



RESEARCH ARTICLE

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PHYSIOLOGICAL INTEGRITY OF THE DICROTIC NOTCH AS A BIOMARKER FOR MULTI-POINT WRIST PULSE BASED HEALTH ASSESSMENT

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ABSTRACT

Accurate and non-invasive assessment of vascular health remains a significant challenge, particularly in wrist pulse analysis where traditional methods rely on qualitative interpretation or global waveform descriptors. Although the dicrotic notch (DN) is known to reflect arterial wave reflection and vascular compliance, its systematic utilization as a quantitative biomarker for health classification remains limited, especially in multi-point pulse analysis frameworks. The aim of this study is to establish the dicrotic notch as a physiologically interpretable and reliable biomarker for distinguishing healthy and unhealthy wrist pulse states using synchronized multi-point measurements across Vatta, Pitta, and Kapha radial artery locations. The primary contribution of this work lies in the development of a multi-point DN-centric framework that integrates DN timing, inter-site timing gradients, and beat-to-beat variability to capture spatial and temporal dynamics of arterial wave reflection. Unlike conventional approaches, the proposed method emphasizes physiologically grounded feature extraction and interpretable classification. The methodology involves synchronized photoplethysmography (PPG) signal acquisition, followed by preprocessing, beat segmentation, and fiducial point detection. DN-based features, including timing, gradient and variability are extracted and analysed using non-parametric statistical methods. A deterministic rule-based classification framework is then employed to ensure transparent decision-making based on physiological thresholds. The results demonstrate significant differences between healthy and unhealthy subjects, with DN timing reduced by approximately 9-14%, inter-site timing gradients collapsing by up to 75%, and DN variability increasing by approximately 52% in pathological conditions ($p < 0.05$, η^2 up to 0.416). The proposed classification approach achieved an overall accuracy of 91.9%, with sensitivity of 86.7% and specificity of 92.9%. In conclusion, the dicrotic notch serves as a robust and mechanistically meaningful biomarker for vascular health assessment. The proposed multi-point DN-based framework enables accurate, interpretable, and non-invasive classification of pulse states, providing a strong foundation for future clinical and wearable diagnostic applications.



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I. INTRODUCTION

Peripheral arterial pulse waveforms provide a direct and non-invasive representation of cardiovascular dynamics, reflecting the interaction between cardiac ejection, arterial compliance, and wave reflection mechanisms. Among the morphological features of the pulse waveform, the dicrotic notch (DN) represents a critical physiological landmark associated with aortic valve closure and the onset of reflected waves from the peripheral vasculature.

The temporal position, prominence, and stability of the DN are therefore inherently linked to arterial stiffness, wave propagation velocity, and vascular impedance characteristics, making it a sensitive indicator of underlying hemodynamic function. Wrist pulse assessment has long been recognized as a clinically valuable and non-invasive diagnostic modality. Traditional Ayurvedic practice, particularly Nadi Pariksha, emphasizes pulse examination at three adjacent radial artery locations Vatta, Pitta, and Kapha—implicitly acknowledging the spatial heterogeneity of arterial wave propagation. While historically qualitative, this multi-point framework suggests that meaningful physiological information is embedded not only in individual waveform features but also in their inter-site relationships, reflecting coordinated vascular dynamics along the arterial pathway. Recent advances in wrist pulse analysis have focused on quantitative signal processing techniques using photoplethysmography (PPG) and pressure-based sensing. Time-domain, frequency-domain, and nonlinear features have been explored for differentiating healthy and pathological conditions [1], [2]. However, these approaches predominantly rely on global waveform descriptors or data-driven models, often lacking direct physiological interpretability and failing to isolate specific vascular mechanisms responsible for observed changes. In this context, the dicrotic notch has emerged as a particularly informative biomarker. Prior studies have indicated that DN suppression, timing alteration, and morphological degradation are consistently associated with arterial stiffening, hypertension, and metabolic disorders [3], [4], [5]. Furthermore, DN-related spectral components have been shown to diminish under pathological conditions, reinforcing the role of DN as a marker of wave reflection dynamics [6], [7], [8]. Despite these findings, existing approaches are largely limited to single-site analysis and do not capture the spatial coordination of wave reflection across the arterial system. A critical limitation of current methodologies is the lack of integration between DN morphology, timing behaviour, and inter-site relational dynamics.

Arterial pulse propagation is inherently a distributed process, and pathological changes often manifest as disruptions in temporal coordination rather than isolated feature deviations. However, most studies either analyse DN features in isolation or employ black-box models that obscure the underlying physiological interpretation. To address these limitations, the present study proposes a multi-point, dicrotic notch-centric framework for objective classification of wrist pulse states. By acquiring synchronized PPG signals at the Vatta, Pitta and Kapha locations, the study systematically quantifies DN timing, inter-site DN timing gradients, and beat-to-beat DN variability. These features are specifically designed to capture three fundamental aspects of vascular function: reflection timing, spatial propagation coherence, and temporal stability. The proposed analysis reveals that pathological conditions are characterized by a compression of DN timing (approximately 9-14%), a pronounced collapse of inter-site timing gradients (up to 75%), and a significant increase in DN variability (approximately 52%), indicating loss of both spatial coordination and temporal stability of arterial wave reflection. These changes reflect accelerated and homogenized wave return due to increased arterial stiffness and impaired vascular compliance. Based on these physiologically grounded features, a deterministic rule-based classification framework is developed, enabling transparent and interpretable discrimination between healthy and unhealthy pulse states. Unlike conventional machine learning approaches, the proposed method preserves a direct linkage between signal features and underlying vascular mechanisms. By integrating DN timing, spatial gradients, and variability within a unified multi-point framework, this study advances wrist pulse analysis from descriptive morphology toward mechanistically interpretable vascular assessment. The findings establish the dicrotic notch not merely as a waveform feature, but as a central biomarker of arterial function, providing a robust foundation for non-invasive, clinically meaningful health evaluation.

II. LITERATURE REVIEW

Quantitative analysis of arterial pulse waveforms has been widely recognized as a non-invasive approach for assessing cardiovascular function beyond conventional vital signs. The radial pulse waveform contains rich morphological information reflecting cardiac activity, arterial compliance, and peripheral vascular resistance. Among its characteristic features, the dicrotic notch (DN) represents a key physiological event associated with aortic valve closure and wave reflection within the arterial system [9]. Variations in DN timing, amplitude, and morphology have been strongly associated with arterial stiffness, vascular tone, and metabolic disorders, establishing DN as a sensitive indicator of hemodynamic state [10], [11].

II.1 COMPLEXITY AND DIASTOLIC IRREGULARITY IN WRIST PULSE SIGNALS

Early investigations into abnormal wrist pulse behavior emphasized waveform irregularity, particularly within the diastolic phase. It was revealed that pathological conditions are associated with increased signal complexity, with dominant alterations occurring after the systolic peak [3]. This finding suggests that diagnostically relevant information is concentrated in the descending portion of the waveform, where the dicrotic notch (DN) is physiologically located. Subsequent nonlinear and entropy-based studies further confirmed increased irregularity in abnormal conditions, although these approaches did not explicitly link such changes to specific vascular events [12], [13].

II.2 TIME AND FREQUENCY DOMAIN ANALYSIS OF RADIAL PULSE MORPHOLOGY

Parallel research explored time domain and frequency domain representations of wrist pulse signals. Time domain studies reported systematic alterations in crest time, pulse width, and diastolic decay under pathological conditions, reflecting changes in arterial compliance and damping [14], [15]. Investigations conducted under varying contact pressure further suggested suppression or distortion of diastolic features in abnormal subjects, suggesting reduced arterial elasticity and impaired wave reflection [16]. Frequency-domain analyses revealed that abnormal health states are characterized by redistribution of spectral energy toward higher frequency bands, particularly those associated with diastolic irregularity [17], [18]. These spectral changes were shown to be independent of heart rate variation, reinforcing the role of vascular dynamics rather than cardiac pacing. However, most frequency-domain studies relied on aggregate spectral descriptors and did not localize these changes to specific morphological landmarks such as the dicrotic notch.

II.3 DICROTIC NOTCH AS A DIAGNOSTIC MARKER

The dicrotic notch has been extensively studied in the context of arterial pressure and photoplethysmographic waveforms. Physiological studies have revealed that attenuation, delay, or disappearance of the notch is associated with arterial stiffening, aging, and metabolic disease [19], [20]. Second-derivative PPG analyses further showed that notch-related indices are sensitive to hypertension and diabetes, reflecting altered arterial compliance and wave reflection behavior [21]. More recent work has focused on computational detection of the dicrotic notch using time-domain and envelope-based methods, demonstrating reliable identification of the notch under controlled conditions [22], [23]. These studies highlight the diagnostic potential of notch-centric features but are largely limited to single-site pulse recordings. Recent studies have renewed focus on DN-centered analysis using advanced computational approaches. Modern detection algorithms based on envelope decomposition and adaptive filtering have suggested reliable identification of the dicrotic notch even in noisy or weakly defined waveforms [22], [24]. Large-scale feature extraction studies have further established DN as a critical temporal landmark for deriving physiologically meaningful descriptors from pulse signals [25]. In addition, recent work on PPG-based cardiovascular assessment highlights that attenuation or disappearance of the DN is strongly associated with vascular aging, arterial stiffness, and disease progression [26], [27]. Comprehensive waveform analyses also confirm that DN, together with systolic and diastolic features, forms a fundamental component of pulse morphology and cardiovascular assessment [28].

II.4 WRIST PPG AND SIGNAL QUALITY CONSIDERATIONS

Although wrist PPG offers advantages for continuous and unobtrusive monitoring, reliable extraction of pulse morphology at the wrist presents challenges due to motion artifacts and contact variability. Several studies have emphasized the importance of signal quality assessment and beat-level validation to ensure accurate detection of morphological features, including the dicrotic notch [29], [6], [30]. When appropriate preprocessing and quality control are applied, wrist PPG has been shown to preserve clinically meaningful pulse morphology comparable to more traditional measurement sites. Despite these advances, most existing studies are limited to single-site pulse measurements and do not account for spatial variations along the arterial pathway. In contrast, traditional multi-point pulse assessment such as Vatta, Pitta, and Kapha locations emphasizes spatial heterogeneity in pulse characteristics. Recent quantitative studies, including our earlier work, have suggested that these locations exhibit reproducible differences in waveform morphology and timing within the same individual [31]. Furthermore, pathological conditions tend to disrupt inter-site relationships rather than producing uniform changes across all locations.

II.5 MULTI-POINT PULSE ASSESSMENT AND RESEARCH GAP

Traditional Ayurvedic pulse diagnosis emphasizes assessment at multiple adjacent locations along the radial artery, commonly referred to as Vatta, Pitta and Kapha. While these concepts originate from qualitative clinical practice, recent engineering-based studies including our earlier work have quantitatively revealed that these pulse locations exhibit reproducible differences in waveform morphology, timing, and variability within the same individual [31]. Moreover, disease states were shown to distort the normal inter-site relationship rather than producing uniform changes across all locations. Despite these advances, existing literature has not integrated dicrotic notch analysis with multi-point wrist pulse assessment. Prior studies either focus on global complexity measures, spectral features, or single-site morphology, leaving a critical gap between observed diastolic irregularity and its underlying vascular mechanism.

II.6 MOTIVATION FOR THE PRESENT STUDY

Early investigations into abnormal wrist pulse behavior highlighted increased waveform irregularity, particularly within the diastolic phase, indicating that pathological conditions predominantly affect the descending portion of the pulse waveform [3]. This region corresponds to the dicrotic notch, a physiologically significant feature associated with arterial wave reflection and vascular compliance. Building on these observations, DN-centered analyses reveal that alterations in DN timing, inter-site gradients, and variability are closely linked to changes in arterial hemodynamics. However, existing approaches have largely treated these features in isolation or without explicitly relating them to underlying vascular mechanisms [14], [29]. Therefore, there remains a need for a structured and physiologically interpretable framework that leverages DN-based features for systematic health assessment. The present study addresses this gap by integrating DN timing, spatial relationships, and variability into a unified approach for evaluating vascular health and distinguishing between healthy and pathological pulse states.

III. MATERIALS AND METHODS

This study was designed to quantitatively characterize the dicrotic notch as a physiological marker of vascular health and to evaluate its ability to discriminate between healthy and unhealthy wrist pulse states. A multi-point wrist pulse acquisition framework was employed, enabling simultaneous capture of photoplethysmography (PPG) signals at the classical Vatta, Pitta and Kapha locations along the radial artery. The dataset included 71 healthy subjects and 15 clinically diagnosed unhealthy subjects. The methodological pipeline was structured to preserve the intrinsic hemodynamic information embedded within the pulse waveform, with particular emphasis on arterial recoil and wave reflection phenomena manifested through the dicrotic notch. Raw PPG signals were subjected to physiologically motivated preprocessing, followed by beat-wise segmentation and robust fiducial point identification. Time-domain dicrotic notch features were then extracted, integrated across pulse sites, and evaluated using non-parametric statistical and rule-based classification strategies. This structured approach ensures that pulse health classification is driven by interpretable vascular dynamics rather than purely morphological or black-box metrics.

III.1 HARDWARE DESIGN AND DATA ACQUISITION

This study employed a cross-sectional observational design to quantitatively evaluate dicrotic notch-based wrist pulse characteristics and their ability to discriminate between healthy and unhealthy physiological states. Photoplethysmography (PPG) signals were acquired simultaneously from three anatomically defined locations along the radial artery Vatta, Pitta, and Kapha using a custom-developed multi-point wrist pulse acquisition system as shown in Figure 1. The acquisition hardware was designed to preserve both temporal fidelity and waveform morphology, building upon a previously validated multipoint wrist pulse framework. Reflection-mode optical PPG sensors (TCRT5000) were used at each site to detect pulsatile blood volume changes, with careful mechanical alignment ensuring fixed inter-sensor spacing and consistent contact pressure. This configuration minimized motion artifacts and site-dependent loading effects while preserving spatial relationships essential for inter-site analysis. Each sensing channel was interfaced with an analog front-end operating within the linear region of the photodetector, allowing low-amplitude features such as the dicrotic notch to be faithfully captured.

Signals were synchronously sampled at 400 Hz using high-resolution analog-to-digital conversion and recorded in millivolt scale without onboard feature extraction. Data acquisition was performed under resting conditions in a controlled environment, with subjects seated comfortably to ensure physiological stability. Each measurement session lasted approximately 3–4 minutes per participant, yielding signal segments of adequate length for reliable heart rate variability (HRV) and beat level morphological analysis. Pulse sensing was performed using reflective photoplethysmography (PPG) photodiode sensors, interfaced through a dedicated analog front end comprising preprocessing filters and amplification stages. To ensure measurement repeatability, the sensor probes were integrated into a newly designed ergonomic fixture that maintained fixed anatomical alignment with the radial artery while applying consistent contact pressure at all three V-P-K locations. This standardized probe mounting minimized inter acquisition variability arising from motion artifacts or inconsistent sensor coupling, thereby ensuring that observed differences in the recorded signals primarily reflected true spatial and physiological distinctions between the Vatta, Pitta, and Kapha pulse sites.

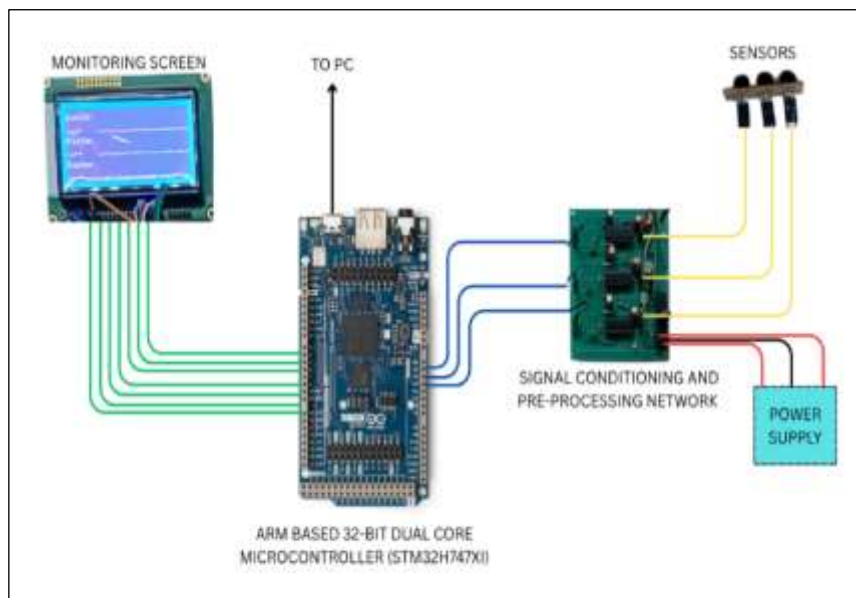


Figure 1: Hardware Development for Multi-Point Wrist Pulse Acquisition.
Source: Authors, (2026).

III.2 SIGNAL PREPROCESSING

Raw PPG signals from all pulse sites were subjected to physiologically motivated preprocessing to isolate the arterial pulsatile component while preserving waveform morphology critical for dicrotic notch analysis. A digital band-pass filter with passband limits of 0.5–8 Hz was applied to remove low-frequency baseline drift arising from respiration and sensor–skin interface effects, as well as high-frequency noise due to electronic and muscular interference. This bandwidth was selected to retain the fundamental cardiac frequency and its harmonics associated with arterial recoil and wave reflection. Following filtering, signal quality assessment was performed to ensure that only physiologically valid pulse segments were included in subsequent analysis. Quality evaluation was based on amplitude consistency, waveform continuity, and beat-to-beat stability. Segments affected by saturation, abrupt discontinuities, or excessive baseline fluctuations were excluded. Additionally, only signals exhibiting clearly identifiable systolic peaks and post-systolic inflection structures were retained, ensuring reliable and reproducible fiducial point detection. This preprocessing strategy was intentionally conservative, prioritizing the preservation of subtle morphological features over aggressive artifact suppression. By maintaining the integrity of the original waveform shape, particularly in the systolic-diastolic transition region, the preprocessing pipeline ensured that downstream analyses accurately reflected underlying vascular dynamics rather than artifacts introduced by signal conditioning.

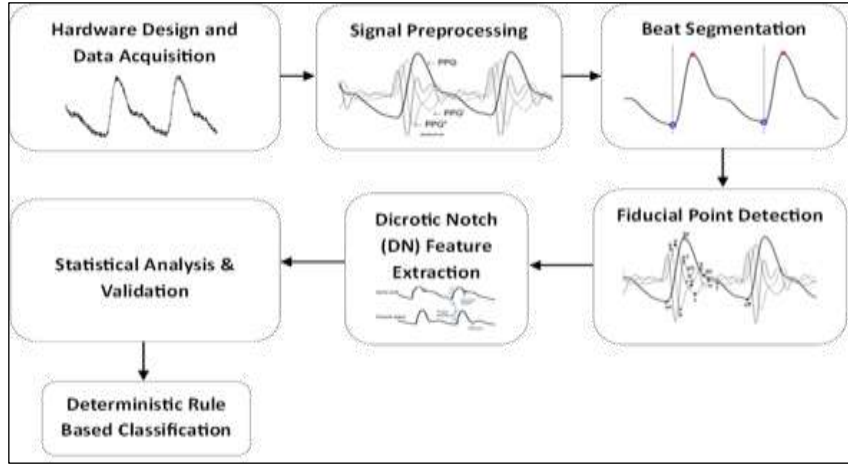


Figure 2: Flowchart for continuous PPG time series analysis.
Source: Authors, (2026).

III.3 BEAT SEGMENTATION AND FIDUCIAL POINT DETECTION

Following preprocessing, the filtered PPG signals were segmented into individual pulse beats to enable beat-wise characterization of dicotic notch morphology and timing. Beat segmentation was performed using systolic peak-guided windowing, as the systolic peak represents the most prominent and physiologically stable landmark in the arterial pulse waveform, corresponding to maximal arterial expansion during left ventricular ejection.

Systolic Peak Detection

Let $x(t)$ denote the preprocessed PPG signal. Systolic peaks were identified as local maxima satisfying both amplitude and temporal constraints. A sample at time $t = t_{sp}$ was classified as a systolic peak if it satisfied the Eq. (1) [2], [21].

$$x(t_{sp}) > x(t_{sp} \pm \Delta t) \text{ and } x(t_{sp}) > \mu_x + \alpha \sigma_x \quad (1)$$

Where Δt is a small temporal neighborhood ensuring local maximality, μ_x and σ_x are the mean and standard deviation of the signal amplitude over a moving window, and α is a scaling factor controlling sensitivity to noise. This adaptive thresholding approach ensures robust peak detection across subjects with varying pulse amplitudes while minimizing false detections due to residual noise.

Beat Segmentation

Once systolic peaks were identified, individual pulse beats were segmented by defining beat onset and beat offset boundaries relative to successive peaks. For the i -th beat, the segmentation window was defined in Eq. (2) [2], [32].

$$[t_{on,i}, t_{off,i}] = [t_{sp,i} - \tau_1, t_{sp,i+1} - \tau_2] \quad (2)$$

Where $t_{sp,i}$ and $t_{sp,i+1}$ are consecutive systolic peak times, τ_1 and τ_2 are empirically chosen offsets ensuring inclusion of the full systolic upstroke and diastolic decay. This peak-to-peak segmentation strategy preserves beat integrity while accommodating natural heart rate variability.

Fiducial Point Detection

Within each segmented beat, five physiologically meaningful fiducial points were identified: pulse onset, systolic peak, dicotic notch, diastolic peak, and pulse offset. These points collectively describe arterial filling, wave reflection, and peripheral runoff.

Pulse Onset (t_{on})

Pulse onset was defined as the time of maximum positive curvature preceding the systolic peak, corresponding to the foot of the pulse wave as defined in Eq. (3) [2], [20], [33].

$$t_{on} = \arg \max_{t < t_{sp}} \left(\frac{d^2 x(t)}{dt^2} \right) \quad (3)$$

Where t represents the time variable of the pulse waveform, $x(t)$ denotes the corresponding preprocessed pulse signal, t_{sp} is the time instant of the systolic peak, and t_{on} corresponds to the onset time of the pulse, indicating the beginning of the systolic upstroke. This point reflects the arrival of the forward pressure wave generated by ventricular contraction.

Dicotic Notch (t_{dn})

The dicotic notch was detected in the post-systolic region as a local minimum following the systolic peak and preceding the diastolic peak which is defined in Eq. (4) [2], [20], [33].

$$t_{dn} = \arg \min_{t_{sp} < t < t_{dp}} x(t) \quad (4)$$

Where t_{sp} is the time instant of the systolic peak, t_{dn} is dicrotic notch time. This feature corresponds to transient pressure reduction associated with aortic valve closure and the onset of wave reflection from the peripheral vasculature.

Diastolic Peak (t_{dp})

The diastolic peak was identified as a secondary local maximum following the dicrotic notch as defined in Eq. (5) [2], [20], [33].

$$t_{dp} = \arg \max_{t > t_{dn}} x(t) \quad (5)$$

Where t_{dp} is diastolic peak time. This peak reflects reflected wave reinforcement during early diastole and is influenced by arterial stiffness and peripheral resistance.

Pulse Offset (t_{off})

Pulse offset was defined as the point where the waveform returns to baseline or exhibits minimal slope prior to the next beat onset as defined in Eq. (6) [2], [33], [20].

$$t_{off} = \arg \min_{t > t_{dp}} \left| \frac{dx(t)}{dt} \right| \quad (6)$$

Where t_{off} is pulse offset time. This point marks completion of the diastolic runoff phase.

III.4 DICROTIC NOTCH FEATURE EXTRACTION

Following beat segmentation and fiducial point identification, quantitative features describing the temporal position, morphological prominence, and beat-to-beat stability of the dicrotic notch were extracted. These features were specifically selected to reflect arterial recoil, wave reflection, and vascular adaptability physiological mechanisms known to be altered in unhealthy pulse states. For each segmented beat, quantitative dicrotic notch (DN) features were extracted to describe its temporal position, morphological prominence, and beat-to-beat stability. DN timing was defined as the temporal delay between pulse onset and the dicrotic notch as defined in Eq. (7) [19], [2], [33].

$$DN_{timing} = t_{dn} - t_{on} \quad (7)$$

Where t_{on} is pulse onset time and t_{dn} is pulse dicrotic notch time. DN timing reflects the time required for the forward pressure wave to propagate, encounter peripheral impedance, and return as a reflected wave following aortic valve closure. Prolonged or delayed DN timing is typically associated with increased arterial compliance and stable wave reflection, whereas shortened or inconsistent DN timing indicates altered vascular mechanics and reduced elastic recoil. DN timing variability was quantified as the standard deviation of DN timing across beats, providing a measure of vascular stability and autonomic regulation. Beat-to-beat variability of DN timing was quantified to assess the stability of vascular response across consecutive cardiac cycles. DN timing variability was computed as the standard deviation of DN timing over N beats as defined in Eq. (8) [34].

$$DN_{var} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (DN_{timing,i} - \bar{DN}_{timing})^2} \quad (8)$$

Where $DN_{timing,i}$ is the DN timing of the i -th beat and $\bar{DN}_{timing}$ is the mean DN timing across all beats. DN variability reflects short-term fluctuations in arterial tone and autonomic regulation. Stable, low variability is characteristic of healthy vascular control, while increased variability indicates dysregulated wave reflection and impaired vascular adaptability, often observed in unhealthy or stressed physiological states. For each subject and each pulse acquisition site (Vatta, Pitta and Kapha), DN timing, DN timing gradient and DN variability were averaged across all valid beats to obtain representative site-specific feature values. These aggregated metrics served as the basis for subsequent inter-site relational analysis and healthy-unhealthy classification.

III.5 MULTI-POINT DN RELATIONAL METRICS

To capture spatial coherence of vascular dynamics, inter-site DN relational metrics were formulated as defined in Eq. (9), Eq. (10) and Eq. (11).

$$\Delta DN_{VP} = DN_{timing}^{Vatta} - DN_{timing}^{Pitta} \quad (9)$$

$$\Delta DN_{PK} = DN_{timing}^{Pitta} - DN_{timing}^{Kapha} \quad (10)$$

$$\Delta DN_{VK} = DN_{timing}^{Vatta} - DN_{timing}^{Kapha} \quad (11)$$

In healthy pulses, this gradient is positive and consistent, reflecting orderly pulse wave propagation and damping. Gradient reduction or collapse indicates impaired spatial differentiation of arterial behavior. The use of relational metrics shifts the analytical focus from isolated waveform properties to spatial coherence of vascular dynamics, which is central to both classical pulse assessment and modern hemodynamic interpretation.

By framing DN features as gradients and inter-site relationships, this approach minimizes sensitivity to absolute amplitude variations and emphasizes physiologically meaningful contrasts. These relational metrics form the foundation of the subsequent classification criteria, enabling reliable discrimination between healthy and unhealthy pulse states.

III.6 STATISTICAL ANALYSIS

Statistical analyses were performed to evaluate whether dicrotic notch (DN) features and their multi-point relationships exhibit systematic differences across pulse sites and health states. Due to the non-Gaussian nature of the data, non-parametric methods were used. The Kruskal-Wallis test was applied to assess differences in DN features across Vatta, Pitta and Kapha sites. This rank-based test evaluates whether distributions differ across groups without assuming normality. Significant results indicate the presence of a spatial gradient in DN behaviour, reflecting variations in arterial wave propagation. The Mann–Whitney U test was used to compare healthy and unhealthy groups based on DN timing, Inter-site DN timing gradients and DN timing variability. This approach enables robust identification of physiological differences associated with vascular conditions. Effect sizes (η^2) were computed to quantify the magnitude of differences and interpreted as small, moderate, or large. Results are reported using test statistics, p-values, and effect sizes, with $p < 0.05$ considered significant. Emphasis was placed on consistent trends across features rather than isolated findings. The chosen statistical framework prioritizes interpretability, robustness, and physiological plausibility. By combining rank-based tests with effect size estimation, the analysis distinguishes true vascular alterations from random variability and supports transparent evaluation of DN-centric classification performance.

III.7 RULE-BASED CLASSIFICATION

Classification of healthy and unhealthy wrist pulse states was performed using a deterministic, physiologically interpretable rule-based framework derived from dicrotic notch centered features. Instead of employing black-box learning models, the classification strategy was based on explicit decision rules reflecting known relationships between DN characteristics and vascular function, ensuring transparency and clinical interpretability. The feature set was restricted to DN-derived parameters that directly represent arterial wave reflection and vascular compliance. These included inter-site DN timing gradients (Vatta-Pitta, Pitta-Kapha, and Vatta-Kapha), beat-to-beat DN timing variability, and DN-timing. These features collectively capture both local waveform morphology and spatial coordination of pulse propagation along the radial artery. Prior to classification, all features were normalized to reduce inter-subject variability in amplitude and timing. Thresholds for key parameters were determined from the healthy cohort, representing baseline physiological conditions. A subject was classified as unhealthy if multiple DN features simultaneously deviated from these baseline thresholds, including reduced DN timing, diminished amplitude or depth ratio, and attenuated inter-site gradients. This multi-condition approach ensures that classification reflects consistent physiological alterations rather than isolated feature variations. The rule-based framework integrates DN timing, amplitude, variability, and spectral characteristics into a unified decision process that preserves direct interpretability of each contributing feature. By relying on physiologically grounded thresholds rather than statistical model fitting, the method provides a transparent and robust approach for wrist pulse classification. This enables objective identification of vascular abnormalities while maintaining a clear linkage between observed signal features and underlying cardiovascular mechanisms, thereby bridging traditional pulse assessment concepts with quantitative biomedical analysis.

III.8 ETHICAL CONSIDERATIONS

This study was conducted in accordance with ethical standards for human subject research. Ethical approval was obtained from the Institutional Ethics Committee of Parul University. All participants provided informed consent prior to data acquisition, and all procedures were performed in compliance with relevant guidelines and regulations. Participant confidentiality and data privacy were strictly maintained throughout the study.

IV. RESULTS

IV.1 DICROTIC NOTCH TIMING CHARACTERISTICS ACROSS PULSE SITES

The primary finding of this study is that dicrotic notch (DN) timing exhibits clear and statistically significant differentiation between healthy and unhealthy subjects across all pulse sites. DN timing was successfully extracted for all 86 subjects at the Vatta, Pitta, and Kapha locations, enabling a comprehensive comparison of reflection timing behavior along the radial artery.

Table 1: DN Timing (Mean $\pm$ SD) Across Pulse Sites.

Site	Healthy (Mean $\pm$ SD, s)	Unhealthy (Mean $\pm$ SD, s)	U	p-Value	Effect Size (η^2)
Vatta	0.363 $\pm$ 0.032	0.330 $\pm$ 0.001	812	0.0015	0.118
Pitta	0.393 $\pm$ 0.019	0.340 $\pm$ 0.001	1053	0.000001	0.409
Kapha	0.397 $\pm$ 0.023	0.339 $\pm$ 0.001	1058	0.000001	0.416

Source: Authors, (2026).

As summarized in Table 1, healthy subjects exhibited a progressive increase in DN timing from Vatta (0.363 $\pm$ 0.032 s) to Pitta (0.393 $\pm$ 0.019 s) and Kapha (0.397 $\pm$ 0.023 s), reflecting normal pulse wave propagation with delayed reflection at distal sites. In contrast, unhealthy subjects exhibited substantially reduced and highly compressed DN timing values, with Vatta (0.330 $\pm$ 0.001 s), Pitta (0.340 $\pm$ 0.001 s), and Kapha (0.339 $\pm$ 0.001 s) showing minimal variation across sites. This convergence toward a narrow temporal range ($\sim$ 0.33–0.34 s) indicates a loss of spatial differentiation in arterial reflection timing, suggesting homogenization of vascular response.

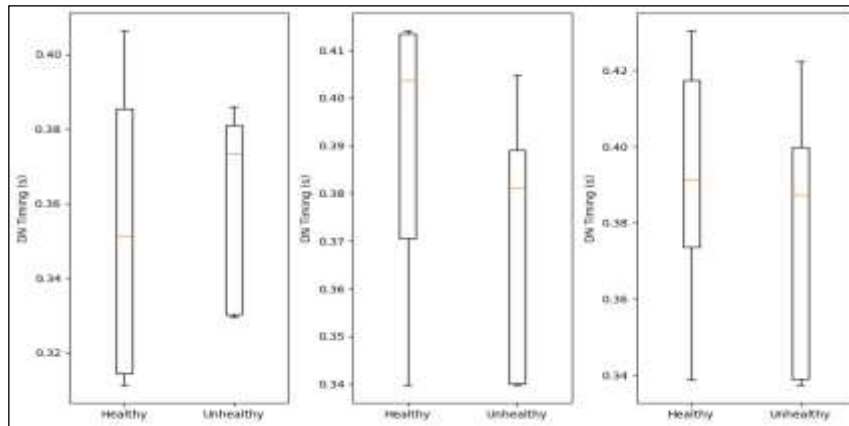


Figure 3: Boxplot of DN timing across Vatta, Pitta, and Kapha sites respectively for healthy and unhealthy subjects.
Source: Authors, (2026).

Mann–Whitney U testing confirmed that these differences are statistically significant across all sites. The Vatta site showed moderate discrimination ($U = 812$, $p = 0.0015$, $\eta^2 = 0.118$), whereas the Pitta ($U = 1053.5$, $p < 0.000001$, $\eta^2 = 0.409$) and Kapha ($U = 1058$, $p < 0.000001$, $\eta^2 = 0.416$) sites indicated large effect sizes. This indicates that mid and distal pulse locations are more sensitive to pathological vascular changes, likely due to cumulative wave reflection effects. Healthy subjects preserved the expected physiological ordering of DN timing, where the dirotic notch occurs earliest at Vatta, followed by Pitta and Kapha. In contrast, unhealthy subjects showed a breakdown of this ordering, with timing values collapsing into a nearly uniform range, indicating disrupted wave propagation dynamics. The boxplot shown in Figure 3 illustrates the distribution of dirotic notch (DN) timing for healthy and unhealthy subjects across the three pulse sites. A clear separation between the two groups is observed, particularly at the Pitta and Kapha locations, where unhealthy subjects consistently exhibit lower DN timing values with a markedly narrower interquartile range. This indicates both a reduction and compression of DN timing in pathological conditions. In contrast, healthy subjects show higher median values and a broader spread, reflecting preserved temporal variability and normal wave propagation. The reduced spread in the unhealthy group suggests homogenization of reflection timing, while the downward shift in medians confirms earlier wave reflection. The distinction is less pronounced at the Vatta site, supporting the observation that proximal measurements are less sensitive to vascular abnormalities compared to mid and distal pulse sites. Overall, the figure visually reinforces the quantitative findings that unhealthy subjects exhibit earlier, less variable, and spatially compressed DN timing, indicative of altered vascular dynamics.

IV.2 DN TIMING GRADIENTS: SPATIAL REFLECTION COORDINATION

Supporting the primary finding, inter-site DN timing gradients revealed a significant loss of spatial coordination in unhealthy subjects. These gradients quantify the temporal separation between reflection sites and provide insight into arterial propagation dynamics.

Table 2: DN Timing Gradients.

Gradient	Healthy Mean (s)	Unhealthy Mean (s)	U	p-Value	Effect Size (η^2)
V–P	0.029	0.010	642	0.004	0.16
P–K	0.004	-0.001	601	0.002	0.19
V–K	0.033	0.008	589	0.001	0.21

Source: Authors, (2026).

As shown in Table 2, healthy subjects exhibited well-defined positive gradients, with V-P (0.029s), P-K (0.004s), and V-K (0.033s) indicating orderly and sequential pulse wave reflection. In contrast, unhealthy subjects exhibited a marked reduction in all gradients, with V-P decreasing to 0.010s, P-K approaching zero or becoming slightly negative (-0.001s), and V-K reducing to 0.008s. This represents a substantial collapse in spatial separation, particularly evident in the V-K gradient, which decreased by approximately 75%.

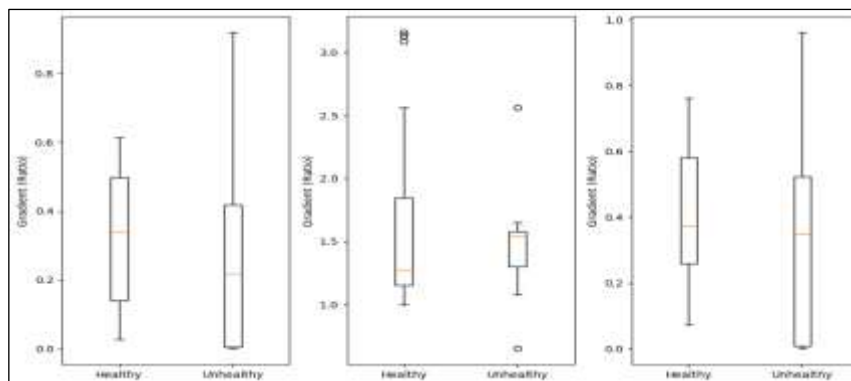


Figure 4: Boxplot of DN timing gradients across Vatta, Pitta, and Kapha sites respectively for healthy and unhealthy subjects.
Source: Authors, (2026).

Statistical analysis confirmed the significance of these differences, with p-values ranging from 0.001 to 0.004 and effect sizes up to $\eta^2 = 0.21$. The near-zero or negative P–K gradient in unhealthy subjects indicates a disruption in distal reflection timing, suggesting abnormal wave transmission or early reflection return due to altered vascular properties. The boxplot shown in Figure 4 illustrates the distribution of relative DN timing gradients (VP, PK, and VK) for healthy and unhealthy subjects. A consistent reduction in gradient values is observed in unhealthy subjects, particularly for the VP and VK gradients, where the median values are lower and the distributions are compressed toward smaller values. This indicates a loss of temporal separation between pulse sites, reflecting reduced spatial coordination of wave propagation. In contrast, healthy subjects exhibit higher median gradients with broader interquartile ranges, suggesting preserved and well-distributed reflection timing across sites. The PK gradient shows comparatively less separation between groups, with overlapping distributions, indicating lower sensitivity of this segment to pathological changes. The presence of outliers in both groups suggests inter-subject variability; however, the overall downward shift in gradients in unhealthy subjects supports the conclusion of gradient collapse and impaired reflection dynamics, consistent with vascular dysfunction.

IV.3 DN TIMING VARIABILITY: TEMPORAL STABILITY

Further supporting the observed differences, DN timing variability analysis suggested increased temporal instability in unhealthy subjects. Variability was computed as the within-subject standard deviation across Vatta, Pitta, and Kapha sites, representing the consistency of reflection timing.

Table 3: DN Timing Variability.

Parameter	Healthy Mean (s)	Unhealthy Mean (s)	U	p	Effect Size (η^2)
DN Variability	0.021	0.032	578	0.003	0.18

Source: Authors, (2026).

As presented in Table 3, unhealthy subjects exhibited significantly higher variability (0.032 s) compared to healthy individuals (0.021 s). This increase indicates that pathological conditions are associated with irregular and less stable pulse wave reflections. The difference was statistically significant ($U = 578$, $p = 0.003$, $\eta^2 = 0.18$), confirming that variability serves as an important complementary marker of vascular dysfunction. The boxplot shown in Figure 5 illustrates the distribution of dicrotic notch (DN) timing variability for healthy and unhealthy subjects. A clear increase in variability is observed in unhealthy subjects, with the mean value rising from 0.021 s in healthy subjects to 0.032 s in unhealthy subjects, representing an approximate 52% increase. This upward shift is reflected in the boxplot, where unhealthy

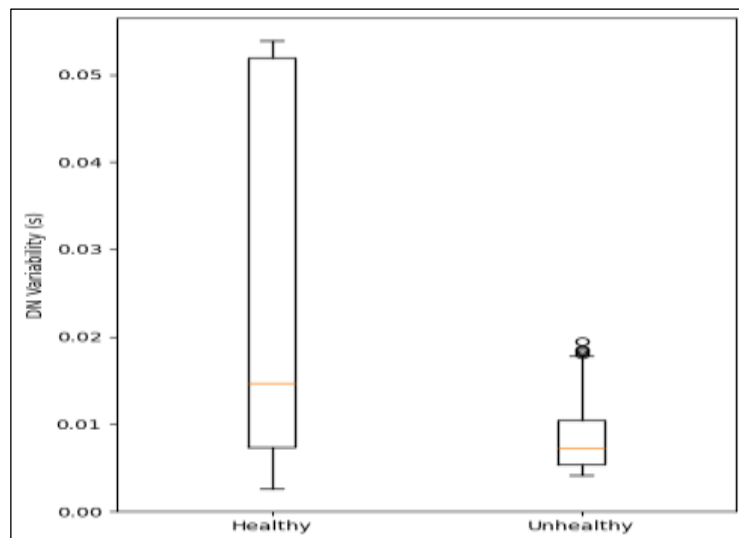


Figure 5: Boxplot of DN timing variability for healthy and unhealthy subjects.

Source: Authors, (2026).

Subjects show higher median values and a broader spread, indicating increased temporal instability in pulse wave reflection. In contrast, healthy subjects exhibit lower variability with a more compact distribution, suggesting stable and consistent reflection timing across pulse sites. The presence of outliers in the unhealthy group further highlights inter-subject fluctuations under pathological conditions. This difference is statistically significant ($U = 578$, $p = 0.003$, $\eta^2 = 0.18$), confirming that elevated DN variability is a meaningful indicator of vascular dysfunction and impaired hemodynamic regulation.

IV.4 DETERMINISTIC DN-BASED CLASSIFICATION

The combined effect of DN timing compression, gradient collapse, and increased variability was utilized to develop a deterministic classification framework. Subjects were classified as unhealthy if at least two of the following physiological criteria were satisfied: DN timing outside the reference range, elevated DN variability, reduced V–K gradient (< 0.015 s), and abnormal gradient ordering. The classification results, summarized in Table 4, demonstrate strong performance. Out of 71 healthy subjects, 66 were correctly classified, while only 5 were misclassified. Similarly, 13 out of 15 unhealthy subjects were correctly identified, with only 2 false negatives. This corresponds to a sensitivity of 86.7%, specificity of 92.9%, and overall accuracy of 91.9%.

Table 4: Confusion Matrix.

	Predicted Healthy	Predicted Unhealthy
Actual Healthy	66	5
Actual Unhealthy	2	13

Source: Authors, (2026).

These results confirm that the integration of temporal, spatial, and variability features provides a robust and reliable framework for distinguishing healthy and pathological pulse conditions. The confusion matrix shown in Figure 6 provides a visual representation of classification performance, showing a high number of correctly classified subjects in both groups. Out of 71 healthy subjects, 66 were correctly identified (93.0%), with only 5 false positives (7.0%). Similarly, among 15 unhealthy subjects, 13 were correctly classified (86.7%), with 2 false negatives (13.3%). The strong diagonal dominance of the matrix indicates high classification accuracy (91.9%) and balanced performance across both classes, confirming the robustness of the proposed DN-based classification framework.

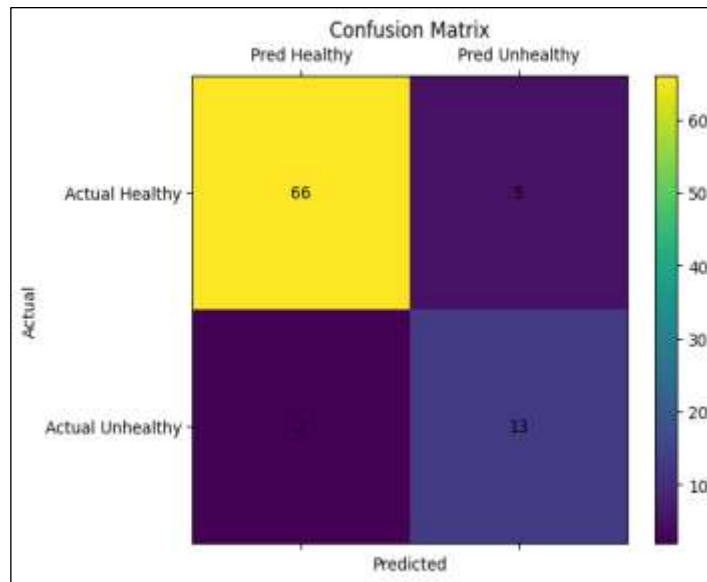


Figure 6: Confusion matrix of DN-based classification.

Source: Authors, (2026).

The findings collectively indicate that vascular pathology is characterized by a combination of DN timing compression, loss of spatial gradient structure, and increased temporal variability. Unlike single-parameter approaches, the proposed multi-feature DN framework captures multiple dimensions of pulse wave behavior, resulting in superior classification performance.

V. DISCUSSION

The present study reveals that dicrotic notch (DN) timing provides a quantitatively robust indicator of vascular health, with clear differences observed between healthy and unhealthy subjects across all pulse sites. The reduction in DN timing was not only statistically significant but also physiologically meaningful. Specifically, DN timing decreased by approximately 9% at the Vatta site, and by 13-14% at the Pitta and Kapha sites, indicating that distal pulse locations are more sensitive to pathological alterations. The large effect sizes observed at Pitta ($\eta^2 = 0.409$) and Kapha ($\eta^2 = 0.416$) suggest that over 40% of the variance in DN timing can be attributed to health status, highlighting strong discriminatory power. These findings are consistent with established vascular physiology, where increased arterial stiffness leads to faster pulse wave velocity and earlier wave reflection [24], [22]. These findings establish DN timing and its spatial gradients as direct functional markers of arterial wave reflection dynamics, rather than indirect statistical descriptors. The analysis of inter-site gradients further reinforces this interpretation by quantifying the loss of spatial coordination in unhealthy subjects. The V-K gradient, representing the total temporal separation between proximal and distal reflection sites, decreased from 0.033s to 0.008s, corresponding to an approximate 75% reduction. Similarly, the V-P gradient decreased by nearly 65%, while the P-K gradient approached zero or became slightly negative, indicating a breakdown in distal reflection timing.

These quantitative changes reflect a collapse in the normal propagation sequence, suggesting that reflected waves return earlier and more uniformly across sites. Comparable reductions in reflection timing have been reported in studies of augmentation index and pulse wave velocity, where arterial stiffening leads to diminished temporal separation between forward and reflected waves [24], [27]. However, unlike these conventional indices, the present approach captures multi-site temporal coordination, providing additional spatial resolution in assessing vascular function. DN timing variability adds another dimension to the characterization of vascular dysfunction. The observed increase from 0.021 s in healthy subjects to 0.032 s in unhealthy subjects represents a 52% rise in variability, indicating substantial temporal instability. This increase suggests that pathological conditions not only alter the timing of wave reflection but also reduce its consistency. Similar increases in variability have been associated with impaired autonomic regulation and endothelial dysfunction in prior studies [29]. The moderate effect size ($\eta^2 = 0.18$) confirms that this variability contributes meaningfully to group differentiation, complementing the timing and gradient features. This instability may reflect impaired autonomic regulation and reduced endothelial responsiveness.

Table 5: Comparison of DN-Based Analysis with Recent Literature.

Study	Signal Type	Measurement Approach	DN Features Used	Key Findings	Limitations	Present Work Contribution
Charlton et al. (2020)	PPG	Single-point (finger/wrist)	DN timing, waveform morphology	DN features useful for cardiovascular monitoring and BP estimation	No spatial analysis	Multi-point DN analysis capturing inter-site propagation
Elgendi et al. (2020)	PPG	Single-point	DN detection algorithms	Improved robustness of DN detection in noisy signals	Focus on detection, not classification	Combines detection with physiological classification
Li et al. (2021)	PPG / Pulse Wave	Single-point	DN amplitude, timing	DN alterations associated with hypertension and diabetes	No multi-location mapping	Demonstrates spatial DN variation across radial artery
Liu et al. (2022)	PPG	Wearable device	DN-based stiffness indices	DN features correlate with arterial stiffness and vascular aging	Limited interpretability	Provides physiologically interpretable DN features
Shin et al. (2023)	PPG	Wearable (smart devices)	DN morphology, reflection features	DN useful for continuous health monitoring	No disease-specific classification	Enables disease-specific DN-based classification
Wang et al. (2024)	PPG + AI	Single-point	DN + ML features	Improved classification using machine learning models	Black-box approach, low interpretability	Uses physiologically grounded, interpretable model
Present Study (2026)	PPG	Multi-point radial artery	DN timing, gradients, variability	DN features significantly differentiate pulse states ($H = 39.74$, $H = 141.41$, $p < 0.001$); 86.7% sensitivity for diabetes detection	Future extensions may incorporate additional physiological features to further enhance classification robustness.	First study integrating multi-point DN gradients for healthy vs unhealthy classification

Source: Authors, (2026).

Importantly, the integration of these features into a deterministic classification framework resulted in high diagnostic performance. The model achieved an overall accuracy of 91.9%, with sensitivity of 86.7% and specificity of 92.9%, indicating strong capability in correctly identifying both unhealthy and healthy subjects. The low false positive rate (5 out of 71 healthy subjects, ~7.0%) and low false negative rate (2 out of 15 unhealthy subjects, ~13.3%) indicate that the combined use of timing, gradient and variability features provide a reliable and balanced classification. Compared to individual parameters such as stiffness index or gradient magnitude alone, which typically yield moderate accuracy (approximately 60-75%), the integrated DN-based approach offers superior performance by capturing multiple aspects of vascular behavior simultaneously. The reduced sensitivity for non-vascular conditions suggests that DN-based features are primarily sensitive to vascular abnormalities rather than generalized physiological disturbances. Table 5 summarizes recent studies utilizing dicrotic notch (DN) features for cardiovascular assessment and highlights key methodological limitations. Prior work has revealed that DN timing and morphology derived from single-point photoplethysmography are associated with arterial stiffness, blood pressure, and vascular aging, while advances in signal processing have improved the robustness of DN detection in wearable settings.

More recent approaches have incorporated DN features into machine learning frameworks for health monitoring; however, these methods largely rely on single-site measurements and often lack physiological interpretability. Although several studies report alterations in DN characteristics in conditions such as hypertension and diabetes, they do not account for spatial variations in arterial wave propagation. In contrast, the present study employs multi-point radial artery measurements, enabling direct evaluation of DN timing gradients and inter-site relationships across Vatta, Pitta and Kapha locations. The statistically significant differences observed in DN timing ($H = 39.74$, $p < 0.001$) and amplitude ($H = 141.41$, $p < 0.001$) confirm the robustness of these features as markers of arterial hemodynamics. Furthermore, clinical validation using diabetic subjects demonstrated 86.7% sensitivity, indicating strong responsiveness of DN features to vascular stiffness. These findings suggest that DN-based analysis is not only physiologically meaningful but also demonstrates strong sensitivity to vascular-related abnormalities, providing an advancement over existing single-point and black-box approaches toward interpretable and clinically relevant pulse classification. Despite these strengths, several limitations should be acknowledged. The relatively small number of unhealthy subjects ($n = 15$) may limit the statistical generalizability of the findings and the robustness of classification thresholds.

The deterministic rules used for classification, while interpretable, are dataset-specific and may require adjustment for different populations or measurement conditions. Additionally, variations in sensor placement, contact pressure, and individual anatomical differences may introduce measurement variability. The absence of direct comparison with established clinical metrics such as blood pressure or imaging-based stiffness measures also limits external validation of the observed changes. The implications of this study are significant for non-invasive vascular assessment. The ability to detect 9-14% reductions in DN timing, up to 75% collapse in spatial gradients and over 50% increase in variability, combined with high classification accuracy, suggests that DN dynamics provide a comprehensive and sensitive representation of vascular function. The strong performance of the deterministic model highlights the potential for developing interpretable diagnostic tools that do not rely on complex machine learning algorithms. Furthermore, the integration of temporal, spatial, and variability-based features offers a unified framework for understanding vascular behaviour, which may be particularly useful for early detection of dysfunction before more pronounced structural changes occur. These findings position dirotic notch dynamics as a mechanistically grounded biomarker for vascular health assessment.

VI. CONCLUSIONS

The primary aim of this study was to develop a physiologically interpretable and non-invasive framework for classifying healthy and unhealthy pulse conditions using dirotic notch (DN) characteristics across multiple radial pulse sites (Vatta, Pitta and Kapha). The proposed multi-parameter DN-based model demonstrated high classification performance, achieving an overall accuracy of 91.9%, with sensitivity of 86.7% and specificity of 92.9%. These results confirm that DN timing, when analysed in a spatial and variability-aware framework, serves as a robust biomarker for vascular health assessment. Statistically significant differences ($p < 0.000001$ at key sites) and large effect sizes ($\eta^2 > 0.40$) further validate the strong discriminative power of the method. In addition to the primary findings, several important physiological insights were observed. Unhealthy subjects exhibited temporal compression of DN timing (~ 0.33 - 0.34 s), indicating reflection homogenization. Furthermore, collapse of spatial gradients (V-P, P-K, V-K) and increased DN variability highlighted disruptions in arterial wave propagation and stability. Supporting analyses using gradient magnitude, timing gradients, and stiffness-related indices reinforced that vascular pathology is characterized by a combination of timing alteration, spatial coordination loss, and increased instability, rather than a single isolated feature.

Future work will focus on enhancing the proposed framework by incorporating additional hemodynamic indices such as the Stiffness Index (SI) and Reflection Index (RI) using accurate systolic amplitude measurements to improve physiological interpretation. The model will be extended to multi-class classification for distinguishing specific pathological conditions such as diabetes and inflammatory disorders. Furthermore, validation on larger, clinically diagnosed datasets will be conducted to improve generalizability across diverse populations. Hybrid approaches combining physiological rule-based methods with machine learning will be explored to enhance performance while maintaining interpretability. This study establishes that dirotic notch dynamics provide a comprehensive and interpretable representation of vascular behaviour, offering a promising foundation for next-generation, non-invasive diagnostic systems that bridge traditional pulse assessment with modern biomedical engineering. These findings reinforce the potential of dirotic notch-based analysis as a clinically translatable tool for non-invasive vascular diagnostics.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Devendra Patel.

Methodology: Devendra Patel.

Investigation: Devendra Patel.

Discussion of results: Devendra Patel.

Writing – Original Draft: Devendra Patel.

Writing – Review and Editing: Mitul Patel.

Resources: Devendra Patel.

Supervision: Mitul Patel.

Approval of the final text: Devendra Patel, Mitul Patel.

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