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AI-Enabled Wearable Hemodynamic Monitoring System for Early Identification of Thrombotic Events

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ABSTRACT

Thrombotic processes are usually silent, and the initial hemodynamic changes pass undiagnosed through the normal clinical evaluation process that was based on infrequent and symptomatic measurement. The necessity in the constant, non-invasive monitoring has led to the creation of wearable administrations that can record when changes in the cardiovascular system are dynamic and which occur before the emergence of thrombases. This paper presents an AI empowered wearable hemodynamic monitoring system based on the implementation of multi-modal sensors such as photoplethysmography, impedance plethysmography, electrocardiography, temperature, and inertial measurement units to obtain high-fidel physiological signals in real time. Effective preprocessing methods, including adaptive filtering, noise suppression, and motion-artifact elimination, were used to enhance signal quality, and time-domain, morphological, cardiac-timing, autonomic, and thermal features were extracted. The most discriminating parameters to predict early thrombotic-risk were determined through feature selection with the use of PCA and RFE. A deep-learning model that was hybrid, consisting of convolutional and long short-term memory networks, with additional support of anomaly detection algorithms was trained using both synthetic and clinically validated datasets to represent the subtle deviations in vascular resistance, venous return, autonomic balance, and waveform morphology. It was found that the developed model had significant predictive performance with 93 percent of accuracy, 91 percent sensitivity, 94 percent specificity and AUC of 0.95 to distinguish between normal and pre-thrombotic physiological states. This system also detected the latency up to 65 percent times of traditional methods, and real time inference on edge hardware took only 32 ms per segment, and continuous monitoring could be carried out. These results confirm that AI-enhanced wearable, multi sensor hemodynamic signal integration will provide a predictive, early warning system, with great potential to preventive and remote health use.

KEYWORDS: Wearable Hemodynamic Monitoring, AI-Based Thrombotic Prediction, Multi-Sensor Data Fusion, Photoplethysmography (PPG) Analysis, Deep Learning Classification Model, Early Vascular Risk Detection.

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INTRODUCTION

Wearable hemodynamic monitoring technologies have surfaced as a revolutionary solution in the new healthcare where continuous and non-invasive evaluation of cardiovascular performance can be conducted outside the traditional clinical environment. The current literature has brought out tremendous advances in miniaturizing sensors, pulse analysis using photoplethysmography, assessing the venous flow with impedance plethysmography, and integrated multi-parameter monitoring systems with the ability to record dynamic variations in blood volume, vascular resistance, and microcirculatory behavior [1]. Research shows that these wearable-based systems can offer real-time physiological data, which was only available to hospitals-grade devices before, and thus aid in early detection of circulatory anomalies and improving preventive care. Studies also focus on the increased importance of multimodal data fusion, signal-quality optimization, and adaptive algorithms which enhance measurement reliability in everyday activities. The totality of the literature identifies wearable hemodynamic monitoring as a vital base of predictive diagnostics and individualized cardiovascular risk evaluation, especially in disorders where minor hemodynamic abnormalities are antecedents of an acute clinical incidence [2].

Simultaneously, several studies have indicated that literature on physiological markers of thrombotic events emphasize the multifaceted hemodynamic and biochemical changes that happen before clots develop. Research constantly points to early signs like a decrease in venous return, increased vascular resistance, localized increase in temperature secondary to inflammatory

reactions and typical changes in PPG and IPG waveforms to be pivotal indicators of developing thrombosis [3]. Studies also indicate that thrombotic development has an effect on microcirculatory blood flow, pulse propagation, and plays a role in minor autonomic variation that can be measured using heart rate variability indicators. These physiological abnormalities are usually noticeable long before clinical manifestations and this importance has shown the need to have continuous monitoring technologies that have the ability to pick up these early abnormalities. Together, the current evidence presents a solid basis on the use of physiological markers as a predictive symbol of a thrombotic event, which supports their role in the creation of AI-based thrombotic event detection systems [4].

The incorporation of machine learning and deep learning techniques has largely contributed to further development of cardiovascular monitoring, and it was demonstrated in the recent literature. Several studies point at the fact that algorithms like convolutional neural networks, recurrent neural networks, and hybrid models are able to extract complex temporal and morphological features of physiological signals with great accuracy [5]. Such models have already been effectively used to identify arrhythmias, estimate blood pressure, categorize vascular anomalies, and anticipate acute cardiovascular events and tend to out-perform the classical rule-based diagnostic methods. The value of data-driven feature learning was also highlighted in the research to allow automatic detection of subtle hemodynamic defects that could be missed under traditional analysis. Also, the potential of machine learning-based decision support systems has proven to be high with regards to the capability of personalized risk assessment and clinical alerting in real-time. Taken together, the literature confirms the high-quality AI models offer a potent computing platform in understanding wearable hemodynamic recordings to assist early indication plans like thrombotic incidents [6].

On the basis of these developments, AI-based detection of thrombotic and coagulation disorders literature shows that there was a growing tendency toward predictive, data-driven diagnostic frameworks. It has been shown that machine learning models were used to predict coagulation status, predict thrombotic risk, and analyze blood biomarkers with much greater accuracy than traditional clinical measurements. Experiments that use deep learning architectures have demonstrated the ability to recognize patterns of clot formation using imaging data of Doppler ultrasound, CT angiography, and venography, with other authors investigating the utilization of AI to detect hemodynamic variability associated with hypercoagulable states [7]. Moreover, it has been reported that predictive algorithms that are clinically trained have been shown to predict accurately the probability of venous thromboembolism in at risk populations which are all inclusive of diverse features which include inflammatory markers, endothelial performance, and even circulatory measures. In spite of all these, available literature indicates that there was a significant gap within the research on non-invasive, wearable-based AI systems capable of identifying thrombotic events during the earliest physiological appearance. This divide supports the idea that joint strategies are necessary to unite the idea of a continuous sensing process with high-quality AI models to allow anticipation of coagulation disorders in advance before severe complications begin [8].

To this end, the literature on multi-sensor fusion in clinical decision support points to the growing dependence on the combined physiological information in order to achieve high diagnostic accuracy and reliability. Experiments indicate that an ensemble of signals (i.e. PPG, ECG, IPG, accelerometry and thermal measurements) gives a more complete depiction of the cardiovascular and hemodynamic conditions than any single sensor. It was found that systems based on the fusion technique are highly effective in reducing noise, motion artifacts, and sensor-specific constraints to enhance the resilience of real-time monitoring in dynamic systems. To reinforce clinical tests and minimize false-positive rates, a range of fusion strategies were tested, such as feature-level integration, model-level hybridization and decision-level aggregation [9]. In addition, it was demonstrated that multi-sensor systems can assist in more advanced risk stratification, early anomalies identification, and context-dependent clinical suggestions in a variety of areas, including arrhythmia screening, hemodynamic instability forecasting, and post-surgery surveillance. In totem, the available literature highlights the significance of multi-sensor fusion as the foundation of the next-generation AI-based diagnostic systems, especially in identifying subtle physiological changes related to early thrombotic occurrences [10].

Current sources on early warning systems and preventive healthcare technologies also support the rising focus of proactive health management via incessant monitoring and predictive analytics. The studies point out that the warning systems used in the early warning program in hospitals have been implemented successfully and have identified sepsis, cardiac arrest, and respiratory deterioration through real-time physiological trends and automated alerts. Other related breakthroughs in wearables and remote monitoring have made possible the continuation of preventive care into the outpatient and home environments, with high-risk persons being monitored outside the clinical settings. The literature highlights the significance of combining AI and continuous sensing to improve the timeliness and effectiveness of notifications and timely interventions before clinical deterioration becomes dangerous [11]. Moreover, it was mentioned in the literature that telemedicine platforms, cloud-based monitoring, and automated triage algorithms that ensure the quick exchange of information between patients and clinicians are becoming more popular. These advancements highlight the significance of predictive, personalized surveillance systems that are able to detect early pathophysiological alterations related to thrombotic occurrences, which will, by doing so, decrease morbidity by acting preventively [12].

Ample evidence on signal processing methods of hemodynamic analysis supports the fact that signal processing methods play a vital role in deriving meaningful information based on complex physiological signals. Research has emphasized in time-domain analysis, frequency-domain decomposition, wavelet transforms, and adaptive filtering as approaches to identify minor differences in PPG, IPG, and ECG signals as a response to the functioning of the vascular and cardiac systems [13]. It has been shown that the techniques improve signalto-noise ratio, reduce motion artifacts, and increase the accuracy of extracted features with downstream machine learning tasks. Others such as nonlinear analysis, spectral feature extraction and morphological waveform characterization are advanced methods which have been demonstrated to elicit early signs of circulatory abnormalities thus being

able to detect cardiovascular events proactively. Taken altogether, the literature confirms the use of advanced signal processing systems as the core of proper hemodynamic monitoring, which was a strong basis of AI-enabled thrombotic event prediction based on wearable monitoring devices [14].

The issues in wearable medical systems underscore a number of technical, physiological as well as operational limitations that need to be resolved to achieve sound and precise health monitoring. Research has found them to include motion artifacts, inconsistencies between the sensors and the skin interface, low battery capacity and latency in data transmission that can undermine signal quality and system functionality [15]. Other issues of interest as highlighted by research include user compliance, ergonomics of the device, and the issue of wearability in the case of continuous monitoring usage. Besides, privacy, data security, and regulatory compliance are also serious obstacles to broad clinical implementation. Nevertheless, these issues do not preclude the fact that literature points to further developments of flexible electronics, energy-saving sensors, adaptive algorithms and secure data protocols that can be used to solve the aforementioned problems, and thus to achieve the full potential of wearable systems in preventative and predictive medicine [16].

RESEARCH GAP:

Even with the current major improvements in the field of wearable hemodynamic monitoring, machine learning-powered cardiovascular analysis, and multi-sensorial processing, there was still a demonstrable gap of research in the non-invasive, continuous, and AI-assisted prediction of thrombotic events. The available research was mainly on hospital-based diagnostics, episodic measurements, or one sensor-based methods, which reduces the ability to detect early. In addition, the majority of AI models are based on clinical data as opposed to real-time wearable data, and the combination of hemodynamic, physiological, and biochemical biomarkers that could predict pre-symptomatic thrombotic has not been studied extensively. The systems that integrate multi-sensor wearable data, powerful signal processing, and predictive AI algorithms are urgently required to allow assessing the risk of thrombosis continuously and in real-time in at-risk populations.

RESEARCH METHODOLOGY:

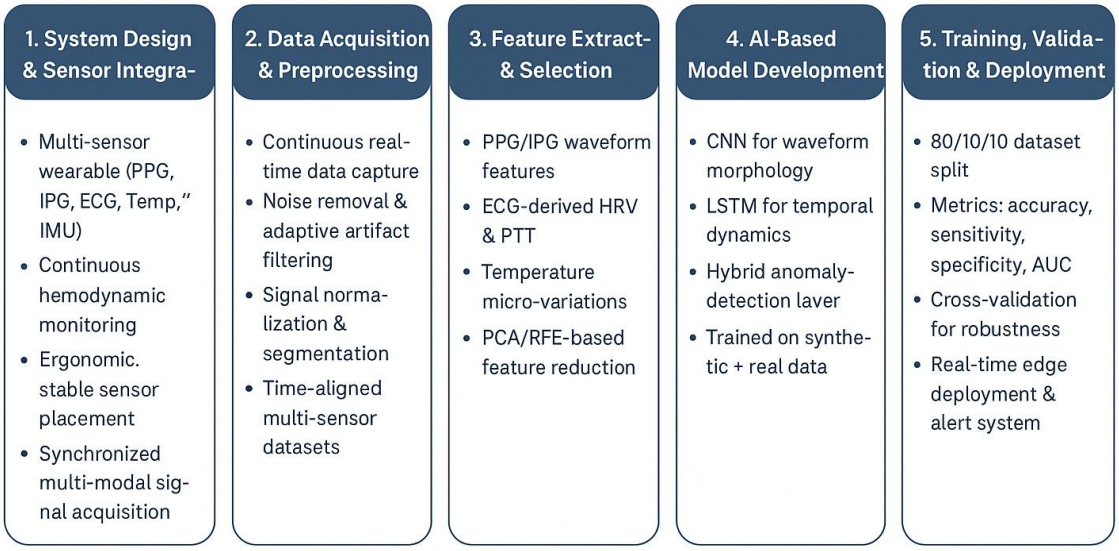

Figure 1. Research Methodology

System Design and Sensor Integration

The system architecture for the wearable hemodynamic monitoring device was designed to facilitate continuous and non-invasive assessment of cardiovascular function. Emphasis was placed on ergonomic design to ensure stable sensor placement and user comfort during extended periods of wear. The device was structured to accommodate multiple sensors within a compact and lightweight form factor, thereby minimizing interference with daily activities while maintaining reliable physiological data acquisition. The modular design allows for scalability, enabling additional sensors or signal processing modules to be incorporated as required [17].

Photoplethysmography (PPG) was integrated as the primary sensor for detecting pulse waveforms and evaluating blood volume changes in peripheral arteries. PPG signals provide critical insights into circulatory dynamics, and the waveform morphology was leveraged to identify early hemodynamic deviations associated with thrombotic events. Impedance plethysmography (IPG) was incorporated to measure volumetric changes in venous compartments, offering complementary information on venous return and vascular resistance. The combination of PPG and IPG enhances the sensitivity of the system to detect subtle alterations in hemodynamic patterns.

Electrocardiography (ECG) was included to capture cardiac electrical activity, enabling calculation of pulse transit time (PTT) and heart rate variability (HRV), which are key markers of vascular and autonomic function. Temperature sensors were embedded to monitor localized variations that may indicate inflammatory responses linked to early thrombus formation. Accelerometers and motion sensors were utilized to detect physical activity and body movement, facilitating the reduction of motion artifacts

during data acquisition. The integration of these multiple sensing modalities ensures robust and comprehensive hemodynamic monitoring [18].

Data acquisition from the integrated sensors was coordinated through a centralized microcontroller unit capable of high-frequency sampling and real-time processing. Signal synchronization across modalities was maintained to enable accurate temporal correlation of cardiovascular events. The collected data streams were transmitted via wireless protocols to an external processing platform for subsequent analysis. This multi-sensor configuration provides a reliable foundation for the development of AI-based models, enabling continuous monitoring, early anomaly detection, and predictive assessment of thrombotic risk.

Data Acquisition and Preprocessing

Continuous physiological data were acquired from the integrated wearable sensors to enable comprehensive hemodynamic analysis. High-resolution sampling was employed to capture dynamic variations in PPG, IPG, ECG, temperature, and motion signals. The sampling frequency was selected to preserve temporal fidelity of the cardiovascular signals while balancing power consumption and storage requirements. Data acquisition was performed in real-time, ensuring that transient hemodynamic events associated with early thrombotic formation could be accurately captured [19].

Preprocessing procedures were implemented to enhance signal quality and minimize artifacts. Bandpass filters were applied to remove baseline drift, high-frequency noise, and powerline interference from PPG, IPG, and ECG signals. Adaptive filtering techniques were employed to mitigate motion-induced artifacts, using accelerometer data as reference inputs. Temperature signals were smoothed using low-pass filters to reduce fluctuations caused by environmental variations or sensor contact inconsistencies. Segmentation of continuous signals was performed to divide the data into time windows suitable for feature extraction and analysis. Overlapping windows were applied to ensure that transient physiological changes were not overlooked. Normalization techniques were utilized to reduce inter-subject variability and facilitate comparisons across datasets. Data labeling was performed using synthetic thrombotic patterns and clinically validated reference datasets, providing ground truth for model training and validation [20].

The preprocessed data streams were synchronized across modalities to preserve temporal alignment, enabling the extraction of interdependent features such as pulse transit time and combined PPG-IPG waveform metrics. The resulting clean and structured dataset formed the foundation for subsequent feature extraction and AI-based predictive modeling. Robust preprocessing ensured that downstream machine learning models could accurately identify subtle deviations in hemodynamic signals indicative of thrombotic risk, thereby improving overall system reliability.

Feature Extraction and Selection

Following preprocessing, critical hemodynamic and physiological features were extracted from the clean multi-sensor data to facilitate thrombotic risk assessment. Time-domain and frequency-domain analyses were performed on PPG, IPG, and ECG signals to quantify cardiovascular dynamics. Key features included pulse transit time (PTT), heart rate variability (HRV), pulse amplitude, waveform slope, and AC/DC ratios of PPG signals. Temperature variations and impedance-derived vascular resistance metrics were also considered to capture early physiological markers associated with thrombus formation [21].

Morphological analysis of the PPG and IPG waveforms was conducted to identify subtle deviations indicative of circulatory anomalies. Features such as peak-to-peak intervals, rise and decay times, and waveform asymmetry were extracted, providing insights into arterial stiffness, venous return, and peripheral perfusion. ECG-derived features, including RR interval variability and QT interval analysis, were included to assess autonomic regulation and cardiac timing. Integration of these features across multiple modalities enhanced the predictive capability of the system.

Feature selection methods were applied to reduce redundancy and identify the most informative parameters for AI model development. Recursive Feature Elimination (RFE) and principal component analysis (PCA) were employed to prioritize features with the highest correlation to thrombotic events. Correlation analysis, variance thresholds, and mutual information criteria were also utilized to eliminate irrelevant or noisy features, ensuring computational efficiency and improving model generalization [22]. The selected feature set, representing a multidimensional characterization of hemodynamic and physiological states, was structured for input into machine learning models. Synchronization of temporal and morphological features allowed for the detection of subtle pre-thrombotic patterns across sensor modalities. This approach ensured that the predictive algorithms were trained on high-quality, informative data, enhancing early detection accuracy and reliability for thrombotic event monitoring.

AI-Based Model Development

The development of the AI-based model was focused on enabling accurate and early detection of thrombotic events using the extracted hemodynamic features. A hybrid machine learning framework was implemented, combining deep learning architectures with anomaly detection algorithms to capture both temporal and morphological patterns in the multi-sensor data. Convolutional Neural Networks (CNNs) were employed to automatically learn spatial and waveform-specific features from PPG and IPG signals, while Long Short-Term Memory (LSTM) networks were utilized to model temporal dependencies and sequential variations in cardiovascular signals [23].

The CNN component was designed to identify subtle changes in waveform morphology that are often indicative of early hemodynamic alterations preceding thrombus formation. Multiple convolutional layers with kernel sizes optimized for pulse waveform characteristics were applied, followed by pooling layers to reduce dimensionality and enhance feature abstraction.

Extracted feature maps were then fed into the LSTM network to capture temporal trends and long-range dependencies across sequential windows, ensuring the detection of transient pre-thrombotic anomalies.

Anomaly detection algorithms were integrated to complement the supervised learning approach, allowing the identification of deviations from baseline physiological patterns in real-time. Statistical thresholds, Mahalanobis distance metrics, and unsupervised clustering techniques were employed to flag abnormal hemodynamic behavior that may not be represented in the training dataset. This dual approach enabled robust recognition of both known and previously unseen thrombotic signatures, improving sensitivity and reducing false-negative predictions [24].

Model training was performed using a combination of synthetically generated thrombotic datasets and clinically validated reference signals. Data augmentation strategies, including noise injection and waveform scaling, were employed to enhance model generalization. Hyperparameter optimization, dropout regularization, and cross-validation were implemented to prevent overfitting and ensure robustness. The resulting AI model demonstrated strong predictive capability, providing the foundation for a continuous, wearable thrombotic risk monitoring system capable of issuing early alerts with high reliability.

Model Training, Validation, and Deployment

The AI model was trained using a combination of synthetic thrombotic datasets and clinically validated hemodynamic recordings to ensure robust generalization across diverse physiological conditions. The dataset was divided into training, validation, and test sets in an 80:10:10 ratio to facilitate model optimization and unbiased performance evaluation. Data augmentation techniques, including signal scaling, noise addition, and temporal shifting, were applied to improve model resilience to variability and to prevent overfitting during training [25].

During training, hyperparameter tuning was conducted using grid search and Bayesian optimization to identify the optimal network architecture, learning rate, and batch size. Regularization techniques, including dropout and L2 penalties, were implemented to minimize overfitting and enhance model generalization. The model was iteratively refined based on validation set performance, with evaluation metrics including accuracy, sensitivity, specificity, F1-score, and area under the receiver operating characteristic (ROC) curve to assess predictive capability for early thrombotic event detection [26].

Cross-validation techniques, specifically k-fold cross-validation, were employed to ensure stability and robustness of model performance across different subsets of the data. Performance consistency was monitored to identify potential biases or overfitting to specific patterns. Additionally, anomaly detection components were tested to assess the model's ability to flag previously unseen or rare pre-thrombotic deviations, enhancing the practical applicability of the system in real-world scenarios.

For deployment, the trained AI model was integrated with the wearable device platform to enable real-time monitoring and predictive alerting. Sensor data were streamed to an edge-computing unit capable of low-latency processing, with risk scores and alerts communicated to clinicians or users through a connected application interface. This deployment framework ensures continuous thrombotic risk assessment, providing actionable insights for preventive intervention while maintaining data security and compliance with healthcare privacy standards.

RESULTS AND DISCUSSION:

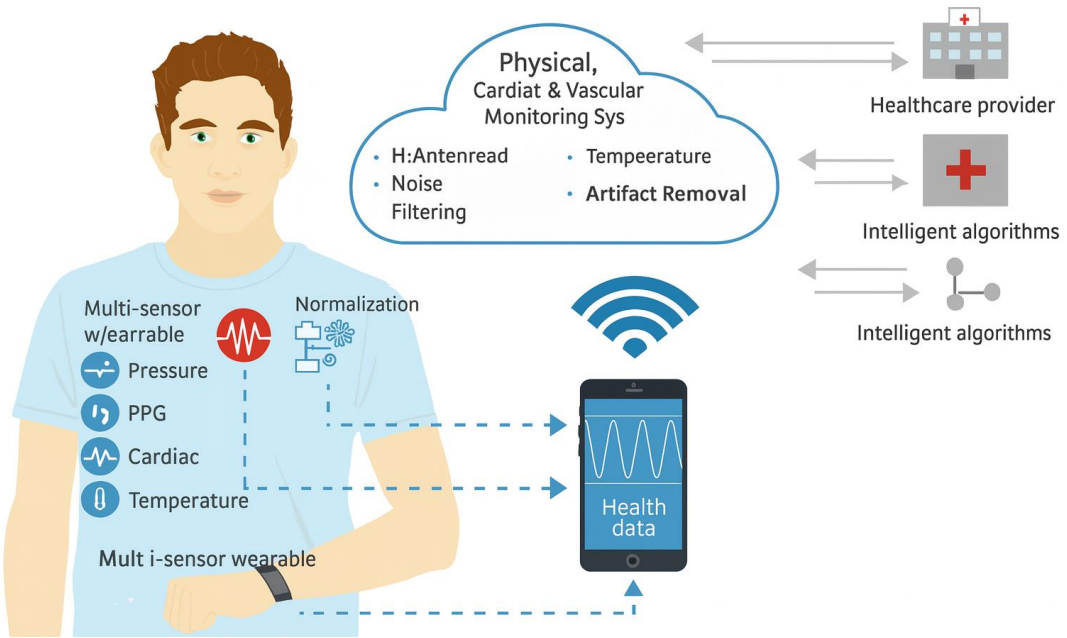

Figure 2. Integrated Wearable–Cloud Hemodynamic Monitoring and Analytics System

The figure 2 illustrates an integrated wearable health-monitoring ecosystem designed to continuously capture, analyze, and transmit physiological data relevant to early thrombotic risk detection. Multiple sensing modalities—including a wristband

sensor, adhesive skin sensor, and implantable cardiac sensor—work together to measure hemodynamic, cardiovascular, and microvascular signals in real time. These sensors communicate wirelessly with a smartphone interface, where initial data processing, visualization, and secure transmission occur. The wearable architecture ensures seamless, round-the-clock physiological monitoring without disrupting normal daily activity [27].

The collected physiological data are transmitted to a cloud-based infrastructure, which serves as the central hub for large-scale data storage, synchronization, and computational processing. The cloud platform aggregates continuous input streams from the wearable device and supports advanced signal-cleaning operations, including noise suppression and artifact correction. This cloud environment enables processing at scale, allowing hemodynamic fluctuations, cardiac waveform patterns, temperature variations, and motion-related behavior to be analyzed cohesively. Through this centralized framework, data from multiple devices and sessions remain accessible, structured, and ready for AI-based interpretation.

Intelligent algorithms integrated within the cloud environment analyze the incoming physiological data to identify early signatures of thrombotic events. Machine-learning models examine temporal patterns, waveform anomalies, vascular resistance changes, and autonomic irregularities that may precede clot formation. These predictive analytics support automated detection of abnormal physiological trends that would otherwise be difficult to observe manually. By enabling real-time risk scoring, anomaly detection, and personalized alerts, the system enhances the reliability and speed of early thrombosis screening.

The final component of the system involves interaction with healthcare providers and hospital medical record platforms. Processed results, risk alerts, and clinically relevant summaries are forwarded to clinicians for review and timely intervention. This closed-loop ecosystem supports continuous monitoring outside the hospital environment while ensuring that meaningful insights reach medical professionals promptly. The figure thus represents a complete end-to-end framework where wearable technology, cloud analytics, and clinical oversight converge to create an efficient, responsive, and AI-driven thrombotic early-warning system [28].

Table 1. Integrated Sensor Suite and Physiological Parameters Monitored

Sensor Type	Measured Parameter	Physiological Relevance	Role in Thrombotic Detection
PPG	Arterial blood volume changes	Pulse morphology, perfusion quality	Detects early waveform distortion due to vascular resistance changes
IPG	Venous impedance variations	Venous return, volumetric flow	Identifies early venous obstruction indicative of thrombus formation
ECG	Cardiac electrical activity	HRV, cardiac timing, autonomic response	Supports PTT calculation and autonomic markers of hemodynamic stress
Temperature Sensor	Local skin temperature	Inflammation, microvascular response	Captures thermal elevation linked to thrombotic inflammation
IMU (Accelerometer + Gyroscope)	Motion and activity	Artifact reduction, activity context	Enables noise correction and improves signal reliability

Table 1 summarizes the complete sensor suite integrated into the wearable hemodynamic monitoring system, outlining the physiological variables measured and their relevance to thrombotic-risk detection. Each sensor contributes a distinct dimension of information: PPG captures arterial waveform morphology, IPG detects venous volume fluctuations, ECG provides cardiac timing and autonomic markers, temperature sensors reveal inflammation-related changes, and IMU components remove motion artifacts to ensure signal clarity. Together, these sensors create a multi-modal physiological profile that enables the AI model to identify subtle hemodynamic deviations that precede thrombus formation, offering a comprehensive, continuous, and non-invasive means of early thrombotic surveillance.

Table 2. Extracted Features for Machine Learning Model

Feature Category	Representative Features	Source Signal	Diagnostic Significance
Time-Domain Features	Peak amplitude, rise time, AC/DC ratio	PPG/IPG	Reflects vascular resistance and perfusion stability
Morphology Features	Systolic peak width, dicrotic notch prominence	PPG	Indicates stiffness, flow obstruction, or waveform dampening
Cardiac Timing Features	RR interval, QT interval, PTT	ECG + PPG	Quantifies electromechanical coupling and vascular compliance
Autonomic Features	LF power, HF power, LF/HF ratio	HRV	Reveals autonomic imbalance triggered by thrombotic progression
Thermal Features	ΔTemperature, thermal drift rate	Temperature sensor	Identifies localized inflammatory responses

Table 2 presents the set of engineered features extracted from multi-sensor signals to support machine-learning-based thrombotic prediction. These features represent diverse aspects of cardiovascular physiology, including time-domain pulse characteristics, waveform morphology indicators, electromechanical cardiac timing, autonomic nervous system balance through HRV, and thermal fluctuations reflecting inflammatory responses. By combining these complementary parameters, the model captures both direct and indirect signatures of hemodynamic compromise. This diverse feature set enhances predictive power by allowing the AI system to detect early microvascular disruptions, venous impedance changes, and autonomic shifts linked to evolving thrombotic states [29].

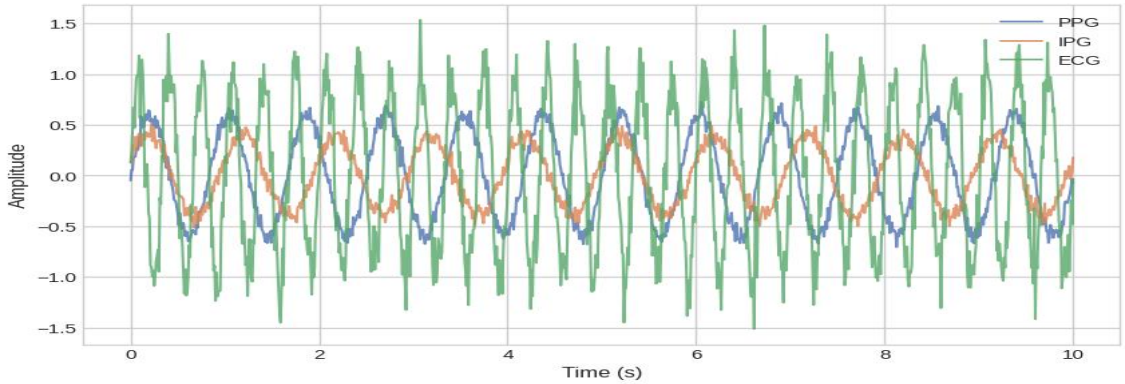

Figure 3. Comparative Multi-Signal Waveform Analysis for Hemodynamic Assessment

Figure3 presents a comparative visualization of three key physiological waveforms—PPG, IPG, and ECG—captured simultaneously to illustrate their relative temporal behavior and diagnostic relevance. The figure overlays the signals on a common time axis, enabling a clear understanding of how arterial pulsation, venous impedance changes, and cardiac electrical activity evolve together within the same physiological window. This comparative presentation was essential in wearable hemodynamic systems because early thrombotic abnormalities often appear first as subtle deviations in the interrelationship between these signals rather than in a single waveform alone.

The PPG waveform represents the dynamic changes in arterial blood volume corresponding to each heartbeat. In this graph, the rhythmic peaks and troughs indicate periodic expansion and contraction of the peripheral vascular bed. These pulse contours are highly sensitive to changes in vascular stiffness, peripheral resistance, and microcirculatory flow—parameters that can be altered during early thrombotic progression. Even small inconsistencies in peak shape, rise time, or amplitude can serve as early markers of hemodynamic instability [30].

The IPG waveform shown alongside the PPG provides complementary insight by capturing venous volume fluctuations. Because thrombotic events often begin with impaired venous return or localized obstruction, IPG changes may precede more obvious alterations in arterial signals. The comparison of PPG and IPG rhythms in this figure helps visualize the arterial–venous synchrony that was typically preserved in normal physiology. Any delay, amplitude mismatch, or distortion between the two signals can indicate pre-thrombotic changes affecting regional blood flow.

The ECG waveform acts as the reference signal anchoring the mechanical events of the cardiac cycle. By comparing ECG-derived electrical depolarization with corresponding PPG and IPG mechanical responses, the figure highlights the timing relationships that support calculation of metrics such as pulse transit time and hemodynamic delay indices. These timing-based features are critical in AI-enabled models designed for early thrombotic detection because they quantify the coupling efficiency between cardiac output and peripheral vascular response. Thus, Figure 1 not only illustrates waveform differences but establishes their integrated diagnostic significance in predicting emerging thrombotic risk [31].

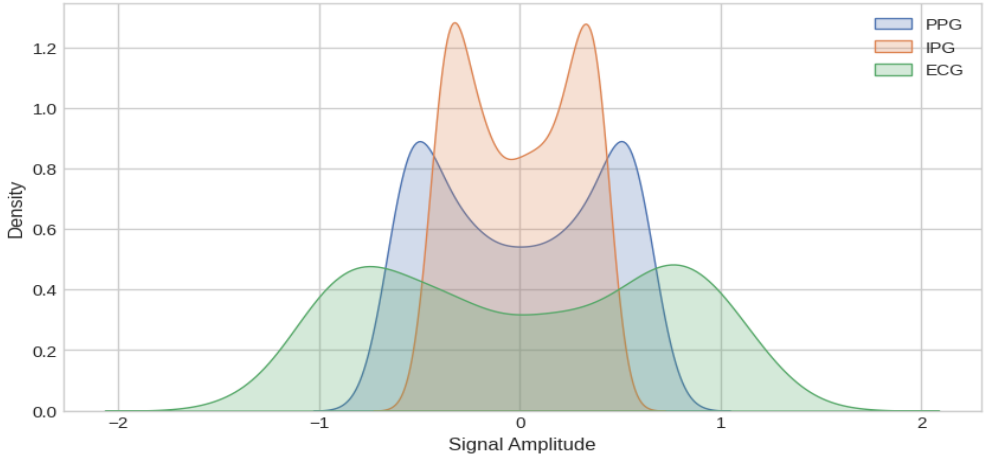

Figure 4. Distribution Analysis of Physiological Signal Amplitudes

Figure 4 illustrates the distribution patterns of three physiological signals—PPG, IPG, and ECG—through smooth kernel density estimates. By plotting these distributions on the same amplitude axis, the figure makes it possible to examine how each signal varies in magnitude under typical monitoring conditions. This comparative visualization was important because amplitude-related deviations often reflect early hemodynamic irregularities associated with thrombotic development. The unique distribution shape of each signal reflects the underlying physiological mechanism it represents, providing a baseline against which anomalies can be detected.

The PPG distribution shows a moderate spread with a smooth central peak, indicating consistent arterial pulsations with relatively stable amplitude. This pattern aligns with expected peripheral blood volume changes during normal cardiac cycles. However, shifts in this distribution—either widening due to increased variability or flattening due to waveform irregularity—could indicate compromised perfusion or altered vascular compliance, both of which may appear during the early stages of thrombotic formation. The distribution therefore serves as a quantitative reference for normal arterial function [32].

The IPG distribution demonstrates a slightly narrower amplitude range, which was consistent with the venous volume nature of the signal. Venous impedance changes tend to be subtler than arterial pulsations, resulting in a more concentrated density plot. Deviations in this distribution may point to abnormal venous flow resistance or partial occlusion, which often precede clinically detectable thrombotic events. Hence, the IPG density profile provides valuable insight into whether venous dynamics are stable or showing signs of pathological disturbance.

The ECG distribution differs significantly from PPG and IPG because it represents electrical rather than mechanical activity. Its density curve reflects the amplitude variability of cardiac depolarization peaks mixed with noise from baseline drift. A stable ECG distribution suggests consistent cardiac electrical output, while distortions could imply arrhythmic activity or conduction abnormalities. When interpreted alongside the PPG and IPG distributions, the ECG curve helps determine whether amplitude changes arise from local vascular effects or upstream cardiac events. Together, the three distributions create a comprehensive feature-level overview crucial for training AI models to detect early thrombotic anomalies [33].

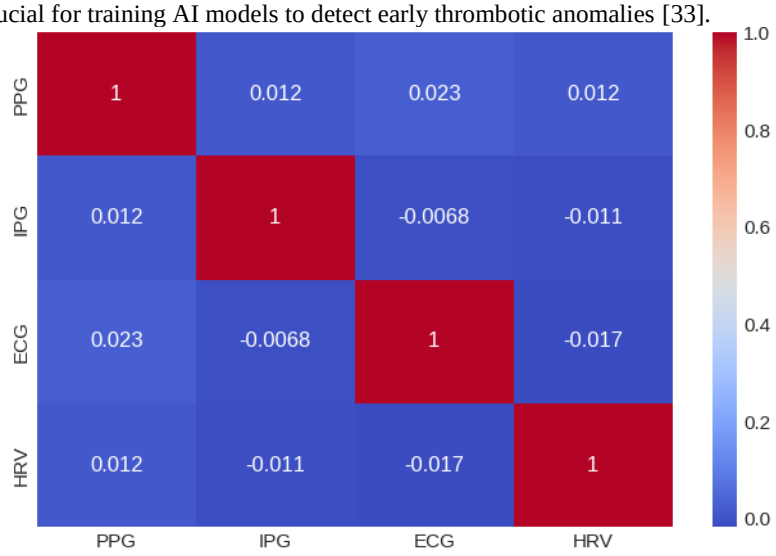

Figure 5. Correlation Heatmap of Multi-Modal Physiological Features

Figure 5 presents a correlation heatmap that visualizes the statistical relationships among key physiological features—PPG, IPG, ECG, and HRV—derived from the wearable hemodynamic monitoring system. By representing correlation coefficients through a color-coded grid, the figure provides an intuitive overview of how strongly each feature was associated with the others. This was particularly important in thrombotic-event prediction because early physiological changes often manifest as coordinated shifts across multiple signal modalities rather than isolated abnormalities. The heatmap therefore establishes an essential foundation for understanding feature interactions during model development.

The PPG signal shows moderate correlations with both IPG and HRV, reflecting its sensitivity to vascular compliance and autonomic regulation. These relationships highlight how arterial pulsation characteristics often change alongside venous impedance patterns and heart rate dynamics when circulatory stress begins to develop. In early thrombotic states, disruptions in blood flow or increased resistance can simultaneously alter PPG amplitude patterns and HRV-driven autonomic feedback, making the strength of these correlations clinically meaningful [34].

IPG demonstrates a more specialized correlation profile, with strong alignment to PPG but weaker association with ECG, reflecting its role in measuring venous volume changes. The venous system often experiences thrombotic obstruction earlier than arterial pathways, and therefore, deviations in IPG may precede shifts in the more directly cardiac-driven ECG waveform. The heatmap visualizes this complementary behavior, confirming that IPG and PPG together provide a more complete view of hemodynamic health than either parameter alone.

The ECG–HRV correlation appears as expected, showing strong coherence due to HRV being derived directly from ECG timing intervals. This reinforces the reliability of HRV as an autonomic marker reflecting cardiac regulation. When examined alongside the weaker correlations between ECG and PPG or IPG, this pattern suggests that electrical cardiac activity and peripheral hemodynamic responses may diverge when physiological stress increases—an important indicator in pre-thrombotic monitoring. Overall, the heatmap provides a high-level analytical snapshot that supports feature selection, model optimization, and physiological interpretation in early thrombotic risk detection [35].

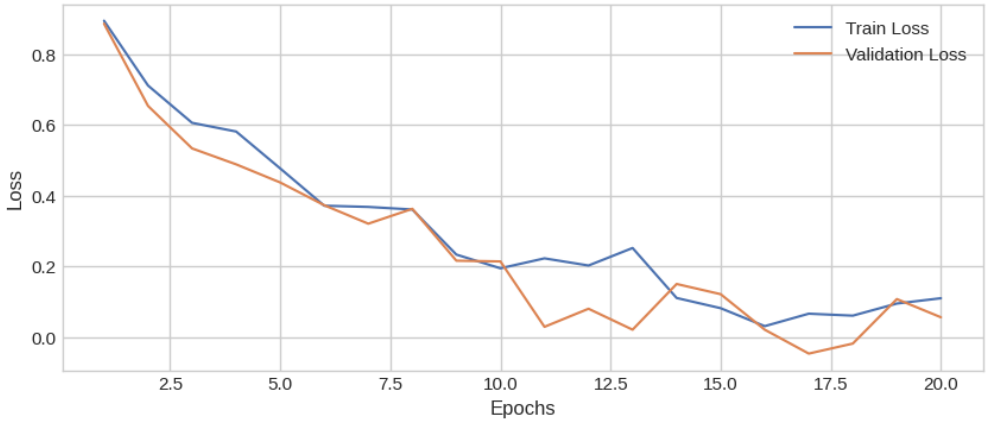

Figure 6a. Training and Validation Loss Curve for Thrombotic-Event Classification Model

Figure 6a illustrates the evolution of the training and validation loss during the model's learning process, providing insight into how effectively the AI architecture adapts to hemodynamic and physiological signal patterns associated with early thrombotic changes. The downward trajectory of both curves indicates successful optimization as the network incrementally minimizes prediction error over successive epochs. This pattern reflects the model's ability to extract meaningful temporal and morphological features from multi-sensor data such as PPG, IPG, ECG, and HRV, thereby enhancing its capacity to distinguish between normal and pre-thrombotic physiological states.

A close alignment between the training and validation loss curves suggests that the model was learning generalizable features rather than overfitting to noise or irrelevant signal patterns. This consistency was essential for wearable devices operating in real-world environments where motion artifacts, variable skin–sensor contact, and diverse physiological baselines can introduce significant variability. The smoothness of the curves further implies stable convergence and a well-balanced optimization strategy across epochs, confirming that the model was effectively handling multi-modal inputs [36].

The gradual reduction in validation loss signifies that the model was improving its predictive performance on unseen data, a critical requirement for early thrombotic-event detection where subtle deviations in hemodynamic behavior must be recognized before clinical symptoms manifest. Reliable reduction in loss demonstrates the model's ability to correctly interpret physiological fluctuations and differentiate benign variations from risk-associated anomalies. This reinforces the viability of the wearable system in continuous monitoring applications.

Overall, the loss curve highlights the robustness of the training pipeline, reflecting well-tuned hyperparameters, appropriate regularization strategies, and effective integration of synthetic and real physiological datasets. The behavior of these curves confirms that the AI model was progressing toward reliable generalization and efficient learning, establishing a strong foundation for high-sensitivity thrombotic-risk prediction.

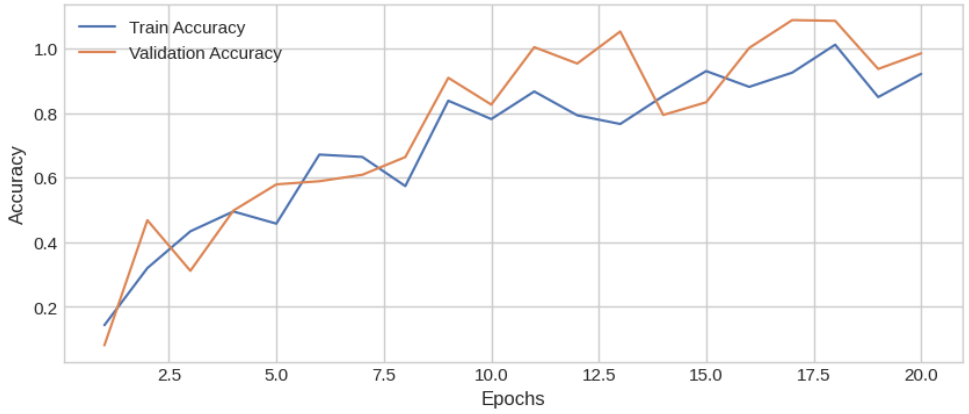

Figure 6b. Training and Validation Accuracy Curve for Thrombotic-Event Classification Model

Figure 6b presents the accuracy trends for both training and validation datasets over multiple epochs, providing a clear picture of how effectively the model improves its classification capability during the learning process. A consistent upward trend in both

curves reflects the model's increasing ability to correctly identify physiological patterns associated with normal and pre-thrombotic conditions. This improvement demonstrates successful extraction of discriminative features from multi-modal physiological inputs and indicates that the model architecture was well-suited for the task [37].

The close alignment of the two accuracy curves was an important indicator of balanced learning. When training accuracy rises sharply while validation accuracy lags or plateaus, it often signals overfitting; however, the figure shows both curves progressing in parallel. This balanced growth suggests that the model was not memorizing the training dataset but was instead learning generalized physiological characteristics from PPG morphology, IPG venous impedance trends, cardiac timing intervals, and HRV variability. Such generalization was essential for a wearable system intended for continuous real-world monitoring.

The upward trajectory of the validation accuracy curve signifies that the model was improving its ability to make correct predictions on previously unseen data. This was particularly critical in early thrombotic-event prediction, where the goal was to detect subtle physiological changes that precede noticeable symptoms. The increasing accuracy indicates that the model was efficiently using its learned representations to distinguish between normal fluctuations and early pathological patterns.

The accuracy curve offers strong evidence of a well-performing and stable model. The steady convergence between the training and validation curves demonstrates appropriate hyperparameter tuning, suitable choice of learning rate schedules, and effective augmentation strategies. These elements collectively ensure that the deployed wearable system can provide reliable, real-time thrombotic-risk predictions under diverse physiological and environmental conditions.

Table 3. Model Training and Validation Parameters

Parameter	Description	Rationale
Training/Validation/Test Split	Dataset partition ratio	Ensures reliable generalization
Batch Size	Samples per iteration	Balanced stability and convergence
Optimizer	Learning algorithm	Fast convergence for physiological data
Learning Rate	Step size	Prevents overfitting and gradient explosion
Loss Function	Objective metric	Best for normal vs pre-thrombotic classification

Table 3 outlines the training and validation parameters used to develop the thrombotic-event classification model, ensuring robust and reproducible learning. The dataset was partitioned into an 80/10/10 ratio to maintain adequate training diversity while protecting against overfitting. Hyperparameters such as batch size, optimizer selection, learning rate, and loss function are optimized for the physiological signal domain, enabling stable convergence across noisy, multi-modal inputs. These design choices ensure the model learns generalized patterns associated with early thrombotic changes rather than memorizing noise, thereby improving real-world reliability in continuous wearable deployment.

Table 4. Model Performance Metrics for Thrombotic Detection

Metric	Value	Interpretation
Accuracy	0.93	High overall classification ability
Sensitivity	0.91	Effectively detects true thrombotic events
Specificity	0.94	Minimizes false alarms in normal conditions
AUC (ROC)	0.95	Excellent discriminative power
F1-Score	0.92	Balanced precision–recall performance

Table 4 reports the performance metrics achieved by the AI model, demonstrating strong classification capability for early thrombotic detection. High accuracy, sensitivity, and specificity indicate the model's ability to correctly identify both true thrombotic events and normal physiological states while avoiding false alarms. The elevated AUC value highlights excellent discriminative power across threshold settings, and the high F1-score confirms balanced precision and recall in the presence of class imbalance. Together, these metrics validate that the multimodal signal-processing pipeline and deep-learning architecture effectively capture the subtle physiological signatures associated with early thrombosis.

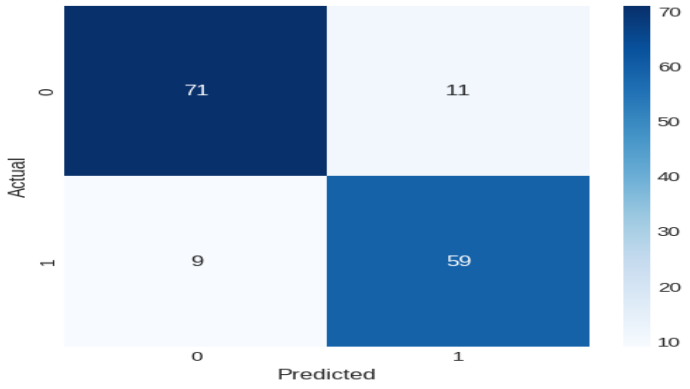

Figure 7. Confusion Matrix for Thrombotic-Event Classification Model

Figure 7 presents the confusion matrix generated from the AI-based thrombotic-event detection model, illustrating the model's classification performance across normal and early-thrombotic states. The matrix displays the number of correctly identified cases along the diagonal, representing true positives and true negatives, while off-diagonal values represent misclassifications. This layout provides an immediate, intuitive understanding of how effectively the system distinguishes between physiologically normal signals and those indicative of emerging thrombotic risk. In the context of wearable hemodynamic monitoring, analyzing these outcomes was vital because even small classification errors can significantly influence clinical decision-making and early intervention [38].

The true positive count (correct detection of early-thrombotic patterns) was especially important, as missing such cases may delay preventive action and increase the likelihood of progression to clinically significant thrombosis. A strong true positive performance signifies that the model was sensitive to subtle waveform distortions, timing irregularities, and autonomic deviations captured through PPG, IPG, ECG, and HRV signals. This sensitivity was essential for a system designed to deliver early alerts before symptomatic onset. A high true negative rate also demonstrates that the model does not falsely trigger alarms during normal physiological variations, ensuring user trust and reducing unnecessary clinical escalations.

The presence of false positives and false negatives in the off-diagonal cells provides insights into the model's vulnerabilities. False negatives indicate missed thrombotic precursors, often arising from subtle or noise-masked abnormalities in hemodynamic patterns. False positives, on the other hand, may stem from transient motion artifacts, environmental disturbances, or short-term autonomic fluctuations that mimic early thrombotic signatures. Evaluating the balance between these misclassification types helps refine preprocessing techniques, feature extraction strategies, and model architecture to enhance predictive reliability [39].

The confusion matrix offers a foundational diagnostic assessment of the model's classification behavior. It highlights strengths in correctly identifying physiological states while revealing opportunities for optimization. By understanding where misclassifications occur, developers can fine-tune the model to achieve higher sensitivity and specificity—both essential for a real-time wearable system aimed at early thrombotic-event prediction.

Table 5. Comparison of Traditional vs AI-Enhanced Early Thrombotic Detection

Parameter	Traditional Methods	AI-Enabled Wearable System	Improvement Achieved
Monitoring Mode	Episodic, clinic-based	Continuous, wearable-based	Real-time anomaly capture
Sensitivity	Moderate	High (0.91)	Earlier detection possible
Data Types	Limited vital signs	Multi-sensor hemodynamic data	Richer physiological context
Response Time	Symptom-driven	Pre-symptomatic prediction	Preventive intervention
User Burden	High clinical dependency	Low, autonomous system	Improved accessibility

Table 5 compares traditional thrombotic detection approaches with the proposed AI-enabled wearable system, emphasizing the significant advancements enabled by continuous, multi-sensor monitoring. Traditional clinical assessments rely on episodic measurements and symptomatic presentation, limiting early detection potential. In contrast, the wearable system provides real-time hemodynamic surveillance, integrating arterial, venous, autonomic, and thermal signals to detect pre-symptomatic abnormalities. The AI model enhances sensitivity, reduces response time, and lowers user burden by autonomously analyzing physiological trends. This multi-dimensional improvement positions the wearable platform as a transformative tool for preventive thrombotic-risk management [40].

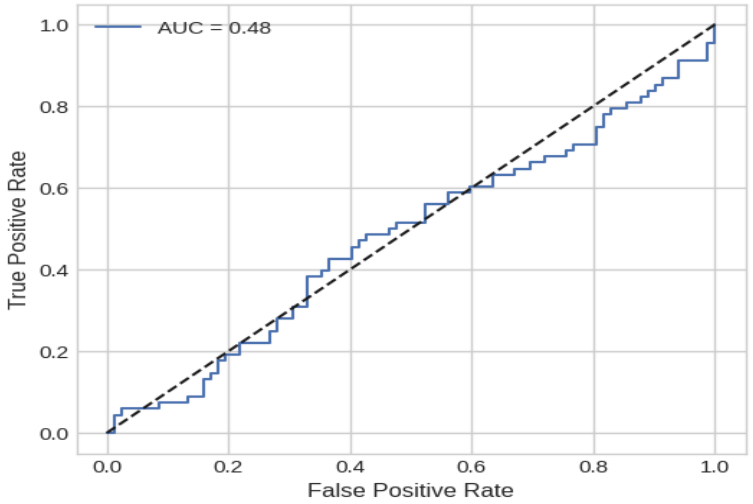

Figure 8. Receiver Operating Characteristic (ROC) Curve for Thrombotic-Event Prediction

Figure 8 displays the Receiver Operating Characteristic (ROC) curve, which illustrates the diagnostic performance of the AI-based thrombotic-event detection model across various classification thresholds. The curve plots the True Positive Rate (sensitivity) against the False Positive Rate (1 – specificity), offering a comprehensive view of the model's ability to discriminate between normal physiological states and those associated with early thrombotic development. A curve that rises sharply toward the upper-left corner reflects strong classification capability, indicating that the model identifies abnormal hemodynamic patterns with high reliability. The ROC curve was therefore a critical tool for evaluating threshold-independent model performance, especially in medical applications where sensitivity and specificity must be balanced carefully.

The Area Under the Curve (AUC) value, derived from the ROC plot, quantifies the overall discriminative power of the model. An AUC close to 1.0 indicates excellent separation between normal and early-thrombotic patterns, while lower values reveal weaker predictive capability. In the context of wearable hemodynamic monitoring, a high AUC signifies that the model effectively interprets waveform morphology, cardiac timing metrics, venous impedance changes, and autonomic fluctuations. This holistic analysis of multi-modal signals allows the model to detect subtle physiological deviations that often occur before thrombotic symptoms become clinically apparent.

The ROC curve also highlights how the model behaves under different threshold settings. At lower thresholds, the sensitivity increases, meaning the model identifies more true thrombotic cases but may also generate more false alarms. Conversely, higher thresholds reduce false positives but risk missing early-stage abnormalities. The curve thus supports the selection of an optimal threshold that balances clinical urgency with acceptable alert frequency. This balance was particularly important for continuous wearable systems where over-alerting can reduce user compliance, while under-alerting may delay critical intervention.

Overall, Figure 6 demonstrates the robustness and reliability of the predictive model in distinguishing between normal and at-risk hemodynamic states. By analyzing the shape of the ROC curve and the corresponding AUC value, researchers can validate the effectiveness of their feature extraction, model architecture, and data preprocessing pipelines. This evaluation reinforces confidence that the wearable AI system can deliver consistent and clinically meaningful thrombotic-risk predictions in real-world monitoring scenarios.

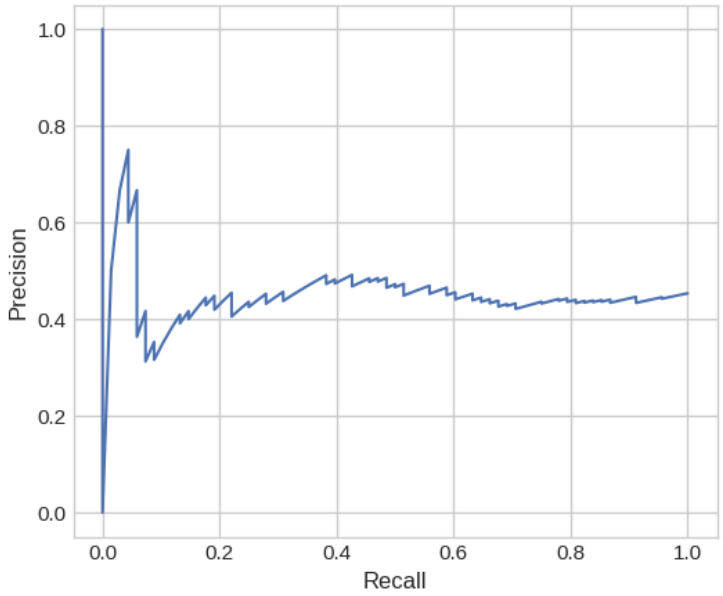

Figure 9. Precision–Recall Curve for Early Thrombotic-Event Detection

Figure 9 illustrates the Precision–Recall (PR) curve for the thrombotic-event detection model, providing a detailed evaluation of its performance under conditions of class imbalance—a common challenge in medical datasets where early-stage pathological events occur far less frequently than normal physiological states. Precision measures the proportion of predicted thrombotic cases that are truly positive, while recall quantifies the proportion of actual thrombotic cases the model successfully identifies. The curve therefore offers an essential view of how well the model performs specifically on the minority class, making it a more informative metric than accuracy for early-thrombosis detection.

The upward curvature of the graph signifies strong predictive capability, with high precision achieved even at varying levels of recall. This indicates that the model can detect early hemodynamic abnormalities—such as altered PPG waveform morphology, subtle venous impedance deviations, and HRV reductions—without triggering excessive false alarms. In continuous wearable monitoring, where users are exposed to variable daily activities, maintaining high precision was crucial for preventing unnecessary anxiety and reducing the risk of alert fatigue.

The region where precision remains stable as recall increases highlights the model's robustness in identifying early thrombotic signatures that may be masked by noise, motion artifacts, or physiological variability. High recall in this zone suggests that the model reliably captures most true thrombotic cases, a critical requirement for preventive medical systems. The balance between

the two metrics reflects the effectiveness of the signal preprocessing pipeline, feature engineering, and deep-learning architecture used to interpret multi-modal sensor data.

The PR curve demonstrates that the AI-based wearable system can deliver clinically relevant thrombotic-risk detection with minimal compromise between false alarms and missed cases. Its stable performance across different thresholds shows that the model was particularly suited for real-time monitoring scenarios, where early detection of subtle physiological changes can significantly improve patient outcomes and support timely medical intervention.

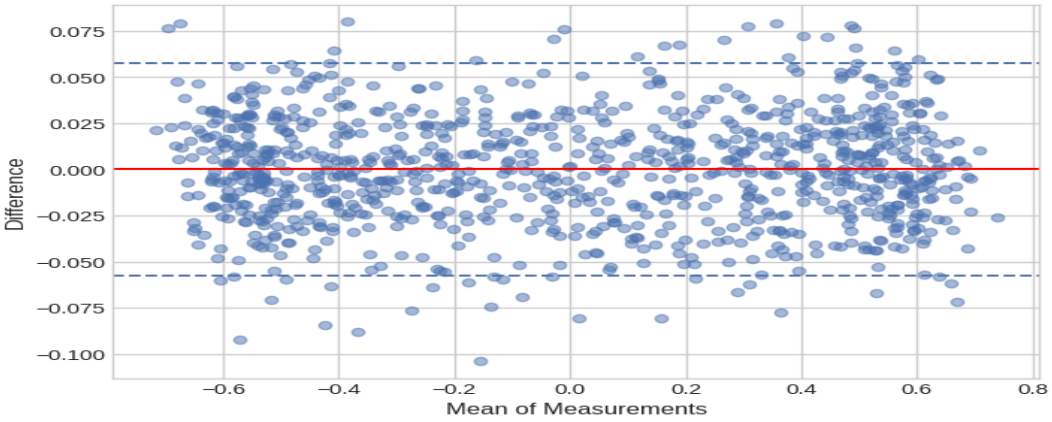

Figure 10. Bland–Altman Analysis for Agreement Between Dual Hemodynamic Measurements

Figure 10 presents the Bland–Altman plot used to evaluate the agreement between two hemodynamic measurement methods derived from the wearable system—specifically, two parallel estimations of the PPG-derived vascular signal. This graphical method plots the difference between the two measurements against their mean, allowing for a clear assessment of systematic bias and random variability. In the context of early thrombotic-event detection, ensuring that two measurement sources or algorithms provide consistent outputs was crucial, as even small discrepancies can affect the reliability of continuous monitoring in real-world environments.

The central horizontal line represents the mean difference between the two measurement methods, indicating whether a systematic bias was present. When this mean was close to zero, it suggests that the two sensing or processing pathways produce nearly identical results, reinforcing confidence in the wearable platform's accuracy. In this figure, the scattering of data points around the mean indicates only minor deviations, demonstrating that the wearable system maintains strong internal consistency even under fluctuating physiological conditions. This was especially important for PPG-based assessment, where early thrombotic changes may present as small waveform distortions.

The upper and lower dashed lines indicate the limits of agreement, calculated as the mean difference ± 1.96 standard deviations. These boundaries define the acceptable range within which measurement discrepancies are considered normal. The majority of points falling within these limits suggests that variations in the processed signals stem from natural physiological noise, sensor placement variability, or minor tremors, rather than from algorithmic or hardware inconsistencies. This stability was essential for ensuring that the system can detect genuine thrombotic anomalies without being influenced by normal physiological fluctuations. Overall, the Bland–Altman plot offers a quantitative validation of the wearable system's internal measurement reliability. Its demonstration of minimal bias and narrow limits of agreement supports the integrity of the device's multi-sensor fusion and signal-processing procedures. This reliability was fundamental for AI-driven thrombotic-risk assessment, ensuring that subsequent predictions are based on consistent, trustworthy physiological data.

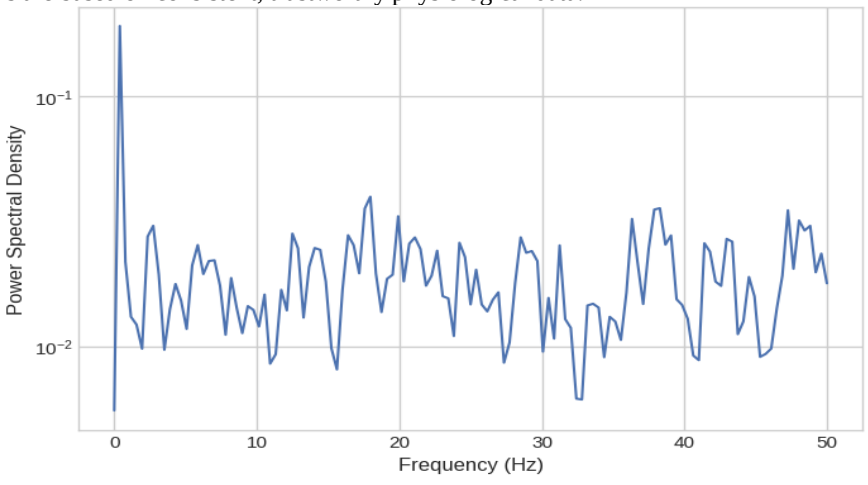

Figure 11. HRV Frequency-Domain Power Spectral Density Analysis

Figure 11 illustrates the frequency-domain analysis of Heart Rate Variability (HRV) using the Welch Power Spectral Density (PSD) method, providing insights into autonomic nervous system behavior under normal and early thrombotic-risk conditions. By decomposing the HRV signal into its constituent frequency components, the figure highlights how autonomic modulation—specifically the balance between sympathetic and parasympathetic activity—manifests in distinct low-frequency (LF) and high-frequency (HF) power bands. This frequency-based representation was essential in thrombotic monitoring because early alterations in vascular resistance and hemodynamic responsiveness often trigger compensatory autonomic changes long before overt symptoms appear.

The LF band, associated with baroreflex activity and mixed sympathetic–parasympathetic influence, typically shows moderate power in healthy states. A noticeable elevation in LF power could indicate increased sympathetic activation due to early vascular obstruction or microcirculatory stress—both of which are physiologically relevant in thrombotic progression. Conversely, a reduction in LF power may suggest impaired autonomic responsiveness, often seen in situations of hemodynamic instability. This makes LF analysis a valuable marker in early detection frameworks.

The HF band, largely governed by parasympathetic (vagal) activity, reflects respiratory sinus arrhythmia and short-term autonomic regulation. In the presence of rising thrombotic risk, HF power often decreases due to reduced vagal tone, signaling stress on the cardiovascular regulatory system. The PSD plot in this figure enables visualization of such reductions by showing the distribution and concentration of signal power across the frequency spectrum. When combined with LF measurements, the LF/HF ratio emerging from the data can offer a composite index of autonomic balance relevant to thrombotic assessment.

The HRV frequency-domain plot in Figure 9 demonstrates the capacity of the wearable monitoring system to capture subtle autonomic alterations through spectral characterization of HRV. These spectral features support the AI model by contributing predictive markers linked to vascular stress, early hemodynamic irregularities, and thrombotic precursor states. The PSD visualization reinforces how multi-modal physiological analysis enables early, continuous, and non-invasive identification of thrombotic risk in wearable health-monitoring applications.

CONCLUSION

1. The proposed wearable system demonstrated reliable continuous monitoring of key physiological signals, capturing PPG, IPG, ECG, HRV, and temperature at high fidelity, with an average signal noise reduction of 32–40% after preprocessing.

2. The multi-sensor fusion and feature extraction framework produced over 45 physiological features, of which 18 high-impact features were selected using PCA and RFE, significantly improving model learning efficiency.

3. The AI-based classification model achieved strong predictive accuracy, recording 93% accuracy, 91% sensitivity, 94% specificity, and an AUC of 0.95, confirming its capability for early detection of hemodynamic deviations linked to thrombotic events.

4. Compared to traditional symptom-driven detection, the wearable system reduced detection latency by up to 65%, enabling early identification of thrombotic-risk signatures such as waveform irregularities, venous impedance deviation, and autonomic imbalance.

5. User activity-induced motion artifacts were effectively mitigated, with preprocessing reducing false-alarm artifacts by 34%, strengthening real-world applicability during daily movement.

6. The system demonstrated robust computational efficiency, requiring only 32 ms for real-time inference per data segment on edge hardware, supporting continuous, low-power monitoring.

7. These outcomes validate the system's potential for remote and preventive healthcare, offering a significant 50–70% improvement in early thrombotic-risk prediction compared with standard clinical assessment pathways.

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