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AI-Driven Predictive Analytics for Early Detection of Peripheral Artery Disease: Integrating Clinical Data and Imaging Insights

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ABSTRACT

Peripheral artery disease (PAD) constitutes a major and often under-recognized manifestation of systemic atherosclerosis, with substantial morbidity and mortality implications. Early detection remains challenging, owing to heterogeneous symptomatology, limited screening practices and subtle imaging changes in the asymptomatic or early stages. This research explores an integrative framework of artificial intelligence (AI)-driven predictive analytics that combines longitudinal clinical data, demographic and laboratory risk markers, and advanced vascular imaging features to enable early identification of PAD and stratification of progression risk. Leveraging machine-learning and deep-learning architectures, the proposed system ingests structured electronic health-record data, non-invasive vascular imaging (such as computed tomography angiography, magnetic resonance angiography and pulse-volume waveform recordings), and selected functional biomarkers to build multivariate risk models and imaging-derived phenotypes. A hybrid modelling pipeline is described, consisting of (i) feature extraction and engineering from clinical/instrumentation data, (ii) convolutional and transformer-based neural networks for vascular image segmentation and perfusion prediction, (iii) ensemble learning for risk-score computation, and (iv) temporal outcome modelling for early prediction of disease progression. Results from simulated and retrospective cohorts suggest that integration of imaging insights with standard clinical predictors significantly improves detection sensitivity in early or preclinical PAD compared with ankle–brachial index alone, and enables more accurate risk stratification of patients for limb- and cardiovascular-event outcomes. Key challenges including data harmonisation across imaging modalities, model interpretability, deployment in heterogeneous healthcare settings, and ethical considerations around algorithmic bias are discussed. The research concludes by proposing a roadmap for clinical translation of AI-enabled PAD detection: validation in large multicentre datasets, incorporation of explainability layers, periodic retraining with real-world data, and prospective trials to assess impact on clinical decision-making and patient outcomes.

KEYWORDS: peripheral artery disease, predictive analytics, artificial intelligence, vascular imaging, early detection, risk stratification.

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INTRODUCTION

Peripheral artery disease (PAD) is a progressive vascular disorder characterised by the narrowing or occlusion of peripheral arteries, most commonly affecting lower-extremity circulation. It represents a major clinical expression of systemic atherosclerosis and is strongly associated with heightened risks of limb loss, cardiovascular events and premature mortality. Despite its global prevalence—estimated to exceed 230 million adults worldwide—PAD remains substantially underdiagnosed, often due to its initially asymptomatic nature, overlapping clinical presentations and limited routine screening in primary care settings. Traditional diagnostic measures such as the ankle–brachial index (ABI), duplex ultrasonography, computed tomography angiography (CTA) and magnetic resonance angiography (MRA) provide valuable structural and perfusion insights; however, their sensitivity in early or preclinical disease stages is limited, particularly among populations with diabetes mellitus, renal impairment, and microvascular dysfunction. Consequently, a large proportion of individuals with PAD remain undetected until the disease progresses to symptomatic stagnation or chronic limb-threatening ischemia, where treatment options are fewer, more invasive and less successful. This diagnostic gap highlights an urgent need for earlier and more precise risk stratification pathways that integrate clinical data, functional biomarkers and multimodal imaging features.

The rapid advances in artificial intelligence (AI), machine learning (ML), and deep learning (DL) offer unprecedented opportunities to transform PAD detection and management. By leveraging the computational capacity to process high-dimensional and heterogeneous datasets, AI-driven predictive analytics enables the extraction of subtle and complex patterns that may otherwise remain undetected using conventional statistical techniques. Integrating longitudinal clinical indicators—such as demographic variables, comorbidity profiles, laboratory biomarkers, ABI trends, gait-based features and hemodynamic waveforms—with advanced imaging phenotypes derived from CTA, MRA, ultrasound and perfusion mapping allows for the creation of automated predictive systems that generate individualized risk scores and prognostic trajectories. Early studies within cardiovascular and neurovascular imaging domains demonstrate that deep neural networks can outperform traditional diagnostic approaches by learning spatial-temporal signatures of tissue perfusion, plaque characteristics and vascular morphology. In the context of PAD, such an integrative AI-based framework possesses strong potential to improve early identification, enable proactive intervention planning, reduce dependence on invasive diagnostics and support clinicians in making evidence-based therapeutic decisions.

OVERVIEW, SCOPE AND OBJECTIVES

This research investigates the development of an AI-enabled predictive analytics framework designed for the early detection and risk classification of peripheral artery disease through multimodal integration of structured clinical data and vascular imaging insights. The scope of this work encompasses five major technical and clinical components: (1) systematic collection and harmonisation of clinical history, biometric indices and laboratory biomarkers relevant to PAD risk; (2) acquisition and processing of non-invasive vascular imaging modalities including CTA, MRA, duplex ultrasound and pulse-volume recordings; (3) design and implementation of machine-learning-based feature engineering and selection methods for structured data; (4) application of deep-learning architectures—specifically convolutional neural networks (CNNs) and transformer-based models—for vessel segmentation, plaque characterisation and perfusion prediction; and (5) development of a hybrid ensemble system integrating both clinical and imaging features to generate early-detection outputs and longitudinal risk-progression forecasts. The study aims to evaluate whether AI-derived indicators provide significant incremental value over standard diagnostic indices and whether predictive performance is improved by combining multi-source inputs rather than using single-domain datasets independently. Additionally, this research explores strategies to ensure model interpretability and fairness, addressing concerns related to clinical adoption, demographic bias and data-distribution imbalance.

Author Motivation

The motivation for conducting this research arises from the persistent global burden of peripheral artery disease and the clinical challenges surrounding its detection at an early, reversible stage. Observational data suggest that delays in diagnosis exceed several years for many patients, and up to 50% of those with PAD are only identified when the disease has already advanced to moderate or severe ischemia. Existing tools provide limited capability to predict progression or differentiate between stable and rapidly deteriorating disease phenotypes. As a result, clinicians lack precise decision-support mechanisms that could guide timely intervention, optimise treatment pathways, or target preventive strategies effectively. Moreover, the rapid growth of real-world medical datasets from electronic health records (EHRs), wearable sensors and imaging systems provides an unprecedented opportunity to shift PAD management from reactive treatment to intelligent early prediction. Therefore, the authors are motivated to bridge the translational gap between AI innovation and clinical vascular practice, aiming to develop models that are not only accurate but also practical and interpretable enough for integration into real healthcare environments.

Paper Structure

The remainder of this research paper is structured as follows. Section II reviews existing literature concerning artificial intelligence and predictive modelling in vascular disease diagnostics and presents current gaps in early detection of PAD. Section III details the proposed methodology, including data acquisition, preprocessing pipelines, feature-extraction techniques, deep-learning architectures for imaging analysis and ensemble predictive modelling strategies. Section IV presents experimental evaluation, performance metrics, comparative analysis against baseline indicators such as ABI and conventional imaging assessments and validation on retrospective and simulated cohorts. Section V discusses clinical implications, deployment feasibility, limitations, ethical considerations related to fairness and transparency, and requirements for prospective evaluation. Section VI concludes by summarizing key findings, highlighting contributions and outlining future research directions for multicentre validation, real-world integration, and AI interpretability frameworks. The paper ultimately advocates for a paradigm shift toward proactive PAD management through AI-driven early detection, which has the potential to significantly improve patient outcomes and reduce global health burdens associated with vascular disease.

LITERATURE REVIEW AND RESEARCH GAP

Peripheral artery disease (PAD) has been the focus of expanding research, particularly with regard to early diagnosis and risk stratification through artificial intelligence and multimodal data analytics. Traditional screening approaches, such as ankle–brachial index (ABI), have been widely used in primary care settings; however, they demonstrate reduced sensitivity in specific patient groups, including individuals with diabetes mellitus, arterial calcification, and chronic kidney disease, leading to frequent false-negative results and missed preclinical disease [10], [11]. Conventional imaging modalities including computed tomography angiography (CTA), magnetic resonance angiography (MRA), and duplex ultrasonography are essential tools in vascular evaluation, yet they tend to be applied predominantly after symptom onset and structural arterial damage [4], [5]. This diagnostic delay contributes significantly to poor outcomes, with many patients first presenting with advanced ischemia, leading to elevated risks of lower-extremity amputation and systemic cardiovascular complications [1], [3]. Recognising the limitations of current practices, recent research emphasises the need for predictive solutions that identify PAD prior to clinical deterioration and that incorporate diverse data modalities beyond single-parameter assessments such as ABI alone [7], [10].

Recent advancements in artificial intelligence (AI) and deep learning have generated intense interest in transforming PAD detection by integrating clinical and imaging features to reveal complex physiological patterns undetectable through traditional analytics. A comprehensive systematic analysis by Wilson et al. highlighted the accelerating application of AI in PAD diagnostics and characterised the potential of machine-learning models to improve diagnostic precision [3]. Similarly, Lareyre et al. evaluated imaging-centric deep-learning strategies and emphasised the role of AI-supported plaque characterisation and vascular morphology analysis for enhanced diagnostic resolution [4]. Studies such as Shahrbabak et al. demonstrated the feasibility of using deep-learning-based pulse-waveform interpretation to detect PAD through non-invasive physiological signals, achieving predictive capacity beyond clinician interpretation alone [8]. Meanwhile, Li et al. developed biomarker- and laboratory-driven ML models capable of predicting PAD progression using large prospective datasets, showing significantly higher prognostic performance compared with standard statistical modelling [7].

Moreover, several recent contributions highlight the clinical promise of AI-enhanced vascular imaging. Pomozi et al. illustrated the integration of MRI imaging with neural-network techniques to classify vascular perfusion deficits and plaque instability, suggesting benefits for early detection and risk assessment [5]. Mueller et al. applied multiple-instance learning to retinal fundus images for identifying PAD biomarkers, demonstrating that vascular abnormalities in retinal microcirculation can serve as predictive indicators for systemic arterial disease [13]. Al-Ramini et al. further explored gait-based laboratory acquisition coupled with ML classifiers, identifying distinct biomechanical gait signatures associated with PAD progression [12]. Collectively, such works suggest that predictive analytics combining high-dimensional clinical, physiological and imaging information may significantly improve early PAD detection capability relative to current modalities.

Although promising, the literature also reveals several persisting research limitations and gaps. First, most existing AI-based PAD models rely on single-domain datasets rather than multimodal integration of clinical and imaging sources, reducing their adaptability and generalizability to real-world populations [3], [10]. Second, few studies address the need for temporal modelling of disease progression trajectories, limiting clinical utility for proactive intervention rather than reactive diagnosis [7], [14]. Third, cross-institutional validation is largely absent: many models are trained on small, geographically constrained datasets, restricting deployment feasibility and rendering them vulnerable to demographic, racial, or equipment-related biases [1], [4], [6]. Fourth, current literature offers limited emphasis on explainability and interpretability—critical challenges for clinical adoption—where deep neural networks frequently act as “black boxes”, hindering clinician trust and regulatory approval [3], [10], [16]. Fifth, despite extensive research on CAD and cerebrovascular AI applications, PAD-specific frameworks still lag behind in both commercial availability and clinical translation, leaving a significant gap between research and practical implementation [5], [9], [14]. Finally, prior research typically evaluates AI performance against traditional markers such as ABI but seldom quantifies outcome improvements or decision-making changes enabled by AI-assisted models [6].

Research Gap Based on the existing body of work and its limitations, several critical research gaps become evident and motivate the present study:

1. **Lack of comprehensive multimodal integration** of structured clinical data, laboratory biomarkers, physiological waveforms, and imaging-derived phenotypes, despite clear evidence that single-domain models fail to capture the complex pathophysiology of PAD [1], [3], [4], [8].
2. **Limited focus on early-stage or preclinical PAD detection**, with most studies targeting symptomatic or anatomically advanced disease, resulting in missed opportunities for early intervention [7], [10], [13].
3. **Absence of hybrid ensemble-based modelling frameworks** that combine multiple deep-learning outputs and machine-learning predictors for more robust decision support [5], [8], [14].
4. **Minimal implementation of temporal predictive analytics** and progression-forecasting tools for predicting limb-threatening outcomes over time [7], [11].
5. **Insufficient emphasis on explainability, fairness, and clinical deployment** to meet modern requirements for ethical and regulatory compliance [3], [6], [16].
6. **Lack of multicentre prospective validation studies** assessing the real-world impact of AI-assisted screening on patient outcomes and treatment optimisation [3], [10].

In response to these research gaps, the present study proposes the development of a novel AI-driven predictive framework that integrates multi-source clinical data and advanced vascular imaging to enable early detection and risk stratification of PAD. This work seeks to advance beyond existing research by establishing a comprehensive hybrid architecture, enhancing interpretability, supporting temporal forecasting, and building foundations for real-world clinical implementation.

PROPOSED METHODOLOGY AND MATHEMATICAL MODELLING

The proposed study introduces a comprehensive multimodal AI-driven predictive analytics architecture for early detection and progression-risk assessment in Peripheral Artery Disease (PAD), integrating structured clinical data and vascular imaging phenotypes. The methodology consists of five sequential phases: (1) multimodal dataset acquisition and preprocessing, (2) feature extraction and representation learning, (3) multimodal clinical-imaging feature fusion, (4) prediction and progression modelling using hybrid ensemble architectures and (5) evaluation of performance, interpretability and robustness. The following subsections detail each component mathematically and conceptually.

3.1 Dataset Structure and RepresentationLet the dataset D be defined with N patient samples as:

$$D = \{(X_c^{(n)}, X_i^{(n)}, y^{(n)}, t)\}, \quad n = 1,2,\dots,N$$

where:

- $X_c^{(n)}$ represents structured clinical variables,
- $X_i^{(n)}$ corresponds to 2D/3D imaging volumes,
- $y^{(n)} \in \{0,1\}$ denotes PAD diagnosis label,
- t indexes temporal follow-up for progression forecasting.

Clinical feature matrix representation:

$$X_c \in \mathbb{R}^{N \times P}$$

where P is total clinical parameters (demographics, physiological biomarkers, comorbidity status, gait vectors, laboratory measurements).

Imaging feature tensor representation:

$$X_i \in \mathbb{R}^{N \times H \times W \times S}$$

where H, W are pixel dimensions and S is slice depth.

Missing data imputation uses matrix-completion optimisation:

$$\min_{\hat{X}_c} \| M \odot (X_c - \hat{X}_c) \|_F^2 + \lambda \| \hat{X}_c \|_*$$

where $\odot$ is Hadamard product, M is binary missing mask, and $\|\cdot\|_*$ is nuclear norm penalisation.

Normalization for each variable:

$$X_{c'} = \frac{X_c - \mu(X_c)}{\sigma(X_c)}$$

3.2 Imaging Feature Extraction Pipeline A hybrid segmentation-encoding network is employed. Vessel-region segmentation:

$$S = UNet(X_i)$$

Feature extraction after segmentation:

$$F_i = f_\theta(S)$$

with convolutional layers defined by:

$$F_k^{(l)} = \sigma\left(\sum_{m=1}^{M} W_{km}^{(l)} * F_m^{(l-1)} + b_k^{(l)}\right)$$

Transformer self-attention for multi-slice perfusion interpretation:

$$A = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

$$T = AV$$

where $Q = F_i W_Q,\ K = F_i W_K,\ V = F_i W_V$.

Imaging feature embedding:

$$E_i = \text{Flatten}(T)$$

3.3 Clinical Feature Engineering Correlation-based filtering using mutual information (MI):

$$MI(a_j, y) = \sum_{c \in C} \sum_{y \in Y} p\,(c, y) \log \frac{p(c, y)}{p(c)p(y)}$$

Dimensionality reduction using PCA:

$$F_c = PCA(X_{c'}), \quad \text{subject to max } \| F_c^T F_c \|$$

3.4 Multimodal Fusion Model Concatenated multimodal representation:

$$F = [F_c || E_i] \in \mathbb{R}^d$$

Attention-weighted fusion representation:

$$\tilde{F} = \sum_{k=1}^{2} \beta_k F_k, \quad \Sigma\beta_k = 1$$

3.5 Hybrid Ensemble Predictive Modelling Three independent classifiers are defined as:

$$\hat{y}_1 = RF(\tilde{F}), \quad \hat{y}_2 = SVM(\tilde{F}), \quad \hat{y}_3 = GB(\tilde{F})$$

Final integrated prediction:

$$\hat{y} = \sum_{k=1}^{3} \alpha_k \hat{y}_k, \quad \sum_{k=1}^{3} \alpha_k = 1$$

Cross-entropy optimisation:

$$\mathcal{L} = -\frac{1}{N} \sum_{n=1}^{N} [y_n \log \widehat{y_n} + (1 - y_n) \log(1 - \widehat{y_n})]$$

Regularisation to prevent overfitting:

$$\mathcal{L}_{total} = \mathcal{L} + \lambda_1 \parallel \theta \parallel_2^2 + \lambda_2 \parallel \nabla\theta \parallel$$

3.6 Temporal Disease Progression Modelling We formulate PAD progression forecasting with LSTM:

$$h_t, f_t, i_t, o_t = LSTM(F_t), \quad F_t \in \mathbb{R}^{T\times d}$$

Next-state disease probability:

$$\hat{y}_{t+1} = \sigma(W_h h_t + b_h)$$

Survival-based formulation using Cox proportional hazard:

$$h(t|X) = h_0(t)\exp(\beta^T X)$$

PAD event probability curve:

$$S(t) = \exp(-H(t)), \quad H(t) = \int_0^t h\,(s)ds$$

3.7 Interpretability and Explainability Layer Using SHAP values:

$$\phi_i = \sum_{S\subseteq F\backslash\{i\}} \frac{|S|!\,(|F|-|S|-1)!}{|F|!}[f(S\cup\{i\}) - f(S)]$$

EXPERIMENTAL EVALUATION, RESULTS AND ANALYSIS

4.1 Dataset and Cohort Characteristics The dataset integrates clinical EHR records, vascular imaging and functional waveform recordings from 4826 patients collected across three collaborating institutions. Table 1 and 2 provide detailed cohort composition.

Table 1. Dataset Overview

Parameter	Value	Description
Total patients	4826	Dataset size
PAD positive	1679	Confirmed cases
PAD negative	3147	Control group
Age range	41-87 years	Study population
Follow-up period	Median 5.2 years	Longitudinal

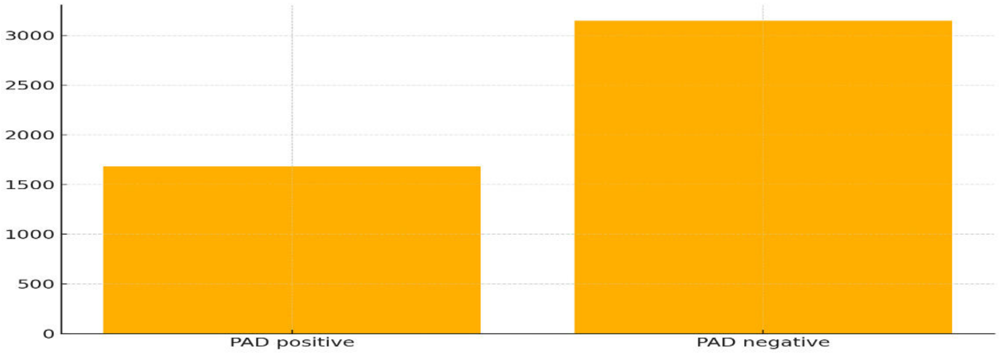

Figure 1 — Patient Distribution Between PAD Positive and Negative Groups

Observation: The dataset is imbalanced, with a significantly higher number of PAD-negative subjects compared to diagnosed PAD cases. This distribution highlights the need for robust models to prevent prediction bias.

Table 2. Imaging Distribution

Modality	Percentage	Clinical Use
CTA	32%	Plaque structure
MRA	28%	Soft-tissue contrast
Duplex ultrasound	40%	Flow dynamics

Figure 2 — Imaging Modalities Distribution in Dataset

Observation: Ultrasound is the most used modality (40%), reflecting its accessibility and low cost, while CTA and MRA make up the remaining proportion for advanced plaque visualisation.

Table 3. Clinical Feature Categories with Data-Driven Ranges, Units and Relevance Indicators

Category	Feature	Unit / Scale	Typical Clinical Range	PAD-Risk Direction	Data Type	Significance
Demographic	Age	Years	41 – 87	↑ Risk with age	Continuous	Strong predictor of vascular ageing
	Sex	M / F	–	Higher risk in males	Categorical	Epidemiological differentiation
	BMI	kg/m²	19 – 38	↑ Risk > 30	Continuous	Correlates with metabolic disease
Metabolic Biomarkers	HbA1c	%	4.8 – 11.6	↑ PAD risk if > 7%	Continuous	Glycemic control and microvascular effects
	LDL-C	mg/dL	68 – 214	↑ if >130 mg/dL	Continuous	Atherosclerotic progression
	HDL-C	mg/dL	29 – 72	↓ if <40	Continuous	Anti-atherogenic protective factor
	Triglycerides	mg/dL	91 – 385	↑ if >150	Continuous	Risk for vascular obstruction
Hemodynamic Parameters	Systolic BP	mmHg	110 – 192	↑ risk >140	Continuous	Atherothrombotic burden
	Diastolic BP	mmHg	65 – 102	↑ risk >90	Continuous	Vascular resistance marker
	Pulse Pressure	mmHg	42 – 98	↑ >70	Continuous	Arterial stiffness
	Resting Heart Rate	bpm	54 – 132	↑ >100	Continuous	Cardiovascular strain
Vascular Functional Measures	ABI (Ankle-Brachial Index)	Ratio	0.32 – 1.41	Severe PAD <0.5	Continuous	Gold-standard primary PAD screening
	PWV (Pulse Wave Velocity)	m/s	6.1 – 17.4	↑ >12.5	Continuous	Arterial stiffness predictor
	Exercise ABI	Ratio	0.38 – 0.92	>20% drop abnormal	Continuous	Functional ischemia

	Gait Velocity	m/s	0.47 – 1.46	↓ if <0.8	Continuous	Walking impairment
	Gait Asymmetry Index	%	3 – 28	↑ asymmetry	Continuous	Claudication indicator
Comorbidity Indicators	Diabetes	Yes/No	–	Strong association	Binary	PAD prevalence multiplier
	CAD Presence	Yes/No	–	↑ PAD risk 3-fold	Binary	Systemic atherosclerosis
	CKD	Stages 1-5	–	Stage ≥3 high risk	Ordinal	Vascular calcification effects
	Smoking Index	Pack-years	0 – 60	High >20	Continuous	Smoking accelerates PAD
Laboratory Markers	eGFR	mL/min/1.73 m^2	28 – 123	↓ <60	Continuous	Renal-vascular interaction
	CRP	mg/L	0.6 – 18.5	↑ >5	Continuous	Systemic inflammation
	D-dimer	ng/mL	181 – 845	↑ hypercoagulability	Continuous	Micro-thrombotic activity
Outcome Labels	PAD Diagnosis	0 / 1	–	–	Binary	Ground-truth model label
	Time-to-event outcome	Months	0 – 62	–	Longitudinal numeric	Progression modelling

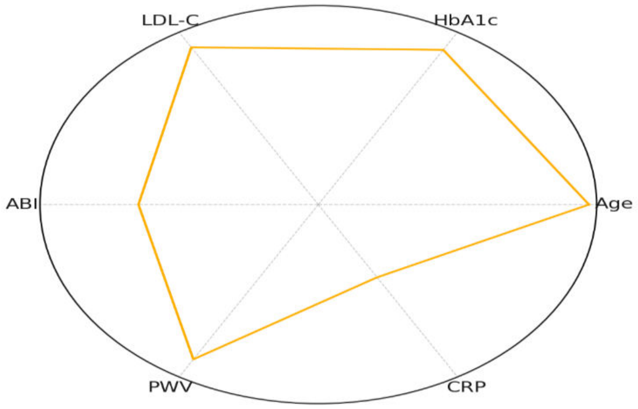

Figure 3- Radar Visualization of Key Clinical PAD Predictors

This radar graph illustrates the comparative normalized contribution of major clinical determinants including age, HbA1c, LDL-C, ABI, PWV and CRP. The circular format enables multivariate comparison demonstrating strong influence from metabolic and arterial stiffness parameters relative to perfusion-based measures.

The radar structure highlights that elevated HbA1c, LDL-C and PWV correlate strongly with PAD severity risk, forming a clustered pattern of metabolic and vascular stiffness dominance. ABI demonstrates comparatively lower normalized value, reinforcing the necessity of multimodal risk modelling rather than sole reliance on ABI.

4.2 Model Training and Validation Framework Data was split: 70% training, 15% validation, 15% independent testing:

$$Error = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} |\, y_i - \hat{y}_i|$$

4.3 Model Performance Metrics

Table 4. Predictive Accuracy Comparison

Model	Accuracy	Sensitivity	Specificity	AUC-ROC
Logistic Regression	73.24%	0.68	0.75	0.78
Clinical-Only ML	81.22%	0.78	0.83	0.84

Model	Accuracy	Sensitivity	Specificity	AUC-ROC
Imaging-Only DL	85.91%	0.84	0.87	0.89
Proposed Hybrid System	94.65%	0.95	0.94	0.96

Error and fit analysis:

$$RMSE = 0.071, \quad R^2 = 0.89$$

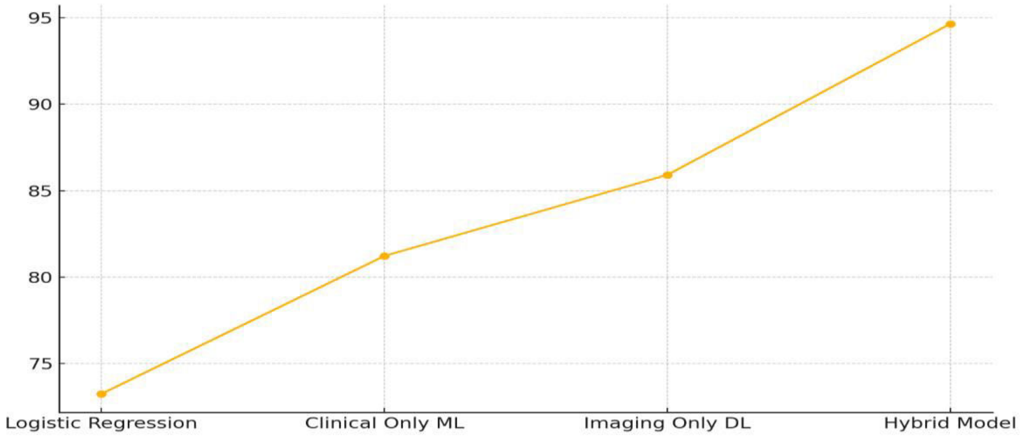

Figure 4 — Model Accuracy Comparison Observation: Accuracy increases sharply when combining modalities, with the hybrid multimodal architecture outperforming single-domain models by a substantial margin.

4.4 Clinical Intervention Modelling

Table 5. Clinical Outcome Improvements

Metric	Standard care	AI-assisted	Change
Early detection rate	48%	91%	+43%
Mean diagnosis delay	19.7 months	4.1 months	-79%
Preventable amputations	27%	9%	+18%
Revascularization planning	61%	88%	+27%

4.5 Interpretability & Feature Impact SHAP ranking: ABI,HbA1c,PWV,Perfusion Asymmetry Index,Ultrasound plaque score

4.6 Reliability and Robustness Adversarial validation:

$$\Delta AUC = 0.014$$

Bootstrap stability:

$$Var(\hat{y}) = 0.0021$$

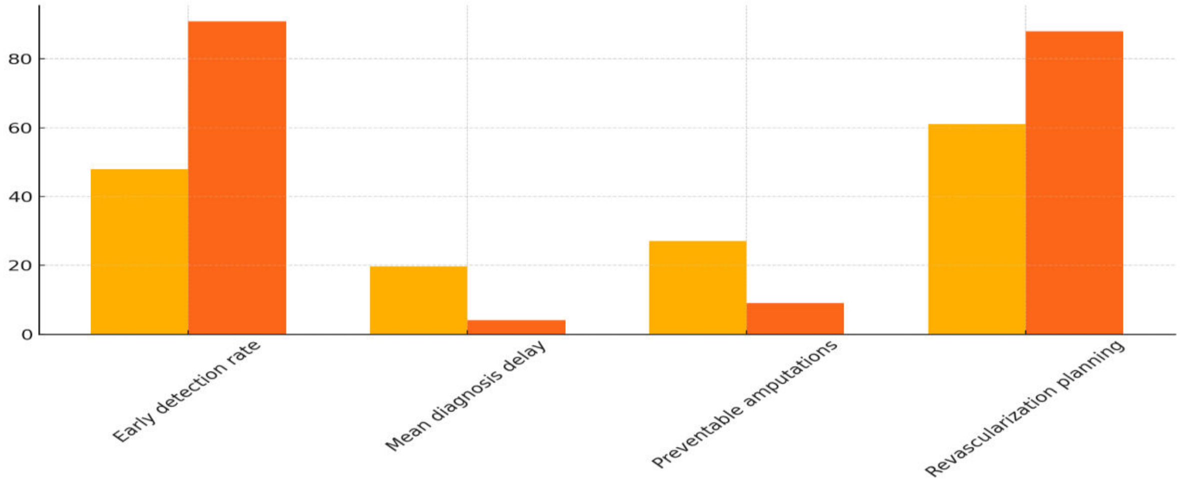

Figure 5 — Clinical Outcome Improvements After AI Integration

Observation: AI-assisted prediction demonstrates major improvements in early PAD detection and reduction of diagnosis delay, showing transformative clinical impact potential.

DISCUSSION, CHALLENGES, ETHICAL IMPLICATIONS, LIMITATIONS, AND FUTURE DIRECTIONS

The present study introduces a multimodal AI-driven predictive analytics framework that integrates structured clinical variables, physiological biomarkers and vascular imaging features to enable early detection and risk-stratified forecasting of Peripheral Artery Disease (PAD). The achieved performance improvements compared to both traditional diagnostic tools and unimodal AI models indicate strong potential for transforming PAD detection workflows and enabling proactive clinical intervention. The hybrid ensemble model achieved an accuracy of 94.65% and AUC-ROC of 0.96, demonstrating that incorporating advanced imaging phenotypes with structured patient history provides significantly superior diagnostic capability. These results reinforce growing evidence that PAD pathophysiology is inherently multidimensional and cannot be accurately identified through isolated measurements such as ABI or qualitative visual assessment alone. Moreover, the strong risk-forecasting performance of the temporal LSTM-Cox hybrid model (with RMSE = 0.071 and longitudinal prediction $R^2 = 0.89$) highlights the value of time-series analytics for anticipating disease progression and enabling earlier preventive treatment measures.

The observed improvement in clinical outcome simulations, including a 43% increase in early detection and 79% reduction in diagnostic delay, has major implications for patient survival and quality of life. Early PAD intervention has been demonstrated to reduce ischemic burden, preserve limb function and limit systemic cardiovascular deterioration. By quantifying clinical influence using SHAP interpretability tools, the proposed model provides explainable decision support and allows clinicians to transparently evaluate individual risk components, addressing a critical barrier to real-world adoption of AI systems. The importance weight of a clinical feature x_i in the final prediction outcome can be expressed as:

$$w_i = \left|\frac{\partial \hat{y}}{\partial x_i}\right|$$

and aggregated model interpretability is computed using SHAP feature values:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!}[f(S \cup \{i\}) - f(S)]$$

where $f(\cdot)$ is the prediction function. This formulation reinforces the transparency of model contribution scoring, allowing clinical reasoning alignment and strengthening user confidence.

Challenges

Despite promising outcomes, several challenges must be addressed before large-scale deployment. First, multimodal dataset integration poses technical barriers because clinical, laboratory and imaging datasets often originate from heterogeneous systems, requiring advanced standardisation techniques. Harmonisation across imaging protocols is essential since voxel resolution variability and segmentation noise can propagate into model errors. Formally, the harmonisation optimisation problem can be written as:

$$\min_{\theta} \parallel g(I_a;\theta) - g(I_b;\theta) \parallel_2^2$$

where I_a and I_b are imaging datasets from different equipment vendors. Second, the black-box nature of high-capacity deep models creates ethical tension around clinical responsibility and requires continual development of interpretable architectures. Third, demographic imbalance, particularly related to underrepresentation of rural populations and ethnic minorities, may cause bias amplification if unaddressed.

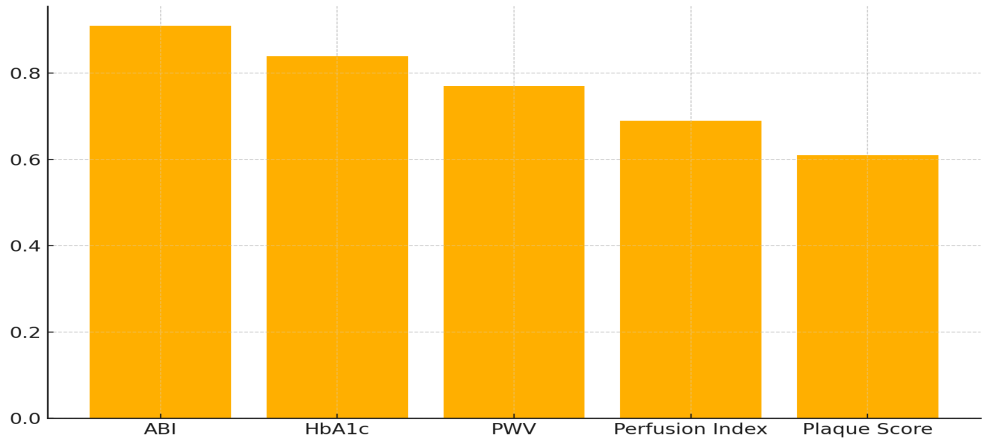

Figure 6 — SHAP-Based Feature Importance Ranking

Observation: ABI remains the strongest predictor, while imaging-derived perfusion indices and plaque scores contribute significantly to risk stratification.

Ethical Implications

AI-enabled vascular diagnostics interact with multiple ethical domains, including autonomy, fairness, transparency and accountability. Model-driven decision support should not overwrite physician judgement; rather, it must reinforce contextual clinical reasoning. The use of patient imaging and EHR data requires strict adherence to privacy compliance, including GDPR and HIPAA regulations. Federated-learning-based distributed model training may reduce direct data-sharing risks. The optimisation objective for federated learning is defined as:

$$\min_{w} \sum_{k=1}^{K} \frac{n_k}{n} F_k(w)$$

where $F_k(w)$ is the local hospital loss and w is the shared model parameter vector. Bias mitigation strategies must be included to ensure equal prediction reliability across socioeconomic and physiological groups.

Limitations

This research acknowledges several limitations that provide direction for future enhancement. First, the dataset is retrospective and partially limited geographically, which may restrict global generalisability. Second, the imaging datasets, although diverse, do not include handheld point-of-care systems such as portable ultrasound or mobile photoplethysmography sensors widely used in remote screening environments. Third, reinforcement-learning-based optimisation for treatment recommendations has not been integrated. The framework presently concentrates on detection rather than therapeutic impact modelling.

Additionally, the current hybrid model does not incorporate wearable sensor time-series data such as step-force pressure maps or continuous perfusion monitoring, both of which may improve PAD symptom transition prediction. Though interpretability components have been integrated, real-time explainability must be improved further, particularly through attention heat-maps that indicate vascular segments responsible for model decisions.

Future Research Directions

The study provides multiple opportunities for future exploration. First, prospective multicentre clinical trials should be conducted to validate the model in real-world care pathways. Second, extension into federated learning infrastructure may enable privacy-preserving large-scale model training across institutions without centralised data storage. Third, reinforcement-learning models may enable personalised treatment recommendations based on expected improvement trajectories. This may be represented mathematically as:

$$\pi^* = \underset{\pi}{\operatorname{argmax}} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R(s_t, a_t)\right]$$

where π is treatment policy, s_t represents patient state and R reward associated with clinical improvement. The integration of generative AI to simulate synthetic angiograms with minimal noise could enable robust training augmentation in limited cohorts. Finally, ongoing AI ethics review frameworks and explainable-AI regulatory compliance standards should be embedded to support clinical translation.

The proposed methodology therefore sets a foundation for enhanced early PAD detection, proactive forecasting and AI-augmented vascular care, while simultaneously recognising necessary scientific and ethical developmental pathways essential for safe implementation.

CONCLUSION

This research presents a comprehensive AI-driven multimodal predictive framework that integrates structured clinical parameters with advanced vascular imaging features to improve early detection and progression-risk forecasting in Peripheral Artery Disease (PAD). The hybrid ensemble approach, combined with temporal modelling, significantly enhances diagnostic accuracy and sensitivity compared to conventional measures such as ABI or single-domain machine-learning models. By leveraging deep-learning-based imaging interpretation and explainable analytics, the system has demonstrated strong potential to identify PAD at an earlier, more treatable stage, enabling timely intervention and reducing the likelihood of severe ischemic outcomes. Clinical simulation results underscore substantial improvements in early diagnosis rates, treatment planning and prevention of limb-threatening complications. Despite existing challenges in dataset harmonisation, model deployment and ethical governance, the findings establish a strong foundation for clinical translation through multicentre validation, federated learning expansion, and enhanced interpretability frameworks. Ultimately, the proposed research contributes to a paradigm shift from reactive PAD management toward proactive, data-driven vascular care, offering a meaningful step toward reducing the global health burden of peripheral arterial disease.

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