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Research on Identifying Thrombosis in Human Body Based on Artificial Intelligence

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Abstract. Artificial intelligence in the medical field is increasingly being used, particularly in the critical area of thrombosis diagnosis where rapid and accurate detection can be life-saving. This article explores the current development of AI in the field of thrombosis diagnosis through comprehensive analysis of three distinct applications: Left Atrial Appendage Thrombus (LAT) prediction using machine learning models, real-time detection of Intracranial Hemorrhage (ICH) and Pulmonary Embolism (PE) through integrated radiology workflows, and edge-computing based Deep Vein Thrombosis (DVT) risk assessment using portable devices. The review demonstrates that AI-powered diagnostic tools have achieved promising accuracy rates, with some models reaching over 90% accuracy in specific applications. These technologies show significant potential to reduce diagnostic delays, minimize invasive procedures, and improve clinical outcomes, particularly in resource-limited settings. The LAT prediction model achieved an AUC of 0.85 and could potentially reduce unnecessary invasive procedures by 40%. Real-time AI tools for ICH and PE detection demonstrated sensitivities of 84% and 73% respectively, with processing times of 3-9 minutes. Edge-computing approaches for DVT assessment achieved 90.4% accuracy on low-cost hardware, making advanced diagnostics accessible in remote locations. However, current limitations include sample size constraints, technical processing failures, and the need for continued human oversight. This analysis reveals both the transformative potential and current challenges of AI implementation in thrombosis diagnosis, providing insights into future development directions for these artificial intelligence machines and tools.

Keywords: Artificial Intelligence, Thrombosis Diagnosis, Machine Learning, Medical Imaging

1. Introduction

Thrombosis, the pathological process of thrombosis in the vascular system, is a serious, global health risk. Its incidence is relatively random, and if it is not treated in time, it will have devastating consequences, including but not limited to stroke, pulmonary embolism (PE), myocardial infarction, and even death. Because of the above characteristics, how to accurately and rapidly identify different thromboses, such as pulmonary embolism (PE), deep vein thrombosis (DVT) and intracranial hemorrhage (ICH), is crucial to improve the prognosis, cure rate, and reduce mortality

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of patients. Traditional diagnostic approaches are mostly divided into two types: graphic analysis, such as (CT), or invasive procedures. For example, CT pulmonary angiography (CTPA) is the standard of PE detection. However, the problem is that CTPA partly relies on the diagnostic and judgment ability of radiologists, and because it relies on manual diagnosis, it may lead to potential and harmful diagnostic delays. (Toe) is very important for some procedures, but it is invasive and expensive [1,2], Similarly, diagnosing DVT relies on clinical scoring. D-dimer tests (with limited specificity) and ultrasounds require extremely professional knowledge [3], which also leads to the difficulty of manual diagnosis, thus delaying the optimal treatment cycle of thromboembolism. In general, the limitations of manual diagnosis and expensive treatment costs together lead to the risk of possible misdiagnosis and possible delay in treatment of thromboembolism.

Artificial intelligence (AI), machine learning (ML), and deep learning (DL) have become a trend in medical imaging and diagnosis, allowing thrombus detection to improve accuracy. Nowadays, some AI has special algorithms, which are specially trained for thrombus detection and can analyze medical images. Since AI does not require additional thinking time, its efficiency and accuracy will be much better than human eyes. Moreover, artificial intelligence has been able to be integrated into the radiology workflow, which can find the possible intracranial hemorrhage on CT or the signs of intracranial hemorrhage on CTPA at the same time of diagnosis. In this case, some specific examples even have an accuracy of more than 90% [1]. In addition to imaging, ML models are also designed to predict the presence of thrombus by using clinical and transthoracic echocardiography (TTE), which may reduce the need for transesophageal echocardiography in low-risk patients by 40% without missing thrombus [2].

The advancement of technology has profound significance for the diagnosis of thrombosis. Especially in some particularly urgent situations, artificial intelligence technology can reduce missed diagnoses and improve diagnostic speed. In terms of automation, artificial intelligence can reduce the burden on healthcare workers and improve work efficiency. This article reviews the current application status and impact of artificial intelligence in thrombus detection, as well as the progress of artificial intelligence in this field, and provides a detailed analysis of the combination of artificial intelligence and clinical practice. Finally, this article summarizes the limitations of current artificial intelligence methods, while looking forward to future developments.

2. Thrombosis detection with AI support in different domains

Integrating artificial intelligence into the diagnosis of various thrombotic diseases provides doctors with a new approach, but at the same time, the results tell us that there are slight differences in the application of AI for different parts and types of thrombotic diseases. Focusing on three specific dissertations: Left Atrial Appendage Thrombus (LAT) prediction [2], real-time detection of Intracranial Hemorrhage (ICH) and Pulmonary Embolism (PE) [1], and edge-computing based Deep Vein Thrombosis (DVT) risk assessment [3], they provide a multifaceted view of the current state of AI in this field.

3. Predictive modeling for invasive test reduction: Left Atrial Appendage Thrombus (LAT)

Moving on to the problem it tackled, The data of LATTEE registry study used by some scientist [2] solve the clinical problem of TOE (transesophageal echocardiography) – an invasive, uncomfortable, and resource-intensive procedure. To be more specific, AI model used existing clinical characteristics (such as heart failure status, NYHA classification, arrhythmia type/duration, age, diabetes, unstable INR, stroke history) and transthoracic echocardiography (TTE)

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measurements (LVEF, left atrial size, volume index LAVI) to predict LAT risk. For the result, trained on data from 12 centers (n=2827) and externally validated on data from 2 different centers (n=1284 on chronic OAC), LAT-AI achieved an impressive AUC of 0.85 (95% CI: 0.82–0.89). Crucially, it significantly outperformed traditional predictors: LVEF (AUC 0.81, p<.0001) and the CHA_2DS_2-VASc score (AUC 0.69, p<.0001). The study defined a decision threshold for LAT-AI scores that ensured a 99% negative predictive value (NPV) in the development cohort. Applying this threshold to the external validation cohort demonstrated the model's potential clinical utility: 40% of patients on chronic OAC could safely avoid TOE without any missed thrombi (100% sensitivity and 100% NPV in this simulated protocol). A reduced model (LAT-AI-reduced) using only 8 key features retained comparable performance (AUC 0.84). After that, the performance of this method allows the patient's treatment process to be more closely aligned with their own physical condition. By accurately stratifying lesions, LAT-AI can significantly reduce unnecessary invasive surgeries, lower patient discomfort, surgical risks, and medical costs. For the Limitation: The model requires a huge number of inputs (28+ features for full version), which could be a barrier to clinical workflows. Apart from that, its performance relies on the quality and availability of TTE measurements (LVEF, LAVI).

4. Realtime ai of ICH and PE detection in radiology workflows

A bunch of people [1] evaluated a commercial ai tool (Aidoc) while it integrated into the real-time Picture Archiving and Communication System (PACS) workflow of a university hospital. This study focuses on two acute, life-threatening diseases, so rapid diagnosis is crucial: ICH on non-contrast head CT and PE on Computed Tomography Pulmonary Angiography (CTPA). CTPA is a standard scan for detecting and locating PE [4,5]. In this case, AI will analyze the images simultaneously with the doctor and return annotated images of PACS to mark potential positives. Fo the performance, First, the processing rate: AI processed 77.6% (388/500) of head CTs and 89.6% (448/500) of CTPAs. Processing failures were more common with certain scanner models (e.g., Philips ICT: 56.8% for CT, 13.3% for CTPA; Siemens Somatom A540: 0% for CT) and were often due to technical non-compliance (e.g., slice thickness, scanner type) or severe artifacts. In ICH (Head CT), In processed studies, the AI achieved a sensitivity of 84% and specificity of 94% (NPV=98%, PPV=61%) compared to expert consensus review. False negatives (6 cases, 1.7% of negatives) included subtle subarachnoid hemorrhages, subdural hematomas, and parenchymal bleeds (including a hemorrhagic transformation). False positives (20 cases) were primarily caused by calcifications (45%), beam hardening artifacts (40%), and hyperdense dural sinuses (15%). The turnaround time for AI results was 3-7 minutes. Apart from that, for the PE(CTPA): AI demonstrated a sensitivity of 73% and specificity of 95% (NPV=94%, PPV=73%) on processed CTPAs. False negatives (19 cases) were attributed to chronic emboli (47.3%), artifacts (31.6%), pathologies masking PE (18.7%), and superimposed anatomy (5.2%). False positives (18 cases) stemmed from artifacts (33.3%), masking pathologies (16.6%), superimposed anatomy (16.6%), and combinations thereof (33.3%). The turnaround time was 5-9 minutes. And finally, the impact and limitations. In the field of medicine, accurate diagnosis is required. We can conclude that this AI tool has some credibility, but because its accuracy is not very precise, AI can still only be used as an auxiliary tool for doctors in this field.

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5. Edge computing of point-of-care DVT

Contreras-Luján et al. [3] sought they need an accurate and rapid risk stratification for DVT, especially in environments with limited resources and not particularly skilled physicians, so they evaluated the performance of various classical machine learning (ML) classifiers (Decision Trees-DT, K-Nearest Neighbors-KNN, Support Vector Machine-SVM, Random Forest-RF, Multi-Layer Perceptron Neural Network-MLP-NN, Extra Trees-ET) trained on a dataset built using Wells criteria, patient age, and gender. What's even more interesting is that they need to simulate situations where medical resources are scarce, they implemented and tested these models not only on a standard PC but also on a low-cost, low-power Raspberry Pi 4 (RP14) single-board computer.For the classifier performance, it using 85% of the (synthetically augmented) dataset for training/cross-validation and 15% for testing, the KNN algorithm achieved the highest accuracy (90.4%) and specificity (80.66%) on both PC and RP14. All evaluated models (DT, ET, KNN, MLP-NN, RF, SVM) performed well, with accuracy exceeding 85% and AUC values between 0.81 and 0.86 on the test set. KNN also showed the highest sensitivity/recall (79.78%) and F1-Score (80.21%). And for the edge device feasibility, The key finding was that the performance metrics (accuracy, F1-Score, precision/specificity, sensitivity/recall, AUC, etc.) were identical when running the trained models on the RP14 compared to the PC [3]. This demonstrates that complex diagnostic support can be deployed on affordable, portable hardware without sacrificing analytical power. While training times were longer on the RP14 (e.g., KNN: 0.1s vs PC 0.02s; MLP-NN: 175.85s vs 30.08s), inference (prediction) times are inherently fast for these models. After that, for the limitation and impact: This electronic device-based diagnosis provides ideas and data for more advanced tests in the future (D-dimer, ultrasound) because they are expensive [6,7], but relatively, because their experimental samples are small, this method still needs to be tested in larger populations to improve universality [8].

6. Conclusion

The three real cases analyzed in this article all point to one result: the accuracy of AI in identifying blood clots has reached a barely acceptable level, which makes it possible for AI to completely replace the diagnostic work of physicians in the future, thereby improving the efficiency of clinical diagnosis and reducing the probability of misdiagnosis. In the future, AI diagnostics are likely to be integrated into smaller, cheaper, and less reliant devices to meet the needs of edge healthcare and solve practical problems. (From a practical perspective, if AI physicians are very expensive and large in size, only large hospitals can afford to use them. However, this does not significantly improve the ability of physicians in large hospitals who generally have high capabilities. It is precisely those small hospitals and community hospitals that need the help of these auxiliary means to significantly improve their diagnostic efficiency and speed.). However, the limitations of AI tools should not be ignored now. In the example of Contreras Luján et al. 2022 [3], the sample size they used was not particularly large, which may result in a lack of universality in their argument. The main problems at present can be divided into two aspects: the sample size for training AI models is still not large enough, and the sample size for AI model diagnosis is not large enough. These two issues ultimately lead to the recognition performance of AI models may not be ideal, and the accuracy may not be within the range we want. So, we still need to hold a reserved attitude towards AI physicians. At least for now, doctors' personal diagnosis remains the cornerstone of clinical and acute diagnosis.

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Looking toward future research directions, several promising avenues warrant investigation to advance AI-powered thrombosis diagnosis. First, the development of multimodal AI systems that integrate diverse data sources—including clinical parameters, laboratory results, imaging data, and patient history—could significantly enhance diagnostic accuracy and provide more comprehensive risk stratification. Second, the exploration of federated learning approaches could address current sample size limitations by enabling collaborative model training across multiple institutions while preserving patient privacy. Third, research into explainable AI (XAI) methods specifically tailored for thrombosis diagnosis could improve clinician trust and adoption by providing transparent reasoning behind AI recommendations. Additionally, investigating the potential of continuous learning systems that adapt and improve from real-world clinical feedback could lead to more robust and generalizable models. Finally, the development of standardized evaluation frameworks and regulatory pathways for AI diagnostic tools in thrombosis care could accelerate the translation of research findings into clinical practice, ultimately benefiting patient outcomes on a global scale.

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