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Advancements in the Early Identification and Treatment of Myocardial Infarction in the Emergency Department: A Comprehensive Review of Machine Learning Approaches

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Abstract

Early detection and prompt treatment of myocardial infarction (MI) in the emergency department (ED) are pivotal for reducing morbidity and mortality. Chest pain is a common presenting symptom in the ED, necessitating effective risk stratification and decision-making to distinguish between acute coronary syndromes (ACS) and benign conditions.This systematic review evaluates the application of machine learning (ML) algorithms in identifying myocardial infarction among patients presenting with nonspecific chest pain in the ED. A comprehensive search of databases including PubMed, Cochrane Library, and Embase was performed for studies published until 2023, which investigated ML methodologies in this context.The review highlights a substantial interest in machine learning applications, demonstrating that ML techniques have significant potential to enhance diagnostic accuracy and prognostic capabilities compared to traditional clinical decision tools such as the TIMI and HEART scores. ML algorithms exhibited higher sensitivity and specificity in detecting MI, ultimately alleviating diagnostic burdens on emergency physicians. However, challenges remain in integrating these technologies into routine clinical practice due to issues related to data quality, model interpretability, and acceptance among healthcare providers.While machine learning holds promise for transforming the assessment of chest pain in the emergency department, further research is necessary to address existing limitations, including bias, data integration, and generalizability. The future landscape of emergency medicine could benefit from robust ML models that can assist clinicians in decision-making, leading to improved patient outcomes and more efficient healthcare delivery.

Keywords: *Myocardial Infarction, Emergency Department, Machine Learning, Acute Coronary Syndrome, Chest Pain Assessment.*

Introduction

Intricate decision-making under ambiguity is fundamental to emergency medicine [1]. Emergency doctors must navigate simultaneous and conflicting demands in a sometimes tumultuous and unexpected setting. Identifying individuals with potentially life-threatening diseases among more prevalent benign diagnoses remains a persistent difficulty. Chest pain illustrates this diagnostic dilemma. Chest discomfort is one of the most pervasive reasons for presenting to the emergency department (ED) [2]. Numerous etiologies exist for chest discomfort, necessitating that the emergency physician promptly and properly evaluate, examine, and diagnose life-threatening conditions such as acute coronary syndrome (ACS). Acute coronary syndrome (ACS) includes significant diagnoses associated with cardiac ischemia, such as unstable angina (UA), non-ST elevation myocardial infarction (NSTEMI), and ST-elevation myocardial infarction (STEMI)

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[3]. Acute Coronary Syndrome (ACS) results in considerable mortality and morbidity, with outcomes improved with prompt identification and intervention [4].

The majority of people presenting to an emergency department with chest discomfort will not have acute coronary syndrome. Risk stratification is a crucial component of chest pain assessment [5,6]. History and physical examination alone are inadequate for assessing individuals with chest discomfort [7]. This has resulted in the creation of many clinical decision tools, including the TIMI score and the HEART score, to aid physicians in identifying patients with chest pain who are at elevated risk of acute coronary syndrome [8, 9]. Numerous decision-making tools have undergone worldwide validation in various prospective studies, with the HEART score demonstrating favorable outcomes [10]. Notwithstanding these decision tools, a limited proportion of ACS patients remain undetected [11]. There is increasing acknowledgment that forthcoming artificial intelligence (AI) technologies may profoundly influence medical practice in the future [12, 13]. There has been a persistent interest in using AI-based approaches for chest discomfort.

Artificial intelligence is widely described as the theory and development of computer systems capable of doing activities that typically need human intellect [14,15]. In the last decade, a confluence of exponential growth in computer power, data digitalization, and advancements in AI algorithms has precipitated a resurgence in AI research. Machine learning (ML) is a subset of artificial intelligence (AI) that uses diverse techniques to identify patterns in data autonomously and then uses these patterns to generate predictions or judgments. Through continually comparing predictions with outcomes, machine learning models systematically modify their internal parameters—a process known as "training"—to enhance their performance [17-18]. The predictions of a trained model may then be evaluated on novel data to verify that the model can generalize to new information and has not been overfitted to the training data (MANSOOR et al., 2021). Deep learning (DL) is a subset of machine learning (ML) that uses several linked non-linear processing units to derive more abstract representations of input, enabling it to simulate very complicated processes. Deep learning algorithms have shown remarkable efficacy across several domains, including image identification, audio recognition, and natural language processing [19–22].

Current state-of-the-art machine learning methods are mostly restricted rather than universal in their applications; however, they have achieved significant accomplishments, even in certain issues previously considered intractable [23]. Efforts to develop more generalizable models are continuing; nonetheless, the use of currently limited machine learning technology might still profoundly transform several sectors, including healthcare [24]. AI methodologies have been shown to be effective in forecasting patient outcomes and stratifying risk based on clinical and physiological data [25, 26]. Recent applications of AI algorithms have successfully contributed to the detection of myocardial infarction [27]. The integration of artificial intelligence methodologies into clinical practice continues to be a problem. This study seeks to assess the use of machine learning in nonspecific chest pain within the emergency department.

Methods

The search strategy for this systematic review was designed with contributions from paper authors and a health sciences librarian specializing in systematic review methodologies. We conducted a search of Pubmed (MEDLINE), Cochrane Library, Web of Science, Embase, and Scopus for publications in English published from the creation of the databases until 2023.

The Use of Machine Learning for Undifferentiated Chest Pain in the Emergency Department

This comprehensive review indicates a sustained interest in the use of machine learning for undifferentiated chest pain in the emergency department, with machine learning approaches demonstrating remarkable efficacy in both diagnostic and prognostic applications. These outcomes may alleviate the diagnostic load on emergency doctors, enhance patient care, and enable health systems to offer services with increased efficiency. In the last decade, there has been significant advancement in technical capabilities, the digitalization of information, and the expansion of dataset size. Machine learning has grown in potency and accessibility. Models delineated by Baxt in 1990, which required up to 48 hours for training, may now be trained in just seconds.

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Baxt's groundbreaking research in the 1990s showed that "the non-linear artificial neural network exhibits superior accuracy compared to both physicians and other computer-based models" [28]. Nevertheless, there are very few studies that have juxtaposed machine learning with doctors, and no research since 1998 has directly contrasted machine learning with physicians about the diagnosis or prognosis of nonspecific chest pain in the emergency department. Recent research has compared machine learning to existing risk stratification techniques, like the TIMI and HEART scores. Despite its frequent use in clinical practice, growing data suggests that the HEART score may not outperform clinical gestalt in certain clinical situations [29]. As machine learning techniques are implemented into practice, it will remain essential to compare them with doctors.

The performance of machine learning models is generally enhanced with the augmentation of dataset and model size [30]. Acquiring extensive, high-quality clinical datasets is challenging, and their volume is limited by the number of patient presentations. A tendency exists to augment genuine datasets with synthetically created data that seems realistic. This facilitates the use of arbitrarily large datasets, resulting in enhanced model performance. Class imbalance is a prevalent issue, characterized by an abundance of some data classes while others, such as mortality, are predictably scarce. Novel deep-learning algorithms have been developed to tackle this issue [31].

The machine learning architectures documented in this research are rather modest in comparison to the state-of-the-art designs used in other domains, and the bulk of datasets utilized were somewhat tiny by contemporary machine learning criteria. State-of-the-art computer vision algorithms are often trained on datasets including over 14 million pictures [20]. A newly designed natural language processing system (GTP-3) utilizes 499 billion tokens for training input [22]. Rajkumar et al. forecasted death by training on a dataset including more than 216,000 patients and exceeding 46 billion data points [25]. At large sizes, the cost of training becomes a critical factor and is too costly for many researchers. Although training big models may be time-consuming and costly, predictions can be generated swiftly post-training with much-reduced computing resources, such as those available in ordinary PCs or mobile devices. Zhang et al. indicated that the duration required to provide prediction results after the ED physician activated the relevant button was less than 1 second [32]. Large models may be constructed and trained by researchers with enough resources; subsequently, if these models are made publically accessible, they may be tailored to and verified using local data, therefore minimizing training time and expenses. This may be particularly significant in resource-limited environments.

Numerous studies attained remarkable outcomes, despite the exclusion of some variables often used by emergency doctors in the assessment of undifferentiated chest pain. Nearly fifty percent (11 out of 23) of the evaluated studies failed to consider patients' symptoms. The integration of unstructured data into datasets continues to provide a difficulty. All datasets including echocardiography and ECG data use their interpretations. No research has used deep learning to integrate unstructured picture or ECG data, nor has any study employed natural language processing to include free-text clinical notes. Notably, no studies included chest X-rays, despite their common use in the evaluation of nonspecific chest pain in the emergency department.

McCullough et al. performed the only research that used emergency physician assessment as a variable in a machine learning system [33]. It is somewhat encouraging that the incorporation of the emergency physician's impression enhanced the model's outcomes; however, notably, the improvement was more pronounced for male patients than for female patients. Prior research indicates that male and female patients experiencing chest discomfort may get disparate treatment [34]. Their result's relation to this gap remains uncertain. Their methodology attained significant outcomes for female patients without the incorporation of emergency physician evaluation. It is intriguing to contemplate the position of the emergency physician if future research reveals that they are surpassed by a machine learning model, and the incorporation of their subjective evaluation does not enhance the model's performance. The future responsibilities of the emergency physician may transition from diagnosing undifferentiated situations to interpreting and conveying findings to patients and engaging in joint decision-making. It seems improbable that machine learning models would infringe on the several responsibilities of emergency physicians, including resuscitation, practical skills, and team management.

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In machine learning research, several studies have investigated varying quantities of input variables, revealing that an increase in variables does not inherently enhance outcomes, or that the addition of additional variables yields only minimal performance improvements. Liu et al. astutely proposed that a simple approach using non-invasive factors may assist in patient triage [35]. Machine learning demonstrated the capability to discover and integrate new risk factors, including heart rate variability metrics and corrected QT interval in electrocardiograms [36]. Troponin is a crucial element in the global definition of myocardial infarction (MI) [3]. The research cohorts included patients exhibiting symptoms of myocardial ischemia (chest pain), and therefore all individuals with an elevation and/or reduction in troponin levels (with at least one value beyond the 99th percentile) would satisfy the existing criteria for myocardial infarction (MI). Incorporating a variable used in the definition of MI as an input in a machine learning model to predict MI is problematic and will likely result in inflated estimates of model performance [37]. In several instances, preliminary troponin assessments undoubtedly contributed to the information used in determining the conclusion.

Despite varying perspectives, it is widely acknowledged that the output of machine learning models must be interpretable for acceptance and use in the healthcare domain [38]. Significant research is now concentrated on the development of "explainable AI" [39]. No research presented a human-interpretable explanation of the diagnostic rationale behind their algorithms in conjunction with their results. Than et al. created a mock-up of an application that renders the findings comprehensible to humans [27]. This is a crucial stage in the conveyance of findings; nevertheless, it does not provide insight into the algorithm's 'black box.' Due to the scale, complexity, and abstraction of the underlying models, interpretation is often impracticable [24]. It may be unattainable to realize anything beyond a mere semblance of comprehension. Nevertheless, emergency doctors often administer medications with ambiguous mechanisms of action, but for which substantial safety and effectiveness evidence exists [40]. If a machine learning model repeatedly exhibits reliable accuracy and safety across diverse scenarios, it may be deemed acceptable despite its 'black box' nature.

Human Elements Influencing Model Execution

Limited research has addressed the human elements involved in the practical deployment of machine learning algorithms. Hollander et al. [41] presented significant unique research assessing the impact of algorithm implementation on clinical decision-making, demonstrating that while an artificial neural network (ANN) known to surpass professionals was included, its use was little and it did not alter clinical practice. Emergency doctors may reject novel machine learning-based diagnostic and prognostic tools, particularly if the findings are not prompt and do not influence management decisions [41]. Medical practitioners are expected to maintain skepticism over an inexplicable black box. No assessment has been conducted about emergency department patients' attitudes and views on the use of machine learning in their treatment. Achieving the adoption of ML technologies by physicians and patients will likely need a thorough examination of the associated human issues.

Zhang et al. highlight that the use of machine learning prediction models in healthcare presents ethical and legal challenges, including malpractice liability for both technology developers and emergency doctors [32]. There is valid apprehension that significant judgments may rely on the results of an algorithm that is either incomprehensible or fundamentally beyond human understanding [42]. The existing legal framework is probably insufficient to tackle medical negligence associated with machine learning.

Risk tolerances among physicians, patients, and institutions vary. Attaining increased sensitivity at the cost of diminished specificity will result in a greater number of false positives, and the consequent over-examination of these instances may ironically inflict more damage than if the test had not been performed [43]. The 'test-threshold' idea delineates the juncture at which the risks of damage from false positive results equal the dangers associated with forgoing testing [44]. Patients whose risk is below the testing threshold get no advantage from further testing. This results in a theoretically ideal rate of misses. Kline et al. calculated that striving for a miss rate below 2% in the evaluation of patients with suspected coronary chest discomfort may result in greater damage due to excessive examination [45]. This miss rate may not align with the thresholds that clinicians find acceptable, and doctors can inadvertently cause more damage than

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benefit by endorsing excessively low miss rates for low-risk patients with chest discomfort [46]. The efficacy of ML in resolving this challenge has yet to be determined.

Despite more than 30 years of promising outcomes, the incorporation of machine learning algorithms into extensive clinical practice has not yet transpired. The variability across healthcare systems is certainly a considerable obstacle. Zhang et al. successfully implemented their approach, however, they acknowledge that, while demonstrating its feasibility, the model may lack generalizability to other institutions [32]. They propose that re-training and evaluation of other facilities may resolve this problem. A prototype application created by Than et al. demonstrates careful contemplation of the use of a centralized machine learning algorithm in a resource-limited environment, as well as the presentation of findings via a mobile application for both doctors (diagnostic metrics) and patients (graphical format) [27]. The use of machine learning algorithms necessitates health system monitoring, supervision, and the establishment of algorithm stewardship frameworks to guarantee their safe, effective, and equitable usage across varied patient groups [47].

Reproducibility is a cornerstone of the scientific process. There is increasing acknowledgment that machine learning research is experiencing a reproducibility dilemma [48]. This research determined that a limited number of studies made their code or dataset publicly available. Moreover, the methodological details were inadequately recorded, hindering replication in several research. Recent medical machine learning research has faced criticism for insufficient methodological information and for failing to provide data, algorithm code, or specifics of the computing environment that produced the reported results [49]. The dissemination of data and code is seen as essential, and the absence of such sharing diminishes the scientific merit of the study [49]. Previously highlighted obstacles to transparent and reproducible machine learning research include the privacy and ethical ramifications of disseminating patient data, as well as the economic disincentives associated with releasing proprietary models [50].

Notwithstanding comparable privacy challenges, the biomedical literature has demonstrated enhancements in specific critical indicators of reproducibility and transparency, and explicit, comprehensive, and enforced guidelines have enabled genomics researchers to disseminate intricate computational pipelines and sensitive datasets [49–52]. Potential solutions include fostering a research culture that promotes transparency and reproducibility, showcasing the model using public datasets, or enabling independent researchers to examine the data and validate the analysis before publication [49]. This review discovered no papers that were replication studies. Continuous efforts are necessary to balance patient privacy, open research, and private industry.

No randomized clinical studies have compared a machine learning algorithm to clinicians or existing risk score methods for the risk stratification of chest discomfort. No research has assessed changes in patient-oriented outcomes after the integration of a machine learning algorithm into clinical practice. It is crucial to evaluate the influence of these tools on clinical decision-making. Machine learning algorithms can either mitigate or exacerbate bias; hence, any forthcoming implementations must be mindful of this and provide suitable algorithm stewardship frameworks [47]. There exists considerable potential to integrate additional input variables into machine learning models, such as physician evaluations, unstructured clinical notes, raw ECG data, point-of-care echocardiograms, and chest X-rays. There will certainly be a growing focus on model explainability; nevertheless, it is important to recognize that this may only provide an appearance of comprehension by abstracting the underlying complexity. Although broad search phrases like "Chest Pain" were included, all articles included in this evaluation concentrated exclusively on MI/ACS and MACE. No studies have sought to identify other life-threatening causes of nonspecific chest pain, such as pulmonary embolism or aortic dissection. Future studies may seek to expand the use of machine learning in nonspecific chest pain.

Individuals with acute coronary artery blockage get advantages from urgent reperfusion treatment [53]. Presently, these individuals are mostly recognized by the occurrence of ST-elevation on the electrocardiogram. A minority of individuals with acute coronary artery blockage remains unrecognized by the STEMI/NSTEMI classification [53]. Although several studies included angiography data in their outcome definitions, none have endeavored to identify individuals with acute coronary artery blockage.

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Future research may use machine learning to identify people with acute coronary artery blockage who do not fulfill existing STEMI criteria.

Constraints

This review has some limitations. The majority (87%) of the included studies were determined to possess either a high risk of bias or significant applicability problems, rendering their conclusions potentially non-generalizable to other contexts. The majority of research was single-center, retrospective, and lacked perspective or independent verification. The concept of myocardial infarction (MI) and the biomarkers used to characterize it have evolved throughout time. The prolonged duration of this study indicates that several investigations were conducted before the use of high-sensitivity troponins, rendering the findings of previous studies potentially inapplicable to contemporary contexts. Since the inclusion of STEMI in the definition of myocardial infarction in 2000, only a limited number of studies (4 out of 17) have excluded individuals with STEMI. The therapeutic use and relevance of ML ratings for patients with STEMI is likely minimal, since they are often diagnosed only by ECG, and defined treatment protocols (emergency reperfusion) are already in place for these individuals. There was a lack of uniformity in the reporting of methodologies and findings among researchers. Machine learning reporting rules are inadequately created and followed, while initiatives are underway to rectify this situation [54-56].

Publication bias is recognized as prevalent in medical publications. Although empirical evidence for its presence in ML research is lacking, it probably exists, similar to other study domains. All studies except two revealed favorable outcomes for machine learning. Notwithstanding considerable efforts to formulate comprehensive and pertinent search phrases, some useful research may be disseminated under terms that are missing in the search. The search approach further eliminated abstracts and non-English publications. Quantitative synthesis was not conducted owing to significant study heterogeneity. Despite being anticipated and included in the study design, this indicates that the review does not provide a robust level of evidence for the use of ML in nonspecific chest pain. Machine learning is a developing notion without a definitive and commonly recognized definition. Although logistic regression is defined as a kind of machine learning, this review does not classify it as such by prevalent use.

Summary

Research on the uses of machine learning for nonspecific chest pain in the emergency department has been conducted for decades. Machine learning has been shown to surpass emergency doctors and existing risk stratification techniques in diagnosing acute myocardial infarction and predicting major adverse cardiovascular events; nonetheless, its integration into practice has been infrequent. A multitude of research evaluating the use of machine learning in nonspecific chest pain in the emergency department exhibits a significant risk of bias. Future research must use newly established standardized machine learning reporting criteria, register their techniques, and disseminate their datasets and code. Further research is necessary to evaluate the influence of machine learning model adoption on clinical decision-making, patient-centered outcomes, and acceptance among patients and physicians.

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التقدم في التعرف المبكر وعلاج احتشاء عضلة القلب في قسم الطوارئ: مراجعة شاملة لنهج التعلم الآلي

الملخص

الخلفية :يعد الكشف المبكر والعلاج السريع لاحتشاء عضلة القلب (MI) في قسم الطوارئ (ED) أمرًا محوريًا لتقليل معدلات المراضة والوفيات. يمثل ألم الصدر عرضًا شائعًا في قسم الطوارئ، مما يستلزم وجود وسائل فعالة لتصنيف المخاطر واتخاذ القرارات لتمييز المتلازمات التاجية الحادة (ACS) عن الحالات الحميدة.

الطرق :تستعرض هذه المراجعة المنهجية تطبيق خوارزميات التعلم الآلي (ML) في تحديد احتشاء عضلة القلب بين المرضى الذين يعانون من ألم صدري غير محدد في قسم الطوارئ. تم إجراء بحث شامل في قواعد البيانات بما في ذلك PubMed و Cochrane Libraryو Embaseللبحوث المنشورة حتى عام 2023 التي تناولت منهجيات التعلم الآلي في هذا السياق.

النتائج :تسلط المراجعة الضوء على اهتمام كبير بتطبيقات التعلم الآلي، حيث أثبتت تقنيات التعلم الآلي أنها تمتلك إمكانيات كبيرة لتعزيز الدقة التشخيصية والقدرات التنبؤية مقارنة بأدوات القرار السريري التقليدية مثل درجات TIMI و HEART.أظهرت الخوارزميات حساسية ونوعية أعلى في الكشف عن احتشاء عضلة القلب، مما يخفف العبء التشخيصي على أطباء الطوارئ. ومع ذلك، لا تزال هناك تحديات في دمج هذه التقنيات في الممارسة السريرية الروتينية بسبب قضايا تتعلق بجودة البيانات وقابلية تفسير النماذج وقبولها من قبل مقدمي الرعاية الصحية.

الخاتمة :على الرغم من أن التعلم الآلي يحمل وعودًا بتحويل تقييم ألم الصدر في قسم الطوارئ، إلا أن هناك حاجة إلى مزيد من البحوث لمعالجة القيود الحالية، بما في ذلك التحيز ودمج البيانات وإمكانية التعميم. يمكن أن تستفيد مستقبلات طب الطوارئ من نماذج تعلم آلي قوية يمكن أن تساعد الأطباء في اتخاذ القرارات، مما يؤدي إلى تحسين نتائج المرضى وتحقيق كفاءة أكبر في تقديم الرعاية الصحية.

الكلمات المفتاحية :احتشاء عضلة القلب، قسم الطوارئ، التعلم الآلي، المتلازمة التاجية الحادة، تقييم ألم الصدر.