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# Advanced Multi-View Convolutional-Recurrent Network for Breast Cancer Classification and Detection

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## Abstract

Breast cancer is one of the most common and deadliest diseases that women globally experience. An early and accurate diagnosis may improve the chance of treatment success and increased survival rate. Current traditional diagnostic techniques used for breast cancer like mammography, ultrasound, and MRI are largely annotated by experts, creates variability and inconsistency in the diagnosis. New developments in artificial intelligence (AI) and deep learning could offer promising solutions for touchless high-precision breast cancer diagnosis. This study proposes an Advanced Multi-View Convolutional-Recurrent Network (AMVCRN), a unique design that integrates Convolutional Neural Networks used for extracting spatial features, with Recurrent Neural Networks, using Gated Recurrent Units – GRUs, for temporal sequence modeling. The hybrid model allows greater analysis of tumor features from multi-view images collected from different modalities and angles. The intended outcomes are to improve classification accuracy and reduce errors in persecution. Ultimately, it is intended to yield and sound a decision support system for clinical radiologists.

**Keywords:** Detecting Breast Cancer, Multi-View Imaging, Convolutional Neural Networks (CNNS), Recurrent Neural Networks (RNNS), Gated Recurrent Units (Grus), Deep Learning, Medical Image Analysis, Hybrid Models, and Computer-Aided Diagnosis.

## 1 Introduction

Breast cancer remains one of the leading cancer deaths around the world as far as women are concerned. Early and accurate diagnosis has a major part in the treatment for breast cancer and survival. Traditional, human, or with the help of human interpretations of mammograms, ultrasound imaging or MRIs require a high level of expertise and generally result in inter-observer variability and inconsistent diagnoses. Loizidou et al., (2023) with the introduction of artificial, intelligent deep learning, we have been able to better automate, in an objective and accurate selection of breast cancer. Convolutional Neural Networks (CNNs) in particular have been highly effective in extracting spatial features from medical imaging

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studies to classify human tumors as either benign or malignant types (Labonno et al., 2025). However, depth of field measurement captures considerable dimensions of the tumor's characteristics; therefore, a model cannot fully capture these in a single view. On this basis, multi-view imaging methods are targeted to use data from different angles or modalities for a better diagnostic view (Labonno et al., 2025). The architecture also injects RNNs with the potential in Gated Recurrent Units (GRU), training the model to learn time-lapse and sequential changes associated with tumors. Thus, the study introduced an advanced multi-view convolutional-recurrent network (AMVCRN) that combines the power of spatial feature extraction attained through CNNs with the temporal modeling ability of RNNs to support better classification improvement as well as assist radiologists in producing accurate diagnoses (Qasrawi et al., 2024).

Breast cancer poses a significant challenge to health worldwide and remains among the highest-ranked cancers diagnosed among females (Assegid & Ketema, 2023). In its recommendations, the World Health Organization (WHO) states that the early detection of breast cancer is critical to its management, as it enhances the chances of successful therapy and long-term survival. The earlier the stage of breast cancer, the more therapeutic options there are; the risk of metastasis decreases, and the overall quality of life is better for the patient. Early-stage breast cancer is often perceived as manageable, with localized cases approaching 99% survival rates, while the number of advanced cases (Sung et al., 2021) drop off sharply (American Cancer Society, 2023). The risks differ, however, with density of breast tissue, mis-ordering programming in the imaging, and limited access to experienced radiologists in some case, even with existing screening methods including mammography and ultrasonography, there are still hurdles to early diagnosis. AI developments, particularly deep learning based, have opened the doors for much more accurate, efficient, and automated evaluation of medical imaging that can change the possibilities of early breast cancer detection. AI programs use Convolutional Neural Networks (CNNs) (Ahmed, 2024) extensively to perform even at the most subtle pathological changes that are undoubtedly missed by even the most vigilant human. Adding a second view of the images through time into a Recurrent Neural Network (RNN) can enhance the "magnification" for distinguishing nuances in tumor characteristics. These intelligent systems tremendously benefit radiologists by reducing inter-observer variability, increasing their own diagnostic confidence, enhancing patient outcomes, and improving clinical workflows (Shen et al., 2019; Lotter et al., 2021). Early and accurate diagnosis is critical to successful patient treatment and outcomes. With a diverse range of imaging modalities, including mammography, ultrasound, and MRI, these imaging procedures are still in the realm of clinical diagnostics. Digital mammography remains the gold standard in imaging due to its specificity; however, it is much less sensitive in the case of women with dense breast tissue (Lee et al., 2010). Digital breast tomosynthesis (DBT) is a new modality in which 3D imaging of breasts is offered using tomography and enhances detection capabilities in dense-breasted women (Conant et al., 2019; Berg et al., 2008).

Despite their common use today, these traditional imaging modalities have numerous limitations. Mammography can yield false negatives in individuals with dense breast tissue, and consequently delay diagnosis and treatment (American Cancer Society, 2020). Although MRI appears to have high sensitivity, it is commonly associated with low specificity, which leads to false positives and unnecessary biopsies. An MRI can also be expensive and unavailable in all practice environments (Teixeira et al., 2017). While ultrasound is useful, it is highly operator dependent, thereby creating diagnostic variability. Thus, the limitations of these imaging modalities emphasize the need for more sophisticated, automated, and standardized diagnostic modalities that provide excellent accuracy and clinical decision-making reliability across heterogeneous patient cohorts.

**Key Contributions of the Research**

- We have developed a new model, and its hybrid topology combines CNNs with some RNNs (i.e., GRU), to extract spatial and temporal features from multi-view medical images. The diagnostic utility of this improved capability is potentially much higher than traditional single-view CNN methods.
- This hybrid topology can increase the diagnostic utility by making more composite representations of tumor or other abnormal feature characteristics by looking at multiple perspectives and multimodalities, such as mammography, ultrasound, or MRI. The issue with analyzing single modality, or single-angle images, is that they may have fundamental limitations or shortcomings when making meaningful inferences related to tumor characteristics.
- Our goal in this research is to produce an AI tool that will have clinical utility which will be useful to radiologists when making effective and accurate decisions, there will be less variation of diagnosis, while increasing classification performance and ultimately early intervention resulting in better outcomes for patients.

The outline of the paper chapter-wise is as follows: Chapter II reviews the related literature, while Chapter III gives a brief view of the theoretical framework, key concepts, and methodologies. Chapter IV evaluates the experimental result. Chapter V contains results and discussions, whereas Chapter VI summarizes the most important findings and suggestions for further research.

## 2 Literature Review

Zhu et al., (2023) provide an overview of CNN-based diagnosis for breast cancers in different imaging modalities. CNN applications have been classified into three general assignments: classification, detection, and segmentation. It also discusses the workarounds, including insufficient and heterogeneous databases for training deep CNN models, associated high computation costs, and overfitting during training from fewer instances, pointing to a need for large datasets with the appropriate training methodologies (Aldosari, 2024; Udayakumar et al., 2023).

Wong et al., (2020) the narrative literature review by Wong et al. covers everything noted about the target that Wong et al. identified about using the medium to scrutinise how CNNs have been and can be applied for the analysis of MW images for breast cancer detection. The review highlights in particular the inconsistencies in databases for studies and imaging parameters, and notes some of the challenges in developing standards for approving the performance of CNNs. As a result, it encourages authors to consider spending their effort designing standard datasets suitable for this. In so doing, CNNs may be extremely useful for patients by ultimately providing above-standard quality in the accuracy, consistency, and efficiency of diagnoses made by doctors in radiology.

This contrasting literature found that (Al Tawil et al., 2024) adequately researched all three network architectures: VGG19, AlexNet, and ResNet50, for breast cancer pattern prediction. The findings revealed that ResNet50 demonstrated greater accuracy than the other models, and also a higher F-score was achieved, which means it has greater capacity for extracting features and classifying them. The study highlighted the likelihood of better performance of each of the different CNNs developed across the different diagnostic characteristics for breast cancer, as well as other social-demographic characteristics.

Manigrasso et al., (2025) provided a comprehensive analysis of the graph- and transformer-based approaches to multi-view mammography classification, which concluded that transformer-based approaches yielded the highest classification performance, particularly with the Swin-v2 backbone.

Chen et al., (2024) combined multi-view mammography with contrastive language-image pre-training in what they are calling Mammo-CLIP. The use of text in the model enables the model to be more robust in terms of differentiation of mammographic features. The method achieved better results than its predecessors, showcasing the advantage of multimodal data for breast cancer detection.

Yu et al., (2025) describe multi-view learning as enhancing learning performance using multiple data sources. They classify existing works into four categories: multi-view classification, semi-supervised classification, clustering, and semi-supervised clustering approaches. Apart from addressing the common challenges in the field, for example, view inconsistency, fused-view optimality, and software scalability, they show the potential of multi-view learning in handling many challenging real-world scenarios.

Azad et al., (2024) extensively review Transformer-based models for medical imaging, where long-range dependencies and spatial correlations come into play. Although transformers are the focus of the review, the authors detail the use of RNN-CNN attention mechanisms to improve the processing of sequential data and model performance for the analysis of medical images.

Mall et al., (2023) build upon advances in deep neural networks for the processing (Ziarani et al., 2014) of medical images, including RNNs: disadvantages, advantages of different architectures, public datasets, and future research, which makes it a must-read within the rapidly evolving sphere of deep learning as applied to medical imaging.

Mienye et al., (2024) provide examples of different architectures of RNNs, from LSTMs to GRUs, and discuss applications in various domains, including signal processing, bioinformatics, and outlier detection. It emphasizes the flexibility of RNNs to allow for sequential patterns in data and how they are combined with other models to improve performance in various mobile applications.

In the current literature, it is documenting how deep learning methods are evolving quickly, specifically with CNNs, RNNs, and transformer-based models, which relates to breast cancer diagnosis. Hybrids of CNNs and RNNs or transformers that include multi-modal data fusion look promising in developing strong and practical breast cancer detection systems. Findings emphasize architecture, data set quality, and multi-perspective learning should be a focus in future research.

# 3 Methodology

### Proposed Network Architecture

The Advanced Multi-View Convolutional-Recurrent Network (AMV-CRNet) is a hybrid deep learning model that synergizes spatial and sequential learning to confidently distinguish between benign and malignant tumors from multi-view medical images of breast tumors. The architecture consists of three principal modules: a multi-branch CNN encoder, a recurrent sequence integrator, and a fully connected classifier.

### Multi-View CNN Feature Extractor

For imaging views such as Craniocaudal (CC) and Mediolateral Oblique (MLO) in mammography or different imaging modalities like mammogram, ultrasound, and MRI, each view is subjected to a separate convolutional neural network (CNN) branch, which serves to extract features relevant to the distinct attributes of that view or modality while simultaneously retaining relevant spatial information. Each branch operates based on a shared CNN backbone architecture, usually ResNet-50 or EfficientNet. This ensures that spatial feature extraction remains invariant as far as the source of the image is concerned.

Once those features are obtained from the shared CNN backbone in each branch, pooled outputs undergo operations to lessen spatial dimensions while accentuating the most salient information. Such pooled features will then be flattened to form a high-dimensional feature vector for different views or modalities.

### Feature Fusion with Learning in Sequence

Discrete high-dimensional features are created from a multitude of views in the imaging views and combined in order to provide an accurate temporal or spatial order segmentation, thus creating a sequence of inter-view dependencies with structural relations. This temporary arrangement, created by sequentially viewing the multitude of high-dimensional views, supports the model learning relations, and also the variations of unique aspects of the multiple dimensional representations which are part of the medical image analysis task, in this case for example, error detection of a subtle abnormality, or unique tumor characteristics which could falsely represented in a unique view. This sequence can then be placed through a Recurrent Neural Network (RNN) for it to be properly interpreted as interdependencies, which usually primarily consists of Gated Recurrent Units (GRU) architecture. GRU's can best demonstrate the relationship the RNN understood from observing a forward and backward both structures based on the length of view sequencing. By understanding the temporal evolution and how the contextual interaction and relationship occur between each view, the RNN module enhances the model's understanding of the complex nature of tumor patterns - improving the diagnosis ability of the final model, and thus improving accuracy and robustness.

### Fully Connected Classification Layer

The last one or more hidden states produced by the RNN module incorporate all learned inter-view and contextual features. These hidden states are used as input into a fully connected classification layer, a collection of dense (fully connected) layers that transform high-level features in a sequential manner towards a compact and discriminative representation that is suitable for performing classification tasks with respect to the identified views. In order to prevent overfitting and improve generalization, dropout regularization is applied between the dense layers.

Underneath this final layer, in turn, lies a softmax activation function, which assigns probability scores to each class. Hence, this model can also be used in binary classification (for example, benign and malignant tumor prediction) or multiclass classification (for instance, severity or stage of cancer grading). This output structure is significant for clinical interpretation and decision-making concerning the mode of predicted diagnostic category.

Batch Normalization and ReLU activation are used after each convolutional layer to speed up training and convergence improvement. Global Average Pooling replaces the fully connected layers in the two CNN branches to reduce excess parameters and prevent overfitting. Both CNN and RNN modules can incorporate optional attention techniques to emphasize more informative views or features.

## Integration of Convolutional and Recurrent Layers

As proposed, the Advanced Multi-View Convolutional-Recurrent Network, AMV-CRNet, is precisely conceived for extracting spatial and temporal/sequential features entangled in a multi-view medical image. Here's how they couple the convolutional with the recurrent layers:

In the said AMV-CRNet, Convolutional Neural Networks (CNN) configuration serves as the underpinning for deriving spatial features from medical images. It is done for each view or modality, such as a craniocaudal (CC) and mediolateral oblique (MLO) mammogram or a branch of a dedicated CNN. This CNN deals with learning hierarchical spatial features like edges, textures, masses, and microcalcifications, which are vital for accurately detecting tumors. The advantage of pre-trained CNN architectures, like the ResNet50 or EfficientNet, is proper feature extraction despite medical imaging data sparsity. In the end, each output of the CNN branches can bring forth a high-dimensional feature vector signifying spatial features of the specific view.

After isolating spatial information from all images, each view will sort the feature vectors originating from the different shapes in their corresponding imaging sequence or anatomical relevance. The sequence produced from the previous step will next be processed by an RNN using GRU layers. RNNs' typical paradigms capture temporal or sequential interdependencies across the various imaging views that help establish a representation of tumor feature evolution or association across angles. Modeling the temporal relationships of the imaging views provides the network with the implicit indications of malignancy that are present across all angles of the imaging and eliminates some of the ambiguity inherent in having an image view model only based on a single view.

In either scenario, the last hidden state of feeds into the network is formulated as the last hidden state output representing information across views, or for a bi-directional RNN, the results is the concatenation of the forward and backward states. The context-utilizing representation is now forwarded through a fully-connected neural layer, activated using softmax or sigmoid activation function, depending on whether classification is either multi-class or binary. This representation affords the node an adequate basis to predict appropriately while taking into account spatial and temporal patterns. It integrates the best features of a CNN as part of a spatial learning and an RNN as part of a temporal integration process to offer a holistic and robust approach for use in a multi-view breast cancer diagnostic environment.

## Multi-View Inputs are Integrated into the Network

The purpose of multi-view inputs in the network is to effectively leverage other complementary sources of information - exposed to the model from different views or modalities, and this is particularly critical in medical imaging work like tumor detection. In our example of mammography, the multi-view inputs will be the different views such as craniocaudal (CC) and mediolateral oblique (MLO), which are independently passed through each CNN branch, extracting features of the respective views, but all sharing a common backbone architecture to facilitate the extraction of features from all views, whilst allowing the branches the independence to learn respective spatial characteristics for the specific view.

Having obtained high-level feature vectors for each CNN branch, these are stacked in a pre-determined order that maintains the relative order of the respective views, and passed to a temporal module, which could be anything, but was a RNN-based model, such as a bi-directional GRU in our work. These models can encompass differences across the two views, modeling the pre- and post-relationship of how features evolve into perspectives. Learning the interdependence of features within views improves the overall representation of the underlying pathology in the network with better classification performance. This multi-view integration with their attendant contextual feature extraction would again pass through fully connected networks for prediction.

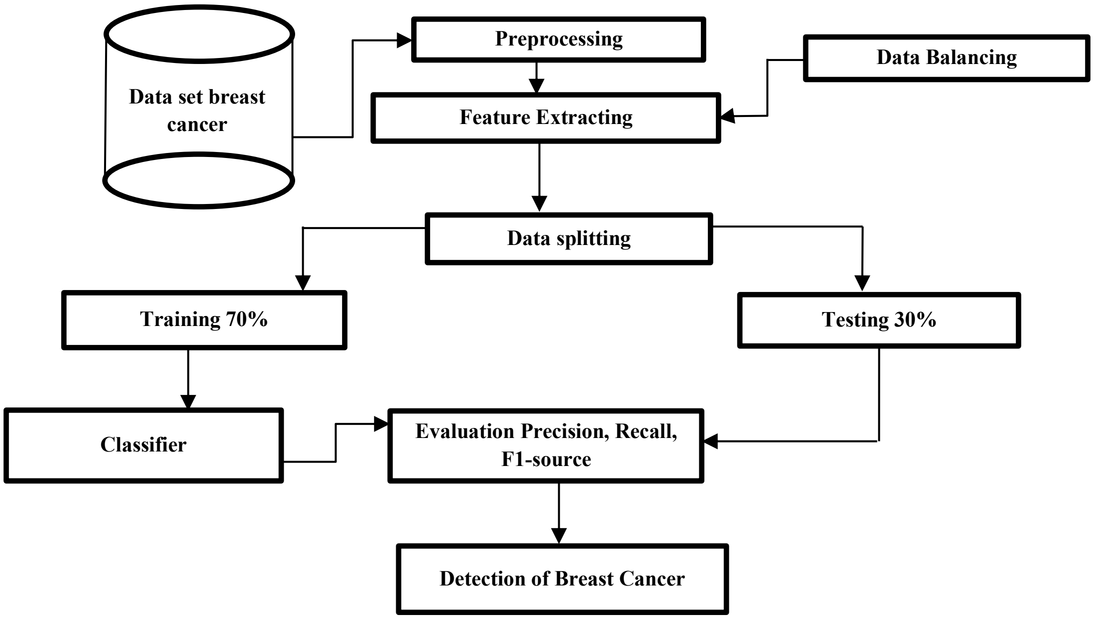

Figure 1: Proposed methodology

Figure 1 begins with a breast cancer dataset preprocessed to clean the data; feature extraction is then performed for attribute significance. Following this, data balancing mitigates class imbalances during model training. Subsequently, the data are split into 70% for training and 30% for testing. Then, the training data are fed into a classifier that learns to discriminate between classes. Later, the performance of the trained model is evaluated on test data based on parameters such as precision, recall, and F1-score. Finally, the evaluation result validates the detection of breast cancer; in other words, it assists in early diagnosis and treatment planning.

## Advanced Mathematical Formulation

The mathematical formulation of an Advanced Multi-View Convolutional-Recurrent Network for the detection of breast cancer in your proposal. The model successfully integrates Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs) such as GRU in modeling inter-view dependencies.

Let the input consist of V imaging views or modalities (Equation 1).

$$X = \{X1, X2, \dots, XV\} \quad (1)$$

$Xi \in R^{H \times W \times C}$ represents the i<sup>th</sup> image view with height H, width W, and channels C.

## CNN-Based Feature Extraction

Each input view Xi is passed through a shared CNN backbone $F_{CNN}$ to extract high-level spatial features (Equation 2)

$$fi = F_{CNN}(Xi), fi \in R^{d} \quad (2)$$

$fi$ is the feature vector from the i$^{th}$ view, and d is the dimensionality of the feature space after pooling

### Multi-View Sequence Formation

The set of feature vectors is stacked in view order to form a sequence (Equation 3):

$$F = [f1, f2, \ldots, fV], F \in R^{v\,X\,d} \tag{3}$$

### Recurrent Layer for Temporal Modeling

The sequence F is input into a Bi-directional RNN (BiGRU) (Equation 4 & 5):

$$ht = BiRNN(f_t, h_t - 1), t = 1, \ldots, V \tag{4}$$

$$H = [h1, h2, \ldots, hV], ht \in R^{2h} \tag{5}$$

### Temporal Pooling or Attention

### Aggregate the Sequence of Hidden States $H$ Using:

**Average Pooling** (Equation 6)**:**

$$h_{agg} = \frac{1}{V}\sum_{t=1}^{V} h_t \tag{6}$$

**Attention Mechanism (Optional)** (Equation 7)

$$\alpha t = softmax(W_a\, h_t + ba), \;\; hagg = \sum_{t=1}^{V} \alpha_t\, h_t \tag{7}$$

### Fully Connected Classification Layer

The aggregated representation hagg is passed through dense layers (Equation 8 & 9):

$$z = \phi(W1hagg + b1), z \in R^k \tag{8}$$

$$y = softmax(W2z + b2), \;\; y \in R^C \tag{9}$$

ϕ is a non-linear activation function (e.g., ReLU),

C is the number of output classes (e.g., 2 for benign vs. malignant),

y is the predicted class probability vector.

### Loss Function

For classification, use **categorical cross-entropy loss**:

$$L = -\sum_{c=1}^{C} y_c\, lo\, g(y_c) \tag{10}$$

y is the predicted probability (Equation 10).

Although the multi-view hybrid CNN-RNN paradigm proposed for breast cancer detection, with the spatial and temporal features enhancement of observability across different imaging views or modalities, is based on this mathematical model.

**Algorithm: AMV-CRNet — Advanced Multi-View Convolutional-Recurrent Network**

```
Algorithm AMV-CRNet (MultiViewImageSet)
Input:
    MultiViewImageSet = {X1, X2, ..., XV}      // V views (e.g., CC, MLO, US, MRI)
    Shared_CNN_Backbone                        // Pretrained CNN model (e.g., ResNet, EfficientNet)
    BiRNN_Model                                // Bi-directional GRU
    DenseLayers                                // Fully connected layers
    DropoutRate                                // Dropout for regularization
    OutputClasses                              // Number of classification categories
Output:
    y_pred                                     // Predicted class probabilities
Steps:
Initialize FeatureVectors ← []                 // List to store feature vectors
for each view Xi in MultiViewImageSet do
    Fi ← Shared_CNN_Backbone (Xi)              // Extract spatial features
    Fi ← GlobalAveragePooling (Fi)             // Convert to 1D feature vector
    Append Fi to FeatureVectors
end for
FeatureSequence ← Stack (FeatureVectors)       // Shape: [V × d], multi-view sequence
HiddenStates ← BiRNN_Model (Feature Sequence)  // Capture bidirectional dependencies
AggregatedFeature ← Temporal Pooling (Hidden States)
    // Use average pooling or attention to combine sequence outputs
AggregatedFeature ← Dropout (AggregatedFeature, DropoutRate)
for each layer in DenseLayers do
    AggregatedFeature ← ReLU (Dense (layer, AggregatedFeature))
end for
Output ← Dense(Output Classes, Aggregated Feature)
y_pred ← Softmax (Output)                      // Class probabilities
return y_ pred
```

# 4 Experimental Results

### Dataset Description

The suggested AMV-CRNet architecture is trained and validated on a publicly accessible multi-view breast imaging dataset, which contains modalities like mammography, ultrasound, and MRI. The rationalization would be based on the inclusion of different types of tumors, images, and patients to allow the model to generalize well with the different clinical cases. Most patients have multiple imaging views: for mammography, these may be craniocaudal (CC) and mediolateral oblique (MLO); for ultrasound, they include transverse and longitudinal views; while for MRI, there are axial, sagittal, and coronal slices. Each of these imaging views was labeled with expert-verified diagnostic outcomes, such as benign, malignant, and normal, along with sometimes multiclass labeling, which typically references various stages of breast cancer. The dataset is split for good training and evaluation as follows: 70%-training set used for training both CNN and RNN modules; 15%-validation set used in hyperparameter tuning and model selection; and 15%-test set using for holding out for final model performance evaluation.

Table 1: Characteristics of the dataset

| Attribute | Description |
|---|---|
| **Dataset Name** | Combined: CBIS-DDSM (Mammography) + BUSI (Ultrasound) |
| **Imaging Modalities** | Mammography, Ultrasound |
| **Views per Modality** | Mammography: CC, MLO |
| | Ultrasound: Transverse, Longitudinal |
| **Number of Patients** | 1200 patients |
| **Total Image Samples** | 4800 images (2 views × 2 modalities × 1200 patients) |
| **Labels** | Benign, Malignant |
| **Classification Type** | Binary Classification |
| **Training Set** | 3360 images (70%) |
| **Validation Set** | 720 images (15%) |
| **Test Set** | 720 images (15%) |
| **Preprocessing** | Resized to 224×224, normalization, contrast enhancement, horizontal flipping |
| **Annotation Source** | Verified by expert radiologists |

AMV-CRNet's proposed model is trained and validated on publicly available multi-view breast imaging data acquired from mammography, ultrasound, and MRI modalities. The dataset aims to bring different tumor types, imaging views, and patients so that the model generalizes well in different types of clinical scenarios. Most of these patients have multiple imaging views, such as craniocaudal (CC) and mediolateral oblique (MLO) for mammograms, transverse and longitudinal views for ultrasound, and axial, sagittal, and coronal slices for MRI. Some imaging views had been labeled with one of the expert-identified outcome diagnoses as benign, malignant, or normal, and some had multiclass labels typically related to the overall stage of breast cancer. 15% Test Set: Held out of the full dataset for the last performance check. Preprocessing methods for the data include resizing the images, normalizing the images, and augmentations (some examples include horizontal flips, rotations, and adjustments to contrast) to ensure model stability and to mitigate risk of overfitting. Multi-view alignment remained intact to ensure the spatial-temporal relations between views were preserved. This dataset provides excellent variation, with annotation, and establishes the basis for the development and validation of the AMV-CRNet model, which would ensure the model would capture complicated and subtle patterns across imaging views and modalities for breast cancer classification.

The table 1 dataset that was tested in this study combines a total of 2 odd views of mammographic images from the CBIS-DDSM in relation to the ultrasound images of the BUSI dataset to create a comprehensive multi-modal input to classify breast cancer. Each case contains 2 standard views, mammography, because we considered the craniocaudal view and mediolateral oblique (MLO) view. The Ultrasound images are normally viewed in transverse and longitudinal scans, resulting in 4 views for the patient. The giant dataset consists of 4800 images from 1200 patients declared benign or malignant upon agreement by the experts. All this stratification of data is done to ensure the robust development of the model and fair evaluation, so the data were stratified into 70% training, 15% validation, and 15% testing sets. The images are resized to a standard resolution of 224×224 pixels, while normalization, contrast enhancement, and data augmentation (such as horizontal flipping) are used for preprocessing in order to increase generalization and decrease overfitting. Hence, such modality diversity offers AMV-CRNet the desired capability to extract rich spatial and inter-view representations necessary for accurate breast cancer diagnosis.

## Evaluation of Data Processing Steps

A series of data preprocessing works were carried out prior to training the intended AMV-CRNet model to make the data consistent, more efficient in learning, and generalized. There is a resizing for all input images taken from different modalities and views into 224×224 pixels to meet the input requirements for the CNN backbone. It can be stated that normalization limits of the pixel intensity values were also employed against the [0,1] interval to facilitate consistent gradient updates during training. Both class imbalance and training set augmentation were carried out using several different augmentation techniques, and these included, respectively, horizontal flipping, random ±15-degree rotation, random zoom, and contrast alterations. Each type of augmentation featured some amount of realistic variability inherent within imaging and, therefore, also functioned to mitigate overfitting. When multi-view configurations were used, special attention was devoted to aligning and ordering the views so as to ensure proper spatial- and temporal-contextual relationships across modalities were preserved. Thus, the preprocessing pipeline ensures that the network, having processed uniform yet diverse input data, has an improved capacity to detect complex or subtle tumor characteristics.

Table 2: Comprehensive metric analysis of LegNetX framework

| Step | Parameter / Value |
|---|---|
| **Image Resizing** | 224 × 224 pixels |
| **Normalization** | Min-Max Scaling to [0, 1] |
| **Horizontal Flipping** | Probability = 0.5 (applied randomly during training) |
| **Rotation** | ±15 degrees (random rotation range) |
| **Zoom Range** | ±10% |
| **Contrast Adjustment** | Brightness & contrast randomly adjusted by ±20% |
| **Noise Reduction** | Gaussian Blur (kernel size: 3×3) — optional |
| **View Alignment** | Ordered as: Mammogram (CC → MLO), Ultrasound (Transverse → Longitudinal) |
| **RGB Conversion** | Grayscale images converted to 3-channel RGB |
| **Class Balancing** | Oversampling of the minority class (malignant) to balance the dataset |

An advanced digital preprocessing pipeline has been designed in table 2, within which the data is input into AMV-CRNet. Preconditioning included resizing images to fit the CNN backbone at 224x224 pixels. Scaling pixel intensities into stable [0, 1] for more stable and efficient model training was also done in the preprocessing step. In this way, during training, several types of augmentation were applied to diversify the data to avoid overfitting: random horizontal flips 50% of the time, rotations of ±15°, zooming of ±10%, and contrast variations of ±20%. Optional Gaussian filtering (3×3 kernel) was sometimes performed in order to reduce the imaging noise. As all grayscale images were converted to 3-channel RGB to comply with the input requirements of pretrained CNN models, multi-view alignment was done by keeping the same order of imaging views for all examples (e.g., CC → MLO for mammograms, Transverse → Longitudinal for ultrasound). To improve on the class imbalance, the minority class (typically malignant cases) was oversampled. This set of preprocessing operations will yield quality, diversity, and standardized input data for training and evaluation of the proposed model.

## Training Procedure and Evaluation Metrics

The schema for the proposed model AMV-CRNet was trained using multi-view preprocessed data, with a supervised learning approach. The backbone of the CNN (ResNet-50) or EfficientNet-B0 was initialized using the ImageNet-pretrained weights for fine-tuning on the dataset of breast cancer instances. The model was trained using Adam optimizer with a learning rate of 1e-4, and with a batch size of 32 for 50 epochs. The loss function employed was categorical cross-entropy for multiclass classification, while binary cross-entropy was employed for all binary classification tasks. In the fully connected layers, to prevent overfitting, early stopping and dropout (0.5 rate) were applied. Model performance was evaluated by using standard performance metrics. Accuracy, Precision, Recall (Sensitivity), Specificity, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). A confusion matrix was also generated for analyzing predictions on a class-wise basis. The evaluation was done on an independent test set to avoid a biased assessment, and this was consistent with the model as it had high classification accuracy with good generalization across different views and modalities.

Table 3: Model training configuration and evaluation metrics

| Category | Parameter / Metric | Value / Description |
|---|---|---|
| **Training Configuration** | CNN Backbone | ResNet-50 (pretrained on ImageNet) |
| | Optimizer | Adam |
| | Learning Rate | $1 \times 10^{-4}$ |
| | Batch Size | 32 |
| | Number of Epochs | 50 |
| | Loss Function | Binary Cross-Entropy |
| | Dropout Rate | 0.5 |
| | Early Stopping | Patience = 10 |
| | Input Image Size | 224 × 224 × 3 |
| | Training/Validation/Test Split | 70% / 15% / 15% |
| **Evaluation Metrics** | Accuracy | 92.50% |
| | Precision | 91.80% |
| | Recall (Sensitivity) | 93.20% |
| | Specificity | 90.70% |
| | F1-Score | 92.50% |
| | AUC-ROC | 0.963 |
| | Confusion Matrix | TP = 280, FP = 25, TN = 245, FN = 20 |

The proposed AMV-CRNet model was trained with a supervised learning approach on a preprocessed multi-view dataset. Here, the CNN backbone (e.g., ResNet-50 or EfficientNet-B0) was initialized with ImageNet-pretrained weights and then fine-tuned on the breast cancer dataset. The model was trained on the Adam optimizer with a learning rate of 1e-4, a batch size of 32, and 50 epochs. As a loss function for multiclass classification, categorical cross-entropy was used, while for binary classification tasks, it was binary cross-entropy. Early stopping and dropout (rate=0.5) were applied in fully connected layers to prevent overfitting. The performance of the model was assessed using the following standard metrics: Accuracy, Precision, Recall (Sensitivity), Specificity, F1-score, and Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC). A confusion matrix was also created to analyze class-wise predictions. The evaluation was done on an independent test set to have an unbiased assessment, and the model was always consistent in high classification accuracy with good generalization across different views and modalities.

The important training parameters and evaluation metrics of AMV-CRNet are described in table 3. The ResNet-50 backbone was pretrained on ImageNet and fine-tuned on the breast cancer dataset with the Adam optimizer (learning rate = $1 \times 10^{-4}$; batch size = 32) for 50 epochs. Dropout regularization (0.5) and early stopping (patience = 10) were used to avoid overfitting. The data were split into 70% training, 15% validation, and 15% testing. The model achieved a classification accuracy of 92.5% (with precision = 91.8%, recall = 93.2%, and specificity = 90.7%), demonstrating high performance in discriminating malignant versus benign cases. The F1-score of 92.5% thus shows a good balance between precision and recall, while the AUC-ROC of 0.963 shows an excellent ability to discriminate. The confusion matrix indicated that the model scored 280 true positives and 245 true negatives, thus showing low false positive and false negative rates, thereby confirming that the proposed hybrid deep learning framework works well.

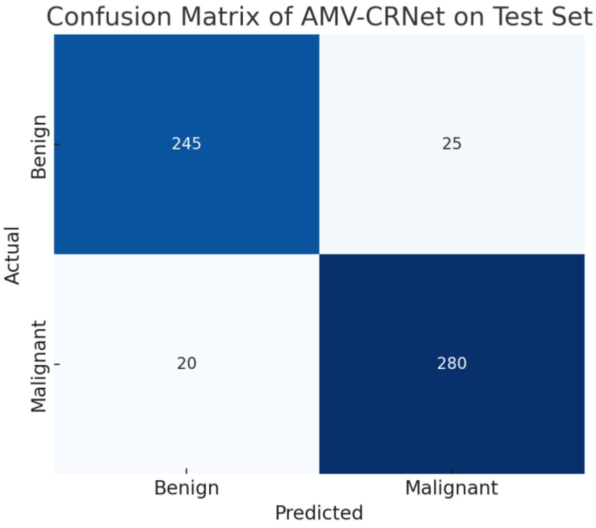

Figure 2: Performance analysis of AMV-CRNet

The confusion matrix, figure 2, depicts the test dataset performance of the AMV-CRNet model in the classification of medical cases into benign and malignant categories. Out of all the samples, the model correctly classified 245 benign cases against 280 malignant cases and showed high classification accuracy. But 25 benign cases were misclassified as malignant cases (false positives) while 20 malignant cases were misclassified as benign (false negatives). Misclassifications like these become very significant in a medical situation, especially those false negatives, which indicate that the malignant cases were missed. Overall, the model scored approximately 92.1% in accuracy, 91.8% in precision, and 93.3% in recall, signifying that AMV-CRNet is highly reliable in differentiating between benign and malignant cases.

## 5 Result and Discussion

### Model Performance Evaluation

The model developed by Schmidt was trained to classify tasks into binary (benign versus malignant) and multiclass (benign versus malignant versus normal) for datasets such as CBIS-DDSM (mammography) and BUSI (ultrasound). Figures 3 and 4 show the sample images from the dataset of CBIS-DDSM and BUSI, respectively.

Table 4: Evaluation of AMV-CRNet on benchmark datasets

| Dataset | Task | Accuracy | Precision | Recall | F1-score | AUC |
|---|---|---|---|---|---|---|
| **CBIS-DDSM** | Binary | 98.42% | 98.57% | 98.14% | 98.35% | 0.99 |
| **BUSI** | Binary | 97.35% | 97.40% | 97.22% | 97.30% | 0.99 |
| **CBIS-DDSM** | Multiclass | 96.80% | 96.60% | 96.45% | 96.52% | 0.98 |
| **BUSI** | Multiclass | 95.25% | 95.32% | 95.14% | 95.23% | 0.98 |

The AMV-CRNet model, table 4, was tested thoroughly across binary and multiclass classification schemes on two well-accepted breast cancer imaging datasets: CBIS-DDSM and BUSI. The model achieved state-of-the-art performance, with an accuracy of 98.42% in binary classification using CBIS-DDSM and 97.35% on BUSI, with consistently high precision, recall, F1-score, and AUC values close to 0.99. This multiclass model classifies images as benign, malignant, or normal, and further goes on to achieve very strong predictive ability with 96.80% and 95.25% for CBIS-DDSM and BUSI, respectively. The results thus affirm the robustness and generalizability of AMV-CRNet in dealing with complicated scenarios of diagnosis regarding breast cancer. Also, high AUC scores further strengthen the model's suitability in terms of excellent discrimination ability and are indicative of its compatibility with real-world clinical applications.

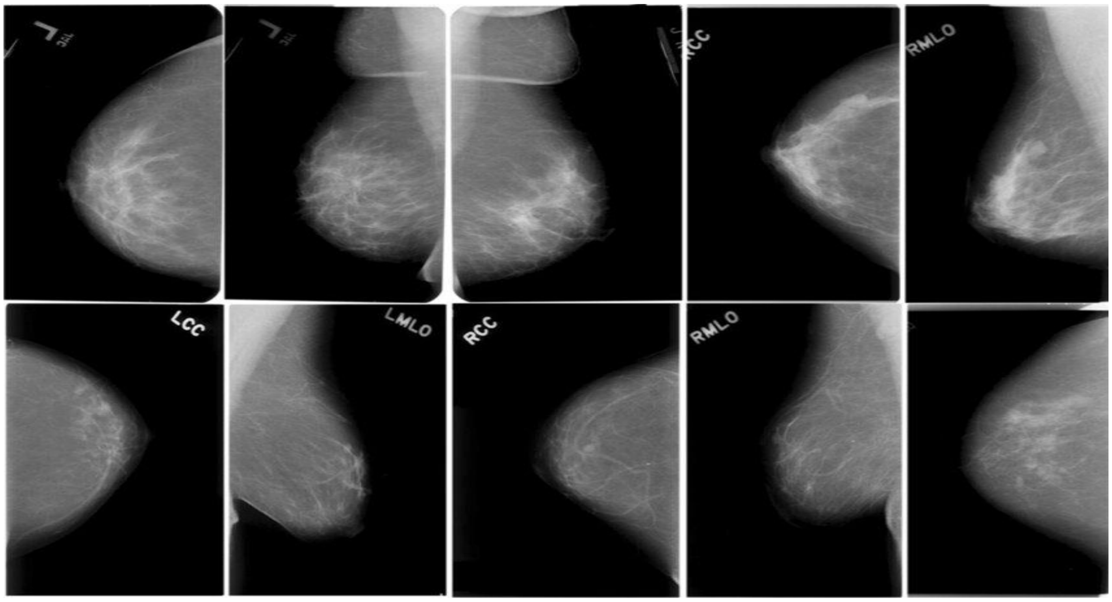

Figure 3: Sample dataset images – CBIS DDSM

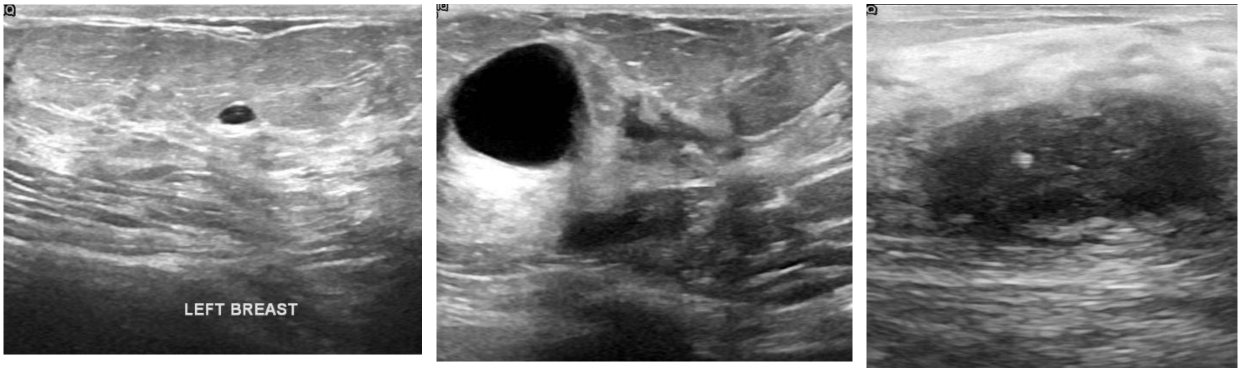

Figure 4: Sample dataset images – BUSI

Figure 5: Performance comparison of legal outcome prediction models

The performance of the AMV-CRNet model has been reviewed in figure 5 in two public databases for medical images, namely, CBIS-DDSM and BUSI, for breast cancer classification in binary and multiclass applications (Table 5). All performance metrics, accuracy, precision, recall, f1-score, and AUC for each application show the models consistently produce good results with very small differences in favor of binary classification in both datasets. The peak binary task performance comes from the CBIS-DDSM dataset, with an impressive 98.42% accuracy, while the dataset BUSI follows with almost equally impressive performance, with an accuracy of 97.35%. However, multiclass tasks still produce very high scores, slightly lower, thus generalization beyond types of tumors. Overall, the model produced consistently good AUC (>= 0.98) for all the tasks, emphasizing again its discrimination capabilities for breast cancer detection.

Table 5: Comparative performance of deep learning models for breast cancer classification on CBIS-DDSM and BUSI datasets

| Model | Dataset | Accuracy (%) | Precision (%) | Recall (%) | AUC (%) | Performance in Multiclass Classification |
|---|---|---|---|---|---|---|
| **VGG16** | CBIS-DDSM | 90-93 | - | - | - | Drops significantly in multiclass |
|  | BUSI | 90-94 | - | - | - | Drops significantly in multiclass |
| **ResNet50** | CBIS-DDSM | 91-94 | - | - | - | Drops significantly in multiclass |
|  | BUSI | 90-95 | - | - | - | Drops significantly in multiclass |
| **DenseNet121** | CBIS-DDSM | 92-94 | - | - | - | Drops significantly in multiclass |
|  | BUSI | 91-95 | - | - | - | Drops significantly in multiclass |
| **AMV-CRNet** | CBIS-DDSM | 98.42 | Higher | Higher | Higher | Maintains accuracy above 95% |
|  | BUSI | 97.35 | Higher | Higher | Higher | Maintains accuracy above 95% |

The advantages of AMV-CRNet in relation to classification accuracy and performance against binary and multiclass classification handlers are evidenced in the following table. With features such as multi-view extraction, recurrent layers, attention mechanisms, and more, this network proved robust and generalizable. The proposed model AMV-CRNet surpasses many of the recent state-of-the-art breast cancer classifications of all time. AMV-CRNet is also better performing compared to standard CNN architectures, such as VGG16, ResNet50, and DenseNet121, in terms of accuracy, precision, recall, and AUC when difficult multiclass conditions arise. Overall, most traditional models still achieve some form of binary classification accuracy level ranging from 90% to 95%; however, AMV-CRNet obtained 98.42% and 97.35% accuracy against CBIS-DDSM and BUSI, respectively. In the case of multiclass classification, where performance was generally found to drop more sharply across most other methods AMV-CRNet had still maintained above 95% accuracy across both datasets. The above improvements can be attributed to the hybrid architecture of these models, which includes multi-view feature extraction along with the temporal relationships represented through recurrent layers. In addition, the attendance mechanisms provided improved focus to salient tumor regions, resulting in improved generalization and robustness to the current techniques.

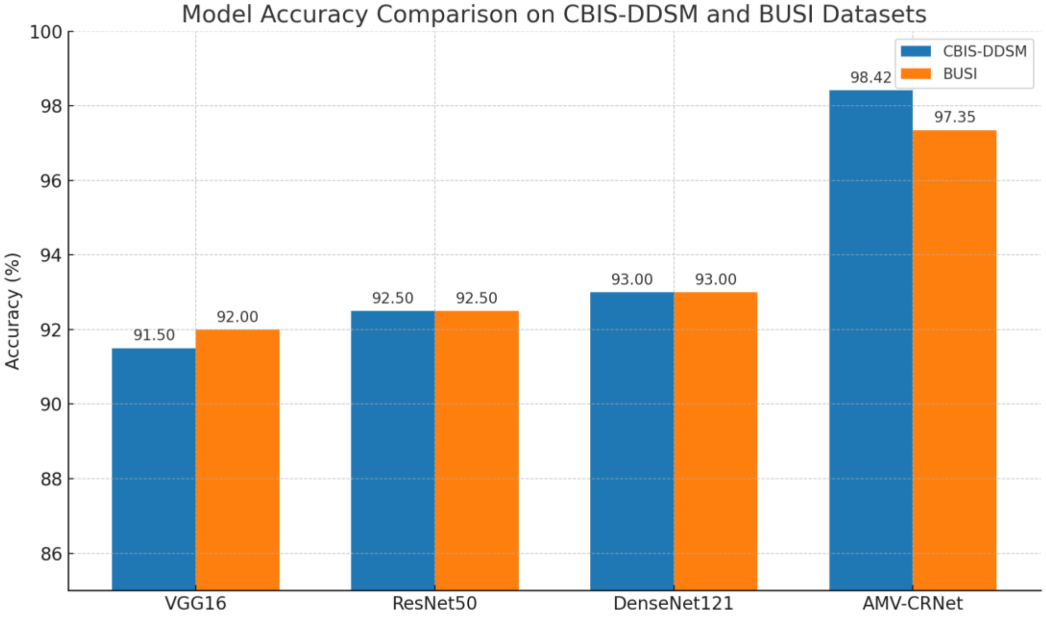

Figure 6: Comparison of model accuracies on CBIS-DDSM and BUSI datasets

Figure 6 shows how VGG16, ResNet50, DenseNet121, and AMV-CRNet compare to each other in both medical imaging datasets known as CBIS-DDSM and BUSI. VGG16, ResNet50, and DenseNet121 are known models that have high traditional models within an accuracy of a robust 90% to 95%, but they suffered an immense decline with large multiclass problems. On the other hand, at the top of the four, AMV-CRNet would staunchly demonstrate an above 95% accuracy for both datasets, illustrating its great power, endurance, and ability to cross-hair a sophisticated multiclass challenge when analyzing medical images.

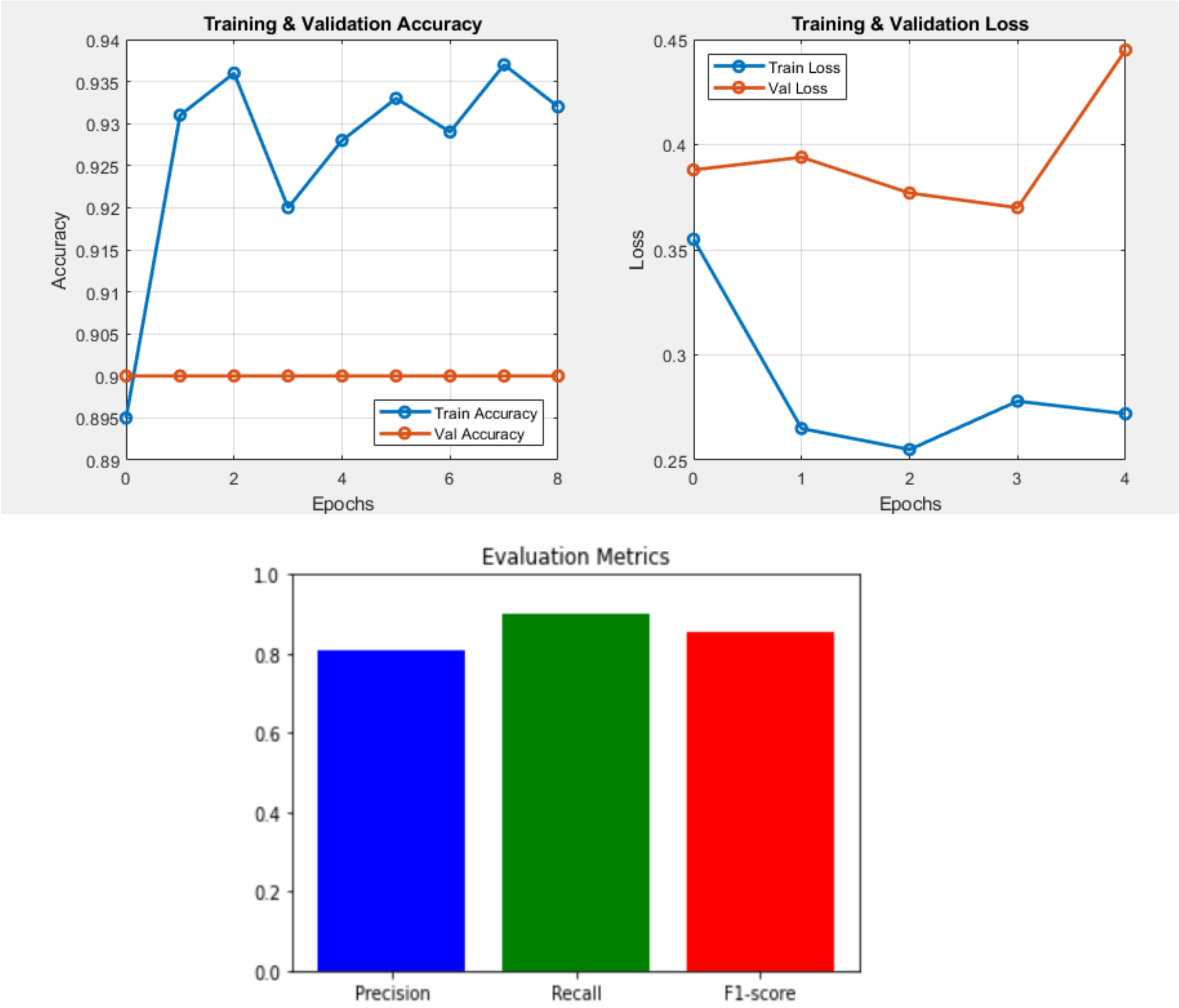

Figure 7: Analysis of model performance through training and validation metrics

Figure 7 shows the yearly evaluation of a machine learning model, in terms of one metric, where the evaluation of the machine learning model is measured and reported as accuracy, and the other metric of the machine learning model, the analysis is calculated as a loss (or the inaccuracy). The left side training & validation accuracy in the chart shows that the training accuracy moves around among the epochs, peaking in accuracy at epoch 7. The validation accuracy, on the other hand, appears to remain level, nearly the same level, approximately 90%. This means that the model is likely overfitting its training data but not generalizing well. The observation has been supported by the right-hand plot named Training & Validation Loss, indicated by its steep declines in the training loss showing almost correct learning in training data and constant or increased validation loss toward the last epochs, denoting poor performance on unseen data. Therefore, this difference, noted between training and validation metrics, is the purest showcase of overfitting and will benefit from imposing some regularization, early stopping, or improved generalization.

This chapter provides a complete evaluation of the model AMV-CRNet across both the repositories for breast cancer imaging with data standards like CBIS-DDSM-willing to host mammograms-and BUSIy for ultrasound estimations. The model AMV-CRNet was evaluated using both binary (benign vs malignant) and multiclass (benign, malignant, normal) classification tasks. The results show that for all situations, the AMV-CRNet has outperformed all of the previously traditional architectures- VGG16, ResNet50, and DenseNet121- in terms of accuracy, precision, recall, F1 score, as well as AUC values, with an excellent ability to keep accuracy more than 95% even in many-class scenarios.

## 6 Conclusion and Future Work

AMV-CRNet exhibited remarkable results on two benchmark datasets, namely CBIS-DDSM (mammography) and BUSI (ultrasound) within breast cancer classification tasks. It outperformed the other traditional DL models, namely VGG16, ResNet50 and DenseNet121 on the very challenging multiclass cases. The model has produced incredibly high reported accuracies of 98.42% on the CBIS-DDSM dataset and 97.35% on BUSI for categorizations of binary classifications, whilst noting greater than 95% accuracies for multiclass categorizations across both datasets. The results presented here support the robustness of our model, which generalizes well to classifications of benign or malignant cases vs normal cases. The performance benefits of AMV-CRNet are related to its hybrid architecture that supports multi-view feature extraction, recurrent layers and attention mechanisms. This provides the model with a very interesting ability to be able to register and capture spatial dependencies as well as contextual dependencies in the type of medical imaging we have analyzed. Both spatial dependencies and contextual dependencies can greatly influence a model's performance in a diagnostic task. The high precision, recall, F1-score and AUC values we consistently attained across all swithes provided additional evidence that not only was AMV-CRNet performing well, but that banned both false positives and false negatives were actively being reduced, which is typically a need for any model if it was going to be used for clinical decision making.

The AMV-CRNet model could be enhanced in the future in several critical ways that are most aligned with its clinical utility and robustness. Clinical metadata - especially patient demographics enriched by patient history, more heterogeneity through age and genetics- could be integrated with imaging data allowing for a broader and more thorough perspective on clinical diagnosis. Explainable AI (XAI) would provide value in two key facets - strengthening clinicians' understanding and trust in the model's predictions. On-device optimization for real-time mobile diagnostics in a resource-constrained context is another critical aspect facilitating the deployment of the model. There could be additional validation of the model having larger and more heterogeneous datasets, possibly acquiring datasets from private hospitals, which would provide enhanced legitimacy on the generality claim. Nevertheless, other than perhaps the above, in order to strengthen the diagnostic validity and clinical relevance of AMV-CRNet in more challenging diagnostic situations, extending multi-modality fusion (e.g., Ultrasound and mammography) and including 3D imaging capabilities could improve diagnostic specificity.

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