Forensic Medicine in Postmortem Diagnosis of Myocardial Infarction: A Survey

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Abstract

The survey paper explores the critical role of forensic medicine in the postmortem diagnosis of myocardial infarction (MI), emphasizing the integration of advanced methodologies to enhance diagnostic accuracy. The paper highlights the significance of accurate MI diagnosis in forensic investigations due to its profound implications for determining the cause of death and guiding legal proceedings. The survey is structured to provide a comprehensive overview of key concepts, methodologies, and challenges in the field. It discusses the utilization of biochemical markers and enzymatic analysis, alongside advanced imaging techniques, to ascertain the cause and timing of death. The importance of sample timing is underscored, as it impacts diagnostic accuracy, with technological advancements playing a pivotal role in optimizing timing protocols. The integration of machine learning and artificial intelligence is identified as transformative, enhancing the analysis of cardiac data and improving diagnostic precision. However, challenges related to data quality, methodological constraints, and technological limitations persist, necessitating continued innovation. The survey concludes by suggesting future research directions, including the integration of diverse data sources and the application of advanced computational models, to address existing limitations and advance forensic diagnostic methodologies.

1 Introduction

1.1 Forensic Medicine and Postmortem Diagnosis

Forensic medicine is essential in bridging medical science and the legal system, providing methodologies for postmortem diagnosis that are critical in forensic investigations [1]. This field plays a pivotal role in accurately classifying causes of death, particularly myocardial infarction (MI), which is a leading global cause of mortality. Recent advancements in automated electrocardiography (ECG) classification methods have significantly improved the precision of postmortem diagnoses [1]. By utilizing these technological innovations, forensic medicine enhances the interpretability and accuracy of postmortem examinations, thereby refining the determination of causes of death.

1.2 Significance of Myocardial Infarction in Forensic Investigations

Accurate MI diagnosis is crucial in forensic investigations due to its implications for establishing causes of death and informing legal proceedings. MI, resulting from coronary artery obstruction, is a significant contributor to mortality rates worldwide [2]. In forensic contexts, precise diagnostic methods are vital to prevent misinterpretation and ensure accurate determinations of death circumstances [3].

The complexity of diagnosing MI is heightened by subtle ECG signal changes, such as variations in the ST segment, T wave, and QRS complex, which may not be immediately detectable [4]. This challenge necessitates advanced analytical techniques, including machine learning and artificial

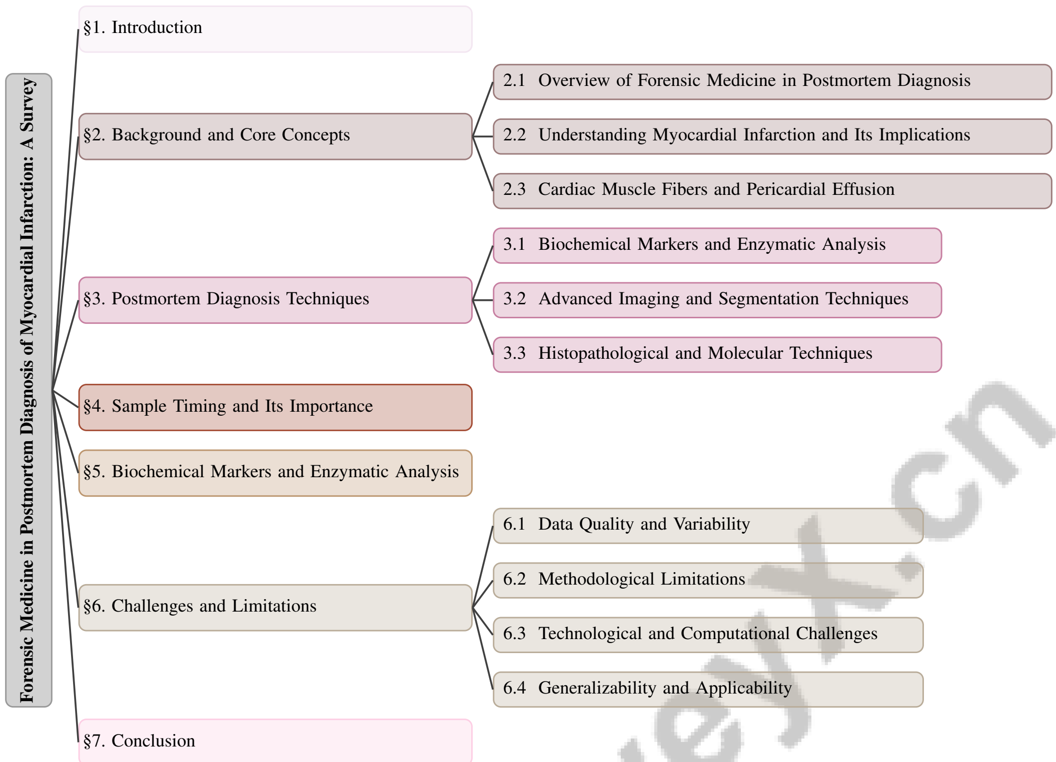

Figure 1: chapter structure

intelligence (AI), to enhance ECG analysis accuracy and interpretability. Explainable AI (XAI) methods have demonstrated potential in improving ECG data interpretability, thereby enhancing MI diagnostic accuracy [5].

Timely MI identification is critical, impacting patient outcomes and legal determinations, especially in acute ischemic heart disease cases [3]. The integration of AI-based approaches for automated MI detection using ECG and other biophysical signals marks a significant advancement in forensic diagnostics [5]. These methodologies facilitate accurate cause of death determinations and contribute to broader public health strategies and legal investigations, underscoring the importance of MI diagnosis in forensic contexts.

1.3 Structure of the Survey

This survey is structured to comprehensively explore forensic medicine's role in postmortem MI diagnosis. The **Introduction** highlights the intersection of forensic medicine and legal investigations, underscoring the importance of accurate postmortem diagnoses in MI cases and discussing technological advancements that enhance diagnostic precision [1].

The subsequent section, **Background and Core Concepts**, establishes foundational terminology and methodologies relevant to the field, addressing myocardial infarction's nature, the significance of cardiac muscle fibers and pericardial effusion, and the role of biochemical markers and enzymatic analysis in forensic investigations.

The survey progresses to , analyzing various methodologies employed in diagnosing MI postmortem. This section emphasizes protein degradation's significance in estimating postmortem intervals and confirming causes of death, highlighting advancements in protein technologies that enhance forensic reliability. It also examines post-mortem cardiac magnetic resonance imaging as a complementary tool to traditional autopsy methods, particularly in sudden cardiac death cases, and discusses serum markers' importance in assessing myocardial damage, illustrating the multifaceted approaches in forensic pathology for accurate MI diagnosis [6, 7, 8, 9, 10]. This includes a detailed discussion on biochemical markers, enzymatic analysis, and advanced imaging techniques to ascertain cause and timing of death.

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The significance of is explored, emphasizing how sample collection timing enhances diagnostic accuracy. This section addresses complexities in identifying optimal sample collection times, particularly in clinical settings with irregular measurement intervals, as observed in studies utilizing Electronic Health Records (EHR) and postmortem biochemical assessments. Understanding these factors is crucial for improving biomarker reliability and clinical predictions, especially in acute medical situations and forensic investigations [8, 11, 7, 12].

The paper examines , focusing on specific biomarkers used in MI diagnosis. It discusses integrating machine learning techniques to enhance analysis accuracy, emphasizing the potential of EHR and advancements in cardiovascular biomarkers, such as troponin and natriuretic peptides, critical for cardiology decision-making. The review also highlights challenges related to postmortem protein degradation and its forensic implications, suggesting that multi-omics approaches could improve protein-based diagnostics in clinical and forensic settings [8, 13, 12].

In the section, the survey addresses obstacles in postmortem diagnosis, including data quality issues, methodological constraints, and technological limitations, while proposing research directions to overcome these challenges.

The final **Conclusion** synthesizes key findings and emphasizes forensic medicine's significance in postmortem diagnostics, suggesting future research avenues and potential solutions to advance forensic diagnostic methodologies.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Overview of Forensic Medicine in Postmortem Diagnosis

Forensic medicine is pivotal in postmortem examinations, employing methodologies to identify causes of death and assess tissue damage from various medical conditions [14]. It integrates macroscopic and microscopic analyses to diagnose sudden cardiac death (SCD) and other conditions, ensuring accurate cause-of-death determinations [15]. In myocardial infarction (MI) cases, histopathological analysis is fundamental for tissue damage assessment [14]. Technological advancements, including tele-electrocardiography and non-invasive methods like photoplethysmography (PPG), enhance pre-hospital management and postmortem evaluations [16, 17].

Machine learning techniques address traditional forensic methods' limitations, improving diagnostic accuracy in postmortem examinations [18]. Innovations like Single Ear ECG Monitoring (SEEM) offer new avenues for cardiac rhythm recording in forensic contexts [19]. Decision support models aid in evaluating forensic methodologies, fostering the development of standardized protocols [20]. Forensic medicine's comprehensive approach supports public health strategies and legal investigations, with applications extending to age assessment and justice [21]. Machine learning benchmarks further elucidate forensic medicine's role across various conditions [22].

2.2 Understanding Myocardial Infarction and Its Implications

Myocardial infarction (MI), a primary global cause of morbidity and mortality, demands precise forensic diagnosis [23]. It results from atherosclerotic plaque rupture and thrombus formation, leading to ischemic necrosis of cardiac tissues [2]. This ischemic event often results in collagen scar tissue, traditionally analyzed through labor-intensive histological methods [24]. Forensic challenges in MI diagnosis include postmortem marker degradation and distinguishing ischemic changes [3]. Advanced imaging, such as cardiac MRI, aids in precise myocardial assessments and infarct delineation.

ECG data is vital for MI detection and localization but is complicated by variability and noise. Machine learning and deep learning models enhance ECG analysis, improving classification accuracy for cardiac diseases [5]. However, model interpretability remains a challenge, as clinicians require transparency for trust [5]. Reliance on International Classification of Diseases (ICD) codes for dataset creation raises concerns about MI representation accuracy, complicating forensic analyses [25]. MI implications extend to heart rate variability (HRV) alterations, highlighting the need for precise diagnostic tools for cardiovascular disease dynamics [26].

2.3 Cardiac Muscle Fibers and Pericardial Effusion

Assessing cardiac muscle fibers and pericardial effusion is critical in postmortem MI diagnosis, providing insights into ischemic and pathological changes. Structural integrity and pathological changes in cardiac muscle fibers reveal past cardiac events and ischemic damage, crucial for MI confirmation [1]. Early ischemic changes detection is challenging as markers like fibronectin (FN) and C5b-9 become positive only post-ischemia [27]. ECG limitations due to noisy MI signals obscure subtle fiber changes [28]. Advanced imaging, such as Cardiovascular Magnetic Resonance Imaging (CMR) with late gadolinium enhancement (LGE), enhances myocardial visualization and infarction assessment [24]. MyoPS-Net's cross-modal feature fusion architecture improves segmentation accuracy, providing a comprehensive myocardial pathology view [24].

Pericardial effusion, fluid accumulation in the pericardial cavity, complicates myocardial damage assessment by obscuring cardiac structures. Pathology intensity distribution heterogeneity and appearance variability across patients necessitate sophisticated imaging alignment methods [25]. Advanced deep learning methods are benchmarked to distinguish normal from pathological cardiac MRI cases, enhancing MI detection and quantification [29]. Machine learning integration in cardiac muscle fiber and pericardial effusion analysis overcomes traditional method limitations. However, challenges persist, including biases in machine learning algorithms towards majority classes in imbalanced datasets, affecting model fairness and interpretability [29]. Existing occlusive myocardial infarction (OMI) detection methods struggle to capture necessary ECG reading features, complicating accurate diagnosis [1].

3 Postmortem Diagnosis Techniques

Category	Feature	Method
Biochemical Markers and Enzymatic Analysis	Probabilistic Classification Transformer-Based Models	MuyGPs[1] ViT-ECG[28]
Advanced Imaging and Segmentation Techniques	Enhanced Feature Representation Multi-Modal Integration	ASDC[30], RSE-Net[31] MS-SVDD[23]
Histopathological and Molecular Techniques	Feature Extraction and Learning Sequential and Integrative Processing Imaging and Segmentation Techniques Real-Time and Dynamic Analysis	ESN[32], OSMLF[24] MPSN[33], CCNNF[34] HOS[35], NQ[36] DDAA[15]

Table 1: This table provides a comprehensive overview of the methods utilized in postmortem myocardial infarction diagnosis, categorized into biochemical markers and enzymatic analysis, advanced imaging and segmentation techniques, and histopathological and molecular techniques. Each category outlines specific features and methodologies, highlighting the integration of computational and deep learning approaches to enhance diagnostic accuracy. The table references key studies that contribute to the development and application of these advanced diagnostic techniques.

In postmortem diagnosis, biochemical markers and enzymatic analyses are foundational in elucidating myocardial infarction (MI). These approaches shed light on biochemical changes following cardiac events, setting the stage for advanced diagnostic methodologies. **??** illustrates the hierarchical structure of postmortem diagnosis techniques, categorizing the primary methodologies into biochemical markers and enzymatic analysis, advanced imaging and segmentation techniques, and histopathological and molecular techniques. Each primary category is further divided into specific subcategories, detailing the significant tools and technologies utilized within each domain to enhance myocardial infarction diagnosis accuracy postmortem. Table 3 presents a detailed summary of the methodologies employed in postmortem myocardial infarction diagnosis, illustrating the integration of biochemical, imaging, and molecular techniques with advanced computational methods. The ensuing subsection focuses on the roles of biochemical markers and enzymatic analysis in enhancing postmortem MI diagnosis accuracy, underscoring their forensic and clinical significance.

3.1 Biochemical Markers and Enzymatic Analysis

Biochemical markers and enzymatic analysis are crucial for postmortem MI diagnosis, providing insights into biochemical and molecular changes indicative of cardiac events. High-sensitivity cardiac troponins, notably troponin T and cardiac troponin I (cTnI), are essential for detecting myocardial cell damage, aiding in determining death timing and cause [27]. Advanced protein technologies like ELISA and proteomics refine myocardial damage assessments in postmortem samples [27].

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Novel markers such as Galectin-3 (Gal-3) and soluble suppression of tumorigenicity 2 (sST2) expand the diagnostic scope by revealing myocardial stress and fibrosis, crucial for understanding MI pathophysiology [27]. Immunohistochemical analysis of matrix metalloproteinases (MMP-2, MMP-9) and tissue inhibitors (TIMP-1) further refines myocardial damage assessments [27].

Computational methodologies enhance traditional biochemical assays. The MuyGPs method, utilizing Gaussian Processes for classifying ECG signals, can quantify prediction uncertainty and improve diagnostic accuracy [1]. Vision transformer models further enhance heart disease detection through advanced ECG image analysis [28].

Deep learning models, employing detection networks for left ventricle identification and Generative Adversarial Networks (GAN) for infarction area segmentation, represent significant advancements in postmortem MI diagnosis [24]. These models, along with Multi-modal Subspace Support Vector Data Description (MS-SVDD), optimize myocardial infarction detection, enhancing diagnostic precision [23].

3.2 Advanced Imaging and Segmentation Techniques

Method Name	Imaging Techniques	Deep Learning Integration	Segmentation Accuracy
MS-SVDD[23]	Echocardiography	-	-
RSE-Net[31]	Lge-MRI	Deep Learning Models	Improving Segmentation Accuracy
ASDC[30]	Cine MR Images	Convolutional Neural Network	Dice Scores

Table 2: This table presents a comparative analysis of advanced imaging and segmentation methodologies utilized in postmortem myocardial infarction diagnosis. It highlights the integration of deep learning models with various imaging techniques, such as echocardiography and late gadolinium enhancement MRI, to enhance segmentation accuracy and diagnostic precision. The table underscores the role of convolutional neural networks in improving myocardial tissue segmentation and classification.

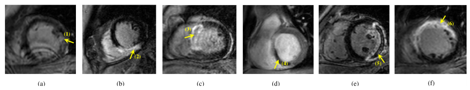
Advanced imaging and segmentation techniques are vital for postmortem MI diagnosis, offering enhanced visualization and precise cardiac pathology assessments. Echocardiography is a fundamental technique for early myocardial infarction detection [23]. Integrating deep learning methodologies, such as convolutional neural networks (CNNs), significantly improves postmortem examination precision and reliability.

Late gadolinium enhancement (LGE) in cardiac magnetic resonance (CMR) imaging effectively visualizes myocardial infarction by highlighting myocardial scarring and fibrosis. A 2.5 D approach with residual blocks and excitation mechanisms improves segmentation accuracy and myocardial damage assessment [31].

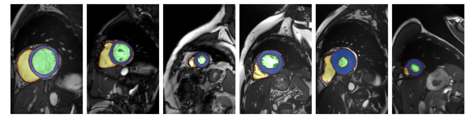
CNNs have revolutionized cardiac image analysis, enabling precise segmentation and classification. Integrating CNNs with residual networks enhances myocardial tissue segmentation, crucial for accurate postmortem MI diagnosis. This approach uses advanced imaging techniques like LGE-MR, T2-weighted MR, and bSSFP cine MR to differentiate between healthy, scarred, and edematous myocardial regions, achieving high precision in tissue viability identification [37, 38, 33].

CNNs for ECG signal classification significantly advance cardiovascular diagnostics. Models utilizing InceptionV3 architecture and fully convolutional networks classify ECG data as grayscale images, achieving high accuracy in myocardial infarction detection. These models, trained on diverse datasets, match human cardiologist performance, enhancing early MI detection accuracy [39, 40].

Integrating advanced imaging modalities like echocardiography and CMR imaging with sophisticated segmentation techniques and deep learning models enhances MI diagnosis accuracy and reliability. Automated pipelines using CNNs demonstrate high MI detection performance, analyzing regional wall motion abnormalities in echocardiographic videos. Deep learning approaches applied to ECG signals streamline diagnostics, reduce observer bias, and enhance classification performance. Innovative architectures like MyoPS-Net combine multiple CMR sequences for precise myocardial pathology segmentation, addressing incomplete imaging data challenges. These advancements significantly improve postmortem MI diagnosis, offering timely and accurate assessments critical in clinical settings [38, 5, 33]. Table 2 provides a detailed overview of the advanced imaging techniques and deep learning integrations employed for myocardial infarction segmentation and diagnosis.



(a) Comparison of MRI Images of the Heart[41]



(b) Comparison of MRI Images with Different Color Coding[30]

Figure 2: Examples of Advanced Imaging and Segmentation Techniques

As shown in Figure 2, advanced imaging and segmentation techniques enhance anatomical assessment accuracy in postmortem diagnosis. The MRI example illustrates these techniques, with grayscale heart images emphasizing structural details and focusing on the left ventricle. Different color coding schemes further differentiate anatomical features, enhancing heart structure visualization. These techniques facilitate comprehensive heart condition examination postmortem and aid in developing effective diagnostic tools [41, 30].

3.3 Histopathological and Molecular Techniques

Histopathological and molecular techniques are integral for postmortem MI diagnosis, providing comprehensive insights into structural and molecular cardiac pathology alterations. As illustrated in Figure 3, these techniques can be hierarchically organized, categorizing key methodologies into segmentation techniques, machine learning applications, and spectral analysis. This organization enhances forensic investigation accuracy by enabling detailed myocardial tissue examination and pathological change identification. Advanced frameworks, like the cascaded framework, improve myocardial infarction area segmentation accuracy, facilitating precise diagnosis [34].

Machine learning frameworks like Nuquantus, which segment, classify, and quantify nuclei in complex tissue images, play a crucial role in cardiac tissue analysis. This approach allows detailed cellular structure examination, essential for understanding myocardial damage extent and nature [36]. Higher-order spectral analysis methods, analyzing short-duration ECG signals through power spectral and bispectral parameters, aid in identifying heart rhythm abnormalities indicative of cardiac conditions [35].

Deep learning architectures, such as ECG-SMART-NET, effectively capture temporal and spatial features critical for occlusive myocardial infarction (OMI) identification. These models enhance MI detection and classification by leveraging unique architectural modifications for comprehensive ECG data analysis [32]. The Dynamic Data Analysis Algorithm (DDAA) enhances postmortem diagnosis techniques by integrating real-time data processing, improving forensic assessment accuracy and reliability [15].

Advanced segmentation techniques, as employed in MyoPS-Net, utilize cross-modal feature fusion modules to extract and combine features from various CMR images, ensuring accurate myocardial pathology segmentation and assessment [33]. One-shot machine learning frameworks for fibrillar collagen segmentation in second harmonic generation (SHG) images of infarcted hearts further highlight these methodologies' potential in enhancing diagnostic precision [24].

Feature	Biochemical Markers and Enzymatic Analysis	Advanced Imaging and Segmentation Techniques	Histopathological and Molecular Techniques
Diagnostic Technique	Biochemical Assays	Imaging Modalities	Molecular Analysis
Technological Integration	Computational Methods	Deep Learning	Machine Learning
Key Features	Troponin, Galectin-3	Echocardiography, Lge	Nuquantus, Ddaa

Table 3: This table provides a comprehensive comparison of methodologies employed in postmortem myocardial infarction diagnosis, highlighting the integration of biochemical, imaging, and molecular techniques with advanced computational methods. It categorizes the diagnostic techniques into three primary domains: biochemical markers and enzymatic analysis, advanced imaging and segmentation techniques, and histopathological and molecular techniques, illustrating their technological integration and key features. The table underscores the synergy between these methodologies and modern computational advancements to enhance diagnostic accuracy and reliability.

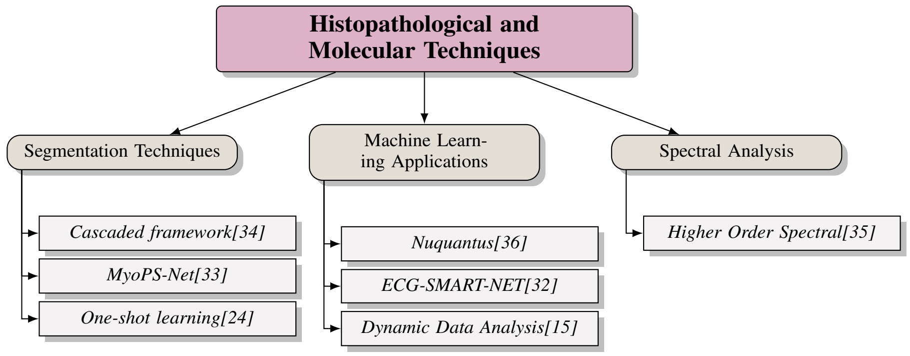


Figure 3: This figure illustrates the hierarchical organization of histopathological and molecular techniques for myocardial infarction diagnosis, categorizing key methodologies into segmentation techniques, machine learning applications, and spectral analysis.

4 Sample Timing and Its Importance

4.1 Impact of Sample Timing on Diagnostic Accuracy

The timing of sample collection is pivotal for accurate postmortem myocardial infarction (MI) diagnosis due to biochemical and molecular changes that occur after death. Precise timing is necessary to ensure diagnostic reliability, as evidenced by the influence of 10-second ECG data collection on diagnostic accuracy [42]. Histological analyses highlight the importance of timely data collection in distinguishing antemortem from postmortem changes, thereby enhancing forensic assessment accuracy [36].

Advanced methodologies such as Data Acquisition Systems (DAQS) and rapid diagnostic methods like Chemiluminescence Vertical Flow Assay (CL-VFA) underscore the significance of optimal sample timing for accurate coronary artery disease (CAD) diagnosis [43]. The effectiveness of diagnostic models, including Multi-Dimensional Reduction Interaction Regression (MDRIR), is enhanced by capturing complex predictor interactions, which is beneficial for disease risk predictions using electronic health records (EHRs) [12, 22].

Intraoperative assessments of myocardial viability, which avoid staining or fixation, further emphasize the need to minimize invasiveness and optimize sample timing [44]. The optimal timing for procedures like coronary arteriography significantly impacts MI diagnostic accuracy [11]. Systematic postmortem changes in serum markers highlight the importance of timing in enhancing diagnostic accuracy [7]. Comprehensive echocardiographic assessments are essential for accurate MI diagnosis, with timing playing a critical role in capturing necessary diagnostic information [45]. The detection of myocardial rupture, particularly within the first 24 hours of MI, underscores the temporal sensitivity of postmortem diagnostic procedures [46].

Figure 4 illustrates the hierarchical structure of the impact of sample timing on diagnostic accuracy, focusing on postmortem myocardial infarction diagnosis, advanced diagnostic methods, and intraoperative assessments. This visual representation reinforces the critical role that timing plays in enhancing diagnostic outcomes across various methodologies.

4.2 Technological Advancements and Sample Timing

Technological advancements have significantly impacted the timing of sample collection in postmortem MI diagnosis. Machine learning integration into diagnostic processes enhances risk assessment and decision-making, critical for determining optimal timing for invasive coronary angiography (ICA) [11]. High-resolution cardiac magnetic resonance imaging (MRI) facilitates precise temporal assessments of myocardial tissue changes, allowing clearer distinctions between antemortem and postmortem alterations.

Timely sampling is vital, as postmortem degradation of proteins and serum markers can affect forensic evidence interpretation, including postmortem interval (PMI) estimation and cause of death determination. Advanced protein technologies and serum marker stability understanding enhance

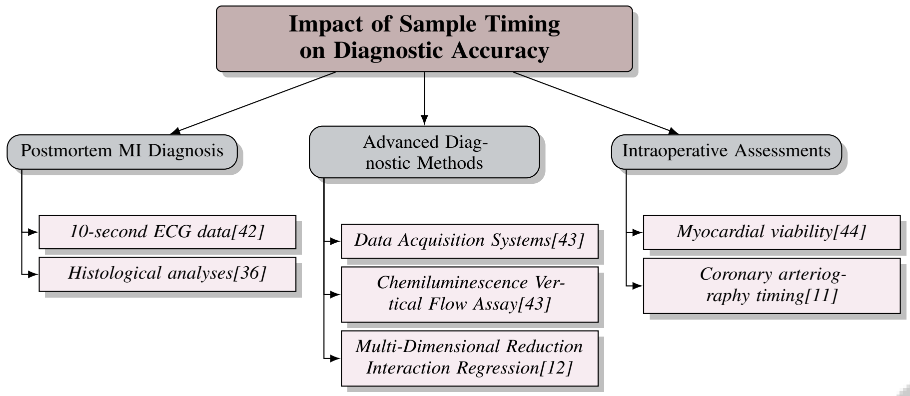


Figure 4: This figure illustrates the hierarchical structure of the impact of sample timing on diagnostic accuracy, focusing on postmortem myocardial infarction diagnosis, advanced diagnostic methods, and intraoperative assessments.

finding reliability [7, 14, 8, 9, 47]. Computational models simulating ischemic event progression provide insights into optimal sample collection timing, improving diagnostic accuracy.

Real-time data acquisition systems and rapid diagnostic assays underscore the necessity for prompt sample collection, enhancing clinical assessment accuracy and biomarker detection related to acute MI events [8, 7, 14, 12]. These technologies enable immediate biochemical and molecular marker analysis, crucial for accurately assessing myocardial damage. Aligning sample collection with peak marker expression can lead to higher diagnostic precision in forensic investigations.

4.3 Clinical Implications of Timing in Interventions

The timing of interventions and sample collection in postmortem MI diagnosis has profound clinical implications, affecting forensic assessment accuracy and subsequent legal and medical decisions. Precise timing is critical for distinguishing between antemortem and postmortem changes, especially in ischemic heart diseases [44]. Accurately determining myocardial event timing informs the differentiation of acute MI from other cardiac conditions, influencing clinical interventions and treatment strategies.

In clinical practice, the timing of invasive procedures like coronary arteriography is vital for accurate diagnosis and effective CAD management. Early intervention can significantly impact patient outcomes, as treatment delays may lead to irreversible myocardial damage and increased mortality [11]. Similarly, echocardiographic assessment timing influences myocardial rupture detection, a critical complication often occurring within the first 24 hours of MI, particularly in vulnerable populations [46].

Timely sample collection is essential for accurately measuring biochemical markers sensitive to postmortem changes. Systematic post-mortem alterations in serum markers necessitate prompt collection to ensure reliable diagnostic outcomes [7]. Advanced imaging techniques and computational models have enhanced myocardial assessment temporal resolution, allowing more precise timing of interventions and sample collection, thus improving postmortem diagnosis accuracy.

5 Biochemical Markers and Enzymatic Analysis

5.1 Key Biochemical Markers in Myocardial Infarction

Biochemical markers are pivotal in postmortem myocardial infarction (MI) diagnosis, offering insights into pathophysiological processes and aiding cause-of-death determinations. Cardiac troponins, particularly cTnT and cTnI, are essential due to their sensitivity and specificity for myocardial damage, validated in both clinical and forensic contexts [48]. Creatine Phosphokinase (CPK) is another reliable indicator of muscle damage, contributing to comprehensive assessments of cardiac events. Integrating diverse medical features, such as laboratory values and vital parameters, enhances MI diagnostic frameworks, allowing for detailed cardiac function evaluations [49].

Advanced computational techniques, including machine learning classifiers like K-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF), are crucial for MI diagnosis, achieving high accuracy rates [50]. Experiments with datasets such as PhysioNet MIT-BIH and the PTB diagnostic dataset demonstrate classification accuracies of up to 99.2% using models like AlexNet, highlighting the effectiveness of multimodal fusion frameworks [51]. Genetic factors, such as the FTO gene's association with body mass index and MI, provide further context for understanding MI risk factors and pathogenesis [52]. Integrating these genetic insights with biochemical markers can enhance forensic investigations and inform public health strategies.

5.2 Integration of Machine Learning in Analysis

The integration of machine learning in biochemical marker analysis represents a transformative shift in postmortem MI diagnosis, enhancing accuracy and efficiency. Convolutional neural networks (CNNs) are dominant tools due to their capacity to handle complex datasets and improve classification performance [53]. These models extract intricate patterns from biochemical data, crucial for accurate MI diagnosis. Techniques like Synthetic Minority Over-sampling Technique (SMOTE) and Generative Adversarial Networks (GANs) address data imbalance, a common issue in medical datasets [53], ensuring balanced training datasets and enhancing predictive accuracy.

Advanced methodologies, such as MuyGPs, improve ECG signal analysis, offering accurate classifications and uncertainty quantification relevant to MI diagnosis [1]. This approach leverages Gaussian Processes to model spatial dependencies in ECG data. Nuquantus software significantly enhances the consistency and speed of cardiac muscle nuclei segmentation compared to manual methods, emphasizing its potential for quantitative image analysis in cardiac pathology [36]. Furthermore, integrating higher order dynamic mode decomposition (HODMD) with CNNs enhances cardiac disease classification by augmenting datasets with extracted features [29], improving classification accuracy and providing a comprehensive framework for analyzing complex cardiac conditions.

5.3 Challenges and Innovations in Marker Analysis

Analyzing biochemical markers in postmortem MI diagnosis presents challenges, yet recent innovations are paving the way for more precise methodologies. Variability in marker levels due to postmortem changes can obscure accurate interpretations of myocardial damage [27]. The degradation of biomarkers like cardiac troponins and CPK complicates determining the timing of myocardial events, necessitating robust analytical techniques. Recent advancements in machine learning and computational methods offer novel solutions. Deep learning models, particularly CNNs, enhance classification accuracy by effectively managing complex, high-dimensional data [51], extracting subtle patterns from noisy datasets to improve postmortem diagnostic reliability.

Innovations in imaging technologies, such as cardiac magnetic resonance imaging (MRI) with late gadolinium enhancement, contribute to improved biochemical marker analysis. These modalities provide detailed myocardial tissue visualization, facilitating comprehensive assessments of infarcted areas and enhancing correlations between imaging findings and biochemical markers [31]. High-throughput machine learning benchmarks facilitate large-scale dataset analyses, enabling the identification of novel biomarkers and improving understanding of their roles in MI [22]. These benchmarks support the validation of new diagnostic markers, refining forensic methodologies.

6 Challenges and Limitations

6.1 Data Quality and Variability

The postmortem diagnosis of myocardial infarction (MI) is significantly hindered by data quality and variability, affecting diagnostic precision. Limited and low-quality echocardiographic datasets pose a substantial challenge, constraining algorithmic efficacy [23]. The reliance on single-modality data further restricts the integration of essential multimodal information crucial for accurate diagnosis [1]. ICD codes as benchmarks often misrepresent patient populations, creating cohort discrepancies [25]. Moreover, using a single unstained image for GAN training limits dataset generalizability [24]. Selecting dynamic mode decomposition (DMD) modes requires precision, as not all modes enhance classification [29].

Advanced machine learning techniques like MuyGPs improve ECG data classification confidence [1], yet ECG variability due to noise and irregular rhythms necessitates meticulous preprocessing. Imaging data quality is critical, with small sample sizes and non-standardized protocols impairing generalizability. Pre-aligned cardiac magnetic resonance (CMR) images can hinder segmentation, especially with anatomical variability and scar tissue [33].

6.2 Methodological Limitations

Methodological constraints significantly impact the reliability of postmortem MI diagnostic techniques. The quality and characteristics of input data profoundly influence diagnostic performance [54]. Single dataset reliance for model training limits result generalizability, potentially overlooking key risk factors [55]. Retrospective study biases further restrict applicability [56]. High-dimensional scenarios and unmet model assumptions complicate estimations [57]. Nuquantus, dependent on specific image types, may require retraining for different tissues or magnifications [36]. Single ear ECG performance varies with signal amplitude and electrode quality [19].

Existing benchmarks, often with small datasets and lacking clinical data association, struggle in clinical practice [26]. Sole reliance on ICD codes misrepresents patient cohorts, introducing methodological challenges [25]. Sparse data or differing external validation datasets complicate robust model performance [4]. Developing adaptive models and integrating comprehensive clinical datasets are essential for improving diagnostic efficiency and accuracy in forensic medicine.

6.3 Technological and Computational Challenges

Postmortem MI diagnosis encounters significant technological and computational challenges affecting forensic accuracy. Scarcity of labeled late gadolinium enhancement (LGE) CMR images limits segmentation algorithm development [41]. Complex image nature complicates segmentation, challenging reliable diagnostics. Incorporating uncertainty into models, such as Learning with Deferral (LDU), reduces deferral rates while maintaining accuracy, enhancing decision-making [58]. Local estimating equations for cumulative hazards on two time scales improve risk assessment accuracy [59].

Addressing technological challenges requires integrating advanced imaging techniques like postmortem cardiac magnetic resonance (PMCMR) and echocardiography with uncertainty-based models accounting for protein degradation. Sophisticated statistical methods, including one-class classification algorithms, can enhance MI detection accuracy and reliability, contributing to improved forensic analysis [9, 8, 60].

6.4 Generalizability and Applicability

The generalizability and applicability of current diagnostic methods in postmortem MI diagnosis face several challenges, necessitating innovative approaches. Traditional methods may limit forensic applicability due to their reliance on established protocols that do not fully capture the dynamic nature of biological interactions [17]. Constant viscosity assumptions in hemodynamic models further limit capturing complex processes during MI [48].

AI integration into forensic diagnostics offers promise, yet questions remain about model generalization across diverse populations and clinical workflow integration [61]. AI and machine learning enhance diagnostic accuracy, but dataset variability and correlated features challenge model generalizability [62]. Explainable AI (XAI) methods, while improving interpretability, face hurdles in ensuring applicability across datasets and models, particularly with complex features [62].

Future research should explore resampling methods, like the lazy bootstrap, to assess their impact on type I errors, power, and computational efficiency in diagnostics. Developing visual methods for model fit assessment could provide insights into diagnostic model applicability, ensuring accuracy and reliability in diverse forensic scenarios [63].

7 Conclusion

7.1 Future Directions and Solutions

Advancements in postmortem myocardial infarction (MI) diagnostics necessitate a multidisciplinary approach, integrating diverse data sources and leveraging cutting-edge methodologies to refine diagnostic precision. Enhancing computational efficiency, particularly through methods like MuyGPs, and exploring innovative techniques for uncertainty quantification in forensic ECG analysis, are pivotal steps forward. Improving model resilience against low-quality data by incorporating additional imaging modalities can substantially elevate diagnostic accuracy.

Exploring the role of Nrf2 in conjunction with various biomarkers and assessing the impact of distinct factors on marker expression within forensic settings can deepen our understanding of MI's molecular underpinnings. Expanding training datasets and strengthening the robustness of generative adversarial networks (GANs) are essential for extending these diagnostic methodologies to encompass a broader spectrum of cardiac conditions, thereby fortifying the reliability of diagnostic models.

Future research should also consider the implications of applying different ICD versions and broaden analyses to include a wider range of medical conditions to enhance diagnostic precision. The adaptation of existing methods to other cardiovascular conditions, alongside the integration of supplementary data sources, can further augment diagnostic capabilities.

Optimizing criteria for selecting dynamic mode decomposition (DMD) modes and expanding datasets to cover a variety of cardiac conditions will improve classification accuracy and provide a comprehensive understanding of cardiac pathologies. These efforts, combined with the development of simultaneous registration and segmentation techniques and the integration of anatomical knowledge into algorithmic frameworks, are crucial for advancing generalization and segmentation performance across diverse patient populations.

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