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Deep Learning Approaches for Thrombosis Detection and Risk Assessment via Ultrasound Imaging

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Deep Learning Approaches for Thrombosis Detection and Risk Assessment via Ultrasound Imaging

Maria Didaskalou

SUMMARY

Thrombosis, the formation of a blood clot inside a blood vessel, is a critical condition with significant health risks, including pulmonary embolism (PE) and chronic post-thrombotic syndrome. Deep learning (DL) approaches have shown promise in enhancing the detection and risk assessment of thrombosis, addressing key challenges in ultrasound (US) imaging interpretation. US imaging remains the method of choice for the initial assessment and monitoring of thrombosis due to its non-invasiveness, real-time capability, and absence of ionizing radiation. However, despite being a cost-effective and widely available tool, its diagnostic accuracy heavily depends on operator expertise, leading to variability in image acquisition and interpretation. The integration of DL techniques in US imaging has the potential to improve diagnostic precision, automate analysis, and reduce operator dependency. This thesis systematically reviews the role of DL in thrombosis detection and risk assessment via US imaging, categorizing approaches based on venous, arterial, and cardiac thrombosis.

A systematic search across PubMed and Scopus identified 233 studies, of which 22 met the inclusion criteria. The review highlights that convolutional neural networks (CNNs), U-Net, ResNet, and artificial neural networks (ANNs) are the most frequently employed models for classification, segmentation, and feature extraction. The study further categorizes DL-based thrombosis detection based on prediction tasks, including thrombus classification, vessel segmentation, flow analysis, and thrombus localization.

For venous thrombosis, DL models have been utilized to detect deep vein thrombosis (DVT) by evaluating vein compressibility, classifying thrombi, and assisting non-specialists in remote diagnosis. AI-guided freehand point-of-care ultrasound (POCUS) methods have been explored, demonstrating high sensitivity and specificity in detecting DVT.

For arterial thrombosis, CNN-based approaches have been applied to classify and segment atherosclerotic plaques, including the detection of vulnerable plaques associated with acute coronary syndrome (ACS). Deep learning models have also been integrated with intravascular ultrasound (IVUS) to enhance 3D vessel reconstruction, aiding in the assessment of plaque burden and stenosis severity. AI-based segmentation models, such as U-Net and Mask-RCNN, have significantly improved vascular lesion classification.

For cardiac thrombosis, DL techniques have been applied in transesophageal echocardiography (TEE) for the classification and segmentation of intracardiac masses, distinguishing thrombi from tumors. Computer-aided diagnostic (CAD) algorithms have enhanced thrombus detection in patients with atrial fibrillation, demonstrating improved sensitivity and specificity when combined with expert evaluation.

Overall, DL-based approaches for thrombosis detection and risk assessment using US imaging have shown considerable advancements in diagnostic accuracy, automation of image analysis, and clinical decision support. However, challenges remain, including dataset availability, variability in US image quality, and the need for multi-

center validation. Future research should prioritize real-world clinical integration, model interpretability, and the development of standardized, publicly available datasets for thrombosis assessment. This systematic review provides insights into the current state, challenges, and future directions of AI-driven vascular imaging, highlighting its potential impact in thrombosis detection and risk assessment across venous, arterial, and cardiac applications.

Προσεγγίσεις Βαθιάς Μάθησης για Ανίχνευση και Εκτίμηση Κινδύνου Θρόμβωσης μέσω Υπερηχογραφικής Απεικόνισης

Μαρία Διδασκάλου

ΠΕΡΙΛΗΨΗ

Η θρόμβωση, ο σχηματισμός θρόμβου αίματος μέσα σε ένα αιμοφόρο αγγείο, αποτελεί μια κρίσιμη παθολογική κατάσταση με σημαντικούς κινδύνους για την υγεία, συμπεριλαμβανομένης της πνευμονικής εμβολής (PE) και του χρόνιου μεταθρομβωτικού συνδρόμου. Οι μέθοδοι βαθιάς μάθησης (Deep Learning - DL) έχουν αναδείξει σημαντικές δυνατότητες στη βελτίωση της ανίχνευσης και αξιολόγησης του κινδύνου θρόμβωσης, αντιμετωπίζοντας προκλήσεις στην ερμηνεία των υπερηχογραφικών εικόνων. Η υπερηχογραφία (US) παραμένει η μέθοδος επιλογής για την αρχική εκτίμηση και παρακολούθηση της θρόμβωσης, λόγω της μη επεμβατικής φύσης της, της ικανότητας πραγματικού χρόνου και της απουσίας ιοντίζουσας ακτινοβολίας. Ωστόσο, παρά το ότι αποτελεί μια οικονομικά προσιτή και ευρέως διαθέσιμη διαγνωστική τεχνική, η ακρίβεια της διάγνωσης εξαρτάται σε μεγάλο βαθμό από την εμπειρία του χειριστή, γεγονός που μπορεί να οδηγήσει σε μεταβλητότητα στην απόκτηση και ερμηνεία των εικόνων. Η ενσωμάτωση τεχνικών DL στην υπερηχογραφία έχει τη δυνατότητα να βελτιώσει την ακρίβεια της διάγνωσης, να αυτοματοποιήσει την ανάλυση και να μειώσει την εξάρτηση από τον ανθρώπινο παράγοντα. Η παρούσα μεταπτυχιακή εργασία πραγματοποιεί μια συστηματική ανασκόπηση του ρόλου των DL μεθόδων στην ανίχνευση και αξιολόγηση του κινδύνου θρόμβωσης μέσω υπερηχογραφίας, κατηγοριοποιώντας τις προσεγγίσεις με βάση τη φλεβική, αρτηριακή και καρδιακή θρόμβωση.

Μέσω συστηματικής αναζήτησης στις βάσεις PubMed και Scopus, εντοπίστηκαν 233 μελέτες, εκ των οποίων 22 πληρούσαν τα κριτήρια ένταξης. Η ανασκόπηση ανέδειξε ότι τα συνελκτικά νευρωνικά δίκτυα (CNNs), το U-Net, το ResNet και τα τεχνητά νευρωνικά δίκτυα (ANNs) είναι τα πιο συχνά χρησιμοποιούμενα μοντέλα για ταξινόμηση, τμηματοποίηση και εξαγωγή χαρακτηριστικών. Η μελέτη κατηγοριοποίησε περαιτέρω τις DL μεθόδους για την ανίχνευση θρόμβωσης με βάση τους στόχους πρόβλεψης, οι οποίοι περιλαμβάνουν ταξινόμηση θρόμβων, τμηματοποίηση αγγείων, ανάλυση ροής και εντοπισμό θρόμβων.

Για τη φλεβική θρόμβωση, τα DL μοντέλα έχουν χρησιμοποιηθεί για την ανίχνευση εν τω βάθει φλεβικής θρόμβωσης (DVT), αξιολογώντας τη συμπίεστικότητα των φλεβών, ταξινομώντας τους θρόμβους και υποστηρίζοντας μη ειδικούς γιατρούς σε απομακρυσμένη διάγνωση. Εξετάστηκαν επίσης μέθοδοι καθοδηγούμενης από AI φορητής υπερηχογραφίας (POCUS), με μελέτες να καταγράφουν υψηλή ευαισθησία και ειδικότητα στην ανίχνευση της DVT.

Για την αρτηριακή θρόμβωση, οι CNN βασισμένες μέθοδοι έχουν εφαρμοστεί για την ταξινόμηση και τμηματοποίηση αθηροσκληρωτικών πλακών καθώς και την ανίχνευση ευάλωτων πλακών που σχετίζονται με το οξύ στεφανιαίο σύνδρομο (ACS). Επιπλέον, μοντέλα βαθιάς μάθησης έχουν ενσωματωθεί στην ενδοαγγειακή υπερηχογραφία (IVUS) για τη βελτίωση της τρισδιάστατης (3D) ανακατασκευής των αγγείων, διευκολύνοντας την εκτίμηση του φορτίου της αθηρωματικής πλάκας και της σοβαρότητας της στένωσης. Μοντέλα

τμηματοποίησης που βασίζονται σε AI, όπως το U-Net και το Mask-RCNN, έχουν επιφέρει σημαντικές βελτιώσεις στην ταξινόμηση αγγειακών βλαβών.

Για την καρδιακή θρόμβωση, οι DL τεχνικές έχουν εφαρμοστεί στην διοισοφάγειο ηχοκαρδιογραφία (TEE) για την ταξινόμηση και τμηματοποίηση ενδοκαρδιακών μαζών, διακρίνοντας τους θρόμβους από τους όγκους. Επιπλέον, οι αλγόριθμοι υποβοηθούμενης από υπολογιστή διάγνωσης (CAD) έχουν βελτιώσει την ανίχνευση θρόμβων σε ασθενείς με κολπική μαρμαρυγή, επιτυγχάνοντας βελτιωμένη ευαισθησία και ειδικότητα όταν συνδυάζονται με την αξιολόγηση ειδικών.

Συνολικά, οι DL μέθοδοι για την ανίχνευση και αξιολόγηση του κινδύνου θρόμβωσης μέσω υπερηχογραφίας έχουν σημειώσει σημαντική πρόοδο στην ακρίβεια της διάγνωσης, την αυτοματοποίηση της ανάλυσης εικόνας και την υποστήριξη κλινικών αποφάσεων. Παρόλα αυτά, παραμένουν προκλήσεις, όπως η διαθεσιμότητα δεδομένων, η ποικιλομορφία της ποιότητας των υπερηχογραφικών εικόνων και η ανάγκη για πολυκεντρική επικύρωση. Μελλοντικές έρευνες πρέπει να επικεντρωθούν στην ενσωμάτωση των AI μοντέλων σε πραγματικές κλινικές εφαρμογές, στη βελτίωση της ερμηνευσιμότητας των DL μοντέλων και στην ανάπτυξη τυποποιημένων και δημόσια διαθέσιμων βάσεων δεδομένων για την ανίχνευση της θρόμβωσης. Αυτή η συστηματική ανασκόπηση παρέχει σημαντικές γνώσεις σχετικά με την τρέχουσα κατάσταση, τις προκλήσεις και τις μελλοντικές κατευθύνσεις της AI-driven αγγειακής απεικόνισης, αναδεικνύοντας την εφαρμογή της στην ανίχνευση και αξιολόγηση κινδύνου της θρόμβωσης σε φλεβικό, αρτηριακό και καρδιακό επίπεδο.

CONTENTS

Chapter 1	Introduction.....	1
1.1.	Artificial Intelligence	1
1.1.1.	AI Technology	2
1.1.2.	Challenges and Applications of AI	4
1.2.	AI in Medical Imaging and Diagnosis.....	7
1.2.1.	Applications of ML in Medical Imaging	7
1.3.	AI in Ultrasound Imaging.....	8
1.3.1.	Beamforming.....	9
1.3.2.	Image Segmentation	9
1.3.3.	Image Classification	10
1.4.	Vascular Ultrasound Imaging	10
1.4.1.	B-Mode Ultrasound Imaging	10
1.4.2.	Spectral Doppler Imaging	11
1.4.3.	Color-Flow Doppler Imaging.....	11
1.4.4.	Intravascular Ultrasound (IVUS)	11
1.4.5.	Transesophageal Echocardiography (TEE)	12
Chapter 2	Related Work.....	13
2.1.	AI in Vascular Surgery and Cardiovascular Risk Assessment	13
2.2.	AI for Vascular Imaging and Plaque Characterization.....	13
2.3.	AI for Thrombosis Detection and Risk Assessment.....	14
2.4.	Comparison of Related Works	15
2.5.	Our Contribution	16
Chapter 3	Methodology.....	17
3.1.	Research Questions.....	17
3.2.	Search Strategy	17
3.3.	Eligibility Criteria	18
3.4.	Selection of Sources	19
3.5.	Data Extraction and Charting	19
3.6.	Synthesis of Results.....	20
Chapter 4	Results	21
4.1.	Selection of Relevant Sources	21

4.2.	Characteristics of Sources and Synthesis of Results	22
4.3.	DL-Based Approaches for Thrombosis Assessment via US Imaging	35
4.3.1.	DL-Based Approaches for Venous Thrombosis	35
4.3.2.	DL-Based Approaches for Arterial Thrombosis	37
4.3.3.	DL-Based Approaches for Cardiac Thrombosis	39
Chapter 5	Discussion	41
5.1.	Summary of Key Findings	41
5.2.	Comparison with Existing Literature	42
5.3.	Strengths and Clinical Implications	42
5.4.	Limitations and Challenges	43
Chapter 6	Conclusions.....	44
6.1.	Future Directions.....	44
6.2.	Final Remarks	45
References	46

LIST OF FIGURES

Figure 1. Timeline of AI (orange) and of AI in medicine (blue). Image available by Avanzo et al., under CC-BY-4.0 [7].	1
Figure 2. Subsections of artificial intelligence. Image available by Mukhamediev et al., under CC-BY-4.0 [9].	2
Figure 3. Source selection process from PubMed and Scopus search engines (PRISMA flowchart).	21
Figure 4. Trend of retrieved and included papers for DL-based thrombosis assessment using US imaging.	29
Figure 5. Distribution of included papers by publication type (journal vs. conference papers).	30
Figure 6. Distribution of primary clinical focus in included papers.	30
Figure 7. Distribution of clinical relevance to thrombosis in the included studies.	31
Figure 8. Distribution of US imaging modalities used in DL studies for thrombosis assessment.	32
Figure 9. Distribution of prediction tasks in DL-based thrombosis assessment.	33
Figure 10. Distribution of deep learning model types used in thrombosis assessment.	34
Figure 11. Distribution of validation methods used in deep learning models to evaluate their performance.	34

LIST OF TABLES

Table 1. A structured comparison of the related works..... 15

Table 2. Research papers included in the systematic review, their characteristics, the clinical primary focus, the relevance to thrombosis, the US imaging method, and the DL problem addressed. 22

Table 3. Descriptive data on the particular DL characteristics (models, validation methods, and performance metrics) presented in each of the papers included in the systematic review. 25

Table 4. Details about the used datasets and the challenges/limitations presented in each of the papers included in the systematic review..... 27

LIST OF ACRONYMS

Acronym	Description
ACS	Acute Coronary Syndrome
AHRQ	Agency for Healthcare Research and Quality
AI	Artificial Intelligence
AI-CDSS	AI-based Clinical Decision Support System
ANN	Artificial Neural Network
AUC	Area Under the Curve (used in ML model evaluation)
AutoML	Automated Machine Learning
BPNN	Back Propagation Neural Network
CAD	Computer Aided Diagnostic Algorithm
CAT	Cancer-Associated Thrombosis
CCI	Charlson Comorbidity Index
CCTA	Coronary Computed Tomographic Angiography
CDSS	Clinical Decision Support System
CNN	Convolutional Neural Network
CT	Computed Tomography
CTEPH	Chronic Thromboembolic Pulmonary Hypertension
CTPA	Computed Tomography Pulmonary Angiography
DBAC	Dynamic Blood Augmentation Cuff
DCCNN	Deep complex Convolutional Neural Network
DL	Deep Learning
DLS	Deep Learning Software

DVT	Deep Vein Thrombosis
FIVES	Fundus Image Vessel Segmentation
FNN	Feed-forward Neural Network
GBDT	Gradient Boosting Decision Tree
ICU	Intensive Care Unit
IVUS	Intravascular Ultrasound
KNN	K-nearest Neighbor
KS	Khorana Score (used for thrombosis risk assessment)
LDA	Linear Discriminant Analysis
LOS	Length of Stay
LR	Logistic Regression
MICCAI	Medical Image Computing and Computer-Assisted Intervention
ML	Machine Learning
MLP	Multi-Layer Perceptron
MRI	Magnetic Resonance Imaging
NHS	National Health Service (UK)
NLP	Natural Language Processing
NRMSE	Normalized Root Mean Square Error
PAD	Peripheral Artery Disease
PAI	Photoacoustic Imaging
PE	Pulmonary Embolism
PNN	Probabilistic Neural Network
POCUS	Point-of-Care Ultrasound
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PSI	Patient Safety Indicator
PSOWNN	Particle Swarm Optimized Wavelet Neural Network
RDF	Random Decision Forest
RF	Random Forest
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic Curve
SROC	Summary Receiver Operating Characteristic Curve
SVM	Support Vector Machine
TEE	Transesophageal Echocardiography
US	Ultrasound
VTE	Venous Thromboembolism
XGBOOST	Extreme Gradient Boosting

Chapter 1| Introduction

1.1. Artificial Intelligence

The term artificial intelligence (AI) refers to the general idea that intelligent behavior can be modeled by a computer with little assistance from humans. It describes how a machine or system can mimic human intelligence and focus on creating a machine that can think and behave like a human, including seeing, thinking, learning, planning, anticipating, and so forth [1].

The goal of the applied science of AI is to make computer systems more capable of carrying out tasks that the average human, and most people agree that the development of robots marked the beginning of AI [2]. Nevertheless, the history of AI has been marked by cycles of optimism and setbacks. In 1956, the Dartmouth Workshop brought together experts from various fields to discuss creating an artificial brain, laying the foundation for AI as a formal discipline. A timeline showing key milestones in AI development is shown in Figure 1. Early pioneers, like Marvin Minsky, were optimistic, predicting rapid advancements, but limited progress and critical reports led to reduced funding, resulting in the first "AI Winter" (1974–1990) [3,4]. AI experienced a revival in the 1980s due to international competition but faced another downturn in 1983-1993 with market collapse and funding withdrawal. Research regained momentum with milestones like IBM's Deep Blue defeating a chess champion and Watson winning *Jeopardy* in 2011, marking a new era of AI [5]. Over the past decade, exponential growth in imaging data and computational power has driven the integration of AI in medical imaging, addressing the need for efficiency and accuracy in processing large datasets [6,7].

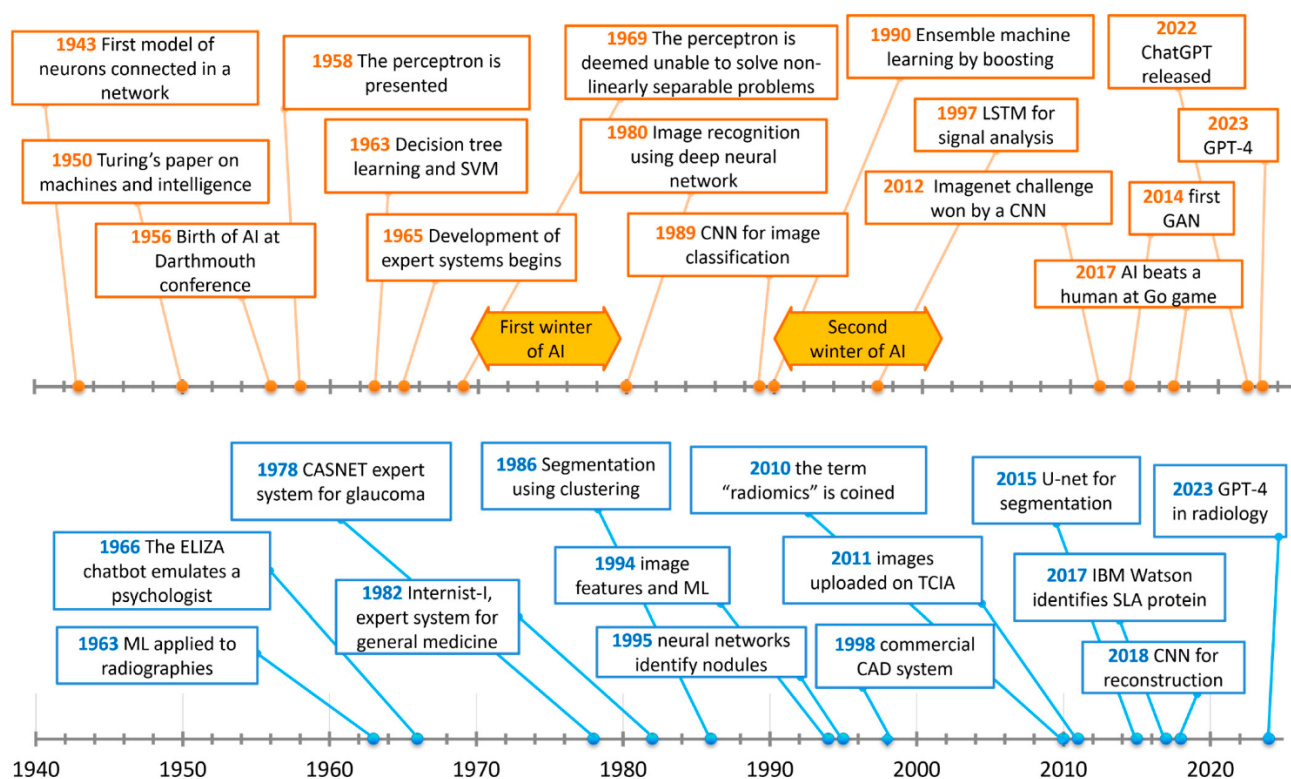


Figure 1. Timeline of AI (orange) and of AI in medicine (blue). Image available by Avanzo et al., under CC-BY-4.0 [7].

AI is now regarded as a technical field that applies innovative ideas and creative ways to tackle difficult problems. AI is now integral to daily life, powering technologies like virtual assistants (e.g., Siri, Alexa), recommendation systems in streaming services and e-commerce, and smart home devices. Other applications will be discussed in detail in the next paragraphs. The significant contribution that modern cybernetics has made to the advancement of AI cannot be overlooked. AI holds vast potential, with advancements expected across various sectors, especially if progress in electronic speed, capacity, and software development continues [8].

1.1.1. AI Technology

AI cover a wide range of technologies, each designed to address specific tasks and challenges. The domains of AI include machine learning, planning, expert systems, natural language processing (NLP), robotics, speech and vision [9]. Figure 2 shows the various subsections of AI.

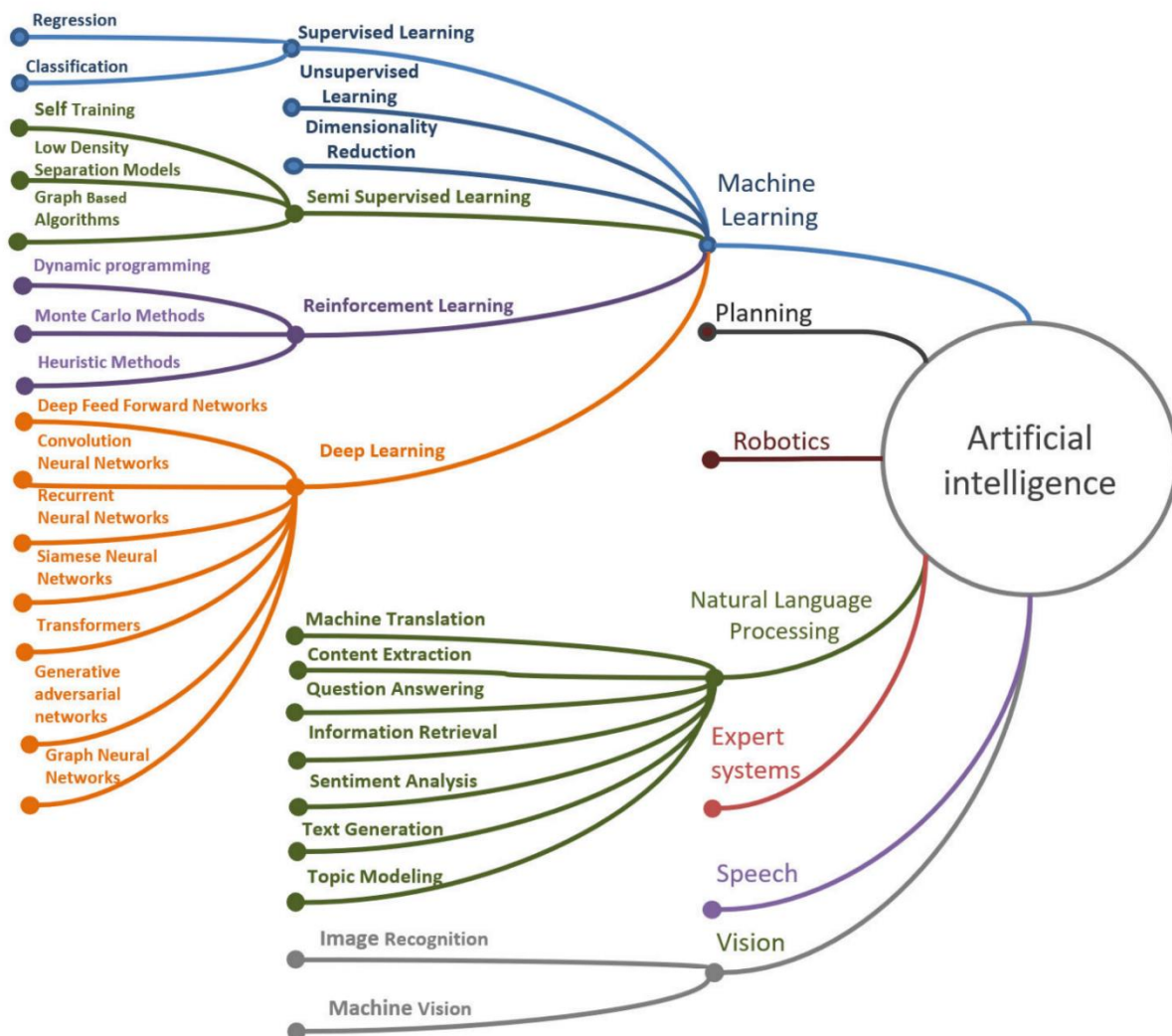


Figure 2. Subsections of artificial intelligence. Image available by Mukhamediev et al., under CC-BY-4.0 [9].

One key category is **Machine Learning (ML)** tools, which help create and train machine learning models. ML is a technology that enables systems to learn and improve from experience automatically, without explicit programming, and is considered a key driver in the Fourth Industrial Revolution (4IR or Industry 4.0). Industry 4.0 represents the ongoing automation of traditional manufacturing and industrial processes, incorporating advanced technologies like machine learning. In this context, machine learning algorithms are essential for intelligently analysing data and developing real-world applications [10].

ML algorithms can be categorized into four major types: supervised learning, unsupervised learning and reinforcement learning. In supervised learning models learn from labelled data. At its most basic level, supervised learning makes use of a data set that comprises the output class or target, which is labeled at the beginning of training, as well as input attributes. After training on the input data set, supervised ML algorithms generate a model that can distinguish between the output labels. Crucially, supervised learning can be further divided into algorithms for regression and classification. Regression algorithms produce continuous, quantitative output, whereas classification algorithms produce qualitative, discrete classes [11,12].

Unsupervised learning identifies patterns in unlabelled data. Dimensionality reduction and clustering are two traditional instances of unsupervised ML. Large data sets can be processed using these techniques without making any presumptions in order to lower the dimensionality of these complicated data sets (by principal component analysis) or identify significant clusters or patterns from abstract data sets (k-means clustering) [13]. Crucially, unsupervised ML can be used to supplement supervised ML techniques by first identifying the most important attributes before supervised ML techniques construct models to differentiate between the classes of interest. Unsupervised learning encompasses several key techniques, including clustering, anomaly detection, association rule learning (ARL) and auto encoders. Clustering groups data into distinct categories such as partitioning, hierarchical, overlapping, and probabilistic clustering. ARL identifies relationships between variables in large datasets and can process non-numeric data. Anomaly detection focuses on identifying outliers that may indicate unusual network activity, faulty sensors, or inconsistencies in data. Lastly, autoencoders use neural networks for representation learning, compressing and reconstructing input data to capture essential patterns and features. These techniques enable machines to find hidden structures in data without labeled examples [14].

An AI agent uses reinforcement learning to learn by interacting with its environment through trial-and-error. It then determines the best course of action based on the reward signals it has received from prior encounters [15]. Reinforcement learning is comparable to instrumental conditioning in physiology. Animals acquire correlations between stimulus and response through instrumental conditioning, such that the animal attempts a response (or action) in response to a stimulus (or environmental state). The relationship between the stimulus and reaction is strengthened if the response outcome for a particular stimulus is favorable [16].

A widely used ML tool is Automated Machine Learning (AutoML) platforms, such as Google Cloud AutoML, H2O.ai, and DataRobot, which aim to simplify the ML process, making it accessible to non-experts, enhance efficiency, and accelerate research. These platforms automate tasks such as data preprocessing, feature engineering, model selection, and hyperparameter tuning, enabling users to deploy powerful ML models with minimal manual intervention. However, despite their focus on automation, human involvement remains essential in key stages such as understanding domain-specific data, defining prediction problems, creating training datasets, and selecting appropriate techniques. These requirements can lead to inefficiencies for both domain experts and data scientists, preventing AutoML systems from achieving full automation [17].

Another important category is **Deep Learning (DL)** frameworks, which are specialized for working with deep neural networks—complex models with many layers that can learn intricate patterns in data. Object recognition, facial recognition, image recognition, text recognition, handwritten digit recognition, and speech recognition all utilize a hierarchical representation to optimize training results. Training a DL model can be a time-consuming process, often taking weeks or even months, and is also highly resource-intensive in terms of computational power. However, frameworks, such as TensorFlow [18], PyTorch [19] and Keras [20], provide powerful libraries and application programming interfaces (APIs) for building and training DL models, enabling advanced tasks such as image and speech recognition, natural language processing (NLP), and game-playing [21]. In this context, NLP Libraries are essential tools for tasks involving human language. Libraries like NLTK, SpaCy, and Hugging Face Transformers provide pre-built models and tools for analyzing and processing text. NLP is crucial for applications such as chatbots, sentiment analysis, language translation, and information retrieval, helping machines understand and interact with human language [22].

In the field of Computer Vision, libraries like OpenCV, TensorFlow, and PyTorch provide algorithms and tools for interpreting visual data. This is a field that mimics human vision, aiming to train computers to perceive, comprehend, and interpret the visual world through various algorithms and applications that underpin this technology. These libraries support tasks such as image recognition, object detection, and image segmentation, with applications in areas like medical imaging, autonomous vehicles, and surveillance [23].

1.1.2. Challenges and Applications of AI

AI has found diverse applications across various industries, significantly transforming how tasks are performed, and problems are solved. AI is revolutionizing education by personalizing learning, automating grading, and enhancing administrative efficiency. It adapts content to individual students' needs, helping accommodate different learning styles through adaptive learning systems and intelligent tutoring. AI also provides immediate feedback through automated grading, allowing teachers to focus more on interactive teaching. Virtual assistants and chatbots offer on-demand support, while predictive analytics help identify at-risk students, enabling early intervention. AI-driven tools like natural language processing assist with language learning and comprehension, and content creation platforms customize materials for diverse needs. Additionally, AI improves classroom engagement through gamification and virtual reality, while also streamlining administrative tasks like scheduling and record-keeping [24].

In retail, AI enhances customer experience through personalization, where algorithms analyze purchasing behaviour to offer tailored product recommendations and promotions. AI is also used in inventory management, predicting demand and automating stock replenishment to ensure efficient supply chain operations. Moreover, AI-driven chatbots in customer service help answer inquiries, resolve issues, and assist in the shopping process, improving customer satisfaction [25]. The transportation industry has also been revolutionized by AI. In autonomous vehicles, AI processes data from sensors, cameras, and radar to navigate and make real-time driving decisions, allowing for the development of self-driving cars. AI optimizes traffic management by analyzing real-time traffic data and adjusting signal timings to minimize congestion. Furthermore, AI aids route optimization, especially for logistics companies, enabling them to find the most efficient paths for deliveries, thereby saving time and fuel costs [26]. Finally, in manufacturing, AI enhances operational efficiency through predictive maintenance, where machine learning algorithms predict when equipment is likely to fail, allowing for timely repairs and reducing downtime. AI also drives robotic process automation (RPA), where robots perform tasks such as assembly, packaging, and quality control with high precision, improving production rates and consistency [27].

In healthcare and medicine, AI has made remarkable advancements, particularly in medical imaging. DL algorithms are used to analyze medical images such as X-rays, MRIs, and CT scans, assisting in detecting abnormalities like tumors or fractures and improving diagnostic accuracy [28]. The role of AI in imaging will be discussed later in this chapter. The enhancement of workflow and efficiency is the second way AI can influence healthcare. AI has reduced patient waiting times for appointments and enhanced surgery scheduling, saving a substantial amount of money. By screening and prioritizing radiographs, AI enables critical patients to receive more attention. In many hectic clinical settings, like the current COVID-19 outbreak, this application would be beneficial [29]. While AI in hospital management systems improves medical records and automates customer and patient data collecting, storage, and outcomes, it also results in a variety of better and synchronized elements and data. With the use of this technology, the vital statistics of the patients and gives both the patient's family and the doctor up-to-date information. Therefore, it helps with health system verification, which efficiently runs the hospital. It forecasts a person's ailment cause with accuracy. Artificial Intelligence offers digital control [30].

AI is also pivotal in personalized medicine, where it helps develop individualized treatment plans by analyzing patient data, including genetic information. To be noted, precision medicine is a quickly developing medical field that aims to tailor treatment by considering each patient's distinct molecular, physiological, ecological, and behavioral traits [31]. AI supports personalized treatment planning by tailoring approaches based on individual patient characteristics and their response to therapy. AI algorithms can analyze diverse data, such as patient medical histories, genetic profiles, and treatment responses, to predict how a patient may react to specific medications or treatment plans. In oncology, this capability is crucial for recommending the most effective chemotherapy drugs while minimizing side effects, based on the tumor's genetic makeup. AI also predicts potential drug interactions and side effects, further customizing treatment plans for safety and efficacy, ultimately improving treatment outcomes and quality of life by reducing unnecessary side effects [32]. Healthcare practitioners can forecast medication reactions and customize treatment regimens based on each patient's unique genetic composition by utilizing AI and ML to evaluate the vast and intricate datasets produced by pharmacogenomics. This individualized strategy may enhance treatment results, decrease adverse drug responses, and increase the efficacy of drugs. Additionally, the use of AI in pharmacogenomics can aid in the creation of new medications and medical equipment and make it easier to clinically incorporate pharmacogenomic data into healthcare decision-making [33].

Another application of AI is as virtual healthcare assistants. These digital assistants use AI-driven applications, chatbots, and interfaces to simulate human conversation and provide personalized medical support. They assist patients by identifying symptoms, offering medical advice, reminding them to take medications, scheduling appointments, and monitoring vital signs. Additionally, they collect daily health data and forward reports to physicians, reducing the workload of healthcare providers and improving patient outcomes. With 24/7 availability, virtual assistants enhance accessibility to healthcare, ensuring timely support for patients [34].

AI has become more and more important in surgical systems during the last 20 years. The Da Vinci surgical AI system is among the most innovative advancements in this industry. With important advantages like increased picture clarity, increased precision, and increased operating convenience, this ground-breaking discovery has revolutionized surgical treatments by making them less intrusive. It also makes remote surgery possible, which increases the scope of contemporary surgical care. Complex procedures that were previously thought to be extremely difficult can now be completed with minimally invasive approaches thanks to the Da Vinci technology [35].

In the medicinal laboratory field, AI accelerates drug discovery by predicting molecular interactions and identifying potential drug candidates more efficiently than traditional methods. AI has accelerated the drug discovery process for pharmaceutical companies by streamlining target identification and facilitating drug repurposing by analyzing off-target compounds, offering new potential uses for existing drugs [36,37]. Finally, AI is revolutionizing clinical trials by improving efficiency and accuracy. It accelerates patient recruitment through data analysis, optimizes trial design with predictive modeling, and enhances monitoring via real-time data from wearables. AI also facilitates adaptive trials by enabling protocol adjustments based on interim results. Clinical Decision Support Systems (CDSS) are increasingly used to assist healthcare professionals in diagnosing conditions and suggest optimal treatment strategies based on patient data. While promising, challenges like data privacy, bias, and regulatory compliance remain [38].

One of the major advantages of AI is that its decisions are based purely on facts rather than emotions. Unlike humans, who are often influenced by personal biases or emotional states, AI systems make objective, data-driven decisions, which can lead to more consistent and reliable outcomes. Another significant benefit is that AI systems do not require rest or sleep, unlike humans. This advantage allows AI to work continuously, overcoming the natural limitations of human fatigue. Moreover, AI offers the possibility of easier knowledge sharing. Once an AI system is trained to perform a specific task, it can be quickly replicated and applied in other situations, dramatically reducing the time and resources required for human training. This capability allows for faster dissemination of knowledge and skills across organizations and industries [39].

Besides its advantages, AI faces several challenges spanning technological, ethical, and societal domains. Data-related issues such as poor-quality data, bias, and privacy concerns remain significant obstacles, as does the scarcity of labeled data in certain fields. Ethical concerns include the potential for biased and unfair outcomes, the lack of transparency in decision-making processes, and the misuse of AI for harmful purposes like surveillance or disinformation. Technological limitations, including high costs, complexity, and the inability of most AI systems to generalize beyond specific tasks, further complicate its development. The economic and workforce impacts are also notable, with AI threatening job displacement and exposing a skills gap in the workforce [40].

Additionally, the absence of standardized regulations and governance frameworks poses risks of inconsistent practices and misuse, while global disparities in AI access exacerbate inequality. Security risks, such as adversarial attacks on AI systems and potential malfunctions in autonomous systems, raise safety concerns. Four main ethical concerns need to be resolved in order to fully realize AI's potential in healthcare: (1) informed consent to utilize data, (2) safety and openness, (3) algorithmic fairness and biases, and (4) data privacy. AI systems can suddenly malfunction in unfamiliar situations, becoming incredibly smart one minute and naive the next. Human decision-makers must be aware of these limits and make sure AI meets their needs, even when bias is controlled. Furthermore, AI creates cybersecurity risks, particularly in surveillance and national security, where mass monitoring and predictive policing could jeopardize fundamental rights. Frequently, these concealed dangers are not recognized until serious harm has been done. Furthermore, there are significant ethical questions raised by the developing lethal autonomous weapon systems, which combine artificial intelligence's capacity for decision-making with the capacity to cause harm, leading to discussions regarding the security and moral consequences of their deployment [41]. Lastly, AI's social and psychological effects, including reduced trust and diminished human interaction, highlight the importance of addressing these challenges through collaborative, ethical, and inclusive efforts [42].

1.2. AI in Medical Imaging and Diagnosis

Medical imaging uses different physical principles to visualize mainly internal body tissues through non-invasive or minimally invasive methods. Major techniques like computed tomography (CT), magnetic resonance imaging (MRI), X-ray radiography, ultrasound, and digital pathology produce crucial healthcare data, which accounts for approximately 90% of medical-derived information. Medical imaging is essential in clinical evaluations and healthcare treatment. This role consists of two key processes: examining images and interpreting the findings, both of which require a combination of technical expertise, clinical knowledge, and analytical skills. Radiologists utilize various imaging technologies to visualize the internal structures of the body. They must have a deep understanding of human anatomy, pathology, and disease processes to accurately assess images and differentiate between normal and abnormal findings[43]. Pattern recognition is a fundamental aspect of their work, enabling them to detect subtle abnormalities that may indicate diseases such as fractures, tumors, infections, or internal bleeding. However, this task is complex, and human interpretation of images can sometimes miss important findings or lead to errors in judgment [44].

The history of AI in medical imaging dated back to the 1960s, when efforts were made to incorporate AI with medical imaging through Computer-Aided Diagnosis (CADx). Note 5 CADx was utilized to enhance mammography and chest x-ray processes [45]. With the advent of ML techniques in the early 2000s, the use of AI in medical imaging made great progress, increasing the precision of abnormality detection and classification. AI was first used by radiologists to improve their skills and increase workflow efficiency. In the United States, 36 million MRI scans were performed by 2017, and Convolutional Neural Networks (CNNs) were frequently employed to diagnose disorders like breast cancer [46].

The emergence of Generative Adversarial Networks (GANs) in 2018 marked the beginning of generative AI, which helped in picture generation, quality improvement, and the production of artificial medical images for training. By 2020, AI applications have developed to encompass more complicated tasks like disease detection, organ localization, and image segmentation. Furthering AI's use in medical diagnostics, the Vision Transformer model became well-known for its ability to analyze medical images by spotting patterns in far-off areas [47].

ML has several key applications in medical imaging, significantly enhancing the diagnostic and treatment process. It plays a crucial role in image segmentation, helping to identify and outline specific structures or areas of interest within medical images. Image segmentation is a critical and complex task in fields like image processing, pattern recognition, and essential for computer vision. It involves dividing an image into meaningful regions, enabling accurate analysis and interpretation. In medical imaging, proper segmentation is vital for diagnosing conditions, identifying abnormalities, and planning treatments, making it an indispensable tool for effective healthcare decision-making [48]. For example, the FIVES dataset, collected for retinal vessel segmentation, includes 800 high-resolution, multi-disease color fundus images with pixelwise manual annotation and is expected to significantly contribute to the advancement of this field [49]. Another study applied the BPNN algorithm for the ultrasound image segmentation diagnosis method for patients with breast cancer. The researchers compared and explored the value of this algorithm in ultrasonic diagnosis after image segmentation. The results showed that the BPNN artificial intelligence algorithm model classification was always greater than the area under the curve of manual segmentation resulting in a better segmentation and therefore diagnostic effect for breast cancer axillary lymph node metastasis [50].

1.2.1. Applications of ML in Medical Imaging

AI helps in the detection and diagnosis of diseases by highlighting abnormalities and enabling early identification of various conditions, regardless of the imaging modality. ML models, particularly DL algorithms, can be trained on datasets of medical images, enabling them to detect patterns associated with various conditions, such as tumors, fractures, or organ abnormalities. These AI systems can highlight areas of concern, allowing healthcare professionals to focus their attention on potential problem areas. One of the key benefits of AI is its ability to detect diseases early, even in the absence of clear symptoms. For instance, a recent study found that a deep learning model outperformed human radiologists in detecting breast cancer from mammograms [51]. The AI system was able to correctly identify malignancies with higher sensitivity, reducing false negatives and aiding early diagnosis. Another worth-mentioning example is DeepGlioma, an AI model that automatically segments and classifies gliomas in brain MRIs. This AI tool helps clinicians by providing consistent and accurate tumor delineation, improving diagnostic workflow [52].

It also contributes to image preprocessing, improving image quality and reconstructing incomplete or noisy data to enhance clarity. The potential of AI to speed up medical picture analysis is among its most noteworthy advantages in this area. Conventional picture interpretation techniques can be laborious and prone to human mistakes. However, AI can interpret and analyze photos far more quickly, which will cut down on the amount of time needed to diagnose a patient. This velocity is especially important in emergency scenarios where every second matters [53].

Additionally, predictive analytics using medical imaging data can forecast disease progression and treatment outcomes, facilitating informed decision-making. AI ensures quality control by detecting artifacts and maintaining high diagnostic image standards. Lastly, it assists in the continuous monitoring and follow-up of disease progression and treatment response, enabling timely adjustments to treatment plans. A recent study showcased the use of DL to predict overall survival in prostate cancer patients, with the Automated Bone Scan Index from bone scintigraphy images identifying those at higher risk for more targeted treatments. Additionally, DL applied to cardiovascular magnetic resonance imaging data helped assess myocardial strain, improving risk stratification after acute myocardial infarction and offering an efficient, automated method for evaluating heart function [54].

1.3. AI in Ultrasound Imaging

Ultrasound (US) imaging stands out among medical imaging methods due to its convenience, non-invasive nature, and real-time capabilities [55]. In contrast, other modalities like computed tomography (CT) pose a risk of radiation exposure, while magnetic resonance imaging (MRI) is expensive and time-consuming. As a result, US imaging is widely used for both screening and diagnosis in various medical fields. Recent advancements in image rendering and the miniaturization of US equipment have made it increasingly suitable for point-of-care testing, including emergency, palliative, and home medical care. Additionally, combining US diagnostics with laboratory tests could enhance clinical outcome predictions [56,57].

However, US imaging faces several challenges related to image quality control. Unlike CT and MRI, which utilize automated acquisition processes with consistent settings, US relies on manual scanning, making image quality highly dependent on the operator's skill. Inexperienced technicians may produce suboptimal images, potentially affecting diagnostic accuracy. Additionally, factors such as acoustic shadows from obstructions like bones can further compromise image clarity. US also struggles with visualizing deep structures, such as those in the abdomen or deep pelvic regions, due to the limited penetration of sound waves. Furthermore, compared to MRI and CT scans, US has lower resolution, making it more difficult to detect small or subtle

abnormalities. These limitations highlight the need for specialized support technologies to standardize scanning techniques and enhance image quality, ultimately improving diagnostic reliability [58].

1.3.1. Beamforming

DL has transformed US beamforming, which combines signals from multiple ultrasound elements to create focused images. Traditional beamforming methods rely on user input and fixed parameters, limiting image quality and accuracy. In contrast, DL models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), learn from large datasets of raw US signals and their corresponding images, allowing them to autonomously extract relevant features and generate high-quality images. This approach is faster and more adaptable than traditional methods, enhancing image resolution, reducing speckle noise, improving contrast, and enabling tasks like tissue characterization and acoustic aberration correction [59].

Several studies have explored bypassing traditional beamforming by using advanced deep learning techniques to directly reconstruct images or perform image segmentation from raw RF data [48]. DL has also been employed to reduce artifacts in multi-line acquisition and multi-line transmission. Research by Luijten et al. [60] has focused on applying deep learning to adaptive beamforming, addressing computational challenges and aiming to enhance ultrasound image quality.

US imaging is widely used in various medical fields due to its non-invasive nature and real-time imaging capabilities. DL has been applied in clinical settings for a range of purposes, including breast imaging, cardiology, prostate imaging, fetal monitoring, thyroid assessments, and brain imaging. In 2018, the authors of [61] used generic deep learning software (DLS) to classify breast cancer in US images, aiming to evaluate its effectiveness and compare its performance with human readers of varying experience levels. The study found that the DLS achieved diagnostic accuracy similar to radiologists and outperformed a medical student with no prior experience.

1.3.2. Image Segmentation

In order to extract significant features like areas and outlines, medical image segmentation is an essential approach that splits images into homogenous subcomponents. It is essential to image analysis because it helps with object representation and feature extraction, which improves the precision of doctors' diagnoses and treatment choices. Numerous segmentation techniques have been developed, including contour extraction, region segmentation, and threshold segmentation. However, manual feature extraction, which is labor-intensive and impacted by doctors' subjective experiences, is frequently used in traditional procedures [62].

In cardiology, echocardiography, which uses US imaging to assess the heart, is a key area of research, especially for automating the segmentation and tracking of the left ventricle, an important factor in diagnosing heart disease. Echocardiography provides detailed images of the heart's size, shape, movement, pumping strength, valves, and blood flow. However, the quality of these images can be affected by factors such as the patient's body type, lung disease, or surgical dressings, making interpretation challenging. Accurate interpretation requires considerable expertise, and sometimes certain views of the heart may not be clearly visualized, limiting the diagnostic information. To analyze echocardiograms, the authors of [63] created the EchoNet DL model. Accurately identifying heart structures, estimating cardiac function, and forecasting systemic characteristics like height, weight, age, and sex are all possible with this approach. In order to diagnose heart problems, EchoNet showed that it could predict clinical characteristics such as ejection fraction and volumes. Additionally, it demonstrated promise in anticipating systemic characteristics that are not readily apparent in

echocardiography pictures [63]. AI models like EchoNet have the potential to significantly improve cardiovascular imaging diagnostics by automating the interpretation of echocardiograms. These findings highlight the crucial role of AI in vascular US imaging that will be discussed in the next chapter.

1.3.3. Image Classification

Generally speaking, image classification uses a classifier to determine the object category after manually extracting features using feature learning techniques to characterize the entire image. Thus, it is particularly crucial to figure out how to extract the image's features. Prior to DL, object classification using the Bag of Words model was frequently employed. The three steps of low-level feature extraction, feature coding, and classifier building comprise the most basic Bag of Words model framework. Prior to 2012, the conventional image classification approach could be finished in these three phases. However, the full development of an image classification model typically involves a number of procedures, including low-level feature learning. However, significant advances in image categorization have been made possible by the development of Convolutional Neural Networks (CNNs), which have demonstrated exceptional performance in extensive visual tasks. The powerful feature-learning capabilities of deep CNNs are the reason for their success. CNN-based classification follows an end-to-end learning process, where training, prediction, and output take place within the network, as opposed to traditional classification techniques that depend on manual feature extraction [64].

Although DL models have demonstrated potential in the classification of images, their "black box" nature makes it difficult to interpret their conclusions, which is a major issue in healthcare analytics. A study used a XAI technique to solve the issue of interpretability of the judgments produced by a CNN for the classification of fetal US images. These findings showed that although the proven solutions are accurate, they are not transparent enough for medical experts to have confidence in the model's predictions. CNN classification with good classification accuracy is interpreted using Local Interpretable Model-agnostic Explanations [65].

1.4. Vascular Ultrasound Imaging

Vascular ultrasound (US) imaging is a non-invasive diagnostic tool widely used to assess blood flow, vessel structure, and vascular abnormalities in the limbs, extracranial arteries, abdomen, and the heart. Over the past 25 years, several advancements have improved the effectiveness and precision of vascular ultrasound, making it the preferred first-line imaging modality for detecting thrombosis and other vascular conditions [66]. The key ultrasound imaging techniques used in vascular diagnostics include B-mode imaging, spectral Doppler, color-flow imaging, intravascular ultrasound (IVUS), and transesophageal echocardiography (TEE). Each of these technologies serves a distinct role, either for evaluating blood vessels externally or for providing in-depth intravascular or cardiac imaging.

1.4.1. B-Mode Ultrasound Imaging

B-mode ultrasound (brightness-mode) is the fundamental imaging modality used in vascular ultrasound. It creates real-time 2D cross-sectional grayscale images that allow clinicians to assess tissue structure and vascular anatomy. This technique works by emitting ultrasound pulses through a transducer, which then detects echoes reflected from organ and tissue boundaries. The received signals are processed into a grayscale image, where highly reflective structures, such as vessel walls and organ boundaries, appear brighter, while fluid-filled or less dense structures, such as blood, appear darker [67,68]. The ability of B-mode imaging to

provide detailed anatomical visualization makes it a critical tool in assessing vascular lumen, thrombi, and atherosclerotic plaques.

While B-mode imaging offers excellent anatomical visualization, it does not provide information about blood flow dynamics. To overcome this limitation, Doppler ultrasound techniques are employed to evaluate blood velocity, direction, and turbulence, which are essential for thrombosis assessment and vascular function analysis.

1.4.2. Spectral Doppler Imaging

Spectral Doppler imaging is used to measure blood velocities at specific locations within blood vessels. This technique operates by emitting high-frequency sound waves that interact with red blood cells moving through the bloodstream. The Doppler effect—a frequency shift caused by the movement of red blood cells—allows for quantification of blood flow speed and direction. The resulting Doppler spectrum provides a graphical representation of velocity changes over time, enabling clinicians to detect abnormal flow patterns indicative of stenosis, turbulence, or thrombus formation [69]. This capability makes spectral Doppler essential for diagnosing deep vein thrombosis (DVT), evaluating arterial narrowing, and identifying circulatory abnormalities.

While spectral Doppler imaging is highly effective in quantifying blood flow, it does not provide a spatial map of flow distribution. To address this limitation, color-flow Doppler imaging is often combined with B-mode and spectral Doppler for a comprehensive vascular assessment.

1.4.3. Color-Flow Doppler Imaging

Color-flow Doppler imaging enhances traditional ultrasound techniques by overlaying color-coded blood flow data on grayscale B-mode images. This technology works by detecting frequency shifts in reflected ultrasound waves to visualize blood movement within vessels. In a standard color Doppler map, red typically represents blood moving toward the transducer, while blue indicates blood moving away. The intensity of the colors correlates with flow velocity, providing clinicians with real-time hemodynamic insights [70,71].

This integration of anatomical and hemodynamic information makes color Doppler imaging indispensable in detecting vascular occlusions, stenoses, and embolic events. In contradiction, spectral Doppler not only shows the direction of blood flow, it also shows the phases (pulsatility) and acceleration of the blood flow. However, for deeper or more complex vascular structures, more advanced catheter-based imaging techniques such as Intravascular Ultrasound (IVUS) are required.

1.4.4. Intravascular Ultrasound (IVUS)

While B-mode and Doppler ultrasound are external imaging modalities, intravascular ultrasound (IVUS) [72] is a catheter-based technique designed for high-resolution cross-sectional imaging of blood vessels. IVUS involves inserting a miniature ultrasound transducer into the bloodstream to visualize the inner layers of vessel walls, enabling precise assessment of arterial structures, plaque burden, and stenosis severity. This technique is particularly useful for detecting and characterizing atherosclerotic plaques, identifying vulnerable lesions, and assessing the risk of thrombosis and acute coronary syndrome (ACS).

By providing detailed 3D reconstructions of arterial morphology, IVUS enhances clinical decision-making in coronary interventions and supports risk stratification for patients with arterial thrombosis. However, while

IVUS is highly effective in evaluating vascular abnormalities, specialized imaging is required for assessing cardiac chambers and thrombi within the heart. In such cases, Transesophageal Echocardiography (TEE) plays a crucial role.

1.4.5. Transesophageal Echocardiography (TEE)

Transesophageal echocardiography (TEE) [73] is a specialized ultrasound technique used for detailed imaging of cardiac structures, particularly for detecting intracardiac thrombi and left atrial appendage (LAA) clots in patients with atrial fibrillation (AF) or stroke risk. Unlike transthoracic echocardiography (TTE), which images the heart through the chest wall, TEE involves inserting a probe into the esophagus, positioning it closer to the heart for higher-resolution imaging. This method is especially valuable in identifying left atrial thrombi, evaluating prosthetic valve function, and guiding cardiac interventions.

Due to its superior image clarity, TEE is considered the gold standard for assessing cardioembolic stroke risk, detecting intracardiac thrombi, and monitoring cardiac function during surgery. However, its semi-invasive nature requires specialized expertise, making it less accessible than conventional transthoracic or vascular ultrasound.

Chapter 2| Related Work

The integration of artificial intelligence (AI) and machine learning (ML) in vascular imaging and thrombosis detection has gained significant attention in recent years. Various studies have explored AI-driven approaches for vascular disease management, atherosclerotic plaque characterization, thrombosis detection, and risk assessment. This chapter presents the related literature, presenting studies in ascending order of relevance to this thesis, beginning with broader applications of AI in vascular medicine and progressing toward thrombosis-specific detection and risk assessment methodologies.

2.1. AI in Vascular Surgery and Cardiovascular Risk Assessment

The application of artificial intelligence (AI) in vascular surgery, cardiovascular disease (CVD) management, and risk assessment has been extensively studied, with significant advancements in predictive modeling and imaging analysis. Although these studies do not focus specifically on thrombosis detection, they provide foundational AI methodologies that can be extended to this domain.

A systematic review of 249 studies published up to February 2021 identified several key AI applications in vascular surgery, including predictive modeling (22%), image segmentation (19.4%), diagnostic methods (18%), and combined applications (37%) [74]. The increasing use of artificial neural networks (ANNs) and support vector machines (SVMs) has been particularly notable in carotid artery disease, abdominal aortic aneurysms, and peripheral arterial disease. Despite AI's expanding role in vascular diagnostics, the integration of AI-based decision support systems into thrombosis detection remains limited, highlighting a gap in practical implementation.

Risk stratification for CVD and stroke has also benefited from AI advancements. A review of AI-based models integrating biomarkers, clinical data, and imaging phenotypes found that deep learning approaches outperform traditional risk assessment models, which often fail to account for complex variable interactions [75]. However, among the studies analyzed, none specifically addressed thrombosis risk prediction, nor did they incorporate ultrasound imaging for thrombus detection, leaving room for improvement in non-invasive thrombosis risk assessment.

Lower limb vascular management has been another area where AI is making an impact. A study on peripheral artery disease (PAD), cerebrovascular disease, and deep vein thrombosis (DVT) examined AI-driven image processing methods applied to contrast-enhanced MRI and ultrasound data [76]. While these solutions demonstrate enhanced diagnostic accuracy, the review identified a lack of extensive AI validation studies for thrombosis detection, limiting clinical adoption in real-world settings.

Beyond vascular surgery, machine learning has also been explored in trauma care. An analysis of 89 studies on ML applications in hemorrhagic trauma risk assessment showed that ML-based prediction models improve trauma-related clinical decision-making, particularly in hemorrhage severity prediction [77]. While these methodologies align with thrombosis risk assessment principles, they do not directly address thrombosis detection or AI-based thrombus segmentation, making their applicability to this thesis more indirect.

2.2. AI for Vascular Imaging and Plaque Characterization

Several studies have explored AI techniques for vascular imaging, atherosclerotic plaque characterization, and segmentation methodologies, which are crucial for thrombus detection and classification. While these studies contribute to arterial and venous disease diagnostics, their focus has primarily been on plaque identification and segmentation rather than thrombosis-specific detection and risk assessment.

A comprehensive review analyzing ultrasound-based AI models for carotid artery stenosis prediction examined segmentation techniques for plaque area, lumen area, and intima-media thickness (IMT) [78]. Among the reviewed methods, deep learning models demonstrated notable improvements in plaque detection and characterization, supporting their relevance for thrombosis-related diagnostics. However, despite its evaluation of various ultrasound image processing methodologies, the study did not include thrombosis detection or AI-based risk assessment, highlighting a gap in thrombus segmentation techniques.

The automation of carotid artery segmentation and lumen characterization has been the focus of several AI-driven studies. A review of deep learning-based segmentation techniques applied to intima-media thickness measurement and plaque segmentation found that AI models outperformed conventional methods in stroke risk prediction and thrombus detection [79]. Despite these advancements, none of the reviewed studies provided an AI-based framework for thrombus classification, nor did they offer solutions for ultrasound-driven thrombosis risk assessment, which remains a significant limitation.

Beyond segmentation, AI has been applied to symptomatic carotid plaque detection to differentiate stable from vulnerable plaques. A study evaluating deep learning-based classification models demonstrated high efficacy in identifying high-risk plaques, an essential precursor to thrombosis diagnosis [80]. While these methods improve vascular disease characterization, they lack direct applicability to thrombosis risk prediction and thrombus segmentation in ultrasound imaging, limiting their clinical integration into thrombosis management.

Non-invasive plaque characterization has also been explored using intravascular ultrasound (IVUS) and coronary computed tomographic angiography (CCTA). An AI-assisted coronary atherosclerotic plaque analysis reviewed 122 studies and concluded that computer-aided diagnosis (CAD) systems significantly enhance plaque classification accuracy [81]. Although these findings underscore AI's potential for cardiovascular imaging, they do not extend to thrombosis detection using ultrasound-based deep learning models, leaving a gap in ultrasound-based thrombus segmentation research.

2.3. AI for Thrombosis Detection and Risk Assessment

A focused subset of studies has directly investigated AI applications for thrombosis detection, venous thromboembolism (VTE) risk prediction, and machine learning-based embolism classification. These studies have demonstrated significant progress in AI-driven diagnostic tools, but they also reveal key limitations in clinical implementation, model generalizability, and thrombosis detection.

A systematic review evaluating 20 studies on AI applications in VTE prediction found that machine learning-based models significantly outperformed conventional risk assessment tools [82]. In particular, AI-driven models achieved a higher mean area under the curve (AUC) than traditional clinical risk scores, demonstrating superior predictive accuracy. However, while these methods improved thrombosis risk stratification, challenges such as high bias risk, missing data, and lack of external validation hinder their clinical applicability. Few of the reviewed studies incorporated ultrasound data, limiting their ability to provide dynamic, real-world thrombus assessment.

A narrative review on machine learning in venous thromboembolism (VTE) explored AI-based solutions for risk prediction, diagnosis, prevention, and prognosis [83]. The review introduced commonly used machine learning algorithms in medicine and evaluated their application to VTE classification. It highlighted that while AI has potential to enhance early diagnosis and personalize patient management, many medical professionals lack familiarity with AI-driven risk models, leading to slow adoption. The study emphasized the need for specialized research on AI for VTE and thrombosis detection, addressing challenges in algorithm transparency and model interpretability.

Deep learning-based tools for chronic pulmonary embolism (CPE) detection have also been explored, with an analysis of five AI models trained on CT pulmonary angiography (CTPA) datasets demonstrating their ability to classify PE severity [84]. The findings emphasize that AI models can detect chronic embolism with high precision, but dataset inconsistencies, variations in training methodologies, and a lack of real-world validation remain significant challenges. Additionally, these studies primarily rely on CT-based imaging, whereas ultrasound—a more accessible, non-invasive modality—has not been widely explored for thrombus characterization.

Machine learning techniques have also been applied to cancer-associated thrombosis (CAT) risk stratification, with an analysis of three AI-driven approaches: computer vision for thromboembolism detection, natural language processing (NLP) for case identification, and predictive AI models for thrombosis risk estimation [85]. While these methods hold promise for enhancing CAT diagnosis and guiding anticoagulation therapy, data heterogeneity, overfitting risks, and model interpretability issues remain key barriers to adoption. Furthermore, the study does not incorporate ultrasound-based thrombosis detection, making it less applicable to thrombus evaluation.

2.4. Comparison of Related Works

A structured comparison of the related works in AI-based thrombosis detection and risk assessment is presented in Table 1. The table categorizes prior studies based on their primary research focus and their relevance to thrombosis detection and risk assessment. This comparative analysis highlights the gaps that our thesis aims to address.

Table 1. A structured comparison of the related works.

Study	Research Focus	Relevance
[74]	Review and bibliometric analysis of AI in vascular surgery	Indirectly Related
[75]	AI-based cardiovascular and stroke risk assessment	Indirectly Related
[76]	AI applications in vascular disease management	Indirectly Related
[77]	AI in hemorrhagic trauma care	Indirectly Related
[78]	Ultrasound image analysis for carotid artery stenosis	Moderately Relevant
[79]	AI segmentation methods for carotid artery imaging	Moderately Relevant
[80]	AI in carotid plaque detection	Moderately Relevant
[81]	AI for coronary atherosclerotic plaque characterization	Moderately Relevant
[82]	AI for venous thromboembolism prediction	Highly Relevant
[83]	ML applications in venous thromboembolism	Highly Relevant
[84]	AI for chronic pulmonary embolism detection	Highly Relevant
[85]	ML in cancer-associated thrombosis detection and risk stratification	Highly Relevant

2.5. Our Contribution

While existing studies provide foundational insights into AI-driven thrombosis detection, plaque characterization, and vascular imaging, none have developed a fully integrated deep learning framework for ultrasound-based thrombosis detection and risk assessment. This thesis advances prior work by systematically reviewing the current state of DL approaches in diagnosing thrombosis using US imaging, highlighting their applications, benefits, and challenges. Vascular ultrasound plays a vital role in diagnosing and monitoring thrombosis, but it faces limitations such as operator dependency and variability in interpretation. AI technologies, and particularly DL, have emerged as transformative tools that can enhance image acquisition, analysis, and diagnostic accuracy.

This thesis provides a comprehensive analysis of the existing literature, focusing on the techniques and methodologies used, clinical applications, and outcomes achieved. It also identifies research gaps, challenges in implementation, and potential future directions for integrating DL in vascular ultrasound for both thrombosis detection and risk assessment. The review analysis covers various applications, including image quality enhancement, vessel segmentation, disease classification, and decision support, with an emphasis on methodologies, performance metrics, and clinical impact.

The results of this thesis serve as a valuable resource for clinicians, researchers, and policymakers, offering a consolidated understanding of advancements in AI for thrombosis detection and risk prediction and providing insights into how these technologies can improve diagnostic precision and patient outcomes in vascular healthcare. Additionally, it guides future research by identifying gaps and suggesting areas for improvement, ultimately aiming to optimize AI's real-world application for better diagnostic accuracy and risk assessment in thrombosis management.

Chapter 3| Methodology

This thesis aims to perform a qualitative systematic review conducted to analyze and synthesize existing research on the application of deep learning (DL) in thrombosis detection and risk assessment using ultrasound imaging. This review follows the PRISMA methodology [86], ensuring a structured, transparent, and reproducible approach to the identification, selection, and synthesis of relevant literature.

3.1. Research Questions

This systematic review aims to address the following research questions (RQs):

- RQ1.** What is the primary clinical focus of the study (i.e., thrombosis or related conditions)?
- RQ2.** How does the study contribute to thrombosis detection, risk assessment, or clinical decision-making in thrombotic conditions?
- RQ3.** What ultrasound imaging method used (e.g., B-mode US, Doppler US)?
- RQ4.** What is the problem addressed by employing a DL model on ultrasound images?
- RQ5.** What DL/ML models are used in thrombosis detection or risk assessment with ultrasound imaging?
- RQ6.** What validation methods have been employed to assess DL models?
- RQ7.** What performance metrics (e.g., sensitivity, specificity, accuracy) have been reported for DL approaches?
- RQ8.** What kind of datasets are being used, and whether the dataset is available?
- RQ9.** What challenges or limitations have been identified in proposed DL approaches?

3.2. Search Strategy

To identify relevant peer-reviewed publications, a systematic search strategy was designed using a combination of Boolean operators, MeSH terms, and relevant keywords. The search was conducted in two primary electronic databases:

- **PubMed** (a key database for biomedical literature)
- **Scopus** (a multidisciplinary scientific database)

The search strings were carefully crafted to optimize the retrieval of relevant studies:

- **PubMed Query:**
("deep learning"[Title/Abstract] OR "neural network"[Title/Abstract] OR "neural networks"[Title/Abstract] OR "deep learning"[MeSH Terms] OR "Neural Networks, Computer"[MeSH Terms] OR (deep[Title/Abstract] AND learning[Title/Abstract])) OR (neural[Title/Abstract] AND network*[Title/Abstract])) AND (ultrasound*[Title/Abstract] OR ultrasonic*[Title/Abstract] OR sonography[Title/Abstract] OR ultrasonography[Title/Abstract] OR echography[Title/Abstract] OR ultrasonographic[Title/Abstract] OR echotomography[Title/Abstract] OR

ultrasonography[MeSH Terms]) AND (thrombosis[Title/Abstract] OR thromboses[Title/Abstract] OR thrombus[Title/Abstract] OR clot*[Title/Abstract] OR atherothrombosis[Title/Abstract] OR thrombosis[MeSH Terms])

– **Scopus Query:**

TITLE-ABS-KEY("deep learning" OR "neural network" OR "neural networks" OR (deep AND learning) OR (neural AND network*)) AND TITLE-ABS-KEY(ultrasound* OR ultrasonic* OR sonography OR ultrasonography OR echography OR ultrasonographic OR echotomography) AND TITLE-ABS-KEY(thrombosis OR thromboses OR thrombus OR clot* OR atherothrombosis)

The search was conducted systematically, with no restrictions on publication year to ensure a comprehensive dataset of relevant research.

3.3. Eligibility Criteria

To ensure that only relevant studies were included, the following inclusion and exclusion criteria were established:

Inclusion Criteria:

1. Study Focus: The study must explore the use of DL models in thrombosis detection and/or risk assessment using ultrasound imaging.
2. Application of AI: Research must focus on image acquisition, enhancement, segmentation, classification, thrombus localization, blood flow analysis, risk prediction, or decision support using AI techniques.
3. Target Medical Condition: Studies must focus on medical conditions related to thrombosis, including but not limited to venous thrombosis (e.g., deep vein thrombosis, pulmonary embolism), arterial thrombosis (e.g., carotid or coronary thrombi, plaque rupture), and cardiac thrombosis (e.g., left atrial appendage thrombi, intracardiac masses).
4. Imaging Modality: The study must use vascular ultrasound (US) or Doppler ultrasound (DUS) as the primary imaging modality, including B-mode US, compression US, intravascular ultrasound (IVUS), or transesophageal echocardiography (TEE).
5. Publication Type: The study must be an original research article, published in peer-reviewed journals or conference proceedings.
6. Language: Studies must be published in English.

Exclusion Criteria:

1. Non-thrombosis or non-ultrasound studies (e.g., studies focusing solely on CT, MRI, or X-ray imaging without ultrasound-based assessment).
2. Studies not involving AI/ML (e.g., manual interpretation, rule-based algorithms, or traditional statistical methods without DL application).

3. Editorials, reviews, positions, opinion pieces, conference abstracts, or commentaries without substantive data analysis.
4. Studies with incomplete AI methodology, such as missing model details, dataset descriptions, performance metrics, or validation strategies.
5. Studies focusing exclusively on vascular diseases without thrombotic relevance (e.g., general atherosclerosis studies without thrombus detection or risk assessment).

The eligibility screening process followed the PRISMA guidelines, with two independent reviewers assessing each study based on the inclusion and exclusion criteria. The primary investigator (thesis student) performed the initial screening, while the supervisor reviewed the selections and resolved any discrepancies. Disagreements were settled through discussion.

3.4. Selection of Sources

The study selection process was carried out in two phases to ensure the inclusion of relevant research aligned with the objectives of this thesis:

1. Title and Abstract Screening:

- Two independent reviewers screened titles and abstracts of retrieved studies.
- Publications unrelated to DL in thrombosis detection or risk assessment using ultrasound imaging were excluded.
- Any discrepancies were resolved through discussion.

2. Full-Text Review:

- A full-text screening was performed on shortlisted articles from the initial screening phase.
- Only original research papers directly addressing the research questions were included.

3.5. Data Extraction and Charting

A standardized data extraction form was developed to systematically collect key information from each included study. The extracted data included:

General Study Information:

- Author(s), Year of Publication
- Type of Publication (Journal/Conference Paper)

Clinical Focus:

- Clinical primary focus (i.e., thrombosis or related conditions)
- Clinical relevance to thrombosis
- US Imaging Modality Used (e.g., B-mode US, Doppler US)

AI Model and Methodology:

- AI Model Used (e.g., CNN, ResNet, U-Net, RF, SVM)
- Type of Task (e.g., Classification, Segmentation)
- Validation Method (e.g., Cross-validation, External Validation)

- Performance Metrics (e.g., Sensitivity, Specificity, Accuracy, F1-Score, AUC)

Training Datasets:

- Dataset Size and Content
- Availability

Challenges and Limitations:

- Model Generalizability
- Interpretability Issues

3.6. Synthesis of Results

The extracted data were analyzed to provide a comprehensive overview of AI-based thrombosis detection using ultrasound imaging. Key findings include the prevalent use of CNN, U-Net, and ResNet models for classification and segmentation tasks, with validation methods primarily relying on cross-validation and external dataset testing. The review highlights that DVT and PE are the most studied thrombosis types, with performance metrics such as sensitivity, specificity, accuracy, and AUC frequently reported. These individual characteristics, including them presented in Section 3.5, of each included publication are presented in tabular form. Computed summaries and graphical representations of charted data frequencies are presented. Finally, the findings for each recognized type of thrombosis are summarized and discussed.

Chapter 4| Results

4.1. Selection of Relevant Sources

A total of 233 records were identified through PubMed (n=64) and Scopus (n=169) in August 2024. After removing 50 duplicates, 183 records underwent screening based on titles and abstracts. Of these, 120 were excluded for reasons such as being literature reviews, editorials, non-English publications, or not being relevant to AI, thrombosis, or ultrasound imaging. The remaining 63 full-text articles were assessed for eligibility, leading to the exclusion of 41 studies due to topic misalignment, lack of focus on thrombosis detection, inaccessibility, or unavailability. In the final selection, 22 studies were included in the systematic review to ensure alignment with the research objectives. The source selection process is shown in Figure 3.

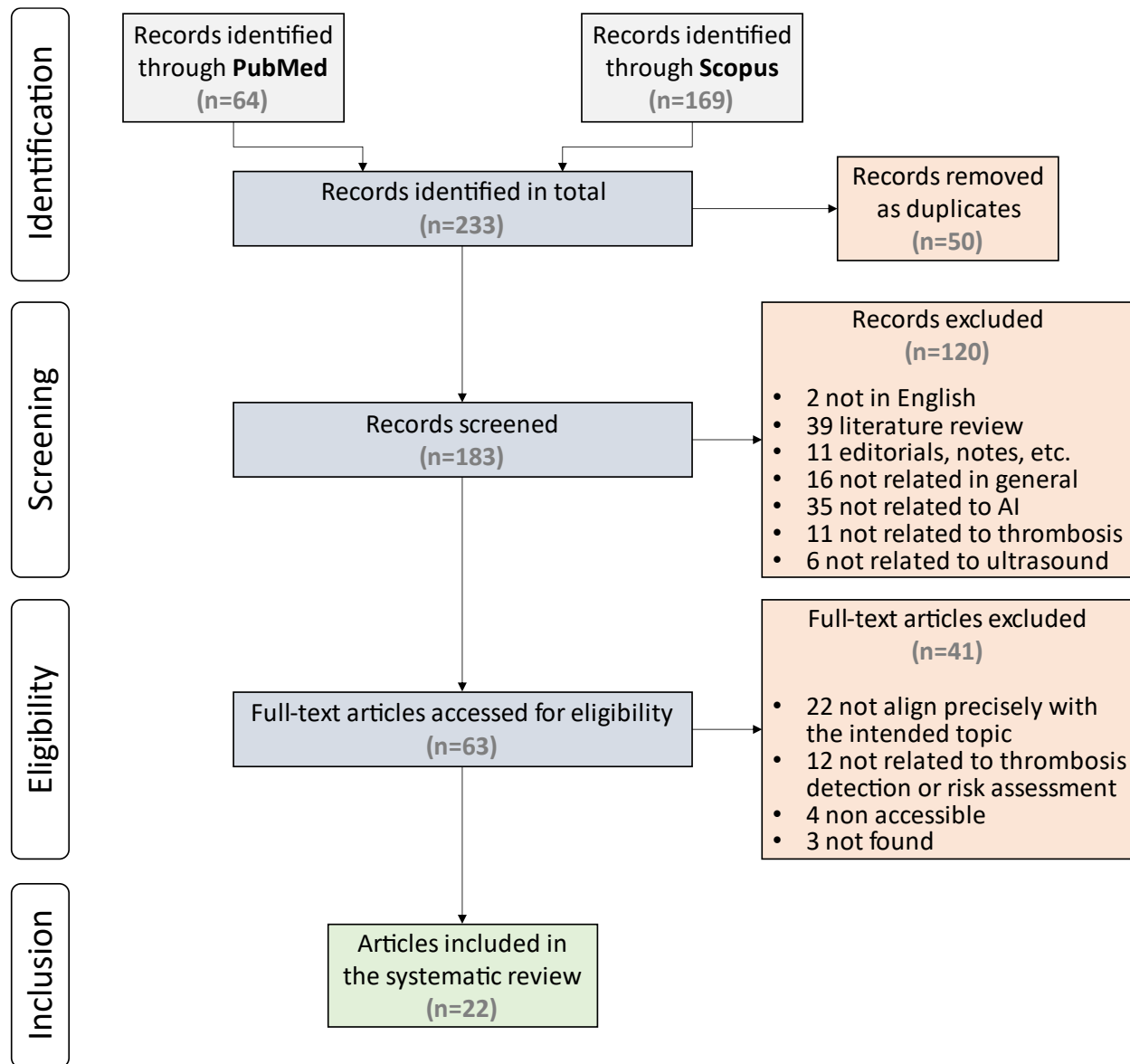


Figure 3. Source selection process from PubMed and Scopus search engines (PRISMA flowchart).

4.2. Characteristics of Sources and Synthesis of Results

The characteristics and data chart answering research question RQ1 to RQ9 for each of the 22 research papers included in the systematic review are presented in Table 2, Table 3 and Table 4.

Table 2. Research papers included in the systematic review, their characteristics, the clinical primary focus, the relevance to thrombosis, the US imaging method, and the DL problem addressed.

Author (year)	Publication Type	RQ1. What is the clinical primary focus?	RQ2. What is the study's clinical relevance to thrombosis?	RQ3. What US imaging method used?	RQ4. What is the problem addressed by employing a DL model?
Gerber et al. (2000) [87]	Article	Intracardiac thrombi, including LA and LAA	Direct thrombosis detection	Transesophageal Echocardiography (TEE)	Classification of intracardiac tumors and thrombi
Kyriacou et al. (2005) [88]	Conference paper	Carotid atherosclerotic plaque	Thrombotic risk assessment	B-mode ultrasound imaging	Classification of carotid plaques as symptomatic (unstable, associated with stroke, TIA, or AF) or asymptomatic
Strzelecki et al. (2006) [89]	Article	Intracardiac thrombi	Direct thrombosis detection	Echocardiography (cardiac ultrasound, transesophageal)	Classification & segmentation of intracardiac thrombi, benign & malignant tumors
Dahabiah et al. (2007) [90]	Conference paper	Venous thrombosis (VT), specifically deep and superficial vein thrombosis	Direct thrombosis detection	B-mode ultrasound imaging	Echogenicity and echostructure characterization of venous thrombosis (VT)
Sun et al. (2014) [91]	Article	Left atrial (LA) and left atrial appendage (LAA) thrombi	Direct thrombosis detection	Transesophageal Echocardiography (TEE)	Detection of left atrial (LA) and left atrial appendage (LAA) thrombi
Smistad & Løvstakken (2016) [92]	Conference paper	Blood vessel segmentation	Potential application for thrombotic risk	B-mode ultrasound imaging	Segmentation of blood vessels (position and size)
Jun et al. (2017) [93]	Conference paper	Coronary thrombosis (thin-cap fibroatheroma)	Thrombotic risk assessment	Intravascular Ultrasound (IVUS)	Classification of thin-cap fibroatheroma (TCFA) vs. non-TCFA

Author (year)	Publication Type	RQ1. What is the clinical primary focus?	RQ2. What is the study's clinical relevance to thrombosis?	RQ3. What US imaging method used?	RQ4. What is the problem addressed by employing a DL model?
Tanno et al. (2018) [94]	Conference paper	Deep Vein Thrombosis (DVT) in the femoral and popliteal veins	Direct thrombosis detection	B-mode compression ultrasound imaging	Classification of vein compressibility and anatomical landmarks
Jun et al. (2019) [95]	Article	Coronary thrombosis	Thrombotic risk assessment	Intravascular Ultrasound (IVUS)	Classification of thin-cap fibroatheroma (TCFA)
Cao et al. (2020) [96]	Conference paper	Coronary plaque rupture leading to thrombosis	Thrombotic risk assessment	Intravascular Ultrasound (IVUS)	Classification of normal vs. bifurcated blood vessels and segmentation of vessel walls in order to 3D reconstruct the segmented blood vessels
Cao et al. (2020) [97]	Article	Atherosclerosis-related plaque rupture & thrombosis	Thrombotic risk assessment	Intravascular ultrasound (IVUS)	Prediction of vulnerable vs. stable plaques
Johnstonbaugh et al. (2020) [98]	Article	Photoacoustic imaging for vascular assessment	Potential application for thrombotic risk	Photoacoustic imaging (PAI) combined with ultrasound detection	Localization of photoacoustic (PA) wavefront origins in deep tissue for potential vascular applications, including deep vein thrombosis (DVT)
Bai et al. (2021) [99]	Article	Iliac Vein Compression Syndrome (IVCS)	Indirect thrombosis assessment	B-mode compression ultrasound imaging	Detection of iliac vein compression points
Kainz et al. (2021) [100]	Article	Deep Vein Thrombosis (DVT) in the femoral and popliteal veins	Direct thrombosis detection	B-mode compression ultrasound imaging	Predict the presence or absence of DVT by analyzing vein compressibility
Hernanda et al. (2022) [101]	Conference paper	Deep Vein Thrombosis (DVT)	Direct thrombosis detection	B-mode ultrasound imaging	Semantic segmentation of venous areas in US images to detect DVT

Author (year)	Publication Type	RQ1. What is the clinical primary focus?	RQ2. What is the study's clinical relevance to thrombosis?	RQ3. What US imaging method used?	RQ4. What is the problem addressed by employing a DL model?
Leblanc et al. (2022) [102]	Article	Peripheral artery disease (PAD) lesions (stenosis/thrombosis)	Indirect thrombosis assessment	B-mode ultrasound imaging	Predict out-of-plane translation for stretched reconstruction of femoral artery from 2D US
Lei et al. (2022) [103]	Conference paper	Carotid artery thrombosis and atherosclerotic plaque	Thrombotic risk assessment	Ultrasound Doppler RF signals	Estimation of carotid blood flow velocity
Olivier et al. (2023) [104]	Conference paper	Deep vein thrombosis (DVT) with prediction of associated pulmonary embolism (PE)	Direct thrombosis detection	B-mode ultrasound imaging	Predicting pulmonary embolism (PE) occurrence in patients with deep vein thrombosis (DVT) using US images and 5 clinical factors
Meng et al. (2023) [105]	Article	Coronary artery thrombi	Thrombotic risk assessment	Intravascular Ultrasound (IVUS)	Segmentation and classification of vascular lesions, including thrombi
Nakayama et al. (2023) [106]	Article	Deep vein thrombosis (DVT) in the popliteal vein	Direct thrombosis detection	B-mode ultrasound imaging (stationary and portable ultrasound diagnostic equipment)	Classification of ultrasound images as "Satisfactory," "Moderately Satisfactory," or "Unsatisfactory"
Moon et al. (2023) [107]	Conference paper	Carotid artery blood clot formation	Thrombotic risk assessment	Laser-Generated Focused Ultrasound (LGFU)	Predicting blood clot thickness in the carotid artery
Huang et al. (2024) [108]	Article	Thromboembolism detection	Direct thrombosis detection	B-mode ultrasound imaging of femoral vein	Detecting Spontaneous Echo Contrast (SEC) associated with thromboembolism risk

Table 3. Descriptive data on the particular DL characteristics (models, validation methods, and performance metrics) presented in each of the papers included in the systematic review.

Author (year)	RQ5. What DL models are used?	RQ6. What DL validation methods are employed?	RQ7. What performance metrics are reported for DL approaches?
Gerber et al. (2000) [87]	Artificial Neural Network (ANN) with statistical texture analysis	Leave-one-out cross-validation	Classification accuracy: 66% (ANN)
Kyriacou et al. (2005) [88]	Probabilistic Neural Network (PNN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN)	Leave-one-out cross-validation	Best diagnostic yield: 67% (SVM), 62% (PNN), 56% (KNN)
Strzelecki et al. (2006) [89]	Feedforward ANN, Network of Synchronized Oscillators (SON)	Training/Test set (108/55)	Classification accuracy: 91% (ANN), Segmentation accuracy: 97% (SON), 95% (ANN)
Dahabiah et al. (2007) [90]	Feedforward ANN including a two-layer ANN with sigmoid and linear activation functions	Experimental validation for fuzzy similarity retrieval precision	Fuzzy similarity, Euclidean distance, and retrieval precision are evaluated
Sun et al. (2014) [91]	ANN with gray level co-occurrence matrix (GLCM)-based texture analysis	Five radiologists independently evaluated images in a blind study	Sensitivity: 95.5%, Specificity: 97.0%, Accuracy: 96.6%, AUC: 0.932
Smistad & Løvstakken (2016) [92]	Deep Convolutional Neural Network (CNN) based on AlexNet	Leave-one-subject-out cross-validation	Accuracy: 94.5% (femoral vessels), 96% (carotid artery vessels)
Jun et al. (2017) [93]	Deep Feed-Forward Neural Network (FFNN)	10-fold cross-validation	AUC: 0.87, Specificity: 78.31%, Sensitivity: 79.02%
Tanno et al. (2018) [94]	Dual-task convolutional neural network (CNN)	Training/Validation/Test set (60/20/20)	F1-score: 91% (vein compressibility), 78% (landmark detection)
Jun et al. (2019) [95]	Feed-Forward Neural Network (FNN), K-Nearest Neighbor (KNN), Random Forest (RF), Convolutional Neural Network (CNN)	5-fold cross-validation	AUC: 0.911 (CNN), 0.844–0.859 (FNN, KNN, RF), Sensitivity: 87.31% (CNN), Specificity: 82.81% (CNN)
Cao et al. (2020) [96]	AlexNet (a CNN for classification), Fully Convolutional Networks (FCN) for segmentation	Accuracy assessment for classification tasks, mean Intersection-over-Union (IoU) for segmentation	Classification accuracy: 97.67%, Segmentation mean IoU: 0.8523
Cao et al. (2020) [97]	Convolutional Neural Network (CNN) based on MatConvNet framework, using VGGNet for classification	Training/Test set (70/30)	Accuracy: 73.4%, Sensitivity: 69.2%, Specificity: 71.4%, AUC: 0.7143 (for best vulnerability index classification point at 1.716)
Johnstonbaugh et al. (2020) [98]	Deep learning architecture using an atrous Nyquist Convolution and a differentiable spatial-to-	Training/Test set (80/20). Performance compared against conventional beamforming	Mean Localization Error: <30 microns (SD 20.9 microns) for targets <40 mm depth, 1.06 mm (SD 2.68 mm) for targets 40–60 mm depth

Author (year)	RQ5. What DL models are used?	RQ6. What DL validation methods are employed?	RQ7. What performance metrics are reported for DL approaches?
	numerical transformer (DSNT), while combining design elements of U-net and ResNet		
Bai et al. (2021) [99]	Dense Multireceptive Field Convolutional Neural Network (DMRF-CNN)	Training/Test set (70/30)	Accuracy: ~95%, Precision: ~94% (based on Figure 7)
Kainz et al. (2021) [100]	Convolutional Neural Network (CNN)	Training/Validation set (90/10), External Validation set (83 subjects)	Sensitivity: 0.82-0.96, Specificity: 0.70-0.82, Positive Predictive Value (PPV): 0.65-0.89, Negative Predictive Value (NPV): 0.98-0.99, Accuracy: 0.75-0.83, AUC: 0.77-0.87
Hernanda et al. (2022) [101]	UNet-ResNet (ResNet-34 as an encoder for UNet)	Intersection-over-Union (IoU) and Dice Loss	IoU: 84.50%, Dice Loss: 0.0857 (for UNet-ResNet)
Leblanc et al. (2022) [102]	Mask-RCNN for artery segmentation, CNN for out-of-plane translation prediction	5-fold cross-validation	Absolute Mean Error: 0.28 ± 0.28 mm, Median Drift Error: 8.98%
Lei et al. (2022) [103]	Deep Complex Convolutional Neural Network (DCCNN)	Comparison with traditional velocimetry methods (High-Pass Filter (HPF) and Singular Value Decomposition (SVD))	Normalized Root Mean Square Error (NRMSE): reduced by 47.20% (comp. to HPF) and 45.45% (comp. to SVD), Goodness-of-fit (R^2): improved by 5.64% (comp. to HPF) and 3.36% (comp. to SVD), Running time: reduced by 82.10% (comp. to HPF) and 21.11% (comp. to SVD)
Olivier et al. (2023) [104]	Deep Convolutional Neural Network (CNN) with 8 or 10 convolutional layers, 3-4 down-sampling operations, and a feature fusion approach	8-fold cross-validation on three different dataset splits (DB1-3)	Accuracy: 0.774 (best on DB1 + fusion + 4 down-sampling), 0.647 (DB1 & 2 + fusion + 3 down-sampling), 0.632 (DB1 & 2 & 3 + only image + 4 down-sampling)
Meng et al. (2023) [105]	Dilated attention U-Net for segmentation, ResNet18 for lesion classification	5-fold cross-validation	Dice Similarity Coefficient (DSC): 79.21% (thrombi segmentation), F1-score: 96.42% (thrombi detection)
Nakayama et al. (2023) [106]	ResNet101 - Convolutional Neural Network (CNN)	5-fold cross-validation	Classification accuracy: 0.76 (portable) and 0.73 (stationary), AUC: 0.89 (portable) and 0.88 (stationary)
Moon et al. (2023) [107]	Multi-Modal Deep Learning model with CNNs for 1D and 2D feature extraction	Cross-entropy loss	Precision: 0.97, Sensitivity: 0.97, F1-score: 0.97, Accuracy: 0.96, AUC: 0.99

Author (year)	RQ5. What DL models are used?	RQ6. What DL validation methods are employed?	RQ7. What performance metrics are reported for DL approaches?
Huang et al. (2024) [108]	Multisequence CNN with ResNetv2 backbone and soft attention	Training/Test set (80/20)	AUC: 0.74, Sensitivity: 0.73, Specificity: 0.68 (with soft attention)

Table 4. Details about the used datasets and the challenges/limitations presented in each of the papers included in the systematic review.

Author (year)	RQ8. What datasets are used and if any are available?	RQ9. What challenges or limitations are identified in the proposed DL?
Gerber et al. (2000) [87]	18 TEE images (9 tumor, 9 thrombi). Not publicly available.	<ul style="list-style-type: none"> - ANN struggled with cases where tumors and thrombi had similar echogenic patterns. - Small dataset. - Lack of standardized echocardiographic settings.
Kyriacou et al. (2005) [88]	274 ultrasound images (137 symptomatic, 137 asymptomatic). Not publicly available.	<ul style="list-style-type: none"> - Difficult segmentation due to plaque edges blending with blood and acoustic shadows. - The diagnostic yield was lower than texture-based approaches.
Strzelecki et al. (2006) [89]	163 annotated echocardiograms (91 thrombi, 28 benign and 44 malignant tumors), 256 gray levels bitmap images, 640x480 pixels. Private dataset.	<ul style="list-style-type: none"> - Ultrasound artifacts. - Training dependence. - Subjectivity in annotations.
Dahabiah et al. (2007) [90]	US images of VT collected for indexing and retrieval. Not publicly available.	<ul style="list-style-type: none"> - High uncertainty in VT characterization. - Operator dependency in US interpretation. - Need for a large, annotated dataset for ANN training. - Variability in echogenicity characterization.
Sun et al. (2014) [91]	650 TEE images from 130 patients with atrial fibrillation. Not publicly available.	<ul style="list-style-type: none"> - High false-positive rate with TEE. - Lower accuracy in junior radiologists without the proposed solution. - Manual selection of region of interest may introduce human error.
Smistad & Løvstakken (2016) [92]	12,804 subimages from 15 subjects. Not publicly available.	<ul style="list-style-type: none"> - Vessel model assumes elliptical shape, which is more suitable for arteries than veins. - No consideration for rotated vessels. - The model is trained only in specific anatomical regions, limiting generalizability.
Jun et al. (2017) [93]	12,325 IVUS images from 100 patients, co-registered with OCT images. Not publicly available.	<ul style="list-style-type: none"> - IVUS has lower resolution than Optical Coherence Tomography (OCT), making TCFA detection challenging. - The model relies on feature extraction rather than direct image classification.
Tanno et al. (2018) [94]	1150 ultrasound videos (100 to 200 frames) from 115 healthy volunteers. Not publicly available.	<ul style="list-style-type: none"> - Limited dataset diversity. - Challenges in generalizing to all vein landmarks. - Domain shift across different ultrasound devices.
Jun et al. (2019) [95]	12,325 IVUS images from 100 patients, co-registered with OCT images. Not publicly available.	<ul style="list-style-type: none"> - The dataset included only patients with plaques above a certain level, limiting generalizability.

Author (year)	RQ8. What datasets are used and if any are available?	RQ9. What challenges or limitations are identified in the proposed DL?
		<ul style="list-style-type: none"> - While CNN achieved the best performance, it lacks interpretability compared to feature-based methods. - The study lacked a true control group of healthy patients.
Cao et al. (2020) [96]	2288 IVUS images (1144 normal and 1144 bifurcated blood vessels) for classification. 6360 IVUS images (1144 bifurcated and 5216 normal blood vessels) for segmentation. Not publicly available.	<ul style="list-style-type: none"> - Difficulty in segmenting bifurcated vessels. - Accuracy of boundary detection for precise 3D reconstruction.
Cao et al. (2020) [97]	3535 IVUS images from 23 atherosclerotic rabbit models. Not publicly available.	<ul style="list-style-type: none"> - No well-established critical value for vulnerability index. - Limited dataset (from animal models, not human). - Need for human data validation to confirm applicability.
Johnstonbaugh et al. (2020) [98]	Simulated photoacoustic signals with 20,300 different target positions in a tissue model (10-50 mm depth). No public dataset mentioned.	<ul style="list-style-type: none"> - Decreased signal intensity at deeper tissue layers. - Optical scattering affecting photoacoustic signals. - Limitations in real-time clinical applicability.
Bai et al. (2021) [99]	699 vein US images from 211 subjects. Available upon request.	<ul style="list-style-type: none"> - Challenges include high noise in vein ultrasound images. - Difficulty in identifying the compression point due to anatomical variations. - Need for further multi-center validation.
Kainz et al. (2021) [100]	1500 ultrasound videos from 255 subjects. External validation on 83 patients (53 UK, 30 Germany). Available upon request.	<ul style="list-style-type: none"> - Operator dependency in free-hand ultrasound. - Domain shift between different ultrasound devices. - Small external validation sample sizes. - Clinical liability issues in replacing expert radiologists.
Hernanda et al. (2022) [101]	536 ultrasound images from phantom-based human body simulations. No public dataset mentioned.	<ul style="list-style-type: none"> - Vanishing gradient problem in deep networks (solved using ResNet encoder). - Difficulty in segmenting veins due to the presence of blood clots.
Leblanc et al. (2022) [102]	111 tracked US videos (left/right femoral arteries) from 18 healthy volunteers. Not publicly available.	<ul style="list-style-type: none"> - Needs further evaluation in patients with PAD. - Limited dataset. - It does not account for orientation. - Segmentation process is time-consuming.
Lei et al. (2022) [103]	Simulated ultrasound data generated using the Field II platform	<ul style="list-style-type: none"> - Noise in clinical ultrasound data affects generalization. - Need for large-scale real patient datasets to improve real-world applicability. - Blood flow patterns in complex cases (e.g., turbulence, vascular stenosis) require further testing.
Olivier et al. (2023) [104]	US images from 178 patients and 3 different vendors (63, 102, 13 patients to 3 splits) gathered from EDITH multi-modality database. Not publicly available.	<ul style="list-style-type: none"> - Model performance varies across databases. - Fusion of clinical data with images only improved accuracy with specific model architectures. - Standardized ultrasound devices and acquisition settings are needed for better reliability.

Author (year)	RQ8. What datasets are used and if any are available?	RQ9. What challenges or limitations are identified in the proposed DL?
Meng et al. (2023) [105]	5,089 IVUS images from 100 patients. Not publicly available.	<ul style="list-style-type: none"> - Limited dataset size (100 patients), single-center study, and need for multi-center validation. - Model refinement is needed for high-risk lesion stratification.
Nakayama et al. (2023) [106]	128,494 US images from stationary and 46,338 from portable equipment (20 subjects). Dataset is not publicly available.	<ul style="list-style-type: none"> - The dataset was limited to healthy individuals. - Performance needs validation in patients with actual DVT.
Moon et al. (2023) [107]	Self-produced dataset (1280 waveforms (1D) for training, 201 frequency spectra (2D) for validation)	<ul style="list-style-type: none"> - The experiment was conducted on self-produced data, requiring further validation for clinical application. - Additional research needed to confirm clinical significance.
Huang et al. (2024) [108]	801 archival ultrasound acquisitions along the femoral vein from 201 patients. Publicly available at GitHub. (https://github.com/Ouwen/automatic-spontaneous-echo-contrast).	<ul style="list-style-type: none"> - SEC detection requires expertise, is not routinely reported, and has challenges in achieving perfect agreement among experts. - Limited large-scale evidence for treatment decisions based on SEC.

Figure 4 illustrates the distribution of retrieved unique papers (green bars) and finally included papers (orange bars) over time, spanning from 1997 to 2024. The number of retrieved papers represents all relevant studies identified, whereas the included papers indicate those that met the selection criteria for our systematic analysis. The trend shows a significant increase in research activity in the field, particularly after 2015, with a rapid rise in publications from 2020 onward. This reflects the growing interest in deep learning and machine learning applications for thrombosis detection and risk assessment using ultrasound imaging. While the number of retrieved papers surged in recent years, only a fraction was ultimately included during the selection process. The peak in 2023 suggests an increasing focus on this topic, aligning with advancements in AI-driven medical imaging technologies.

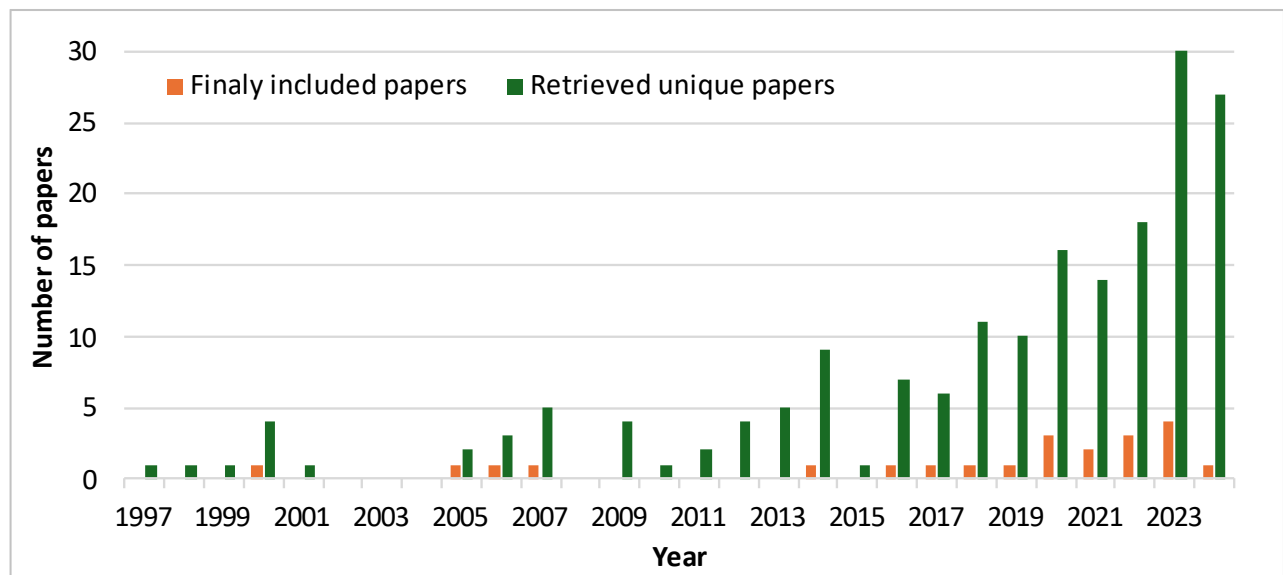


Figure 4. Trend of retrieved and included papers for DL-based thrombosis assessment using US imaging.

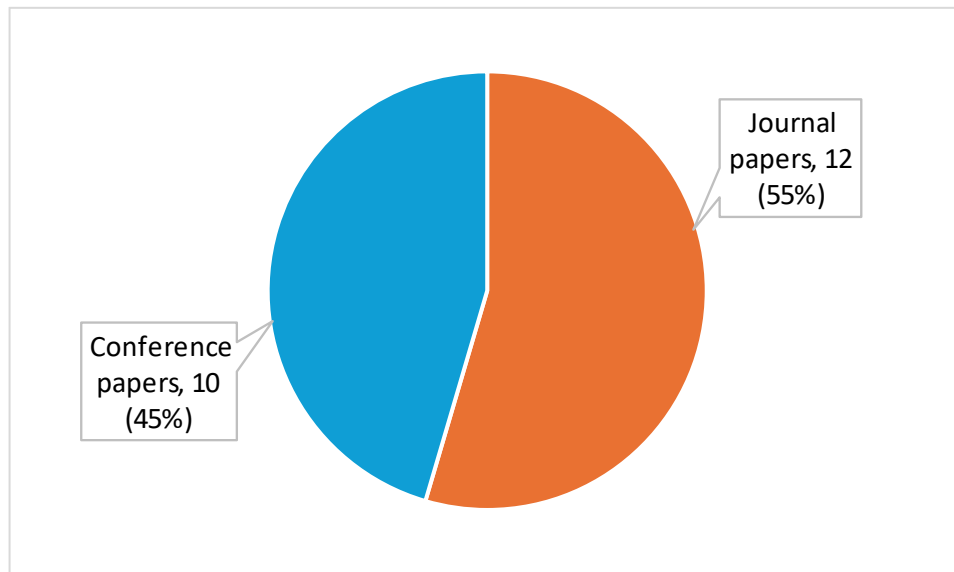


Figure 5. Distribution of included papers by publication type (journal vs. conference papers).

The distribution of the included papers based on their publication type: journal papers (55%) and conference papers (45%) is presented in Figure 5. Out of the total selected studies, 12 papers were published in journals, while 10 papers were presented at conferences. The relatively balanced distribution indicates that both journal and conference publications contributed somewhat equally to research on deep learning-based thrombosis detection and risk assessment using ultrasound imaging. Journals provide comprehensive and peer-reviewed studies, whereas conferences showcase cutting-edge developments and emerging trends in the field.

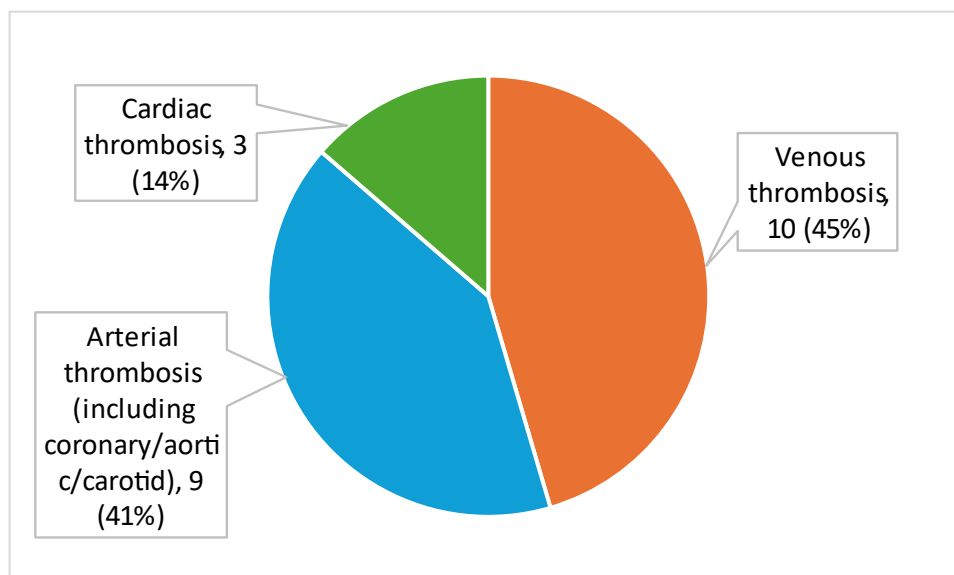


Figure 6. Distribution of primary clinical focus in included papers.

Figure 6 illustrates the primacy clinical focus of studies examined in the included publications. The distribution is as follows:

- Venous thrombosis (45%) – Representing the largest portion, 10 studies focused on thrombosis in veins, including deep vein thrombosis (DVT) and pulmonary embolism (PE).
- Arterial thrombosis (41%) – 9 studies examined arterial thrombotic conditions, including coronary artery disease, carotid thrombosis, and aortic thrombosis. Some of these studies also assessed plaque vulnerability, which is closely linked to thrombosis risk.
- Cardiac thrombosis (14%) – 3 studies investigated intracardiac thrombi, including left atrial and left atrial appendage (LAA) thrombi.

Additional studies focused on vascular conditions indirectly related to thrombosis detection, such as carotid atherosclerotic plaque characterization, iliac vein compression, and peripheral artery disease. These studies primarily assess the risk of thrombosis rather than detecting an existing thrombus.

The relatively balanced focus on venous and arterial thrombosis highlights the versatility of deep learning models in various vascular conditions. However, cardiac thrombosis remains a smaller research area, particularly in earlier studies (before 2014).

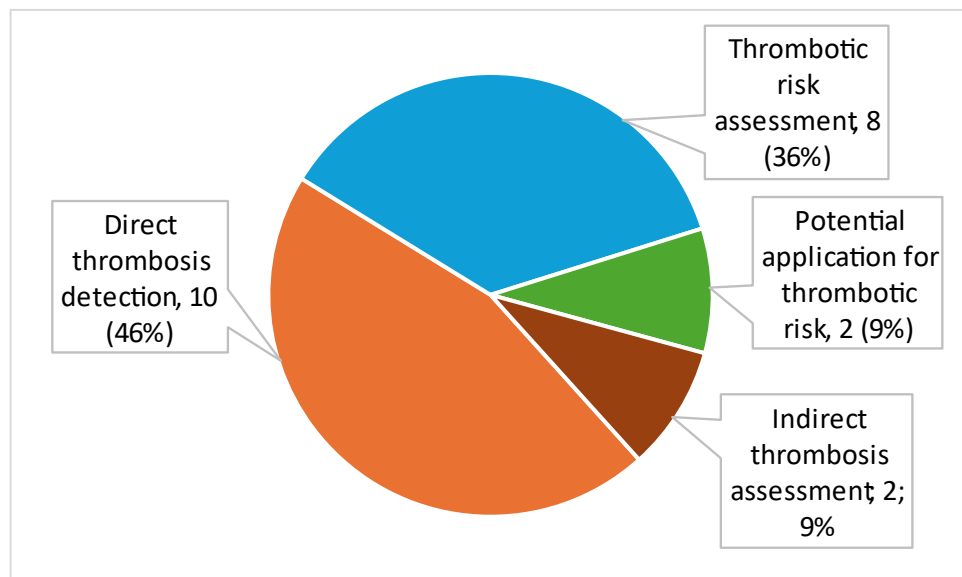


Figure 7. Distribution of clinical relevance to thrombosis in the included studies.

Figure 7 illustrates the distribution of the clinical relevance of the included studies in relation to thrombosis detection and risk assessment. The studies were categorized into the following groups:

- Direct thrombosis detection (10 studies, 46%) – These studies specifically focused on identifying thrombi in veins, arteries, or cardiac chambers using ultrasound imaging and deep learning techniques.
- Thrombotic risk assessment (8 studies, 36%) – These studies aimed to evaluate thrombotic risk factors, such as vulnerable plaques, vessel abnormalities, and blood flow characteristics, which may contribute to thrombosis formation.
- Indirect thrombosis assessment (2 studies, 9%) – These studies examined conditions that are indirectly linked to thrombosis, such as iliac vein compression syndrome (IVCS), which can predispose patients to deep vein thrombosis.

- Potential application for thrombotic risk (2 studies, 9%) – These studies primarily focused on vascular structures, such as blood vessel segmentation, which could serve as a supporting tool for thrombotic risk evaluation.

The distribution highlights that the majority of studies (46%) directly targeted thrombus detection, while a significant proportion (36%) were dedicated to assessing risk factors associated with thrombosis development. The remaining studies focused on supporting diagnostic capabilities and related vascular conditions, which could contribute to advancements in thrombosis prediction and prevention.

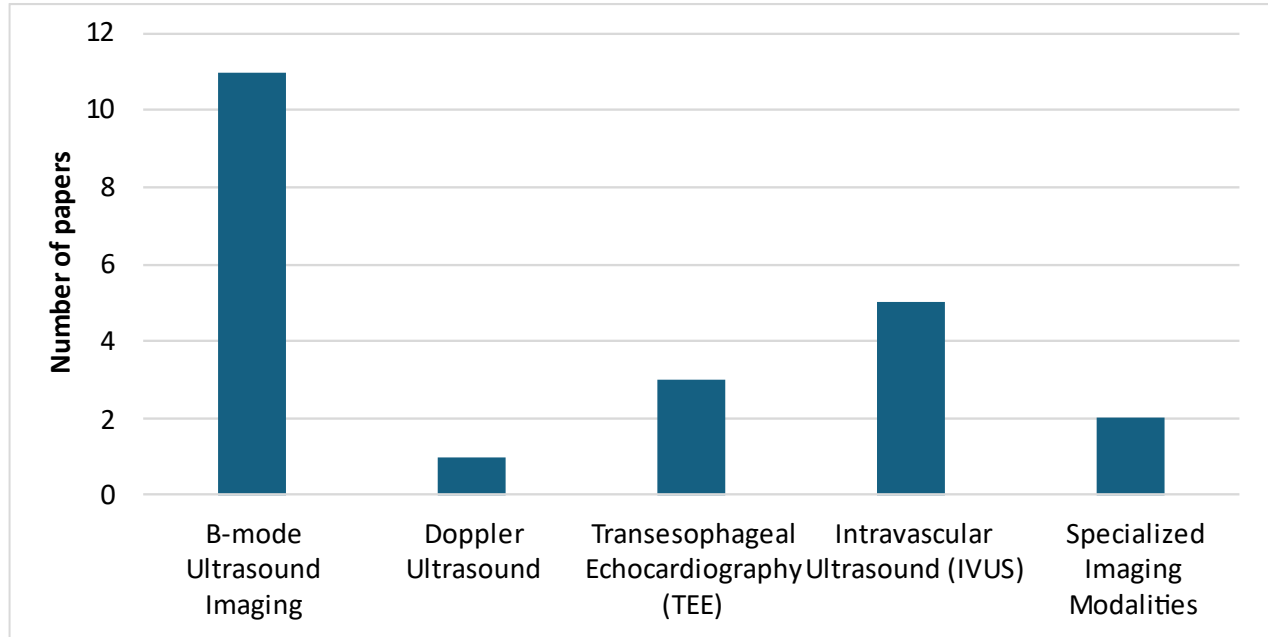


Figure 8. Distribution of US imaging modalities used in DL studies for thrombosis assessment.

Figure 8 presents the distribution of ultrasound imaging modalities used in deep learning-based thrombosis detection and/or risk assessment studies. The number of papers utilizing each modality is shown, highlighting the dominant imaging techniques:

- B-mode Ultrasound Imaging (10+ papers) – The most commonly used modality, applied in vein compressibility analysis for DVT detection, arterial plaque segmentation, and general thrombus identification.
- Doppler Ultrasound (1 paper) – Less frequently used, but valuable for assessing carotid blood flow velocity, contributing to thrombotic risk prediction.
- Transesophageal Echocardiography (TEE) (3 papers) – Primarily used for cardiac thrombus detection, particularly in left atrial (LA) and left atrial appendage (LAA) thrombi.
- Intravascular Ultrasound (IVUS) (5 papers) – Applied in arterial thrombosis studies, enabling detailed imaging of arterial walls, plaque characterization, and vulnerable lesion detection.
- Specialized Imaging Modalities (2 papers) – Includes photoacoustic imaging (PAI) and laser-generated focused ultrasound (LGFU), which provide enhanced visualization of vascular structures and thrombosis features.

The predominance of B-mode ultrasound underscores its role as the primary imaging technique for deep learning applications in thrombosis detection. Other modalities provide specialized diagnostic advantages, supporting risk assessment and thrombosis characterization in specific vascular conditions.

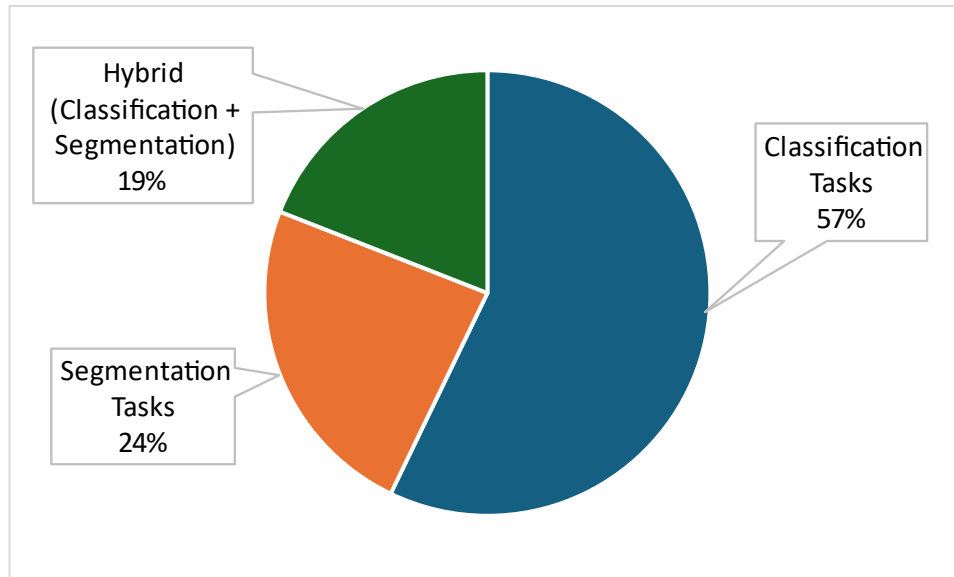


Figure 9. Distribution of prediction tasks in DL-based thrombosis assessment.

Figure 9 presents the distribution of prediction tasks in deep learning models applied to thrombosis assessment using ultrasound imaging. The studies are categorized into three main task types:

- Classification Tasks (57%) – The majority of models focus on classification-based predictions, such as distinguishing between thrombi and tumors, vulnerable and stable plaques, or identifying specific thrombotic conditions.
- Segmentation Tasks (24%) – These models are designed for automatic segmentation of vascular structures, such as blood vessels, thrombi, and plaques, allowing for precise localization and quantification.
- Hybrid Tasks (19%) – Some studies employ a combination of classification and segmentation, integrating detailed structural analysis with predictive modeling to enhance diagnostic capabilities.

The prevalence of classification-based tasks highlights the importance of automated thrombus identification, while segmentation plays a crucial role in detailed structural analysis for medical imaging applications.

Figure 10 shows the distribution of different deep learning model types applied in thrombosis assessment using ultrasound imaging. The models are categorized into five main groups:

- Standard CNN-based Models (35%) – The most common approach, utilizing conventional convolutional neural networks (CNNs) for feature extraction and classification.
- ANN-based Models (26%) – Includes various artificial neural networks (ANNs), such as feedforward ANN, probabilistic neural networks (PNN), and other statistical ANN-based techniques.
- Advanced CNN-based Models (17%) – Encompasses more complex architectures, including ResNet, and multi-modal CNN approaches that enhance performance.

- Segmentation-focused Models (13%) – Includes U-Net, Mask-RCNN, and similar deep learning architectures designed for precise segmentation of thrombi and vascular structures.
- Other Models (9%) – Covers alternative machine learning methods such as random forests, support vector machines (SVMs), or hybrid approaches.

The dominance of CNN-based models reflects the strong reliance on deep learning for feature extraction and pattern recognition in ultrasound-based thrombosis detection, while segmentation-focused models are crucial for detailed anatomical and thrombus visualization.

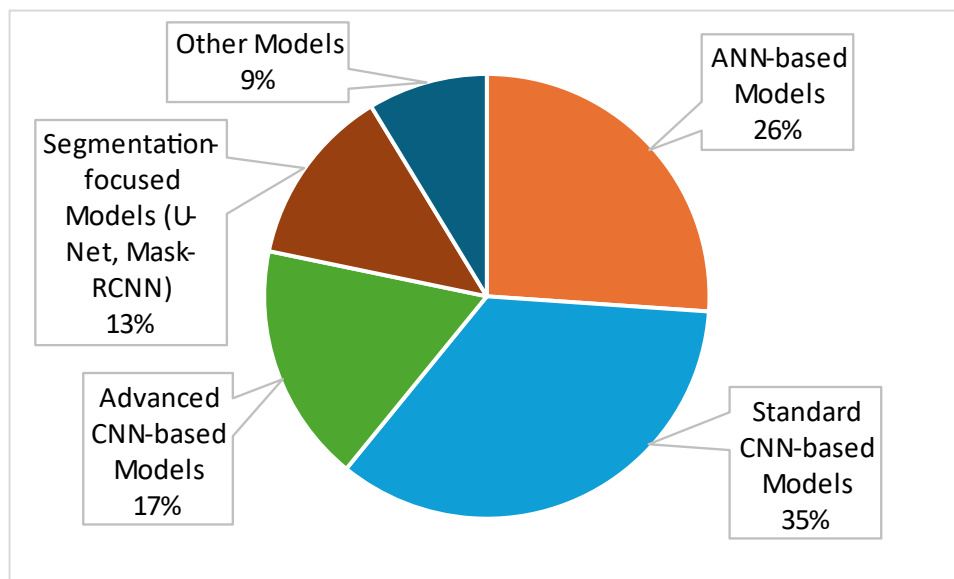


Figure 10. Distribution of deep learning model types used in thrombosis assessment.

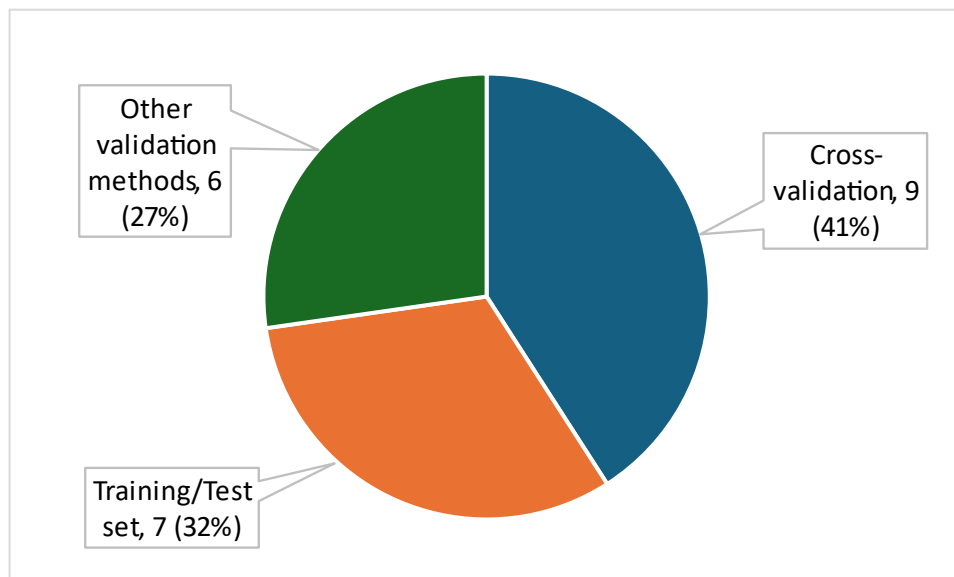


Figure 11. Distribution of validation methods used in deep learning models to evaluate their performance.

Finally, the distribution of validation methods used in deep learning models is shown in Figure 11. The most frequently employed approach is cross-validation (41%), where datasets are split into multiple folds for training and testing, ensuring robust model generalization. The training/test set method (32%) is also commonly used, dividing the dataset into separate training and test sets to evaluate model performance on unseen data. Additionally, 27% of studies utilize other validation methods, including external dataset validation, cross-entropy loss or expert comparison studies. The dominance of cross-validation highlights its effectiveness in enhancing model robustness and mitigating overfitting, while training/test set approaches remain widely used for straightforward performance assessment.

4.3. DL-Based Approaches for Thrombosis Assessment via US Imaging

In the following subsection, a detailed description of deep learning (DL)-based approaches for thrombosis detection and risk assessment via ultrasound (US) imaging will be presented, organized according to venous, arterial, and cardiac thrombosis.

4.3.1. DL-Based Approaches for Venous Thrombosis

Artificial intelligence (AI) and deep learning (DL) models have been extensively explored for diagnosing venous thrombosis, particularly deep vein thrombosis (DVT). One study proposed an advanced approach for indexing and retrieving venous thrombosis ultrasound (US) images, addressing challenges such as operator dependence and diagnostic uncertainty in traditional analyses. The method combined neural network-based venous thrombosis (VT) characterization with fuzzy similarity measures to improve image retrieval precision. Three types of image descriptors—sliding window, wavelet coefficient energy, and co-occurrence matrix—were processed by neural networks to generate VT characterizations. These values were mapped onto fuzzy membership functions and compared using fuzzy similarity, outperforming conventional methods like nominal and Euclidean distances. This approach improved retrieval accuracy, accommodated diagnostic uncertainty, and allowed users to prioritize specific image features, making it a valuable tool for medical image indexing and data mining [90].

Another DL-based method was developed for real-time detection of blood vessels in B-mode US images, aiding applications such as DVT detection, anesthesia guidance, and catheter placement. The model determined vessel position and size with high accuracy, using 12,804 subimages of the femoral region from 15 subjects. Leave-one-subject-out cross-validation yielded an average accuracy of 94.5%, significantly outperforming prior methods (84%). Additionally, validation on a carotid artery dataset demonstrated the model's generalizability, achieving 96% accuracy [92].

Tanno et al. [94] proposed a dual-task convolutional neural network (CNN), called AutoDVT, to automate real-time DVT diagnosis by evaluating vascular compressibility at anatomically defined landmarks using ultrasound (US) images. The method was tested on 1,150 five-to-ten-second compression image sequences from 115 healthy volunteers, totaling approximately 200,000 labeled images. The system achieved a theoretical inference frame rate of over 500 frames per second, with 15 model configurations evaluated. The CNN focused on two femoral vein landmarks, achieving high accuracy in identifying vein compressibility. The model could determine whether a vein fully compresses with an F1 score exceeding 90% during manual probe pressure application.

An evaluation of this approach was performed in [109], where AutoDVT was tested in a clinical setting to assist non-specialists in acquiring compression ultrasound images for DVT triaging. The study involved 73 patients with suspected DVT across two clinical centers, where nonspecialists used an AI-guided two-point compression protocol. The collected images were remotely reviewed by five qualified physicians, with 88.57% of the completed scans deemed to be of adequate image quality. Among these, 47 were classified as diagnostic quality, achieving a sensitivity of 100% and specificity of 95.12% in detecting proximal DVT. Additionally, the study demonstrated that implementing an AI-assisted triaging algorithm could reduce the need for formal duplex ultrasound scans by 53.42%, highlighting the potential of AI in optimizing DVT diagnostic workflows and reducing clinical burden.

When accessing DVT, photoacoustic imaging (PAI) can provide good results because it overcomes the optical diffusion limit, providing high-resolution, label-free images of human vasculature with high contrast. However, the depth-dependent optical attenuation limits the visibility of deep-tissue vasculature. To address this, a CNN was developed to localize photoacoustic (PA) wavefronts in deep tissue [98]. The network was trained on simulated PA signals from 16,240 blood-vessel targets with optical scattering and noise. Test results on 4600 simulated and five experimental PA signals showed localization accuracy with a mean error of less than 30 microns for targets under 40 mm and 1.06 mm for targets between 40-60 mm, demonstrating that the method can be used in DVT as well as in melanoma cell detection.

A DL-based approach was also proposed for diagnosing iliac vein compression syndrome and assisting clinicians in disease detection. Bai et al. [99] preprocessed US images from patients with thrombotic chronic venous disease and DVT and constructed a DL model to detect venous compression and differentiate between benign and malignant lesions. Patients were divided into a DL algorithm imaging group and a control group. Results indicated that the DL imaging group had superior diagnostic accuracy, better treatment outcomes, and improved detection of May-Thurner syndrome compared to the control group. Additionally, patients in the DL group exhibited less venous swelling and greater pain relief post-treatment. The study concluded that AI-based US image analysis effectively enhances the detection and recognition of lower extremity vein lesions, laying a strong foundation for future research and clinical applications.

More recently, studies have explored the use of ML-guided devices for free-hand DVT detection. In this context, Kainz et al. [100] developed a DL algorithm to guide free-hand ultrasound (US) use, assisting non-specialists in DVT detection. Trained on US videos from 255 volunteers, the algorithm was evaluated on 53 patients from an NHS DVT diagnostic clinic and 30 from a German DVT clinic. The results demonstrated superior sensitivity, specificity, positive predictive value, and negative predictive value compared to the clinical gold standard. Furthermore, a cost analysis suggested that the technology could provide a positive net monetary benefit.

An evaluation of this approach was conducted in [110], assessing the effectiveness of AI-guided point-of-care ultrasound (POCUS) used by non-specialists to acquire valid US images for remote DVT diagnosis. Over a 3.5-month period, 91 predominantly older female patients with suspected DVT underwent AI-guided handheld US scans, followed by formal DVT imaging. Among the scans, 18% were incomplete, while 91% of the remaining scans were of sufficient quality. The findings support the utility of AI-guided POCUS for remote DVT diagnosis, as remote clinicians classified 64% of these scans as either "compressible" or "incompressible." Additionally, the sensitivity and specificity for adequately imaged scans were 100% and 91%, respectively. Notably, 53% of patients were identified as low risk, potentially reducing the need for formal imaging.

Another DL model, UNet-ResNet, was employed for segmenting venous areas in 2D US images. The model utilized a pre-trained UNet architecture with a ResNet-34 encoder and was trained on images from phantoms—a human body simulation tool. Model performance was evaluated using Intersection-over-Union (IoU) and Dice Loss metrics, achieving an IoU score of 81.22% and a Dice Loss of 0.1341. Incorporating the ResNet-34 encoder further improved performance, yielding an IoU of 84.50% and a Dice Loss of 0.0857, demonstrating that the ResNet-34 encoder enhances segmentation accuracy in the UNet architecture [101].

In cases where pulmonary embolism (PE) occurs in patients with DVT, a model was developed to predict PE occurrence using both clinical data and ultrasound images of proximal thrombosis. A deep learning model integrated image data with five clinical factors, and its performance was compared to CNN models that relied only on image inputs. Results showed that both models outperformed state-of-the-art methods. While the contribution of clinical factors remained unclear, an improvement in accuracy was observed when using smaller models [104].

To enhance accessibility to DVT diagnostics, Nakayama et al. developed a ResNet101-based learning model to automatically identify cross-sectional US images suitable for DVT diagnosis, enabling disaster victims to self-assess their risk. Ultrasonographic images of the popliteal vein were collected from 20 subjects using both stationary and portable US devices. Video frames were extracted and classified into "Satisfactory," "Moderately satisfactory," and "Unsatisfactory" based on popliteal vein visualization. Results showed classification accuracy of 0.76 with portable devices and 0.73 with stationary devices, suggesting the feasibility of AI-driven automated DVT image quality assessment, particularly with portable US equipment [106].

Finally, a deep learning approach [108] was introduced for detecting spontaneous echo contrast (SEC) in vascular US images, which is associated with increased thromboembolism risk. The study utilized a multisequence CNN with a ResNetv2 backbone and a soft attention mechanism to identify SEC in archival femoral vein US images. The model was trained and tested on a dataset of 801 acquisitions from 201 patients, achieving an AUC of 0.74, with sensitivity of 0.73 and specificity of 0.68. The attention mechanism highlighted key frames for SEC classification, enhancing interpretability. The study suggests that automated SEC detection could serve as a screening tool, enabling broader data discovery and reducing expert burden in thromboembolism risk assessment. The dataset and code were made publicly available to support further research and clinical implementation.

4.3.2. DL-Based Approaches for Arterial Thrombosis

Deep learning (DL) techniques have been increasingly applied in the assessment of arterial thrombosis, particularly in characterizing atherosclerotic plaques, identifying high-risk lesions, and improving vascular imaging. Various machine learning (ML) and DL models have been developed to analyze ultrasound (US) images for diagnosing arterial conditions associated with thrombosis.

One study explored the potential of multiscale morphological analysis in evaluating atherosclerotic carotid plaques. US images from 137 asymptomatic and 137 symptomatic plaques were analyzed and converted into binary images at different intensity levels to highlight distinct plaque components. Morphological pattern spectra were computed, and classification was performed using K-Nearest Neighbor (KNN), Probabilistic Neural Network (PNN), and Support Vector Machine (SVM). The method achieved a diagnostic accuracy of 67%, which was slightly lower than texture-based analysis on the same dataset but still demonstrated the potential of morphological analysis in plaque characterization [88].

A novel method for detecting thin-cap fibroatheroma (TCFA) in intravascular ultrasound (IVUS) images was proposed in [93]. A dataset comprising 12,325 IVUS images from 100 patients, labeled using optical coherence tomography, was utilized. A deep feed-forward neural network (FNN) was employed to extract the most relevant features using Fisher's exact test. The model achieved an area under the curve (AUC) of 0.87, with specificity and sensitivity of 78.31% and 79.02%, respectively, for TCFA detection, demonstrating its capability in identifying high-risk plaques prone to rupture.

Coronary thrombosis, a leading cause of acute coronary syndrome (ACS), often results from the rupture of atherosclerotic plaques, particularly TCFA. Given the diagnostic challenges of identifying TCFA using IVUS, ML techniques were explored for automated classification. Several classifiers, including FNN, KNN, random forest (RF), and convolutional neural networks (CNNs), were trained on 12,325 IVUS images labeled using optical coherence tomography. Performance evaluation showed AUC scores of 0.859 (FNN), 0.848 (KNN), 0.844 (RF), and 0.911 (CNN), with CNN outperforming other methods. Feature-based classifiers (FNN, KNN, RF) identified key diagnostic features consistent with clinical assessment criteria, reinforcing the role of ML in improving the precision of vulnerable plaque detection and ACS risk assessment [95].

A deep learning-based approach was also introduced for 3D vessel reconstruction using IVUS imaging. This method leverages CNNs for image segmentation and feature extraction, enabling the generation of high-resolution 3D representations of vascular structures. Traditional vessel reconstruction techniques often struggle with noise, artifacts, and imaging inconsistencies, but the proposed DL method improves vessel wall segmentation, lumen boundary detection, and overall reconstruction fidelity. The results demonstrated enhanced diagnostic accuracy, providing clinicians with a more reliable tool for vascular assessment and interventional planning [96].

Another study aimed to improve the classification of vulnerable plaques in IVUS images by introducing a neural network-based vulnerability index. Using MatConvNet, intravascular US images labeled with different vulnerability index values were analyzed to determine the optimal threshold for distinguishing stable and unstable plaques. The study identified an optimal vulnerability index point of 1.716 for IVUS images and 1.607 for aortic artery component data. The model achieved an AUC of 0.7143 on the validation set, demonstrating its potential in aiding cardiovascular risk stratification and decision-making [97].

Beyond coronary artery thrombosis, US imaging is also widely used in diagnosing peripheral artery disease (PAD). Leblanc et al. [102] developed a DL-based method for 3D reconstruction of the femoral artery from 2D B-mode US frames, improving preoperative planning for PAD interventions. The approach employed Mask-RCNN for artery segmentation in 2D frames, in-plane registration by aligning segmentation masks, and a CNN for predicting out-of-plane translations. The method was validated on 111 US sequences from 18 healthy volunteers using fivefold cross-validation, achieving a mean error of 0.28 ± 0.28 mm and a median drift error of 8.98%. This approach offers an alternative to traditional 3D imaging for assessing stenosis or thrombosis lesions non-invasively.

Accurate blood flow measurement in carotid arteries is essential for detecting thrombosis formation. A novel DL-based method utilizing a deep complex convolutional neural network (DCCNN) was proposed to enhance carotid artery blood flow measurement, addressing the limitations of conventional non-parametric techniques. The model employed supervised learning with complex convolutional and fully connected layers to filter clutter signals and estimate blood flow velocity. Validation with simulations and in vivo data from healthy volunteers showed that DCCNN reduced normalized root mean square error (NRMSE) by over 45%, improved goodness-of-fit, and significantly decreased processing time compared to traditional methods such

as high-pass filtering and singular value decomposition. These findings suggest that DCCNN provides a more accurate and efficient approach for carotid blood flow velocimetry [103].

Furthermore, a study by Meng et al. [105] focused on detecting arterial thrombi using a DL-based framework for segmenting and classifying vascular lesions in IVUS images. A dataset of 5,089 IVUS frames from 100 patients with angina pectoris was analyzed using a two-stage diagnostic framework. Segmentation was performed using a dilated attention U-Net, followed by classification with ResNet18 into six lesion categories (fibrous, lipid, calcified plaques, dissections, hematomas, and thrombi). The model was evaluated using the Dice similarity coefficient and 95% Hausdorff distance for segmentation, as well as sensitivity, specificity, AUC, and F1 scores for classification. Results showed high segmentation accuracy, with Dice scores of 80.75% for dissections, 86.68% for hematomas, and 79.21% for thrombi. Classification performance was also strong, achieving F1 scores of 94.89% for dissections, 95.91% for hematomas, and 96.42% for thrombi. The study highlights the potential of DL-based segmentation and classification methods in improving the detection of high-risk vascular lesions.

Finally, Moon et al. [107] proposed a method to measure blood clot thickness in carotid arteries using self-generated ultrasound data to prevent brain damage caused by blocked blood flow. The approach extracted one-dimensional data, including bandwidth and center frequency, from blood clot backscatter signals and converted the bandwidth into 2D image data through amplitude-frequency conversion. A deep learning model leveraging multi-modality integrated features from both data types to predict clot thickness. The method achieved a high accuracy of 96%, demonstrating its potential for precise and reliable measurement of blood clot thickness in critical blood vessels.

Overall, based on the previously presented DL-based approaches for arterial thrombosis detection, significant advancements have been demonstrated in the analysis of atherosclerotic plaques, thrombi detection, and vascular imaging. Various ML and DL techniques, including CNNs, FNNs, U-Net, and Mask-RCNN, have been applied to IVUS and B-mode US images to enhance classification, segmentation, and 3D reconstruction of vascular structures. These methods show promise in improving diagnostic accuracy, reducing reliance on manual interpretation, and supporting clinical decision-making in the management of arterial thrombosis and related conditions.

4.3.3. DL-Based Approaches for Cardiac Thrombosis

Deep learning has been explored as a tool for the classification and segmentation of intracardiac thrombi and tumors in ultrasound imaging, aiming to enhance diagnostic accuracy and support clinical decision-making.

One study investigated the feasibility of using a neural network (NN) to classify ultrasound images of intracardiac tumors and thrombi, comparing its performance with that of experienced echocardiographers. The NN analyzed statistical descriptors of echocardiographic textures, while echocardiographers classified enlarged image regions without access to clinical data. The NN achieved 66% accuracy, compared to 83% for the echocardiographers, with both agreeing on 88% of the images. While human observers typically rely on clinical context for classification, the NN demonstrated the ability to recognize quantitative textural differences between tumors and thrombi, suggesting its potential as a diagnostic aid when clinical data is limited [87].

Expanding on automated classification, another study introduced an approach to distinguish different types of intracardiac masses, including thrombi and tumors, using echocardiographic imaging. The study leveraged image texture analysis techniques to extract numerical parameters representing histological features of the

masses. Additionally, a network of synchronized oscillators was employed as a segmentation method, enhancing the localization and differentiation of cardiac thrombi from benign and malignant tumors. The segmentation accuracy was compared with artificial neural networks (ANNs), demonstrating the reliability of the proposed method in detecting intracardiac masses despite challenges such as image artifacts and variations in texture. The findings suggest that automated classification and segmentation can improve diagnostic accuracy, reduce dependency on expert interpretation, and assist in clinical management [89].

Another study explored whether integrating transesophageal echocardiography with a computer-aided diagnostic (CAD) algorithm could improve the detection of left atrial and left atrial appendage thrombi in patients with atrial fibrillation. In this study, transesophageal echocardiography images were processed using a CAD system that employed an artificial neural network for feature analysis. Five radiologists independently assessed both the original and CAD-processed images. The results demonstrated that the CAD-assisted approach significantly enhanced transesophageal echocardiography's diagnostic performance, improving sensitivity, specificity, positive predictive value, accuracy, and the area under the receiver operating characteristic curve. These improvements were consistent across all radiologists, underscoring the potential of CAD in increasing the reliability and precision of transesophageal echocardiography for detecting left atrial and left atrial appendage thrombi [91].

Chapter 5 | Discussion

The results of this systematic review highlight the increasing role of Deep Learning (DL) in thrombosis detection and risk assessment using ultrasound (US) imaging. Across the 22 included studies, various DL architectures—ranging from convolutional neural networks (CNNs) to hybrid models integrating clinical data—demonstrated significant potential for classification, segmentation, thrombus risk prediction, and automation of vascular ultrasound analysis. These findings reinforce the growing impact of AI-driven diagnostic tools in enhancing non-invasive thrombus detection, reducing operator dependency, and improving clinical decision-making.

5.1. Summary of Key Findings

This systematic review aimed to comprehensively analyze deep learning (DL) approaches for thrombosis detection and risk assessment via ultrasound imaging, focusing on their methodological strengths, clinical applicability, and limitations. Several key findings emerged from the synthesis of included studies.

Firstly, convolutional neural networks (CNNs), U-Net, ResNet, and artificial neural networks (ANNs) were identified as the predominant deep learning architectures applied in ultrasound-based thrombosis diagnostics. CNNs demonstrated superior diagnostic performance in prediction tasks including thrombus classification, vessel segmentation, and thrombus localization. Notably, the CNN-based AutoDVT [109] achieved exceptional sensitivity (100%) and specificity (95.12%) in identifying proximal deep vein thrombosis, underscoring their clinical utility and ability to streamline diagnostic processes by significantly reducing dependency on expert interpretation.

Secondly, significant heterogeneity was observed in dataset characteristics, model validation strategies, and performance metrics used across reviewed studies. This variation highlights a critical gap regarding standardization, making direct comparisons challenging. Despite this, studies consistently reported high sensitivity and specificity, indicating robust DL capabilities in accurately identifying thrombosis across venous, arterial, and cardiac domains [101,103,105].

Thirdly, ultrasound imaging modalities such as B-mode ultrasound, Doppler ultrasound, intravascular ultrasound (IVUS), and transesophageal echocardiography (TEE) were successfully integrated with DL algorithms. B-mode ultrasound was particularly prevalent due to its accessibility and real-time diagnostic capability. DL approaches utilizing IVUS achieved high accuracy in detecting thrombotic lesions, significantly contributing to cardiovascular risk assessment and lesion classification [103,105].

Moreover, DL-driven ultrasound assessments showed considerable promise in mitigating operator dependency and variability associated with traditional ultrasound interpretation. AI-guided point-of-care ultrasound (POCUS) techniques particularly showcased high sensitivity and specificity, emphasizing their potential for widespread application in emergency and remote care settings [106,109,110].

Finally, despite these advancements, persistent challenges were identified including limited availability of large-scale, publicly accessible datasets, variability in image quality, and the need for explainable AI models to enhance clinical acceptance. Addressing these challenges through future research and collaborative efforts would significantly enhance the generalizability, robustness, and practical adoption of DL models in clinical settings [104,107,108].

Collectively, these key findings illustrate the promising potential and current limitations of DL-based ultrasound imaging in thrombosis detection and risk assessment, laying a strong foundation for future research aimed at enhancing clinical diagnostic capabilities and patient outcomes.

5.2. Comparison with Existing Literature

The findings of this systematic review align with and extend previous research on deep learning (DL) and machine learning (ML) applications in vascular imaging and thrombosis detection. Prior bibliometric analyses have highlighted the increasing role of AI in vascular surgery, with a focus on carotid artery disease, abdominal aortic aneurysms, and peripheral arterial disease [74]. The present study reinforces these trends by demonstrating that AI-driven ultrasound imaging plays a crucial role in thrombosis detection and risk assessment.

In venous thrombosis detection, previous studies acknowledged the operator dependency of compression ultrasound techniques and the variability in human interpretation [82]. AI-assisted point-of-care ultrasound (POCUS) has been explored as a solution, but most earlier studies lacked clinical validation. The reviewed studies demonstrated that AI models such as AutoDVT significantly improve DVT detection, achieving a sensitivity of 100% and specificity of 91%, thus reducing the need for formal duplex scans [109]. This aligns with prior research advocating for automated, expert-independent DVT diagnostics [83].

For arterial thrombosis, earlier studies explored AI applications in detecting vulnerable plaques using intravascular ultrasound (IVUS) but relied heavily on manual feature extraction and semi-automated classification [81]. The present review found that CNN-based approaches for arterial thrombosis detection achieved an AUC of 0.911, surpassing conventional methods [95]. The transition from manual feature-based models to fully automated deep learning segmentation and classification systems is a significant advancement, reducing subjectivity in plaque stability assessment and improving risk prediction for acute coronary syndrome (ACS).

In cardiac thrombosis detection, transesophageal echocardiography (TEE) has long been considered the gold standard, but manual interpretation poses limitations in diagnostic efficiency and interobserver variability [75]. The reviewed studies show that AI-assisted CAD systems for TEE imaging enhance thrombus detection accuracy, particularly for left atrial thrombi [91]. Furthermore, DL models using texture-based feature extraction demonstrated the ability to differentiate between intracardiac thrombi and tumors, a challenge previously addressed through subjective expert evaluation [89].

Compared to existing literature, this systematic review, performed in this thesis, uniquely consolidates DL applications across venous, arterial, and cardiac thrombosis using ultrasound imaging, highlighting the evolution from semi-automated models to fully AI-driven workflows. The findings reinforce the growing role of AI in real-time, remote, and non-specialist-assisted diagnostics [82,83]. Future research should emphasize large-scale validation, clinical integration, and regulatory approval to ensure AI-driven thrombosis detection is effectively incorporated into clinical practice.

5.3. Strengths and Clinical Implications

This review highlights several important strengths of AI-driven thrombosis detection:

1. Increased diagnostic accuracy: DL-based segmentation and classification models achieved high sensitivity, specificity, and AUC scores, suggesting strong potential for clinical adoption [95,111].
2. Reduction in operator dependency: AI-guided imaging allows non-experts to perform POCUS assessments, reducing the burden on radiologists and vascular specialists [100].
3. Efficiency and cost reduction: Automated classification could streamline diagnostic workflows, reducing the need for unnecessary imaging studies and shortening diagnostic delays [100].
4. Potential for remote and point-of-care applications: AI-enabled handheld US devices could expand thrombosis screening capabilities in rural and low-resource settings, improving early detection and intervention [109].

5.4. Limitations and Challenges

Despite the promising findings, several limitations must be acknowledged:

- Dataset Availability and Bias: Many studies relied on proprietary or small-scale datasets, limiting the generalizability of their findings. The lack of open-access, standardized thrombosis imaging datasets hinders broader AI development.
- Lack of Prospective Clinical Validation: While most studies reported high accuracy in retrospective datasets, real-world clinical validation remains limited. Further prospective trials are needed to assess AI performance in diverse patient populations.
- Computational Requirements and Model Interpretability: Complex DL models often require significant computational resources, making them less accessible in low-resource clinical settings. Additionally, the "black box" nature of deep learning models raises concerns about explainability and clinical trust.
- Regulatory and Ethical Considerations: AI deployment in thrombosis diagnostics faces regulatory challenges, including FDA/EMA approval and ensuring compliance with medical AI guidelines.

Chapter 6| Conclusions

This master's thesis through a systematic review has comprehensively examined the role of deep learning (DL) in thrombosis detection and risk assessment using ultrasound (US) imaging, emphasizing the transformative potential of artificial intelligence (AI) in vascular diagnostics. Across the 22 included studies, a variety of DL models—including convolutional neural networks (CNNs), U-Net, ResNet, and artificial neural networks (ANNs)—were applied to detect, classify, segment, and assess thrombotic risk across venous, arterial, and cardiac systems. These findings underscore DL's pivotal role in enhancing vascular imaging, reducing operator dependency, improving diagnostic precision, and enabling automation of image analysis.

For venous thrombosis, AI-based approaches demonstrated high accuracy in detecting deep vein thrombosis (DVT) by evaluating vein compressibility, thrombus localization, and classification. AI-assisted point-of-care ultrasound (POCUS) has further showcased the feasibility of assisting non-specialists in capturing high-quality US images, extending diagnostic capabilities to remote, resource-limited, and emergency care settings. Additionally, DL models were effectively applied in detecting iliac vein compression syndrome (IVCS), reinforcing AI's role in vascular disease diagnosis beyond direct thrombus detection.

For arterial thrombosis, DL-based methods have been instrumental in classifying, segmenting, and assessing the risk of atherosclerotic plaques and vulnerable lesions. Intravascular ultrasound (IVUS)-enabled AI approaches demonstrated high-accuracy detection of thin-cap fibroatheroma (TCFA), a key predictor of acute coronary syndrome (ACS) and arterial thrombotic events. Furthermore, 3D reconstruction of vascular structures using DL models has significantly improved plaque characterization and stenosis evaluation, providing enhanced decision support for interventional procedures, such as stenting or bypass surgery.

Finally, for cardiac thrombosis, DL-assisted transesophageal echocardiography (TEE) has shown promising results in detecting left atrial thrombi, aiding stroke prevention strategies and risk stratification. Additionally, AI-based texture and motion analysis enabled accurate differentiation of intracardiac thrombi from benign or malignant tumors, which is critical for treatment planning and anticoagulation decisions. Computer-aided diagnostic (CAD) systems have been found to improve sensitivity and specificity in thrombus detection, indicating that AI could serve as an invaluable assistive tool for echocardiographers, particularly in challenging manual interpretation scenarios.

6.1. Future Directions

To maximize the clinical impact of AI in thrombosis detection and risk assessment, future research should focus on:

1. **Developing Large-Scale, Multicenter Datasets:** Establishing publicly available annotated ultrasound datasets will improve model generalization and robustness.
2. **Enhancing Model Explainability:** Implementing attention-based visualization techniques could help clinicians better understand model predictions and build trust in AI-driven diagnoses.
3. **Integration with Clinical Workflows:** AI models should be seamlessly integrated into real-time ultrasound systems, providing instant decision support during scans.
4. **Expanding AI-Guided Point-of-Care Applications:** Further validation of AI-assisted POCUS for DVT and cardiac thrombi detection will facilitate broader clinical adoption.

5. Regulatory Approval and Ethical AI Implementation: Future efforts should align with medical AI ethics and regulatory frameworks to ensure safe deployment in clinical practice.

6.2. Final Remarks

Deep learning approaches for thrombosis detection and risk assessment using ultrasound imaging hold great potential for transforming vascular diagnostics. The findings of this systematic review underscore the ability of AI not only to enhance diagnostic accuracy but also to automate image analysis, reduce operator dependency, and improve clinical decision-making.

By streamlining workflows, AI-driven ultrasound solutions can facilitate faster and more reliable thrombus detection, particularly in point-of-care and non-specialist settings, such as emergency departments and remote healthcare environments. Additionally, the application of AI in risk stratification enables early identification of patients at higher thrombotic risk, supporting preventive strategies and optimizing treatment plans.

However, despite the promising advancements, challenges remain, including dataset limitations, variability in ultrasound imaging quality, and the need for explainable AI models to enhance clinical trust. Future developments should prioritize large-scale clinical validation, improved model interpretability, and compliance with regulatory standards, ensuring that AI-driven solutions are both effective and ethically implemented in routine medical practice.

With continued progress in deep learning and medical imaging, the future will likely witness greater AI integration into real-time vascular diagnostics, enhanced standardization of AI-assisted ultrasound tools, and improved regulatory acceptance. These advancements will pave the way for a more AI-assisted future in vascular medicine, ultimately improving patient outcomes, diagnostic efficiency, and accessibility to high-quality thrombosis detection worldwide.

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