A Dataset for Benchmarking Machine Learning Models for Autonomous Deep Vein Thrombosis Detection Based on Compression Ultrasound Videos

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Abstract: Deep vein thrombosis (DVT) is a major vascular condition associated with substantial morbidity, mortality and healthcare burden. Compression ultrasonography, performed and interpreted by medical experts, is the primary diagnostic method. Advances in machine learning (ML) and deep learning (DL) offer promising opportunities to support automated and real-time DVT assessment by non-experts. However, existing approaches rely on pixel-wise vessel annotations, which are costly to generate, posing difficulties in developing models that generalize across devices and acquisition protocols. To address these limitations, we introduce the ThrombUS+ Dataset #1. The Dataset is based on 2919 segmentation-free compression ultrasound videos from 742 patients suspected of DVT, acquired from a multicenter cohort study across 5 European hospitals.

1 INTRODUCTION

Venous thromboembolism (VTE), defined as deep vein thrombosis (DVT) and/or pulmonary embolism (PE), represents the third most common cause of vascular mortality worldwide after heart attack and stroke (Waheed et al., 2024). The incidence rate for DVT and PE ranges between 53 to 162 and between 39 to 115 per 100,000, respectively. It is estimated that PE alone causes nearly 300,000 deaths per year in the United States. A previous study from six European countries estimated that deaths related to venous thromboembolism conditions to be around 370,000 in a year. Importantly, the study also indicates that one-third of deaths occurred suddenly, before therapy could be initiated (Konstantinides et al., 2020). Furthermore, the

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yearly expenditure for preventing and treating VTE-related conditions are estimated to be around €8.5 billion in the European Union (Barco et al., 2016).

Deep vein thrombosis is characterized by the presence of a blood clot within the deep veins of the body, usually the deep veins of lower limbs. The presence of clots impairs normal blood flow often causing pain and swelling, although, there are cases where no clinical symptoms are present or symptoms may overlap with those of other conditions. Notably, clots may detach from the primary formation site, travel through the veins and block an artery in the lungs, causing pulmonary embolism, an acute and often fatal complication.

The likelihood of clot formation differs between the anatomical sites of the lower limbs. The likelihood is 40% for the distal veins, 16% for the popliteal, 20% for the femoral and common femoral, respectively, and only 4% for the iliac vein (Stubbs et al., 2018). However, proximal clots pose higher risk of causing PE than distal ones (Moser & LeMoine, 1981; Zhang et al., 2020).

X-ray venography is deemed the "gold standard" for DVT diagnosis. However, due to their invasive nature and their limitations, X-ray venography-based methods are barely used in everyday clinical practice. Ultrasound-based examination is preferred as the method of choice of suspected DVT in the lower limbs (Bates et al., 2012; Bernardi & Camporese, 2018). Yet, many thrombi cannot be visualized directly with an ultrasound scanner due to their anechoic properties. Thereby, expert physicians in ultrasound assess vein compressibility: while scanning deep veins of the lower limb, ultrasound operators apply enough pressure with the ultrasound probe until the nearby pulsatile artery starts to compress slightly. At this point, the nearby vein is expected to fully collapse in the absence of a blood clot. If the vein does not fully collapse, this is indicative of a clot present around the scanning anatomical site (Figure 1).

Expert physicians in ultrasound recommend assessing vein compressibility of the whole limb, from the inguinal ligament to the ankle, with a 2-cm compression interval, and also incorporating Doppler measurements in specific anatomical sites (Needleman et al., 2018). Whole leg scanning is timely, requires dedicated equipment and is generally performed by expert sonographers. Consequently, there are circumstances in which a complete study cannot be performed in a clinically relevant time window e.g. in emergency departments.

To address this issue, point-of-care ultrasound (POCUS) protocols limit the scanning areas from the inguinal ligament to the popliteal veins. POCUS is a clinician-performed, clinician-interpreted bedside ultrasound examination, with diagnostic accuracy for proximal DVT comparable to examinations performed in the radiology or vascular departments (Burnside et al., 2008; Pedraza García et al., 2018; Pomero et al., 2013; "Ultrasound Guidelines," 2017; Varrias et al., 2021).

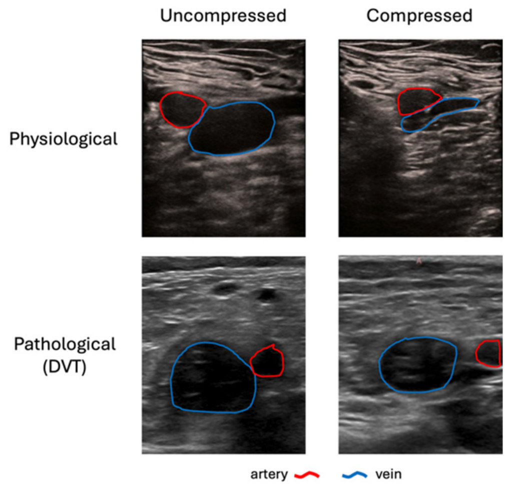

Figure 1: Indicative images of ultrasound images before compression and after compression. The top row represents a physiological condition, with the vein (blue) fully collapsing when pressure is applied. The bottom row represents a pathological condition, where the vein (blue) does not collapse when pressure is applied. In this specific case, the thrombus is also visible within the vein.

There are primarily two POCUS protocols for assessing DVT in the lower limbs. In the "2-point" protocol, the common femoral vein (CFV), from the inguinal ligament until it becomes femoral vein, and the popliteal vein (PV) are scanned. Thereby, it should be noted that the "2-point" protocols do not explicitly refer to two specific scanning levels of the lower limb. Similarly, in the "3-point" protocol the common femoral vein (CFV) and the popliteal vein (PV) are assessed, as in the "2-point" protocol, but further scanning of the femoral vein (FV) in the proximal thigh is undertaken (Varrias et al., 2021).

Prompt diagnosis of DVT is essential to decrease the risk of fatal complications. Two prospective studies found that general practitioners and nurses, after receiving a 3-month training, can diagnose DVT using POCUS-based protocols with an accuracy similar to experts in vascular ultrasonography. These results demonstrate the efficacy of alternative methods to expert-performed compression ultrasound for managing patients suspected of deep vein thrombosis. By reducing diagnosis time, these alternative POCUS-based methods allow for a prompt treatment (Mumoli et al., 2014, 2017; Kaldoudi et al., 2024).

In recent years, machine learning (ML) models have emerged as a valuable tool for managing DVT-suspected patients and assisting prompt diagnoses (Qatawneh et al., 2019; Fong-Mata et al., 2020; Kainz et al., 2021; Chen et al., 2024). In their work, Kainz et al., developed a triple-task convolution neural network (CNN) for real-time assessment of DVT using POCUS-based compression ultrasound video recordings (Kainz et al., 2021; Tanno et al., 2018). In a similar work, Chen et al., utilized the ResUNet architecture to segment veins and arteries from ultrasound videos and quantify the degree of vein compressibility via measuring the cross-sectional rate of change (Chen et al., 2024). Although both methods demonstrate strong performance in diagnosing DVT, they depend on training data containing pixel-wise vessel annotation, particularly for identifying veins and arteries. Generating the annotation requires expert knowledge and is highly time-consuming. As a result, segmentation-based approaches may be constrained by the limited availability of annotated training data, which in turn hinders their ability to generalize to images acquired from different ultrasound devices, different imaging protocols or patient-specific anatomical variances.

Taken together, these limitations underscore the need for alternative strategies that reduce or eliminate dependence on pixel-wise vessel annotations. To address these limitations and foster the development of more robust, scalable and annotation-efficient machine learning approaches, we propose the creation of a dedicated dataset focused on DVT diagnosis directly from compression ultrasound videos without requiring pixel-level annotations.

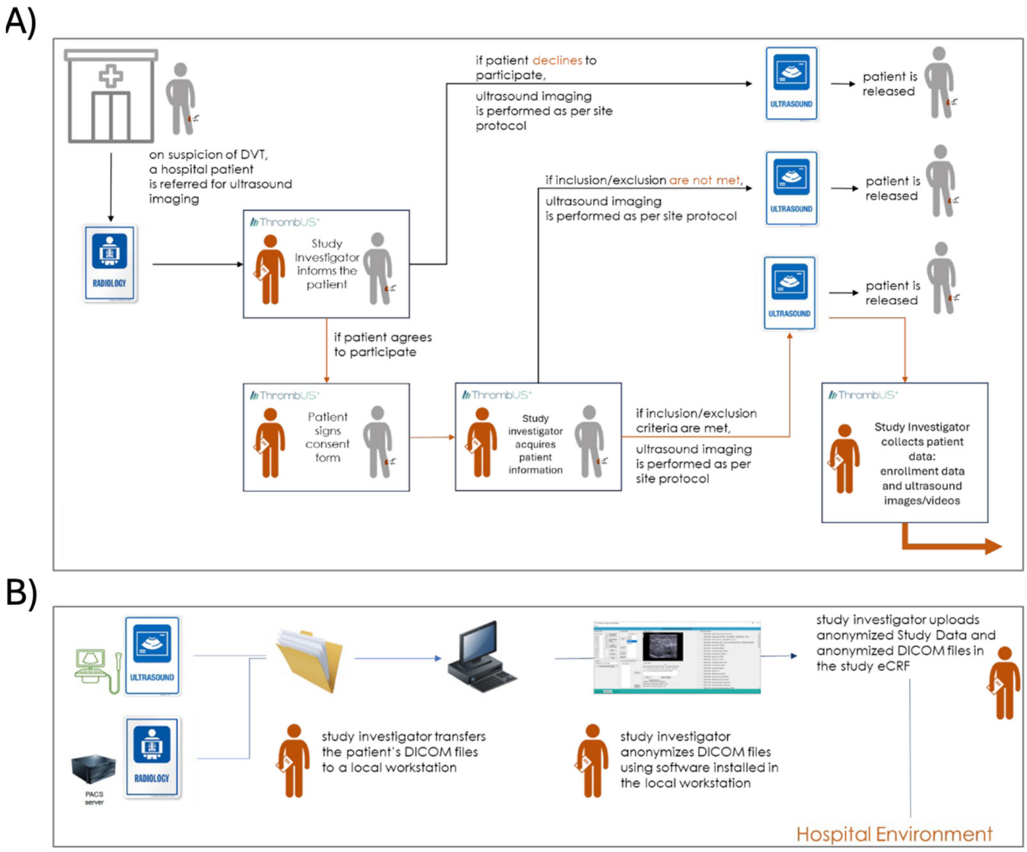

Figure 2: Overview of the data collection protocol. A) Patients suspected of deep vein thrombosis (DVT) and referred for compression ultrasonography are asked to participate in the study. Upon signing the informed consent form and inclusion/exclusion criteria are met, during the per-site conventional ultrasound scan, the required data are collected and patient is released. B) The acquired data are anonymized and stored in an electronic form (eCRF).

2 DATA COLLECTION PROCESS

The dataset includes compression ultrasound videos from four anatomical sites of patients suspected for deep vein thrombosis (DVT) of the lower limb, together with relevant patient demographics and biometrics and medical expert assessment on the vein compressibility and DVT diagnosis. Data have been collected via a multicenter cohort study, from five hospitals across Europe (two from Greece, and one from Italy, France and Lithuania) (Kaldoudi et al., 2024). Data are recorded from patients suspected of DVT and scanned using conventional ultrasound machines and protocols after signing an informed consent form. The clinical study protocol is available via the ClinicalTrials.gov protocol registration platform (https://clinicaltrials.gov/study/NCT06989255). All participating hospitals have acquired ethics approvals from their respective local ethics committee (Drougka, 2024; Drougka et al., 2025).

2.1 Data Collection

Data were acquired from patients suspected of deep vein thrombosis (DVT) who were referred for conventional ultrasound examination as per hospital's standard clinical protocol. The workflow for patient recruitment and data acquisition is illustrated in Figure 2. Briefly, patients with clinical suspicion on DVT were informed about the study, and those who agreed to participate provided written informed consent. Patients who met the inclusion and exclusion criteria were considered eligible for participation, and their data were collected. Patients who declined participation or did not meet the eligibility criteria were managed exclusively according to the hospital's conventional clinical protocol, and no study-related data were acquired. For eligible patients, after conventional ultrasound examination for DVT was completed, additional compression ultrasound videos were recorded solely for the purpose of the dataset. Compression videos from four anatomical sites were acquired from left, right or both legs, depending on the clinical symptoms. In all preset scanning positions, the probe was positioned perpendicular to the respective vein, and during compression, the probe compressed the tissue until the pulsatile artery started to slightly deform.

The first ultrasound compression video was acquired near the inguinal ligament, where the common femoral vein (CFV) and the common femoral artery (CFA) are visualized. The second compression video was recorded a few centimeters distally to the previous site, where the great saphenous vein (GSV) branches off of the common femoral vein (CFV). The third compression video was acquired in the middle of the thigh, where the femoral vein (FV) is visualized. Finally, compression of the popliteal vein (PV), below the knee, was recorded. Figure 3 presents the four anatomical sites of the right lower limb along the corresponding probe positions used during compression ultrasound video recording. These standardized acquisition locations were selected to ensure consistent anatomical coverage and to capture venous segments that are most commonly assessed during routine DVT evaluation.

2.2 Data Preparation

Study data have been recorded using an electronic case report file (eCRF) system hosted specifically for the clinical study, based on LibreClinica, an open-source electronic data capture (EDC) system designed to streamline and support clinical trials (LibreClinica, 2024). This platform built on established standards, such as those provided by CDISC (Clinical Data Interchange Standards Consortium) and supports compliance with GCP (Good Clinical Practice) guidelines (International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use, 2016) and 21 CFR Part 11 (U.S. Food and Drug Administration, 2003), which govern electronic records and signatures in clinical trials. These standards ensure that the platform is reliable for regulatory submissions, fostering adherence to strict quality, security, and ethical requirements in clinical research. It is worthy to note that the workflow supported by the LibreClinica software offers a number of checks by local investigators in each participating hospital which include the checking of the anonymisation of data before uploading. In the context of the particular data collection, specific adaptations have been made to the LibreClinica v1.3.0 system to support large ultrasound DICOM image files. This customized fork of LibreClinica is publicly available at GitHub (https://github.com/thrombusplus/LibreClinica-ThrombUS). Ultrasound data were acquired as DICOM videos and were anonymized using an open-source software, that allows for DICOM field anonymisation, image cropping and filename tagging (Pechlivanis et al., 2025).

During the anonymisation process the above four mentioned tags (CFV, GS, FV, PV), representing the anatomical site visualized were added to the DICOM filename, along a tag representing the left (L) or right (R) limb, respectively (Table 1).

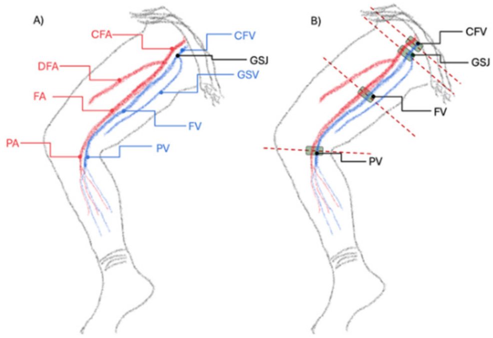

Figure 3: Crude vascular anatomy of the lower limb (A) with the four anatomical sites where ultrasound compression videos were recorded (B). CFV/A: common femoral vein/artery, GSV: great saphenous vein, GSJ: great saphenous junction, FV/A: femoral vein/artery, PV/A: popliteal vein/artery.

Table 1: Available tags used to compose the filename of compression ultrasound videos in the dataset.

Tag	Description
CFV	Common femoral vein
GS	Great saphenous junction
FV	Femoral vein
PV	Popliteal vein
R	Right limb
L	Left limb

In addition to the compression ultrasound videos, other data, including sex, age, height, weight, body mass index and a structured report on the compressibility of the veins, were recorded for each patient. The structured report is based on the compression ultrasound video interpretation by medical experts.

For each available anatomical site, physicians reported the compressibility (as no, partial, or yes) and the presence of thrombosis (as no or yes). Consequently, the filenames of the ultrasound video data are constructed via tags denoting the data recorded in the eCRF system, i.e. the anatomical site, whether the recording is from the left or right limb, the compressibility of the respective vein and whether thrombosis is present (Table 1).

Thereby this information can be used as the ground truth annotations made by expert physicians and subsequently employed for training and validating machine or deep learning models (Table 2).

3 DATASET DESCRIPTION

The dataset includes 2,919 compression ultrasound videos, resulting from 742 enrolled patients. Patients were recruited from 5 European hospitals, two from Greece (GR1, GR2), one from Lithuania (LT1), one from Italy (IT1) and one from France (FR1). The distribution of enrolled patients per hospital and the distribution of recorded videos per hospital are shown in Figure 4A and Figure 4B, respectively.

Table 2: Ground truth annotations by combining filename-based tags and eCRF-based data per recorded video.

Column Label	Label Description	Label Values	Comments
File Name	Full video filename as exported by the anonymizing software including name-based tags	n/a	DICOM filenames have been replaced with anonymized hash values. For the training set, all annotations are provided in the accompanying CSV file. For the test set, only the hashed filenames and non-label metadata are included.
SubjectID	Subject ID assigned during recruitment	n/a	Label format: SSN-XXXX, where SSN is the hospital's unique ID [GR1, GR2, IT1, FR1, or LT1] and XXXX a unique 4-digit patient ID.
Age	Age of patients in years	Value range: [18, 115]	n/a
Height	Height of patient in cm	Value range: [140, 240]	n/a
Weight	Weight of patient in kg	Value range: [35, 200]	n/a
Limb	Denotes the left or right limb	R or L	R: for right limb and L: for left limb
Thigh Circumference	The circumference of the limb in cm, measured at the FV site	n/a	n/a
Anatomical Site	Represents the anatomical site visualized	CFV, GS, FV, PV	CFV: common femoral vein, GS: great saphenous FV: femoral vein PV: popliteal vein
Compressibility	Represents the vein compressibility as assessed by the medical expert	2, 1, 0	2: Fully compressible 1: Partially compressible 0: Uncompressible
Thrombosis	Whether DVT is present at the scanning anatomical site as assessed by medical expert	1, 0	1: Thrombosis (DVT) is present 0: No thrombosis (DVT) is present

We recruited 742 patients (408 women, 55%, Figure 4C) with mean age 65.01 ± 15.24 years (standard deviation, SD), mean height 167.79 ± 9.82 cm (SD) and a mean weight of 80.53 ± 19.20 kg (SD) (Figure 4E).

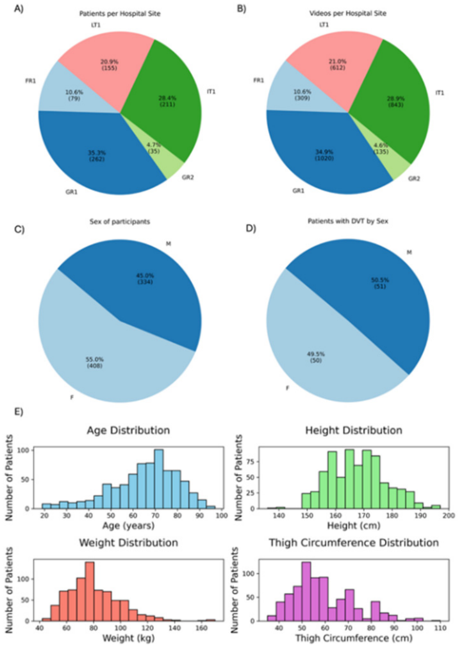

Figure 4: Number of enrolled patients (A) and video recordings (B) per hospital. Number of patients per sex (C) and number of DVT positive patients per sex (D). The age (65.01 ± 15.24; mean ± SD), height (167.79 ± 9.82 cm) and weight (80.53 ± 19.20 kg) distributions of enrolled patients (n=742) are shown in (E).

Overall, 101 (13.6%) were classified as DVT positive patients [51, (50.5%) women]. In 734 (25.1%) out of the 2,919 available videos in the dataset, compression ultrasound was recorded on the CFV, in 726 (24.9%) on the GS, in 733 (25.1%) on the FV and in 726 (24.9%) on the PV (Figure 5A). Similarly, when comparing laterality, we found that the proposals are very similar, with 1,480 (50.7%) corresponding to left limb and 1,439 (49.3%) to the right limb (Figure 5B). These metrics indicate a nearly balanced dataset with respect to the limbs and the anatomical sites.

Out of the 2,919 videos, only 199 (6.8%) correspond to DVT positive scans with the remaining 2,720 (93.0%) fully compressible veins, indicating the absence of thrombosis at the respective anatomical site (Figure 5C). The prevalence of positive to thrombosis scans varies across anatomical sites in the particular dataset. In most cases, DVT is present in the left PV (L-PV; 19.3%, n=39 cases). The left FV (L-FV) and the left common femoral vein (L-CFV) follow, with a percentage of 17.6% (n=35) and 17.1% (n=34), respectively. Thrombosis in the right PV (R-PV) is the fourth most frequent, representing 14.6% (n=29) of the positive cases. Subsequently, thrombosis in the left GS (L-GS; 10.1% n=20), in the right FV (R-FV; 8.0%, n=16), lastly in the right CFV (R-CFV; 6.5%, n=13) and in the right GS (R-GS; 6.5%, n=13) are observed (Figure 5D).

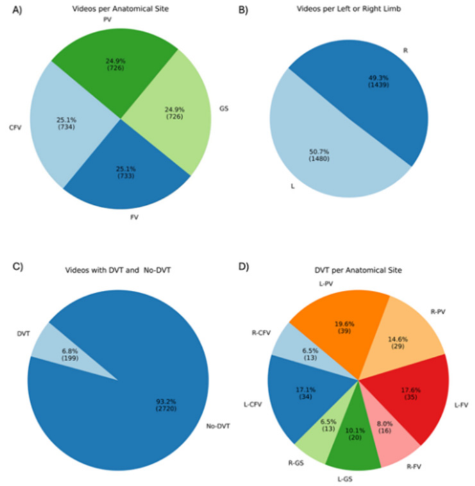

Figure 5: (A) Video distribution per anatomical site. (B) Video distribution per limb. (C) Video distribution per DVT or Not-DVT. (D) DVT positive video distribution per anatomical site.

4 DATASET PREPARATION FOR MACHINE LEARNING

The scope of the dataset is to enable the training of robust machine and deep learning models capable of analysing medical compression ultrasound videos of the lower limbs with precision, without relying on time-consuming manual pixel-based annotation. The dataset can support machine learning tasks including:

1) Detection of the anatomical site: Classify videos to determine whether the anatomical site pertains to the common femoral vein (CFV), great saphenous junction (GS), femoral vein (FV) or popliteal vein (PV).
2) Detection of DVT: To assess the compression ultrasound recording to detect the presence or absence of DVT, an essential diagnostic goal that can significantly impact future patient management and treatment.

To this end, the dataset was divided into training and testing using an 80/20 split. This resulted in two nearly balanced subsets with respect to participants' sex, demographics, biometric parameters, number of videos per anatomical site, and scans on the left and right limbs (Figure 6 and Figure 7).

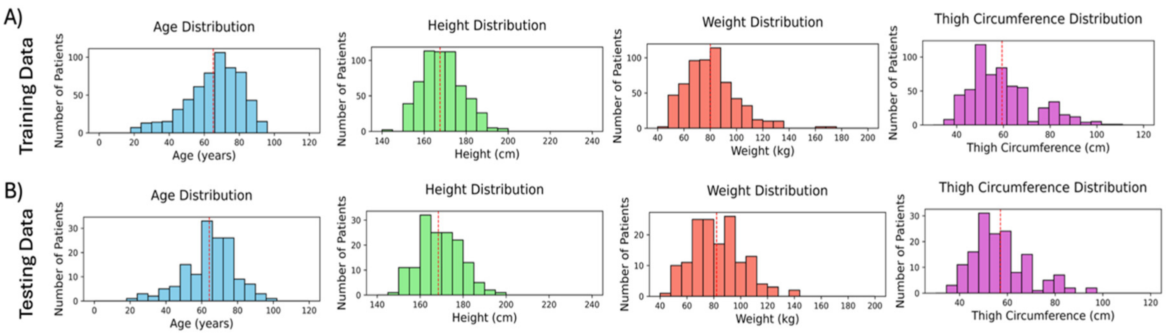

Figure 6: Patient age and biometrics distributions for the training (A) and testing (B) subsets. Red lines represent mean values. Age: 65.19 ± 15.51 years and 64.27 ± 14.16 years for training and testing, respectively. Height: 167.62 ± 9.78 cm and 168.46 ± 9.99 cm for training and testing, respectively. Weight: 80.14 ± 19.26 kg and 82.11 ± 18.93 kg for the training and testing, respectively. Thigh Circumference: 59.44 ± 13.49 cm and 57.13 ± 11.90 cm (p=0.04) for the training and testing, respectively. All values represent the mean ± SD from N= 578 patients in the training set and N=148 patients in the testing set. Welch's t-test was applied.

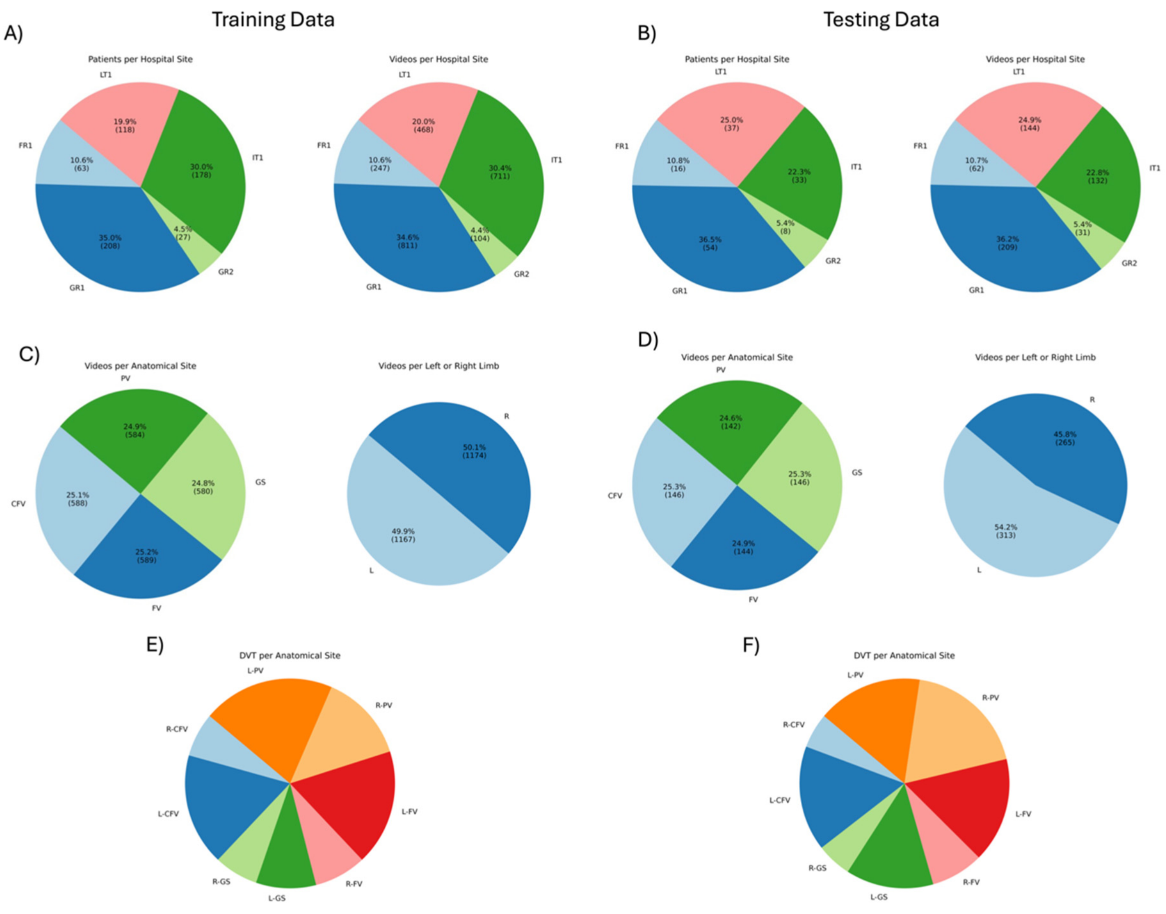

Figure 7: Comparison between the training (left) and testing (right) subsets. Number of patients and number of videos per hospital for the A) training and for the B) testing subsets. The number of videos per anatomical site and the number of videos of left or right limbs for the C) training and for the D) testing subsets. Proportion of DVT-positive videos per anatomical site included in the E) training and in the F) testing subsets (the exact distributions are not disclosed at to maintain scientific rigor and prevent data dredging in the challenge that is organized based on these data).

The training subset consists of 2,341 videos from 594 unique participants while the testing set consists of 578 videos from 148 unique participants. No significant differences observed for the two subsets in terms of age, height, weight. In contrast, thigh circumference showed a significant difference between groups. Specifically, the mean age of participants between the two subsets are 65.2 years and 64.3 years, respectively with corresponding mean heights of 167.6 cm and 168.5 cm. In addition, the mean weights for the training and testing sets are 80.1 kg and 82.1 kg, respectively, with a mean thigh circumference of 59.4 cm and 57.1 cm (Figure 6).

Moreover, the proportion of patients and the corresponding proportion of videos per hospital site, are similar between the two subsets (Figure 7A and B). In addition, with respect to the number of videos per anatomical site, the two subsets present similar distributions (Figure 7C and D). In terms of limb laterality, the training subsets contains similar number of videos from the left and right limb. In contrast, the testing set that contains slightly more compression videos from the left limb (Figure 7C and D). Finally, and most importantly, the proportion of DVT positive scans per anatomical site, is similar for the two subsets as indicated in Figure 7E, and F.

The two subsets are available via the ThrombUS+ Zenodo repository following the links:

- https://zenodo.org/records/17659415
- https://zenodo.org/records/17664207

All ultrasound compression videos are provided in DICOM format, while metadata and annotations for all videos are provided in single UTF-8 encoded CSV file.

5 DISCUSSION

This paper presents a dataset of 2,919 compression ultrasound videos of the lower limb, acquired through a multicenter cohort study from patients suspected with DVT. The dataset provides a comprehensive coverage of videos from the four key anatomical sites scanned by medical experts during DVT examinations, along expert-validated labels on compressibility and the presence of thrombosis. We believe the dataset will enable the development of models capable of supporting real-world clinical decision making.

To support the transparent training and testing of machine learning models, the dataset was split into a training and a testing subset, well balanced in terms of demographics, biometric characteristics, and with respect to the number of videos per anatomical site. The datasets are freely available via Zenodo: Training subset: https://zenodo.org/records/17659415; and Testing subset: https://zenodo.org/records/17664207.

A potential limitation of the dataset is the inherent class imbalance in the DVT detection task, with DVT-positive cases representing 6.8% of the available compression ultrasound videos. This imbalance reflects real-world clinical prevalence but may pose challenges for training machine learning models, particularly in avoiding bias toward the majority class. Researchers using the dataset may consider applying appropriate strategies during model development, such as class weighting or data augmentation approaches.

To facilitate model development and promote transparency in model accuracy and efficiency, two separate data challenges were created via the online Kaggle platform (https://kaggle.com). For each competition created, participants submit a file with model predictions and the platform evaluates automatically model performance producing a score and a leaderboard. For models detecting the anatomical site of visualized veins, the Accuracy Score metric was selected. This metric compared the predicted class (CFV, GS, FV, PV) with the ground truth. For models addressing to detect the presence of DVT, the Log Loss metric was selected. This score compares the probability of having DVT with the ground truth.

Full instructions of the datasets and to the respective competitions are available following the links:

- https://www.kaggle.com/competitions/Thrombus_challenge_1_1/
- https://www.kaggle.com/competitions/Thrombus_challenge_1_2

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