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Deep Learning Approaches for Thrombosis Detection and Risk Assessment via Ultrasound Imaging: A Scoping Review

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Abstract

Objective: Thrombosis, the formation of clots in blood vessels, poses serious health risks such as pulmonary embolism and post-thrombotic syndrome. Ultrasound (US) imaging is widely used for its safety and real-time capability but suffers from operator dependency. This scoping review explores the application of deep learning (DL) methods to improve thrombosis detection and risk assessment using US imaging, focusing on venous, arterial, and cardiac contexts.

Methods: A scoping review was conducted in accordance with PRISMA-ScR methodology. Searches in PubMed and Scopus combined MeSH terms and keywords related to DL, ultrasound, and thrombosis. Studies were eligible if they applied DL to US imaging for thrombus detection, classification, segmentation, or risk prediction. Only original, English-language research using vascular US modalities (e.g., B-mode, Doppler, Intravascular Ultrasound [IVUS], or Transesophageal Echocardiography [TEE]) was included. Screening and full-text review were conducted independently, and data were extracted using a standardized charting form.

Results: From 233 records, 22 studies met the inclusion criteria. Convolutional Neural Networks (CNNs), U-Net, Residual Neural Network (ResNet), and Artificial Neural Networks (ANNs) were commonly used for classification, segmentation, and thrombus localization. DL models supported Deep Vein Thrombosis (DVT) diagnosis via vein compressibility analysis as well as Point-of-Care Ultrasound (POCUS). Arterial thrombosis detection leveraged plaque segmentation and IVUS-based vessel reconstruction, while cardiac applications used TEE to differentiate thrombi from tumours. Cross-validation and external datasets were frequently used, with sensitivity, specificity, accuracy, and Area Under the Curve (AUC) among reported metrics.

Conclusion: DL-based methods have shown substantial potential to improve diagnostic accuracy, automate image analysis, and support clinical decision-making in thrombosis management. Despite these advances, challenges such as limited datasets, image quality variability, and a lack of multi-centre validation remain. Future research should focus on real-world clinical integration and the development of standardized, publicly available datasets.

Keywords: Deep Learning, Thrombosis, Ultrasound Imaging, Scoping Review, PRISMA-ScR.

1. Introduction

Thrombosis [1], the pathological formation of blood clots within blood vessels, remains a major global health concern due to its association with life-threatening conditions such as pulmonary embolism (PE), stroke, myocardial infarction, and chronic post-thrombotic syndrome. Early detection and accurate risk stratification are critical for preventing severe complications and improving patient outcomes. Among imaging modalities, ultrasound (US) has long been established as the preferred method for diagnosing vascular conditions, particularly due to its real-time capabilities, portability, non-invasiveness, and absence of ionizing radiation [2,3].

Despite its advantages, the accuracy and reliability of US imaging are often constrained by operator dependency, variability in interpretation, and image quality limitations, especially in deep or complex anatomical structures [4]. These limitations underscore the need for automated and objective interpretation tools that can assist clinicians in diagnosis and risk assessment tasks. In this context, Artificial Intelligence (AI), and more specifically Deep Learning (DL), has emerged as a transformative tool in medical imaging, capable of enhancing image analysis, enabling real-time decision support, and reducing inter-observer variability [5–7].

While individual studies and reviews have demonstrated promising applications of artificial intelligence (AI) and machine learning (ML) in vascular medicine, a focused synthesis on deep learning (DL) methods specifically for thrombosis detection and risk assessment using ultrasound (US) imaging remains absent. Several reviews have explored AI applications in vascular surgery, cardiovascular disease risk prediction, and plaque characterization, often emphasizing imaging modalities like computed tomography (CT), magnetic resonance imaging (MRI), or invasive angiography over ultrasound. For instance, a bibliometric analysis of AI in vascular surgery found notable progress in predictive modelling and diagnostic tools but lacked thrombosis-specific implementations [8]. Similarly, reviews on cardiovascular risk stratification using AI noted strong performance in predictive modelling but did not address thrombus detection or use US imaging [9].

Other related works have explored AI-driven analysis of peripheral artery disease, cerebrovascular disease, and deep vein thrombosis (DVT), often applying ML techniques to contrast-enhanced MRI or CT images [10]. While such approaches demonstrate enhanced diagnostic capabilities, they fall short in terms of generalizability and practical integration in real-time clinical settings, particularly for non-invasive US imaging. Studies applying DL to plaque characterization using US—such as segmentation of intima-media thickness or vulnerable plaque detection—provide insights relevant to thrombotic risk, but they rarely include thrombus classification or US-based risk assessment [11–14].

More directly relevant literature on venous thromboembolism (VTE) prediction and embolism classification has demonstrated that DL and ML models outperform traditional clinical scoring systems [15,16]. Nevertheless, challenges such as limited dataset quality, high bias risk, lack of external validation, and a reliance on non-ultrasound modalities remain common limitations [17,18]. In short, while related works show the potential of AI in vascular diagnostics, they fall short of delivering an end-to-end framework for DL-based thrombosis detection using ultrasound.

To address these gaps, the present scoping review provides a consolidated and structured evaluation of DL applications specific to thrombosis detection and risk assessment via US imaging. This includes analysis of clinical applications, model architectures, validation strategies, and performance metrics reported in the literature. It aims to serve as a resource for clinicians, researchers, and policymakers, guiding future AI development in this domain and supporting real-world implementation of DL tools in thrombosis diagnostics. More specifically, this review focuses on providing answers to 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?

2. Materials and methods

This work aims to perform a qualitative scoping review conducted to analyse 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-ScR methodology [19], ensuring a structured, transparent, and reproducible approach to the identification, selection, and synthesis of relevant literature.

2.1. 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.

2.2. 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-ScR guidelines, with two independent reviewers assessing each study based on the inclusion and exclusion criteria. The primary investigator (first author) performed the initial screening, while the other (second author) reviewed the selections and resolved any discrepancies. Disagreements were settled through discussion.

2.3. 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 work:

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.

2.4. 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

2.5. Synthesis of Results

The extracted data were analysed 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 previous section, 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.

3. Results

3.1. 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 scoping review to ensure alignment with the research objectives. The source selection process is shown in Figure 1.

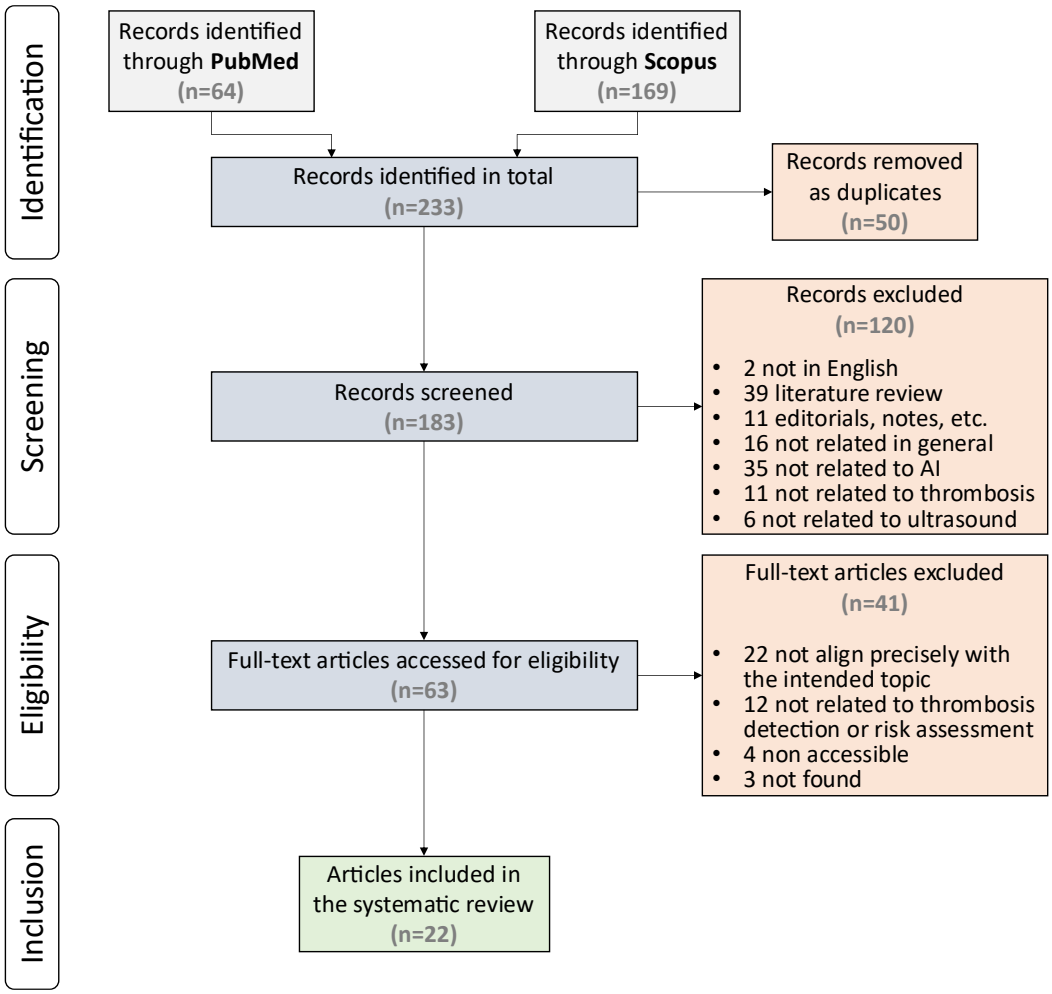

Figure 1. Source selection process from PubMed and Scopus search engines (PRISMA flowchart).

3.2. 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 scoping review are presented in Table 1, Table 2 and Table 3.

Table 1. Research papers included in the scoping 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) **[20]**	Article	Intracardiac thrombi, including LA and LAA	Direct thrombosis detection	Transesophageal Echocardiography (TEE)	Classification of intracardiac tumours and thrombi
Kyriacou et al. (2005) **[21]**	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) **[22]**	Article	Intracardiac thrombi	Direct thrombosis detection	Echocardiography (cardiac ultrasound, transesophageal)	Classification & segmentation of intracardiac thrombi, benign & malignant tumours
Dahabiah et al. (2007) **[23]**	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) **[24]**	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) **[25]**	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) **[26]**	Conference paper	Coronary thrombosis (thin-cap fibroatheroma)	Thrombotic risk assessment	Intravascular Ultrasound (IVUS)	Classification of thin-cap fibroatheroma (TCFA) vs. non-TCFA
Tanno et al. (2018) **[27]**	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) **[28]**	Article	Coronary thrombosis	Thrombotic risk assessment	Intravascular Ultrasound (IVUS)	Classification of thin-cap fibroatheroma (TCFA)
Cao et al. (2020) **[29]**	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) **[30]**	Article	Atherosclerosis-related plaque rupture & thrombosis	Thrombotic risk assessment	Intravascular ultrasound (IVUS)	Prediction of vulnerable vs. stable plaques

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?
Johnstonbaugh et al. (2020) **[31]**	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) **[32]**	Article	Iliac Vein Compression Syndrome (IVCS)	Indirect thrombosis assessment	B-mode compression ultrasound imaging	Detection of iliac vein compression points
Kainz et al. (2021) **[33]**	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 analysing vein compressibility
Hernanda et al. (2022) **[34]**	Conference paper	Deep Vein Thrombosis (DVT)	Direct thrombosis detection	B-mode ultrasound imaging	Semantic segmentation of venous areas in US images to detect DVT
Leblanc et al. (2022) **[35]**	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) **[36]**	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) **[37]**	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) **[38]**	Article	Coronary artery thrombi	Thrombotic risk assessment	Intravascular Ultrasound (IVUS)	Segmentation and classification of vascular lesions, including thrombi
Nakayama et al. (2023) **[39]**	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) **[40]**	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) **[41]**	Article	Thromboembolism detection	Direct thrombosis detection	B-mode ultrasound imaging of femoral vein	Detecting Spontaneous Echo Contrast (SEC) associated with thromboembolism risk

Table 2. Descriptive data on the particular DL characteristics (models, validation methods, and performance metrics) presented in each of the papers included in the scoping 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) **[20]**	Artificial Neural Network (ANN) with statistical texture analysis	Leave-one-out cross-validation	Classification accuracy: 66% (ANN)
Kyriacou et al. (2005) **[21]**	Probabilistic Neural Network (PNN), Support Vector Machine (SVM), K-Nearest Neighbour (KNN)	Leave-one-out cross-validation	Best diagnostic yield: 67% (SVM), 62% (PNN), 56% (KNN)
Strzelecki et al. (2006) **[22]**	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) **[23]**	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) **[24]**	ANN with grey 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) **[25]**	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) **[26]**	Deep Feed-Forward Neural Network (FFNN)	10-fold cross-validation	AUC: 0.87, Specificity: 78.31%, Sensitivity: 79.02%
Tanno et al. (2018) **[27]**	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) **[28]**	Feed-Forward Neural Network (FNN), K-Nearest Neighbour (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) **[29]**	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) **[30]**	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) **[31]**	Deep learning architecture using an atrous Nyquist Convolution and a differentiable spatial-to-numerical transformer (DSNT), while combining design elements of U-net and ResNet	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
Bai et al. (2021) **[32]**	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) **[33]**	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

Author (year)	RQ5. What DL models are used?	RQ6. What DL validation methods are employed?	RQ7. What performance metrics are reported for DL approaches?
Hernanda et al. (2022) **[34]**	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) **[35]**	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) **[36]**	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) **[37]**	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) **[38]**	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) **[39]**	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) **[40]**	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
Huang et al. (2024) **[41]**	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 3. Details about the used datasets and the challenges/limitations presented in each of the papers included in the scoping 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) **[20]**	18 TEE images (9 tumour, 9 thrombi). Not publicly available.	- ANN struggled with cases where tumours and thrombi had similar echogenic patterns. - Small dataset. - Lack of standardized echocardiographic settings.
Kyriacou et al. (2005) **[21]**	274 ultrasound images (137 symptomatic, 137 asymptomatic). Not publicly available.	- 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) **[22]**	163 annotated echocardiograms (91 thrombi, 28 benign and 44 malignant tumours), 256 grey levels bitmap images, 640x480 pixels. Private dataset.	- Ultrasound artifacts. - Training dependence. - Subjectivity in annotations.

Author (year)	RQ8. What datasets are used and if any are available?	RQ9. What challenges or limitations are identified in the proposed DL?
Dahabiah et al. (2007) **[23]**	US images of VT collected for indexing and retrieval. Not publicly available.	- 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) **[24]**	650 TEE images from 130 patients with atrial fibrillation. Not publicly available.	- 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) **[25]**	12,804 subimages from 15 subjects. Not publicly available.	- 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) **[26]**	12,325 IVUS images from 100 patients, co-registered with OCT images. Not publicly available.	- 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) **[27]**	1150 ultrasound videos (100 to 200 frames) from 115 healthy volunteers. Not publicly available.	- Limited dataset diversity. - Challenges in generalizing to all vein landmarks. - Domain shift across different ultrasound devices.
Jun et al. (2019) **[28]**	12,325 IVUS images from 100 patients, co-registered with OCT images. Not publicly available.	- The dataset included only patients with plaques above a certain level, limiting generalizability. - 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) **[29]**	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.	- Difficulty in segmenting bifurcated vessels. - Accuracy of boundary detection for precise 3D reconstruction.
Cao et al. (2020) **[30]**	3535 IVUS images from 23 atherosclerotic rabbit models. Not publicly available.	- 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) **[31]**	Simulated photoacoustic signals with 20,300 different target positions in a tissue model (10-50 mm depth). No public dataset mentioned.	- Decreased signal intensity at deeper tissue layers. - Optical scattering affecting photoacoustic signals. - Limitations in real-time clinical applicability.
Bai et al. (2021) **[32]**	699 vein US images from 211 subjects. Available upon request.	- Challenges include high noise in vein ultrasound images. - Difficulty in identifying the compression point due to anatomical variations. - Need for further multi-centre validation.
Kainz et al. (2021) **[33]**	1500 ultrasound videos from 255 subjects. External validation on 83 patients (53 UK, 30 Germany). Available upon request.	- 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) **[34]**	536 ultrasound images from phantom-based human body simulations. No public dataset mentioned.	- Vanishing gradient problem in deep networks (solved using ResNet encoder). - Difficulty in segmenting veins due to the presence of blood clots.

Author (year)	RQ8. What datasets are used and if any are available?	RQ9. What challenges or limitations are identified in the proposed DL?
Leblanc et al. (2022) **[35]**	111 tracked US videos (left/right femoral arteries) from 18 healthy volunteers. Not publicly available.	- Needs further evaluation in patients with PAD. - Limited dataset. - It does not account for orientation. - Segmentation process is time-consuming.
Lei et al. (2022) **[36]**	Simulated ultrasound data generated using the Field II platform	- 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) **[37]**	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.	- 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.
Meng et al. (2023) **[38]**	5,089 IVUS images from 100 patients. Not publicly available.	- Limited dataset size (100 patients), single-centre study, and need for multi-centre validation. - Model refinement is needed for high-risk lesion stratification.
Nakayama et al. (2023) **[39]**	128,494 US images from stationary and 46,338 from portable equipment (20 subjects). Dataset is not publicly available.	- The dataset was limited to healthy individuals. - Performance needs validation in patients with actual DVT.
Moon et al. (2023) **[40]**	Self-produced dataset (1280 waveforms (1D) for training, 201 frequency spectra (2D) for validation)	- 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) **[41]**	801 archival ultrasound acquisitions along the femoral vein from 201 patients. Publicly available at GitHub. (https://github.com/Ouwen/automatic-spontaneous-echo-contrast).	- 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 2 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.

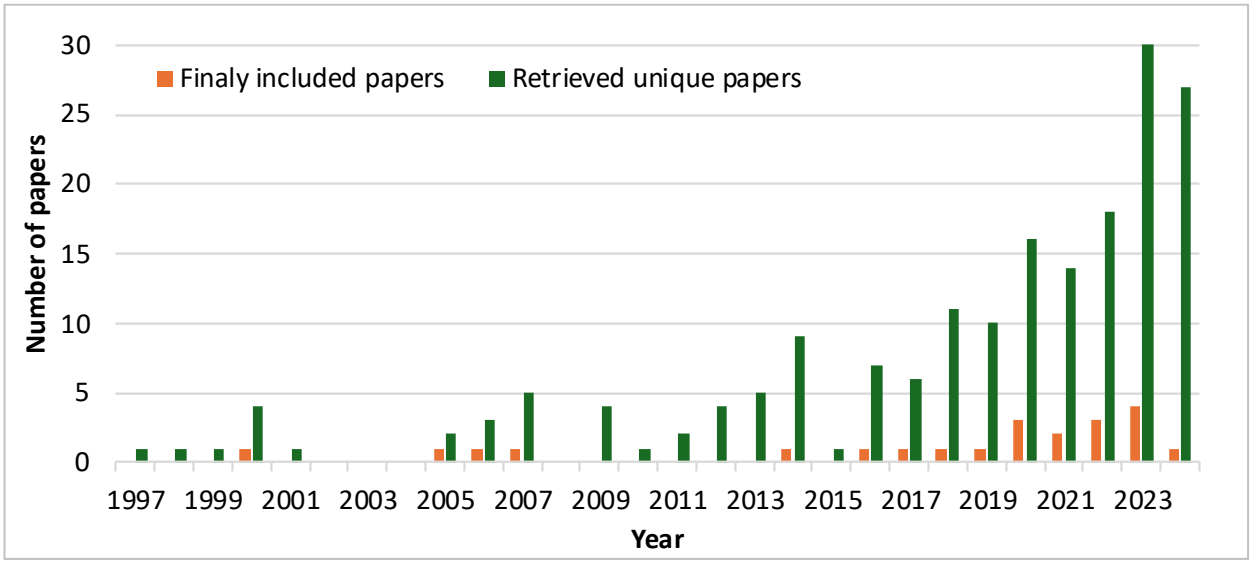

Figure 2. Trend of retrieved and included papers for DL-based thrombosis assessment using US imaging.

The distribution of the included papers by publication type—journal articles (55%) and conference papers (45%)—is presented in Figure 3. 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.

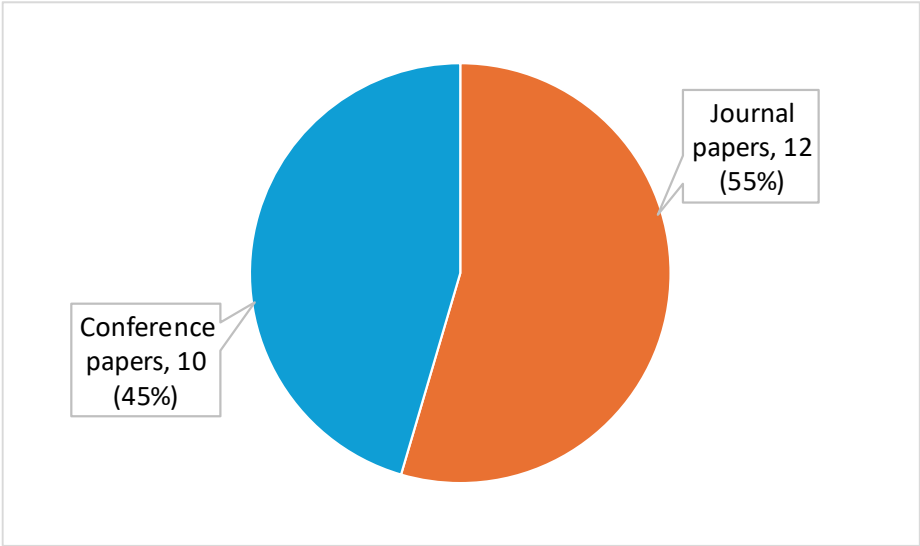

Figure 3. Distribution of included papers by publication type (journal vs. conference papers).

Figure 4 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).

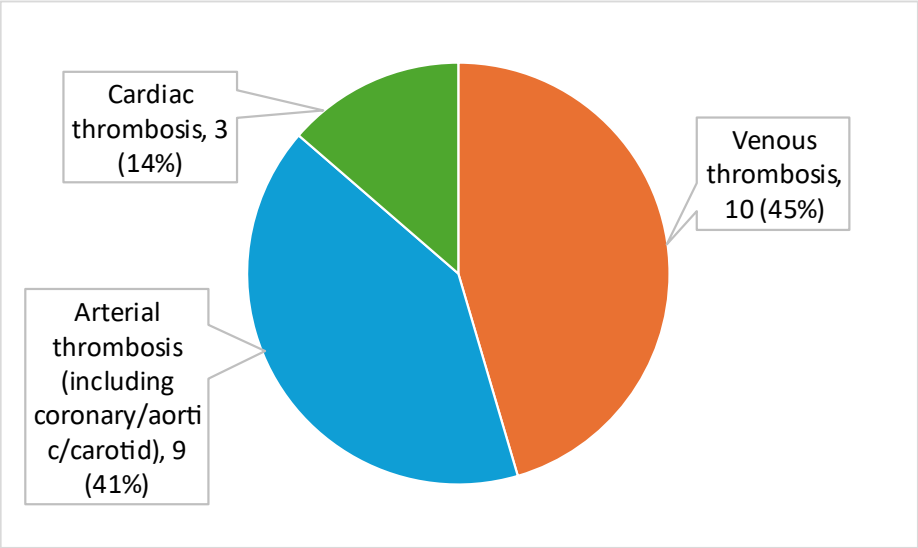

Figure 4. Distribution of primary clinical focus in included papers.

Figure 5 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.

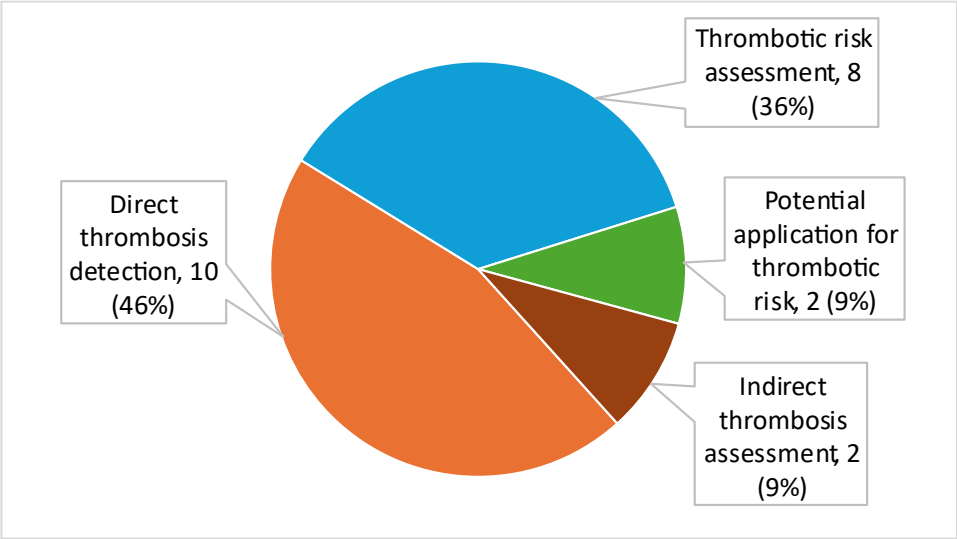

Figure 5. Distribution of clinical relevance to thrombosis in the included studies.

Figure 6 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 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.

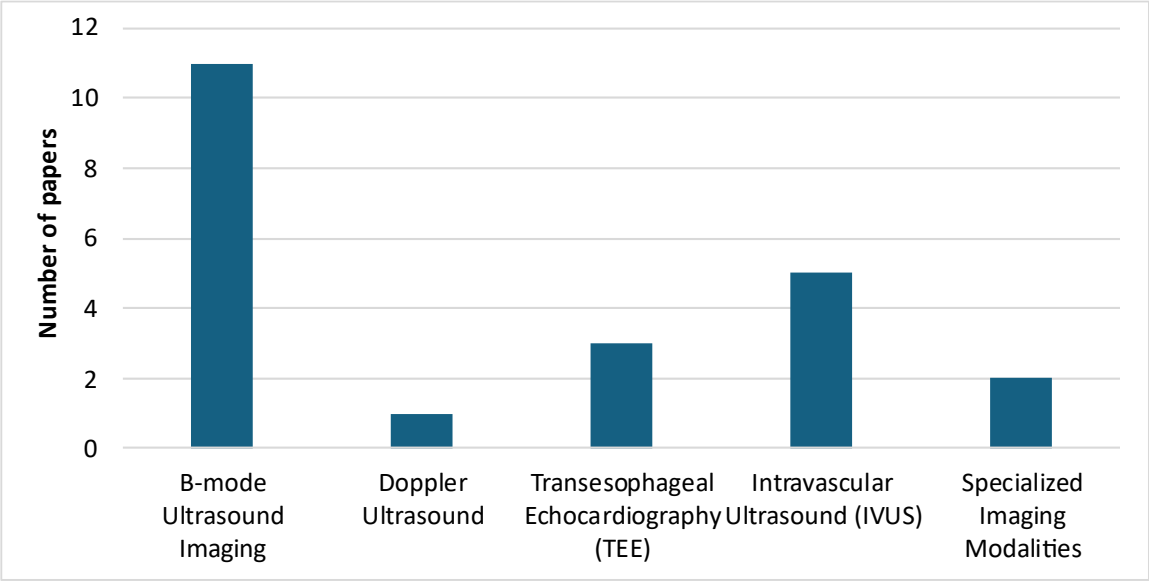

Figure 6. Distribution of US imaging modalities used in DL studies for thrombosis assessment.

Figure 7 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 tumours, 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 modelling 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.

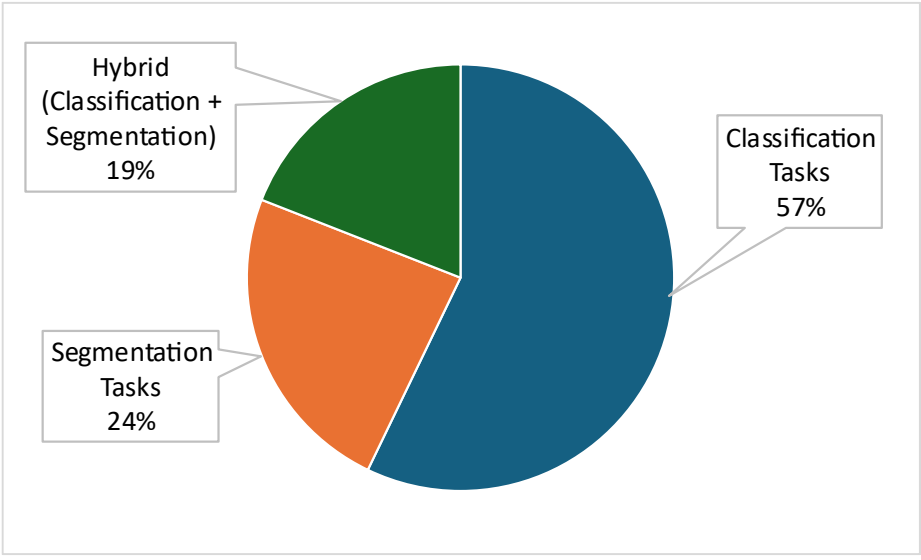

Figure 7. Distribution of prediction tasks in DL-based thrombosis assessment.

Figure 8 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.

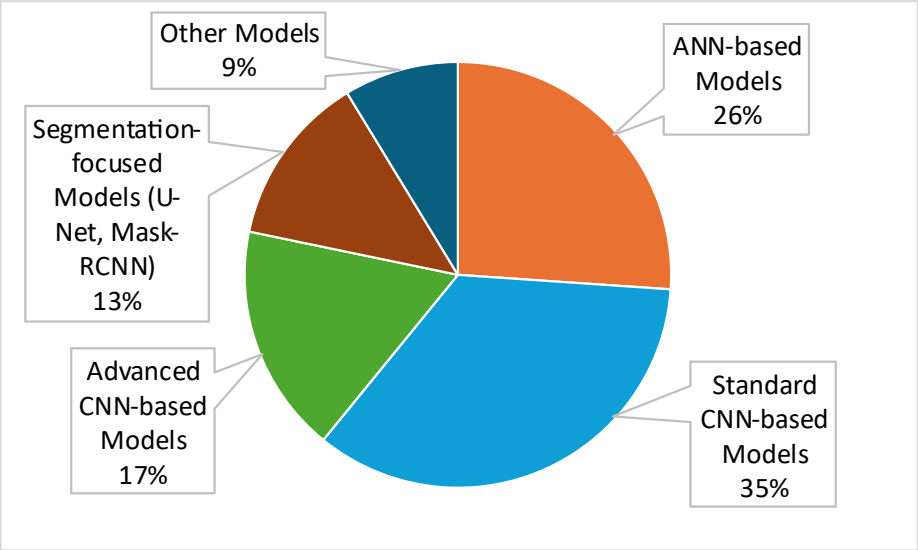

Figure 8. Distribution of deep learning model types used in thrombosis assessment.

Finally, the distribution of validation methods used in deep learning models is shown in Figure 9. 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. Only two studies within the included literature have progressed beyond algorithm development to clinical evaluation settings. Oppenheimer et al. [42] conducted a study to assess the feasibility of AI-assisted DVT triage using AutoDVT [27], reporting 100% sensitivity and 95.12% specificity in scans obtained by non-specialists, and a 53% reduction in the need for formal duplex ultrasound imaging. Similarly, Nothnagel and Aslam [43] evaluated AI-guided point-of-care ultrasound (POCUS) [33] among older patients in a remote triage scenario, finding that 91% of complete scans were diagnostically sufficient and enabled clinicians to triage 53% of patients as low risk without further imaging.

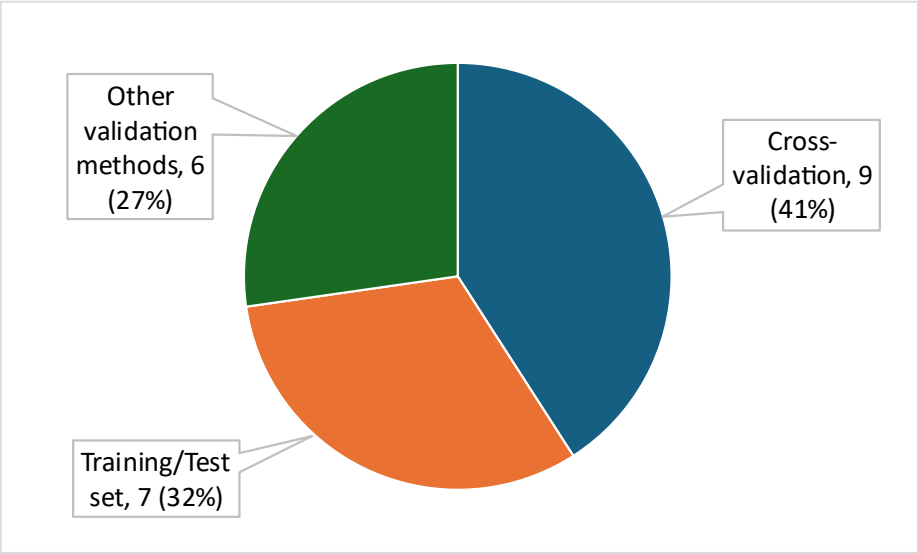

Figure 9. Distribution of validation methods used in deep learning models to evaluate their performance.

4. Discussion

This scoping review highlights 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.

4.1. Summary of Key Findings

This scoping review aimed to comprehensively analyse 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 [42] 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 [34,36,38].

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 [36,38].

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 [39,42,43].

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 [37,40,41].

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.

4.2. Comparison with Existing Literature

The findings of this scoping 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 [8]. 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 [15]. 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 [42]. This aligns with prior research advocating for automated, expert-independent DVT diagnostics [16].

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 [14]. The present review found that CNN-based approaches for arterial thrombosis detection achieved an AUC of 0.911, surpassing conventional methods [28]. 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 [9]. The reviewed studies show that AI-assisted CAD systems for TEE imaging enhance thrombus detection accuracy, particularly for left atrial thrombi [24]. Furthermore, DL models using texture-based feature extraction demonstrated the ability to differentiate between intracardiac thrombi and tumours, a challenge previously addressed through subjective expert evaluation [22].

Compared to existing literature, this scoping review 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 [15,16]. Future research should emphasize large-scale validation, clinical integration, and regulatory approval to ensure AI-driven thrombosis detection is effectively incorporated into clinical practice.

4.3. Strengths and Clinical Implications

This review identifies several notable strengths of DL-based thrombosis detection using US imaging:

1. Increased diagnostic accuracy: DL-based segmentation and classification models achieved high sensitivity, specificity, and AUC scores, suggesting strong potential for clinical adoption [28,44].
2. Reduction in operator dependency: AI-guided imaging allows non-experts to perform POCUS assessments, reducing the burden on radiologists and vascular specialists [33].
3. Efficiency and cost reduction: Automated classification could streamline diagnostic workflows, reducing the need for unnecessary imaging studies and shortening diagnostic delays [33].

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 [42].

4.4. Limitations and Challenges

Despite the promising findings, several limitations remain that must be addressed in future work:

- 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.

5. Conclusions

This scoping review examined the role of deep learning (DL) in thrombosis detection and risk assessment using ultrasound (US) imaging across venous, arterial, and cardiac domains. The 22 included studies demonstrated that DL models—particularly convolutional neural networks (CNNs), U-Net, and ResNet—consistently achieved high performance in thrombus classification, vessel segmentation, and risk prediction tasks. These approaches enhance diagnostic accuracy, reduce operator dependency, and enable automation in vascular ultrasound analysis.

In venous thrombosis, DL methods showed strong capabilities in detecting deep vein thrombosis (DVT) and evaluating vein compressibility, with AI-assisted point-of-care ultrasound (POCUS) extending diagnostic access to remote and emergency settings. For arterial thrombosis, DL algorithms integrated with intravascular ultrasound (IVUS) enabled accurate detection of high-risk atherosclerotic plaques, while 3D reconstruction tools improved vascular lesion assessment. In cardiac applications, DL-enhanced transesophageal echocardiography (TEE) facilitated the detection and classification of intracardiac thrombi, supporting stroke prevention and treatment planning.

Despite these advances, key challenges remain, including the need for large-scale, annotated ultrasound datasets, improved model explainability, and real-world clinical validation. Future research should focus on developing interpretable, ethically aligned AI systems that can be seamlessly integrated into existing diagnostic workflows.

Ultimately, AI-enhanced ultrasound offers a scalable and cost-effective solution for improving diagnostic precision and patient outcomes in thrombosis care. As regulatory frameworks and technological standards evolve, the adoption of trustworthy and clinically validated DL models will be essential to achieving widespread, equitable implementation of AI in vascular medicine.

Conflict of interest

The authors declare no competing interests.

CRediT authorship contribution statement

Maria Didaskalou: Writing – original draft, Methodology, Investigation, Visualization, Formal analysis. George Ioannakis: Validation. Eleni Kaldoudi: Validation, Funding acquisition. George Drosatos: Conceptualization, Data curation, Writing – review & editing, Supervision, Project administration.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 4o in order to assist with language refinement, content structuring, and editing support. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Data availability

No data sets were generated or analyzed during the current study.

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