arteries. The method improves the accuracy, recall, specificity, and sensitivity of the disease detection process.

2.1 Research Gap and Problem Statement

While previous studies have proposed deep learning architectures, attention mechanisms, generation algorithms based on GANs, ensemble learning, and lightweight edge models for healthcare analytics for wearable devices, there are still several key research gaps to be addressed. Traditional approaches usually fail to provide an integrated mechanism to consider selective physiological stream prioritization and imbalance-aware synthetic data harmonization. The methods fail to preserve hierarchical pathological features and learn long-range temporal dependency. Most models treat all incoming streams from wearables equally, resulting in the same computational resources, analytical burden and false predictions under real time scenarios. Furthermore, high minority class imbalance due to rare physiological abnormalities still limits the anomaly sensitivity and capability to generalize diagnoses.

Current methods also fail to preserve fine-grained physiological structures, as most of the conventional convolutional and recurrent learning mechanisms tend to lose information about the subtle pathological dependency in feature compression. Additionally, there is limited research on interoperability between heterogeneous wearables. This leads to unstable inference results in case of changes in sensor modalities, resolution, or transmission properties within the healthcare system.

In order to overcome these issues, a scalable and interoperable framework of health care intelligence is needed. The framework must be capable of providing strong imbalance correction, and deliver clinically relevant real-time analytics in a heterogeneous wearable context. As a result, a new data-centric architecture is presented in this research named Cross-Platform Interoperability for Real-time Analytics and Wearable Sensor Data Management with Gated Capsule-Transformer Network (GCT-Net). The proposed framework targets better diagnostics accuracy, anomaly sensitivity and analytical efficiency, with clinical support in real time, in large wearable healthcare ecosystems.

3 Proposed Cross-Platform Interoperability for Real-time Analytics and Wearable Sensor Data Management Framework

3.1 Framework Description

This part of the article introduced the proposed framework with descriptive analysis. The proposed framework is introduced to thwart the inconsistencies such as data imbalance, scalability, and heterogeneity support in medical diagnosis. In particular, the inconsistencies due to wearable sensor accumulated data are addressed through specific counter functions and learning model uses. Before proceeding with the problem solution, the framework is first introduced (in Fig. 1) with a description.

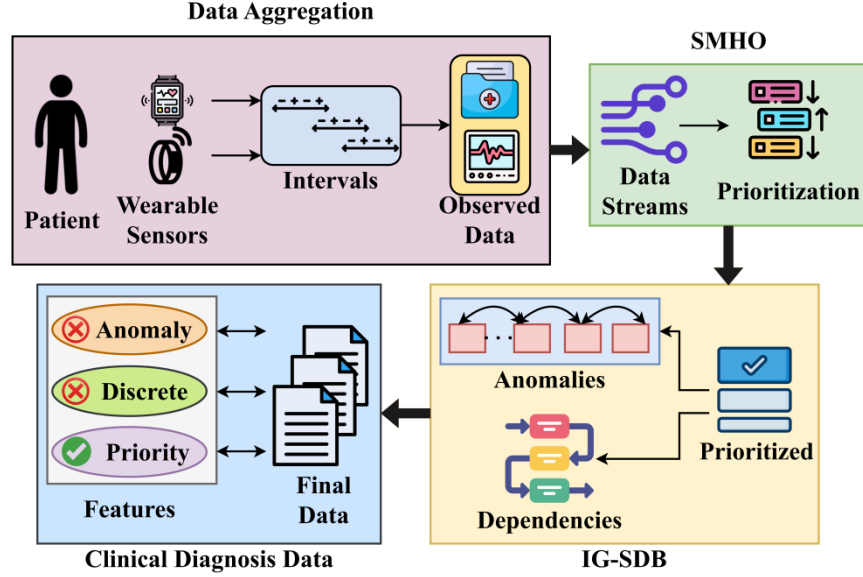


Fig. 1 Illustrating the Proposed Framework Using Different Functions such as SMHO and IF-SDB

As illustrated in the Fig. 1, the proposed framework houses main functions: Selective Meta-Heuristic Optimization (SMHO) and Integrated Generative-Synthetic Data Balancing (IG-SDB). The first function is responsible for streamlining WS data streams and prioritizing them for selection. This prioritized data is used by the second model to reduce anomalies and dependencies. The anomalies refer to discreteness or missing inputs and the dependencies refer to the time shared by two or more sensors. These functions are covered by the gated capsule-transformer network to ensure interpretable and scalable solutions are provided across different intervals. In particular, the number of data streams, observation intervals, operational sensors, data types, etc. decides the reliability of clinical diagnosis required data. In the above illustration, data aggregation to diagnosis parts is represented separately. Following this illustrative description is the taxonomy and the preliminary details required for the proposed concept.

3.2 Taxonomy and Significance

3.2.1 Meta-Heuristic Optimization

In the proposed framework, meta-heuristic optimization is used as an intelligent adaptive search mechanism that selects reliable physiological sensor streams from wearable devices. The optimization is used to analyze the anomaly contribution, signal relevance, transmission reliability, and temporal urgency, which reduce the latency during analytical processing. A SMHO process is proposed in this article, which reduces the latency and computational cost of

the communication services. It also increases the stability, scalability, and quality of deep learning factors in GCT-Net.

3.2.3 Data Balancing

In the proposed work, data balancing is a process that is used to equalize the majority and minority physiological data that are collected from heterogeneous wearable sensor devices. In this, the IG-SDB mechanism is utilized to analyze the sensor characteristics that balance the behavioral patterns. The medical data and abnormalities that are collected via devices are managed via a deep learning optimization algorithm. It is performed to enhance the sensitivity in anomaly detection and to minimize the false positive and false negative rates during prediction processes.

3.3 Preliminaries

The preliminary denotes the data representation and the inconsistency encountered in data aggregation. Let D_t^N denote the data stream of a sensor N operating at time t , such that,

$$D_t^N = \begin{bmatrix} n_{11} & n_{12} & \cdots & n_{1N} \\ n_{21} & n_{22} & \cdots & n_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ n_{f1} & n_{f2} & \cdots & n_{fN} \end{bmatrix} \times \begin{bmatrix} 1 \\ 2 \\ \vdots \\ t \end{bmatrix} \quad (1a)$$

And the cumulative data stream (γD_t^N) is,

$$\gamma D_t^N = \sum_{i=1}^N \sum_{j=1}^t f_{ij} (n_{ij} - l_{i-1,j-1}) \quad (1b)$$

In equation (1a), the variable f denotes the operational frequency i.e. the active interval of the sensor $n \in N$. The variable l denotes the loss in data stream accumulated in the previous interval. This l is used to define the inconsistency/uncertainty in modelling diagnosis data. Therefore, considering the interval $[0, t]$ of any n , objectives for inconsistency (∇) is defined as,

$$\forall f_{fN} \in [0, t], \arg \min \sum_{i=0}^t \text{modulus} \|\gamma D_i^N - D_i^N\| \quad (2a)$$

Such that,

$$\nabla = \begin{cases} 0, & \text{if } l = 0 \\ 1, & \text{otherwise} \end{cases} \quad (2b)$$

And,

$$l = \sum_{i=0}^t \text{modulus} \left\| \text{difference}(\gamma D_i^N, D_i^S)_i \right\| \quad (2c)$$

From the above equations, the inconsistency based on data loss is estimated. The proposed framework targets $l \rightarrow 0$ and $\nabla \rightarrow 0$ based on this above equation in any $[0, t]$. In the above equations, the data aggregation and inconsistency definitions are provided. To be

specific, ∇ is observed when two or more N have the same f (or) $[0, t]$ interval has many missing f (or) D_t^N is unavailable. Irrespective of these problems, the proposed framework uses the two distinct functional models to ensure the data is not impacted by ∇ (or) l .

3.4 Selective Meta-Heuristic Optimization (SMHO)

In the proposed framework, a Selective Meta-Heuristic Optimization (SMHO) function is employed. It is used as an adaptive physiological prioritization mechanism for the deep feature extraction process. In this, heterogeneous wearable healthcare devices are used to collect raw sensor streams or data, which provide reliable data for detection and prediction services. Different sensors transmit data streams for centralized analytics, which creates major congestion and unstable convergence to the disease detection and diagnosis services. To eliminate such issues, SMHO model is used. The streams are analyzed to reduce the contextual dependencies and latency in the optimization layer. A multi-dimensional utility vector is employed in the model to enhance the delivery and consistency metrics of the sensor devices. This is performed by utilizing a hybrid meta-heuristic search strategy, which reduces the latency of the communication and transmission services. The accumulated ∇D_t^N utilization (U) is estimated using equation (3a). This utilization is required to emphasize the significance of N input. The optimization process enhances this utility after inconsistency reduction. Therefore, this is estimated as,

$$U = (\alpha_1 \cdot \nabla) + [\alpha_2 \cdot \text{difference}(\nabla D_i^N, D_i^S)] + [\alpha_3 \cdot (\frac{1-f}{N})] \quad (3a)$$

Such that,

$$\sum_{i=1}^3 \alpha_i = 1 \text{ (or) } (\alpha_1 + \alpha_2 + \alpha_3) = 1 \quad (3b)$$

In the above equation (3a), α_1, α_2 , and α_3 are the emphasizing coefficients. The emphasizing coefficient is to be adjusted periodically $[0, t]$ to ensure ∇ is less and l is retained to 0 (minimum). The change in sensor operational f is another emphasizing factor to reduce collision or interval sharing of two/more N . Adaptive exploration and exploitation behaviors are detected to reduce noise and latency during the transmission process. An iterative reward-guided optimization is utilized in the SMHO model to identify the priority of the data streams. The significance (φ) in the search space $\in [0, t]$ is to be updated for a change in $(\alpha_1, \alpha_2, \alpha_3)$ to ensure the U is maximum. If this U is maximum then the WS data support for clinical diagnosis is high. This factor is estimated using equation (4) for the cumulative $D_T^N \in [0, t]$ as,

$$\varphi = (1 - \nabla) + \mathcal{L} \left(\frac{\partial \alpha_1}{\partial U} + \frac{\partial \alpha_2}{\partial U} + \frac{\partial \alpha_3}{\partial U} \right) - \left(1 - \frac{l}{N} \right) \cdot \mathbb{F} \quad (4a)$$

Where,

$$\mathbb{F} = \sum_{i=1}^{(N \times f)} \frac{U_i \cdot (1 - \nabla) \cdot (\alpha_1 + \alpha_2 + \alpha_3)_i}{1 + \nabla [\text{diff}(t, t+1)] + \left(l \cdot \frac{N}{f} \right)} \quad (4b)$$

In equation (4a), $\mathbb{F}$ is the fitness value that emphasizes either α_1, α_2 , and α_3 . The fitness is high if equation (2b)'s $\nabla = 0$ is satisfied failing which results in a degradation. This $\mathbb{F}$ parameter is tuned in the search pursued in $[0, t]$ the search for emphasized D_t^N parameter is performed. The main objective of the SMHO model is to reduce the analytical cost and to enhance the accuracy of the disease diagnosis in healthcare applications. To achieve this, the exploration and exploitation processes are recurrently employed to process the data streams from heterogeneous WS. The exploration and exploitation for any search process the optimized output of this function. The optimized output $Opt(D_t^N)$ is defined using equation (5).

$$Opt(D_t^N) = \gamma D_t^N \cdot (1 - l) + \left(\frac{\alpha_1 + \alpha_2 + \alpha_3}{3} \right) [\varphi \cdot D_t^N - (1 - \nabla) \cdot U] \quad (5)$$

The above equation considers γD_t^N and D_t^N (individual) to validate the loss and uncertainty impact over the φ . Therefore, the search and output focuses on γD_t^N (or) D_t^N provide $l = 0$ and $\nabla = 0$ is satisfied in any $[0, t]$. The above optimal D_t^N is available in various intervals such that the final set of data streams i.e. $C(D_t^N)$ is,

$$C(D_t^N) = \arg \max_{\varphi} [\mathbb{F} - (1 - \nabla) \sum_{i=1}^N (1 - l)] \cdot Opt(D_t^N) \quad (6)$$

In the above equation (6), the cumulative optimal data streams in $[0, t]$ are collected using the exploration of $(N \times f)$ and exploitation of $\mathbb{F}$. This is performed targeting the U through the optimization based on $\mathcal{L} \cdot \left(\frac{\partial}{\partial U} \right)$ factor. The streams that are expelled from the above cumulative collection are regarded as low contribution for clinical support. Here, low-contributed streams are suppressed, which enhances the dominant streams during transmission and detection processes. This is done to reduce the computational cost during pack deliveries and to minimize the communication overheads in smart health care platforms. The SHMO function's decisions are diagrammatically explained using Fig. 2.

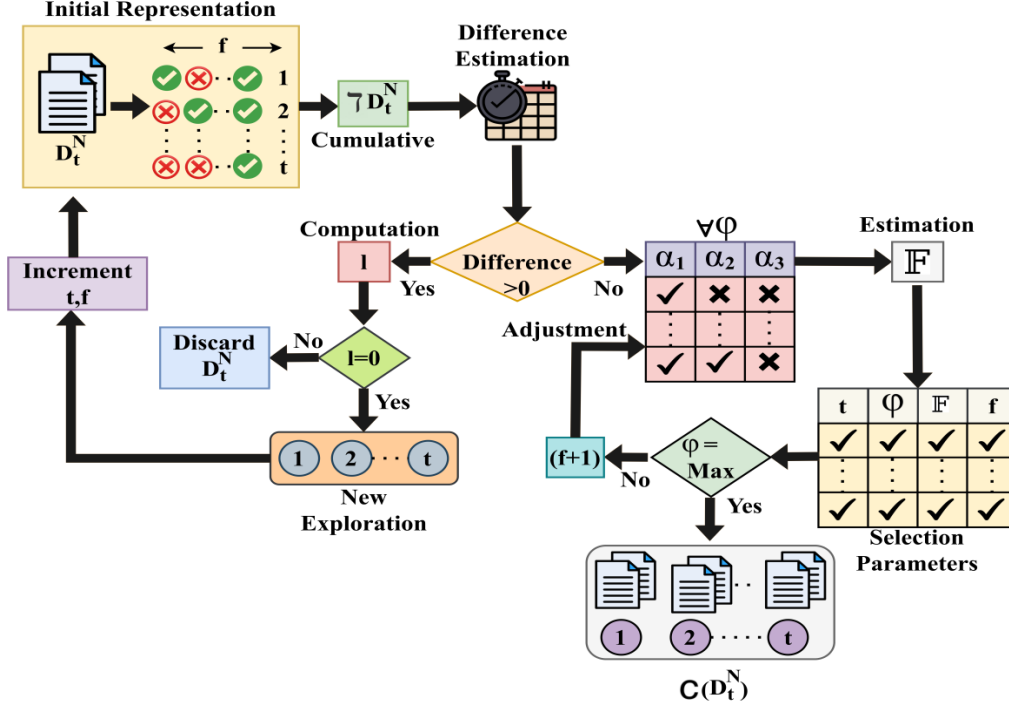


Fig. 2 Decision Progress of SHMO Function

The decision process in the SHMO function is detailed in Fig. 2 above. The prime classification starts with the difference estimation for $\sum D_t^N$ accumulations. In this difference estimation, $l = 0$ and $l \neq 0$ cases decide the new exploration and data discard outcomes respectively. Data discard for the clinical support is performed due to the existence of ∇ . In contrast if there are no difference, then $(\alpha_1, \alpha_2, \alpha_3)$ estimation for φ is used to define $\mathbb{F} \forall \sum D_t^N$. Considerably, the $\mathbb{F} = \text{high}$ output intervals are estimated to compute $\varphi, \mathbb{F}$ and its corresponding f . These serve as the selection parameters wherein $\varphi = \text{max}$ outcome are used to represent $C(D_t^N)$ data. This data is used for clinical diagnosis recommendations with high U such that uncertainty is avoided. If φ is minimum, then the next occurrence of D_t^N is considered for n_{fN} to generate a new data. Therefore, the maximum number of trails for data accumulation is précised under l and $(1 - l)$ for performing the decision of $C(D_t^N)$ accumulation. The SMHO model is used as a stabilization for heterogeneous devices, which reduces the failures and missing data in healthcare applications. The function achieves high precision in achieving stability and reliability in physiological data processing and monitoring systems.

3.5 Integrated Generative-Synthetic Data Balancing (IG-SDB)

Next to meta-heuristic optimization or stream prioritization, the Integrated Generative-Synthetic Data Balancing (IG-SDB) module is designed to identify the critical limitations during

WS data analysis. This module is used to analyze the physiological data streams that are collected from various heterogeneous wearable sensor devices. It is designed to balance inconsistent distribution and class imbalance from collected data. Real-time clinical datasets contain certain demerits, such as neurological fluctuations, metabolic anomalies, and other aspects, when compared with physiological WS data streams. To overcome these issues, the IG-SDB module is used via a dual-stage approach, generating a balancing mechanism. The extracted streams are mapped to get inter-class and intra-class continuity for further processes. The mapping (m) for continuity is estimated as,

$$m = \frac{1}{(1+e^{-\nabla})} \left[\varphi \cdot C(D_t^N) + \left(1 - \frac{l}{f}\right) \cdot U \right] \quad (7)$$

In equation (7), $\frac{1}{(1+e^{-\nabla})}$ is the non-linear activation function. The mapping encloses cumulative (filtered) and utilization data accumulated from the WS. The mapping is required to ensure continuity between D_t^N and $\gamma D_t^N \in [0, t]$ such that $(\nabla \rightarrow 0)$. In the mapping process, the sequence between 0 and t is verified for the high φ (prioritized). Besides, the dependency and anomaly (missing sequences) are identified if $\frac{1}{(1+e^{-\nabla})}$ computation fails. Also, if $\left(1 - \frac{l}{f}\right) < 0$ then either of the anomalies is present indicating the requirement for data balance. Later, an adaptive synthetic generation mechanism is employed in the model to get minority samples from heterogeneous sensor devices. These are done to minimize the latency and to presser temporal dependencies between multimodal sensor channels. The minority $Opt(D_t^N)$ due to anomalies (Λ) is estimated using equation (8).

$$\Lambda = C(D_t^N) + l \left[\text{modulus} \left\| \text{difference}(Opt(D_t^N), \gamma D_t^N) \right\| \right] + \left(1 - \frac{m}{N}\right) \quad (8)$$

In equation (8), the sequences where anomalies due to missing input streams occur are identified. This identification is performed in all $[0, t]$ intervals provided the chances of l and ∇ are confined. However, the variation in $\text{difference}(Opt(D_t^N), \gamma D_t^N)$ is irresistible due to different f and n_{fN} and therefore, this anomaly detection is necessary. Based on this difference, data alignment for a consistent (balanced) U is achieved. IG-SDB uses a context-aware synthetic reconstruction using temporal-transition learning and regularization. The dynamic transitions that are generated from the sensors are classified based on normal and abnormal physiological streams. Similarly, a discrepancy minimization layer is used to align the distributions that are collected from heterogeneous wearable sensor devices. Considering the Λ existence, the

alignment for confining l or ∇ impact is performed. The alignment ($\mathring{A}$) is mathematically expressed as,

$$\mathring{A} = \text{modulus} \|Opt(D_t^N) - \nabla D_t^N\|^2 + \frac{\|C(D_t^N) - (\nabla \times f)\|}{C(D_t^N)} + \frac{\|\varphi - l\|}{\varphi} \quad (9a)$$

Equation (9) focuses on aligning data streams adaptable to overcome ∇ and l . The influenced factors f and φ for maximum U is considered along the Λ occurrences. Therefore, for an aligned (balanced) input stream, the following conditions are to be satisfied.

$$\sum_{i=0}^t U_i = \arg \max_{\varphi} C(D_t^N) - \nabla \quad (9b)$$

(or)

$$\arg \max_m \forall [0, t] \in \arg \max_{\mathbb{F}} (D_t^N - l) \quad (9c)$$

(or)

$$\arg \min_{\Lambda} \forall Opt(D_t^N) = \arg \max_{\mathbb{F}} \arg \max_{\varphi} U \quad (9d)$$

In the above equations (9b) to (9d), the possible combinations for mapping distinct sequences are considered. Under all the possible combinations, if either of the above is satisfied, then ∇D_t^N is said to be balanced such that $l \rightarrow 0$ and $\nabla \rightarrow 0$ is true. If the above conditions are satisfied, then the objectives defined in equations (2a) and (2b) are also satisfied. This mechanism is employed to balance the class and type of heterogeneous sensor domains, which reduces the latency of the detection process. This balancing mechanism improves the stability and reliability of the optimization process. Apparently, the IG-SDB module improves the capacity, sensitivity, and decreases the uncertainty during the disease diagnosis process. To achieve these aspects, GCT-Net is employed in the model, which enhances the reliability of the feature representation process via a data balancing mechanism.

3.6 Gated Capsule-Transformer Network (GCT-Net)

In the proposed model, a Gated Capsule-Transformer Network (GCT-Net) module is designed to identify the challenges that cause specific latency during heterogeneous fusion and anomaly prediction processes. It is designed to balance the scalability and manage the physiological representations that are collected from heterogeneous wearable devices. In SMHO, the initial stages are used to prioritize the sensor streams that provide temporal aspects and factors of physiological datasets. Deep feature learning is employed to select optimal input, which reduces the computational cost and latency of the detection process. Both stream

prioritization and generative balancing mechanisms are combined to stabilize the analytical aspects and spatiotemporal representation of the learning model. However as mentioned earlier, the change in $Opt(D_t^N)$ from ∇D_t^N is unavoidable. Therefore, verifying the consistency ($\mathbb{C}$) of the WS data for clinical support is mandatory. This tasks place after the $\mathbb{A}$ such that latency/cost based issues due to data augmentation is confined. The verification for non-impacting ∇ (or) l consistency is derived as,

$$\mathbb{C} = \sum_{i=0}^t \left(modulus\|\Lambda - \nabla\|^2 - modulus\|\Lambda - l\|^2 + modulus\|\mathbb{A} - \Lambda\|^2 \right)_i \quad (10)$$

The above equation (10), defines the temporal sequence of various $[0, t]$ intervals such that the anomalies and dependencies on m are restricted. If these two processes are restricted within the search of $[0, t]$ under the exploration and exploitation, then U and φ for the accumulated data becomes high without additional cost/latency. In GCT-Net, encoding the gated capsules is the major component that is used to extract spatial-hierarchical physiological features from inputs. A dynamic mapping is exploited in the model to identify the relationship between the capsules. It is done to detect the exact pathological patterns of the capsules for the pooling function. The first layer contains capsule projection based on $\mathbb{C}$ and $\mathbb{A}$ such that the representation $\mathbb{R}$ of a single capsule is defined as,

$$\left. \begin{aligned} \mathbb{R} &= [D_t^N]^T \cdot \left(\frac{1}{N} \right) + \left(\frac{\nabla - l}{\nabla} \right) \cdot (1 - m) \cdot \mathbb{C}(D_t^N) \\ &\quad \text{such that} \\ \mathbb{A} \cdot \mathbb{C} \forall [0, t] &\text{ generates a unified matrix i.e } [D_t^N]^T \cdot [D_t^N] = 1 \end{aligned} \right\} \quad (11a)$$

Equation (11a) defines the capsule representation conjoining the data stream representations. These capsules are similar to the neurons in a neural learning model that changes its state. The states between m (existing) and a new dynamic m i.e. m^* are the transition. The transition occurs if either $\nabla \neq 0$ (or) $l \neq 0$ regardless of the $\mathbb{C}$ instances. This transition influenced m^* is computed as,

$$m^* = \frac{expr(\mathbb{R} \cdot \nabla - \mathbb{R} \cdot l)}{\sum_{i=1}^t (\mathbb{R} \cdot \mathbb{C})_i} = \frac{expr \mathbb{R}(\nabla - l)}{\sum_{i=1}^t (\mathbb{R} \cdot \mathbb{C})_i} \quad (11b)$$

Such that,

$$\left. \begin{aligned} &\text{if } \nabla > l, \text{ then } m \rightarrow m^* \\ &\text{if } \nabla < l, \text{ then } m^* \rightarrow m \\ &\text{if } \nabla = l, \text{ then } m^* \equiv m^* \\ &\quad m \equiv m \end{aligned} \right\} \quad (11c)$$

The above equation (11b) distinguishes the maximum possible transition using ∇ and l variants. Depending on the above categorization, grouping of ∇D_t^S is performed; φ based significance is provided for different $\mathbb{A}$ data streams. Simultaneously, a gating mechanism is also employed here to regulate or manage the propagation of diagnosis relevance. The irrelevant activations or features are suppressed or eliminated to reduce the uncertainty in diagnosis. The model provides clinically significant boundaries via SMHO prioritization. High and effective pathological signatures are obtained via propagation, which minimizes the latency of the process. Now, the features of $\mathbb{A}$ data based on equation (11b) are to be distinguished and gated together. This gating process (G) ensures appropriate features are aggregated such that it is represented as,

$$G = \begin{cases} \mathbb{R}(\nabla - l) \cdot \mathbb{C}, & \text{if } \nabla > l \\ \mathbb{A} + \mathbb{R}(\nabla - l), & \text{if } \nabla < l \\ \mathbb{A} \cdot \mathbb{C}, & \text{if } \nabla = l = 0 \end{cases} \quad (12a)$$

This gating categorization relies on multiple intervals of $[0, t]$ identifying the $\mathbb{F}$ induced features is failed and therefore a new $Opt(D_t^N)$ is required. Depending on this factor, each capsule is pinned to represent a G . However, a normalization of the G range is required to confine the uncertainty (∇ or l variation). This range is confined by $\mathcal{L}$ in all the K capsule connected transformer layers. Therefore, the range normalization for G i.e. $\bar{\bar{G}}$ is estimated using equation (12b).

$$\bar{\bar{G}} = \frac{\text{modulus}\|G\|^2}{1 + \text{modulus}\|G\|^2} \cdot \frac{\|G - \Lambda \cdot \varphi\|}{1 + \|G\|} \quad (12b)$$

This range normalization target (0 to max) value for any G output such that the values < 0 are confined by tuning α_1, α_2 , or α_3 as in equation (3a). This ensures the data is streamlined with a direct propagation to the transformer layer for latency reduction. In particular, the cost and latency causing parameter Λ is the objective parameter for confinement. The capsule to transformer layer propagation (ρ) is defined using $\bar{\bar{G}}$ to prevent complex computations or repeated $\mathbb{A}$ and $\mathbb{C}$. This propagation is defined as,

$$\rho = \frac{1}{(1 + e^{-\nabla})} [D_t^N(\bar{\bar{G}} \odot G) + m^* \cdot U] \quad (13)$$

The propagation encloses activation function to confine the abnormal cases defined in equation (11b). Depending on the number of K , the ρ is filtered using $\bar{\bar{G}}$ aiming for a range ≥ 0 . This controls the number of layers required in the transformer layer. In this, the second layer in GCT-Net is the customized transformer analysis layer, which provides long-range temporal

dependencies over capsule-generated representations. A transformer subsystem is employed in the model, which reduces the complexity of the sequence representation process. The attention computation for the active K is estimated using equation (14).

$$V(\rho, K, \bar{G}) = \frac{e^{-\nabla}}{\sum_{i=1}^t (e^{-\nabla})_i} \left[\frac{\rho \cdot K^T}{\sqrt{G - \Lambda \cdot \varphi}} + \varphi \cdot U \right] \cdot \bar{G} \quad (14)$$

Equation (14) encloses a softmax function based on ∇ to ensure if any of the activation inputs is dwelled into uncertainty. Besides, a careful selection of ρ to K ensures the dependencies are temporal without interference in f . This ensures a robust and prolonged retention of $\mathbb{A}$ post $\mathbb{C}$ along the different t . A customized transformer learning module is employed in this layer, which is inherited from the SMHO model, and the inputs are stabilized from the IG-SDB module. The temporal attention of the clinical factors is guided to reduce the high-risk aspects. The network module enhances the temporal progression patterns and features of the medical conditions that are collected from pathological streams.

From gated capture routing and transformer-based model, a new residual fusion layer is integrated here to identify the clinical representation of the data streams. The structural and inter-sensor relation between capsules is detected, which provides contextual and temporal dependencies. The final fused ($\mathcal{F}$) combination of WS data streams is a collection of the above functions induced by the learning model. This fusion output is the combination of prioritized, anomaly reduced projections to the K of the transformer. Additionally these projections must satisfy $V \forall \nabla = l = 0$ under m or m^* to improve U . Thus, the fusion is derived as,

$$\mathcal{F}(G) = \mathcal{L}[G + V(\rho, K, \bar{G}) + \{(\mathbb{R} - \nabla) \otimes [V(\rho, K, \bar{G})]\}] \quad (15)$$

Equation (15) consolidates the temporal data stream balancing ∇ and mitigating l under all $\rho \rightarrow K$. Therefore, the data streams categorized under the above are utilized for medical diagnosis through U and φ . An adaptive feature calibration layer is used here to combine the representations, which provide a high-quality U for the disease diagnosis. The proposed model uses prioritized streams from SMHO and balanced distribution factors from IGSDDB, which improves the stability of the training and processing phases. The model enhances the reliability and minimizes the noise in datasets from real-time healthcare applications. The GCT-Net model with its functions is diagrammatically depicted in Fig. 3.

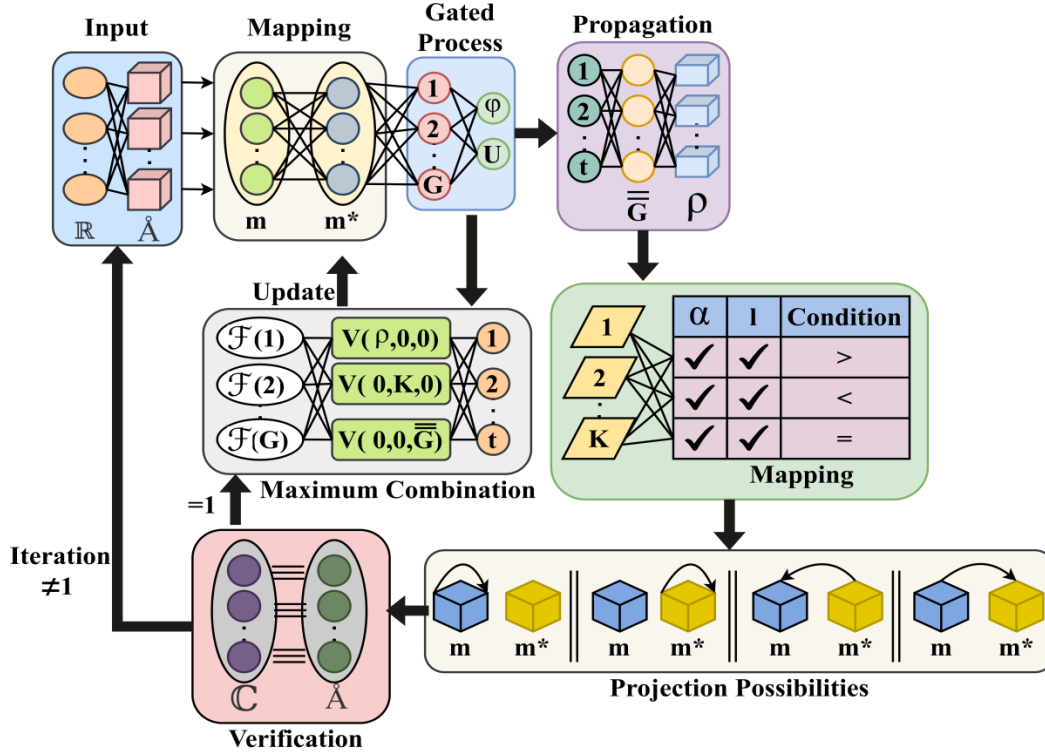


Fig. 3 Depiction of the Proposed GCT-Net Model

The gated transformer network model is diagrammatically depicted in the above Fig. 3. The illustration shows a part-by-part model for mapping, propagation, and combined $\mathcal{F}$. The mapping is first directly mapped to verify its transition. In the gated process (φ, U) is the output required with $\bar{G}$ range across different γD_t^N . The ρ possibilities for each t is identified from this $\bar{G}$ (the range is modified $\forall \mathcal{L}$ update). Now, the K layers are mapped for $(\nabla, l, \text{condition})$ as defined in equation (11c). The target is the $\nabla = l = 0$ for any number of ρ possibilities. The minimum requirement in any $\mathbb{C}$ must achieve a maximum mapping such that $\mathcal{F}(G)$ is extracted. In contrast, if $(\mathbb{C}, \mathbb{A} \neq 1)$, then the $\mathbb{R}$ is revisited using new γD_t^N with a new iteration. This new iteration follows $(\mathcal{L} - l)$ based learning rate to maximize the U . The G and $\mathbb{R}$ outcomes are updated periodically to maximize the data collection without ∇ (or) l . As a result, the implementation of SMHO, IG-SDB, and GCT-Net modules enhances the significance of intelligent healthcare applications. The model resolves the issues that cause latency and critical limitations to the big-data analysis process. Here, SMHO is used to reduce the computational latency, IG-SDB is used to balance the datasets, and the GCT-Net module is employed to manage the spatiotemporal physiological space for the disease diagnosis process. The model improves the accuracy of

anomaly detection, reduces the latency, and maximizes the robustness of the clinical decision-making process via heterogeneous wearable sensor devices in smart healthcare applications.

4 Discussion

The discussion section presents a detailed ablation study and metric comparison to evaluate the performance of the proposed framework. First, the dataset descriptions are provided from which data is extracted and used for analysis. Based on two distinct dataset inputs, the ablation study is performed.

4.1 Data Collection and Description

As mentioned earlier, for a cross-validation, two distinct datasets are referenced in this study. The first is the Multimodal Cardio-Vascular wearable dataset [36] (Dataset 1) and Real-time Multi-Modal Internet of Medical Things healthcare dataset [37] (Dataset 2). A schematic representation of data collection and representation from both references is illustrated in Fig. 4 below.

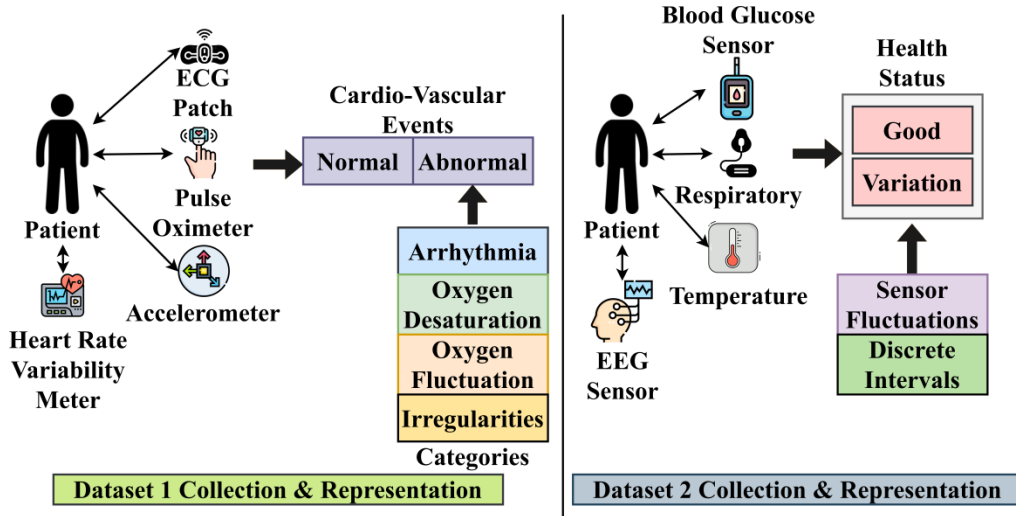


Fig. 4 Data Collection and Representation from Two Distinct Datasets

The first dataset is used to identify minor cardio-vascular anomaly from the given inputs. Regardless of the inputs being overlapped/discrete, the proposed framework targets detection precision. This dataset contains 48K sample inputs obtained from ECG, PPG, SPO₂, and motion sensors. Data sampling frequency is 250 Hz and the uncertainty impacts is 1/9 entries based on a 10-fold (2 interval) validation. From this, 31K inputs (continuous + discrete) ensured for training the capsule-transformer and 9K inputs are used for testing.

The second dataset provides 62.5K samples collected from glucose, EEG, respiratory, and temperature sensors. Data sampling frequency varies between 50 and 500 Hz with a 5-fold cross validation (1 interval). From this dataset, 14K inputs are tested and 47K inputs are used for training the learning model. The target of the proposed framework is to detect health status as good or variable based on the inputs provided.

From the learning model's perception, it is designed with 15 layers ($K = 15$) and a learning rate of 0.5 ($\mathcal{L} = 0.5$). The number of iteration is 1200 with a target epoch of 30 and the fallback rate is 0.1. Based on these inputs and parameters setting, data stream selection sensitivity, scalability assessment, data alignment, and ROC analysis study are performed.

4.2 Ablation Study

To validate the contribution and effectiveness of each major component of the proposed framework in the heterogeneous wearable healthcare environments, the ablation study has been designed. The study quantitatively illustrates that prioritization of streams, and gated capsule transformer learning all contribute to enhanced diagnostic accuracy, computational efficiency, and analysis speed in real-time applications. This is achieved by systematically disabling or fine-tuning specific modules and measuring their impact on the system's performance. The ablation results also show that heuristic stream selection and balanced multimodal representation learning has a significant effect on enhancing the performance of deep inference in the presence of imbalanced physiological conditions.

4.2.1 Data Stream Selection Sensitivity

This parameter used to test the number of physiological streams to be retained after SMHO function. The study examines the relationship between efficiency of the computation and the completeness of the diagnosis. The data stream selection sensitivity is defined using equation (16).

$$Sensitivity = \frac{opt(D_t^N)}{\gamma D_t^N} \quad (16)$$

In Fig. 5, the sensitivity analysis under various inputs of the datasets is presented.

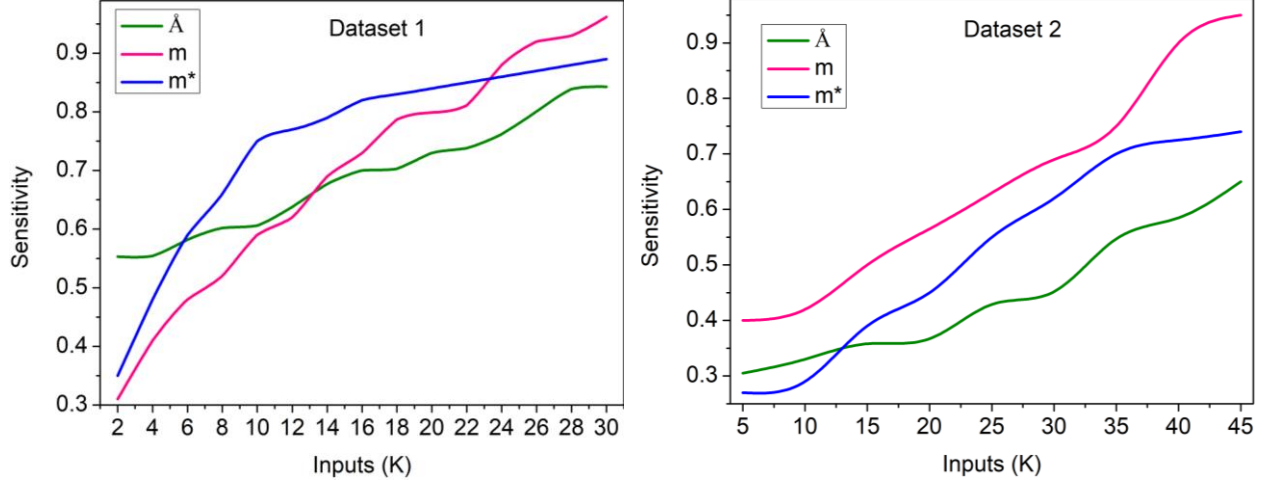


Fig. 5 Sensitivity Analysis for Two Dataset Inputs

The Data Stream Selection Sensitivity analysis is assessing the effectiveness of the SMHO mechanism in selecting the physiologically important data streams at different densities of wearable data. For MCWD dataset, the temporal importance level is different for different signals depending on the intensity of disease progression. The SMHO process automatically allocates a higher φ to unstable abnormal streams, and suppresses redundant normal physiological patterns. Moreover, in the RMI-HD data set, EEG fluctuations during seizures and respiratory distress patterns are highlighted in order to document periods of normal, stable physiology. In the RMI-HD data set, the EEG fluctuations associated with seizures and the respiratory distress pattern is selectively highlighted. This adaptive stream sensitivity causes much better Λ visibility, less computation congestion and more stable deep feature propagation within GCT-Net. Thus, the framework is robust in terms of sensitivity to diagnosis and analytical efficiency even in continuously changing input conditions for multimodal wearable input (Fig. 5). Lowering the stream selection decreases the overhead of N inputs, and also speeds up the time required for inferences. But too many stream elimination attempts can result in the suppression of clinically relevant $\|\text{difference}(\text{Opt}(D_t^N), \gamma D_t^N)\|$. The opposite is also true, the higher sensitivity, the more diagnostic γD_t^N , but the time requirement is high. The stream selection ensures stable real-time analytic, with continued sensitivity to anomalies (Fig. 5).

4.2.2 Scalability Assessment

This parameter runs the test to check the stability of the proposed framework when the load of the N is increased. This results in increase in high data accumulation through various observation intervals. The scalability factor is computed as,

$$\text{Scalability Factor} = \frac{N}{1+\text{diff}(t,t-1)} \quad (17)$$

The scalability factor assessment for the two dataset inputs is given in Fig. 6.

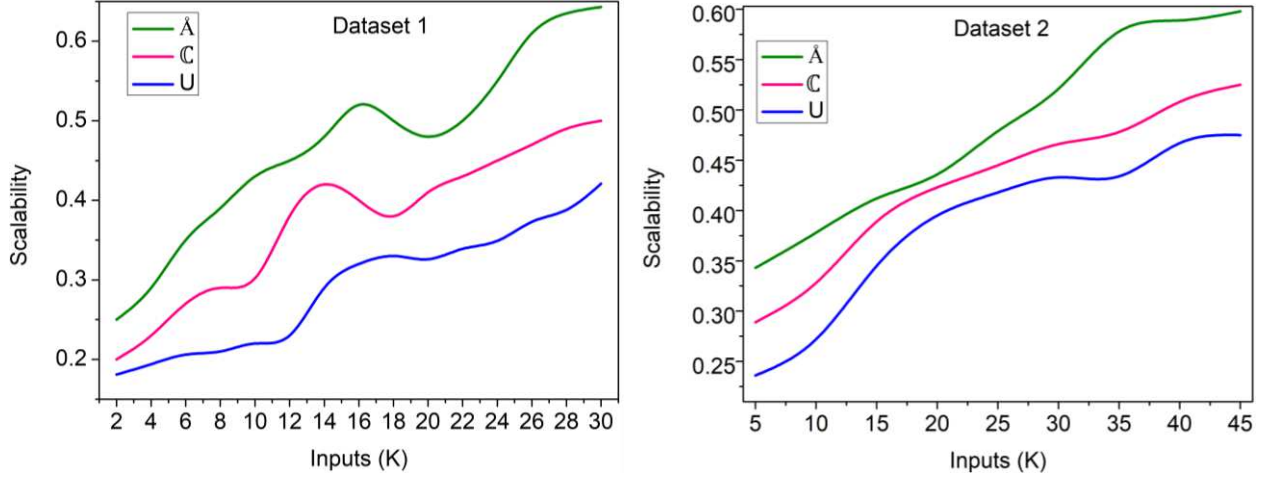


Fig. 6 Scalability Factor Analysis for $\hat{A}$, $\mathbb{C}$, and U Variants

As the amount and diversity of health-related data collected with wearables varies, the scalability infers the capacity of the proposed framework to maintain consistent diagnostic accuracy. As sensor modality, sampling frequency and concurrent N increase the communication overhead and computational complexity significantly becomes higher in the MCWD and RMI-HD dataset. The proposed framework tackles this challenge by reducing the $\| \text{difference}(\gamma D_i^N, D_i^S)_i \|$ to only the ones that are clinically relevant through SMHO to be analyzed. GCT-Net is optimized to do parallel spatiotemporal inference with minimized ∇ accumulation related to the data-centric architecture. Efficient modelling of long-range m with large-scale sequential data ρ and G avoids feature amplification with fluctuating data in high-volume processing. The framework is therefore scalable, with low latency and accurate diagnostics, even with higher loads on the wearable health care system (Fig. 6). The greater the load on the devices, the more congested the communications and the longer the processing time. The proposed SMHO aims to reduce the unnecessary overhead in the transmission of the stream and to maintain an interoperable large-scale healthcare system.

4.2.3 Data Alignment

This eliminates the IG-SDB domain harmonization layer to check the stability of the interoperability of different platforms. The data alignment process is described using confusion

matrix for the two distinct datasets considered. In Fig. 7, the confusion matrix for the categories (Dataset 1= Normal, Abnormal) and (Dataset 2= Good, Variation) is presented.

$\hat{\mathbb{A}}$			$\mathbb{C}$			Dataset 1
Abnormal	0.304K	2.4K	Abnormal	0.212K	2.17K	
Normal	5.3K	0.812K	Normal	5.18K	0.631K	
	Normal	Abnormal		Normal	Abnormal	
$\hat{\mathbb{A}}$			$\mathbb{C}$			Dataset 2
Variation	0.54K	3.86K	Variation	0.406K	3.55K	
Good	8.34K	1.09K	Good	8.09K	0.864K	
	Good	Variation		Good	Variation	

Fig. 7 Confusion Matrix for Dataset Based Classification

In MCWD, data alignment is concerned with the harmonization between physiological distributions of normal cardiovascular behavior and abnormal pathological situations. There may be different temporal amplitude of abnormal cardiac events and the feature distribution of those events may be irregular due to the difference in patients' physiology and WS variability. The IG-SDB alignment mechanism minimizes these differences by aligning normal and abnormal cardiovascular representations using a shared latent representation while maintaining pathological distinctiveness. The $\bar{G}$ is used for stabilizing the normal physiological sequences while minority reconstruction and temporal consistency preservation are applied for enhancing the abnormal cardiac transitions. This $\hat{\mathbb{A}} \cdot \mathbb{C} \forall [0, t]$ greatly enhances the differentiation of the normal and abnormal classes. Therefore GCT-Net is able to detect subtle differences in pathological deviations better. Thus, the clinical inference is greatly simplified from a diagnostic point of view since there is slighted variation between stable cardiac rhythms and developing cardiovascular abnormality.

The $\hat{\mathbb{A}} \cdot \mathbb{C} \forall [0, t]$ is done between the physiologic state defined as good (stable states) and the variation (dynamically changing physiologic states) which includes conditions of WS inputs in the RMI-HD dataset. Heterogeneous physiological distributions are common with WS platforms because of the different resolutions of sensors, the inconsistencies in the signal transmitted, and the different sampling rates. IG-SDB overcomes this by harmonizing the

domain of the stable baseline $\mathbb{R}$ with the variable abnormal transition states through latent distribution correction. Good-state physiological patterns are normalized to keep baseline characteristics consistent and variation-state patterns are adaptively balanced to ensure clinically-relevant fluctuation dynamics. The $\mathbb{A}$ process enhances the temporal consistency and decreases the ∇ of distribution in multimodal fusion within GCT-Net. Therefore, the framework provides more stable separation of stable and unstable physiological states in real time with wearable monitoring in healthcare.

4.2.4 ROC Analysis

Inconsistent and unstable feature learning occurs with heterogeneous wearable distributions when they are not aligned. The alignment mechanism can greatly enhance the consistency and generalization of interoperability in multi-device healthcare systems. Following the above is the ROC analysis for the two datasets considered for analysis. Fig. 8 discloses the ROC analysis of different dataset inputs.

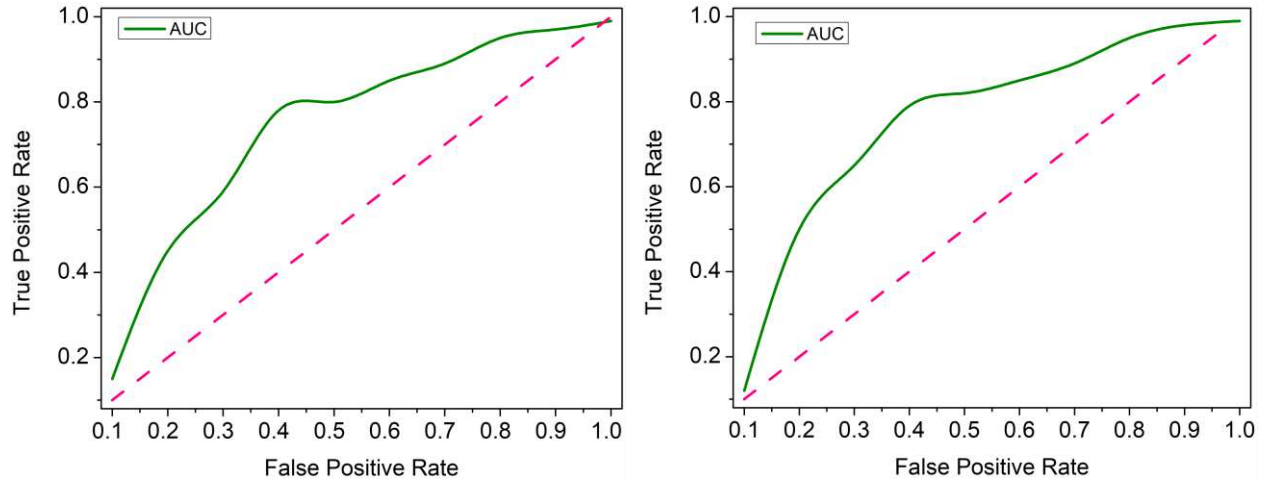


Fig. 8 ROC Analysis for Different Datasets Considered for their Classifications

Multimodal Cardio-Vascular Wearable Dataset (MCWD) is utilized to obtain a reliable ROC curve with an area under the curve (AUC) of 0.966. The proposed GCT-Net framework achieves high sensitivity with low false positive rates. It is calculated based on the position of the curves. Comparative analysis shows that the proposed SMHO (prioritization) and IG-SDB (data balancing) mechanisms enhance the precision of anomaly detection.

For the Real-Time Multimodal IoMT Healthcare Dataset (RMI-HD), the ROC analysis gets a high AUC value of 0.947. The proposed GCT-Net framework maximizes the true positive

rates while reducing analytical uncertainty during disease diagnosis. The framework also minimizes the inconsistencies, which enhances the reliability of the detection process (Fig. 8).

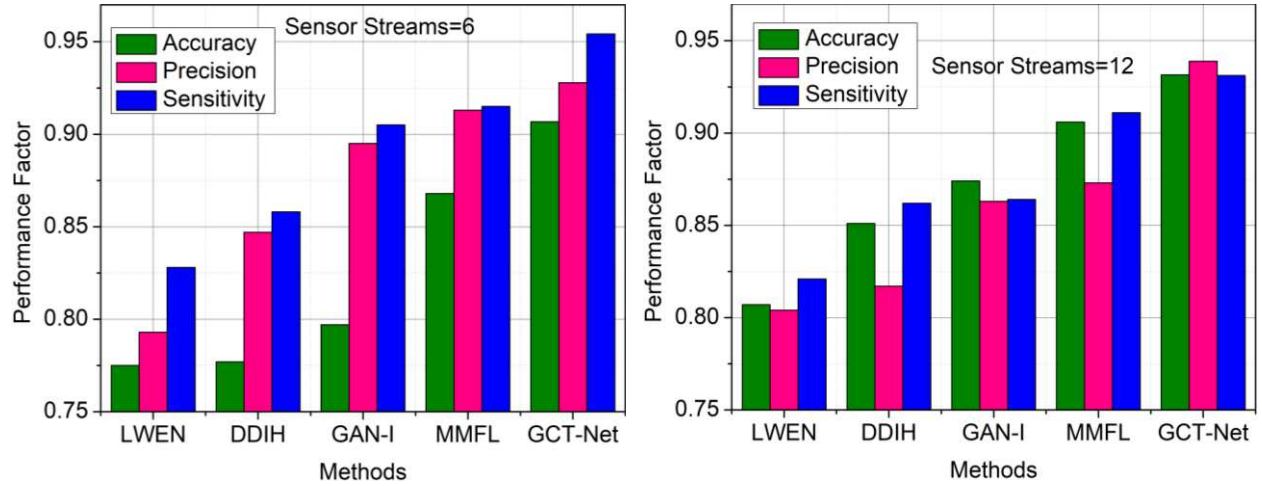
$$\text{True Positive Rate (TPR)} = \frac{TP}{(TP+FN)} \quad (18a)$$

$$\text{False Positive Rate (FPR)} = \frac{FP}{(FP+TN)} \quad (18b)$$

Where, TP , TN , FP , and FN indicates the true positives, true negatives, false positives, and false negatives, respectively. The proposed GCT-Net framework maximizes the overall metrics such as sensitivity, precision, and accuracy of the superior classification process. High AUC values minimize the diagnostic error ratio, which improves anomaly detection in real-time wearable healthcare analytics applications.

4.3 Comparative Study

In the comparative study, the price metrics such as accuracy, precision, sensitivity, false positive rate, and uncertainty factor are validated. The validation is performed alongside LWEN [33], DDIH [28], GAN-I [32] and MMFL [21] methods. The number of sensor streams in the X-variant considered for this comparative analysis. The results are presented in Figs. 9 and 10 grouping the performance factors together appropriately.



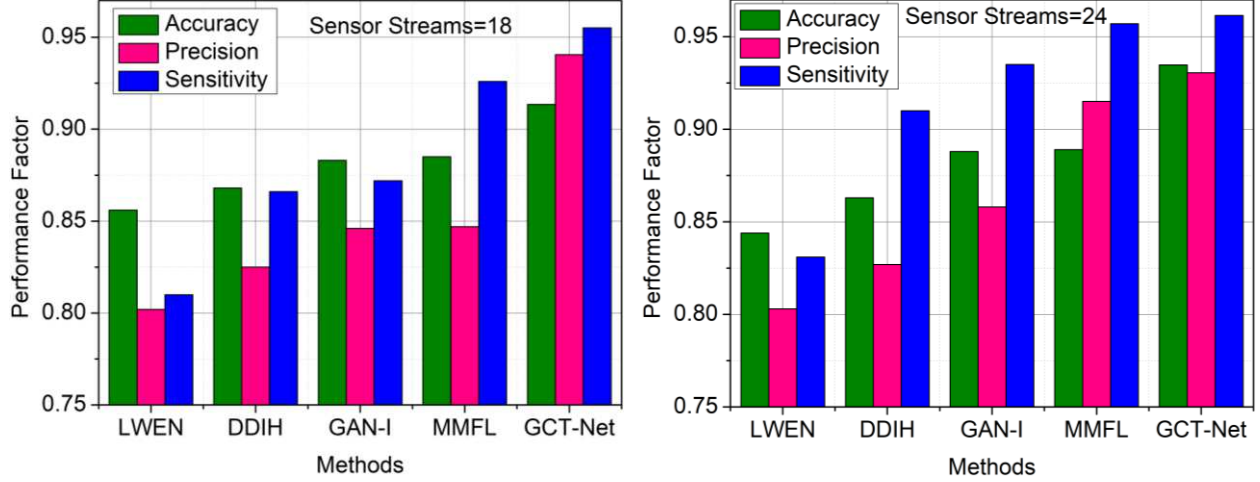


Fig. 9 Accuracy, Precision, and Sensitivity Comparative Study for Different Methods and Sensor Streams

The proposed framework is able to obtain a high diagnostic accuracy by integrating the operation of SMHO, IG-SDB and GCT-Net. The SMHO mechanism only selects $Opt(D_t^N)$ which are $\mathbb{F}$ significant to avoid redundant data from deep learning inference. IG-SDB addresses $\|\text{difference}(Opt(D_t^N), \gamma D_t^N)\|$ while addressing the challenges of heterogeneous sensor distribution that results in biased learning convergence. In the context of GCT-Net, the learning mechanism maintains the hierarchical $\mathbb{C}$ based ρ between capsules and the transformer $V(\rho, K, \bar{G})$ long-range temporal relationships between multimodal stream capsules. The gated $\bar{G}$ further reduces unstable activations, while improving clinically-relevant $\mathcal{F}(G)$. The framework thus acquires extremely discriminative G , which greatly enhance classification performance even in the presence of challenging wearable health settings.

The proposed framework is designed to minimize the number of false abnormal predictions made from the $\mathbb{C}(D_t^N)$ to obtain high precision. The SMHO optimization module filters out sensor signals with low φ and emphasizes high $\mathbb{F}$ sensor inputs. IG-SDB also creates realistic D_t^N besides Λ and addresses the *modulus* $\|\gamma D_i^N - D_i^N\|$ between wearable devices which help to enhance $\mathcal{L}\left(\frac{\partial \alpha_1}{\partial u} + \frac{\partial \alpha_2}{\partial u} + \frac{\partial \alpha_3}{\partial u}\right)$. In GCT-Net, the G selectively enhances relevant pathological activities and suppresses irrelevance due to $\left(\frac{\nabla-l}{\nabla}\right)$ in the sensors and disturbances in the transmission. In addition, contextual attention further enhances the separation between subtle abnormal and normal $m \rightarrow m^*$ (or) $m^* \rightarrow m$ (or) $m^* \equiv m^*$ (or) $m \equiv m$. These combinations

greatly minimize misclassification of abnormal and enhance the uniformity of positive predictions in various healthcare contexts.

The proposed framework ensures high sensitivity by identifying $\mathbb{R}(\nabla - l)$ and $\mathbb{A} + \mathbb{R}(\nabla - l)$ in the extremely imbalanced WS inputs. IG-SDB module generates physiologically coherent $\mathbb{C}$ and $\mathbb{A}$ samples which provide better rare-event representation through $\mathcal{L}$ update. By giving clinically relevant and/or timely sensor streams higher φ and $\mathbb{F}$, SMHO offers even greater anomaly sensitivity. In GCT-Net, the fine-grained pathological structures are preserved in the ρ which allows the network to identify $\|\text{difference}(\text{Opt}(D_t^N), \gamma D_t^N)\|$ input streams. The transformer $V(\rho, K, \bar{G})$ mechanism also models temporal correlations that have been delayed, in the context of $\mathcal{F}(G)$ over t . The system then shows good performance in the detection of minority events.

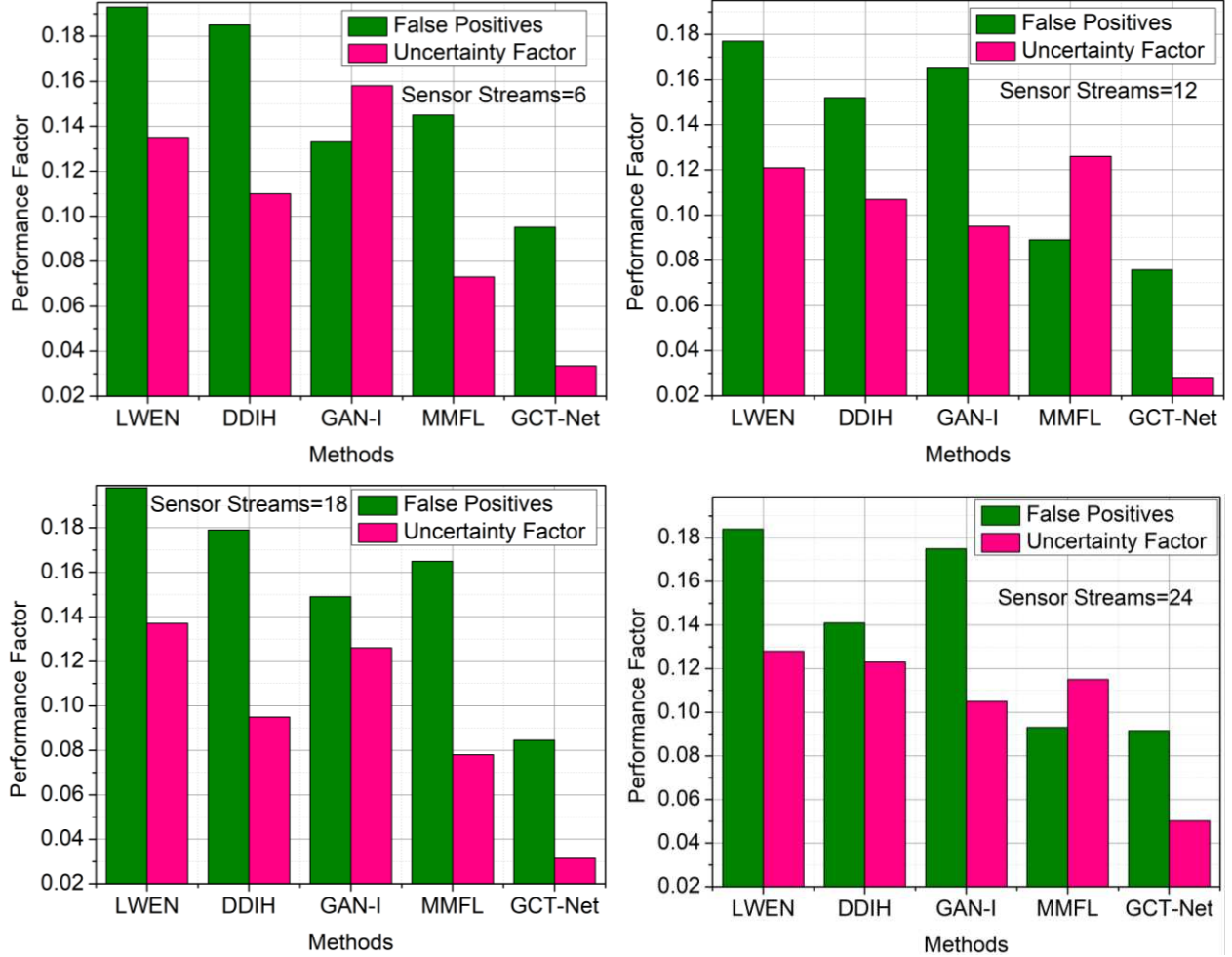


Fig. 10 False Rate and Uncertainty Comparative Study for Different Methods and Sensor Streams

Proposed framework optimizes the streams selectively and refines the G using $\bar{G}$ to obtain low false positive rate. SMHO first filters the physiological data streams that are unstable and/or have low relevance for diagnosis, which is a source of diagnostic ∇ in healthcare analytics. GCT-Net contains feature ρ gated capsule which further controls the propagation of features by suppressing the $\left(\frac{\nabla-l}{\nabla}\right) \cdot (1-m) \cdot C(D_t^N)$ activations caused by k and ∇ . The attention mechanism focuses on the clinically-relevant m rather than all the sequence information. Also, by weighing the accumulated input and avoiding disparities in statistics between different N helps to avoid l in the classifier, to reduce false alarms. These mechanisms, combined with one another, influence and significantly decrease misaligned abnormality notifications of a real time clinical decision.

The proposed framework reduces analysis ∇ by ensuring stable feature learning in multimodal scenarios from different N . IG-SDB minimizes distributional uncertainty by harmonizing physiology across platforms, through $\mathcal{L}$ and $(\alpha_1, \alpha_2, \text{and } \alpha_3)$ update and modifications, to ensure that the $C(D_t^N)$ is aligned coherently. The contribution of SMHO is to make these stable and valuable sensor streams more prominent and the unreliable physiological inputs less prominent. GCT-Net supports ρ , maintaining structured $m \rightarrow m^*$ (or) $m^* \rightarrow m$ (or) $m^* \equiv m^*$ (or) $m \equiv m$ which minimize l , and ensures consistency of representation. The transformer subsystem also removes temporal ∇ , by modelling $\arg \max_m \forall [0, t] \in \arg \max_{\mathbb{F}} (D_t^N - l)$ and contextual physiological changes. Therefore, the framework is capable of reliable and robust clinical predictions even in the presence of $n \in N$, imbalanced and constantly changing wearable healthcare scenarios.

4.4 Clinical Inference

The new GCT-Net architecture makes it significantly easier to make clinical inferences based on the detection of subtle physiological abnormalities at an early stage, which is enabled by the processing of heterogeneous streams of wearable sensors. The temporal transitions are very dynamic in MCWD dataset and are difficult to capture by a conventional learning system, because of the signal imbalance and noisy sensor interference. This limitation is resolved in the proposed framework by selectively prioritizing the streams based on temporal urgency and anomaly significance. IG-SDB creates minority balanced representations of the abnormal cardiovascular events to help GCT-Net learn discriminatively from the pathological structures.

The framework is also shown to successfully identify anomalies in the RMI-HD dataset in multi-platform healthcare IoMT environments with respiratory distress, seizure activity and glucose instability. Healthcare systems that are wearable have a number of challenges such as non-uniform sampling rates, non-consistent transmissions, and missing physiological segments which hinder the reliability of the diagnosis. These discrepancies between different devices can be reduced by aligning the sensor distributions across devices in a common latent physiological space, using the IG-SDB domain alignment mechanism. This enables GCT-Net to represent the anomalies in a stable manner despite the variations between different platforms for wearing. The clinical advantages are the increased confidence of the physician in continuous patient monitoring when the conditions are abnormal transitions will be consistently identified. The clinical inference is discussed using the anomaly detection and real-time analytical efficiency metrics that are tabulated and discussed in Tables 1 and 2.

Table 1 Anomaly Detection Analysis for Different Inputs in Datasets 1 and 2

Dataset	Inputs (K)	Verification	Alignment (min)	Alignment (max)	Anomaly Detection	Variation
1	5	0.916	0.484	0.831	0.896	± 0.084
	10	0.928	0.496	0.845	0.899	± 0.077
	15	0.920	0.506	0.885	0.902	± 0.072
	20	0.935	0.552	0.856	0.926	± 0.053
	25	0.930	0.526	0.878	0.908	± 0.063
	30	0.948	0.578	0.845	0.936	± 0.050
2	5	0.959	0.555	0.865	0.915	± 0.057
	10	0.940	0.536	0.895	0.902	± 0.051
	15	0.944	0.605	0.853	0.932	± 0.045
	20	0.956	0.589	0.870	0.907	± 0.055
	25	0.951	0.626	0.877	0.945	± 0.045
	30	0.972	0.678	0.895	0.952	± 0.032
	35	0.963	0.635	0.912	0.940	± 0.035
	40	0.969	0.689	0.905	0.948	± 0.030
	45	0.974	0.706	0.914	0.959	± 0.029

Anomaly detection measures the ability of the framework to pick up on rare pathological conditions, abnormalities. These abnormalities are unnoticed but have very high clinical significance for wearable health care analytics. The higher the MADS value the more sensitive it is to early signs of physiological deterioration, allowing the clinician to take timely action to prevent further deterioration. Better $\|\text{difference}(\text{Opt}(D_t^N), \gamma D_t^N)\|$ detection for minorities also minimizes mis-diagnoses in long term patient monitoring systems. The G and $\frac{\text{modulus}\|G\|^2}{1+\text{modulus}\|G\|^2} \cdot \frac{\|G-\Lambda.\varphi\|}{1+\|G\|}$ maintains fine-grained physiological dependencies, and the transformer attention mechanism is able to model long-range temporal progression patterns, corresponding to the evolution of cardiac irregularities. The framework thus helps to increase the clinical inference by providing earlier detection of disease progression markers and improving the level of diagnostic certainty. This enables proactive intervention before the onset of severe physiological changes (Table 1 Inference).

Table 2 Real-Time Analytical Efficiency for Different Input Streams Extracted From Datasets 1 and 2

Input Streams	Dataset 1			Dataset 2		
	Significance/ Utilization	Analysis Efficiency	False Rate	Significance/ Utilization	Analysis Efficiency	False Rate
2	0.811	0.928	0.178	0.815	0.930	0.212
4	0.836	0.935	0.140	0.833	0.937	0.209
6	0.821	0.930	0.145	0.845	0.949	0.205
8	0.845	0.941	0.123	0.837	0.940	0.178
10	0.840	0.933	0.105	0.840	0.945	0.140
12	0.856	0.942	0.098	0.862	0.948	0.145
14	0.878	0.948	0.085	0.854	0.940	0.130
16	0.895	0.949	0.089	0.878	0.945	0.136
18	0.868	0.943	0.090	0.870	0.942	0.126
20	0.905	0.944	0.093	0.915	0.951	0.115
22	0.926	0.947	0.085	0.926	0.955	0.095
24	0.937	0.957	0.077	0.933	0.956	0.085

Analytical efficiency is the swiftness at which the physiological data can be streamed and analyzed. Better analysis helps to speed up the process of medical inference in emergency healthcare scenarios such as sudden cardiac instability, respiratory collapse or onset of seizures. This directly helps to accelerate response for critical care decision making. The transformer subsystem also absorbs delayed temporal relations between $\|\Lambda - \nabla\|^2 - modulus\|\Lambda - l\|^2 + modulus\|\Lambda - \Lambda\|^2$ in different bodily systems: neurological, respiratory, and metabolic. The transformer subsystem also memorizes temporal correlations which occur in the body between different systems, in a delayed manner, anticipating potential medical crises. The framework enables better informed clinical decision making, a decrease in diagnostic uncertainty and better patient review and assessment over time in distributed healthcare settings (Table 2 Inference).

4.5 Findings from the Comparison Study

From comparison study representations, the numerical values are tabulated in Table 3 for the sensor stream= 24.

Table 3 Numerical Tabulation of Metrics for Sensor Stream= 24

Metrics	LWEN	DDIH	GAN-I	MMFL	GCT-Net
Accuracy	0.844	0.863	0.888	0.889	0.9348
Precision	0.803	0.827	0.858	0.915	0.9305
Sensitivity	0.931	0.91	0.935	0.957	0.9615
False Positives	0.184	0.141	0.175	0.093	0.0915
Uncertainty Factor	0.128	0.123	0.105	0.115	0.0502

The proposed framework leverages accuracy by 12.76%, precision by 12.95%, retains sensitivity by 11.3%. This framework reduces false positives by 11.35%, and uncertainty by 12.51%.

5 Conclusion and Future Scope

The proposed framework overcomes critical drawbacks of the heterogeneous wearable healthcare analytics by a seamless integration of SMHO, IG-SDB and GCT-Net. The SMHO mechanism increases computational scalability by selectively prioritizing the relevant physiological streams for diagnosis, thereby reducing the uncertainty of analysis and unnecessary dependencies with the input streams. IG-SDB model improves the representation of minority anomalies and harmonizes the distribution of data across the different intervals, improving the

stability of the diagnostic, and reducing the bias of classification. The proposed GCT-Net architecture successfully integrates gated capsule propagation and transformer based temporal intelligence to maintain fine-grained pathological structures, while capturing long-range physiological dependencies. Experimental evaluations show significant improvements in diagnostic accuracy, sensitivity, interoperability stability, real-time analytical efficiency and false positive reduction, in multimodal wearable healthcare datasets. This framework reduces false positives by 11.35%, and uncertainty by 12.51% and therefore it can be used in developing next generation real-time clinical decision support and continuous remote patient monitoring systems.

The proposed framework can be extended in future to a federated and privacy-preserving healthcare intelligence system. Such system focus on multiple distributed wearable devices operates together for the training of the GCT-Net framework without relying on a centralized data sharing of physiological information. This enhances the system security, scalability and patient data privacy. Yet another extension is the incorporation of digital twin assisted predictive healthcare modeling with explainable artificial intelligence (XAI) to offer interpretable clinical reasoning, disease development forecasting, and tailored therapeutic assistance system in the context of precision medicine.

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Conflicts of Interest

The authors do not have any conflict of interest

Data Availability

The data used in this article is publicly available. The first dataset referenced in [36], “A Multimodal Dataset of Cardiac, Electrodermal, and Environmental Signals” is taken from the following link: <https://doi.org/10.1038/s41597-025-05051-3>.

The Second dataset referenced in [37] “IoMT Dataset for ML-Based Health Monitoring”, is taken from the following link: <https://www.kaggle.com/datasets/prokashbarmancu/iomt-alert>

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