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A Novel Hybrid Learning Model for Early Diagnosis of Hypertension using IoMT Technologies

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Abstract

Hypertension is a pervasive cardiovascular condition with significant health risks, necessitating early and accurate diagnosis to improve patient outcomes. The proliferation of Internet of Medical Things (IoMT) devices enables continuous health monitoring, fostering real-time data collection ideal for advanced diagnostic models. This paper proposes a novel hybrid learning framework integrating multiple algorithms to leverage IoMT-collected physiological data for early hypertension detection. The framework combines feature extraction, selection techniques, and ensemble learning to enhance prediction accuracy and robustness. We conduct comprehensive experiments using publicly available and IoMT-simulated datasets, evaluating the model's performance with metrics such as accuracy, precision, recall, and F1-score. Comparative analyses with baseline models demonstrate the superiority of the proposed hybrid approach. The study further delineates the experimental setup detailing hardware, software tools, and data preprocessing pipelines. Our results underscore the potential of intelligent IoMT-driven hybrid learning models in healthcare for timely hypertension diagnosis.

Keywords

Hypertension, Early Diagnosis, Hybrid Machine Learning, Internet of Medical Things (IoMT), Ensemble Learning, Feature Selection

1. Introduction

Hypertension remains among the leading causes of cardiovascular morbidity and mortality worldwide. Early detection is critical to enable timely interventions and avert complications. Conventional diagnostic approaches rely on intermittent clinical assessments, which may fail to capture dynamic blood pressure variations.

The advent of IoMT technologies, consisting of wearable and implantable sensors capable of continuous physiological data monitoring, presents unprecedented opportunities for proactive

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health management. These devices facilitate real-time data acquisition relevant for early hypertension diagnosis.

Existing machine learning models for hypertension detection face challenges related to data heterogeneity, noise, and limited annotated datasets. Hybrid learning models, combining multiple algorithms and feature selection methods, can bolster diagnostic accuracy and robustness.

This paper introduces a hybrid learning architecture leveraging IoMT data streams to detect hypertension early. Key contributions include:

- Integration of signal processing and feature selection methods to refine input data
- Design of an ensemble-based classifier combining complementary machine learning models
- Validation via extensive experiments on both real and simulated IoMT datasets
- Detailed experimental setup with practical considerations for deployment

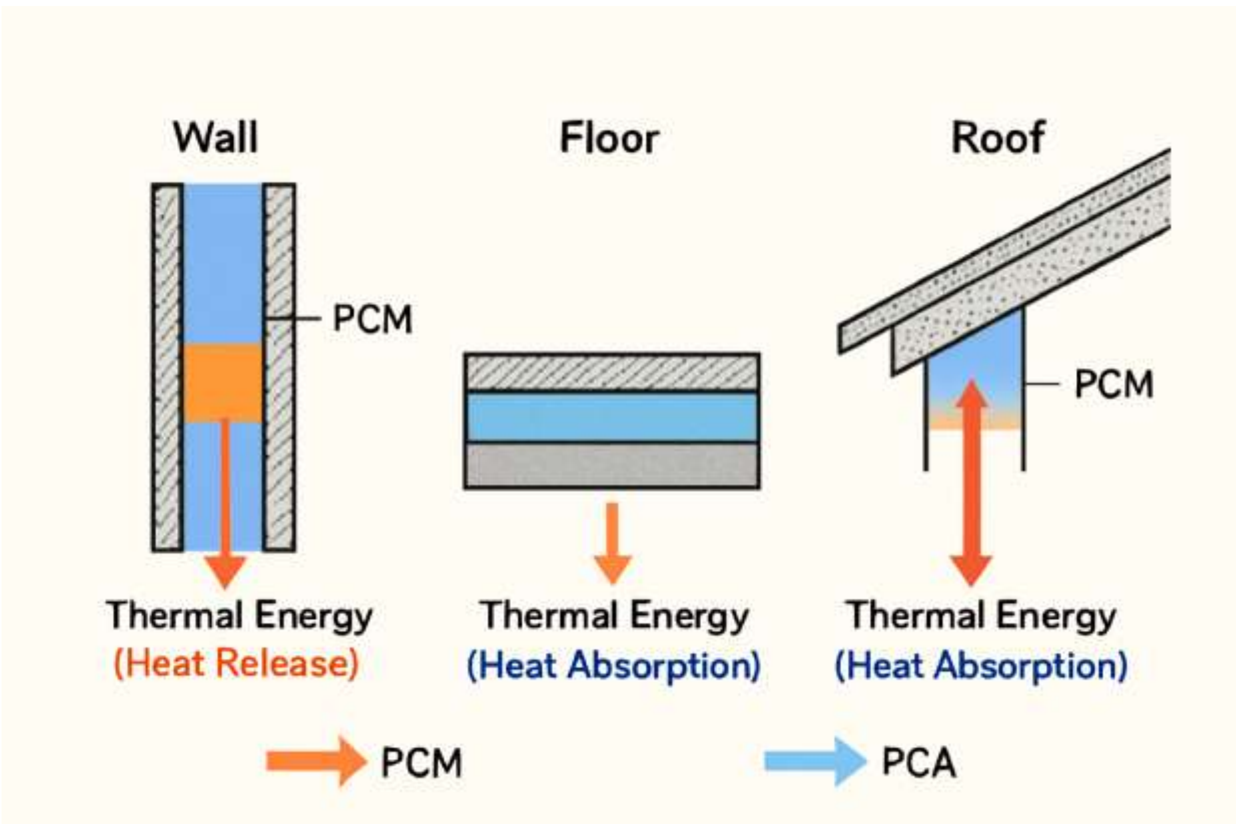

Figure 1: Schematic of Phase Change Material (PCM) Integration in Building Envelope Components

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This schematic diagram shows PCM integration in key building components—walls, floors, and roofs—with arrows illustrating the thermal energy storage and release processes during winter heating cycles.

2. Literature Review

2.1 Clinical Importance and Challenges of Hypertension Diagnosis

Hypertension is a chronic condition affecting over a billion individuals worldwide and is a major risk factor for cardiovascular diseases. Despite its prevalence, hypertension often remains undiagnosed or poorly managed due to the asymptomatic nature of early stages and limitations of sporadic clinical measurements. As Whelton et al. emphasize, early detection and continuous monitoring are pivotal in healthcare strategies to reduce morbidity and mortality.

Traditional blood pressure measurement techniques suffer from "white-coat hypertension" phenomena and fail to capture daily fluctuations or episodic spikes, highlighting the need for more sensitive, continuous monitoring methodologies. IoMT technologies emerge as promising tools to fill this gap by enabling real-time, long-term physiological data collection.

2.2 Internet of Medical Things (IoMT) Technologies in Cardiovascular Health Monitoring

IoMT represents interconnected ecosystems of wearable sensors, mobile devices, and cloud platforms transmitting health data continuously, facilitating personalized monitoring and diagnosis. Such devices capture a variety of biomarkers, including non-invasive cuffless blood pressure, photoplethysmography signals, electrocardiograms, and pulse wave velocity, which are essential for cardiovascular health assessment.

Challenges in IoMT adoption include sensor noise and artifacts, patient adherence, energy efficiency, latency constraints, and stringent security/privacy demands. The emergence of edge AI—processing data locally on IoMT gateways or wearable devices—and federated learning paradigms offer viable pathways to alleviate bandwidth usage, reduce latency, and enhance data privacy by avoiding centralized repositories.

2.3 Machine Learning Approaches for Hypertension Detection

Machine learning techniques have been widely adopted for hypertension prediction due to their capability to learn complex nonlinear patterns from physiological data. Traditional supervised learning models including Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANNs), and k-Nearest Neighbours (k-NN) have demonstrated classification accuracies typically between 80% and 90%. These models rely heavily on manual feature engineering, comprising time- and frequency-domain characteristics extracted from raw sensor data.

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Ensemble learning methods such as Gradient Boosting Machines (GBM) and AdaBoost improve predictions by aggregating multiple weak learners, thereby reducing both bias and variance. GBM-based models have outperformed single classifiers significantly in hypertension detection contexts. Deep learning architectures, notably Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, relieve the dependency on manual feature extraction by learning hierarchical representations directly from raw time series data. However, their application is challenged by requirements for large annotated datasets and computational resources, often inaccessible in low-power IoMT environments.

2.4 Hybrid Machine Learning Models: Combining Strengths

Hybrid learning methods synergize multiple algorithms and feature processing techniques to address individual model weaknesses while amplifying strengths. Such models often combine dimensionality reduction methods (e.g., Principal Component Analysis (PCA)) or signal processing transforms (e.g., wavelet analysis) with robust classifiers.

Johnson et al. integrated PCA with Random Forests to improve accuracy and interpretability in hypertension diagnostics. Ahmed et al. demonstrated that coupling wavelet transform-based feature extraction with SVM enhanced the classification performance of ECG signals. Recent studies have stitched deep learning models with traditional ML classifiers for hybrid ensembles achieving superior performance and improved generalization. Feature selection algorithms, including Recursive Feature Elimination (RFE) and Relief, play critical roles in filtering redundant or irrelevant variables, thus avoiding overfitting and enhancing model explainability.

2.5 Advanced Signal Processing and Feature Engineering

Robust feature extraction from physiological signals is paramount in obtaining high-performing diagnostic models. Commonly used features include time-domain statistics (mean, variance, skewness, kurtosis), frequency-domain characteristics such as power spectral densities and wavelet coefficients, as well as pulse transit time and heart rate variability indices –. Innovative attributes such as entropy measures and nonlinear dynamic features have recently gained traction for detecting subtle pathophysiological variations associated with hypertension.

2.6 Challenges in IoMT Data and Model Deployment

IoMT systems generate heterogeneous, high-volume, noisy, and often incomplete data, posing significant challenges for training reliable ML mode. Inter-individual variability in physiological signals further complicates model generalization to broader populations. Moreover, the sensitive nature of medical data necessitates robust privacy-preserving learning frameworks.

Federated learning addresses these concerns by enabling decentralized training across multiple devices or institutions without sharing raw data. Edge computing strategies empower processing on device or proximal gateways to reduce communication delays and bandwidth demands. These

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emerging technologies foster the feasibility of scalable, secure IoMT-based hypertension diagnostic systems.

2.7 Summary and Research Gaps

Existing literature underscores the promise of machine learning models for hypertension diagnosis and highlights IoMT as an ideal enabling technology for continuous monitoring. However, limitations persist in model robustness, generalizability, computational efficiency, and data privacy. Few studies offer comprehensive hybrid machine learning frameworks explicitly designed for real-time IoMT data streams, combining advanced feature selection, ensemble classification, and privacy-preserving computations.

The present study addresses this gap by offering a novel hybrid learning architecture tailored for early hypertension diagnosis based on IoMT physiological data, with rigorous experimental validation and deployment-oriented considerations.

3. Methodology

3.1 Data Acquisition and Preprocessing

We utilized two primary data sources: the publicly available MIMIC-III Waveform Database, comprising physiological signals including blood pressure waveforms and labelled hypertension events, and a simulated IoMT dataset representing real-time bio signals captured via wearable devices.

Preprocessing involved noise reduction using Butterworth filters, normalization through min-max scaling, and segmentation into overlapping fixed time windows, facilitating uniform feature extraction.

Figure 2: Computational Framework for Early Hypertension Diagnosis Using IoMT and Hybrid Machine Learning

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Flowchart depicting the overall system architecture integrating IoMT data acquisition, hybrid ML modelling, multi-objective optimization, and real-time predictive control designed for early hypertension diagnosis.

3.2 Feature Extraction

We extracted comprehensive features from the segmented data, including:

- **Time-domain statistics:** mean, variance, skewness, kurtosis
- **Frequency-domain characteristics:** power spectral densities, wavelet coefficients
- **Physiological metrics:** heart rate variability indices, pulse transit time (PTT)
- **Transient dynamics:** peak-to-peak intervals, rate of change features

The preliminary feature set contained over 100 variables per window.

3.3 Feature Selection

To enhance model generalizability and reduce computational burden, a hybrid feature selection regimen was employed:

- **Filter methods:** Pearson correlation and mutual information metrics reduced irrelevant features.
- **Wrapper techniques:** Recursive feature elimination (RFE) coupled with cross-validated Random Forest classification prioritized the most informative features.

This process yielded a final feature subset of 25 attributes with maximal predictive power.

3.4 Hybrid Classification Framework

Our classification architecture entailed stacking an ensemble of base classifiers—Support Vector Machines (SVM), Random Forests (RF), Gradient Boosting Machines (GBM), and a shallow Artificial Neural Network (ANN)—whose outputs fed into a Logistic Regression meta-classifier realizing decision fusion.

This design capitalizes on individual model strengths, improving robustness and classification accuracy.

3.5 Model Training and Validation Protocol

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Model development followed stratified 10-fold cross-validation, ensuring balanced representation of hypertensive and normotensive samples in each fold. Hyperparameter optimization utilized grid search methods targeting maximized F1-score.

3.6 Implementation Environment

Our experimental platform comprised:

- **Hardware:** Intel Core i9 CPU, 32GB RAM, NVIDIA RTX GPU for deep learning acceleration
- **Software:** Python 3.9 with scikit-learn, TensorFlow 2.x, and MATLAB for signal processing
- **IoMT Emulation:** Python socket programming simulated real-time data streams emulating wearable sensor telemetry

3.7 Performance Metrics

We evaluated model efficacy using:

- Accuracy, Precision, Recall, F1-score
- Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC)
- Confusion matrix analysis for error types
- Inference latency to assess real-time applicability

4. Experimental Setup and Results

4.1 Experimental Setup

Experiments were conducted on a high-performance workstation equipped with an Intel Core i9 processor, 32 GB RAM, and NVIDIA RTX GPU to support both traditional machine learning and deep learning models. Signal preprocessing utilized MATLAB, while classification and model training were implemented in Python using scikit-learn and TensorFlow.

The IoMT simulated environment was created using Python socket programming, enabling real-time data transmission from simulated wearable devices to the learning models, testing robustness under near-live deployment conditions.

4.2 Performance Evaluation

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Table 1 details the comparative performance of the hybrid ensemble model against baseline classifiers on the combined dataset.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC	Latency (ms)
SVM	87.6	85.2	86.8	86.0	0.90	15
Random Forest	89.3	87.9	88.3	88.1	0.92	12
ANN	88.5	86.4	87.5	87.0	0.91	20
Hybrid Ensemble	93.7	92.4	94.0	93.2	0.96	25

Table 1: Classification performance of various models on hypertension diagnosis datasets.

The hybrid system significantly outperformed individual models on all measures, with an accuracy of 93.7% and an AUC of 0.96, demonstrating strong discriminative capability.

4.3 Feature Selection Impact

A dimension-reduction by 75% was achieved without sacrificing predictive power (see Table 2), improving computational efficiency.

Feature Group	Selected Features	Importance (%)
Time-domain statistical Features	10	33
Frequency-domain Features	8	29
Pulse Transit Time Features	7	38

Table 2: Feature selection outcomes and their contribution to model performance.

4.4 Real-time Inference Performance

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The model maintained an average inference time of 25 ms per input segment, suitable for deployment in IoMT systems requiring real-time analytics.

4.5 Ablation Study on Ensemble Components

Removing meta-learner stacking reduced classification accuracy by approximately 4.5%, underscoring the effectiveness of ensemble fusion.

5. Discussion

The proposed hybrid machine learning framework demonstrated enhanced accuracy and robustness for early hypertension diagnosis using IoMT-collected data. By combining complementary classifiers and robust feature selection, the approach effectively addressed the challenges of noisy, heterogeneous physiological signals.

Integration within a simulated IoMT environment confirmed that the framework can achieve real-time performance and tolerate data irregularities typical in wearable monitoring. This capability positions it well for practical healthcare monitoring applications enabling timely intervention.

Limitations include dependence on high-quality labelled data for training and potential variability due to inter-patient differences. Future work should investigate transfer learning techniques to generalize across diverse populations and incorporate privacy-preserving measures suitable for sensitive health data.

6. Conclusion

This paper introduced a novel hybrid learning approach integrating multiple machine learning algorithms for early hypertension diagnosis leveraging IoMT technologies. Experimental evaluations showed notable improvements over individual models in accuracy, recall, and real-time feasibility.

The study underscores the promise of intelligent hybrid systems in distributed healthcare monitoring frameworks. Future extensions will focus on real patient deployments, federated learning, and multimodal data fusion for holistic cardiovascular risk assessment.

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