Predictive Spatio-Temporal Analytics for Early Detection of Lower Limb Ischemia Using Multi-Modal Clinical Data

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ABSTRACT

Lower limb ischemia remains one of the most dangerous vascular conditions due to its rapid progression and the narrow time window for clinical intervention. Traditional diagnostic pathways rely heavily on clinician judgment, intermittent imaging, and episodic physiological measurements, which often fail to capture the dynamic onset of ischemic deterioration. This study introduces a predictive spatio-temporal analytics framework that integrates multi-modal clinical data, including Doppler waveforms, perfusion indices, thermographic patterns, gait-cycle temporal signals, and vascular laboratory markers. Using a hybrid deep learning architecture combining convolutional feature extraction, temporal encoding, and probabilistic risk modelling, the system predicts ischemic onset up to 48 hours earlier than standard clinical assessment. Spatial tissue signatures extracted from thermography and duplex ultrasound were fused with sequential hemodynamic measurements using an attention-based encoder, enabling robust early-stage detection even in irregular, noisy clinical environments. Model interpretability methods were incorporated to ensure transparent decision reasoning, highlighting anatomical regions and temporal segments contributing to high-risk predictions. Results demonstrate substantial improvements in sensitivity, reduced false negatives, and enhanced early risk stratification for patients with peripheral arterial disease. The findings underscore the potential of spatio-temporal clinical analytics to transform ischemia screening, triage, and intervention planning in vascular care settings.

KEYWORDS: lower limb ischemia, spatio-temporal analytics, deep learning, perfusion imaging, Doppler waveform analysis, multi-modal fusion, early ischemia detection, vascular diagnostics.

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INTRODUCTION

Lower limb ischemia represents a critical vascular threat driven by impaired arterial perfusion that progressively compromises muscle viability, sensory function, and limb integrity. The condition can escalate rapidly from mild perfusion deficits to irreversible tissue necrosis within hours, demanding early and precise clinical recognition. Conventional diagnostic pathways rely primarily on ankle–brachial index (ABI), duplex ultrasonography, angiographic visualization, and clinician interpretation of symptoms such as pain, pallor, pulselessness, and paresthesia. While these approaches remain central to vascular medicine, they often function as static assessments rather than dynamic monitoring tools. Since ischemic progression is inherently time-dependent and spatially heterogeneous across the limb, episodic measurements fail to capture fine-grained physiological changes that precede critical deterioration. This diagnostic gap has led to delays in intervention, higher amputation rates, and increased morbidity among high-risk populations including diabetics, elderly patients, and individuals with chronic peripheral arterial disease. Recent advances in biomedical sensing, perfusion imaging, and machine learning provide a transformative opportunity to reframe ischemia assessment as a continuous, data-driven process rather than an episodic clinical event. By leveraging multi-modal clinical signals and analysing their spatial and temporal evolution, ischemia risk can be detected earlier, more accurately, and with greater clinical confidence.

Predictive spatio-temporal analytics creates a pathway to quantify perfusion deficits long before they manifest in overt clinical symptoms. Modern vascular diagnostics now generate diverse forms of data: duplex ultrasound waveforms depicting flow acceleration and turbulence patterns, infrared thermograms representing tissue-level temperature variation, time-series hemodynamic data capturing systolic–diastolic fluctuations, and gait-cycle biomarkers linked to compensatory muscular adaptations. Integrating these heterogeneous signals into a single predictive model requires sophisticated computational architectures capable of learning spatial patterns, temporal dependencies, and “physiological interactions. Deep learning frameworks incorporating convolutional neural networks (CNNs), long short-term memory units (LSTMs)”, temporal transformers, and feature fusion strategies are particularly suited for this task. These architectures can uncover latent ischemic signatures that clinicians cannot visually detect, such as micro-patterns of flow instability, subtle thermal asymmetry, and early gait compensation. However, deploying such systems in clinical settings necessitates strict adherence to interpretability, transparency, and medical accountability. Predictive models must not only flag future ischemic events but also provide clinicians with anatomically and temporally meaningful explanations. This research develops a structured, multi-modal, spatio-temporal predictive framework designed for real-world vascular diagnostics. It integrates imaging, physiological signals, and sequential measurements into a unified risk model capable of forecasting ischemia onset and progression with high sensitivity. By extending traditional vascular assessment with computational intelligence, this study demonstrates how predictive analytics can significantly improve clinical triage, intervention timing, and patient outcomes in the management of lower limb ischemia.

RELATED WORKS

Early approaches to lower limb ischemia diagnosis primarily focused on physiological markers such as ABI, segmental pressures, and Doppler waveform morphology. While effective for baseline screening, these methods lack the granular spatio-temporal resolution required for early-stage ischemia prediction. Recent research has progressed towards more advanced waveform analytics, where spectral indices and flow acceleration patterns have been used to quantify early perfusion decline [1]. Studies incorporating near-infrared spectroscopy (NIRS) demonstrated the utility of continuous tissue oxygenation monitoring for early ischemia detection, showing strong correlations between perfusion deficits and muscle oxygenation kinetics [2]. Machine learning models, including random forests and logistic regression classifiers, have been applied to hemodynamic datasets to identify ischemia risk factors, yet their predictive accuracy remains limited due to the absence of multi-modal integration [3]. Thermal imaging research further reveals temperature asymmetry patterns associated with impaired microvascular perfusion, supporting the feasibility of infrared thermography as a non-invasive ischemia detection tool [4]. Collectively, these findings highlight the need for integrated systems capable of analysing complex, heterogeneous vascular signals.

Deep learning has increasingly shaped modern ischemia research due to its ability to extract latent spatial and temporal features from high-dimensional clinical data. Convolutional networks have been widely adopted for analyzing duplex ultrasound images, enabling automated detection of arterial stenosis, plaque formation, and flow-turbulence patterns with high precision [5]. Temporal models such as LSTMs and gated recurrent units (GRUs) have been used to model sequential hemodynamic behavior, outperforming traditional time-series methods for identifying perfusion instability [6]. Spatio-temporal fusion models have also been developed for diabetic foot ischemia prediction, integrating thermal maps with plantar pressure distributions and achieving strong early-detection performance [7]. Transformer-based architectures have recently emerged as powerful sequence encoders capable of capturing long-range temporal dependencies in vascular data, particularly when predicting progressive ischemic decline [8]. Despite these advances, most existing studies rely on a single modality of data, limiting their generalizability and real-world clinical applicability.

Multi-modal integration represents the next frontier in ischemia prediction research. Several works have attempted to fuse thermal imaging with Doppler signals, demonstrating improved classification performance over single-modality systems [9]. Others have combined gait analysis with perfusion metrics to identify compensatory biomechanical adaptations indicative of early ischemia progression [10]. Bayesian fusion frameworks have shown promise in combining probabilistic risk indicators derived from disparate vascular measurements, providing more robust ischemia risk stratification [11]. However, gaps remain in developing models that explicitly incorporate both spatial tissue signatures and temporal hemodynamic patterns within a unified predictive architecture. Moreover, limited attention has been given to model interpretability, which is crucial for clinical adoption. Studies on explainable AI in medical imaging emphasize the need for heatmaps, feature attribution maps, and interpretable risk curves that give clinicians insight into both anatomical and temporal factors contributing to ischemia predictions [12]. Several recent papers highlight the importance of early-detection models capable of forecasting ischemic risk 24 to 48 hours before clinical manifestation, with deep ensemble systems showing strong potential in this regard [13]. Research in vascular informatics also underscores the importance of incorporating multi-modal data from wearables, bedside monitors, and lab tests to improve ischemia prognosis and triage efficiency [14]. Despite these advances, the literature lacks a robust, clinically interpretable, spatio-temporal predictive model using a comprehensive suite of multi-modal vascular data. Addressing these limitations, the current research proposes a hybrid spatio-temporal deep learning framework combining imaging, physiological signals, waveform sequences, and laboratory parameters to predict ischemia onset with enhanced accuracy and early-warning capabilities [15].

METHODOLOGY

3.1 Research Design

This study develops a hybrid spatio-temporal predictive framework using multi-modal clinical data to detect impending ischemia.

The research design integrates:
(1) spatial feature extraction from thermography and duplex ultrasound;
(2) temporal modelling of hemodynamic sequences such as systolic–diastolic cycles, flow velocity time-series, and tissue oxygenation curves;
(3) clinical biomarkers including lactate levels, ABI trends, and inflammatory markers.

The pipeline employs convolutional networks for spatial signature extraction, transformer encoders for temporal dependency learning, and a multimodal fusion block that unifies spatial–temporal features. The dataset includes thermographic images (N=12,800), Doppler waveform sequences (N=9,600), sequential perfusion metrics (N=22,000 time-series samples), and electronic health record variables. Clinical labels distinguishing early ischemia, borderline perfusion, and non-ischemic states were verified by vascular specialists [16].

3.2 Multi-Modal Data Sources and Feature Definitions

Data were collected from vascular clinics using standardized acquisition protocols. Thermographic images were captured in controlled environments to ensure reliable thermal gradients. Doppler waveforms were sampled at high temporal resolution to capture fine-grained flow turbulence. Hemodynamic time-series included continuous ABI monitoring, toe pressure variations, and pulse-volume recordings. Clinical biomarkers included lactate, CRP, D-dimer, and serum creatinine, each associated with systemic perfusion dynamics [17]. Spatial features included thermal asymmetry indices, tissue temperature variance, and perfusion gradients. Temporal features included peak–trough flow oscillation patterns, temporal turbulence markers, and autoregressive perfusion trends [18].

Table 1. Multi-Modal Feature Categories

Feature Type	Example Indicators	Data Source
Spatial Perfusion Signatures	Thermal asymmetry, perfusion gradients	Infrared thermography
Temporal Hemodynamic Signals	Flow velocity waveform cycles, ABI sequences	Doppler ultrasound, vascular sensors
Clinical Bio-Markers	Lactate, CRP, inflammatory markers	EHR laboratory data
Gait & Musculoskeletal Patterns	Stance duration asymmetry, cycle timing	Gait analysis

3.3 Spatial Analytics Engine

Thermal and Doppler images were processed via a convolutional backbone fine-tuned on vascular imaging datasets. Grad-CAM maps were used to highlight ischemic regions, providing interpretability. Ultrasound frames were processed using dual-branch convolutional layers to capture both anatomical structure and flow morphology [20]. Spatial embeddings were produced for fusion with temporal signals.

3.4 Temporal Modelling Framework

Time-series ischemia signals were encoded using transformer-based temporal encoders. These models leveraged attention mechanisms to identify critical segments of perfusion deterioration. Sequential fusion layers integrated Doppler waveform patterns with ABI and oxygenation trends [21].

Table 2. Machine Learning Models Used

Model	Input	Purpose
CNN Backbone	Thermal + Doppler frames	Spatial ischemia detection
Transformer Encoder	Hemodynamic sequences	Temporal deterioration modelling
Fusion Network	Combined embeddings	Risk prediction
Explainability Engine	All modalities	Clinical interpretation

3.5 Fusion and Risk Prediction Layer

Spatial and temporal embeddings were concatenated through a gated fusion module, followed by a probabilistic risk output layer generating ischemia likelihood scores. Bayesian uncertainty estimation was incorporated to flag ambiguous predictions requiring clinician review [22].

3.6 Validation and Reliability

The model was validated using 10-fold cross-validation. Performance metrics included accuracy, F1-score, sensitivity, and early-detection latency. Specialist review confirmed label consistency ($\kappa = 0.86$). Fairness checks ensured age- and comorbidity-neutral predictions [23].

RESULT AND ANALYSIS

4.1 Overall Model Performance

The fused spatio-temporal model achieved high discriminatory power, detecting early ischemic signals with an average accuracy above 0.92. Sensitivity was strongest for early ischemia, outperforming isolated single-modality baselines. The system predicted ischemic onset an average of 36–48 hours earlier than standard clinical workflows. Risk stratification curves demonstrated stable predictive behaviour across age groups and comorbidity categories.

4.2 Spatial Feature Contributions

Thermal asymmetry was a key early predictor, especially in mid-calf and dorsal foot regions. Doppler spatial signatures showing flow turbulence and spectral broadening correlated strongly with high-risk predictions. Grad-CAM visualizations highlighted arterial segments contributing most to ischemia risk classification.

Table 3. Spatial–Ischemic Correlation Indicators

Indicator	Correlation with Early Ischemia
Thermal asymmetry index	0.82
Flow turbulence ratio	0.77
Perfusion gradient variance	0.69

4.3 Temporal Signal Analysis

The transformer encoder found clear deterioration patterns in ABI sequences 12–24 hours before clinical ischemia confirmation. Temporal waveform compression and peak velocity drop-off patterns were highly predictive. Tissue oxygenation time-series showed characteristic oscillation loss preceding ischemic onset.

4.4 Model Performance by Modality

Single-modality models underperformed compared to the fused approach. Spatial-only systems failed to capture deterioration timing, while temporal-only systems lacked anatomical specificity. The fused architecture consistently demonstrated superior predictive stability.

Table 4. Detection Accuracy by Modality

Modality	Accuracy
Spatial only	0.81
Temporal only	0.84
Clinical markers only	0.76
Fused spatio-temporal model	0.92

4.5 Risk Profiling and Heatmaps

Risk heatmaps revealed progression patterns moving proximally from distal ischemic zones. Temporal risk curves exhibited consistent early-warning peaks, enabling proactive intervention. Patients with diabetes displayed unique risk-elevation dynamics due to microvascular instability.

CONCLUSION

This study demonstrates that predictive spatio-temporal analytics built on multi-modal clinical data can dramatically improve early detection of lower limb ischemia. By integrating spatial tissue signatures, temporal hemodynamic sequences, and laboratory biomarkers, the proposed framework bridges critical diagnostic gaps associated with traditional vascular assessment. The hybrid deep learning architecture successfully isolates ischemic precursors that clinicians often miss in early stages, enhancing sensitivity while maintaining strong interpretability. Spatial features such as thermal asymmetry and Doppler turbulence provide anatomical grounding, while temporal encoders capture perfusion deterioration patterns hours or days earlier than existing diagnostic methods. This model holds significant clinical value in triage optimization, expedited vascular intervention planning, and prevention of amputations. Future vascular care will increasingly depend on continuous, multi-modal monitoring systems capable of dynamic ischemia prediction. The findings reinforce the potential for AI-enhanced vascular diagnostics to become an essential component of early intervention strategies across high-risk populations.

FUTURE WORK

Future research will expand multi-modal data streams by incorporating wearable perfusion sensors, microcirculatory imaging, and electrophysiological signals for finer temporal granularity. Integrating real-time monitoring from smart insoles or continuous perfusion trackers may further improve early-warning accuracy. Cross-population validation across diverse comorbidity groups such as diabetics and renal patients will enhance model generalizability. Additional exploration of reinforcement learning–based triage models may guide clinicians toward optimal intervention timing. Ensuring regulatory compliance, clinical usability, and integration into hospital workflows will be essential to translating predictive ischemia analytics into routine practice.

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