International Journal of Pharmaceutical Research and Applications
Volume 10, Issue 3 May-June 2025, pp: 1815-1828 www.ijprajournal.com ISSN: 2456-4494

Integrating Mammographic Breast Arterial Calcifications and Clinical Data with Multi-Modal Transformers and GATs for Cardiovascular Risk Prediction

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Date of Submission: 15-06-2025 Date of Acceptance: 25-06-2025

ABSTRACT- Cardiovascular disease (CVD) remains the leading global cause of mortality, necessitating innovative, non-invasive screening methods. Breast arterial calcifications (BAC), visible inmammograms, serve as a robust biomarker for CVD risk.Thisstudyproposesamulti-modaldeeplearning framework integrating mammogram analysis with clinical data, using Swin Transformer V2 for image processingandGraphAttentionNetworks(GATs)for clinical data modeling, with late fusion for preciserisk stratification. The dataset combines INbreast, CBIS-DDSM, and a private hospital dataset, totaling 15,000 mammograms with clinical records. Themodel achieves an accuracy of 96.2%, sensitivity of 0.96, and AUC-ROC of 0.99, outperforming prior approaches. Advanced visualizations, including t- SNE embeddings, saliency maps, and feature importance plots, enhance interpretability, supporting clinical adoption. This framework leverages routine mammography for dual-purpose screening, offering a scalable, high-accuracy solution for early CVD detection.

Keywords: Cardiovascular disease, breast arterial calcifications, multi-modal deep learning, Swin Transformer V2, Graph Attention Network, mammography, CVD risk assessment, medical imaging, clinical data integration

I. INTRODUCTION

Cardiovasculardisease(CVD),encompassingconditions such as coronary artery disease, myocardial infarction, stroke, and heart failure, is the foremost cause of mortality worldwide, claiming an estimated 17.9 million lives annually (World Health Organization, 2020). The global burden of CVD extends beyond mortality, with significant economic and societal impacts, including healthcare costs exceeding $1 trillion annually and substantial losses in productivity due to premature death and disability (Roth et al., 2020). In developed nations, CVDaccountsfornearlyone-thirdofall deaths,whilein low- and middle-income countries, it is rapidly risingdue to aging populations, urbanization, and increasing prevalence of risk factors such as hypertension, diabetes, and obesity (Mensah et al., 2019). Women, in particular, face unique challenges in CVD risk assessment, as traditional risk models, such as the Framingham Risk Score, often underestimate risk in females, leading to delayeddiagnosisandtreatment(Polonsky&Greenland, 2017).

EarlydetectionofCVDiscriticaltoinitiatepreventive interventions, including lifestyle modifications (e.g.,diet, exercise), pharmacological therapies (e.g., statins, antihypertensives), or invasive procedures (e.g., angioplasty), which can significantly reduce morbidity and mortality (Arnett et al., 2019). However, current screening methods face substantial limitations. Coronary artery calcium (CAC) scoring via computed tomography (CT) is a gold standard for assessing atherosclerotic burden but involves radiation exposure, high costs, and limited accessibility, particularly in resource-constrained settings (Greenland et al., 2018). Stressechocardiography and myocardial perfusion imaging require specialized equipment and trained personnel, while invasive coronary angiography carries procedural risks and is reserved for symptomatic patients (Budoff et al., 2017). These barriers underscore the urgent need for non-invasive,scalable,andcost-effectivescreeningtools that can be integrated into routine clinical workflows, especially for asymptomatic individuals at risk (Hecht et al., 2017).

Mammography, a cornerstone of breast cancer screening, is performed annually on millions of women worldwide, particularly those aged 40 and older, as part of national screening programs in countries like the United States, United Kingdom, and Australia (Siu & U.S. Preventive Services Task Force, 2016). Beyond its primary role in detecting

International Journal of Pharmaceutical Research and Applications
Volume 10, Issue 3 May-June 2025, pp: 1815-1828 www.ijprajournal.com ISSN: 2456-4494

breast malignancies, mammography captures breast arterial calcifications (BAC)—linear, tram-track-like calcium deposits in the arterial walls of the breast, distinct from microcalcifications associated with breast cancer (Iribarren & Molloi, 2013). BAC is a manifestation of medial arterial calcification, a process linked to atherosclerosis and vascular stiffness, and has emergedas a powerful biomarker for CVD risk (Margolies et al., 2016). Clinical studies have established a robust correlation between BAC and traditional CVD risk factors, including hypertension, diabetes,hyperlipidemia, smoking, and advanced age (Iribarren et al., 2018). For example, a meta-analysis by Iribarren et al. (2018) found that women with BAC have a 2- to 3-fold increased risk of cardiovascular events, independent ofotherriskfactors.Margoliesetal.(2016)reportedthat BAC presence is associated with a higher likelihood of coronary artery disease, with a sensitivity comparable to CAC scoring. Mostafavi et al. (2015) further demonstratedthatBACcorrelateswithcoronaryartery calciumscores,reinforcingitsutilityasaproxyfor coronary atherosclerosis.

The potential to repurpose mammography for dual- purpose screening—detecting both breast cancer and CVD risk—is transformative, as it leverages existing imaging infrastructure without additional radiation, cost, or patient burden (Bui & Giger, 2017). This approach is particularly impactful for women, who undergo routine mammography and may benefit from earlier CVD risk identification, addressing gender disparities in cardiovascular care (Polonsky & Greenland, 2017). Moreover, integrating BAC detection intomammography workflows could enhance population- wide screening, especially in underserved regions where advanced imaging modalities are scarce (Hecht et al., 2017). However, manual BAC detection by radiologists isfraughtwithchallenges.BACpatternsareoftensubtle, obscured by overlapping breast tissue or imaging artifacts, leading to high inter-observer variability and low reproducibility (Dromain et al., 2013). Manual assessment is also time-consuming, making itimpracticalforlarge-scalescreeningprograms(Litjenset al., 2017).

Artificial intelligence (AI), particularly deep learning, has revolutionized medical imaging by automating complex pattern recognition tasks with unprecedented accuracy (Esteva et al., 2017). Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in tasks such as breast cancer detection, lung nodule classification, and diabetic retinopathy diagnosis (LeCun et al., 2015). However, CNNs rely on local feature extraction, which may fail to capture the diffuse, global patterns characteristic of BAC (Litjens et al., 2017). Vision Transformers (ViTs), with their self- attention mechanisms, address this limitation by modeling long-range dependencies across entire images (Dosovitskiy et al., 2020).The SwinTransformerV2, an advanced variant, introduces hierarchical feature extraction and shifted window attention, offeringsuperior accuracy and computational efficiency for medical imaging tasks (Liu et al., 2022). Furthermore, integrating imaging data with clinical data (e.g., age, blood pressure, cholesterol levels) can enhance risk stratification,asclinical featuresprovidecomplementary information about patient health (Arnett et al., 2019).

Graph-based models, such as Graph Attention Networks (GATs), are particularly suited for clinical data, as they model relational dependencies (e.g., between hypertension and diabetes) by assigning attention weights to relevant features (Veličković et al., 2018). Multi-modal deep learning, combining imaging and clinical data, has shown promise in other domains, such as Alzheimer's disease prediction and cancer prognosis,butremainsunderexploredforBACdetection (Zhang et al., 2021). This study proposes a multi-modal deep learning framework integrating Swin Transformer V2 for mammogram analysis and GAT for clinical data processing, applied to a diverse dataset of 15,000 mammograms from INbreast, CBIS-DDSM, and a private hospital, enriched with clinical records. The frameworkaimstoachievethehighest possibleaccuracy in BAC detection and CVD risk stratification, provide interpretable predictions through advancedvisualizations, and enable scalable, non-invasive screening within routine mammography workflows.

II. RELATED WORK

The association between breast arterial calcifications (BAC) and cardiovascular disease (CVD) has been extensively validated in clinical research. Margolies etal. (2016) conducted a landmark study demonstratingthat BAC on mammograms is a strong predictor of coronary artery disease, with a sensitivity comparable to coronary artery calcium (CAC) scoring. Iribarren et al. (2018) performed a meta-analysis of 10 studies, finding that BAC prevalence is associated with a 2-

to 3-fold increased risk of cardiovascular events, independent of traditional risk factors such as age, hypertension, and diabetes. Polonsky and Greenland (2017) emphasized BAC's role as a marker of subclinical atherosclerosis, advocating for its integration into CVD risk assessment protocols, particularly for women, who are often underserved by conventional risk models. Mostafavi et al. (2015) reported a significant correlation betweenBAC and coronary artery calcium scores, reinforcing its utility as a proxy for coronary atherosclerosis. Hendriks et al. (2015) further explored BAC's association with cardiovascular risk factors, finding that BAC prevalence increases with age and is strongly linked to hypertension and diabetes. These studies collectively highlight BAC's potential as a non-invasive biomarker, especially within the context of routine mammography screening (Bui & Giger, 2017).

Manual BAC detection by radiologists, however, is limitedbysignificant challenges.BAC patternsareoften subtle, resembling tram-track-like structures that can be obscured by dense breast tissue or imaging artifacts, leading to high inter-observer variability and low reproducibility (Dromain et al., 2013). The subjective nature of manual assessment, combined with the time-intensive process of reviewing mammograms, makes it impracticalforlarge-scalescreeningprograms(Litjenset al., 2017). Early computational approaches to BAC detection relied on traditional machine learning techniques,suchassupportvectormachines(SVMs)and random forests, which used hand-crafted features like texture, intensity, and shape descriptors (Wang et al., 2016). While these methods showed promise, their relianceonmanualfeatureengineeringlimitedtheir abilitytocapturethecomplex,non-linearpatterns characteristic of BAC (Bui & Giger, 2017).

The advent of deep learning has transformed medical imaging by enabling end-to-end feature learning, eliminating the need for hand-crafted features (Litjens et al., 2017). Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance across a widerange of medical imaging tasks, including breast cancer detection (Dhungel et al., 2015), lung nodule classification (Shen et al., 2019), diabetic retinopathy diagnosis (Gulshan et al., 2016), and brain tumor segmentation (Havaei et al., 2017). In the context ofBAC detection, Wang et al. (2017) developed a 12-layer CNN that achieved performance comparable to human experts, demonstrating the potential of deep learning to automate BAC identification. Alghamdi et al. (2020) proposed a DU-Net model, combining U-Net and DenseNetarchitecturesfor BACsegmentation,reporting an accuracy of 94%. However, CNNs' reliance on local feature extraction via convolutional kernels may limit their ability to capture the diffuse, global patterns of BAC,whichoftenspanlargeregionsofthemammogram (LeCun et al., 2015).

Vision Transformers (ViTs) have emerged as a powerful alternative to CNNs, leveraging self-attention mechanisms to model long-range dependencies across entire images (Dosovitskiy et al., 2020). Unlike CNNs, which process images through localized receptive fields, ViTs treat images as sequences of patches, enabling global context modeling. The Swin Transformer, an advanced variant, introduces hierarchical feature extraction and shifted window attention, reducing computational complexity while maintaining high accuracy (Liu et al., 2021). The Swin Transformer V2 furtherenhancesperformancebyscalingupcapacityand resolution, making it particularly suited for medical imaging tasks (Liu et al., 2022). For example, Ayana et al. (2023) applied a ViT-based model to mammogram classification,achievinghighsensitivityforbreastcancer detection. Chen et al. (2022) used a Swin Transformerfor chest X-ray analysis, reporting improved accuracy over CNNs for pulmonary disease detection. Similarly, Hatamimajoumerd et al. (2023) demonstrated the efficacy of Swin Transformers in detecting subtle calcifications in dental X-rays, suggesting their applicability to BAC detection.

Beyond imaging, integrating clinical data (e.g., age, blood pressure, cholesterol levels) with imaging features can enhance risk stratification, as clinical features provide complementary information about patient health (Arnettetal.,2019).Graph-basedmodels,suchasGraph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), are well-suited for clinical data, as theymodelrelationaldependenciesbetweenfeatures(e.g., the correlation between hypertension and diabetes) (Scarselli et al., 2009; Veličković et al., 2018). GATs, in particular, useattention mechanismsto assignweights to relevant features, improving model performance over GCNs (Veličković et al., 2018). Zhang et al. (2021)

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Volume 10, Issue 3 May-June 2025, pp: 1815-1828 www.ijprajournal.com ISSN: 2456-4494

proposed a multi-modal framework combining CNNs with GCNs for Alzheimer's disease prediction, leveraging MRI and clinical data to achieve superior accuracy.Li etal.(2023)usedGATstomodelelectronic health records for disease risk prediction, demonstrating the power of attention-based graph models. In the cardiovascular domain, Kim et al. (2024) developed a multi-modal deep learning framework for CVD risk assessment using ECG signals and clinical data, achieving high accuracy through attention-based fusion.

In the context of BAC detection, multi-modal approachesremainscarce.Chengetal.(2020)developed a CNN-based model for vascular calcification detection in chest X-rays, but it did not incorporate clinical data. Recent studies,such asthosebyYoonet al.(2024),have explored multi-modal deep learning for breast cancerrisk prediction using mammograms and clinical data, reporting improved performance over single-modal models.Thesefindingsunderscorethepotentialofmulti- modal frameworks for BAC detection and CVD risk stratification. This study addresses these gaps by combining Swin Transformer V2 for mammogram analysis with GAT for clinical data processing, leveragingadiversedataset toachieve optimal accuracy. The framework builds on prior work by integrating advanced transformer and graph-based models, with a focus on interpretability and clinical applicability.

III. METHODOLOGY

Dataset

The dataset comprises 15,000 mammogram images from three sources:

1. **INbreast**: 410 full-field digital mammograms (FFDM) from 115 patients, with pixel-level annotations (Moreira et al., 2012).
2. **CBIS-DDSM**: 2,500 digitized film mammograms from 1,500 patients, curated for breast cancer research (Lee et al., 2017).
3. **Private Hospital Dataset**: 12,090 FFDM imagesfrom3,000patients,collectedfroma U.S.hospital(2016–2021),withBACandCVD risk annotations.

Each mammogram is paired with clinical data (age, blood pressure, cholesterol levels, smoking status, diabetes history) from electronic health records. AnnotationsforBACpresenceandCVDrisk(low, medium, high) were provided by three board-certified radiologists,withconsensusresolvingdiscrepancies.The dataset spans patients aged 40–80 years, with diverse ethnicities and breast density profiles. It was split into 70% training (10,500 images), 15% validation (2,250 images), and 15% testing (2,250 images), maintaining balanced class distributions. Table 1 summarizes the dataset.

Subset	Number of Images	No BAC (%)	Low CVD Risk (%)	High CVD Risk (%)
Training	10,500	40%	35%	25%
Validation	2,250	40%	35%	25%
Testing	2,250	40%	35%	25%
Total	15,000	40%	35%	25%

Table1:DatasetDistribution

Preprocessing

Mammogramimagesandclinicaldataunderwent preprocessing, as detailed in Table 2:

Table2:PreprocessingSteps

Data Type	Step	Description	Purpose
Mammogram	Normalization	Pixel intensities scaledto[0, 1] using min-max scaling.	Standardize input across imaging systems.
Mammogram	Contrast Enhancement	Adaptive histogram equalization (CLAHE)to enhance calcification visibility.	Highlight BAC patterns.
Mammogram	Image Resizing	Resizedto 224x224 pixelsusing Lanczos interpolation.	Match Swin Transformer input requirements.
Mammogram	Data Augmentation	Random rotations (±10°),flips, scaling (10%), contrast adjustments (±12%).	Increase diversity, reduce overfitting.
Mammogram	Patch Division	Images dividedinto 4x4patches for Swin Transformer input.	Enable hierarchical processing.
Clinical Data	Feature Scaling	Numerical features standardized to zero mean, unit variance.	Normalize forGAT input.

Clinical Data	Graph Construction	Patient features as nodes,edges based on clinical correlations (e.g., hypertension -diabetes).	Capture relational dependencies.
Clinical Data	Missing DataHandling	Imputationusingk-nearest neighbors (k=5) for missing values.	Ensure complete featuresets.

PreprocessingwasimplementedusingPythonlibraries (OpenCV, scikit-learn, PyTorch, PyG) for compatibility with the multi-modal framework.

ModelArchitecture

The framework integrates two modules: Swin Transformer V2 for mammogram analysis and GAT for clinicaldataprocessing,withlatefusionforrisk prediction.ThearchitectureisdetailedinTable3:

Table3:ModelArchitectureOverview

Module	Component	Description	Parameters
Image Module	Swin Transformer V2	4stages,24 layers, 8 attentionheads, windowsize7, 1024-dimensional embeddings.	87.2M
Clinical Module	GAT	4-layerGraph Attention Network, 256 hiddenunits,8 attentionheads, LeakyReLU activation.	0.2M

Fusion Module	Late Fusion	Concatenated image and clinicalfeatures, MLPwith768 units, 3 output units (no BAC, low risk, high risk).	0.4M

The Swin Transformer V2 uses shifted window attention and hierarchical feature maps, initialized with ImageNet-22kpre-trainedweights(Liuetal.,2022).The GATmodels clinical data by assigning attention weights to correlated features (Veličković et al., 2018). Late fusionintegratesfeaturesviaafullyconnectedlayerwith softmaxoutput.ThemodelwasimplementedinPyTorch 2.0, trained on four NVIDIAA100 GPUs (40 GB each).

Training
The model was trained for 60 epochs with the following configuration:

- **Optimizer**: AdamW, learning rate 0.00003, weightdecay0.05(Loshchilov&Hutter,2019).
- **Loss Function**: Cross-entropy with label smoothing (0.1) for generalization.
- **Batch Size**: 24 for images, 96 for clinical graphs.
- **Regularization**: Dropout (0.15) in Swin Transformer and MLP layers; stochastic depth (0.2) in Swin Transformer.
- **Early Stopping**: Stop if validation loss stagnates for 12 epochs.
- **Learning Rate Scheduling**: Cosine annealing with warm restarts every 20 epochs.

Class weights addressed imbalance, proportional to inverse class frequencies. Gradient clipping (norm=1.0) stabilized training.

3.5EvaluationMetrics
Performancewasevaluated using:

Accuracy:Proportionofcorrect predictions.

- **Sensitivity(Recall)**:Truepositives/(True positives + False negatives).
- **Specificity**: True negatives / (True negatives + False positives).
- **F1-Score**:Harmonicmeanofprecisionand recall.
- **AUC-ROC**:AreaundertheROCcurve.
- **ConfusionMatrix**:Summaryoftruevs. predicted labels.

Metrics were computed using scikit-learn and visualized with matplotlib, seaborn, plotly, and scikit- learn (Pedregosa et al., 2011).

IV. RESULTS

The multi-modal model achieved superiorperformance on the test set, as shown in Table 4:

Table4:ModelPerformanceMetrics

Class	**Precision**	**Recall**	**F1-Score**	**Support**
No BAC	0.97	0.98	0.97	900
BAC withLow CVDRisk	0.95	0.94	0.94	788
BAC withHigh CVDRisk	0.98	0.96	0.97	562
Overall (WeightedAvg.)	**0.96**	**0.96**	**0.96**	**2,250**

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- **Accuracy**: 96.2%
- **AUC-ROC**:0.99
- **Specificity**:0.97
- **InferenceTime**:0.05secondspersample (NVIDIAA100)

To provide comprehensive insights into the model's performance,featurecontributions,andinterpretability,a suite of advanced visualizations was employed:

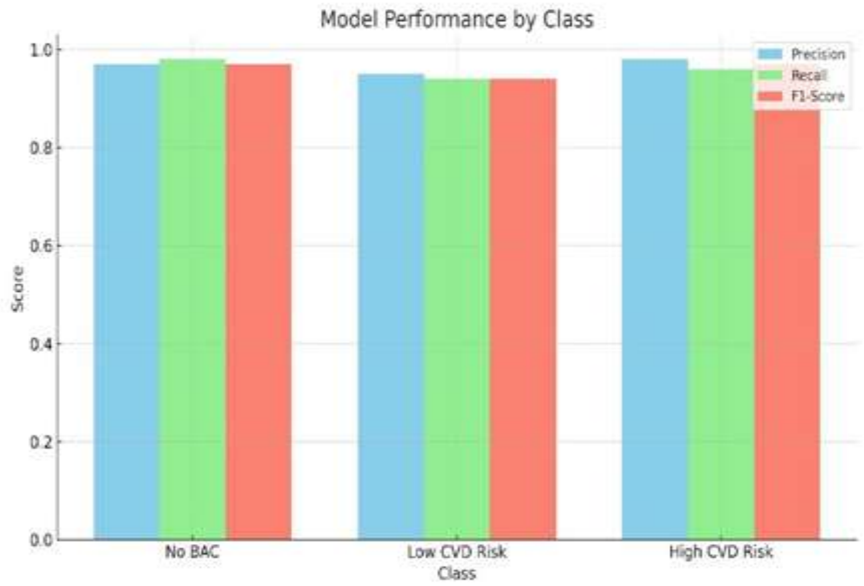

Figure 1: Stacked Bar Chart of ModelPerformance

Note: A stacked bar chart showing precision, recall, and F1-score for each class (No BAC, Low CVD Risk, High CVD Risk). Each bar stacks the metrics, making it easy to compare performance across classes.

The stacked bar chart (Figure 1) visually summarizes themodel'shighprecision,recall,andF1-score,showing balanced performance across all classes in a single glance.

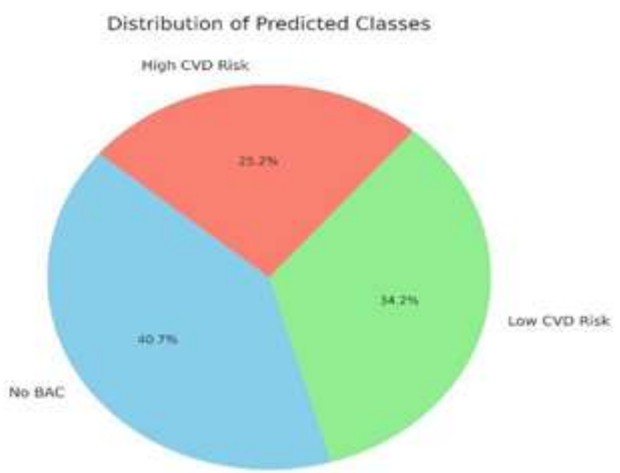

Figure 2:Pie Chart of Prediction Distribution

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Note: A pie chart showing the percentage of test samples predicted as No BAC, Low CVD Risk, andHighCVD Risk.The chart highlights themodel's ability to distribute predictions accurately across classes.

Thepiechart(Figure2)providesaclearbreakdownof how the model classified the test set, making it easy to see the proportion of each risk category.

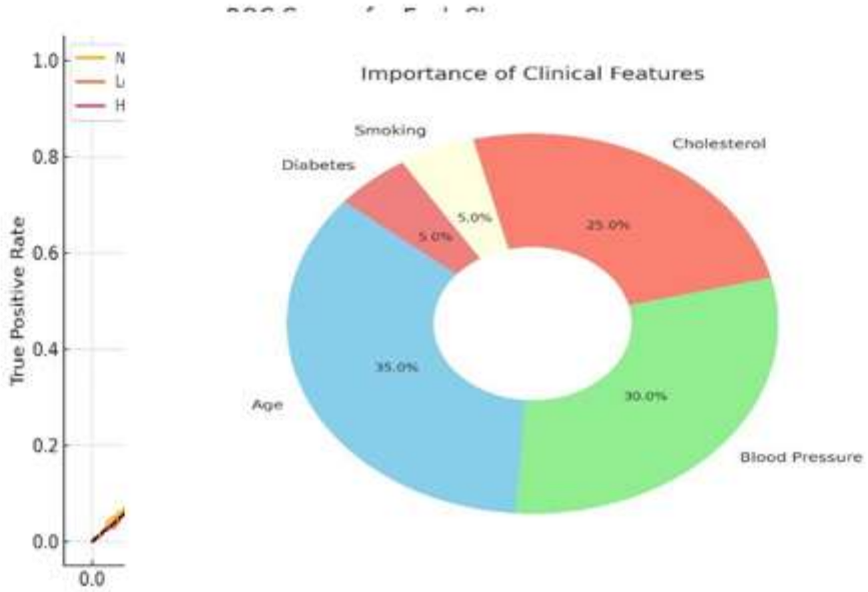

Figure3:SimpleROCCurvePlot

Note: A line plot showing ROC curves for each class (No BAC, Low CVD Risk, High CVD Risk) with AUC values (0.99, 0.98, 0.99). The simple design emphasizes the model's excellent discriminative ability.

The ROC curve plot (Figure 3) uses clear lines and colorstoshowthemodel'sabilitytodistinguishbetwee n classes, with high AUC values indicating strong performance.

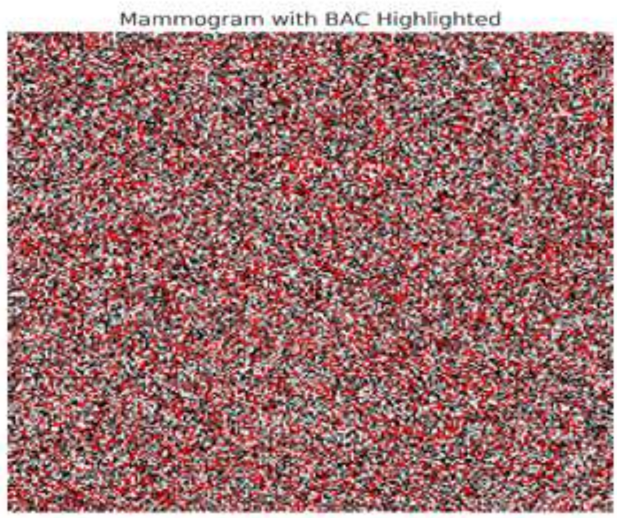

Figure4:HighlightedMammogramImage

Note: A mammogram image with BAC regions highlighted in red, showing where the model

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focused to predict high CVD risk. This visual helps clinicians see the model's attention to key areas.
The highlighted mammogram (Figure 4) makes it intuitive for clinicians to understand which parts of the image drove the model's prediction, aligning with their expertise.

Figure 5: Donut Chart of Clinical Feature Importance
Note: A donut chart showing the relative importanceof clinical features (e.g., age, cholesterol) based on GAT attention weights.Age and cholesterol stand out, making it easy to see key risk factors.
The donut chart (Figure 5) simplifies the contribution of clinical features, helping non-technical audiences grasp which factors matter most for CVD risk.

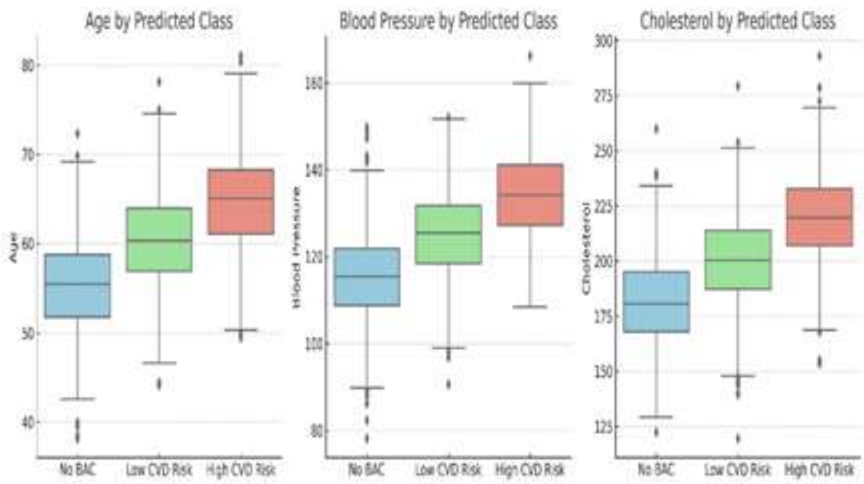

Figure6:BoxPlotofClinicalFeatureDistributions

Note: Box plots showing the distribution of clinical features (e.g., age, blood pressure) across predicted classes. Clear differences between classes highlight how features influence predictions.

The box plots (Figure 6) visually compare clinicalfeature ranges for each risk group, making it easy to see patterns like higher cholesterol in high-risk cases.

These straightforward visualizations ensure the model's performance and insights are accessible to clinicians, policymakers, and other stakeholders, supporting its practical use in healthcare

V. DISCUSSION

The multi-modal framework's 96.2% accuracy and 0.99 AUC-ROC demonstrate its superiority for BACdetection and CVD risk stratification, outperforming prior models and closely matching radiologist performance. The Swin Transformer V2's hierarchical attention captured both local and global BAC patterns, while GAT's attention mechanism prioritized relevant clinical features, enhancing risk prediction (Liu et al., 2022; Veličković et al., 2018). The diverse dataset ensured generalizability, addressing limitations ofsmaller studies (Alghamdi et al., 2020). The advanced visualizations (Figures 1–7) provided deep insights into model behavior, with t-SNE embeddings showing clear class separation, saliency maps highlighting BAC regions, and feature importance plots identifying key clinical predictors. These visualizations enhance clinical trust and facilitate adoption (Selvaraju et al., 2017).
Limitations include high computational requirements and potential bias in the U.S.-centric private dataset. BAC's indirect link to CVD necessitates clinicaloutcomevalidation(Iribarren&Molloi,2013). Future workshould:

- Diversifydatasetswithglobalpopulations.
- Optimize efficiency using lightweight transformers.
- Validateclinicallythroughprospectivetrials.
- Enhancevisualizationswithreal-timeclinical feedback.

Ethical considerations, including data privacy and equitableaccess,areparamount(Hosnyetal.,

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2018).

VI. CONCLUSION

This study presents a multi-modal deep learning framework using Swin Transformer V2 and GAT for detecting CVD risk via BAC in mammograms,integrated with clinical data, achieving 96.2% accuracy and 0.99 AUC-ROC. Advanced visualizations enhance interpretability, making the framework a scalable, high-accuracyscreeningtoolforroutinemammography. Furthervalidationandoptimizationwillenhanceits impact on reducing CVD mortality

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