A Versatile Foundation Model for AI-enabled Mammogram Interpretation

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Abstract

Breast cancer is the most commonly diagnosed cancer and the leading cause of cancer-related mortality in women globally. Mammography is essential for the early detection and diagnosis of breast lesions. Despite recent progress in foundation models (FMs) for mammogram analysis, their clinical translation remains constrained by several fundamental limitations, including insufficient diversity in training data, limited model generalizability, and a lack of comprehensive evaluation across clinically relevant tasks. Here, we introduce VersaMammo, a versatile foundation model for mammograms, designed to overcome these limitations. We curated the largest multi-institutional mammogram dataset to date, comprising 706,239 images from 21 sources. To improve generalization, we propose a twostage pre-training strategy to develop VersaMammo, a mammogram foundation model. First, a teacher model is trained via self-supervised learning to extract transferable features from unlabeled mammograms. Then, supervised learning combined with knowledge distillation transfers both features and clinical knowledge into VersaMammo. To ensure a comprehensive evaluation, we established a benchmark comprising 92 specific tasks, including 68 internal tasks and 24 external validation tasks, spanning 5 major clinical task categories: lesion detection, segmentation, classification, image retrieval, and visual question answering. VersaMammo achieves state-of-the-art performance, ranking first in 50 out of 68 specific internal tasks and 20 out of 24 external validation tasks, with average ranks of 1.5 and 1.2, respectively. These results demonstrate its superior generalization and clinical utility, offering a substantial advancement toward reliable and scalable breast cancer screening and diagnosis.

Keywords: Artificial Intelligence, Breast Cancer, Mammogram, Foundation Model, Knowledge Distillation, Generalizability, Multi-institutional Dataset.

1 Introduction

Breast cancer is the most common malignancy worldwide and the leading cause of cancer-related mortality among women [1, 2]. Early screening and accurate diagnosis are crucial for improving survival rates and treatment outcomes. Mammography is a key tool in breast cancer screening and diagnosis due to its effectiveness in detecting early lesions [3, 4]. However, mammograms contain a variety of tissue types, lesion characteristics, and individual differences, which complicate interpretation and place high demands on the knowledge and experience of medical professionals. Even experienced radiologists may encounter misdiagnoses with complex images.

With the rapid advancement of artificial intelligence (AI) [5–9], particularly in the field of medical image analysis [10–13], new opportunities have emerged to address the challenges of interpreting the mammogram [14–16]. These traditional AI approaches typically focus on specific tasks, such as classification, segmentation, or detection of breast cancer, by designing and optimizing dedicated models for each specific task. Although these methods have achieved some success under specific datasets and task configurations, they still have shortcomings in real clinical settings. The tasks involved in mammography are diverse and complex, with factors such as different patient populations, imaging equipment, and disease presentations leading to highly heterogeneous image data. The generalizability of previous methods is often inadequate when confronted with these varied mammography tasks, as they struggle to effectively transfer knowledge learned from one task or dataset to others with different distributions, resulting in significant performance declines in new scenarios.

In recent years, foundation models (FMs) [17], pre-trained on large-scale datasets, have demonstrated remarkable generalization and multitasking abilities across various domains including natural language processing [18–20], computer vision [21–24], and medical image analysis [25–31]. These achievements are closely tied to effective pre-training strategies, which can generally be categorized into three paradigms: unsupervised/self-supervised learning, weakly supervised pre-training, and supervised learning. Unsupervised/Self-Supervised Learning methods [22, 23, 25, 32] learn generic representations from unlabeled data through pretext tasks such as Masked Image Modeling (MIM) or contrastive learning. While this approach leverages abundant unlabeled data and learns transferable features without annotation cost, it may capture features that are not optimally aligned with specific downstream tasks. Weakly Supervised Pre-training models [28, 33] utilize imperfect supervisory signals such as image-text pairs or noisy labels to train models. This approach reduces annotation effort while enabling cross-modal understanding and robustness to real-world noise. However, the inherent noise and incompleteness in labels may limit the precision of the learned representations. Supervised Learning methods [24, 26] rely on largescale accurately labeled datasets to optimize task-specific performance. This method often yields state-of-the-art results on target tasks but requires substantial annotation resources and may lack generalization beyond the labeled domains. These pre-training strategies enable FMs to learn rich, generalizable features that facilitate strong performance across diverse applications. Their success has inspired recent work in medical imaging, such as Mammo-CLIP [34] and multi-view alignment methods [35] using the EMBED dataset [36], demonstrating the potential of FMs in specialized domains like mammogram analysis.

Existing mammogram foundation models (FMs) [34, 35] rely on high-quality paired image-report data for training. However, the development of such FMs faces significant challenges due to the unavailability of open-access datasets and the difficulty in acquiring large-scale clinically paired image-report data. These constraints lead to fundamental issues such as insufficient data volume and inadequate diversity, which severely hinder model development. For example, MammoCLIP [34] was trained on only 13,829 patient-report pairs, comprising 25,355 screening mammograms that were exclusively limited to Bi-Rads 0–2 categories. This results in severe limitations in both dataset scale and clinical coverage—particularly regarding malignant cases. Although MAMA [35] attempted to mitigate data scarcity by generating structured reports from publicly available data embeddings, this synthetic strategy still fails to adequately capture the full spectrum of clinical presentations and pathological variations. Consequently, owing to limitations in both data scale and diversity, these models often exhibit poor generalization capability when confronted with unseen image data, which considerably restricts their applicability and reliability in real-world clinical practice.

Furthermore, existing research does not comprehensively evaluate foundation models (FMs), as illustrated in Fig. 2 (a). Most studies focus on a limited number of common downstream tasks, such as classification or lesion detection, while neglecting other clinically significant tasks including lesion segmentation, image retrieval, and mammogram visual question answering. This narrow evaluation paradigm fails to capture the full spectrum of model capabilities, thereby limiting the assessment of their true practical utility in real clinical settings.

To address the key challenges in mammogram foundation models, we propose VersaMammo, a comprehensive foundation model trained on the largest multi-institutional mammogram dataset to date. The model employs a novel two-stage pre-training strategy that integrates self-supervised and supervised learning, and is evaluated through an extensive benchmark covering 13 clinical task types and 92 specific tasks. This approach enables a robust and holistic assessment of its diagnostic and generalization capabilities. Our contributions are summarized as follows:

- We curated the largest and most diverse mammogram dataset to date, consisting of 706,239 mammograms from 21 datasets (16 public and 5 private), supporting the development of VersaMammo and the evaluation of existing foundational models.
- We introduced VersaMammo, a novel FM for mammograms aimed at improving breast cancer screening and diagnosis. Our unique two-stage pre-training strategy combines self-supervised learning to extract features and integrates clinical insights through supervised learning and knowledge distillation.
- We established a comprehensive benchmark covering five clinical task types, totaling 92 specific tasks, including lesion detection, segmentation, image retrieval, VQA, and nine clinical classification tasks, a total of 68 specific internal tasks and 24 specific external validation tasks for evaluation.
- Extensive results demonstrate that VersaMammo significantly outperforms stateof-the-art models, ranking first in 50 out of 68 specific internal tasks (average

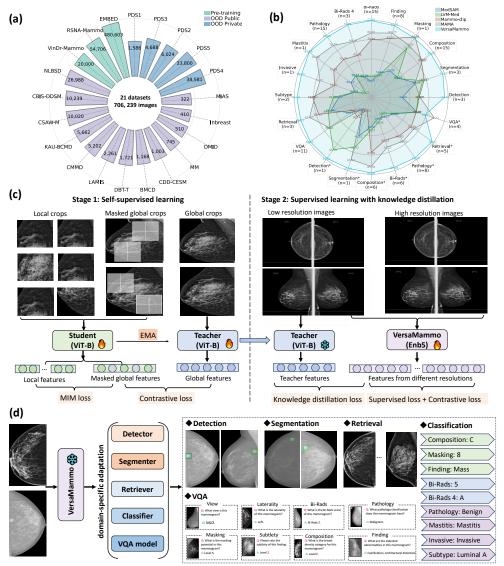


Fig. 1: Overview of the VersaMammo. (a): The VersaMammo dataset comprises a large-scale collection of 706,239 mammograms spanning 21 datasets, enabling comprehensive model training and evaluation. "OOD Public" and "OOD Private" denote out-of-domain datasets from public sources and private institutions, respectively. (b): Average performance of foundation models (FMs) across a diverse set of tasks. n is the number of datasets used to evaluate specific tasks. Asterisk (*) indicates the results on external validation datasets. If there are different backbones of the same FM, only the best model is presented here. (c): Overview of the two-stage hybrid pre-training strategy for VersaMammo. In the first stage, a teacher model is trained using self-supervised learning, involving Masked Image Modeling (MIM) loss and contrastive loss. The parameters are updated through Exponential Moving Average (EMA). The second stage incorporates distillation loss, supervised loss, and contrastive loss to merge the teacher model with clinical knowledge. (d): Downstream tasks used to evaluate the FMs. Details of the classification task are provided in Extended Data Tables A27-A29.

rank 1.5) and 20 out of 24 specific external validation tasks (average rank 1.2), as shown in Extended Data Table A1 and Fig. 2 (b-g), confirming its exceptional versatility and generalization. Additionally, it is noteworthy that VersaMammo's performance in the Bi-Rads assessment task significantly surpassed that of junior radiologists and approached the level of senior radiologists (Sec. 2.3.4).

2 Results

To comprehensively evaluate the performance of our proposed VersaMammo and existing FMs in mammogram analysis, we conducted experiments on 21 datasets across 5 key downstream tasks (a total of 92 specific tasks), including detection task, segmentation task, retrieval task, clinical classification tasks and visual question answering (VQA) task, as shown in Extended Data Table A1 and Fig. 2 (b-g). Given the heterogeneous evaluation metrics across tasks, we used an average ranking approach to assess the overall performance of the FMs and summarized the results in a critical difference (CD) diagram [37, 38]. Among the seven models evaluated, the best-performing model is ranked 1st, and the lowest-performing model is ranked 7th. VersaMammo achieves state-of-the-art performance, ranking first in 50 out of 68 specific internal tasks and 20 out of 24 specific external validation tasks, with average ranks of 1.5 and 1.2, respectively. This significantly surpasses the second-best model, MAMA [35], which ranks first in only 13 specific internal tasks and 3 specific external validation tasks.

Besides, to evaluate the significance of VersaMammo's ranking score relative to other FMs, we performed the Nemenyi statistical test [37], as presented in Fig. 2 (d). The results demonstrate that VersaMammo exhibited a statistically significant critical difference compared to the other six FMs. Additional performance metrics are reported in Extended Data Table A1-A23. These results, evaluated from both ranking and average metric perspectives, clearly establish that VersaMammo achieves state-of-the-art performance while demonstrating significantly better generalizability than other FMs.

2.1 Lesion Detection

Lesion Detection is the task of identifying the presence and approximate location of suspicious abnormalities, such as masses or calcifications, within a mammogram. Accurate localization of breast lesions—such as masses and calcifications—is critical for early diagnosis and effective treatment of breast cancer, directly influencing patient outcomes. Automated detection systems can assist radiologists by identifying regions of interest, thereby improving diagnostic consistency and reducing interpretation workload. To evaluate the detection performance of various foundation models (FMs), we compared their results across three mammogram datasets using Intersection over Union (IoU) at multiple resolutions. Additionally, we assessed inference efficiency by measuring the average processing time per image under consistent hardware conditions using an NVIDIA L20 GPU with 48GB memory.

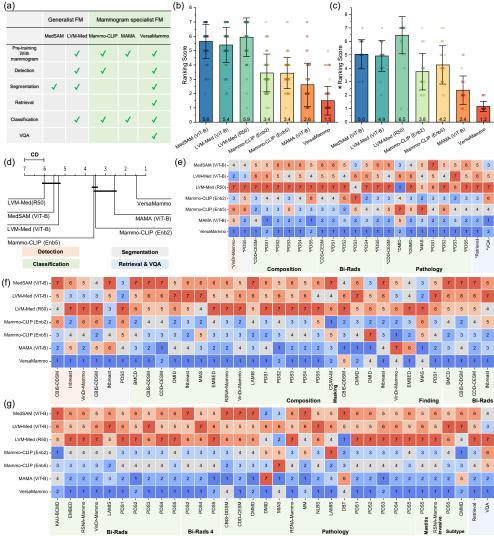


Fig. 2: Comprehensive Comparison of Foundation Models (FMs) across 92 specific tasks. (a): Comparison of different FMs. (b-c): Average rank of FMs across 68 specific internal downstream tasks and 24 specific external validation tasks. The error bars indicate the 95% CI and the box limits represent the standard error. (d): Critical differences (CD) diagram of average ranking score with the Nemenyi test. In the CD figure, there are no significant differences between the models covered by the black line. (e)-(g): Ranking order of FMs across 68 specific internal tasks and 24 specific external validation tasks, respectively. If a model achieves the best performance, its rank value is set to 1. If two models have the same metric value, indicating a tie, the average rank value is assigned to all the tied models. * represents external validation cohorts. The evaluation metrics utilized to derive the ranking scores for the remaining tasks are consistent with those applied in subfigure (b). Details of the classification task are provided in Extended Data Tables A27-A29.

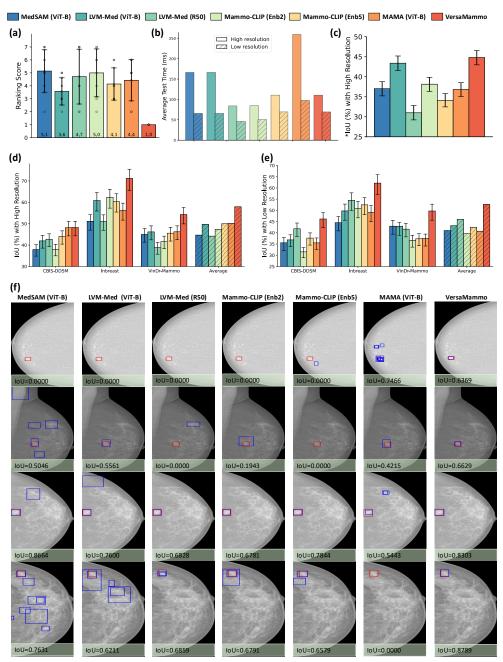


Fig. 3: Performance of FMs on lesion detection tasks. (a): Average ranking of FMs based on IoU of different resolutions across all lesion detection tasks. (c): Average test time of different resolutions. (c-e): IoU of detection tasks. Error bars represent 95% CI. * represents external validation cohorts. (f): Visualization results of lesion detection. Red bounding boxes represent ground truth annotations, while blue bounding boxes indicate model predictions. Additional results are shown in Extended Data Tables A2-A4.

VersaMammo achieved the highest overall performance in all lesion detection tasks, attaining a top average rank of 1.0 (ranked first across every task), significantly outperforming the second-best models, LVM-Med (R50) [25], which had an average rank of 3.6 (Fig. 3 (a)). Detailed results are provided in the Extended Data Table A2.

In high-resolution settings, VersaMammo attained IoU scores of 48.24% on CBIS-DDSM, 71.20% on Inbreast, and 54.32% on VinDr-Mammo, yielding a mean IoU of 57.92% (Fig. 3 (d) and Extended Data Table A2). Notably, on the Inbreast dataset, VersaMammo exceeded the performance of the second-best models, MAMA (ViT-B), by approximately 10%, underscoring its superior detection accuracy. Remarkably, our method achieved this state-of-the-art performance while maintaining exceptional computational efficiency. With an average inference time of only 110 ms per image for high-resolution detection, it was approximately 1.5 times faster than MedSAM (ViT-B) (166 ms) and LVM-Med (ViT-B) (166 ms), and significantly more efficient than MAMA (ViT-B) (259 ms), while delivering superior detection accuracy (Fig. 3 (b)).

To further validate generalizability, we conducted an external comparison using high-resolution mammograms under consistent settings (Extended Data Table A4). VersaMammo delivered state-of-the-art performance, achieving an IoU of 44.81% on the VinDr-Mammo dataset, surpassing all other publicly available FMs, including LVM-Med (ViT-B) (43.39%) and MedSAM (ViT-B) (37.02%). This result reinforces its robustness and cross-institutional applicability.

In low-resolution evaluations, VersaMammo continued to excel, achieving IoU values of 46.18% (CBIS-DDSM), 62.15% (Inbreast), and 49.74% (VinDr-Mammo), with an average IoU of 52.69% (Fig. 3 (e)). It notably exceeded the second-best models, LVM-Med, (R50) by 7.66% on Inbreast, while processing low-resolution images in just 69 ms on average—approximately 1.1 times faster than MedSAM (ViT-B) (65 ms) and significantly outperforming MAMA (ViT-B) (97 ms) in both accuracy and efficiency. Most importantly, our method demonstrated the best accuracy-efficiency trade-off among other models, achieving superior detection performance with competitive inference speed. Notably, compared to ViT-B architectures, our method showed substantial improvements: $1.5\times$ faster than MedSAM (ViT-B) and LVM-Med (ViT-B) with significantly higher accuracy, and $2.4\times$ faster than MAMA (ViT-B) while maintaining superior detection performance across all datasets.

Visualization of detection outputs further corroborates the efficacy in localizing breast lesion (Fig. 3 (f)). Taken together, these results affirm that VersaMammo not only achieves state-of-the-art detection performance across varied datasets and resolutions but also offers superior inference efficiency compared to ViT-B based FMs, providing an optimal balance between accuracy and speed that is particularly suitable for clinical deployment. This marks a substantial advance in automated breast cancer diagnosis.

2.2 Lesion Segmentation

Lesion segmentation provides pixel-level delineation of lesion contours, offering critical morphological information for clinical assessment. By precisely defining the size, shape, and extent of suspicious findings such as masses and calcifications, it enables

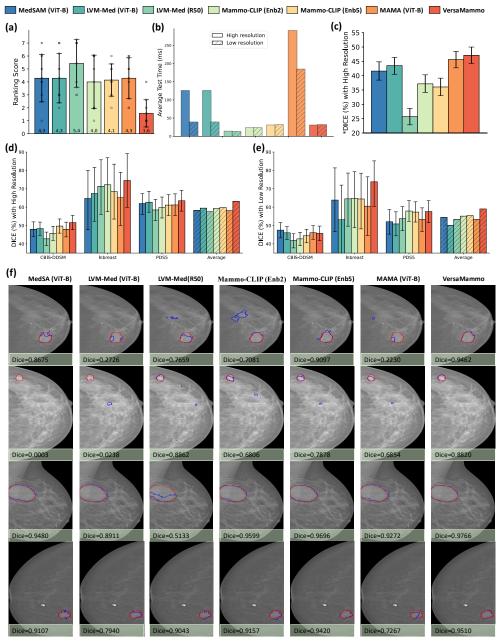


Fig. 4: Performance of FMs on lesion segmentation tasks. (a): Average ranking of FMs based on DICE across all lesion segmentation tasks. (b): Average test time across resolutions. (c-e): DICE scores of segmentation tasks. Error bars indicate 95% confidence intervals. * denotes external validation cohorts. (f): Representative visualization of lesion segmentation. Red regions denote ground truth masks, while blue regions represent predictions generated by the proposed model. Additional results are provided in Extended Data Tables A5-A7.

quantitative feature analysis and supports treatment planning. We evaluated VersaMammo and other FMs on segmentation performance using the Dice Similarity Coefficient (DICE) across multiple resolutions. Additionally, we assessed inference efficiency by measuring the average processing time per image under consistent hardware conditions using an NVIDIA L20 GPU with 48GB memory.

VersaMammo achieved the highest average rank of 1.6 across all segmentation tasks, surpassing the second-best models, Mammo-CLIP (Enb2), which attained an average rank of 4.0 (Fig. 4 (a)). Detailed results are available in Extended Data Table A5. In high-resolution evaluations, VersaMammo yielded DICE scores of 51.61% on CBIS-DDSM, 74.53% on Inbreast, and 63.50% on PDSS, resulting in a mean DICE of 63.21% (Fig. 4 (d)). Notably, on the Inbreast dataset, it exceeded the performance of LVM-Med (ViT-B) by 7.1%, underscoring its segmentation precision. In terms of computational efficiency, our method demonstrated exceptional performance, requiring only 30 ms per image on average for high-resolution segmentation. This represents a remarkable 4.2-fold speed advantage over MedSAM (ViT-B) (126 ms) and LVM-Med (ViT-B) (126 ms), and a 9.7-fold improvement over MAMA (ViT-B) (290 ms), while simultaneously delivering superior segmentation accuracy (Fig. 4 (b) and Extended Data Table A6).

To further examine cross-dataset generalization, we conducted an external comparison under standardized high-resolution settings, as summarized in Extended Data Table A7. VersaMammo achieved state-of-the-art performance, with a DICE of 47.12% on the PDS5 dataset, outperforming all other publicly available FMs, including MAMA (ViT-B) (45.64%) and LVM-Med (ViT-B) (43.52%). This result highlights its strong generalization capability across institutions and data sources.

Under low-resolution settings, VersaMammo continued to excel, achieving DICE scores of 45.71% (CBIS-DDSM), 73.79% (Inbreast), and 57.63% (PDSS), with an average of 59.04% (Fig. 4 (e)). It notably outperformed Mammo-CLIP (Enb2) by 9.05% on the Inbreast dataset, while processing low-resolution images in just 32 ms per image—achieving comparable efficiency to the fastest specialized models like LVM-Med (R50) (13 ms) and Mammo-CLIP (Enb2) (23 ms), yet delivering significantly superior segmentation accuracy. Most importantly, our method demonstrated a 5.8-fold speed advantage over MAMA (ViT-B) (184 ms) while maintaining the highest segmentation performance. Our method achieved the optimal balance between accuracy and efficiency.

Visualization of segmentation outputs further confirms VersaMammo's ability to accurately outline lesion boundaries (Fig. 4 (f)). These results collectively demonstrate VersaMammo's state-of-the-art segmentation performance coupled with superior computational efficiency across diverse datasets and resolutions, showing strong potential for clinical adoption.

2.3 Mammogram Classification for Diverse Clinical Tasks

We evaluated VersaMammo's performance across multiple clinically relevant classification tasks, encompassing breast composition assessment (Sec. 2.3.1), masking potential risk evaluation (Sec. 2.3.2), finding abnormality identification (Sec. 2.3.3), Bi-Rads assessment (Sec. 2.3.4), Bi-Rads 4 subclassification (Sec. 2.3.5), pathological

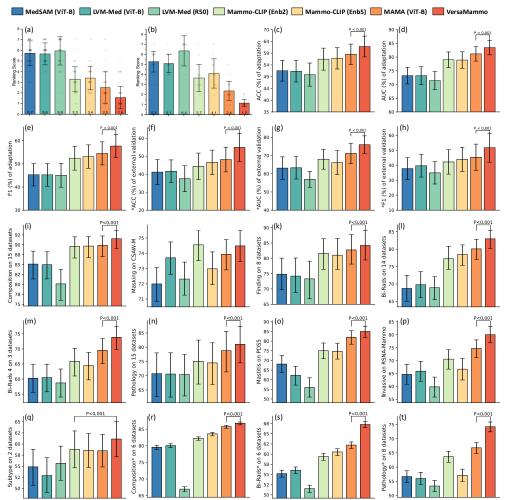


Fig. 5: Performance evaluation of FMs across classification tasks. (a) Average model ranking based on AUC across 60 specific internal classification tasks. (b) Average ranking across 20 external validation tasks. (c-e) Mean balanced accuracy (ACC), AUC, and weighted F1 score for internal tasks. (f-h) Corresponding metrics for external validation tasks. (i-q) AUC performance on specific internal tasks: breast composition assessment, masking potential risk evaluation, finding abnormality identification, Bi-Rads assessment, Bi-Rads 4 subclassification, pathological diagnosis prediction, mastitis differentiation, invasive status determination, and molecular subtype prediction. Details of the classification task are provided in Extended Data Tables A27-A29. (r-t) External validation performance for breast composition assessment, Bi-Rads assessment, and molecular subtype prediction. Error bars represent 95% confidence intervals; box limits indicate standard errors. Asterisks denote external validation cohorts.

diagnosis prediction (Sec. 2.3.6), mastitis differentiation (Sec. 2.3.7), invasive status determination (Sec. 2.3.8), and molecular subtype prediction (Sec. 2.3.9). These tasks, validated through radiological expertise and histopathological confirmation (Extended Data Tables A27-A29), carry substantial clinical implications for diagnostic accuracy and therapeutic decision-making. Our analysis included 80 specific tasks, comprising 60 specific internal tasks and 20 specific external validation tasks.

As shown in Fig. 5 (a), VersaMammo achieved a mean ranking of 1.6 across internal tasks, significantly outperforming the second-best model MAMA (ViT-B) (rank 2.5). Similarly, for external validation tasks (Fig. 5 (b)), VersaMammo attained a superior mean rank of 1.2 compared to MAMA's 2.4. The model demonstrated consistently high performance across all evaluation metrics (ACC, AUC, F1) for both internal (Fig. 5 (c-e)) and external validation tasks (Fig. 5 (f-h)), confirming its robustness and generalizability. Detailed results are provided in Extended Data Tables A8-A17. Additionally, it is noteworthy that VersaMammo's performance in the Bi-Rads assessment task significantly surpassed that of junior radiologists and approached the level of senior radiologists (Sec. 2.3.4).

2.3.1 Breast Composition Assessment.

Breast composition evaluates tissue density and fibroglandular patterns, which significantly influence mammographic sensitivity and cancer detection rates. The American College of Radiology Bi-Rads system categorizes breast composition into four density classes (Density A - Density D) [36, 39, 40] and three background tissue types (fatty-glandular, fatty, dense-glandular) [41, 42] as detailed in Extended Data Table A27. Accurate density assessment is clinically critical for guiding personalized screening protocols and determining the necessity of supplemental imaging modalities, thereby directly impacting early cancer detection and patient management.

VersaMammo demonstrated high diagnostic accuracy with an AUC of 91.53% (95% CI: 89.09%–93.55%) in 15 specific internal tasks (Fig. 5 (i), Extended Data Table A8) and maintained robust performance in 6 specific external validation tasks with an average AUC of 86.80% (95% CI: 86.30%–87.17%) (Fig. 5 (r), Extended Data Table A9), significantly outperforming all comparator models (p < 0.001). These results underscore its strong generalizability and potential clinical utility in standardizing and improving breast density assessment.

2.3.2 Masking Potential Risk Evaluation.

Masking potential risk evaluation identifies cases where dense breast tissue may obscure malignant lesions, a critical factor in reducing false-negative interpretations and missed diagnoses. This task employs an 8-level classification system (Level 1 to Level 8) based on the likelihood that breast density could mask underlying malignancies, from lowest to highest obscuration risk [43] (Extended Data Table A27). Accurate assessment of masking risk is essential for guiding clinical decisions on supplemental imaging, such as ultrasound or MRI, which can significantly improve early cancer detection in dense breast populations.

On the CSAW-M [43] dataset (Fig. 5 (k), Extended Data Table A11), VersaMammo achieved the highest accuracy (27.74%) in masking risk evaluation, surpassing the

second-best model by 0.54%, while maintaining competitive AUC (74.48%) comparable to the top performer. This demonstrates its strong capability in identifying cases where dense tissue may obscure malignancies, supporting reliable clinical decisions for supplemental imaging.

2.3.3 Finding Abnormality Identification.

Finding abnormality identification encompasses a comprehensive spectrum of clinically significant mammographic findings, including calcifications, masses, architectural distortions, asymmetries, nipple retraction, suspicious lymph nodes, skin thickening, skin retraction, and other miscellaneous findings [36] (Extended Data Table A27). This detailed 10-category classification system provides critical support for radiologists in case prioritization, diagnostic workflow optimization, and ensuring thorough evaluation of potentially malignant features.

VersaMammo demonstrated exceptional diagnostic capability in this comprehensive abnormality detection task, attaining an average AUC of 84.21% (95% CI: 79.47%-89.15%) in 8 specific tasks (Fig. 5 (m), Extended Data Table A11). The model's performance represented a statistically significant improvement over all competing models (p < 0.001), highlighting its potential to enhance diagnostic accuracy, reduce oversight of subtle abnormalities, and improve workflow efficiency in clinical mammogram interpretation.

2.3.4 Bi-Rads Assessment.

The Bi-Rads system standardizes mammographic reporting through seven assessment categories (Bi-Rads 0 to 6) [36, 39, 40, 44, 45]. Since Bi-Rads 6 represents known biopsy-proven malignancy, we focus on the clinically critical differential diagnosis of Bi-Rads categories 0-5, annotated by radiologists, as defined in Extended Data Table A27. Accurate classification within this 0-5 spectrum is essential for appropriate patient triage, guiding follow-up management decisions, and reducing diagnostic variability across clinical settings.

VersaMammo demonstrated robust clinical utility in Bi-Rads classification (Extended Data Tables A12-A13), achieving diagnostic performance comparable to senior radiologists. Internally, the model attained an average AUC of 82.95% (95% CI: 80.20–85.36%) in 14 specific internal tasks (Fig. 5 (l), Extended Data Table A12), matching senior radiologist performance (83.50%, 95% CI: 76.80–90.20%) and exceeding both junior radiologists (75.30%, 95% CI: 67.40–83.10%) [46] and the second-best model MAMA (ViT-B). Externally, VersaMammo achieved an average AUC of 67.26% (95% CI: 66.49%–67.93%) in 6 specific external validation tasks (Fig. 5 (s), Extended Data Tables A12-A13), with a statistically significant 5.04% absolute improvement over MAMA (ViT-B) (p < 0.001). These results underscore VersaMammo's potential to standardize mammographic interpretation, enhance diagnostic consistency, and support clinical decision-making—particularly in settings with limited access to specialized radiologists.

2.3.5 Bi-Rads 4 Subclassification.

Bi-Rads 4 subclassification plays a crucial clinical role in risk-stratifying suspicious findings requiring tissue diagnosis, with three clinically distinct subcategories (Bi-Rads 4A, 4B, and 4C) representing low to high suspicion, as detailed in Extended Data Table A27 [44]. Accurate stratification within this category is essential for optimizing biopsy decisions, balancing cancer detection against avoiding unnecessary invasive procedures, and guiding appropriate clinical management pathways.

VersaMammo demonstrated clinically significant performance in this critical task, achieving an average AUC of 73.81% (95% CI: 69.78%-77.53%) in 3 specific tasks (Fig. 5 (m), Extended Data Table A14). The model significantly outperformed MAMA (ViT-B) (69.49%, 95% CI: 65.10%-73.46%) by an absolute margin of 4.32% (p < 0.001), highlighting its potential to enhance preoperative risk assessment and support more precise biopsy recommendations in clinical practice.

2.3.6 Pathological Diagnosis Prediction.

This task aims to non-invasively differentiate between malignant and benign breast lesions using mammography alone, without requiring biopsy or additional diagnostic procedures. The binary classification predicts pathological outcomes based solely on mammographic features, as validated against biopsy-confirmed ground truth (Extended Data Table A29) [41, 42, 47, 48].

VersaMammo demonstrated strong predictive capability for pathological diagnosis directly from mammograms, achieving an average AUC of 81.04% (95% CI: 74.51%-87.35%) in 15 specific internal tasks (Fig. 5 (n), Extended Data Table A15) and 74.24% (95% CI: 72.43%-75.89%) in 8 specific external validation tasks (Fig. 5 (t), Extended Data Table A16). The model significantly outperformed existing approaches by 2.25%-10.32% (p < 0.001), highlighting its potential to provide accurate non-invasive pathological assessment and reduce unnecessary biopsies in clinical practice.

2.3.7 Mastitis Differentiation.

Mastitis classification distinguishes between inflammatory breast conditions (mastitis) and cancerous lesions (malignancy) with similar radiographic presentations (Extended Data Table A29) [49]. This clinically critical binary classification task prevents unnecessary invasive procedures for benign inflammatory conditions while ensuring timely detection of malignant lesions, thereby optimizing patient management and reducing diagnostic delays.

VersaMammo established new state-of-the-art performance on the PDS5 dataset with an AUC of 85.00% (95% CI: 81.87%-87.69%) (Fig. 5 (o), Extended Data Table A17), significantly outperforming all comparator models (p < 0.001). This high diagnostic accuracy demonstrates the model's potential to support differential diagnosis in challenging cases where clinical and mammographic findings overlap.

2.3.8 Invasive Status Determination.

Invasive status determination differentiates between non-invasive (in situ) and invasive breast cancers (Extended Data Table A29) [40]. This binary classification task directly influences treatment planning and therapeutic strategies, as invasive cancers require more aggressive interventions including lymph node assessment and systemic therapy, while non-invasive cancers may be managed with local treatment alone.

VersaMammo achieved state-of-the-art performance on the RSNA-Mammo dataset with an AUC of 80.05% (95% CI: 76.91%-83.30%) (Fig. 5 (p), Extended Data Table A18), representing a 5.34% improvement over MAMA (ViT-B) (p < 0.001). This capability to preoperatively predict invasive status can guide surgical planning and adjuvant therapy decisions.

2.3.9 Molecular Subtype Prediction.

Molecular subtyping categorizes breast tumors into four main subtypes based on receptor status and gene expression (Luminal A, Luminal B, HER2-enriched, and Triple-negative breast cancer) as defined in Extended Data Table A29 [50–52]. This classification enables precision medicine approaches to treatment selection, as different subtypes respond differently to targeted therapies, endocrine treatments, and chemotherapy regimens.

VersaMammo demonstrated superior performance in molecular subtyping with an average AUC of 61.12% (95% CI: 57.12%-65.01%) in 2 specific internal tasks (Fig. 5 (q), Extended Data Table A19), significantly outperforming existing mammogram FMs by >2% (p < 0.001). This non-invasive prediction of molecular subtypes has significant implications for personalized treatment planning, potentially reducing the time from diagnosis to appropriate therapy initiation.

In summary, VersaMammo demonstrates consistent superiority across diverse mammographic classification tasks, exhibiting robust performance in breast composition assessment, masking potential risk evaluation, finding abnormality identification, Bi-Rads assessment, Bi-Rads 4 subclassification, pathological diagnosis prediction, mastitis differentiation, invasive status determination, and molecular subtype prediction. These capabilities position VersaMammo as a valuable tool for enhancing breast cancer screening, diagnostic accuracy, and personalized treatment planning in clinical practice.

2.4 Mammogram Retrieval

The goal of mammogram retrieval is to accurately and efficiently search the most pertinent information from a vast collection for a given request, which plays an essential role in clinical mammogram analysis, enabling physicians to identify similar cases from large-scale multi-institutional datasets. This capability is particularly valuable for diagnosing rare or complex breast lesions by leveraging historical cases with known outcomes. However, significant domain shifts caused by differences in imaging protocols and equipment across institutions present substantial challenges for generalizable retrieval.

VersaMammo demonstrated superior performance across all mammogram retrieval tasks, achieving the highest ranking among all FMs (Fig. 6 (a)). On internal datasets, VersaMammo attained leading scores of 55.86% for Acc@1 and 77.66% for Acc@3, with non-overlapping 95% confidence intervals confirming statistical significance (Extended Data Table A20). These results represent a meaningful improvement over the second-best model, MAMA (ViT-B), which achieved 53.82% (Acc@1) and 77.40% (Acc@3).

Notably, VersaMammo maintained robust performance on external validation tasks, achieving 39.03% Acc@1 and 68.31% Acc@3 (Table A20). The model showed significantly less performance degradation on external datasets compared to other models, with its Acc@3 performance on external datasets reaching nearly 90% of its internal performance. This minimal performance drop underscores VersaMammo's exceptional generalization capabilities across diverse clinical environments. For comparison, MedSAM (ViT-B) achieved only 34.71% Acc@1 on external datasets, while VersaMammo surpassed this by a substantial margin (Fig. 6 (c)).

These findings demonstrate that VersaMammo significantly improves adaptability to new clinical settings without compromising retrieval accuracy. The model's stable cross-institutional performance suggests its potential as an intelligent platform for connecting healthcare institutions and facilitating diagnostic knowledge sharing.

2.5 Mammogram Visual Question Answering

Visual Question Answering (VQA) VQA is an exciting field of artificial intelligence that aims to enable machines to answer questions about visual content. In the domain of mammogram, VQA systems allow clinicians and researchers to quickly and accurately extract relevant information from mammograms. We evaluated multiple FMs in eight VQA tasks, including view classification, laterality classification, composition, breast composition assessment, masking potential risk evaluation, finding abnormality identification, Bi-Rads assessment, and pathological diagnosis prediction (Extended Data Tables A27-A29). VersaMammo achieved the highest overall performance, with an average rank of 1.4, surpassing all other models (Fig. 6 (b)). Detailed results are provided in Extended Data Table A21 and Fig. 6 (e).

To further assess generalizability, we conducted an external validation across multiple VQA metrics (Extended Data Table A22). VersaMammo achieved competitive performance: it attained an AUC of 74.95% in VQA for composition. In pathology classification question, it achieved the top accuracy of 38.37% and F1 of 35.04%, outperforming other FMs including MAMA (ViT-B). While MAMA (ViT-B) led in certain tasks such as Bi-Rads classification question, VersaMammo consistently demonstrated strong and balanced performance across diverse question types.

These results underscore VersaMammo's robustness and adaptability in handling clinically varied visual-language tasks, highlighting its potential as a valuable tool for augmenting mammogram interpretation and supporting diagnostic workflows.

2.6 Ablation Study

To understand the contributions of different components of the VersaMammo model, we conducted an ablation study that systematically removed each key element and

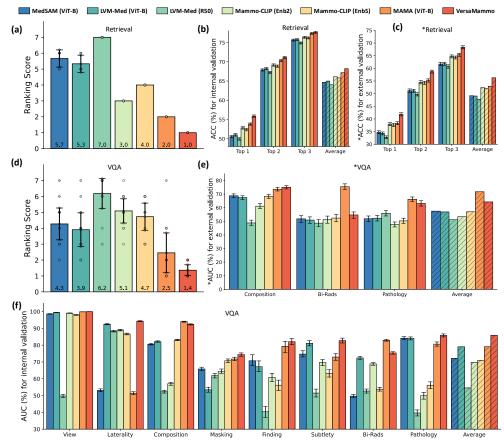


Fig. 6: Performance of FMs on image retrieval and visual question answering tasks. (a) Average ranking of FMs on image retrieval tasks based on top-1 to top-3 accuracy across internal and external datasets. (b-c) Top-1 to top-3 accuracy and mean average precision of different FMs on image retrieval tasks. (d) Average ranking of FMs on VQA tasks based on AUC across eight different question types. (e-f) AUC performance of different FMs on VQA tasks for eight question types. Error bars represent 95% confidence intervals; box limits indicate standard error. Asterisks indicate external validation cohorts.

evaluated the resulting performance (Fig. 7). The detailed results of this analysis are summarized in Extended Data Table A23, which presents ACC, F1 score, and AUC for VersaMammo and its ablated versions across multiple tasks.

Ablation Study Design. The study systematically removes or modifies key components of VersaMammo to observe changes in performance. Variations include:

• w/o Mammogram represents the pre-trained FM without using mammogram data compared with VersaMammo.

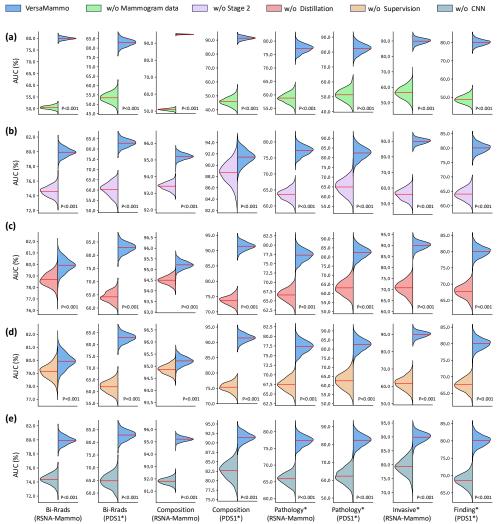


Fig. 7: The effectiveness of different components of the VersaMammo across 8 tasks. w/o Mammogram represents the pre-trainined FM without using mammogram data compared with VersaMammo. w/o Stage 2 represents the omission of the second stage of pre-training VersaMammo. w/o Distillation represents the removal of the knowledge distillation component in the second stage of pre-training VersaMammo. w/o Supervision represents the elimination of the supervision component in the second stage of pre-training VersaMammo. w/o CNN represents replacing the CNN-based backbone with a ViT-B in the second stage. * represents the task or the dataset is not seen in pre-training.

- \bullet w/o Stage 2 represents the omission of the second stage of pre-training VersaMammo.
- w/o Distillation represents the removal of the knowledge distillation component in the second stage of pre-training VersaMammo.
- w/o Supervision represents the elimination of the supervision component in the second stage of pre-training VersaMammo.
- w/o CNN represents removing the convolutional neural network (CNN) feature extractor, using Vision Transformer (ViT) backbone in both stages to validate the necessity of CNN in local texture feature modeling.

Impact of Mammogram Dataset The performance of the VersaMammo model is heavily reliant on the quality of the mammogram dataset used for training (Fig. 7 (a) and Extended Data Table A23). When mammogram data was excluded from the training process, a significant decline in performance was observed across all tasks. For instance, in the Bi-Rads classification on the RSNA-Mammo [40]dataset, the accuracy dropped from 57.03% to 33.29%, and the area under the receiver operating characteristic curve (AUC) fell from 79.92% to 50.55%. This reduction of 23.74 percentage points in accuracy and 29.37 percentage points in AUC clearly demonstrates the critical importance of mammogram data, as it serves as the foundation for accurate classification and effective model training. In the case of the Finding* (PDS1*) task, the absence of mammogram data results in an AUC of only 48.80%, indicating near-random performance. On average across all tasks, removing mammogram data resulted in severe performance degradation, with average ACC dropping from 62.98% to 37.01%, F1 score from 63.77% to 32.90%, and AUC from 84.90% to 51.98%. These results underscore the fundamental importance of specific internal data for building effective mammography analysis models.

Impact of Stage 2 Pre-training. The second stage of pre-training is critical for enhancing model performance, as shown in Fig. 7 (b) and Extended Data Table A23. When Stage 2 is omitted, the model shows a noticeable decline in performance across various tasks. For example, in the Bi-Rads classification on the PDS1 dataset, the accuracy drops from 54.47% to 22.12%, indicating a loss of 32.35 percentage points. This decline illustrates that the second stage of training is essential for adapting to the specific characteristics of the task. The results demonstrate that while the initial pre-training provides a strong foundation, the second stage is necessary for optimizing the model for specific tasks and improving overall accuracy, as evidenced by the accuracy increasing from 22.12% back to 54.47% when Stage 2 is included. The average performance metrics confirm this pattern, with ACC decreasing from 62.98% to 51.45%, F1 score from 63.77% to 50.61%, and AUC from 84.90% to 70.72% when Stage 2 pretraining is omitted. These consistent performance drops across all evaluation metrics emphasize the importance of the second stage for task-specific adaptation.

Impact of Knowledge Distillation. The knowledge distillation component significantly enhances the model's performance, particularly in scenarios where the dataset is unseen but the labels have been encountered. As shown in Fig. 7 (c) and Extended Data Table A23, in the task of *Composition (PDS1*)*, removing the distillation component resulted in a collapse of the F1 score from 49.3% to 23.4%, and the AUC for *Bi-Rads (PDS1*)* decreased by approximately 18-19 percentage points,

dropping from 82.97% to 64.15%. This data indicates that distillation helps the model generalize better to new input distributions, acting as a critical safety net when the model is applied to data from different hospitals or devices. The average performance analysis reveals that removing knowledge distillation reduces overall ACC from 62.98% to 51.18%, F1 score from 63.77% to 47.13%, and AUC from 84.90% to 72.37%. These consistent declines across all metrics demonstrate that knowledge distillation contributes substantially to the model's robustness and generalization capabilities.

Impact of Supervision. The supervision component, which involves training the classifier with specific labels, is vital for the model's adaptability, as shown in Fig. 7 (d) and Extended Data Table A23. In scenarios where the dataset (only the training images) has been seen but the labels are new, such as in Invasive* (RSNA-Mammo) and Pathology* (RSNA-Mammo), removing the supervision resulted in a significant drop in AUC, e.g., 28 percentage points for Invasive (from 81.16% to 53.16%) and 10 percentage points for Pathology (from 55.80% to 45.80%). This data clearly shows that introducing task-specific labels through supervised learning is essential for achieving high performance in familiar domains. In the Finding* (PDS1*) task, where both the dataset and labels are unseen, the absence of supervision leads to an AUC of 67.56%, which is significantly lower than the performance with supervision. The average performance across all tasks shows that removing supervision reduces ACC from 62.98% to 54.41%, F1 score from 63.77% to 48.60%, and AUC from 84.90% to 71.37%. These results highlight the crucial role of supervised learning in adapting the model to specific clinical tasks.

Impact of CNN-based Architecture. The CNN feature extractor plays a crucial role in capturing local texture features essential for mammogram analysis, as shown in Fig. 7 (e) and Extended Data Table A23. When replaced with a ViT backbone in the Stage 2 (w/o CNN), performance consistently degraded across all tasks. For instance, in Bi-Rads classification on RSNA-Mammo, AUC decreased from 79.92% to 74.39%, while in Composition classification on PDS1, AUC dropped from 91.50% to 82.70%. This performance reduction demonstrates the CNN's superior ability in modeling local texture patterns compared to ViT, highlighting the importance of incorporating inductive biases suitable for medical image analysis. The average performance analysis shows that replacing CNN with ViT reduces overall ACC from 62.98% to 54.80%, F1 score from 63.77% to 53.48%, and AUC from 84.90% to 73.74%. These results indicate that while ViT can capture global contextual information effectively, CNN's local feature extraction capabilities are essential for achieving optimal performance in mammography analysis tasks that require precise localization of subtle abnormalities.

Overall Performance Comparison. In summary, the ablation study highlights the distinct roles of the components within the VersaMammo model. The comprehensive ablation study reveals the relative importance of each component in the VersaMammo framework. As shown in Extended Data Table A23, the complete model achieves the best average performance across all metrics (ACC: 62.98%, F1: 63.77%, AUC: 84.90%). Among the ablated variants, the model without mammogram data performs the worst (ACC: 37.01%, F1: 32.90%, AUC: 51.98%), emphasizing the fundamental importance of specific mammogram pre-training. Models without Stage 2

pre-training (ACC: 51.45%, F1: 50.61%, AUC: 70.72%) and without supervision (ACC: 54.41%, F1: 48.60%, AUC: 71.37%) show similar performance degradation patterns, indicating that both components contribute significantly to the model's effectiveness. The variant without knowledge distillation (ACC: 51.18%, F1: 47.13%, AUC: 72.37%) and without CNN (ACC: 54.80%, F1: 53.48%, AUC: 73.74%) demonstrate moderate performance drops, suggesting that while important, these components have somewhat less impact than specific internal data and knowledge distillation.

3 Discussion

3.1 Advancements over Existing FMs

VersaMammo marks a significant advancement in the field of mammogram analysis by leveraging the largest multi-institutional dataset to date, comprising 706,239 mammograms sourced from 21 datasets. This extensive dataset not only addresses critical issues of data scarcity and diversity but also provides a robust foundation for training models that can generalize effectively across varied clinical contexts. Central to VersaMammo's innovation is a two-stage hybrid pre-training strategy that integrates self-supervised learning with supervised knowledge distillation. In the first stage, a Vision Transformer (ViT)-based teacher model is trained to extract high-level features from mammograms, enhancing the model's ability to discern complex patterns. The second stage incorporates clinical insights through supervised learning, allowing the model to refine its understanding based on real-world diagnostic criteria. This dual approach significantly enhances both global and local perception capabilities, enabling the model to excel across diverse downstream tasks. We established a comprehensive benchmark that encompasses five clinical task types, including 68 specific internal specific tasks and 24 external validation specific tasks, such as lesion detection, segmentation, clinical classification, image retrieval, and visual question answering (VQA) This rigorous evaluation framework provides compelling evidence of VersaMammo's practical applicability in breast cancer screening and diagnosis, ultimately contributing to improved patient outcomes and quality of care. The results from extensive experiments demonstrate that VersaMammo outperforms existing state-of-the-art models, ranking first in 50 out of 68 specific internal tasks and 20 out of 24 external validation tasks. These findings underscore VersaMammo's exceptional versatility and robust generalization capabilities, highlighting its potential to enhance the reliability and effectiveness of breast cancer screening and diagnosis.

3.2 Limitations and Future Directions

This study has several limitations that point to important future research directions. First, the unimodal nature of our model restricts its capacity for cross-modal integration, highlighting the need to develop vision-language architectures that can align mammogram images with clinical text for accurate visual question answering and automated report generation. Second, while our dataset is substantial, real-world clinical

deployment requires further validation in diverse healthcare settings to ensure robustness across varying imaging protocols, patient populations, and clinical workflows. To address these challenges, we identify two critical research directions:

Multimodal Vision-Language Integration. Future work should focus on developing cross-modal architectures that jointly process mammogram images with structured and unstructured clinical data. Incorporating vision-language pretraining will be essential for aligning visual features with clinical language, enabling accurate visual question answering and automated report generation. This approach will facilitate comprehensive patient profiling through multimodal fusion techniques such as attention mechanisms and graph neural networks, while addressing challenges like modality-specific noise and temporal discrepancies. The integration of clinical text with imaging data will significantly enhance the model's utility in supporting diagnostic decision-making.

Real-World Clinical Deployment and Validation. A crucial next step involves rigorous validation of the model's performance in real clinical environments. This includes investigating model compression techniques, such as task-specific adapters and pruning methods, to maintain high performance while conforming to hospital computing infrastructure constraints. Future research should prioritize the development of lightweight models deployable on edge devices, ensuring accessibility across diverse healthcare settings. Additionally, establishing collaborative frameworks with healthcare professionals will be essential to validate real-time decision support capabilities and ensure alignment with clinical workflows. This direction will also involve creating mechanisms for continuous learning to adapt to evolving imaging protocols and clinical guidelines without catastrophic forgetting.

In conclusion, addressing these limitations through focused research on multimodal integration and real-world clinical deployment will significantly enhance the capabilities of mammogram analysis models. These advancements will ultimately improve patient outcomes and elevate the quality of breast cancer care in clinical practice.

4 Methods

4.1 Data Collection and Processing

Data collection. To support the development of VersaMammo and evaluate existing foundational models, we curate the largest and most diverse mammogram dataset to date, consisting of 706,239 mammograms from 21 datasets, as shown in Fig. 1 (a). Specifically, we collected a total of 612,560 mammograms from 16 public datasets, the details and acquisition paths of which are provided in Extended Data Table A24. The private data were collected from five institutes across five years, namely private dataset 1 (PDS2, Shenzhen People's Hospital), private dataset 2 (PDS2, Guangzhou First People's Hospital), private dataset 3 (PDS3, The Third Affiliated Hospital, Sun Yat-sen University), private dataset 4 (PDS4, Sun Yat-sen Memorial Hospital, Sun Yat-sen University), and private dataset 5 (PDS5, Yunnan Cancer Hospital), with a total of 84,679 mammograms. The details are presented in Extended Data Table A26.

Pre-processing the Images. Following Mammo-CLLIP [34], we use a rule-based approach to find the breast's ROI for all the datasets. We set values less than 40

to 0 and eliminate the consistently identical rows and columns, as they denote the background. Finally, we resize the images to 224×224 or 512×512 or 518×518 to verify the performance of different FMs at different resolutions.

4.2 Model Design and Pre-training for VersaMammo

The development of generalist AI models for medical imaging is hampered by two major challenges: the scarcity of large, finely-annotated datasets, and the computational impracticality of deploying massive, task-specific models in clinical settings. To address these limitations, we introduce VersaMammo, a versatile mammogram foundation model based on a computationally efficient architecture. VersaMammo is pre-trained using a novel two-stage hybrid strategy that synergistically combines self-supervised learning on unlabeled data with supervised distillation of clinical expertise, thereby enhancing both global contextual understanding and local feature perception for diverse downstream tasks (Fig. 1 (c)).

Stage 1: Unsupervised Pre-training with Self-Supervised Learning. To learn robust and generalizable representations without the constraints of specific annotation protocols, our first stage focuses exclusively on unsupervised pre-training. Inspired by Dinov2 [22], we train a Vision Transformer (ViT) using a combination of contrastive learning and Masked Image Modeling (MIM) on a large-scale dataset of unlabeled mammograms. The contrastive objective teaches the model to recognize invariant features across different augmented views of the same image, while the MIM objective forces it to develop a deep understanding of anatomical context by reconstructing masked portions of the input. This pre-training phase conducted on the unlabeled training split to prevent data leakage, establishes a rich feature hierarchy that serves as a foundational prior for mammogram analysis. The choice of a ViT at this stage is deliberate, capitalizing on its strength in modeling long-range dependencies to build a comprehensive understanding of global breast anatomy.

Stage 2: Supervised Learning with Knowledge Distillation. While the ViT teacher model excels at capturing global context, its computational demands can be prohibitive for real-world deployment. Conversely, Convolutional Neural Networks (CNNs) offer a favorable balance of strong local feature extraction and operational efficiency. The goal of the second stage is, therefore, to transfer the acquired general knowledge from the ViT into a more practical architecture while simultaneously infusing it with expert clinical reasoning. We achieve this through a supervised knowledge distillation framework [53, 54], using an EfficientNet-b5 (ENb5) as the student model (VersaMammo). This student model is trained not only on ground-truth labels—including Bi-Rads classifications and breast composition—to absorb radiologists' diagnostic logic but is also guided by the feature representations of the ViT teacher. This distillation process ensures that the final, efficient CNN model inherits the robust, generalizable features learned in the first stage. Furthermore, we incorporate a contrastive learning scheme to enhance the model's resilience to variations in image resolution, a critical requirement for handling heterogeneous clinical data. The validation set was used for model selection prior to final testing, ensuring a rigorous and unbiased evaluation.

This two-stage pre-training paradigm equips VersaMammo with a unique combination of broad visual knowledge and targeted clinical understanding. As a result, the model demonstrates remarkable versatility and state-of-the-art performance across a wide spectrum of tasks, including lesion detection, segmentation, classification, image retrieval, and visual question answering, paving the way for powerful and adaptable AI tools in breast cancer screening.

4.3 Comparison Methods

To rigorously evaluate VersaMammo's performance, we conducted comprehensive comparisons with both generalist medical FMs and mammogram-specialist FMs. Our baseline selection includes the following models ((Fig. 2 (a)).

Generalist Medical FMs include MedSAM(ViT-B) [26], a SAM-based model pretrained on 1.1 million medical images across 24 modalities, and LVM-Med(ViT-B&R50) [25], vision transformers pretrained on 1.5 million multimodal medical images, including mammograms. These models leverage large-scale and diverse medical datasets to learn general features and knowledge, enabling them to perform well across various medical image analysis tasks.

Mammogram-Specialist FMs, such as Mammo-CLIP (Enb2&Enb5) [34], vision-language models pretrained on 25,355 mammogram-report pairs, and MAMA (ViT-B) [35], a multi-view alignment model trained on the EMBED dataset, focus on mammogram analysis. These specialist models are designed to excel in tasks related to breast cancer detection and diagnosis by utilizing mammogram data and specific training strategies.

All models were evaluated using consistent input resolutions and pre-processing pipelines. Feature extraction was performed using each model's recommended protocol, with task-specific heads trained from scratch for fair comparison.

4.4 Downstream Task Evaluation

4.4.1 Evaluation Protocol.

To comprehensively evaluate the performance of different FMs across various downstream tasks, we designed a rigorous testing framework and selected appropriate evaluation metrics for each task. For a fair comparison, all models and their pre-trained parameters were kept constant during the downstream task testing. Additionally, we maintained the same training-validation-test split ratio of 7:1:2 based on patients and images, respectively, to prevent data leakage and ensure reliable evaluation results. We also adhered to the same data preprocessing and augmentation techniques for all models to maintain consistency in the evaluation process. More specifically, we provided two types of testing results: specific internal and external validation.

Internal Tasks: In this scenario, we utilized the training set from specific datasets to fine-tune the pre-trained models. The validation set was then used to select the best-performing model based on its ability to generalize to the validation data. Finally, the test set, which was also derived from the same dataset, was employed to evaluate the model's performance quantitatively. This approach allows us to measure how well the

model adapts to specific tasks and datasets, providing insights into its effectiveness in familiar environments.

External Validation: In contrast, the external validation testing involved completely independent and unseen test data. This dataset was not used during the training or validation phases. By evaluating the model's performance on this external dataset, we can assess its generalization capabilities and robustness in real-world scenarios.

4.4.2 Lesion Detection

To evaluate the detection performance of different FMs, we adopted a standardized Faster R-CNN [55] framework while maintaining consistent testing protocols across all models. Given the inherent architectural differences among FMs, the output feature maps varied in size even for identical input resolutions. To ensure fair comparison, we resized the four feature maps from models with input resolution 224×224 to dimensions of 56×56 , 28×28 , 14×14 and 7×7 , while those from 512×512 , 518×518 inputs were resized to 128×128 , 64×64 , 32×32 and 16×16 . These features were then processed through a feature pyramid network (FPN [56]) to construct multi-scale representations, followed by a region proposal network (RPN) to generate candidate bounding boxes. The Region of Interest (RoI) Align module extracted fixed-size features from these proposals, which were fed into the detection head for final box predictions. Non-maximum suppression (NMS) with a threshold of 0.5 was applied to eliminate overlapping boxes and filter low-confidence detections. During training, we employed random horizontal and vertical flips for data augmentation, and optimized the models using AdamW with a learning rate of $1e^{-3}$ and a batch size of 8, validating every 500 iterations and implementing early stopping after 20 consecutive validation rounds without performance improvement. Model performance was quantitatively assessed using the Intersection over Union (IoU) metric, which measures the overlap ratio between predicted and ground-truth regions.

To assess the lesion detection performance of the models, we employed the Intersection over Union (IoU) metric. The IoU measures the overlap between the predicted bounding boxes and the ground truth, with a higher IoU value indicating better alignment between the predicted and ground truth bounding boxes. This metric provides a direct measure of the model's accuracy in detecting lesions and its ability to precisely localize them in the mammograms.

4.4.3 Lesion Segmentation

To evaluate the segmentation performance of different FMs with different model architectures, we implemented a standardized evaluation framework tailored to each type of model. For ViT [57]-based models, such as MedSAM (Vitb) [26], LVM-Med (Vitb) [25] and MAMA (Vitb) [35], we employed the TransUNet [58] architecture, in which input images were first processed through a ResNetV2 [59] backbone for feature extraction, followed by feature projection into the transformer network (with the patch embedding layer removed) and subsequent decoding through a convolutional decoder. In contrast, for CNN-based models, such as LVM-Med (R50) [25], Mammo-CLIP (Enb2) [34], Mammo-CLIP (Enb5) [34], and VersaMammo, we adopted a conventional UNet [60]

framework, using FMs as encoder components paired with a symmetric convolutional decoder. This approach enabled us to fairly compare the segmentation capabilities of different FMs with different model architectures. Internal testing used combined CBIS-DDSM and INbreast datasets (1,668 image-mask pairs), split into training (70%), validation (10%) and test sets (20%). External validation was performed on our private dataset (565 image-mask pairs). The training protocol incorporated a composite loss function combining binary cross-entropy and Dice loss, with data augmentation limited to random horizontal and vertical flips to preserve anatomical plausibility. Optimization was performed using AdamW [61] with a learning rate of $1e^{-3}$ and a batch size of 8, with validation conducted every 500 iterations and early termination triggered after 20 consecutive validation rounds without performance improvement.

To evaluate the lesion segmentation performance of the models, we employed the Dice Similarity Coefficient (DICE) [62]. The DICE is defined as twice the area of overlap divided by the total number of pixels in both the predicted and ground truth masks. This metric provides a measure of the similarity between the predicted segmentation and the ground truth, with a value of 1 indicating a perfect match. The Dice coefficient offers a comprehensive evaluation of the model's ability to accurately segment lesions in the mammograms.

4.4.4 Mammogram Classification

To evaluate the classification performance of different FMs, we utilized a standard classification model architecture and followed a consistent testing methodology across all models. Specifically, we extracted features from the input images using the respective FMs and then fed these features into a linear classifier for the final classification decision. This approach allowed us to assess the models' ability to generalize across different classification tasks while maintaining a fair comparison. Optimization was performed using AdamW [61] with a learning rate of $1e^{-3}$ and a batch size of 64, with validation conducted every epoch and early termination triggered after 10 consecutive validation rounds without performance improvement.

To assess the classification performance of the models, we employed several metrics, including Area Under the Curve (AUC), accuracy (ACC), and F1 score. For multiclass and binary classification tasks, ACC refers to the balanced accuracy, which is calculated as the average of the recall obtained on each class. This metric ensures that the model's performance is not biased towards the majority class and provides a more accurate representation of its ability to classify different classes. The AUC measures the model's ability to distinguish between classes, with a higher value indicating better performance. The F1 score provides a balance between precision and recall, offering a comprehensive evaluation of the model's performance in classification tasks.

4.4.5 Mammogram Retrieval

For the mammogram retrieval task, we aimed to retrieve images that share the same class label as a given query image, facilitating efficient image retrieval across different medical centers. To perform the retrieval, we first embedded all images using the respective FMs. Each image in the test set was treated as a query and compared against the images in the training set. To ensure that all features have a comparable

impact on the computation of similarity, we independently normalized each feature component to the range [0, 1] according to [63]. This normalization process involved calculating the mean and variance of the training set features, which were then used to normalize both the training and testing features. This approach allowed us to assess the models' ability to accurately retrieve relevant mammograms based on the query image.

To evaluate the retrieval performance, following [64, 65], we employed the top-k accuracy as the evaluation metric. The top-k accuracy evaluates the proportion of times the correct item is found among the top-k predictions. We used the L2 distance metric to evaluate the similarity between the query image and candidate images, with lower distance values indicating higher similarity. The retrieved images were subsequently ranked based on their similarity scores, and the corresponding class labels were utilized to evaluate the success of the retrieval process. This metric provides a direct measure of the model's ability to accurately retrieve relevant mammograms based on the query image.

4.4.6 VQA Task

To evaluate the visual question answering (VQA) performance of different FMs, we adopted a standardized ViLT [66] framework while maintaining consistent testing protocols across all models. Specifically, we extracted visual features from input images using the respective FMs and combined them with text embeddings in the ViLT architecture. The output representations from ViLT were then fed into a linear classifier for final answer prediction. This approach enabled us to assess the models' ability to generalize across diverse question topics while ensuring fair comparison conditions. During training, we employed the AdamW optimizer with a learning rate of $1e^{-3}$ and a batch size of 16, conducting validation after each epoch and implementing early stopping if no performance improvement was observed for one consecutive validation round. For performance evaluation, we utilized the same comprehensive metrics as in classification tasks, including AUC, ACC, and F1 score, to thoroughly assess the models' VQA capabilities.

In the VQA task, we employed the ViLT model, which is a vision-and-language transformer designed to effectively process and understand both visual and textual information. To test the VQA performance, we followed a standardized procedure where the input images and corresponding questions were encoded using the ViLT model, and the output answers were generated based on the learned representations. This approach allowed us to evaluate the models' ability to accurately answer questions based on the given images.

To evaluate the VQA performance of the models, we utilized accuracy (ACC) as the primary metric. In this context, ACC represents the proportion of correctly answered questions out of the total number of questions. This metric provides a direct measure of the model's ability to accurately answer questions based on the given images, reflecting its understanding and reasoning capabilities in VQA tasks.

5 Data Availability

The training and validation datasets in the public domain used in this study are available and can be downloaded via the links provided in Extended Data Table A24. For the data from PDS1 to PDS5, these datasets are not publicly available due to patient privacy obligations, institutional review board requirements, and data use agreements. However, researchers interested in accessing deidentified data may submit a reasonable request directly to the corresponding authors, subject to obtaining the necessary ethical approvals and complying with institutional policies.

6 Code Availability

The code and weights of the VersaMammo will be made available upon acceptance.

7 Ethics Declarations

This project has been reviewed and approved by the Human and Artefacts Research Ethics Committee (HAREC). The protocol number is HREP-2025-0025.

8 Author Contributions

F.H. and H.C. conceived and designed the study. F.H. collected all public datasets, developed the technical framework, performed model pre-training, and evaluated downstream tasks. J.Z. assisted in dataset collection and conducted evaluations of multiple existing FMs on downstream tasks. Y.Y., Y.X., Y.G., Q.K., M.W., Y.T., Z.H., and L.M. (medical professionals) collected and annotated private clinical datasets from hospitals. J.M., Z.L., Z.X., Z.C., X.W., J.H, and L.Z. provided critical feedback on the manuscript and experimental design. F.H. wrote the manuscript with input from all authors. Q.L., Z.L., H.Y., and H.C. supervised the research. All authors reviewed and approved the final manuscript.

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Appendix A Extended Data

Table A1: Average performance of FMs for diverse tasks across different datasets. It is evaluated using Intersection over Union (IoU) for detection tasks, Dice coefficient (DICE) for segmentation tasks, average Area Under the Curve (AUC) for visual question answering (VQA) tasks, average accuracy for image retrieval tasks, and AUC for classification tasks. Details of the classification task are provided in Extended Data Tables A27-A29. If there are different backbones of the same FM, only the best model is presented here. Asterisk (*) indicates the results on external validation datasets. Bold values represent the highest performance, while underlined values represent the second-highest performance in each task.

Task	Class	Dataset	MedSAM	LVM-Med	Mammo-CLIP	MAMA	VersaMammo
Detection	2	3	44.68%	49.67%	49.97%	50.21%	57.92%
Segmentation	2	3	58.24%	59.49%	59.77%	58.09%	63.21%
Composition	3-4	15	85.15%	84.99%	89.68%	89.87%	$\boldsymbol{91.53\%}$
Masking	8	1	71.99%	73.70%	74.55%	73.93%	74.48%
Finding	2-10	8	74.82%	74.20%	81.67%	82.75%	84.21 %
Bi-Rads	3-6	14	68.70%	69.78%	78.46%	80.07%	82.95 %
Bi-Rads 4	3	3	60.25%	60.46%	65.88%	69.49%	73.81 %
Pathology	2	15	70.72%	70.59%	75.07%	78.79%	81.04 %
Mastitis	2	1	68.10%	62.22%	75.07%	82.00%	$\pmb{85.00\%}$
Invasive	2	1	64.65%	70.57%	66.69%	74.71%	$\boldsymbol{80.05\%}$
Subtype	4	2	54.85%	55.65%	58.78%	58.47%	$\boldsymbol{61.12\%}$
Retrieval	6	3	64.68%	64.99%	66.11%	67.17%	68.21%
VQA	2-10	11	72.17%	79.02%	70.98%	79.11%	$\pmb{85.88\%}$
Detection*	2	1	37.02%	43.39%	38.14%	36.82%	44.81%
Segmentation*	2	1	41.61%	43.52%	37.15%	45.64%	47.12 %
Composition*	4	6	79.56%	80.07%	83.60%	85.78%	86.80%
Bi-Rads *	6	6	55.19%	56.06%	60.53%	62.22%	67.26%
Pathology*	2	8	56.77%	55.53%	63.65%	65.52%	$\boldsymbol{71.39\%}$
Retrieval*	6	5	49.20%	49.08%	52.40%	52.94%	$\boldsymbol{56.27\%}$
VQA*	2-6	4	57.47%	56.89%	56.98%	$\overline{71.72\%}$	64.25%

Table A2: Comparison of detection performance (IoU) across different FMs on high resolution (518×518 for MAMA (ViT-B), 512×512 for others) and low resolution (224×224) mammograms. The best performing model for each metric is **bolded** and the second-best performing model is <u>underlined</u>.

Dataset	CBIS-DDSM	Inbreast	VinDr-Mammo	Avg.
		High resolution		
MedSAM (ViT-B)	37.92%(34.85%,40.21%)	51.13% (46.99%,54.23%)	45.00% (41.36%,47.75%)	44.68%
LVM-Med (ViT-B)	41.98% (38.58%,44.52%)	60.85% (55.93%,64.57%)	46.18% (42.45%, 48.98%)	49.67%
LVM-Med (R50)	42.68% (39.22%,45.27%)	51.03% (46.90%,54.14%)	38.88% (35.74%,41.24%)	44.20%
Mammo-CLIP (Enb2)	38.06% (34.98%,40.36%)	62.32% (57.27%,66.08%)	41.67% (38.30%,44.17%)	47.35%
Mammo-CLIP (Enb5)	44.03% (40.46%,46.66%)	60.32% (55.44%,63.99%)	45.57% (41.89%, 48.32%)	49.97%
MAMA (ViT-B)	48.18% (44.28%,51.07%)	56.22% (51.67%,59.61%)	46.23% (42.49%,48.99%)	50.21%
VersaMammo (Ours)	48.24% (44.33%,51.14%)	71.20% (65.44%,75.47%)	$5\overline{4.32\%}$ (49.92%,57.57%)	57.92%
		Low resolution		
MedSAM (ViT-B)	35.58% (32.13%,37.94%)	44.56% (40.86%,47.28%)	42.97% (39.40%,45.59%)	41.01%
LVM-Med (ViT-B)	36.87% (33.81%,39.12%)	49.77% (45.63%,52.80%)	42.95% (38.92%,44.60%)	43.20%
LVM-Med (R50)	41.82% (38.35%,44.37%)	54.49% (49.96%,57.81%)	41.65% (38.19%,44.19%)	45.99%
Mammo-CLIP (Enb2)	31.54% (28.92%,33.46%)	50.90% (46.68%,54.00%)	36.66% (33.62%,38.90%)	39.70%
Mammo-CLIP (Enb5)	37.67% (34.54%,39.97%)	52.47% (48.11%,55.67%)	37.35% (34.25%,39.63%)	42.50%
MAMA (ViT-B)	35.55% (32.60%,37.72%)	49.11% (45.03%,52.10%)	37.53% (34.12%,39.43%)	40.73%
VersaMammo (Ours)	46.18% (42.35%,48.99%)	62.15% (56.99%,65.94%)	49.74% (45.61%,52.77%)	52.69%

Table A3: Average test time per image across different FMs on the detection task for high resolution and low resolution mammograms. The best performing model for each metric is **bolded** and the second-best performing model is <u>underlined</u>. The standard deviation is included.

Model	High resolution	Low resolution
MedSAM (ViT-B)	$166 \text{ms} \pm 110 \text{ms}$	$65 \text{ms} \pm 103 \text{ms}$
LVM-Med (ViT-B)	$166 \text{ms} \pm 110 \text{ms}$	$65 \text{ms} \pm 103 \text{ms}$
LVM-Med $(R50)$	$83\mathrm{ms}{\pm}107\mathrm{ms}$	$45\mathrm{ms}{\pm}96\mathrm{ms}$
Mammo-CLIP (Enb2)	$84\text{ms}\pm131\text{ms}$	$50 \text{ms} \pm 111 \text{ms}$
Mammo-CLIP (Enb5)	$110 \text{ms} \pm 132 \text{ms}$	$69 \text{ms} \pm 126 \text{ms}$
MAMA (ViT-B)	$259 \text{ms} \pm 262 \text{ms}$	$97 \text{ms} \pm 156 \text{ms}$
VersaMammo (ViT-B)	$259 \text{ms} \pm 262 \text{ms}$	$97 \text{ms} \pm 156 \text{ms}$
VersaMammo (Ours)	$110 \text{ms} \pm 132 \text{ms}$	$69 \text{ms} \pm 126 \text{ms}$

Table A4: External comparison of detection performance (IoU) across different FMs on high resolution (518×518 for MAMA (ViT-B), 512×512 for others) mammograms. The best performing model for each metric is **bolded** and the second-best performing model is <u>underlined</u>.

Dataset Model	VinDr-Mammo
MedSAM (ViT-B)	$37.02\% \ (35.22\%, 38.78\%)$
LVM-Med (ViT-B)	$43.39\% \ (41.56\%, 45.19\%)$
LVM-Med $(R50)$	$\overline{31.00\% \ (29.22\%, 32.82\%)}$
Mammo-CLIP (Enb2)	$38.14\% \ (36.34\%, 39.87\%)$
Mammo-CLIP (Enb5)	$34.05\% \ (32.47\%, 35.78\%)$
MAMA (ViT-B)	$36.82\% \ (35.06\%, 38.52\%)$
VersaMammo (Ours)	$44.81\% \; (42.98\%, 46.55\%)$

Table A5: Comparison of segmentation performance (DICE) across different FMs on high resolution (512×512) and low resolution (224×224) mammograms. The best performing model for each metric is **bolded** and the second-best performing model is <u>underlined</u>.

Dataset Model	CBIS-DDSM	Inbreast	PDS5	Avg.
		High resolution		
MedSAM (ViT-B)	47.98%(44.11%,51.99%)	64.73%(47.67%,80.03%)	62.00%(56.07%,67.35%)	58.24%
LVM-Med (ViT-B)	48.34%(44.67%,51.87%)	67.43%(52.35%,81.68%)	62.71% (57.25%,68.61%)	59.49%
LVM-Med (R50)	42.77%(39.12%,46.42%)	71.35% (56.12%,85.78%)	58.49%(52.75%,64.23%)	57.54%
Mammo-CLIP (Enb2)	45.78%(41.97%,49.59%)	72.19% (57.49%,86.89%)	59.81% (54.11%, 65.51%)	59.26%
Mammo-CLIP (Enb5)	49.71% (45.85%,53.57%)	68.46%(53.52%,83.40%)	61.13%(55.42%,66.84%)	59.77%
MAMA (ViT-B)	47.91%(43.80%,51.83%)	65.16%(50.02%,79.00%)	61.22% (55.47%, 67.25%)	58.10%
VersaMammo (Ours)	51.61% (47.71%,55.51%)	74.53% (59.89%,89.17%)	63.50% (57.85%,69.15%)	63.21%
		Low resolution		
MedSAM (ViT-B)	47.52% (43.26%,51.61%)	63.88% (46.65%,81.37%)	52.08% (45.32%,58.66%)	54.49%
LVM-Med (ViT-B)	46.06% (42.42%,49.41%)	53.17% (33.96%,72.00%)	50.88% (44.38%,57.46%)	50.04%
LVM-Med (R50)	41.87% (37.81%,45.51%)	64.54% (49.66%,78.56%)	53.73% (47.23%,60.31%)	53.38%
Mammo-CLIP (Enb2)	42.75% (39.00%,46.33%)	64.74% (48.85%,79.28%)	57.91% (52.31%,63.60%)	55.13%
Mammo-CLIP (Enb5)	44.44% (40.60%,47.97%)	64.46% (48.16%,78.48%)	57.33% (51.89%,62.90%)	55.41%
MAMA (ViT-B)	46.12% (42.51%,49.93%)	60.55% (44.54%,76.51%)	53.32% (46.76%,59.62%)	53.33%
VersaMammo (Ours)	45.71% (41.79%,49.69%)	73.79% (60.42%,85.19%)	57.63% (51.59%,63.55%)	59.04%

Table A6: Average test time per image across different FMs on the segmentation task for high resolution and low resolution mammograms. The best performing model for each metric is **bolded** and the second-best performing model is <u>underlined</u>. The standard deviation is included.

Model	High resolution	Low resolution
MedSAM (ViT-B)	$126 \text{ms} \pm 73 \text{ms}$	$39 \text{ms} \pm 61 \text{ms}$
LVM-Med (ViT-B)	$126 \text{ms} \pm 73 \text{ms}$	$39 \text{ms} \pm 61 \text{ms}$
LVM-Med $(R50)$	$14 \mathrm{ms} \pm 42 \mathrm{ms}$	$13\mathrm{ms}{\pm}40\mathrm{ms}$
Mammo-CLIP (Enb2)	$23\text{ms}\pm51\text{ms}$	$23 \text{ms} \pm 55 \text{ms}$
Mammo-CLIP (Enb5)	$30 \text{ms} \pm 51 \text{ms}$	$32 \text{ms} \pm 59 \text{ms}$
MAMA (ViT-B)	$290 \text{ms} \pm 613 \text{ms}$	$184 \text{ms} \pm 144 \text{ms}$
VersaMammo (ViT-B)	$290 \text{ms} \pm 613 \text{ms}$	$184 \text{ms} \pm 144 \text{ms}$
VersaMammo (Ours)	$30 \text{ms} \pm 51 \text{ms}$	$32 \text{ms} \pm 59 \text{ms}$

Table A7: External comparison of segmentation performance (DICE) across different FMs on high resolution (512×512) mammograms. The best performing model for each metric is **bolded** and the second-best performing model is <u>underlined</u>.

Dataset	PDS5
Model	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
MedSAM (ViT-B)	41.61%(38.45%,44.83%)
LVM-Med (ViT-B)	43.52%(40.47%,46.38%)
LVM-Med $(R50)$	25.73% (22.85%,28.57%)
Mammo-CLIP (Enb2)	37.15%(34.14%,40.30%)
Mammo-CLIP (Enb5)	36.06%(33.04%,39.14%)
MAMA (ViT-B)	45.64% (42.73%,48.48%)
VersaMammo (Ours)	$4\overline{7.12\%} \ (44.26\%, 49.99\%)$

Table A8: Performance of breast composition assessment for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC		F1	AUC
MedSAM (ViT-B)	57.29% (52.10%,	Average 52 40%) 52 12%	(46.25%, 59.08%)	85.15% (81.38%, 88.40%)
LVM-Med (ViT-B)	56.43% (51.44%,	61.40%) 52.20%	(45.87%, 59.14%)	84.99% (81.40%, 88.24%)
LVM-Med (R50)	51.16% (46.62%, 5	55.54%) 48.98%	(41.61%, 54.59%)	80.15% (75.98%, 83.76%)
Mammo-CLIP (Enb2)	62.41% (57.38%, 6	67.41%) 59.64%	(52.98%, 64.73%)	89.60% (86.66%, 92.01%)
Mammo-CLIP (Enb5)	63.86% (58.67%,		(53.76%, 66.71%)	89.68% (86.78%, 92.07%)
MAMA (ViT-B)	64.28% (58.68%,		(52.85%, 66.40%)	89.87% (87.03%, 92.23%)
VersaMammo (Ours)	67.25% (62.34%,	72.25%) 63.95% BMCD	(57.71%, 69.32%)	91.53% (89.09%, 93.55%)
MedSAM (ViT-B)	71.25% (61.25%, 8	81.25%) 51.80%	(41.69%, 70.49%)	88.51% (83.36%, 93.05%)
LVM-Med (ViT-B)	78.75% (68.75%, 8	87.50%) $74.62%$	(54.31%, 86.64%)	94.01% (90.01%, 97.21%)
LVM-Med (R50)	73.75% (63.75%, 8		(47.15%, 83.05%)	90.04% (84.18%, 94.23%)
Mammo-CLIP (Enb2)	88.75% (81.25%, 9	95.00%) 87.80%	(68.71%, 96.19%)	97.99% (96.00%, 99.51%)
Mammo-CLIP (Enb5) MAMA (ViT-B)	85.00% (77.47%, 9 83.75% (76.22%, 9		(66.43%, 93.40%) (59.41%, 91.79%)	95.81% (92.74%, 98.33%) 97.54% (95.36%, 99.16%)
VersaMammo (Ours)	92.50% (86.25%,	97.50%) 94.55%	(89.59%, 98.17%)	98.92% (97.37%, 99.89%)
		CBIS-DDSM		
MedSAM (ViT-B)	61.07% (57.74%, 6	64.69%) 61.11%	(57.26%, 65.06%)	85.01% (83.17%, 86.89%)
LVM-Med (ViT-B)	61.79% (58.03%, 667.00% (63.24%, 5	55.27%) 60.79%	(56.65%, 64.12%)	85.96% (83.98%, 87.78%)
LVM-Med (R50) Mammo-CLIP (Enb2)	73.23% (70.04%,	76 70%) 73 93%	(61.99%, 69.42%) (69.23%, 76.25%)	87.65% (85.88%, 89.40%) 91.52% (89.97%, 92.91%)
Mammo-CLIP (Enb5)	73.81% (70.77%,	76.99%) 73.11%	(69.73%, 76.51%)	91.92% (90.61%, 93.23%)
MAMA (ViT-B)	73.08% (69.61%,	76.27%) 72.00%	(68.14%, 75.40%)	92.35% (91.10%, 93.64%)
VersaMammo (Ours)	74.82% (71.78%,	78.15%) 74.02%	(70.48%, 77.55%)	92.46% (91.12%, 93.82%)
16 16 17 (TVITE D)	WO 0467 (00 W067 4	CDD-CESM	(00.0007 #4.4007)	OF 0457 (#0.4057 00.4857)
MedSAM (ViT-B) LVM-Med (ViT-B)	70.81% (63.78%, 76.22% (70.27%, 8	((.50%) 47.14%	(39.02%, 71.12%) (44.89%, 74.80%)	85.91% (78.12%, 89.45%) 88.88% (83.23%, 92.16%)
LVM-Med (ViT-B) LVM-Med (R50)	76.22% (70.27%, 8		(44.89%, 74.80%) (64.37%, 85.00%)	88.88% (83.23%, 92.16%) 91.27% (84.95%, 94.26%)
Mammo-CLIP (Enb2)	80.54% (74.05%, 8	85 95%) 82 69%	(69.12%, 87.67%)	92.06% (85.04%, 95.48%)
Mammo-CLIP (Enb5)	80.54% (75.12%, 8		(64.95%, 85.85%)	93.04% (87.60%, 95.81%)
MAMA (ViT-B)	81.08% (75.14%,	85.95%) 84.15%	(72.39%, 88.95%)	94.49% (90.28%, 96.51%)
VersaMammo (Ours)	77.84% (72.42%, 8	83.78%) 72.68%	(51.55%, 84.56%)	94.43% (90.05%, 96.60%)
14 10 114 (TVIT D)	04 0807 (80 8007)	DMID	(00 8007 84 0007)	or 1007 (== 0007 00 ==07)
MedSAM (ViT-B) LVM-Med (ViT-B)	81.37% (73.53%, 8 80.39% (72.55%, 8	88.24%) 46.30%	(36.59%, 54.22%) (37.20%, 62.05%)	85.18% (77.29%, 92.75%) 70.99% (60.93%, 82.19%)
LVM-Med (R50)	86.27% (78.43%, 9		(40.34%, 81.51%)	82.12% (72.18%, 91.59%)
Mammo-CLIP (Enb2)	83.33% (76.47%, 9	90.20%) 49.98%	(42.29%, 57.54%)	89.18% (82.36%, 95.54%)
Mammo-CLIP (Enb2) Mammo-CLIP (Enb5)	87.25% (80.39%, 9		(44.13%, 61.62%)	89.13% (81.75%, 95.10%)
MAMA (ViT-B)	82.35% (74.51%, 8	89.22%) 50.63%	(42.14%, 58.51%)	88.05% (79.18%, 94.90%)
VersaMammo (Ours)	88.24% (82.35%,		(48.48%, 62.75%)	90.78% (83.91%, 96.89%)
MedSAM (ViT-B)	56.79% (45.68%,	INbreast 55 96%	(39.76%, 67.40%)	81.90% (75.72%, 87.49%)
LVM-Med (ViT-B)	55.56% (45.68%, 6	65.43%) 53.90%	(41.31%, 65.44%)	81.72% (75.72%, 87.33%)
LVM-Med (R50)	59.26% (48.15%, 6		(45.24%, 70.35%)	85.17% (79.00%, 90.46%)
Mammo-CLIP (Enb2)	66.67% (56.79%,	76.54%) 63.25%	(50.38%, 73.84%)	89.39% (84.45%, 93.81%)
Mammo-CLIP (Enb5)	70.37% (60.49%, 8	80.25%) 67.64%	(53.94%, 78.20%)	92.39% (88.54%, 95.87%)
MAMA (ViT-B) VersaMammo (Ours)	66.67% (55.56%, 77.78% (67.90%,	76.54%) 63.37%	(48.11%, 75.86%) (68.20%, 87.68%)	88.05% (83.20%, 92.53%) 94.60% (90.80%, 97.75%)
versamanimo (Ours)	11.1870 (01.9070,	MIAS	(08.2076, 87.0876)	34.00% (50.80%, 51.13%)
MedSAM (ViT-B)	76.92% (66.15%, 8		(66.46%, 86.53%)	90.43% (84.06%, 95.67%)
LVM-Med (ViT-B)	69.23% (58.46%, 8	80.00%) 68.67%	(57.48%, 78.83%)	85.43% (78.39%, 91.87%)
LVM-Med (R50)	73.85% (61.54%, 8	84.62%) 73.25%	(61.11%, 82.84%)	91.11% (85.08%, 96.00%)
Mammo-CLIP (Enb2) Mammo-CLIP (Enb5)	73.85% (63.08%, 8	84.62%) 72.63%	(61.15%, 82.86%) (68.21%, 88.18%)	92.27% (86.76%, 96.54%) 91.05% (84.27%, 96.31%)
MAMA (ViT-B)	80.00% (69.23%, 8 76.92% (66.15%, 8	87 69%) 76 48%	(65.82%, 86.92%)	92.02% (86.29%, 96.84%)
VersaMammo (Ours)	84.62% (75.38%,	92.31%) 83.35%	(73.28%, 91.54%)	95.22% (90.53%, 98.71%)
		EMBED		
MedSAM (ViT-B)	58.34% (56.94%, 5		(60.28%, 63.00%)	93.13% (92.63%, 93.54%)
LVM-Med (ViT-B) LVM-Med (R50)	62.26% (60.81%, 6 41.24% (40.73%, 4		(63.49%, 66.54%) (42.01%, 43.60%)	93.48% (92.97%, 93.86%) 83.38% (82.76%, 83.97%)
Mammo-CLIP (Enb2)	65.76% (64.30%, 6	57 34%) 42.74% 67 34%) 68 14%	(42.01%, 43.60%)	94.57% (94.28%, 94.79%)
Mammo-CLIP (Enb5)	66.69% (65.23%, 6	68.04%) 67.86%	(66.63%, 69.07%)	94.59% (94.30%, 94.83%)
MAMA (ViT-B)	76.93% (75.88%,	77.94%) 69.61%	(68.87%, 70.38%)	95.23% (94.90%, 95.51%)
VersaMammo (Ours)	73.25% (71.79%,	74.76%) 72.92%	(71.78%, 74.17%)	96.06% (95.80%, 96.28%)
M 10 AM (W.T. D.)		RSNA-Mamme		01 0007 (01 4007 00 4007)
MedSAM (ViT-B)	69.06% (67.36%,		(68.18%, 71.39%)	91.96% (91.49%, 92.48%)
LVM-Med (ViT-B) LVM-Med (R50)	70.08% (68.36%, 52.60% (50.86%, 5	11.10%) 10.00% 54.44%) 59.77%	(69.17%, 72.11%) (51.15%, 54.50%)	92.35% (91.86%, 92.87%) 83.48% (82.65%, 84.24%)
Mammo-CLIP (Enb2)	70.27% (68.55%, 7	71.97%) 71.88%	(70.32%, 73.45%)	93.42% (92.93%, 93.86%)
Mammo-CLIP (Enb5)	69.77% (68.04%,	71.47%) 71.50%	(69.82%, 73.23%)	93.42% (92.91%, 93.84%)
MAMA (ViT-B)	74.87% (73.32%,	76.54%) 74.84%	(73.44%, 76.31%)	94.57% (94.19%, 94.96%)
VersaMammo (Ours)	76.22% (74.70%,	77.87%) 76.50%	(75.03%, 77.94%)	95.22% (94.87%, 95.58%)
MedSAM (ViT-B)	55.23% (51.13%, 5	VinDr-Mamme 59.66%) 57.60%	(54.01%, 61.13%)	91.34% (90.34%, 92.35%)
LVM-Med (ViT-B)	52.82% (49.52%, 5	56.75%) 56.90%	(52.08%, 61.90%)	90.78% (89.65%, 91.87%)
LVM-Med (R50)	42.64% (41.20%,	44.10%) 41.97%	(40.65%, 43.31%)	78.29% (76.03%, 80.53%)
Mammo-CLIP (Enb2)	57.38% (52.56%,	62.39%) 60.55%	(55.91%, 64.78%)	93.30% (92.66%, 93.97%)
Mammo-CLIP (Enb5)	60.44% (55.73%, 6	65.93%) 63.75%	(59.43%, 68.47%)	92.94% (92.31%, 93.68%)
MAMA (ViT-B)	54.51% (51.29%, 5		(48.69%, 57.41%)	92.02% (91.38%, 92.62%)
VersaMammo (Ours)	70.67% (65.84%,	75.18%) 70.18%	(66.54%, 73.92%)	94.98% (94.47%, 95.49%)

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	Table A8 - conti	nued from previous page	
Model	ACC	F1	AUC
		LAMIS	
MedSAM (ViT-B)	48.73% (43.37%, 55.08%)	48.99% (42.97%, 54.97%)	80.57% (77.08%, 84.08%)
LVM-Med (ViT-B)	42.83% (37.80%, 48.53%)	43.57% (37.53%, 49.42%)	80.73% (77.55%, 83.73%)
LVM-Med (R50)	41.76% (37.15%, 47.04%)	44.04% (37.82%, 50.07%)	81.21% (77.76%, 84.29%)
Mammo-CLIP (Enb2)	50.45% (44.57%, 56.40%)	51.83% (44.95%, 57.82%)	81.61% (78.11%, 84.81%)
Mammo-CLIP (Enb5)	50.39% (44.93%, 56.48%)	51.36% (45.39%, 57.16%)	82.73% (79.19%, 85.87%)
MAMA (ViT-B)	51.38% (45.30%, 57.51%)	51.16% (45.07%, 56.74%)	82.67% (79.44%, 85.66%)
VersaMammo (Ours)	49.64% (44.12%, 56.21%)	51.72% (45.40%, 58.46%)	82.94% (79.56%, 86.28%)
` '	, , ,	PDS1	` '
MedSAM (ViT-B)	42.07% (36.16%, 48.05%)	40.65% (34.60%, 46.77%)	84.43% (79.90%, 88.67%)
LVM-Med (ViT-B)	39.14% (33.19%, 45.03%)	41.40% (34.23%, 47.54%)	84.81% (81.01%, 88.22%)
LVM-Med (R50)	31.88% (27.21%, 37.35%)	31.91% (26.20%, 38.06%)	68.79% (62.64%, 74.67%)
Mammo-CLIP (Enb2)	47.49% (41.17%, 54.24%)	46.15% (40.35%, 51.55%)	88.35% (84.57%, 91.55%)
Mammo-CLIP (Enb5)	52.07% (45.26%, 58.56%)	48.40% (42.83%, 53.52%)	89.40% (85.80%, 92.58%)
MAMA (ViT-B)	44.65% (38.63%, 50.63%)	39.40% (33.28%, 44.93%)	86.73% (82.79%, 90.10%)
VersaMammo (Ours)	56.67% (50.48%, 62.78%)	49.26% (44.72%, 53.96%)	91.50% (88.83%, 93.74%)
versamanino (Ours)	00.0170 (00.4070, 02.1070)	PDS2	31.0070 (88.8870, 38.1470)
MedSAM (ViT-B)	31.77% (29.72%, 33.85%)	31.55% (29.22%, 33.97%)	69.70% (66.83%, 72.32%)
LVM-Med (ViT-B)	35.23% (32.76%, 37.64%)	32.01% (29.81%, 34.10%)	67.76% (64.92%, 70.39%)
	26.41% (25.06%, 27.88%)	22.60% (20.90%, 24.40%)	60.03% (56.87%, 63.04%)
LVM-Med (R50)			
Mammo-CLIP (Enb2)	39.02% (36.13%, 42.54%)	35.77% (31.91%, 40.19%)	73.54% (70.78%, 76.11%)
Mammo-CLIP (Enb5)	38.49% (35.71%, 41.53%)	37.02% (33.80%, 40.85%)	73.86% (71.42%, 76.32%)
MAMA (ViT-B)	39.44% (36.39%, 42.60%)	38.61% (34.75%, 42.65%)	74.98% (72.58%, 77.51%)
VersaMammo (Ours)	38.52% (36.03%, 40.85%)	35.13% (32.95%, 37.20%)	74.95% (72.19%, 77.54%)
14 10114 (TUE D)	10 =007 (11 1=07 =0 0007)	PDS3	= 1 0=07 (00 0007 = 0 0107)
MedSAM (ViT-B)	48.70% (44.17%, 52.89%)	44.95% (39.96%, 49.48%)	74.27% (68.99%, 79.64%)
LVM-Med (ViT-B)	34.66% (30.36%, 39.22%)	34.52% (29.64%, 39.45%)	82.78% (78.69%, 86.57%)
LVM-Med (R50)	25.52% (24.62%, 27.05%)	22.80% (21.36%, 25.45%)	60.80% (54.61%, 67.28%)
Mammo-CLIP (Enb2)	51.92% (46.84%, 56.76%)	46.88% (42.22%, 51.31%)	88.57% (85.84%, 91.10%)
Mammo-CLIP (Enb5)	47.85% (43.51%, 52.12%)	42.45% (37.57%, 46.98%)	86.49% (83.42%, 89.18%)
MAMA (ViT-B)	52.91% (47.44%, 58.19%)	48.45% (43.40%, 53.17%)	89.88% (87.25%, 92.31%)
VersaMammo (Ours)	48.83% (44.21%, 53.70%)	44.35% (39.95%, 49.27%)	90.78% (88.46%, 92.88%)
		PDS4	
MedSAM (ViT-B)	$34.68\% \ (33.18\%,\ 36.30\%)$	33.29% (31.69%, 34.87%)	83.44% (81.46%, 85.23%)
LVM-Med (ViT-B)	$33.77\% \ (32.37\%,\ 35.13\%)$	30.94% (29.86%, 32.03%)	82.71% (80.22%, 84.70%)
LVM-Med (R50)	31.11% (29.85%, 32.31%)	29.89% (28.82%, 30.90%)	77.93% (75.63%, 80.00%)
Mammo-CLIP (Enb2)	34.55% (33.15%, 36.10%)	31.57% (30.38%, 32.99%)	86.05% (84.92%, 87.07%)
Mammo-CLIP (Enb5)	42.16% (36.95%, 50.87%)	41.42% (33.12%, 51.15%)	86.00% (84.90%, 87.20%)
MAMA (ViT-B)	50.04% (41.34%, 59.19%)	46.79% (35.11%, 55.82%)	86.57% (85.44%, 87.65%)
VersaMammo (Ours)	$43.37\% \ (37.96\%, \ 52.02\%)$	43.13% (34.65%, 53.00%)	87.10% (85.94%, 88.27%)
		PDS5	
MedSAM (ViT-B)	52.50% (51.28%, 53.99%)	53.63% (52.04%, 55.85%)	91.41% (90.32%, 92.36%)
LVM-Med (ViT-B)	53.68% (52.72%, 54.63%)	51.27% (50.43%, 52.11%)	92.40% (91.82%, 92.89%)
LVM-Med (R50)	36.22% (35.66%, 36.79%)	35.65% (34.97%, 36.32%)	81.00% (79.47%, 82.37%)
Mammo-CLIP (Enb2)	52.93% (51.79%, 54.39%)	52.59% (51.04%, 54.87%)	92.23% (91.16%, 93.03%)
Mammo-CLIP (Enb5)	53.05% (51.19%, 55.20%)	53.31% (50.43%, 56.40%)	92.46% (91.91%, 92.94%)
MAMA (ViT-B)	55.58% (53.44%, 58.26%)	57.48% (54.12%, 61.18%)	92.88% (92.10%, 93.54%)
VersaMammo (Ours)	55.84% (53.84%, 58.15%)	56.35% (53.07%, 59.65%)	93.00% (92.39%, 93.56%)
rereamanno (Ours)	00.0170 (00.0470, 00.1070)	33.3370 (33.3170, 33.3370)	00.0070 (02.0070, 00.0070)

Table A9: External validation on breast composition assessment task for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC		F1	AUC
		Averag		
MedSAM (ViT-B)	44.92% (43.79%,		.46% (41.66%, 43.72%)	79.56% (78.81%, 80.11%)
LVM-Med (ViT-B)	41.85% (40.86%,	,	.18% (42.22%, 45.05%)	80.07% (79.44%, 80.59%)
LVM-Med (R50)	33.79% (33.15%,		.46% (32.79%, 34.23%)	66.95% (66.20%, 67.65%)
Mammo-CLIP (Enb2)	43.22% (42.39%,		.35% (41.40%, 43.87%)	82.25% (81.68%, 82.70%)
Mammo-CLIP (Enb5)	49.01% ($47.93%$,		.01% (47.92%, 50.77%)	83.60% (83.00%, 84.03%)
MAMA (ViT-B)	48.83% (47.85%,		.44% (48.36%, 50.63%)	85.78% (85.24%, 86.15%)
VersaMammo (Ours)	55.38% (54.37%,		55% (55.53%, 57.85%) 86.80% (86.30%, 87.17%)
		CDD-CE		
MedSAM (ViT-B)	45.66% (43.91%,		.77% (41.33%, 44.13%)	84.69% (83.40%, 85.74%)
LVM-Med (ViT-B)	50.26% (48.49%,	,	.21% (48.63%, 51.41%)	82.69% (81.36%, 83.77%)
LVM-Med (R50)	56.52% (54.82%,		.03% (52.57%, 55.72%)	70.73% (69.35%, 72.22%)
Mammo-CLIP (Enb2)	43.51% (41.70%,		.56% (44.35%, 48.29%)	85.22% (83.95%, 86.31%)
Mammo-CLIP (Enb5)	70.08% (68.17%,		.31% (70.42%, 74.20%)	86.63% (85.37%, 87.60%)
MAMA (ViT-B)	47.96% (46.26%,		.03% (49.09%, 52.56%)	84.73% (83.46%, 85.63%)
VersaMammo (Ours)	73.40% (71.70%,		29% (75.53%, 78.82%) 88.27% (87.26%, 89.17%)
		PDS1		
MedSAM (ViT-B)	55.41% (54.00%,		.17% (46.11%, 49.06%)	85.06% (84.20%, 85.80%)
LVM-Med (ViT-B)	38.60% (37.26%,		.31% (35.19%, 37.66%)	80.58% (79.76%, 81.34%)
LVM-Med (R50)	29.88% ($28.82%$,	,	$.50\% \ (28.25\%, \ 30.59\%)$	67.86% (66.73%, 68.91%)
Mammo-CLIP (Enb2)	49.17% (47.82%,		.93% (46.54%, 49.63%)	87.43% (86.68%, 88.06%)
Mammo-CLIP (Enb5)	47.36% (45.90%,	,	.25% (43.95%, 47.21%)	89.72% (89.09%, 90.20%)
MAMA (ViT-B)	59.97% (58.41%,		.12% (55.51%, 59.09%)	$92.21\% \ (91.69\%, \ 92.65\%)$
VersaMammo (Ours)	62.47% (60.85%,	64.36%) 61.3	38% (59.87%, 63.26%) 92.09% (91.47%, 92.61%)
		PDS2		
MedSAM (ViT-B)	28.89% (28.69%,		.87% (28.66%, 29.08%)	58.33% (57.94%, 58.67%)
LVM-Med (ViT-B)	31.16% (30.94%,		.85% (28.62%, 29.79%)	60.17% (59.75%, 60.53%)
LVM-Med (R50)	27.05% (26.86%,	27.66%) 27	.01% (26.78%, 27.59%)	56.47% (56.08%, 56.81%)
Mammo-CLIP (Enb2)	30.78% (30.59%,	31.41%) 28	.46% (28.22%, 29.61%)	63.25% (62.71%, 63.61%)
Mammo-CLIP (Enb5)	31.20% ($31.02%$,	31.40%) 29	.11% (28.91%, 29.31%)	64.14% (63.63%, 64.51%)
MAMA (ViT-B)	30.81% (30.64%,	31.00%) 28	.63% (28.43%, 28.81%)	69.18% (68.73%, 69.48%)
VersaMammo (Ours)	34.62% (34.42%,	35.22%) 35.0	02% (34.76%, 36.17%) 70.06% (69.53%, 70.36%)
		PDS3		
MedSAM (ViT-B)	50.71% (48.76%,	53.33%) 51	.97% (50.14%, 54.75%)	83.95% (82.65%, 84.94%)
LVM-Med (ViT-B)	50.01% (48.21%,	52.99%) 55	.54% (53.49%, 59.11%)	87.25% (86.43%, 87.98%)
LVM-Med (R50)	35.65% (34.79%,	36.69%) 36	.49% (35.47%, 37.65%)	74.03% (73.05%, 74.93%)
Mammo-CLIP (Enb2)	45.86% ($44.49%$,	48.88%) 49	.78% (48.09%, 53.90%)	88.88% (88.38%, 89.40%)
Mammo-CLIP (Enb5)	52.46% (50.26%,	55.12%) 56	.02% (53.59%, 58.94%)	87.17% (86.33%, 87.80%)
MAMA (ViT-B)	56.46% (54.20%,	59.08%) 59	.73% (57.26%, 62.58%)	90.40% (89.92%, 90.82%)
VersaMammo (Ours)	55.56% (53.38%,	58.36%) 62. 2	20% (59.89%, 65.04%) 91.55% (91.03%, 91.99%)
· · · · · · · · · · · · · · · · · · ·	,	PDS4	•	
MedSAM (ViT-B)	40.54% (39.27%,	42.99%) 34	.89% (34.77%, 35.93%)	80.20% (79.87%, 80.36%)
LVM-Med (ViT-B)	37.57% (36.88%,		.91% (39.26%, 43.53%)	82.20% (81.90%, 82.34%)
LVM-Med (R50)	27.52% (27.50%,	,	.50% (28.48%, 28.61%)	73.35% (72.97%, 73.58%)
Mammo-CLIP (Enb2)	38.80% (38.68%,		.66% (37.54%, 37.76%)	85.03% (84.95%, 85.11%)
Mammo-CLIP (Enb5)	42.45% (41.74%,		04% (42.38%, 46.63%	
MAMA (ViT-B)	39.18% (39.07%,		.53% (38.43%, 38.63%)	85.70% (85.51%, 85.81%)
VersaMammo (Ours)	43.44% (43.33%,		.21% (38.13%, 38.31%)	86.46% (86.37%, 86.54%)
	(. 2070)	PDS5		(, , , , , , , , , , , , , , , ,
MedSAM (ViT-B)	48.33% (48.12%,		.06% (48.95%, 49.35%)	85.12% (84.80%, 85.17%)
LVM-Med (ViT-B)	43.48% (43.38%,		.23% (48.11%, 48.78%)	87.54% (87.46%, 87.57%)
LVM-Med (R50)	26.10% (26.09%,	,	.22% (25.20%, 25.23%)	59.27% (59.03%, 59.43%)
Mammo-CLIP (Enb2)	51.22% (51.07%,		.73% (43.67%, 44.01%)	83.70% (83.41%, 83.73%)
Mammo-CLIP (Enb5)	50.53% (50.50%,		.30% (48.27%, 48.32%)	88.38% (88.25%, 88.40%)
, , ,	58.61% (58.49%,		.58% (61.43%, 62.09%)	92.48% (92.12%, 92.51%)
MAMA (ViT-B) VersaMammo (Ours)	62.76% (62.56%,		.58% (61.43%, 62.09%) L 8% (65.01%, 65.51%	

Table A10: Performance of masking potential risk evaluation for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
MedSAM (ViT-B)	24.50% (22.70%, 26.25%)	15.23% (13.62%, 16.51%)	71.99% (70.86%, 73.06%)
LVM-Med (ViT-B)	27.20% (25.25%, 29.09%)	19.80% (18.22%, 21.28%)	73.70% (72.62%, 74.74%)
LVM-Med (R50)	25.10% (23.25%, 26.95%)	17.77% (16.25%, 19.34%)	72.31% (71.26%, 73.42%)
Mammo-CLIP (Enb2)	27.00% (25.10%, 28.79%)	24.97% (23.07%, 26.74%)	74.55% (73.51%, 75.49%)
Mammo-CLIP (Enb5)	26.15% (24.25%, 27.99%)	23.41% (21.48%, 25.26%)	72.98% (71.95%, 74.09%)
MAMA (ViT-B)	24.75% (22.85%, 26.55%)	21.12% (19.34%, 22.88%)	73.93% (72.91%, 74.89%)
VersaMammo (Ours)	27.74% (25.85%, 29.84%)	22.66% (21.04%, 24.42%)	74.48% (73.46%, 75.48%)

Table A11: Performance of finding abnormality identification for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
		Average	
MedSAM (ViT-B)	62.10% (54.97%, 69.20%)	42.19% (36.34%, 47.44%)	74.82% (69.77%, 80.06%)
LVM-Med (ViT-B)	62.12% (55.15%, 69.20%)	41.39% (36.28%, 46.73%)	74.20% (68.86%, 80.10%)
LVM-Med (R50)	59.97% (53.38%, 67.08%)	39.92% (34.27%, 45.19%)	73.30% (66.78%, 79.08%)
Mammo-CLIP (Enb2)	63.59% (56.98%, 70.22%)	$48.21\% \ (42.82\%, \ 52.98\%)$	81.67% (76.43%, 86.40%)
Mammo-CLIP (Enb5)	64.21% (57.27%, 71.47%)	$48.65\% \ (42.81\%,\ 53.83\%)$	81.03% (76.40%, 86.49%)
MAMA (ViT-B)	61.23% (48.06%, 62.07%)	48.53% (41.43%, 51.92%)	82.75% (78.12%, 87.76%)
VersaMammo (Ours)	70.40% (63.30%, 77.30%)		84.21% (79.47%, 89.15%)
		CBIS-DDSM	
MedSAM (ViT-B)	88.66% (86.13%, 90.90%)	88.64% (86.08%, 90.87%)	95.66% (94.30%, 96.98%)
LVM-Med (ViT-B)	86.97% (84.59%, 89.36%)	86.97% (84.58%, 89.36%)	94.67% (92.93%, 96.13%)
LVM-Med (R50)	86.97% (84.45%, 89.36%)	86.97% (84.45%, 89.35%)	94.52% (92.99%, 95.99%)
Mammo-CLIP (Enb2)	91.46% (89.22%, 93.56%)	91.46% (89.22%, 93.54%)	96.74% (95.50%, 97.87%)
Mammo-CLIP (Enb5)	89.78% (87.54%, 92.02%)	89.78% (87.52%, 92.01%)	95.73% (94.25%, 97.04%)
MAMA (ViT-B)	91.46% (89.36%, 93.56%)		$96.83\% \ (95.58\%,\ 97.91\%)$
VersaMammo (Ours)	87.25% (84.73%, 89.64%)	87.25% (84.73%, 89.60%)	95.08% (93.66%, 96.51%)
		CMMD	
MedSAM (ViT-B)	60.93% (57.60%, 64.53%)	$53.85\% \ (51.22\%, \ 56.62\%)$	$60.33\% \ (56.24\%, \ 64.49\%)$
LVM-Med (ViT-B)	61.87% (58.40%, 65.33%)	46.88% (46.20%, 47.55%)	56.98% (52.93%, 60.64%)
LVM-Med (R50)	61.87% (58.27%, 65.20%)	57.27% (54.52%, 60.16%)	64.39% (60.01%, 68.51%)
Mammo-CLIP (Enb2)	68.27% (64.93%, 71.60%)	76.83% (74.10%, 79.30%)	76.06% (71.91%, 79.80%)
Mammo-CLIP (Enb5)	70.40% (67.20%, 73.73%)	77.66% (74.66%, 80.38%)	75.71% (71.77%, 79.45%)
MAMA (ViT-B)	72.80% (69.87%, 76.13%)		80.56% (76.79%, 83.88%)
VersaMammo (Ours)	70.27% (66.67%, 73.34%)	77.18% (74.48%, 79.69%)	76.96% (73.06%, 80.65%)
		DMID	
MedSAM (ViT-B)	50.57% (40.23%, 60.92%)	$38.72\% \ (30.64\%, \ 45.74\%)$	81.78% (75.96%, 89.13%)
LVM-Med (ViT-B)	49.43% (40.20%, 59.80%)	31.04% (25.16%, 36.40%)	80.29% (73.93%, 87.69%)
LVM-Med (R50)	50.57% (40.23%, 60.92%)	34.25% (26.20%, 41.04%)	78.12% (70.95%, 84.88%)
Mammo-CLIP (Enb2)	42.53% (32.18%, 52.87%)	31.50% (25.26%, 37.47%)	83.14% (75.31%, 88.53%)
Mammo-CLIP (Enb5)	47.13% (35.63%, 57.47%)	34.76% (26.70%, 41.05%)	77.12% (72.02%, 85.00%)
MAMA (ViT-B)	48.28% (37.93%, 59.77%)	38.83% (32.18%, 45.22%)	85.89% (78.00%, 91.15%)
VersaMammo (Ours)	55.17% (44.83%, 65.55%)) 41.98% (31.21%, 51.27%)	81.50% (75.51%, 88.03%)
		INbreast	
MedSAM (ViT-B)	51.22% (40.24%, 62.20%)	16.06% (14.57%, 17.53%)	70.43% (63.24%, 77.40%)
LVM-Med (ViT-B)	48.78% (37.80%, 58.54%)	24.18% (18.67%, 30.07%)	72.44% (66.27%, 81.95%)
LVM-Med (R50)	52.44% (41.46%, 63.41%)	27.30% (20.31%, 34.21%)	80.95% (67.47%, 87.28%)
Mammo-CLIP (Enb2)	68.29% (58.54%, 78.05%)	44.60% (38.10%, 50.46%)	91.52% (85.21%, 95.66%)
Mammo-CLIP (Enb5)	58.54% (47.56%, 68.32%)	36.65% (30.03%, 42.82%)	91.12% (86.87%, 94.75%)
MAMA (ViT-B)	65.85% (54.88%, 75.61%)	39.82% (33.11%, 45.72%)	89.04% (86.06%, 97.14%)
VersaMammo (Ours)	73.17% (63.41%, 81.71%)		94.70% (90.29%, 97.39%)
		inDr-Mammo	· · · · · · · · · · · · · · · · · · ·
MedSAM (ViT-B)	59.51% (54.87%, 63.72%)	34.87% (26.30%, 41.18%)	85.49% (83.08%, 87.69%)
LVM-Med (ViT-B)	61.28% (56.86%, 65.71%)	40.14% (32.50%, 45.58%)	87.66% (85.10%, 90.06%)
LVM-Med (R50)	57.74% (52.88%, 62.39%)	23.83% (19.18%, 28.23%)	83.91% (80.93%, 86.30%)
Mammo-CLIP (Enb2)	61.06% (56.42%, 65.71%)	41.75% (34.62%, 47.16%)	87.80% (85.11%, 90.55%)
Mammo-CLIP (Enb5)	61.50% (56.86%, 65.93%)	42.33% (34.83%, 47.12%)	88.59% (85.57%, 91.65%)
MAMA (ViT-B)	41.67% (20.83%, 62.50%)	26.53% (13.68%, 37.50%)	70.67% (58.53%, 85.20%)
VersaMammo (Ours)	61.50% (57.30%, 65.93%		86.81% (84.30%, 89.34%)
		EMBED	
MedSAM (ViT-B)	84.07% (83.83%, 84.29%)	11.82% (11.61%, 12.02%)	66.86% (65.17%, 68.57%)
LVM-Med (ViT-B)	84.07% (83.83%, 84.29%)	11.82% (11.61%, 12.02%)	66.86% (65.17%, 68.57%)
LVM-Med (R50)	83.57% (83.34%, 83.81%)	10.95% (10.80%, 11.12%)	62.89% (60.22%, 65.29%)
Mammo-CLIP (Enb2)	84.18% (83.94%, 84.40%)	12.85% (12.66%, 13.06%)	72.71% (71.15%, 74.36%)
Mammo-CLIP (Enb5)	84.25% (84.00%, 84.47%)	13.18% (12.98%, 13.40%)	73.07% (70.80%, 75.19%)
MAMA (ViT-B)	49.92% (49.61%, 50.23%)	12.24% (11.88%, 12.67%)	66.01% (64.28%, 67.73%)
VersaMammo (Ours)	84.69% (84.45%, 84.93%)		76.75% (74.59%, 78.69%)
	(, , ,, ,	MIAS	(
MedSAM (ViT-B)	45.83% (25.00%, 66.67%)	37.55% (20.55%, 53.33%)	73.64% (62.84%, 85.38%)
LVM-Med (ViT-B)	50.00% (29.17%, 70.83%)	35.64% (22.92%, 51.87%)	76.92% (64.57%, 89.69%)
LVM-Med (R50)	33.33% (16.67%, 54.17%)	26.94% (12.30%, 39.60%)	58.78% (46.71%, 73.86%)
Mammo-CLIP (Enb2)	29.17% (12.50%, 45.83%)	21.48% (9.69%, 31.35%)	65.29% (52.78%, 79.62%)
Mammo-CLIP (Enb5)	37.50% (20.83%, 58.33%)	29.61% (16.91%, 41.96%)	68.81% (57.03%, 85.63%)
MAMA (ViT-B)	64.38% (59.73%, 68.59%)		92.18% (89.89%, 93.88%)
VersaMammo (Ours)	50.00% (29.17%, 70.83%)	35.04% (19.62%, 48.18%)	71.95% (58.29%, 89.44%)
	(=0.1170, 10.0070)	PDS1	
MedSAM (ViT-B)	55.97% (51.82%, 60.39%)	56.02% (49.73%, 62.19%)	64.35% (57.33%, 70.87%)
LVM-Med (ViT-B)	54.57% (50.32%, 59.72%)	54.41% (48.59%, 60.99%)	57.79% (49.97%, 66.07%)
LVM-Med (R50)	53.27% (49.77%, 57.35%)	51.82% (46.39%, 57.84%)	62.83% (54.97%, 70.53%)
Mammo-CLIP (Enb2)	63.72% (58.12%, 69.71%)	65.23% (58.91%, 71.50%)	80.08% (74.47%, 84.83%)
Mammo-CLIP (Enb5)	64.61% (58.52%, 71.49%)	65.22% (58.88%, 71.92%)	78.09% (72.88%, 83.19%)
MAMA (ViT-B)	55.45% (51.42%, 59.92%)	55.18% (49.10%, 61.43%)	80.82% (75.82%, 85.21%)
VersaMammo (Ours)	81.16% (75.86%, 86.43%)		89.92% (86.02%, 93.17%)
· c. samanino (Odis)	01.1070 (10.0070, 30.4070	,	00.0270 (00.0270, 00.1170)

Table A12: Performance of Bi-Rads assessment task for different FMs. Non-parametric bootstrapping with $1{,}000$ bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC			F1		AUC
ModSAM (Witt D)	38.17% (34.36%,	49.20%	Average	(24.48%,	22 22%)	68.70% (65.04%, 72.48%)
MedSAM (ViT-B) LVM-Med (ViT-B)	37.49% (33.71%,	41 42%)	28.42%	(24.48%, (25.08%,	32.76%)	69.78% (66.05%, 73.52%)
LVM-Med (R50)	39.42% (35.65%,	43 21%)	32 25%	(27.84%,	36.72%)	68.91% (65.48%, 72.09%)
Mammo-CLIP (Enb2)	45.55% (41.28%,	49.78%)	39.76%	(34.63%,	44.59%)	77.25% (74.17%, 80.83%)
Mammo-CLIP (Enb5)	46.59% (42.15%,		41.81%	(36.44%,	46.89%)	78.46% (75.34%, 81.22%)
MAMA (ViT-B)	50.31% (45.56%,	54.73%)	43.27%	(37.04%,	49.05%)	80.07% (77.01%, 82.80%)
VersaMammo (Ours)	53.17% (48.43%,	57.75%)	47.06%	(41.00%,	53.07%)	82.95% (80.20%, 85.36%)
MedSAM (ViT-B)	45.00% (35.00%,	55.00%)	BMCD 32.11%	(23.63%,	42.55%)	68.70% (61.88%, 75.46%)
LVM-Med (ViT-B)	42.50% (31.25%,			(22.77%,		74.37% (67.71%, 80.64%)
LVM-Med (R50)	55.00% (43.75%,	66.25%)	50.11%	(32.58%,	65.51%)	80.73% (74.22%, 86.86%)
Mammo-CLIP (Enb2)	70.00% (60.00%,	80.00%)	75.03%	(66.11%,	83.10%)	88.15% (82.35%, 93.28%)
Mammo-CLIP (Enb5)	73.75% (63.75%,	82.50%)	78.53%	(68.84%,	85.82%)	89.93% (84.36%, 94.36%)
MAMA (ViT-B)	67 50% (56 25%	76 28%)	65.02%	(44.63%,	76.95%)	88.93% (83.14%, 93.63%)
VersaMammo (Ours)	72.50% (62.50%,	81.25%)	73.81%	(54.07%,	82.78%)	91.10% (86.52%, 95.00%)
MedSAM (ViT-B)	E1 6607 (40 1007		BIS-DDSM	(27.53%,	95 4707)	74.19% (71.60%, 76.88%)
	51.66% (48.19%, 52.53% (48.63%,	56.43%)	49 6197	(27.33%, (38.88%,	47 6697)	76.76% (74.21%, 70.38%)
LVM-Med (ViT-B) LVM-Med (R50)	62.52% (59.04%,			(55.74%,		76.76% (74.31%, 79.13%) 82.72% (80.41%, 85.00%)
Mammo-CLIP (Enb2)	64.83% (61.07%,	69 169%			64.60%)	84.64% (82.45%, 86.63%)
Mammo-CLIP (Enb5)	62.23% (58.61%,	65.70%)		(51.87%,		83.37% (81.27%, 85.33%)
MAMA (ViT-B)	63.53% (59.91%,	67 15%)	57.68%	(53.56%,	61.36%)	83.35% (81.00%, 85.55%)
VersaMammo (Ours)	64.25% (60.35%,	67.73%)	57.05%	(52.88%,	60.74%)	84.76% (82.72%, 86.70%)
		(CDD-CESM			
MedSAM (ViT-B)	48.00% (41.00%,		31.43%	(24.61%,	37.75%)	$71.24\% \ (66.95\%, \ 75.71\%)$
LVM-Med (ViT-B)	47.50% (41.00%,	54.00%)	35.95%	(29.83%,	41.78%)	74.26% (69.66%, 78.78%)
LVM-Med (R50)	55.00% (48.00%,	61.51%)		(42.27%,		74.99% (69.82%, 79.66%)
Mammo-CLIP (Enb2)	49.00% (41.99%,	56.00%)		(33.28%,		78.45% (74.18%, 82.39%)
Mammo-CLIP (Enb5)	56.00% (49.50%,				58.13%)	79.80% (75.55%, 84.12%)
MAMA (ViT-B)	58.00% (51.50%,	65.00%)	39.58%	(33.82%,	49.98%)	83.20% (79.38%, 86.96%)
VersaMammo (Ours)	62.00% (55.00%,	68.51%)	INbreast	(41.96%,	63.03%)	85.81% (82.21%, 89.32%)
MedSAM (ViT-B)	46.34% (35.37%,	57.32%)		(12.95%,	30.61%)	59.00% (50.37%, 69.20%)
LVM-Med (ViT-B)	39.02% (28.05%,			(12.12%,		58.88% (51.76%, 68.18%)
LVM-Med (R50)	50.00% (39.02%,			(17.37%,		71.28% (62.84%, 77.84%)
Mammo-CLIP (Enb2)	54.88% (43.90%,	64.63%)	33.12%	(22.53%,	49.19%)	69.71% (64.84%, 84.33%)
Mammo-CLIP (Enb5)	54.88% (43.90%.	64.63%)	35.18%	(24.73%,	51.37%)	84.23% (78.20%, 88.16%)
MAMA (ViT-B)	60.98% (50.00%,	70.73%)	37.27%	(25.92%,	53.50%)	79.20% (71.48%, 84.14%)
VersaMammo (Ours)	67.07% (57.32%,	76.83%)	46.00%	(35.40%,	64.13%)	87.55% (81.20%, 91.93%)
MedSAM (ViT-B)	77 2007 (72 5407		AU-BCMD	(20.2007	94 0507)	81.54% (77.41%, 86.02%)
LVM-Med (ViT-B)	77.29% (73.54%, 79.79% (76.25%,	99 549%)	32.20%	(29.28%, (34.18%,	34.8370)	88.28% (84.76%, 91.52%)
LVM-Med (R50)	82.29% (78.75%,	85.83%)	37.42%	(34.18%, (34.89%,	30.00%)	89.61% (87.17%, 91.82%)
Mammo-CLIP (Enb2)	82.71% (79.17%,	86.04%)		(39.75%,		93.91% (92.32%, 95.36%)
Mammo-CLIP (Enb5)	83.33% (79.79%,	86.46%)	59.34%	(45.56%,	68.01%)	93.50% (91.33%, 95.26%)
MAMA (ViT-B)	85.42% (82.50%,	88.54%)	60.82%	(45.19%,	70.54%)	93.50% (91.33%, 95.26%) 93.40% (90.86%, 95.62%)
VersaMammo (Ours)	85.00% (81.87%,	88.33%)	58.13%	(45.74%,	65.04%)	93.78% (92.15%, 95.36%)
M-JCAM (WIT D)	DE DEO7 (DE 4407	26 2007)	EMBED	(02.7207	24 6297)	68.82% (68.16%, 69.52%)
MedSAM (ViT-B) LVM-Med (ViT-B)	25.85% (25.44%, 26.63% (26.07%,	27.30%)	25.10%	(23.73%, (25.21%,	26.51%)	72.98% (72.41%, 73.57%)
LVM-Med (R50)	22.90% (22.33%,	27.29%)	21.50%	(23.21%, (21.03%,	20.31%)	67.01% (66.24%, 67.79%)
Mammo-CLIP (Enb2)	30.28% (29.33%,	31 28%)		(26.48%,		73.48% (72.91%, 74.02%)
Mammo-CLIP (Enb5)	29.21% (28.44%,			(26.01%,		74.22% (73.60%, 74.79%)
MAMA (ViT-B)	30.58% (29.73%,	31.53%)	28.84%	(28.15%,	29.59%)	76.67% (76.11%, 77.22%)
VersaMammo (Ours)	37.53% (36.31%,	38.83%)	32.37%	(31.74%,	33.01%)	78.79% (78.25%, 79.34%)
		RS	SNA-Mammo			
MedSAM (ViT-B)	45.90% (44.51%,			(45.66%,		69.65% (68.35%, 71.01%)
LVM-Med (ViT-B)	49.51% (47.96%,	51.11%)		(49.57%,		72.10% (70.73%, 73.35%)
LVM-Med (R50)	41.60% (40.45%,	42.93%)	41.99%	(40.53%,	43.67%)	63.40% (61.97%, 64.80%)
Mammo-CLIP (Enb2) Mammo-CLIP (Enb5)	52.72% (51.12%,			(53.57%,		76.28% (74.93%, 77.51%)
Mammo-CLIP (Enb5) MAMA (ViT-B)	51.65% (50.07%, 56.56% (54.76%,	50.15%)	54.36%	(52.41%, (55.18%,	59.6607	76.61% (75.39%, 77.85%) 78.10% (76.90%, 79.32%)
VersaMammo (Ours)	57.03% (55.40%,	58.74%)	59.91%	(58.18%)	61.82%)	79.92% (78.73%, 81.08%)
		Vi	nDr-Mammo			· · · · · · · · · · · · · · · · · · ·
MedSAM (ViT-B)	29.88% (27.61%,		30.43%	(27.97%,	33.00%)	69.01% (67.37%, 70.70%)
LVM-Med (ViT-B)	30.04% (27.56%,	32.58%)	26.74%	(24.93%,	28.63%)	68.87% (67.28%, 70.54%)
LVM-Med (R50)	29.08% (27.29%,	30.98%)	26.72%	(24.90%,	28.55%)	64.72% (63.17%, 66.10%)
Mammo-CLIP (Enb2)	35.77% (33.39%,	38.38%)	39.26%	(36.36%,	42.24%)	76.69% (75.18%, 78.17%)
Mammo-CLIP (Enb5)	37.66% (34.80%,			(38.04%,		77.79% (76.31%, 79.17%)
MAMA (ViT-B) VersaMammo (Ours)	47.70% (45.20%, 50.70% (48.47% ,	49.89%) 52.97%)	40.40% 54.25%	(44.11%, (51.81%,	48.49%) 56.62%)	79.42% (78.15%, 80.63%) 84.69% (83.51%, 85.77%)
			LAMIS			
MedSAM (ViT-B)	36.46% (33.61%,	40.39%)	36.65%	(32.47%,	42.54%)	72.57% (66.78%, 78.31%)
LVM-Med (ViT-B)	32.19% (30.14%,	34.42%)	30.85%	(28.52%,	33.33%)	$69.55\% \ (63.29\%, \ 75.60\%)$
LVM-Med (R50)	40.24% (35.19%,	45.48%)	41.67%	(35.08%,	47.46%)	77.85% (73.51%, 81.69%)
Mammo-CLIP (Enb2)	42.01% (36.88%,	47.36%)	43.47%	(36.65%,	49.34%)	79.38% (73.71%, 84.70%)
Mammo-CLIP (Enb5)	46.76% (39.97%,	55.18%)	49.92%	(41.41%,	58.38%)	81.66% (77.72%, 85.37%)
MAMA (ViT-B)	51.86% (45.83%,	57.41%)	50.81%	(45.31%,	55.51%)	79.90% (74.73%, 85.09%)
VersaMammo (Ours)	48.57% (40.38%,	57.03%)	49.88%	(41.36%,	58.07%)	85.52% (82.65%, 88.36%)
						Continued on next page

24 1 1		nued from previous page	ALIC
Model	ACC	F1	AUC
		PDS1	
MedSAM (ViT-B)	21.59% (19.50%, 23.88%)	19.31% (16.15%, 22.55%)	59.61% (54.02%, 64.95%)
LVM-Med (ViT-B)	21.11% (19.82%, 22.81%)	$16.22\% \ (14.11\%,\ 18.68\%)$	$54.22\% \ (48.50\%, 59.79\%)$
LVM-Med (R50)	22.84% (20.55%, 25.37%)	$19.30\% \ (17.02\%, \ 21.85\%)$	$50.61\% \ (45.15\%, 56.46\%)$
Mammo-CLIP (Enb2)	32.71% (29.58%, 36.02%)	31.18% (27.72%, 34.78%)	71.23% (64.89%, 77.18%)
Mammo-CLIP (Enb5)	31.44% (27.82%, $34.94%$)	30.25% (26.65%, 33.54%)	$70.49\% \ (64.99\%, 75.51\%)$
MAMA (ViT-B)	39.34% (30.86%, 47.06%)	36.98% (29.75%, 43.85%)	75.19% (71.39%, 78.94%)
VersaMammo (Ours)	$54.47\% \ (46.21\%,\ 62.52\%)$	$58.24\% \ (49.90\%,\ 65.87\%)$	82.97% (79.03%, 86.52%)
		PDS2	
MedSAM (ViT-B)	27.27% (24.59%, 29.95%)	19.20% (17.60%, 20.82%)	64.71% (62.88%, 66.72%)
LVM-Med (ViT-B)	25.56% (23.19%, 27.99%)	14.59% (13.54%, 15.57%)	68.47% (66.59%, 70.18%)
LVM-Med (R50)	21.30% (20.39%, 22.23%)	16.09% (14.98%, 17.17%)	53.09% (51.01%, 55.05%)
Mammo-CLIP (Enb2)	27.92% (25.54%, 30.29%)	16.25% (15.02%, 17.57%)	73.21% (71.61%, 74.77%)
Mammo-CLIP (Enb5)	27.48% (25.01%, 29.92%)	16.55% (15.26%, 17.96%)	72.97% (71.38%, 74.47%)
MAMA (ViT-B)	30.89% (28.54%, 33.31%)	23.57% (21.62%, 25.47%)	77.43% (76.04%, 78.97%)
VersaMammo (Ours)	34.48% (32.02%, 36.96%)	25.93% (24.21%, 27.80%)	77.16% (75.54%, 78.66%)
` /	, , , , , , , , , , , , , , , , , , , ,	PDS3	, , , , , , , , , , , , , , , , , , , ,
MedSAM (ViT-B)	24.24% (20.70%, 28.71%)	21.90% (16.94%, 26.87%)	67.40% (62.54%, 72.15%)
LVM-Med (ViT-B)	23.52% (20.23%, 27.40%)	21.42% (16.77%, 26.48%)	60.71% (52.70%, 68.25%)
LVM-Med (R50)	22.08% (19.63%, 25.61%)	18.53% (15.36%, 22.55%)	61.22% (56.52%, 65.86%)
Mammo-CLIP (Enb2)	31.55% (26.30%, 37.13%)	29.36% (23.85%, 35.36%)	73.78% (68.86%, 78.44%)
Mammo-CLIP (Enb5)	29.89% (24.59%, 35.30%)	27.85% (21.76%, 33.66%)	70.93% (64.14%, 77.42%)
MAMA (ViT-B)	41.27% (35.85%, 46.22%)	37.10% (31.05%, 43.44%)	77.51% (72.37%, 82.22%)
VersaMammo (Ours)	37.41% (32.68%, 41.26%)	30.67% (27.03%, 34.97%)	78.92% (72.67%, 84.26%)
versumanno (e urs)	07:1170 (02:0070, 11:2070)	PDS4	10.0270 (12.0170, 01.2070)
MedSAM (ViT-B)	31.14% (29.00%, 33.44%)	33.64% (30.36%, 36.80%)	75.12% (73.27%, 76.73%)
LVM-Med (ViT-B)	30.90% (28.47%, 33.67%)	31.37% (28.42%, 34.41%)	76.88% (75.49%, 78.11%)
LVM-Med (R50)	27.33% (25.77%, 29.03%)	28.44% (25.98%, 30.81%)	72.70% (71.02%, 74.23%)
Mammo-CLIP (Enb2)	34.61% (31.68%, 37.80%)	31.58% (28.06%, 35.01%)	78.86% (77.62%, 80.02%)
Mammo-CLIP (Enb5)	37.79% (34.53%, 41.42%)	34.84% (31.54%, 38.19%)	78.42% (77.07%, 79.54%)
MAMA (ViT-B)	37.12% (34.26%, 40.36%)	38.88% (34.94%, 42.74%)	81.14% (80.19%, 82.00%)
VersaMammo (Ours)	37.54% (34.41%, 40.88%)	37.33% (33.30%, 41.40%)	81.27% (79.75%, 82.48%)
versamanino (ours)	31.0470 (34.4170, 40.0070)	PDS5	01.2170 (10.1070, 02.4070)
MedSAM (ViT-B)	23.69% (22.98%, 24.45%)	14.32% (13.84%, 14.81%)	60.20% (58.97%, 61.35%)
LVM-Med (ViT-B)	23.09% (22.98%, 24.45%) 24.12% (23.30%, 24.96%)	12.62% (12.25%, 12.97%)	60.59% (59.49%, 61.70%)
LVM-Med (R50)	19.65% (18.94%, 20.43%)	12.68% (11.99%, 13.50%)	54.84% (53.66%, 56.05%)
Mammo-CLIP (Enb2)	28.72% (28.01%, 29.47%)	18.92% (18.38%, 19.46%)	63.70% (62.52%, 64.86%)
Mammo-CLIP (Enb2)	30.25% (29.37%, 31.04%)	23.19% (22.56%, 23.79%)	64.54% (63.39%, 65.68%)
MAMA (ViT-B)	33.65% (32.71%, 34.48%)	25.92% (25.29%, 26.57%)	67.58% (66.39%, 68.90%)
VersaMammo (Ours)	35.84% (35.11%, 36.60%)	27.00% (26.39%, 27.65%)	69.06% (67.88%, 70.25%)

Table A13: External validation on Bi-Rads assessment task for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
		Average	
MedSAM (ViT-B)	21.16% (20.65%, 21.88%)		$55.19\% \ (54.35\%, \ 56.04\%)$
LVM-Med (ViT-B)	25.11% (24.61%, 25.70%)	18.18% (17.74%, 18.72%)	56.06% (55.23%, 56.84%)
LVM-Med (R50)	20.45% (20.12%, 20.86%)	16.14% (15.69%, 16.51%)	51.53% (50.58%, 52.38%)
Mammo-CLIP (Enb2)	24.84% (23.90%, 25.86%)	20.15% (19.60%, 20.95%)	59.39% (58.50%, 60.17%)
Mammo-CLIP (Enb5)	29.53% (28.56%, 30.60%)	22.51% (21.89%, 23.40%)	60.53% (59.65%, 61.31%)
MAMA (ViT-B)	31.30% (30.35%, 32.15%)	22.01% (21.48%, 22.67%)	62.22% (61.34%, 62.98%)
VersaMammo (Ours)	36.29% (35.17%, 37.51%	(a) 26.41% (25.82%, 27.16%)	67.26% (66.49%, 67.93%)
		CDD-CESM	
MedSAM (ViT-B)	23.04% (22.40%, 23.79%)	15.80% (15.13%, 16.35%)	56.87% (55.77%, 57.98%)
LVM-Med (ViT-B)	27.72% (26.59%, 28.92%)	23.25% (21.85%, 24.72%)	58.60% (57.48%, 59.74%)
LVM-Med (R50)	21.91% (21.09%, 22.74%)	16.43% (15.25%, 17.49%)	53.63% (52.51%, 54.73%)
Mammo-CLIP (Enb2)	27.70% (26.27%, 29.07%)	25.88% (24.46%, 27.26%)	60.00% (58.77%, 61.12%)
Mammo-CLIP (Enb5)	32.93% (31.55%, 34.39%)	31.87% (30.51%, 33.23%)	63.42% (62.22%, 64.62%)
MAMA (ViT-B)	38.16% (36.50%, 39.71%)	37.59% (36.11%, 39.05%)	67.94% (66.86%, 68.93%)
VersaMammo (Ours)	41.84% (40.32%, 43.37%	(a) 40.95% (39.46%, 42.33%)	74.54% (73.46%, 75.58%)
		PDS1	
MedSAM (ViT-B)	22.09% (21.11%, 23.98%)	15.08% (14.40%, 15.77%)	49.83% (48.28%, 51.56%)
LVM-Med (ViT-B)	20.74% (20.14%, 21.35%)	19.19% (18.60%, 19.68%)	53.39% (51.55%, 55.08%)
LVM-Med (R50)	20.16% (20.16%, 20.29%)	13.90% (13.66%, 13.96%)	45.91% (44.63%, 47.35%)
Mammo-CLIP (Enb2)	34.20% (31.85%, 36.62%)	27.85% (26.98%, 29.76%)	62.46% (60.30%, 64.04%)
Mammo-CLIP (Enb5)	38.35% (35.83%, 40.86%)	32.40% (31.11%, 34.71%)	65.59% (63.41%, 66.97%)
MAMA (ViT-B)	35.57% (33.39%, 37.53%)	30.89% (29.77%, 32.32%)	66.45% (64.30%, 67.78%)
VersaMammo (Ours)	48.61% (46.41%, 49.81%	(a) 38.88% (38.17%, 39.98%)	72.77% (71.25%, 73.91%)
		PDS2	
MedSAM (ViT-B)	22.38% (22.12%, 22.71%)	18.66% (18.51%, 18.85%)	61.44% (61.23%, 61.68%)
LVM-Med (ViT-B)	37.95% (37.86%, 38.25%)	12.99% (13.00%, 13.48%)	64.92% (64.71%, 65.13%)
LVM-Med (R50)	20.20% (20.00%, 20.50%)	17.47% (17.32%, 17.66%)	54.09% (53.89%, 54.29%)
Mammo-CLIP (Enb2)	19.39% (19.10%, 19.72%)	19.93% (19.71%, 20.15%)	61.32% (61.09%, 61.55%)
Mammo-CLIP (Enb5)	39.95% (39.66%, 40.30%)	21.71% (21.60%, 22.09%)	66.09% (65.87%, 66.33%)
MAMA (ViT-B)	39.38% (39.11%, 39.68%)	18.62% (18.49%, 18.99%)	64.96% (64.74%, 65.18%)
VersaMammo (Ours)	42.22% (41.93%, 42.52%	(a) 22.74% (22.61%, 23.15%)	70.71% (70.50%, 70.94%)
		PDS3	
MedSAM (ViT-B)	23.04% (21.90%, 24.19%)	20.18% (19.55%, 20.83%)	57.00% (55.21%, 58.64%)
LVM-Med (ViT-B)	23.37% (22.22%, 24.58%)	19.50% (18.90%, 20.14%)	54.45% (52.99%, 55.66%)
LVM-Med (R50)	22.13% (21.18%, 23.16%)	19.27% (18.20%, 20.15%)	55.91% (53.22%, 57.90%)
Mammo-CLIP (Enb2)	22.89% (21.50%, 24.33%)	16.00% (15.21%, 17.11%)	53.69% (52.37%, 55.16%)
Mammo-CLIP (Enb5)	23.03% (21.60%, 24.45%)	20.56% (19.68%, 21.69%)	55.42% (54.20%, 56.93%)
MAMA (ViT-B)	29.47% (28.30%, 30.46%	6) 19.79% (19.36%, 20.37%)	57.71% (56.30%, 59.40%)
VersaMammo (Ours)	27.22% (24.94%, 31.01%)	21.60% (20.47%, 23.07%)	59.35% (57.94%, 60.68%)
		PDS4	
MedSAM (ViT-B)	18.40% (18.36%, 18.63%)	18.02% (17.99%, 18.06%)	51.40% (51.08%, 51.66%)
LVM-Med (ViT-B)	22.15% (22.12%, 22.38%)	20.73% (20.69%, 20.89%)	48.74% (48.45%, 49.06%)
LVM-Med (R50)	20.09% (20.09%, 20.09%)	15.73% (15.72%, 15.73%)	47.49% (47.22%, 47.79%)
Mammo-CLIP (Enb2)	25.77% (25.59%, 26.32%)	18.72% (18.69%, 18.82%)	58.13% (57.83%, 58.34%)
Mammo-CLIP (Enb5)	23.24% (23.05%, 23.77%)	15.81% (15.78%, 15.95%)	53.39% (53.01%, 53.65%)
MAMA (ViT-B)	26.16% (25.75%, 26.46%)	11.89% (11.88%, 11.93%)	55.14% (54.81%, 55.38%)
VersaMammo (Ours)	34.72% (34.29%, 35.03%	6) 14.85% (14.83%, 14.97%)	63.42% (63.11%, 63.59%)
	-	PDS5	
MedSAM (ViT-B)	17.99% (17.99%, 18.00%)	12.85% (12.84%, 12.85%)	54.62% (54.53%, 54.72%)
LVM-Med (ViT-B)	18.73% (18.72%, 18.74%)	13.42% (13.41%, 13.42%)	56.26% (56.17%, 56.36%)
LVM-Med (R50)	18.22% (18.20%, 18.40%)	· · · · · · · · · · · · · · · · · · ·	52.12% (52.03%, 52.22%)
Mammo-CLIP (Enb2)	19.09% (19.08%, 19.12%)		60.73% (60.63%, 60.82%)
Mammo-CLIP (Enb5)	19.68% (19.65%, 19.85%)		59.26% (59.17%, 59.37%)
MAMA (ViT-B)	19.05% (19.04%, 19.08%)		61.12% (61.02%, 61.21%)
VersaMammo (Ours)	23.14% (23.10%, 23.31%		62.75% (62.66%, 62.85%)

Table A14: Performance of Bi-Rads 4 subclassification for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
		Average	
MedSAM (ViT-B)	45.22% (41.45%, 49.15%)	43.58% (39.51%, 47.77%)	60.25% (55.57%, 64.85%)
LVM-Med (ViT-B)	42.73% (39.69%, 45.95%)	40.05% (36.25%, 44.02%)	60.46% (55.76%, 64.91%)
LVM-Med (R50)	42.13% (38.97%, 45.45%)	39.63% (36.05%, 43.27%)	58.70% (54.02%, 63.34%)
Mammo-CLIP (Enb2)	52.13% (47.51%, 56.55%)	47.60% (43.48%, 51.47%)	65.88% (61.02%, 70.21%)
Mammo-CLIP (Enb5)	49.24% (44.73%, 53.59%)	46.11% (41.75%, 50.23%)	64.48% (59.71%, 68.85%)
MAMA (ViT-B)	52.04% (47.68%, 56.33%)	50.16% (46.05%, 54.32%)	69.49% (65.10%, 73.46%)
VersaMammo (Ours)	58.53% (54.40%, 62.57%)	54.94% (51.04%, 58.60%)	73.81% (69.78%, 77.53%)
		PDS2	
MedSAM (ViT-B)	60.61% (54.71%, 66.58%)	61.24% (54.85%, 67.69%)	59.99% (52.14%, 68.00%)
LVM-Med (ViT-B)	57.96% (52.51%, 63.18%)	58.57% (52.18%, 64.39%)	62.38% (54.35%, 69.54%)
LVM-Med (R50)	55.75% (51.72%, 60.31%)	55.11% (49.10%, 61.47%)	60.35% (52.61%, 68.52%)
Mammo-CLIP (Enb2)	68.07% (61.20%, 74.05%)	66.37% (60.23%, 71.83%)	67.96% (59.67%, 75.07%)
Mammo-CLIP (Enb5)	66.08% (59.68%, 72.25%)	66.76% (60.08%, 73.02%)	67.85% (59.65%, 75.36%)
MAMA (ViT-B)	69.65% (63.50%, 75.14%)	70.03% (63.98%, 75.59%)	75.77% (68.65%, 82.12%)
VersaMammo (Ours)	80.07% (74.35%, 85.77%)	81.25% (75.80%, 86.19%)	84.58% (78.35%, 90.01%)
		PDS4	
MedSAM (ViT-B)	40.53% (37.32%, 44.16%)	40.85% (37.28%, 44.76%)	68.09% (64.66%, 71.09%)
LVM-Med (ViT-B)	34.34% (32.62%, 36.50%)	32.93% (30.42%, 35.98%)	66.34% (63.03%, 69.76%)
LVM-Med (R50)	37.71% (34.84%, 40.69%)	35.24% (32.78%, 37.72%)	66.67% (63.48%, 69.73%)
Mammo-CLIP (Enb2)	50.87% (46.49%, 55.60%)	45.87% (42.45%, 49.36%)	72.13% (68.80%, 75.23%)
Mammo-CLIP (Enb5)	45.79% (41.15%, 50.01%)	41.39% (37.86%, 44.53%)	70.45% (67.35%, 73.20%)
MAMA (ViT-B)	48.28% (44.26%, 52.47%)	45.09% (41.68%, 48.82%)	73.44% (70.36%, 76.18%)
VersaMammo (Ours)	55.84% (51.97%, 59.30%)	48.14% (44.95%, 51.10%)	77.88% (74.89%, 80.80%)
		PDS5	
MedSAM (ViT-B)	34.53% (32.33%, 36.72%)	28.64% (26.40%, 30.87%)	52.68% (49.91%, 55.47%)
LVM-Med (ViT-B)	35.88% (33.95%, 38.17%)	28.66% (26.15%, 31.70%)	52.67% (49.90%, 55.43%)
LVM-Med (R50)	32.94% (30.34%, 35.34%)	28.55% (26.26%, 30.61%)	49.08% (45.98%, 51.77%)
Mammo-CLIP (Enb2)	37.45% (34.83%, 40.01%)	30.55% (27.76%, 33.23%)	57.54% (54.58%, 60.34%)
Mammo-CLIP (Enb5)	35.84% (33.36%, 38.50%)	30.18% (27.32%, 33.13%)	55.13% (52.14%, 58.00%)
MAMA (ViT-B)	38.19% (35.29%, 41.39%)	35.35% (32.50%, 38.54%)	59.27% (56.29%, 62.09%)
VersaMammo (Ours)	39.69% (36.88%, 42.63%)	35.42% (32.36%, 38.52%)	58.97% (56.09%, 61.78%)

Table A15: Performance of pathological diagnosis prediction for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

MedSAM (VIT-B)	C
LVM-Med (VIT-B)	
LVM-Med (R50)	
Mammo-CLIP (Enbb)	%, 78.04%)
Mammo-CLIP (Enbb) 65.54% (59.21%, 71.72%) 65.04% (61.33%, 71.35%) 74.51% (66.94%, 94.85%) 74.51% (66.94%, 94.85%) 74.51% (66.94%, 94.85%) 74.51% (66.94%, 94.85%) 74.51% (69.94%, 54.51%) 75.95% (71.34%) <td>%, 77.47%)</td>	%, 77.47%)
MANA (VIT-B)	
VersaMammo (Ours)	%, 81.55%)
MedSAM (VIT-B)	%, 85.56%)
MedSAM (VIT-B)	% , 87.35%)
LVM-Med (R50)	07 55 0007)
LVM-Med (R50)	70, ((1.86%)
Mammo-CLIP (Enb2)	%, 83.05%)
Mammo-CLIP (Enb5) 67.68% (64.29%, 70.73%) 68.11% (65.26%, 71.60%) 83.36% (80.87%, versal/mmm (Ours) 66.81% (64.13%) 66.18% (64.13%, 70.08%) 83.38% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 82.26%) 83.28% (81.41%, 54.26%) 83.28% (81.26%) 83.28% (81.26%)	%, 81.91%)
MedSAM (ViT-B)	%, 84.73%)
MedSAM (ViT-B)	
MedSAM (ViT-B)	%, 86.07%)
MedSAM (ViT-B)	70, 83.7070)
LVM-Med (ViT-B) 52.50% (46.00%, 59.50%) 51.12% (44.13%, 75.75%) 75.00% (69.83%, Mammo-CLIP (Enb5) 61.00% (54.50%, 68.00%) 60.91% (53.94%, 67.49%) 76.92% (71.46%, MAMA (ViT-B) 63.00% (55.50%, 69.00%) 61.82% (54.94%, 68.16%) 80.03% (74.88%, MAMA (ViT-B) 63.00% (55.50%, 69.50%) 61.82% (57.40%, 07.37%) 84.41% (80.22%, VersaMammo (Ours) 65.50% (58.50%, 72.00%) 64.72% (57.64%, 70.73%) 84.41% (80.22%, LVM-Med (ViT-B) 70.13% (66.67%, 73.33%) 59.22% (55.21%, 63.03%) 69.64% (65.56%, LVM-Med (R50) 71.47% (68.40%, 74.67%) 58.43% (54.67%, 62.32%) 68.99% (65.11%, Mammo-CLIP (Enb5) 72.13% (68.80%, 76.33%) 62.71% (58.74%, 66.44%) 73.40% (69.49%, VersaMammo (Ours) 69.60% (66.27%, 72.67%) 64.43% (62.63%, 70.46%) 76.12% (72.48%, VersaMammo (Ours) 69.60% (66.27%, 72.67%) 64.43% (62.63%, 70.46%) 76.12% (72.48%, VersaMammo (Ours) 77.01% (67.82%, 85.06%) 69.58% (57.41%, 79.92%) 81.35% (70.83%, LVM-Med (ViT-B) 77.01% (67.82%, 85.06%) 69.58% (57.41%, 79.92%) 81.35% (70.83%, LVM-Med (ViT-B) 73.56% (64.37%, 82.76%) 70.00% (59.72%, 79.20%) 81.85% (70.83%, MAMA (ViT-B) 73.56% (64.37%, 82.76%) 70.93% (64.13%, 82.76%) 70.93% (84.13%, 82.76%) 70.93	%, 78,23%)
LVM-Med (R50)	%. 79.76%)
Mammo-CLIP (Enb2)	%. 78.95%)
Mammo-CLIP (Enb5) 62.50% (56.00%, 69.00%) 61.82% (54.94%, 68.16%) 80.03% (74.88%, VersaMammo (Ours) 80.03% (74.88%, eb.50%) 81.17% (77.06%, eb.50%) VersaMammo (Ours) 65.50% (58.50%, 72.00%) 61.82% (57.64%, 70.73%) 84.41% (80.22%, eb.41%, eb.20%) MedSAM (ViT-B) 69.07% (65.73%, 72.40%) CMMD CMMD LVM-Med (ViT-B) 70.13% (66.67%, 73.33%) 59.22% (55.21%, 63.03%) 69.64% (65.56%, 66.18%, 66.40%, 74.67%) 58.43% (54.67%, 62.32%) 68.90% (65.11%, 66.40%) 69.64% (65.56%, 66.40%) 69.64% (65.56%, 73.33%) 69.64% (65.64%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 73.40% (69.49%, 68.40%) 76.12% (72.45%, 69.30%) 76.12% (72.45%, 69.30%) 76.12% (72.45%, 69.30%) 76.12% (72.45%, 69.30%) 76.12% (72.45%, 69.30%) 73.40% (69.49%, 68.40%) 76.12% (72.45%, 69.30%) 73.40% (69.49%, 68.40%) 76.12% (72.45%, 69.30%) 77.10% (67.82%, 85.09%) 62.11% (68.45%, 70.40%) 77.10% (67.82%, 85.09%) 77.10% (67.82%, 85.09%) 77.12% (67.82%, 85.09%) 77.12% (67.82%, 85.09%) <t< td=""><td>% 81.80%)</td></t<>	% 81.80%)
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VersaMammo (Ours)	% 86 04%)
MedSAM (ViT-B)	
LVM-Med (ViT-B)	
LVM-Med (ViT-B)	%, 72.57%)
Mammo-CLIP (Enb2)	%, 73.70%)
Mammo-CLIP (Enb2)	%, 72.95%)
Mammo-CLIP (Enb5) 72.13% (68.80%, 75.33%) 62.71% (58.74%, 66.74%) 73.50% (69.30%, NAMA (ViT-B)) 73.50% (69.30%, 66.37%) 66.44% (62.63%, 70.46%) 76.12% (72.48%, 69.60%) 76.03%, 76.04% (72.53%, 76.04%) 76.04%	%, 77.07%)
MAMA (ViT-B)	%, 77.22 $%$)
VersaMammo (Ours) 69.60% (66.27%, 72.67%) 64.84% (61.14%, 68.36%) 76.04% (72.53%, DMID) MedSAM (ViT-B) 77.01% (67.82%, 85.09%) 71.23% (60.52%, 81.17%) 83.63% (74.91%, LVM-Med (R50) 77.01% (67.79%, 85.06%) 69.58% (57.41%, 79.92%) 81.35% (70.83%, 70.83%, 75.28% (64.39%, 84.23%) 82.28% (71.91%, 79.20%) 81.35% (70.83%, 75.28% (64.39%, 84.23%) 82.28% (71.91%, 79.20%) 81.87% (72.59%, 75.28% (64.39%, 84.23%) 82.28% (71.91%, 73.49% (63.39%, 82.16%) 83.22% (73.43%, 73.49% (63.39%, 82.16%) 83.22% (73.43%, 73.49% (63.39%, 82.16%) 83.22% (73.43%, 73.49% (63.39%, 82.16%) 83.22% (73.43%, 73.49% (64.55%, 80.77%) 78.46% (66.87%, 83.91%) 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 82.72%) 85.50% (76.99%, 73.87% (64.11%, 74.91%) 82.28% (71.91%, 74.91%) 85.50% (76.99%, 73.87% (%, 79.74%)
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MedSAM (ViT-B) 88.09% (78.83%, 96.06%) 91.28% (83.21%, 97.02%) 97.46% (92.22%, 12.20%) LVM-Med (ViT-B) 91.57% (84.06%, 98.15%) 92.90% (86.49%, 97.71%) 98.06% (95.80%, 98.15%) LVM-Med (R50) 92.31% (84.61%, 98.15%) 95.10% (89.59%, 98.87%) 99.06% (96.86%, 19.10%, 99.10%) Mammo-CLIP (Enb2) 95.41% (88.91%, 99.64%) 95.41% (90.22%, 98.96%) 99.00% (96.89%, 19.10%,	70, 80.25%)
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MedSAM (ViT-B) 50.00% (50.00%, 50.00%) NLBS 49.68% (49.60%, 49.76%) 60.66% (53.61%,	
MedSAM (ViT-B) 50.00% (50.00%, 50.00%) 49.68% (49.60%, 49.76%) 60.66% (53.61%,	_,
	%, 67.31%)
10.00% (30.00% (30.00%) 49.00% (49.00%, 49.10%) 57.19% (49.88%,	%, 64.91%)
LVM-Med (R50) 50.00% (50.00%, 50.00%) 49.68% (49.60%, 49.76%) 58.01% (51.63%,	%, 64.93%)
Mammo-CLIP (Enb2) 51.66% (49.98%, 54.16%) 52.86% (49.65%, 57.28%) 68.56% (61.18%,	%, 75.25 $%$)
Mammo-CLIP (Enb5) 50.00% (50.00%, 50.00%) 49.68% (49.59%, 49.76%) 65.71% (59.40%,	%, 72.26%)
MAMA (ViT-B) 52.45% (49.95%, 55.60%) 54.08% (49.68%, 59.25%) 75.31% (68.61%,	%, 81.42%)
VersaMammo (Ours) 56.63% (52.51%, 60.82%) 60.98% (54.23%, 66.84%) 82.49% (77.19%,	% , 87.84%)
LAMIS	
MedSAM (ViT-B) 55.24% (49.88%, 61.88%) 57.85% (48.55%, 67.58%) 78.12% (69.03%,	
LVM-Med (ViT-B) 56.90% (51.30%, 64.70%) 60.24% (51.06%, 70.60%) 77.64% (68.70%,	
LVM-Med (R50) 53.45% (49.76%, 59.26%) 54.87% (48.25%, 63.81%) 78.47% (69.52%,	
Mammo-CLIP (Enb2) 56.90% (51.27%, 63.76%) 60.24% (51.06%, 69.41%) 72.14% (60.28%, 60.28%, 75.48%) Mammo-CLIP (Enb5) 61.90% (54.64%, 70.46%) 65.96% (56.28%, 75.48%) 84.55% (75.45%, 60.28%, 75.45%)	
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MAMA (ViT-B) 67.62% (59.13%, 76.92%) 73.82% (63.30%, 83.26%) 83.78% (74.14%,	% , 92.33%)
VersaMammo (Ours) 75.94% (66.46%, 85.94%) 78.80% (69.16%, 86.91%) 95.23% (92.27%,	
Continued on	on next page

	Table A15 - cont	inued from previous page	
Model	ACC	F1	AUC
		DBT	
MedSAM (ViT-B)	50.00% (32.14%, 67.95%)	49.74% (31.35%, 67.49%)	54.08% (32.31%, 75.52%)
LVM-Med (ViT-B)	57.14% (38.54%, 75.00%)	57.14% (38.56%, 74.18%)	56.63% (33.33%, 77.02%)
LVM-Med (R50)	67.86% (49.23%, 84.63%)	67.82% (48.96%, 85.03%)	78.06% (59.90%, 93.75%)
Mammo-CLIP (Enb2)	71.43% (53.08%, 86.65%)	71.28% (52.37%, 85.73%)	66.33% (42.77%, 88.72%)
Mammo-CLIP (Enb5)	64.29% (48.71%, 80.21%)	62.57% (44.66%, 78.57%)	58.16% (36.72%, 79.14%)
MAMA (ViT-B)	50.00% (32.12%, 67.95%)	48.96% (29.91%, 67.25%)	56.12% (33.16%, 78.07%)
VersaMammo (Ours)	50.00% (31.53%, 67.97%)	49.74% (30.00%, 67.82%)	57.65% (35.09%, 80.51%)
		PDS1	
MedSAM (ViT-B)	52.72% (49.37%, 56.61%)	49.87% (43.96%, 55.94%)	56.26% (48.04%, 63.69%)
LVM-Med (ViT-B)	51.54% (50.00%, 53.85%)	45.71% (42.53%, 50.17%)	57.57% (49.65%, 65.91%)
LVM-Med (R50)	50.00% (50.00%, 50.00%)	42.53% (42.53%, 42.53%)	49.66% (41.52%, 58.19%)
Mammo-CLIP (Enb2)	52.81% (50.23%, 55.89%)	48.50% (43.83%, 54.01%)	69.03% (60.91%, 77.34%)
Mammo-CLIP (Enb5)	54.03% (50.42%, 58.15%)	51.64% (45.36%, 58.01%)	67.80% (59.37%, 75.20%)
MAMA (ViT-B)	73.83% (67.67%, 80.57%)	74.66% (68.56%, 80.92%)	79.61% (72.69%, 86.02%)
VersaMammo (Ours)	68.34% (62.22%, 74.80%)	70.84% (63.75%, 77.70%)	82.35% (75.77%, 88.72%)
		PDS2	
MedSAM (ViT-B)	59.35% (56.68%, 61.86%)	59.21% (56.41%, 61.84%)	62.56% (59.57%, 65.65%)
LVM-Med (ViT-B)	59.87% (56.82%, 62.67%)	59.88% (56.78%, 62.70%)	63.43% (60.06%, 66.56%)
LVM-Med (R50)	53.95% (51.26%, 56.89%)	53.84% (51.04%, 56.79%)	55.27% (52.09%, 58.61%)
Mammo-CLIP (Enb2)	63.80% (61.07%, 66.37%)	63.85% (61.09%, 66.43%)	67.73% (64.74%, 70.56%)
Mammo-CLIP (Enb5)	62.16% (59.25%, 64.84%)	62.20% (59.26%, 64.89%)	65.50% (62.36%, 68.39%)
MAMA (ViT-B)	64.66% (62.11%, 67.48%)	64.57% (61.88%, 67.53%)	68.71% (65.81%, 71.79%)
VersaMammo (Ours)	67.43% (64.98%, 70.02%)	67.26% (64.54%, 69.98%)	74.47% (71.59%, 77.24%)
versumanine (euro)	0111070 (0110070, 1010270)	PDS3	111170 (1110070, 1112170)
MedSAM (ViT-B)	59.17% (54.55%, 64.44%)	60.36% (54.43%, 66.59%)	70.03% (62.91%, 76.38%)
LVM-Med (ViT-B)	62.23% (55.91%, 68.23%)	62.92% (56.15%, 68.91%)	68.42% (61.26%, 75.34%)
LVM-Med (R50)	57.89% (52.74%, 63.29%)	58.69% (52.57%, 64.92%)	61.28% (53.90%, 68.48%)
Mammo-CLIP (Enb2)	71.87% (65.89%, 77.80%)	71.34% (65.58%, 76.75%)	79.41% (73.10%, 85.27%)
Mammo-CLIP (Enb5)	66.62% (60.67%, 72.10%)	68.39% (61.89%, 74.10%)	72.48% (64.96%, 79.40%)
MAMA (ViT-B)	74.81% (69.10%, 80.74%)	76.16% (70.41%, 81.98%)	80.85% (74.50%, 86.62%)
VersaMammo (Ours)	72.58% (66.76%, 78.28%)	75.09% (69.12%, 80.61%)	79.74% (73.18%, 85.50%)
versamanino (ours)	12.00% (00.10%, 10.20%)	PDS4	13.1470 (13.1670, 60.0070)
MedSAM (ViT-B)	77.45% (71.34%, 82.93%)	79.74% (74.00%, 84.75%)	86.68% (81.13%, 91.49%)
LVM-Med (ViT-B)	78.88% (73.34%, 84.23%)	79.87% (75.02%, 84.72%)	85.10% (78.79%, 90.96%)
LVM-Med (R50)		81.92% (76.50%, 86.63%)	84.31% (77.75%, 89.90%)
	78.76% (72.90%, 83.93%) 84.48% (79.37%, 89.78%)	84.29% (79.74%, 88.90%)	87.98% (81.52%, 93.14%)
Mammo-CLIP (Enb2)			
Mammo-CLIP (Enb5)	84.05% (78.31%, 89.03%)	84.43% (79.69%, 88.53%)	87.68% (81.39%, 92.62%)
MAMA (ViT-B)	83.99% (78.13%, 88.78%)	85.57% (80.40%, 89.82%)	90.44% (85.52%, 94.42%)
VersaMammo (Ours)	86.22% (81.11%, 90.70%)	83.74% (79.46%, 87.64%)	$92.72\% \ (88.95\%,\ 95.95\%)$
M ICAM (WEED)	CO 1407 (CO FEDT CF 4407)	PDS5	CD 0007 (CC 4007 F1 F107)
MedSAM (ViT-B)	63.14% (60.75%, 65.44%)	62.41% (60.16%, 64.65%)	68.98% (66.43%, 71.51%)
LVM-Med (ViT-B)	58.19% (56.00%, 60.43%)	57.74% (55.14%, 60.40%)	71.07% (68.49%, 73.58%)
LVM-Med (R50)	60.65% (58.23%, 63.23%)	60.87% (58.38%, 63.55%)	64.89% (62.22%, 67.71%)
Mammo-CLIP (Enb2)	68.17% (65.86%, 70.42%)	68.58% (66.24%, 70.81%)	78.98% (76.82%, 81.15%)
Mammo-CLIP (Enb5)	67.66% (65.26%, 69.93%)	68.45% (65.89%, 70.86%)	80.24% (77.93%, 82.24%)
MAMA (ViT-B)	73.12% (70.66%, 75.48%)	73.24% (70.81%, 75.54%)	83.66% (81.73%, 85.48%)
VersaMammo (Ours)	76.42% (74.11%, 78.70%)	76.83% (74.57%, 79.12%)	$86.84\% \ (85.01\%,\ 88.43\%)$

Table A16: External validation on pathological diagnosis prediction for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
MedSAM (ViT-B)	53.35% (52.33%, 54.54%)	Average 50.03% (48.57%, 51.39%)	56.70% (54.58%, 58.73%)
LVM-Med (ViT-B)	53.93% (52.44%, 55.64%)	53.11% (51.51%, 55.20%)	56.02% (53.92%, 58.20%)
LVM-Med (R50)	53.02% (51.84%, 54.26%)	50.13% (48.37%, 51.79%)	53.38% (51.38%, 55.32%)
Mammo-CLIP (Enb2)	59.84% (58.06%, 61.62%)	58.72% (56.77%, 60.70%)	63.70% (61.71%, 65.59%)
Mammo-CLIP (Enb5)	57.52% (55.89%, 59.29%)	56.18% (54.31%, 58.08%)	57.11% (54.93%, 59.29%)
MAMA (ViT-B)	60.21% (58.55%, 61.96%)	59.81% (57.89%, 61.73%)	66.81% (64.85%, 68.66%)
VersaMammo (Ours)	68.44% (66.81%, 70.19%)	67.17% (65.40%, 69.02%)	74.24% (72.43%, 75.89%)
,		DD-CESM	
MedSAM (ViT-B)	50.85% (49.90%, 51.61%)	43.08% (41.82%, 44.32%)	$44.08\% \ (42.40\%,\ 45.77\%)$
LVM-Med (ViT-B)	50.32% (48.81%, 51.82%)	$50.03\% \ (48.52\%, \ 51.55\%)$	$47.15\% \ (45.47\%,\ 48.87\%)$
LVM-Med (R50)	$48.59\% \ (47.65\%, \ 49.54\%)$	40.06% (38.76%, 41.34%)	38.53% (36.91%, 40.14%)
Mammo-CLIP (Enb2)	57.99% (56.67%, 59.50%)	57.20% (55.83%, 58.72%)	55.65% (53.96%, 57.33%)
Mammo-CLIP (Enb5)	$52.77\% \ (51.53\%, \ 54.27\%)$	51.04% (49.75%, 52.59%)	46.47% (44.89%, 48.17%)
MAMA (ViT-B)	59.45% (57.95%, 60.96%)	$59.21\% \ (57.70\%, \ 60.72\%)$	61.15% (59.45%, 62.69%)
VersaMammo (Ours)	68.44% (66.94%, 69.95%)	68.40% (66.90%, 69.91%) DMID	74.22% (72.74%, 75.66%)
MedSAM (ViT-B)	50.00% (50.00%, 50.00%)	39.58% (39.16%, 40.00%)	60.70% (58.18%, 63.22%)
LVM-Med (ViT-B)	51.75% (50.00%, 54.30%)	51.73% (49.97%, 54.34%)	51.40% (48.63%, 54.27%)
LVM-Med (R50)	58.07% (56.40%, 60.05%)	57.41% (55.21%, 59.53%)	66.32% (63.68%, 68.77%)
Mammo-CLIP (Enb2)	58.51% (55.96%, 60.97%)	58.62% (56.03%, 61.21%)	56.32% (53.46%, 59.18%)
Mammo-CLIP (Enb2)	52.19% (50.53%, 54.31%)	49.78% (47.35%, 52.12%)	44.85% (41.99%, 47.86%)
MAMA (ViT-B)	49.65% (47.98%, 51.72%)	49.78% (47.33%, 32.12%) 46.65% (44.16%, 49.03%)	53.22% (50.53%, 56.08%)
VersaMammo (Ours)	59.82% (58.16%, 61.84%)	59.20% (56.92%, 61.39%)	65.32% (62.21%, 68.01%)
versawammo (Ours)	00.0270 (00.1070, 01.0470)	CMMD	00.0270 (02.2170, 00.0170)
MedSAM (ViT-B)	55.00% (54.78%, 55.22%)	53.77% (53.46%, 54.08%)	64.64% (64.30%, 64.95%)
LVM-Med (ViT-B)	57.01% (56.79%, 57.30%)	56.90% (56.62%, 57.27%)	61.81% (61.46%, 62.16%)
LVM-Med (R50)	51.67% (51.55%, 51.89%)	46.37% (46.23%, 46.78%)	52.74% (52.39%, 53.11%)
Mammo-CLIP (Enb2)	62.32% (62.00%, 62.54%)	55.76% (55.49%, 56.03%)	65.40% (65.08%, 65.68%)
Mammo-CLIP (Enb5)	61.09% (60.78%, 61.32%)	55.81% (55.54%, 56.08%)	64.11% (63.78%, 64.40%)
MAMA (ViT-B)	59.33% (59.11%, 59.57%)	59.56% (59.28%, 59.84%)	69.85% (69.56%, 70.13%)
VersaMammo (Ours)	69.64% (69.33%, 69.87%)	63.13% (62.88%, 63.40%)	74.16% (73.89%, 74.43%)
		MIAS	
MedSAM (ViT-B)	$52.86\% \ (47.55\%, 59.80\%)$	49.58% (41.98%, 56.45%)	56.43% (46.43%, 65.73%)
LVM-Med (ViT-B)	57.86% (51.11%, 65.56%)	56.36% (49.58%, 66.06%)	$62.14\% \ (52.59\%,\ 72.14\%)$
LVM-Med (R50)	56.43% (51.40%, 61.48%)	52.53% (44.44%, 59.66%)	56.43% (47.55%, 65.19%)
Mammo-CLIP (Enb2)	62.86% (54.44%, 71.11%)	62.50% (53.12%, 71.88%)	72.14% (63.64%, 80.00%)
Mammo-CLIP (Enb5)	59.29% (51.11%, 67.78%)	59.01% (49.91%, 68.12%)	$52.86\% \ (42.65\%, \ 62.86\%)$
MAMA (ViT-B)	59.29% (51.11%, 67.78%)	59.01% (49.91%, 68.12%)	68.57% (60.00%, 76.43%)
VersaMammo (Ours)	67.86% (60.00%, 76.43%)	68.12% (59.66%, 77.23%)	85.00% (77.86%, 91.43%)
1. 10.11. (TUE D)	F4 4407 (F0 F407 F0 4007)	PDS1	F4 0.407 (F0 F007 F0.4.407)
MedSAM (ViT-B)	51.41% (50.71%, 52.10%)	48.13% (47.04%, 49.18%)	51.94% (50.78%, 53.14%)
LVM-Med (ViT-B)	53.95% (53.18%, 54.72%)	52.52% (51.35%, 53.66%)	56.70% (55.48%, 57.89%)
LVM-Med (R50)	54.10% (53.33%, 54.86%)	53.59% (52.57%, 54.59%)	52.01% (50.84%, 53.15%)
Mammo-CLIP (Enb2)	57.48% (56.72%, 58.32%)	57.76% (56.77%, 58.75%)	64.48% (63.28%, 65.59%)
Mammo-CLIP (Enb5)	58.81% (58.05%, 59.64%) 65.82% (65.05%, 66.59%)	59.27% (58.47%, 60.08%)	60.22% (59.01%, 61.49%) 74.89% (73.72%, 75.78%)
MAMA (ViT-B) VersaMammo (Ours)	77.59% (76.75%, 78.36%)	66.72% (65.96%, 67.47%) 76.77% (75.98%, 77.38%)	78.22% (77.02%, 79.32%)
versamanino (Ours)	11.39% (10.13%, 18.30%)	PDS2	18.22% (11.02%, 19.32%)
MedSAM (ViT-B)	53.94% (53.81%, 54.08%)	52.60% (52.44%, 52.78%)	55.02% (54.84%, 55.19%)
LVM-Med (ViT-B)	54.60% (54.43%, 54.76%)	54.29% (54.12%, 54.46%)	55.58% (55.41%, 55.77%)
LVM-Med (R50)	53.47% (53.31%, 53.64%)	53.46% (53.30%, 53.63%)	52.97% (52.79%, 53.16%)
Mammo-CLIP (Enb2)	53.81% (53.70%, 53.94%)	49.94% (49.81%, 50.13%)	58.35% (58.17%, 58.53%)
Mammo-CLIP (Enb5)	54.32% (54.19%, 54.46%)	50.86% (50.73%, 51.05%)	54.59% (54.40%, 54.77%)
MAMA (ViT-B)	59.30% (59.17%, 59.44%)	58.11% (57.96%, 58.29%)	64.06% (63.89%, 64.22%)
VersaMammo (Ours)	60.86% (60.75%, 60.98%)	58.38% (58.25%, 58.57%)	65.54% (65.37%, 65.72%)
		PDS3	
MedSAM (ViT-B)	58.78% (58.12%, 59.45%)	59.53% (58.81%, 60.25%)	63.64% (62.72%, 64.57%)
LVM-Med (ViT-B)	52.23% (51.60%, 52.84%)	49.56% (48.53%, 50.55%)	55.67% (54.75%, 56.63%)
LVM-Med (R50)	53.61% (52.94%, 54.28%)	52.66% (51.64%, 53.66%)	58.50% (57.51%, 59.37%)
Mammo-CLIP (Enb2)	64.58% (63.91%, 65.24%)	66.88% (66.13%, 67.62%)	70.53% (69.49%, 71.52%)
Mammo-CLIP (Enb5)	61.24% (60.58%, 61.91%)	63.00% (62.19%, 63.80%)	67.48% (66.55%, 68.35%)
MAMA (ViT-B) VersaMammo (Ours)	60.67% (60.00%, 61.33%) 68.71% (68.05%, 69.38%)	62.69% (61.70%, 63.66%) 72.32% (71.58%, 73.04%)	70.23% (69.22%, 71.26%) 71.89% (70.87%, 72.85%)
versamanino (Odrs)	00.1170 (00.0070, 09.3870)	PDS5	11.00/0 (10.01/0, 12.85%)
MedSAM (ViT-B)	53.92% (53.78%, 54.06%)	53.95% (53.81%, 54.09%)	57.13% (56.98%, 57.27%)
LVM-Med (ViT-B)	53.70% (53.57%, 53.83%)	53.52% (53.38%, 53.67%)	57.69% (57.54%, 57.84%)
LVM-Med (R50)	48.20% (48.11%, 48.31%)	44.97% (44.84%, 45.10%)	49.52% (49.36%, 49.65%)
Mammo-CLIP (Enb2)	61.17% (61.05%, 61.30%)	61.11% (61.00%, 61.25%)	66.71% (66.58%, 66.86%)
Mammo-CLIP (Enb5)	60.48% (60.38%, 60.62%)	60.65% (60.55%, 60.79%)	66.29% (66.15%, 66.42%)
MAMA (ViT-B)	68.18% (68.05%, 68.32%)	66.55% (66.42%, 66.67%)	72.53% (72.41%, 72.65%)
VersaMammo (Ours)	74.59% (74.50%, 74.68%)	71.07% (71.00%, 71.20%)	79.58% (79.48%, 79.69%)

Table A17: Performance of mastitis differentiation on PDS5 for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
MedSAM (ViT-B)	55.75% (52.80%, 58.68%)	56.88% (52.90%, 60.63%)	68.10% (63.74%, 72.57%)
LVM-Med (ViT-B)	52.02% (50.22%, 53.97%)	51.34% (48.37%, 54.48%)	62.22% (57.22%, 66.96%)
LVM-Med (R50)	53.14% (50.63%, 55.84%)	53.45% (50.12%, 56.93%)	55.95% (51.01%, 60.98%)
Mammo-CLIP (Enb2)	67.63% (63.65%, 71.52%)	62.45% (59.40%, 65.43%)	75.04% (70.87%, 79.04%)
Mammo-CLIP (Enb5)	64.55% (60.43%, 68.71%)	62.83% (59.27%, 66.48%)	74.67% (70.69%, 78.95%)
MAMA (ViT-B)	73.02% (68.90%, 76.96%)	70.12% (66.59%, 73.67%)	82.00% (78.41%, 85.43%)
VersaMammo (Ours)	74.80% (70.81%, 78.88%)	68.99% (65.92%, 72.27%)	85.00% (81.87%, 87.69%)

Table A18: Performance of invasive status determination on RSNA-Mammo for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
MedSAM (ViT-B)	50.00% (50.00%, 50.00%)	49.56% (49.56%, 49.56%)	64.65% (60.86%, 68.58%)
LVM-Med (ViT-B)	50.00% (50.00%, 50.00%)	49.56% (49.56%, 49.56%)	65.90% (62.00%, 69.71%)
LVM-Med (R50)	50.00% (50.00%, 50.00%)	49.56% (49.56%, 49.56%)	59.83% (55.89%, 63.61%)
Mammo-CLIP (Enb2)	50.00% (50.00%, 50.00%)	49.56% (49.56%, 49.56%)	70.57% (66.71%, 74.25%)
Mammo-CLIP (Enb5)	51.49% (50.43%, 52.82%)	52.32% (50.46%, 54.54%)	66.69% (62.50%, 70.83%)
MAMA (ViT-B)	56.77% (54.40%, 59.21%)	57.42% (54.83%, 59.90%)	74.71% (71.14%, 78.04%)
VersaMammo (Ours)	54.18% (52.35%, 56.31%)	57.09% (53.96%, 60.51%)	80.05% (76.91%, 83.30%)

Table A19: Performance of breast cancer molecular subtype prediction for different FMs. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	ACC	F1	AUC
		Average	
MedSAM (ViT-B)	34.94% (32.03%, 37.50%)	20.78% (19.00%, 22.69%)	54.85% (50.67%, 58.82%)
LVM-Med (ViT-B)	35.91% (32.46%, 39.64%)	19.57% (17.47%, 22.18%)	52.89% (49.07%, 56.92%)
LVM-Med (R50)	34.23% (31.49%, 37.20%)	22.15% (20.43%, 23.96%)	55.65% (51.81%, 59.52%)
Mammo-CLIP (Enb2)	35.65% (32.38%, 39.19%)	25.90% (22.31%, 29.87%)	58.78% (54.64%, 62.94%)
Mammo-CLIP (Enb5)	35.21% (31.33%, 39.18%)	23.43% (19.87%, 27.38%)	58.59% (54.73%, 62.36%)
MAMA (ViT-B)	34.18% (30.85%, 37.64%)	23.68% (20.47%, 26.94%)	58.47% (54.83%, 62.19%)
VersaMammo (Ours)	37.01% (32.72%, 41.22%)	28.54% (24.48%, 32.33%)	61.12% (57.12%, 65.01%)
		CMMD	
MedSAM (ViT-B)	44.94% (39.24%, 50.00%)	21.38% (17.88%, 25.16%)	56.85% (52.26%, 61.22%)
LVM-Med (ViT-B)	46.20% (40.51%, 51.91%)	17.50% (15.00%, 20.38%)	54.64% (50.48%, 59.00%)
LVM-Med (R50)	43.35% (37.97%, 49.05%)	23.85% (20.66%, 27.00%)	59.38% (55.34%, 63.79%)
Mammo-CLIP (Enb2)	45.25% (39.87%, 50.63%)	29.55% (24.46%, 34.58%)	62.14% (57.94%, 66.48%)
Mammo-CLIP (Enb5)	43.67% (37.97%, 49.05%)	23.33% (19.12%, 27.98%)	60.10% (55.90%, 64.07%)
MAMA (ViT-B)	43.35% (37.97%, 48.73%)	25.50% (20.88%, 29.84%)	59.03% (55.04%, 63.03%)
VersaMammo (Ours)	44.30% (38.92%, 49.69%)	31.57% (26.26%, 36.47%)	61.31% (56.82%, 65.56%)
		PDS5	
MedSAM (ViT-B)	24.93% (24.81%, 25.00%)	20.18% (20.12%, 20.22%)	52.84% (49.08%, 56.41%)
LVM-Med (ViT-B)	25.62% (24.40%, 27.37%)	21.64% (19.94%, 23.98%)	51.13% (47.65%, 54.83%)
LVM-Med (R50)	25.11% (25.00%, 25.34%)	20.44% (20.20%, 20.92%)	51.91% (48.27%, 55.25%)
Mammo-CLIP (Enb2)	26.04% (24.89%, 27.74%)	22.24% (20.16%, 25.15%)	55.41% (51.33%, 59.39%)
Mammo-CLIP (Enb5)	26.75% (24.68%, 29.30%)	23.53% (20.62%, 26.77%)	57.07% (53.56%, 60.65%)
MAMA (ViT-B)	25.00% (23.73%, 26.55%)	21.86% (20.06%, 24.04%)	57.91% (54.61%, 61.35%)
VersaMammo (Ours)	29.71% (26.52%, 32.75%)	25.50% (22.69%, 28.18%)	60.93% (57.41%, 64.46%)

Table A20: Mammogram retrieval average accuracy (%) for different FMs on 3 internal datasets and 5 external datasets. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

Model	Acc@1	Acc@2	Acc@3
	3 internal (EMBED, R.	SNA-Mammo, VinDr-Mammo)	
MedSAM (ViT-B)	50.52% (50.22%, 50.83%)	67.87% (67.60%, 68.15%)	75.65% (75.38%, 75.90%)
LVM-Med (ViT-B)	51.00% (50.69%, 51.32%)	68.20% (67.92%, 68.49%)	75.76% (75.49%, 76.01%)
LVM-Med (R50)	49.95% (49.63%, 50.26%)	67.22% (66.95%, 67.51%)	74.91% (74.63%, 75.15%)
Mammo-CLIP (Enb2)	52.81% (52.51%, 53.14%)	69.15% (68.87%, 69.45%)	76.38% (76.12%, 76.63%)
Mammo-CLIP (Enb5)	52.36% (52.04%, 52.65%)	68.88% (68.58%, 69.16%)	76.19% (75.94%, 76.45%)
MAMA (ViT-B)	53.82% (53.53%, 54.10%)	70.30% (70.02%, 70.58%)	77.40% (77.14%, 77.65%)
VersaMammo (Ours)	55.86% (55.56%, 56.17%)	71.11% (70.84%, 71.38%)	77.66% (77.42%, 77.91%)
	5 external da	taset (PDS1-PDS5)	
MedSAM (ViT-B)	34.71% (34.14%, 35.31%)	51.19% (50.54%, 51.86%)	61.69% (61.05%, 62.33%)
LVM-Med (ViT-B)	34.32% (33.71%, 34.87%)	51.10% (50.49%, 51.70%)	61.81% (61.16%, 62.42%)
LVM-Med (R50)	32.73% (32.16%, 33.31%)	49.76% (49.08%, 50.40%)	60.70% (60.08%, 61.39%)
Mammo-CLIP (Enb2)	37.95% (37.32%, 38.54%)	54.52% (53.86%, 55.15%)	64.72% (64.13%, 65.29%)
Mammo-CLIP (Enb5)	37.62% (37.00%, 38.22%)	54.25% (53.63%, 54.88%)	64.28% (63.69%, 64.85%)
MAMA (ViT-B)	38.29% (37.71%, 38.88%)	55.20% (54.57%, 55.82%)	65.34% (64.76%, 65.96%)
VersaMammo (Ours)	39.03% (38.43%, 39.79%)	55.20% (53.92%, 55.20%)	68.31% (67.71%, 68.91%)

Table A21: Comprehensive VQA Performance of different FMs. Non-parametric bootstrapping with $1{,}000$ bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded**.

bolded.			
Model	ACC	F1	AUC
	00 100 (00 110 00~;	View	00 8007 (00 4407 00 5-27)
MedSAM (ViT-B)	96.40% (96.11%, 96.68%)	96.38% (96.08%, 96.66%)	98.59% (98.41%, 98.76%)
LVM-Med (ViT-B)	97.37% (97.13%, 97.60%)	97.36% (97.11%, 97.59%)	99.45% (99.35%, 99.54%)
LVM-Med (R50)	50.00% (50.00%, 50.00%)	33.66% (33.30%, 34.00%)	$49.75\% \ (48.84\%, \ 50.65\%)$
Mammo-CLIP (Enb2)	96.70% (96.43%, 96.97%)	96.67% (96.40%, 96.94%)	99.04% (98.89%, 99.19%)
Mammo-CLIP (Enb5)	97.37% (97.13%, 97.63%)	97.36% (97.12%, 97.62%)	97.98% (97.71%, 98.26%)
MAMA (ViT-B)	98.76% (98.60%, 98.94%)	98.77% (98.60%, 98.94%)	99.86% (99.82%, 99.90%)
VersaMammo (Ours)	99.23% (99.10%, 99.36%)	99.23% (99.10%, 99.36%)	99.92% (99.88%, 99.96%)
		aterality	
MedSAM (ViT-B)	50.00% (50.00%, 50.00%)	34.07% (33.74%, 34.38%)	53.08% (52.26%, 53.99%)
LVM-Med (ViT-B)	$84.57\% \ (84.06\%,\ 85.11\%)$	$84.64\% \ (84.13\%,\ 85.18\%)$	$92.47\% \ (92.13\%,\ 92.84\%)$
LVM-Med (R50)	$83.00\% \ (82.48\%,\ 83.58\%)$	83.07% (82.53%, 83.65%)	88.34% (87.84%, 88.86%)
Mammo-CLIP (Enb2)	84.19% (83.67%, 84.70%)	84.26% (83.73%, 84.77%)	88.98% (88.49%, 89.46%)
Mammo-CLIP (Enb5)	83.42% (82.86%, 83.96%)	83.45% (82.90%, 83.99%)	86.65% (86.12%, 87.18%)
MAMA (ViT-B)	50.00% (50.00%, 50.00%)	$34.07\% \ (33.75\%,\ 34.39\%)$	$51.43\% \ (50.57\%, \ 52.28\%)$
VersaMammo (Ours)	84.54% (84.00%, 85.04%)	84.59% (84.06%, 85.09%)	94.30% (94.00%, 94.59%)
		position Assessment	
MedSAM (ViT-B)	37.53% (37.13%, 38.00%)	34.52% (34.13%, 35.00%)	80.57% (80.11%, 81.03%)
LVM-Med (ViT-B)	38.19% (37.74%, 38.67%)	34.91% (34.48%, 35.38%)	82.11% (81.63%, 82.56%)
LVM-Med (R50)	$25.00\% \ (25.00\%, \ 25.00\%)$	$17.25\% \ (17.05\%,\ 17.46\%)$	$52.28\% \ (51.48\%, \ 53.15\%)$
Mammo-CLIP (Enb2)	$26.93\% \ (26.45\%,\ 27.40\%)$	$24.42\% \ (23.95\%,\ 24.88\%)$	57.03% (56.14%, 57.86%)
Mammo-CLIP (Enb5)	40.32% (39.89%, 40.78%)	36.07% (35.62%, 36.57%)	83.09% (82.62%, 83.54%)
MAMA (ViT-B)	72.60% (71.50%, 73.73%)	72.64% (71.60%, 73.70%)	93.98% (93.68%, 94.27%)
VersaMammo (Ours)	63.07% (61.79%, 64.22%)	65.90% (64.61%, 67.13%)	92.38% (92.00%, 92.70%)
		Masking	
MedSAM (ViT-B)	$12.50\% \ (12.50\%, \ 12.50\%)$	3.08% (2.80%, 3.38%)	65.84% (64.84%, 66.90%)
LVM-Med (ViT-B)	12.50% (12.50%, 12.50%)	$3.94\% \ (3.64\%,\ 4.22\%)$	53.41% (51.99%, 54.97%)
LVM-Med (R50)	$12.50\% \ (12.50\%, \ 12.50\%)$	$3.94\% \ (3.65\%, \ 4.25\%)$	61.89% (60.48%, 63.12%)
Mammo-CLIP (Enb2)	16.87% (15.54%, 18.25%)	9.40% (8.45%, 10.29%)	64.39% (63.17%, 65.80%)
Mammo-CLIP (Enb5)	25.99% (24.53%, 27.41%)	14.85% (13.52%, 16.05%)	70.71% (69.57%, 71.78%)
MAMA (ViT-B)	18.68% (17.88%, 19.50%)	9.08% (8.40%, 9.71%)	71.75% (70.72%, 72.82%)
VersaMammo (Ours)	27.54% (25.83%, 29.06%)	19.30%~(17.90%,~20.51%)	74.40%~(73.33%,~75.39%)
		onormality	
MedSAM (ViT-B)	77.45% (76.45%, 78.36%)	$14.20\% \ (13.90\%, \ 14.50\%)$	$70.74\% \ (67.86\%, 74.29\%)$
LVM-Med (ViT-B)	76.91% (75.85%, 77.84%)	$13.56\% \ (13.24\%, \ 13.88\%)$	67.18% (64.18%, 70.63%)
LVM-Med (R50)	74.75% (73.73%, 75.86%)	$8.56\% \ (8.49\%,\ 8.63\%)$	$40.36\% \ (36.98\%, \ 43.57\%)$
Mammo-CLIP (Enb2)	$69.07\% \ (67.97\%, \ 70.24\%)$	8.68% (8.61%, 8.75%)	60.79% (58.30%, 63.26%)
Mammo-CLIP (Enb5)	65.78% (64.67%, 66.92%)	8.44% (8.36%, 8.51%)	56.19% (52.89%, 59.19%)
MAMA (ViT-B)	74.86% (73.81%, 75.83%)	$15.10\% \ (14.73\%, \ 15.48\%)$	$79.35\% \ (75.45\%,\ 82.31\%)$
VersaMammo (Ours)	79.62% (78.62%, 80.57%)	14.83% (14.52%, 15.12%)	82.08% (80.25%, 83.99%)
		Subtlety	
MedSAM (ViT-B)	$16.67\% \ (16.67\%, \ 16.67\%)$	11.09% (10.66%, 11.49%)	$74.70\% \ (72.99\%, \ 76.66\%)$
LVM-Med (ViT-B)	$32.11\% \ (31.66\%,\ 32.51\%)$	$23.65\% \ (22.94\%,\ 24.37\%)$	81.13% (79.58%, 82.72%)
LVM-Med (R50)	$16.67\% \ (16.67\%, \ 16.67\%)$	$11.09\% \ (10.67\%, \ 11.48\%)$	51.51% (49.15%, 53.85%)
Mammo-CLIP (Enb2)	$21.26\% \ (19.89\%, \ 22.75\%)$	$18.47\% \ (16.87\%, \ 20.09\%)$	69.69% (67.76%, 71.43%)
Mammo-CLIP (Enb5)	$16.67\% \ (16.67\%, \ 16.67\%)$	11.09% (10.69%, 11.48%)	63.29% (61.01%, 65.43%)
MAMA (ViT-B)	$17.34\% \ (16.79\%, \ 17.82\%)$	12.38% (11.48%, 13.23%)	72.92% (70.97%, 74.93%)
VersaMammo (Ours)	31.42% (30.58%, 32.13%)	22.53% (21.77%, 23.22%)	82.74% (81.29%, 84.19%)
		Bi-Rads	
MedSAM (ViT-B)	$16.67\% \ (16.67\%, \ 16.67\%)$	$12.29\% \ (12.17\%,\ 12.41\%)$	$49.67\% \ (48.68\%, \ 50.66\%)$
LVM-Med (ViT-B)	25.61% (24.92%, 26.27%)	21.41% (20.75%, 22.00%)	72.41% (71.51%, 73.31%)
LVM-Med (R50)	$16.67\% \ (16.67\%, \ 16.67\%)$	12.29%~(12.18%,~12.41%)	52.68%~(51.47%,~53.88%)
Mammo-CLIP (Enb2)	$18.71\% \ (18.25\%, \ 19.19\%)$	$15.38\% \ (14.79\%, \ 16.00\%)$	$68.85\% \ (67.99\%, \ 69.62\%)$
Mammo-CLIP (Enb5)	$16.67\% \ (16.67\%, \ 16.67\%)$	12.29%~(12.16%,~12.42%)	$53.79\% \ (52.65\%,\ 54.94\%)$
MAMA (ViT-B)	$29.88\% \ (28.82\%,\ 30.96\%)$	27.43%~(26.07%,~28.87%)	$82.92\% \ (82.37\%,\ 83.51\%)$
VersaMammo (Ours)	$33.19\% \ (32.46\%,\ 33.97\%)$	27.03% (26.39%, 27.66%)	75.39% (74.65%, 76.09%)
		Pathology	
MedSAM (ViT-B)	57.66% (56.49%, 58.96%)	50.07% (48.77%, 51.34%)	84.17% (83.22%, 85.12%)
LVM-Med (ViT-B)	55.17% (53.82%, 56.49%)	48.27% (47.01%, 49.55%)	84.01% (83.10%, 84.90%)
LVM-Med (R50)	33.33% (33.33%, 33.33%)	21.55% (20.85%, 22.22%)	39.63% (37.85%, 41.45%)
Mammo-CLIP (Enb2)	33.33% (33.33%, 33.33%)	21.55% (20.86%, 22.27%)	49.90% (47.86%, 51.92%)
	33.33% (33.33%, 33.33%)	21.55% (20.88%, 22.24%)	56.17% (54.06%, 58.15%)
Mammo-CLIP (Enb5)			
MAMA (ViT-B) VersaMammo (Ours)	54.14% (52.76%, 55.52%) 57.35% (56.14%, 58.52%)	47.19% (45.84%, 48.51%) 50.12% (48.90%, 51.37%)	80.63% (79.41%, 81.91%) 85.81% (84.89%, 86.68%)

Table A22: Comprehensive VQA performance of different FMs for external validation. Non-parametric bootstrapping with 1,000 bootstrap replicates is used for statistical analysis. The 95% CI is included in parentheses. The best performing model for each metric is **bolded** and the second-best performing model is <u>underlined</u>.

		-	
Model	ACC	F1	AUC
	Breast Comp	position Assessment	
MedSAM (ViT-B)	28.27% (27.39%, 29.12%)	13.03% (12.09%, 14.01%)	68.73% (67.31%, 70.13%)
LVM-Med (ViT-B)	28.95% (27.98%, 29.90%)	14.35% (13.38%, 15.28%)	67.44% (65.94%, 68.72%)
LVM-Med (R50)	25.00% (25.00%, 25.00%)	5.31% (4.75%, 5.88%)	48.80% (46.97%, 50.85%)
Mammo-CLIP (Enb2)	28.03% (26.69%, 29.29%)	16.09% (15.12%, 17.09%)	61.11% (59.33%, 63.06%)
Mammo-CLIP (Enb5)	31.54% (30.07%, 32.79%)	19.65% (18.53%, 20.71%)	68.28% (66.73%, 69.73%)
MAMA (ViT-B)	39.83% (37.44%, 42.55%)	32.07% (29.66%, 34.75%)	73.55% (72.25%, 74.94%)
VersaMammo (Ours)	37.95% (35.80%, 40.17%)	30.64% (28.00%, 33.24%)	74.95% (73.74%, 76.19%)
	1	Bi-Rads	
MedSAM (ViT-B)	25.00% (25.00%, 25.00%)	14.57% (14.02%, 15.08%)	51.79% (49.26%, 54.16%)
LVM-Med (ViT-B)	24.97% (24.92%, 25.00%)	14.56% (14.01%, 15.06%)	50.93% (48.48%, 53.23%)
LVM-Med (R50)	25.00% (25.00%, 25.00%)	14.57% (14.07%, 15.08%)	48.66% (46.13%, 51.26%)
Mammo-CLIP (Enb2)	25.57% (24.84%, 26.59%)	15.67% (14.30%, 17.32%)	51.27% (48.56%, 53.83%)
Mammo-CLIP (Enb5)	25.00% (25.00%, 25.00%)	14.57% (14.02%, 15.08%)	52.37% (49.64%, 55.01%)
MAMA (ViT-B)	30.13% (27.99%, 32.50%)	22.67% (19.68%, 25.87%)	75.41% (73.47%, 77.51%)
VersaMammo (Ours)	25.54% (24.81%, 26.59%)	12.55% (11.51%, 14.43%)	54.69% (52.20%, 56.87%)
	P	athology	
MedSAM (ViT-B)	35.81% (34.59%, 37.03%)	33.12% (31.74%, 34.41%)	51.89% (49.81%, 53.91%)
LVM-Med (ViT-B)	34.05% (33.13%, 34.94%)	26.56% (25.22%, 27.71%)	52.29% (50.25%, 54.32%)
LVM-Med (R50)	33.33% (33.33%, 33.33%)	19.75% (19.11%, 20.41%)	55.92% (53.91%, 57.87%)
Mammo-CLIP (Enb2)	33.33% (33.33%, 33.33%)	19.75% (19.09%, 20.38%)	47.70% (45.84%, 49.50%)
Mammo-CLIP (Enb5)	33.33% (33.33%, 33.33%)	19.75% (19.12%, 20.37%)	50.30% (48.41%, 52.29%)
MAMA (ViT-B)	33.96% (33.51%, 34.39%)	22.22% (21.32%, 23.18%)	66.19% (64.37%, 67.87%)
VersaMammo (Ours)	38.37% (37.07%, 39.62%)	35.04% (33.67%, 36.35%)	63.12% (61.16%, 65.09%)

Table A23: The effectiveness of different components of the VersaMammo. w/o Mammogram represents the pre-trainined FM without using mammogram data compared with VersaMammo. w/o Stage 2 represents the omission of the second stage of pre-training VersaMammo. w/o Distillation represents the removal of the knowledge distillation component in the second stage of pre-training VersaMammo. w/o Supervision represents the elimination of the supervision component in the second stage of pre-training VersaMammo. w/o CNN represents replacing the CNN-based backbone with a ViT-B in the second stage. * represents the task or the dataset is not seen in pre-training. The best performing model for each metric is **bolded**.

Method	ACC	F1	AUC
W W (0)	Bi-Rads (F 57.03% (55.26%, 58.86%)	RSNA-Mammo)	WO 0007 (WO WART 01 0407)
VersaMammo (Ours)		59.91% (57.93%, 61.84%)	79.92% (78.74%, 81.04%)
w/o Mammogram	33.29% (33.23%, 33.32%)	24.82% (24.80%, 24.84%)	50.55% (49.15%, 52.06%)
w/o Stage 2	54.64% (52.95%, 56.31%)	57.07% (55.27%, 58.81%)	74.61% (73.25%, 75.89%)
w/o Distillation	56.44% (54.81%, 58.01%)	50.21% (48.65%, 51.60%)	78.67% (77.51%, 79.78%)
w/o Supervision	57.77% (56.06%, 59.42%)	53.03% (51.42%, 54.59%)	79.16% (78.03%, 80.33%)
w/o CNN	54.20% (52.45%, 55.96%) Bi-Rad	55.46% (53.65%, 57.22%)	74.39% (72.91%, 75.69%)
VersaMammo (Ours)	54.47% (45.53%, 62.60%)	ls (PDS1*) 58.24% (48.97%, 65.67%)	82.97% (79.26%, 86.46%)
w/o Mammogram	18.10% (15.77%, 20.54%)	16.30% (13.67%, 18.86%)	53.32% (48.08%, 58.58%)
w/o Stage 2	22.12% (19.82%, 24.61%)	19.83% (16.57%, 23.21%)	60.17% (53.15%, 66.53%)
w/o Distillation	26.28% (20.55%, 32.80%)	23.41% (16.65%, 29.94%)	64.15% (60.37%, 68.09%)
w/o Supervision	31.83% (24.44%, 38.98%)	27.32% (20.73%, 33.40%)	62.11% (57.24%, 66.66%)
w/o CNN	31.87% (27.54%, 36.20%)	31.38% (26.90%, 35.96%)	64.84% (59.41%, 69.94%)
w/o civit		ssessment (RSNA-Mammo)	04.0470 (03.4170, 03.3470)
VersaMammo (Ours)	76.22% (74.54%, 77.79%)	76.50% (75.04%, 77.89%)	95.22% (94.87%, 95.55%)
w/o Mammogram	24.18% (23.57%, 24.88%)	21.69% (21.13%, 22.35%)	50.86% (49.66%, 52.03%)
w/o Stage 2	73.18% (71.43%, 74.88%)	73.08% (71.61%, 74.52%)	93.43% (93.02%, 93.83%)
w/o Stage 2 w/o Distillation	74.36% (72.82%, 76.03%)	75.15% (73.72%, 76.65%)	94.51% (94.12%, 94.86%)
w/o Supervision	75.29% (73.60%, 76.99%)	76.01% (74.62%, 77.45%)	94.87% (94.51%, 95.23%)
w/o CNN	73.45% (71.91%, 75.11%)	69.17% (67.83%, 70.69%)	91.81% (91.32%, 92.29%)
W/O CIVIN		n Assessment (PDS1*)	91.81/6 (91.32/6, 92.29/6)
VersaMammo (Ours)	56.67% (50.78%, 62.62%)	49.26% (44.89%, 53.99%)	91.50% (89.14%, 93.70%)
w/o Mammogram	19.68% (12.96%, 26.51%)	6.50% (4.10%, 9.03%)	45.83% (40.09%, 52.18%)
w/o Stage 2			
w/o Stage 2 w/o Distillation	54.42% (47.47%, 61.14%)	50.82% (44.34%, 57.55%)	88.71% (84.87%, 92.01%)
w/o Distination w/o Supervision	36.40% (32.76%, 39.53%) 36.74% (32.53%, 40.43%)	23.35% (21.41%, 25.44%) 24.68% (22.33%, 26.88%)	73.75% (71.04%, 76.49%) 75.42% (72.37%, 78.23%)
w/o CNN	50.05% (43.04%, 57.11%)	44.21% (38.92%, 49.45%)	82.70% (77.80%, 86.96%)
W/O CIVIN		RSNA-Mammo*)	82.10% (11.80%, 80.90%)
VersaMammo (Ours)	55.80% (53.85%, 57.82%)	58.93% (56.01%, 61.87%)	77.30% (74.27%, 80.33%)
w/o Mammogram	50.00% (50.00%, 50.00%)	49.42% (49.42%, 49.42%)	58.84% (55.45%, 62.24%)
w/o Stage 2	50.14% (49.71%, 50.78%)		63.59% (60.23%, 66.96%)
w/o Stage 2 w/o Distillation	55.64% (53.38%, 58.09%)	49.94% (49.27%, 50.98%) 52.13% (50.96%, 53.29%)	66.59% (63.43%, 69.74%)
w/o Supervision	56.24% (53.89%, 58.65%)	52.84% (51.60%, 54.13%)	67.55% (64.30%, 70.56%)
w/o Supervision w/o CNN	50.59% (49.74%, 51.61%)	50.68% (49.60%, 52.00%)	66.02% (62.68%, 69.09%)
W/O CIVIN	Patholog		00.0276 (02.0876, 09.0976)
VersaMammo (Ours)	68.34% (61.72%, 74.26%)	70.84% (63.06%, 77.26%)	82.35% (75.60%, 88.45%)
w/o Mammogram	48.98% (45.32%, 53.06%)	46.22% (41.49%, 51.73%)	51.08% (43.56%, 59.06%)
w/o Stage 2	53.91% (49.52%, 59.06%)	52.84% (46.63%, 59.71%)	64.99% (57.45%, 72.64%)
w/o Stage 2 w/o Distillation	55.65% (49.46%, 62.66%)	55.84% (49.23%, 62.97%)	62.81% (55.45%, 71.23%)
w/o Supervision	59.83% (53.10%, 66.85%)	59.04% (52.60%, 65.63%)	62.49% (54.16%, 70.87%)
w/o CNN	56.53% (51.60%, 61.96%)	56.17% (49.21%, 63.40%)	62.14% (53.76%, 70.12%)
W/O CIVIN		RSNA-Mammo)	02.1470 (33.7070, 70.1270)
VersaMammo (Ours)	81.16% (75.51%, 86.51%)	79.42% (74.38%, 84.53%)	89.92% (86.19%, 93.34%)
w/o Mammogram	51.70% (49.20%, 55.20%)	48.71% (44.49%, 54.27%)	56.55% (48.82%, 64.12%)
w/o Stage 2			56.16% (49.25%, 63.39%)
w/o Stage 2 w/o Distillation	52.75% (49.45%, 56.25%)	50.83% (45.56%, 56.26%)	
	50.00% (50.00%, 50.00%)	43.94% (43.94%, 43.94%) 43.94% (43.94%, 43.94%)	70.68% (64.32%, 76.84%) 61.78% (54.68%, 68.78%)
w/o Supervision w/o CNN	50.00% (50.00%, 50.00%) 71.19% (64.46%, 76.98%)	70.09% (64.05%, 75.54%)	79.40% (73.19%, 84.75%)
W/O CIVIN			79.40% (73.19%, 84.73%)
VersaMammo (Ours)	Finding 54.18% (52.36%, 56.31%)	g* (PDS1*) 57.09% (54.03%, 60.41%)	80.05% (76.71%, 83.30%)
w/o Mammogram	50.00% (50.00%, 50.00%)	49.56% (49.56%, 49.56%)	48.80% (44.91%, 53.04%)
w/o Stage 2	50.43% (49.89%, 51.25%)	50.46% (49.51%, 51.92%)	64.13% (60.45%, 68.15%)
w/o Stage 2 w/o Distillation	54.65% (52.25%, 57.11%)	52.97% (51.35%, 54.59%)	67.78% (63.70%, 71.52%)
w/o Supervision	57.60% (54.78%, 60.43%)	51.91% (50.87%, 53.02%)	67.56% (64.17%, 71.10%)
w/o Supervision w/o CNN	50.53% (49.76%, 51.60%)	50.65% (49.44%, 52.25%)	68.58% (64.89%, 72.09%)
W/O CIVIN		verage	00.0070 (04.0070, 12.0970)
VersaMammo (Ours)	62.98% (58.71%, 67.36%)	verage 63.77% (59.29%, 67.93%)	84.90% (81.86%, 87.39%)
w/o Mammogram	37.01% (35.01%, 39.19%)	32.90% (31.08%, 34.76%)	51.98% (47.59%, 56.66%)
w/o Stage 2	51.45% (49.42%, 56.74%)	50.61% (46.00%, 54.25%)	70.72% (65.16%, 76.28%)
w/o Distillation	51.18% (52.51%, 57.14%)	47.13% (47.50%, 53.11%)	72.37% (69.99%, 74.55%)
w/o Supervision w/o CNN	54.41% (49.80%, 56.34%) 54.80% (51.31%, 58.32%)	48.60% (45.89%, 51.38%) 53.48% (49.95%, 57.06%)	71.37% (67.56%, 75.22%) 73.74% (69.50%, 77.62%)
W/O CIVIN	04.00/0 (01.01/0, 00.02/0)	00.40/0 (45.50/0, 01.00/0)	10.14/0 (05.00/0, 11.02/0)

 ${\bf Table~A24}\hbox{:} \ {\bf The~number~of~images~of~the~public~datasets~used~in~this~study.~Some~datasets~require~permission~for~access.}$

Dataset	Images	Download link
BMCD [67]	1,168	https://zenodo.org/records/5036062
CBIS- DDSM [47]	10,239	https://www.cancerimaging archive.net/collection/cbis-ddsm/
CDD- CESM [48]	1,003	https://wiki.cancerimaging archive.net/pages/viewpage.action?pageId = 109379611
DMID [41]	510	$https://figshare.com/articles/dataset/Digital_mammography_Dataset_for_Breast_Cancer_Diagnosis_Research_DMID/24522883$
INbreast [68]	410	https://www.kaggle.com/datasets/tommyngx/inbreast2012
MIAS [42]	322	https://www.kaggle.com/datasets/kmader/mias-mammography
CSAW-M [43]	10,020	$https://figshare.scilifelab.se/articles/dataset/CSAW-M_An_Ordinal_Classification_Dataset_for_Benchmarking_Mammographic_Masking_of_Classification_full and the control of $
CMMD [69]	5,020	https://www.cancerimaging archive.net/collection/cmmd/
KAU- BCMD [44]	5,662	https://www.kaggle.com/datasets/asmaasaad/king-abdulaziz-university-mammogram-dataset
VinDr- Mammo [39]	20,000	https://www.physionet.org/content/vindr-mammo/1.0.0/
RSNA- Mammo [40]	54,706	$https: \\ //www.kaggle.com/competitions/rsna-breast-cancer-detection/data$
EMBED [36]	480,603	https://registry.opendata.aws/emory-breast-imaging-dataset-embed/
DBT [70]	1,721	https://www.cancerimagingarchive.net/
LAMIS [45]	2,261	$https://github.com/LAMISDMDB/LAMISDMDB_Sample$
MM [71]	745	https://data.mendeley.com/datasets/fvjhtskg93/1
NLBS [72]	23,706	$https://www.frdr-dfdr.ca/repo/dataset/cb5ddb98-ccdf-455c-886c-c97\\50a8c34c2$
Total	612,560	-

Table A26 : The number of patient and mammogram in private datasets (PDS).

Dataset	Patient	Mammogram
PDS1	413	1,586
PDS2	1,506	6,024
PDS3	$1,\!172$	4,688
PDS4	9,462	38,581
PDS5	7,971	33,800
Total	20,524	84,679

 ${\bf Table~A27}\hbox{: Specific label descriptions used for the classification task, where the ground truths are annotated by radiologists.}$

Task	Description	Category description
Composition: breast composition assessment [36, 39–42]	There are two types of classification for breast composition as follows. Breast density [36, 39, 40]: The proportion of glandular and fibrous tissue to fatty tissue in the breast. Background tissue [41, 42]: The type of breast tissue visible on mammograms.	 Breast density Density A: The breast is almost entirely fatty. Density B: There are scattered areas of fibroglandular density. Density C: The breasts are heterogeneously dense, which may obscure small masses. Density D: The breasts are extremely dense, which lowers the sensitivity of mammography. Background tissue Fatty-glandular: Indicates a mix of fatty and fibrous tissues. Fatty: Majority of the breast tissue is fat, which may make it easier to spot abnormalities. Dense-glandular: Indicates high density of glandular tissue, which can sometimes make it hard to detect
Masking: masking potential risk evaluation [43]	The possibility for cancer to be obscured in a mammogram.	tumors due to less fat. • Level 1 to Level 8: Lowest potential to be obscured to highest potential to be obscured.
Finding: abnormality identification [36]	Any unusual or atypical finding in the breast tissue that differs from the normal appearance.	 Normal: No abnormalities. Calcification: Small calcium deposits. Mass: A space-occupying lesion. Architectural distortion: Distortion of normal breast structure. Asymmetry: Unequal tissue density. Miscellaneous: Other rare findings. Nipple retraction: Inward-turning nipple. Suspicious lymph node: Unusual lymph nodes. Skin thickening: Thickened breast skin.
Bi-Rads : Bi-Rads assessment [36, 39, 40, 44, 45]	A system used to categorize the findings on mammograms into levels that describe the risk of cancer.	 Skin retraction: Skin pulling inward. Bi-Rads 0: Need additional imaging evaluation. Bi-Rads 1: Negative. Bi-Rads 2: Benign finding. Bi-Rads 3: Probably benign finding. Bi-Rads 4: Suspicious abnormality.
Bi-Rads 4: Bi-Rads 4 sub- classification [44]	A suspicious finding with a moderate risk of malignancy (2–95%), requiring biopsy for definitive diagnosis.	 Bi-Rads 5: Highly suggestive of malignancy. Bi-Rads 4A: Low suspicion (2–10% malignancy risk). Bi-Rads 4B: Intermediate suspicion (10–50% malignancy risk). Bi-Rads 4C: High suspicion (50–95% malignancy risk).

Table A29: Specific label descriptions used for the classification task, where the ground truths come from additional biopsy or surgical excision.

Task	Description	Category description
Pathology: pathological diagnosis prediction [41, 42, 47, 48]	The definitive tissue diagnosis from biopsy or surgical excision.	 Malignant: Cancerous through biopsy confirmation. Benign: Non-cancerous through biopsy confirmation.
Mastitis: mastitis differentiation [49]	Differentiation between inflammatory breast conditions and cancerous lesions.	 Mastitis: Benign inflammatory condition. Malignancy: Cancerous through biopsy confirmation.
Invasive: invasive status determination [40]	Classification based on whether cancer cells have spread beyond the ducts or lobules into surrounding breast tissue.	 Non-Invasive: Cancer cells are confined within the ducts or lobules and have not invaded surrounding tissues (e.g., Ductal Carcinoma In Situ (DCIS), Lobular Carcinoma In Situ (LCIS)). Invasive: Cancer cells have penetrated the surrounding breast tissue, indicating a more aggressive form of cancer (e.g., Invasive Ductal Carcinoma (IDC), Invasive Lobular Carcinoma (ILC)).
Subtype: molecular subtype prediction [50–52]	Categorized by receptor status and gene expression. The ground truths come from additional surgical excision.	 Luminal A: Characterized by positive estrogen (ER+) and progesterone (PR+) receptors, HER2 negative, and low proliferation index, typically associated with a good prognosis and responsiveness to hormonal therapy. Luminal B: Defined by positive ER, variable PR status, and either HER2 positive or negative, with a high proliferation index, usually associated with a poorer prognosis and may require chemotherapy in addition to hormonal therapy. HER2-enriched: Characterized by negative ER and PR status, but with overexpression of the HER2 protein, often aggressive and requiring targeted HER2 therapies. Triple-Negative Breast Cancer (TNBC): Defined by the absence of ER, PR, and HER2, this subtype is often more aggressive with limited treatment options and a poorer prognosis.

 ${\bf Table~A31} \hbox{: Distribution of breast composition assessment (Background tissue categories)} \\$

Label	Fatty-glandular	Dense-glandular	Fatty
DMID	426	16	66
MIAS	104	112	106

Table A32: Distribution of breast composition assessment (Breast density A-D categories)

Label	Density A	Density B	Density C	Density D
BMCD	40	228	112	20
CBIS-DDSM	425	1,207	952	517
CDD-CESM	8	70	515	329
INbreast	131	144	97	27
EMBED	51,443	$200,\!274$	197,532	$27,\!458$
RSNA-Mammo	3,105	$12,\!651$	$12,\!175$	1,539
VinDr-Mammo	103	$2,\!157$	2,757	$16,\!867$
LAMIS	486	1,343	263	120
PDS1	40	77	1,165	304
PDS2	182	1,544	3,417	851
PDS3	24	216	1,304	185
PDS4	40	1,236	33,241	1,691
PDS5	197	2,214	21,269	4,426

Table A33: Distribution of masking classification task across different mammogram datasets.

Label	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
CSAW-M	720	1,269	1,340	1,931	1,838	1,090	858	974

 ${\bf Table~A34} \hbox{: Distribution of findings classification task across different mammogram datasets.}$

Finding	CBIS-DDSM	CMMD	INbreast	DMID
No finding	0	0	68	0
Mass	1,696	3,220	108	255
Architectural distortion	0	0	3	15
Nipple retraction	0	0	0	0
Calcification	1,542	1,446	308	128
Asymmetry	0	0	14	5
Miscellaneous	0	0	0	93
Dataset	MIAG	W. D. M	EMDED	PDS1
Finding	MIAS	VinDr-Mammo	EMBED	PDSI
No finding	0	0	401,240	1,186
Mass	43	2,228	17,858	0
Architectural distortion	19	221	3,421	0
Nipple retraction	0	58	0	0
Calcification	27	897	22,031	400
Asymmetry	15	750	31,565	0
Suspicious lymph node	0	82	0	0
Skin thickening	0	92	0	0
Skin retraction	0	31	0	0
Mass + Asymmetry	0	0	1,986	0
Asymmetry + Calcification	0	0	1,061	0
Mass + Calcification	0	0	860	0
Mass + Asymmetry + Calcification	0	0	94	0
Mass + Architectural distortion	0	0	84	0
Arch. $distortion + Calcification$	0	0	75	0
Miscellaneous	15	0	0	0

 ${\bf Table~A35} \hbox{: Distribution of Bi-Rads classification task across different mammogram datasets. 0 to 5 represent Bi-Rads 0 to Bi-Rads 5 categories. }$

Label	0	1	2	3	4	5
BMCD	0	88	112	0	192	8
CBIS-DDSM	238	3	356	423	1,543	540
CDD-CESM	0	371	167	136	195	130
INbreast	0	67	220	23	43	49
KAU-BCMD	0	1,863	0	387	100	20
EMBED	$60,\!576$	306,708	$75,\!377$	24,824	10,419	999
RSNA-Mammo	8,249	15,772	$2,\!265$	0	0	0
VinDr-Mammo	0	13,406	4,676	1,060	1,661	1,081
LAMIS	0	910	1,150	0	74	78
PDS1	1	399	785	130	247	24
PDS2	9	8	1,359	1,915	2,343	310
PDS3	2	32	405	1,076	119	91
PDS4	7	400	$7,\!529$	$24,\!359$	$5,\!655$	204
PDS5	399	$8,\!265$	$5,\!666$	6,036	$3,\!187$	2,567

Table A36: Distribution of Bi-Rads 4 subcategories classification task across different mammogram datasets.

Dataset	Label	Bi-Rads 4A	Bi-Rads 4B	Bi-Rads 4C
PDS2		1,075	0	310
PDS4		4,492	475	467
PDS5		903	888	1,392

 ${\bf Table~A37} \hbox{: Distribution of pathology classification task across different mammogram datasets.}$

Label	Benign	Malignant
CBIS-DDSM	1,911	1,327
CMMD	1,112	2,632
DMID	284	153
MIAS	68	51
CDD-CESM	331	331
RSNA-Mammo	53,548	1,158
MM	620	125
NLBS	23,400	306
LAMIS	2,060	152
DBT	70	65
PDS1	1,002	182
PDS2	3,342	2,774
PDS3	1,378	355
PDS4	2,058	297
PDS5	5,099	2,772

 ${\bf Table~A38}\hbox{: Distribution of mastitis classification task across different mammogram datasets.}$

Label	Malignant	Mastitis
PDS5	5,099	674

 ${\bf Table~A39} \hbox{: Distribution of invasive classification task across different mammogram datasets}.$

Label	Non-invasive	Invasive
RSNA-Mammo	53,888	818

 ${\bf Table~A40} \hbox{: Distribution of subtype classification task across different mammogram datasets}.$

Labe	Luminal A	Luminal B	HER2-enriched	Triple-negative
CMMD	304	752	270	172
PDS5	1,212	2,995	266	257