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Original Research Article

Machine Learning–Enabled Rupture Risk Prediction in Aortic Aneurysms Using Imaging Biomarkers and Clinical Profiles

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Abstract: Aortic aneurysm rupture is a life-threatening event associated with high mortality, often occurring without warning despite routine surveillance. Current clinical decision-making relies heavily on aneurysm diameter and growth rate, which fail to capture the complex biomechanical and biological factors contributing to rupture risk. Advances in medical imaging and machine learning (ML) provide an opportunity to move beyond size-based criteria toward personalized, data-driven risk prediction. This paper presents a conceptual framework for machine learning–enabled rupture risk prediction in aortic aneurysms by integrating imaging-derived biomarkers with patient-specific clinical profiles. Imaging features such as aneurysm morphology, wall stress indicators, thrombus characteristics, and texture-based radiomics are combined with demographic, physiological, and comorbidity data to support individualized risk stratification. The study positions ML not as a replacement for clinical judgment but as an intelligent decision-support mechanism that enhances early detection, surveillance planning, and intervention timing. The framework provides a foundation for future empirical validation and clinical translation in vascular medicine.

Keywords: Aortic Aneurysm, Rupture Risk Prediction, Machine Learning, Imaging Biomarkers, Clinical Decision Support.

INTRODUCTION

Aortic aneurysms represent a progressive vascular pathology characterized by localized dilation of the aortic wall, most commonly affecting the abdominal and thoracic segments. The primary clinical concern associated with aortic aneurysms is rupture, an event associated with catastrophic internal hemorrhage and high fatality rates. Early identification of patients at elevated rupture risk is therefore critical to improving

outcomes through timely intervention.

Current clinical guidelines predominantly rely on aneurysm diameter thresholds and growth rates to guide surveillance and surgical decision-making. While these metrics are simple and widely used, numerous studies have demonstrated that rupture can occur in aneurysms below recommended size thresholds, whereas many large aneurysms remain stable for extended periods. This discrepancy highlights the limitations of size-based criteria and underscores the need for more comprehensive risk assessment strategies.

Medical imaging modalities such as computed tomography angiography (CTA) and magnetic resonance imaging (MRI) provide rich structural and functional information beyond diameter measurements. Imaging biomarkers including aneurysm shape, wall thickness, intraluminal thrombus characteristics, and biomechanical stress indicators offer valuable insights into aneurysm instability. However, the high dimensionality and complexity of these features limit their integration into routine clinical workflows using traditional analytical approaches.

Machine learning offers a powerful solution for extracting predictive patterns from complex, multimodal datasets. By integrating imaging biomarkers with patient-specific clinical profiles including age, sex, blood pressure, smoking history, and comorbidities ML models can support personalized rupture risk prediction. This paper proposes a structured conceptual framework for ML-enabled rupture risk assessment, emphasizing clinical interpretability, safety, and decision support rather than automated diagnosis.

II. RELATED WORK

Research on aortic aneurysm rupture risk has historically been grounded in **biomechanical modeling and population-level statistical risk assessment**. Clinical practice guidelines for both abdominal aortic aneurysms (AAA) and thoracic aortic aneurysms (TAA) continue to rely predominantly on maximum aneurysm diameter and expansion rate as primary indicators for rupture risk and surgical intervention [1], [2]. While these metrics offer simplicity and reproducibility, substantial clinical evidence indicates that aneurysm rupture can occur in lesions below recommended size thresholds, whereas many large aneurysms remain stable for prolonged periods [3]. This inconsistency has prompted extensive investigation into alternative and complementary predictors of aneurysm instability.

Biomechanical studies have proposed **peak wall stress (PWS)** and **wall strength estimates** as more physiologically relevant indicators of rupture risk. Finite element analysis–based modeling has demonstrated that rupture often occurs at locations of locally elevated stress rather than at points of maximal diameter [4], [5]. Several studies report stronger associations between PWS and rupture events compared to size-based criteria alone, suggesting that biomechanical stress distributions better reflect the underlying failure mechanisms of the aortic wall [6]. However, biomechanical modeling approaches require complex assumptions regarding wall material properties, geometry, and boundary conditions, limiting their scalability and routine clinical use.

In parallel, advances in medical imaging have enabled the extraction of **quantitative imaging biomarkers** from computed tomography angiography (CTA) and magnetic resonance imaging (MRI). Beyond simple diameter measurements, imaging biomarkers now include aneurysm morphology, surface curvature, wall thickness, calcification patterns, and intraluminal thrombus (ILT) characteristics. Several studies have shown that ILT volume, asymmetry, and spatial distribution influence wall stress and may contribute to localized hypoxia, inflammation, and wall weakening [7], [8]. These findings suggest that imaging-derived structural features capture important aspects of aneurysm biology not reflected in size metrics alone.

More recently, **radiomics** has emerged as a promising approach for quantifying high-dimensional imaging features related to texture, intensity heterogeneity, and spatial complexity. Radiomics-based analyses of CTA data have demonstrated that texture features can differentiate stable aneurysms from ruptured or symptomatic cases with improved predictive performance [9], [10]. Shape-based radiomic features, including sphericity, elongation, and surface irregularity, have also been associated with aneurysm instability [11]. Despite these advances, radiomics studies often suffer from variability in image acquisition protocols, feature reproducibility concerns, and limited sample sizes, which complicate clinical translation.

The increasing availability of imaging and clinical data has motivated the application of **machine learning (ML) techniques** to aneurysm rupture risk prediction. Supervised learning models such as support vector machines, random forests, gradient boosting, and neural networks have been used to classify rupture risk by combining imaging features with patient-specific clinical variables, including age, sex, blood pressure, smoking history, and comorbidities [12], [13]. These studies consistently demonstrate improved discrimination performance compared to traditional statistical models, highlighting the value of multimodal data integration.

Deep learning approaches, particularly convolutional neural networks (CNNs), have also been explored for

automated feature learning directly from imaging data. CNN-based models show promise in capturing complex spatial patterns associated with aneurysm instability without manual feature engineering [14]. However, deep learning models are often limited by data scarcity, class imbalance, and lack of interpretability—factors that pose significant challenges in safety-critical clinical applications such as rupture risk prediction.

A recurring limitation across ML-based studies is the **lack of external validation and generalizability**. Many published models are trained and tested on single-center datasets with limited demographic diversity, raising concerns about performance robustness across institutions and imaging protocols [15]. Furthermore, most models report classification accuracy or area-under-the-curve metrics without addressing uncertainty estimation or clinical decision thresholds, which are essential for real-world adoption.

Another critical challenge is **model interpretability**. Clinicians require transparent and explainable decision support tools to trust ML-generated risk predictions, particularly when recommendations may influence invasive interventions. Black-box models that provide risk scores without explanatory context face resistance in clinical settings [16]. Recent efforts in explainable AI, including feature attribution methods and attention mechanisms, aim to bridge this gap, but their integration into aneurysm risk prediction pipelines remains limited.

Importantly, existing research largely treats imaging biomarkers, clinical variables, and ML models as **isolated components**, rather than elements of a unified clinical decision-support system. Few studies propose an end-to-end framework that systematically integrates imaging feature extraction, clinical profile fusion, ML-based risk modeling, and clinician-facing interpretability tools. This fragmentation hinders the translation of research findings into practical, workflow-compatible solutions.

In summary, while substantial progress has been made in biomechanical modeling, imaging biomarker discovery, and machine learning–based prediction, the field lacks a **system-level, clinically grounded framework** that unifies these advances into a coherent rupture risk assessment pipeline. Addressing this gap requires an approach that emphasizes multimodal data integration, interpretability, uncertainty awareness, and clinician-in-the-loop decision support. The present work is motivated by this need and aims to provide a structured conceptual framework for ML-enabled rupture risk prediction in aortic aneurysms.

III. METHODOLOGY

A. Research Design and Methodological Rationale

This study adopts a **conceptual–analytical research methodology** to develop a machine learning–enabled framework for rupture risk prediction in aortic aneurysms. Given the clinical complexity of aneurysm pathology, the heterogeneity of patient populations, and the ethical constraints associated with rupture events, a conceptual systems-oriented approach is appropriate at this stage of research. Rather than proposing or validating a single predictive model, the methodology focuses on **integrating imaging biomarkers, clinical profiles, and machine learning techniques into a coherent decision-support architecture**.

The methodological approach is grounded in biomedical engineering, medical imaging analysis, and clinical decision-support theory. The objective is to identify structural relationships and data flows that support individualized rupture risk stratification while maintaining clinical interpretability and safety.

B. Framework Development Process

The proposed framework was developed through a structured, multi-stage process:

1. **Literature Synthesis**
   Peer-reviewed studies on aortic aneurysm biomechanics, imaging biomarkers, radiomics, and machine learning–based risk prediction were systematically analyzed. This step identified commonly used features, modeling limitations, and gaps related to interpretability and clinical integration.
2. **Data Domain Identification**
   Two primary data domains were defined: (i) **Imaging-derived biomarkers** obtained from CTA or MRI, and (ii) **Clinical profiles**, including demographic, physiological, and comorbidity-related variables.
   This separation ensures clarity in feature provenance and supports multimodal data fusion.
3. **System-Level Integration**
   Imaging and clinical features were conceptually integrated into a unified ML pipeline designed to support risk stratification rather than automated diagnosis. Emphasis was placed on modularity to allow future adaptation to different imaging protocols and clinical settings.

C. Imaging Biomarker Representation

Imaging biomarkers are conceptualized as quantitative descriptors capturing aneurysm instability beyond diameter measurements. These include morphological features (shape irregularity, curvature), texture-based radiomic features (intensity heterogeneity), intraluminal thrombus characteristics, and biomechanical indicators such as stress

surrogates. Feature extraction is assumed to follow standardized preprocessing, segmentation, and normalization procedures to ensure reproducibility.

Rather than privileging any single biomarker, the methodology treats imaging features as **complementary indicators** whose combined patterns may better reflect rupture susceptibility.

D. Clinical Profile Integration

Clinical variables are incorporated to contextualize imaging findings within patient-specific risk environments. These include age, sex, blood pressure, smoking history, cardiovascular comorbidities, and medication use. Clinical data are conceptualized as modifiers of structural vulnerability, enabling personalized risk estimation when fused with imaging-derived information.

E. Machine Learning Risk Modeling Layer

The machine learning component is designed to support **multimodal feature fusion and risk estimation**. The methodology remains model-agnostic, allowing the use of classical ML algorithms or deep learning approaches depending on data availability. Emphasis is placed on:

- Feature importance analysis
- Uncertainty awareness
- Model interpretability

This ensures alignment with clinical decision-making requirements.

F. Validation Logic and Assumptions

As a conceptual study, validation is achieved through **theoretical triangulation**, ensuring consistency with established vascular biology, imaging science, and ML literature. The framework assumes access to standardized imaging data and curated clinical records. Limitations include the absence of empirical testing, which is intentionally deferred to future prospective and retrospective validation studies.

RESULTS

This section presents the analytical results derived from evaluating the proposed machine learning–enabled framework for rupture risk prediction in aortic aneurysms. As the study is conceptual in nature, the results are expressed as **system-level insights** that emerge from integrating imaging biomarkers, clinical profiles, and machine learning–based risk modeling, rather than from empirical performance metrics. The analysis focuses on how this integration improves rupture risk stratification beyond traditional size-based assessment.

A. Limitations of Size-Based Risk Stratification

The first analytical outcome highlights the structural limitations of diameter-based decision criteria. While aneurysm size and growth rate are convenient clinical indicators, they fail to capture localized wall weakening, heterogeneous stress distributions, and biological degeneration processes. The framework analysis confirms that reliance on size alone leads to **risk underestimation in small but unstable aneurysms** and **risk overestimation in large but mechanically stable aneurysms**.

By contrast, integrating imaging biomarkers allows rupture risk to be assessed as a **multifactorial phenomenon**, reflecting both global geometry and local structural instability. This shift from single-variable thresholds to pattern-based risk estimation represents a fundamental improvement in predictive reasoning.

B. Contribution of Imaging Biomarkers to Risk Discrimination

The analysis indicates that imaging biomarkers provide the primary structural signal for rupture susceptibility. Morphological irregularity, asymmetry, surface curvature variation, and intraluminal thrombus heterogeneity collectively reflect regions of altered wall stress and potential mechanical failure. Texture-based radiomic features further capture subtle spatial heterogeneity associated with inflammatory activity and tissue degeneration.

Importantly, no single imaging feature dominates risk prediction. Instead, rupture risk emerges from **combinations of imaging-derived patterns**, reinforcing the suitability of machine learning methods for feature interaction modeling.

Table I summarizes the analytical role of major imaging biomarker categories.

Table I
Analytical Contribution of Imaging Biomarkers

Biomarker Category	Structural Insight	Contribution to Risk Assessment
Morphology	Shape irregularity, asymmetry	Identifies geometric instability
Radiomics	Texture heterogeneity	Captures microstructural degeneration
Thrombus Features	Volume, eccentricity	Reflects wall hypoxia and stress
Stress Surrogates	Wall deformation indicators	Approximates biomechanical vulnerability

C. Role of Clinical Profiles in Personalized Risk Contextualization

The analytical results show that clinical variables function as **risk modifiers** rather than primary predictors. Demographic factors such as age and sex, combined with physiological variables like hypertension and smoking status, influence the susceptibility of the aortic wall to rupture under similar structural conditions.

When integrated with imaging biomarkers, clinical profiles enable **personalized risk contextualization**, allowing structurally similar aneurysms to be differentiated based on patient-specific vulnerability. This fusion reduces false uniformity in risk classification and supports individualized surveillance and intervention planning.

D. Machine Learning as an Integrative Risk Modeling Mechanism

The framework analysis confirms that machine learning plays a critical role as an **integration and pattern-recognition mechanism**, rather than as an autonomous decision-maker. ML models enable nonlinear fusion of high-dimensional imaging features with clinical data, capturing interactions that are not tractable through conventional statistical modeling.

Crucially, the analysis emphasizes the importance of **model interpretability and uncertainty awareness**. In rupture risk prediction, ML outputs are most clinically useful when presented as probabilistic risk strata with explanatory feature contributions, rather than as binary predictions. This aligns the framework with clinician-in-the-loop decision support principles.

E. Comparative Risk Assessment Paradigms

To clarify the analytical advantage of the proposed framework, a comparative assessment was conducted between conventional and ML-enabled rupture risk paradigms.

Table II
Comparison of Rupture Risk Assessment Approaches

Criterion	Conventional Approach	ML-Enabled Framework
Primary Metric	Diameter, growth rate	Multimodal risk patterns
Risk Representation	Threshold-based	Continuous, probabilistic
Personalization	Limited	High
Interpretability	High but simplistic	Moderate, explainability-assisted
Clinical Adaptability	Static	Adaptive

The comparison demonstrates that the ML-enabled framework offers **greater sensitivity to early instability signals** while preserving clinical oversight through explainable outputs.

F. Clinical Stability and Risk Stratification Zones

The analysis further identifies three conceptual **risk stratification zones** that emerge from the integrated framework:

1. **Low-Risk Zone:**
   Structurally stable imaging patterns with low-risk clinical profiles.
2. **Intermediate-Risk Zone:**
   Mixed imaging signals with moderate clinical risk modifiers, requiring closer surveillance.
3. **High-Risk Zone:**
   Imaging patterns indicative of instability combined with adverse clinical profiles, warranting early intervention consideration.

This zoning approach supports **graduated clinical decision-making** rather than binary surgical thresholds.

G. System-Level Implications

At a system level, the results indicate that ML-enabled rupture risk prediction reframes aneurysm management as a **dynamic, personalized risk monitoring process**. The framework supports earlier identification of high-risk patients, optimized surveillance intervals, and more informed intervention timing.

Overall, the analysis confirms that rupture risk is not a single measurable quantity but an emergent property of **structural, biological, and clinical interactions**. Machine learning, when embedded within a transparent and clinically grounded framework, enables these interactions to be operationalized into actionable decision support.

CONCLUSION

This study presented a conceptual framework for machine learning–enabled rupture risk prediction in aortic aneurysms by integrating imaging-derived biomarkers with patient-specific clinical profiles. The analysis highlights the limitations of traditional size-based assessment strategies and demonstrates how multimodal data integration can support more nuanced and personalized risk stratification. By treating rupture risk as an emergent property of structural, biological, and clinical interactions, the proposed framework moves beyond simplistic

thresholds toward pattern-based risk reasoning.

The findings indicate that imaging biomarkers such as aneurysm morphology, radiomic texture heterogeneity, intraluminal thrombus characteristics, and stress-related surrogates provide critical insights into aneurysm instability that are not captured by diameter measurements alone. When contextualized with clinical factors including demographic characteristics and comorbidities, these biomarkers enable individualized risk assessment aligned with patient-specific vulnerability. Machine learning functions as an integrative mechanism that fuses these heterogeneous data streams and identifies nonlinear interactions relevant to rupture susceptibility.

Importantly, the framework emphasizes clinical interpretability and decision support rather than automated diagnosis. By supporting probabilistic risk stratification and explainable feature contributions, the approach aligns with clinician-in-the-loop principles and promotes responsible adoption in vascular practice. Overall, this work contributes a system-level perspective that bridges medical imaging, machine learning, and clinical decision-making, offering a foundation for more precise and patient-centered management of aortic aneurysms.

VI. FUTURE WORK

Several directions for future research emerge from this study. First, empirical validation of the proposed framework using large, multi-center datasets is essential to evaluate predictive performance, robustness, and generalizability across diverse patient populations and imaging protocols. Prospective studies would be particularly valuable for assessing clinical impact on surveillance strategies and intervention timing.

Second, future work should focus on integrating longitudinal imaging and temporal clinical data to capture aneurysm progression dynamics rather than

static risk snapshots. Time-aware machine learning models may further improve early detection of instability and risk escalation.

Third, advancing explainable artificial intelligence (XAI) techniques tailored to medical imaging is critical for enhancing clinician trust and facilitating regulatory approval. Methods that clearly communicate how imaging features and clinical variables influence risk predictions will be essential for routine clinical use. Future research should address clinical translation challenges, including workflow integration, ethical considerations, data governance, and patient communication. Addressing these issues will ensure that machine learning–enabled rupture risk prediction systems are not only accurate but also safe, transparent, and aligned with clinical practice standards.

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