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PATCHDETECT: BREAST CANCER DETECTION COMBINING UNET-RESNET-50 AND PATCH EMBEDDING LSTM.

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ABSTRACT

This study presents a novel framework for breast cancer detection, combining patch embedding, feature extraction using a pre-trained Convolutional Neural Network (CNN) model (ResNet50), Long Short-Term Memory (LSTM) networks for image sequence analysis, and Fully Connected Layers for final classification. The model's performance was optimized using various hyperparameters, achieving an accuracy of 94%, recall of 93%, precision of 92%, and F-measure of 92% while maintaining a minimal error rate of 6%. The findings emphasize the importance of integrating pre-trained CNNs with sequential analysis via LSTMs for feature-rich and temporal data like mammographic patches. The study also highlights the impact of parameter tuning on classification performance, paving the way for more accurate, automated, and non-invasive breast cancer diagnostic tools.

I. INTRODUCTION

Breast cancer remains a major public health problem worldwide. In 2022, there were 2.3 million new cases among women, making it the most common cancer in many countries. In the same year, around 670,000 deaths from breast cancer were recorded, underlining the urgent need to improve screening and diagnosis strategies [1].

Mammography (see figure 1), currently considered the gold standard for screening, can detect abnormalities before clinical symptoms appear. However, it is not without its limitations, including false-negative or false-positive results, which can lead to unnecessary invasive biopsies or delays in diagnosis [2].

These technical and clinical limitations of mammography have prompted researchers to explore the solutions offered by artificial intelligence (AI) techniques. Recent literature highlights the growing impact of machine learning (ML) and deep learning (DL) approaches on breast cancer screening. According to Yao et al [3], these approaches have considerably improved the processing of mammographic images, particularly in terms of mass detection, segmentation and classification.

However, these techniques still face significant challenges, such as the need for large datasets for training, the high costs of advanced algorithms, and the difficulty of achieving accurate lesion recognition, particularly in dense breast tissue.

In response to these obstacles, we suggest the incorporation of recurrent neural networks, particularly Long Short-Term Memory (LSTM) networks, as a promising alternative. In contrast to conventional methods, which typically rely on Convolutional Neural Networks (CNNs), our approach enables the sequential analysis of images after they have been segmented into regions. This segmentation, when combined with patch embedding and position encoding techniques, improves the capacity to identify subtle patterns that are indicative of malignancy, which are frequently imperceptible to the human eye. This innovative approach seeks to enhance the quality-of-care pathways and increase the likelihood of patient survival by decreasing the dependence on invasive biopsies and enhancing diagnostic accuracy.

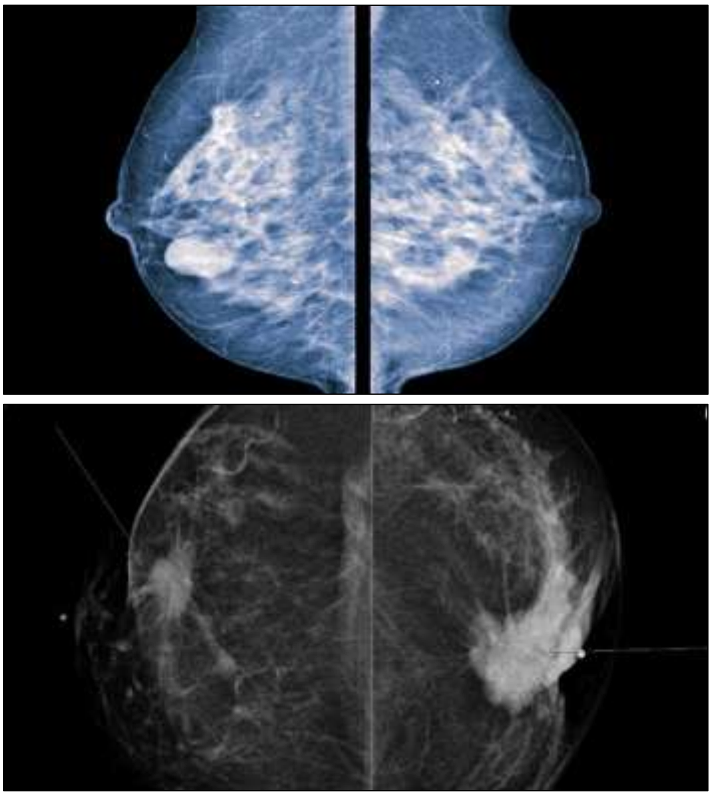


Figure 1: Screening mammography for breast cancer
Source: [1].

The structure of this paper will be organized as follows: We will begin with a review of the essential works on this topic to establish a state-of-the-art foundation. Next, we will detail our approach and the proposed components. Following that, we will conduct an experimental and comparative study to present the best results obtained. Finally, we conclude with a discussion of the key challenges and unresolved questions in the field, as well as potential directions for future research. We also reflect on the broader implications of our findings and the opportunities for advancing the state-of-the-art in this area.

II. REVIEW OF LITERATURE

The most important works around the problem of breast cancer detection are detailed in this section:

Breast cancer detection has improved significantly over the years, as many studies have employed machine learning techniques to enhance diagnostic accuracy. These advancements demonstrate how computer models can facilitate early detection and improve treatment outcomes. For instance, in 2011, Rakhi Malpani and his team[4] used the WEKA API to analyze mammography data from the Digital Database for Screening Mammography (DDSM), achieving an accuracy of 79.36%. Although there was room for improvement, this early work proved that rule-based methods can be useful in analyzing medical images. Building on this foundation, Vikas Chaurasia and Saurabh Pal in 2017 applied boosting techniques like IBK, SMO, and BFtree with the same WEKA API and DDSM dataset [5]. Their model achieved a higher accuracy of 86.2%, showing that combining different classifiers can yield more reliable predictions by addressing the limitations of individual models. Similarly, Gouda Salama in 2012 adopted methods such as SMO, J48, MLP, and IBK to classify data from the WDBC and WPBC datasets, attaining an accuracy of 77.32% [6] While this result was lower than Chaurasia and Pal's, it underscored the potential of ensemble methods to work well across diverse datasets. These variations in performance highlighted the importance of selecting models that best align with dataset characteristics to optimize accuracy.

In another innovative approach, Jahanvi Joshi and her team in 2014 [7] utilized a clustering method called 2-means in WEKA to analyze the UCI dataset. They achieved an accuracy of 83%, emphasizing the effectiveness of unsupervised learning techniques like k-means clustering, especially in scenarios with limited labeled data. Furthermore, in 2019, Xuan Tran and colleagues highlighted that while many AI applications in cancer research outperform traditional methods, thorough evaluation and clinical validation are necessary to substantiate these findings[8]. This insight emphasized the critical need for assessing AI technologies within clinical settings.

In 2021, Kumar and colleagues reviewed various AI cancer prediction models and noted the increasing adoption of deep learning techniques, particularly Convolutional Neural Networks (CNNs), to improve diagnostic accuracy[9] . However, they also pointed out persistent challenges in the early detection of less-explored cancers, such as head and neck cancers, thereby calling for further research in these areas. Similarly, Munir Shah and his team, in a 2021 review[10], focused on breast cancer detection and observed that traditional imaging is prone to human errors. They highlighted the growing reliance on AI for automated image analysis, which not only reduces errors but also enhances accuracy in identifying cancer [11].

Meanwhile, in 2015, Nerea Matamala investigated the use of microRNAs for early breast cancer detection, contributing to the trend of exploring molecular markers for non-invasive cancer detection. While specific datasets or accuracy metrics were not provided, her work involved analyzing miRNA expression in tissue samples from 122 breast tumors and 11 healthy controls. Additionally, she validated the results in a larger cohort, demonstrating the potential of combining molecular markers with traditional imaging for comprehensive diagnostic approaches [12]. Manjurul Ahsan and Siddique in 2021[13] discussed the advantages of machine learning in disease diagnosis. They highlighted how these algorithms can accelerate diagnostic processes, particularly in resource-limited settings, while addressing the limitations of traditional methods. Their work reinforced the importance of adopting machine learning systems to improve both diagnostic accuracy and efficiency. Koh in [14] reviews the expanding role of AI and ML in cancer imaging, highlighting the need for multidisciplinary collaboration to ensure effective tool development and validation.

Annother reviews prenented by Hunter et all [15] discusses the role of artificial intelligence in enhancing early cancer diagnosis, a priority outlined by the World Health Organization. The review outlines how AI can assist in screening asymptomatic individuals, triaging symptomatic patients, and detecting cancer recurrence. It highlights the use of various AI approaches—from logistic regression to deep learning—across multiple data types, such as medical records, imaging, pathology, and blood samples. The study also explores current clinical applications, while addressing challenges like ethical concerns, data security, and the strain on diagnostic resources.

Musa and his team [16] conducted a bibliometric analysis of the top 100 most-cited articles on AI and ML in cancer research, highlighting key technologies such as ANN, CNN, and deep learning models. The study emphasizes the role of these innovations in improving cancer detection, diagnosis, and prevention, guiding future research efforts.

Zajnulina [17] reviewed the growing role of AI in enhancing cancer diagnostics, particularly through MRI, CT, and emerging spectroscopy-based techniques. The study highlights how AI-integrated spectroscopy can enable fast, low-invasive, and chemical-free tissue classification, marking a promising direction for safer and more efficient cancer diagnosis.

Habchi and his team[18] present a comprehensive review of AI in thyroid cancer diagnosis, analyzing supervised, unsupervised, and ensemble learning techniques including deep learning and probabilistic models. The study highlights key datasets, feature extraction methods, evaluation metrics, and outlines current challenges and future research directions.

In the studies of Bechelli [19], a comprehensive review is provided on the use of machine learning and deep learning for cancer diagnosis, examining the steps involved in developing efficient algorithms for cancer detection, classification, and prediction, while addressing the challenges and advancements in utilizing various imaging techniques.

Aamir et all [20] conducted a comprehensive review on the integration of Artificial Intelligence (AI) in healthcare, emphasizing its growing role in disease diagnosis. The study highlights the use of machine learning and deep learning techniques to enhance diagnostic accuracy and clinical efficiency.

Building upon the existing body of work in cancer detection through machine learning and deep learning, our study introduces a novel framework for breast cancer detection. Unlike traditional methods, which often rely on standalone techniques, our approach integrates patch embedding, feature extraction via a pre-trained Convolutional Neural Network (CNN) model (ResNet50), and Long Short-Term Memory (LSTM) networks for analyzing image sequences. Additionally, we employ Fully Connected Layers for the final classification step, optimizing the model's performance using a variety of hyperparameters. This combination of advanced techniques aims to improve the accuracy and efficiency of breast cancer detection, marking a significant advancement in the field.

With this foundational understanding of the existing methods and their limitations, we now turn to the details of our proposed approach. The following section outlines the novel framework developed for breast cancer detection, emphasizing the integration of cutting-edge techniques such as patch embedding, Unet-ResNet50 for seglentation and feature extraction, LSTM networks for image sequence analysis, and Fully Connected Layers for classification. We will also explore the optimization process, including the hyperparameter tuning that was crucial for enhancing the model's performance.

III. PROPOSED SOLUTION

Our solution (see figure 3) combines U-Net-ResNet50 segmentation to identify regions of interest (ROIs) in mammography images, extracts and embeds patches from these ROIs, and uses an LSTM to model spatial dependencies between patches before final classification with DenseNet . By integrating localized patch-level analysis with global image features, the approach enhances the accuracy of breast cancer classification while leveraging the strengths of sequential modeling and hierarchical feature extraction.

III.1 DATASET USED

Curated Breast Imaging Subset of DDSM (CBIS-DDSM): The CBIS-DDSM is an updated and standardized subset of the Digital Database for Screening Mammography (DDSM) , which originally consisted of 2,620 scanned film mammography studies as illustrated in figure 2. While the DDSM includes normal, benign, and malignant cases with verified pathology information, its non-standard format and lack of precise annotations limited its usability. The CBIS-DDSM addresses these challenges by curating a targeted selection of DDSM data, decompressing images into DICOM format, and providing updated ROI segmentations, bounding boxes, and pathologic diagnoses for training. This enhanced dataset includes approximately 1,566 unique participants (though metadata suggests 6,671 due to multiple patient IDs) and encompasses a wide range of cases: normal cases with no abnormalities, benign cases featuring non-cancerous lesions, and malignant cases with cancerous tumors or anomalies. These are distributed across cranio-caudal (CC) and mediolateral oblique (MLO) projections, ensuring comprehensive coverage of breast structures. With thousands of annotated images spanning hundreds of cases per class the CBIS-DDSM provides a robust foundation for developing and testing decision support systems, including CADx and CADe algorithms, for accurate breast cancer detection and diagnosis [21].

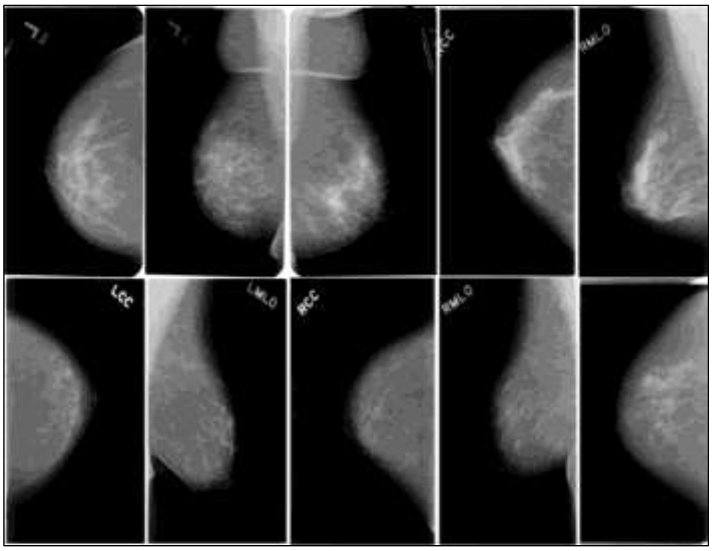


Figure 2: image mammography from CBIS-DDSM dataset
Source: [21].

III.2 DATA PREPROCESSING AND AUGMENTATION

The DDSM images, often large and containing noise or lighting variations, require rigorous pretreatment. Normalization is used to homogenize contrasts and reduce the variability in medical equipment quality. Image augmentation techniques like rotation, zoom, and contrast adjustment are also used to maximize data diversity and ensure the model's robustness against slight variations in images.

III.3 SEGMENTATION AND FEATURES EXTRACTION

In this step (figure 4) , we use U-Net with ResNet-50 Backbone , where the encoder part of U-Net is replaced by ResNet-50 to enhance feature extraction. To use U-Net with ResNet-50 for the segmentation of mammography breast cancer images, the process involves leveraging the strengths of both architectures to achieve precise pixel-level annotations. ResNet-50 serves as the encoder in the U-Net framework, replacing the default convolutional layers typically used for feature extraction. The pre-trained ResNet-50 backbone extracts high-level features from the mammography images, capturing intricate patterns such as masses, calcifications, or other abnormalities. These features are then passed through the decoder part of the U-Net, which uses upsampling and skip connections to reconstruct the segmentation map at the original image resolution. The skip connections ensure that spatial information lost during downsampling in the encoder is reintegrated, enabling accurate localization of lesions. During training, the model is fed annotated mammography images from datasets like CBIS-DDSM , where ground truth masks highlight regions of interest (e.g., benign or malignant tumors). A loss function such as Dice Loss or Binary Cross-Entropy is used to optimize the network for pixel-wise predictions. Once trained, the U-Net-ResNet50 model can segment suspicious regions in new mammograms(figure 5), aiding radiologists by providing detailed delineations of potential cancerous areas for further analysis and diagnosis. This approach combines the hierarchical feature extraction capabilities of ResNet-50 with the precise localization strengths of U-Net, making it highly effective for medical image segmentation tasks.

ResNet-50 offers several advantages when adapted for segmentation tasks. Its pretrained weights , often trained on large datasets like ImageNet, provide a strong starting point for transfer learning in segmentation tasks. The deep architecture of ResNet-50 allows it to learn rich, hierarchical features, which are critical for distinguishing fine details in segmentation tasks. Moreover, its versatility enables integration into various segmentation frameworks, making it adaptable to different applications and datasets. These strengths make ResNet-50 a popular choice as a backbone in segmentation models, especially in medical imaging applications. The residual blocks in ResNet50 enable the network to learn more complex features and deeper representations, which are crucial for accurate segmentation

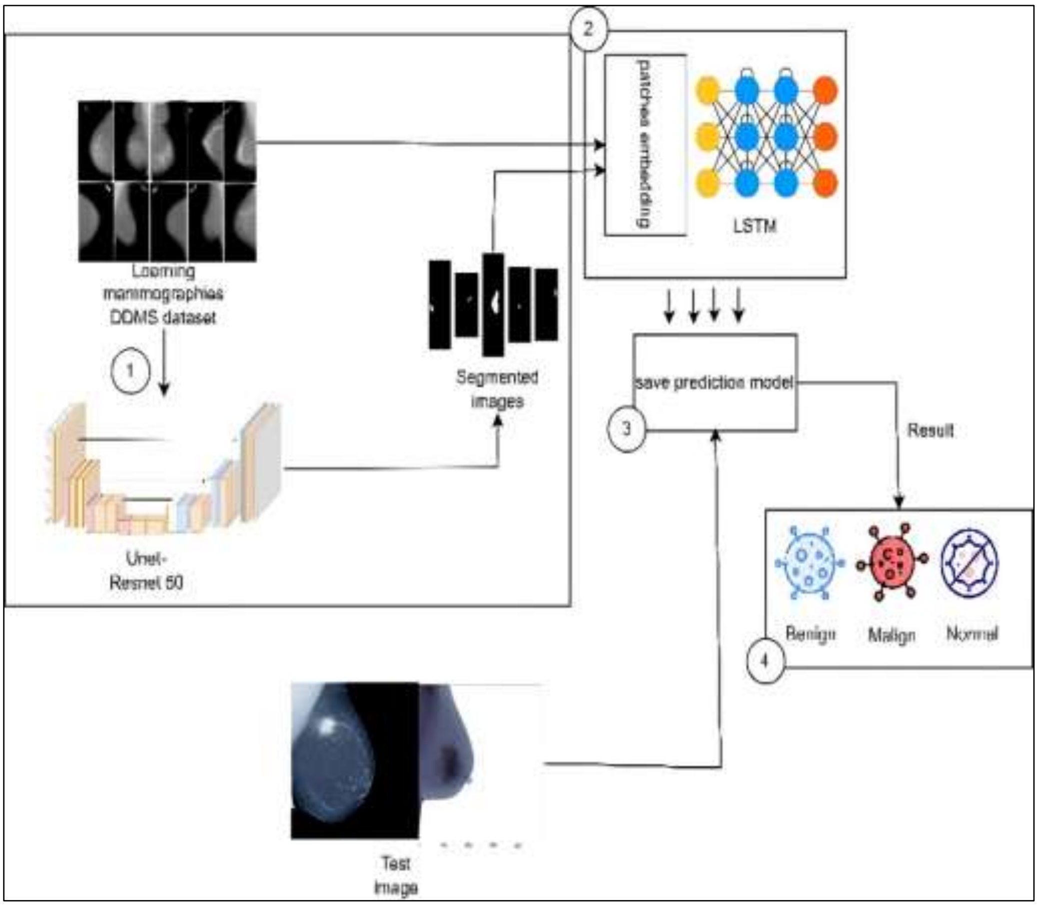


Figure 3: Generale process of the proposed solution. 1)features and ROI extraction using Unet-Resnet50.2). 2) patches+LSTM for learning step and classification part. 3) prediction model saved. Classification of test image.

Source: Authors, (2025).

III.4 PATCHES EMBEDDING + LSTM BLOCKS

III.4.1.PATCHES EMBEDDING + LSTM MODEL

The solution leverages U-Net-ResNet50 for precise segmentation of mammography images, identifying regions of interest (ROIs) such as masses or calcifications, which are then divided into localized patches. These patches are processed by a Patch_Embedding_Model , a CNN-based sub-model that extracts hierarchical features and reduces them to compact embeddings. The sequential relationships between these embedded patches are captured using an LSTM (figure 7), which models spatial dependencies and contextual information across patches, while dense layers perform the final classification into categories like benign, malignant, or normal. By combining U-Net-ResNet50's localization accuracy, CNN feature extraction, and LSTM's sequential learning, the pipeline ensures both fine-grained details and broader contextual relationships are utilized for robust breast cancer diagnosis.

To prevent overfitting, Dropout regularization is applied to the LSTM layers, enhancing generalization. The entire process integrates patch-level analysis with global modeling, treating patches as sequences to capture complex spatial relationships and improve diagnostic accuracy. This hybrid approach enables comprehensive mammography analysis, effectively leveraging spatial and temporal dependencies for more reliable cancer detection and classification.

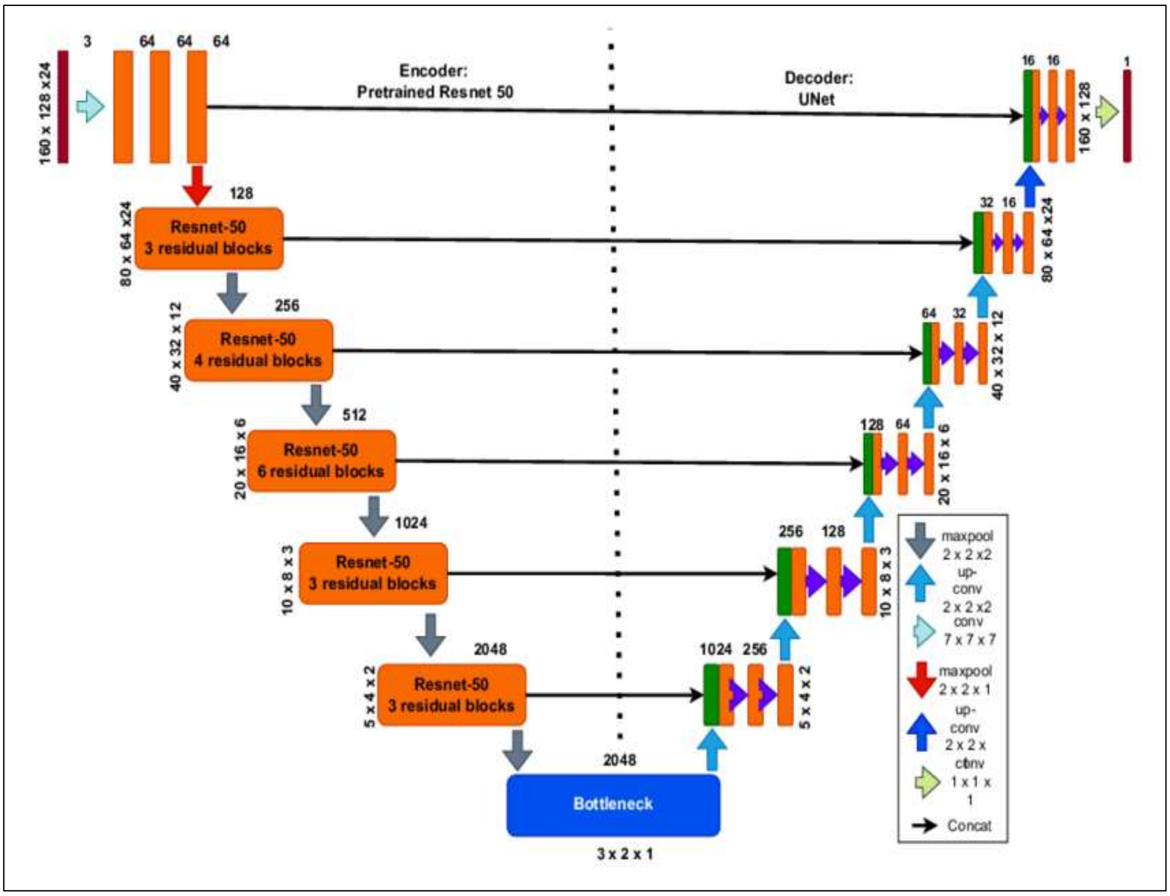
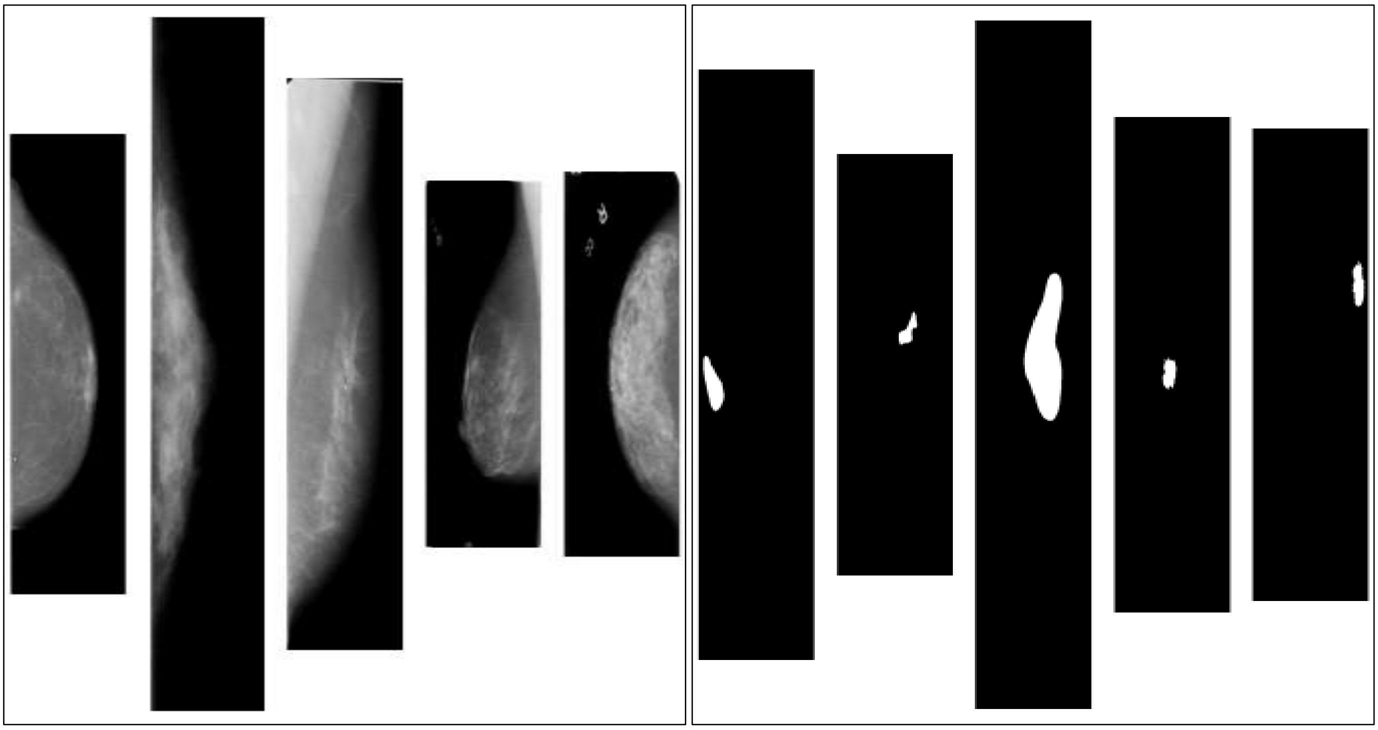


Figure 4: The Segmentation architecture of Unet with pretrained Resnet50 as backbone
Source: Authors, (2025).



(a) (b)

Figure 5: mammography breast cancer segmentation using Unet-Resnet50 to extract ROI. a) Original image from dataset DDSM b)segmented image after applying Unet-Resnet50
Source: Authors, (2025).

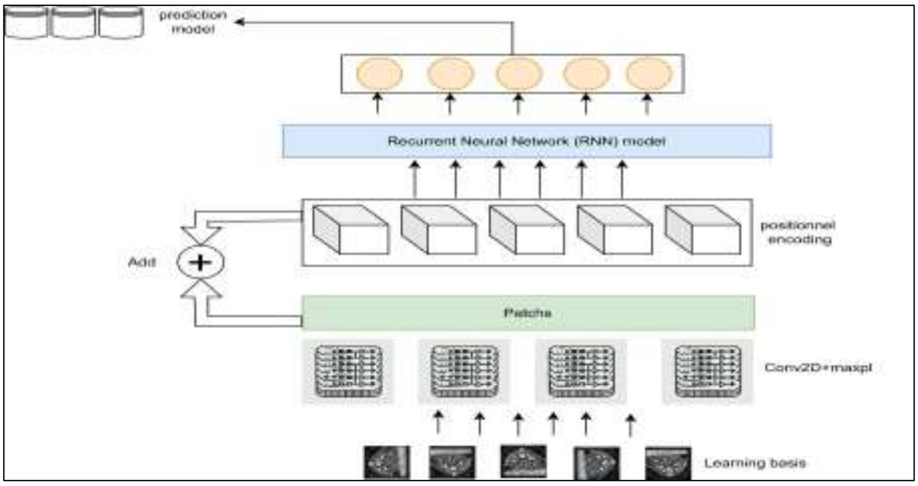


Figure 6: General architecture of patches RNN for breast cancer detection.
Source: Authors, (2025).

```
_________________________________________________________________
Layer (type)                Output Shape            Param #
=================================================================
Sequence_Input (InputLayer)     [(None, None, 64, 64, 1)] 0
_________________________________________________________________
TimeDistributed_Patch_Embedding  (None, None, 1600)      73792
_________________________________________________________________
| Patch_Embedding_Model        |
|  Conv2D_1 (Conv2D)          (None, 64, 64, 32)      320    |
|  MaxPooling2D_1 (MaxPooling2D)(None, 32, 32, 32)      0      |
|  Conv2D_2 (Conv2D)          (None, 32, 32, 64)      18496  |
|  MaxPooling2D_2 (MaxPooling2D)(None, 16, 16, 64)      0      |
|  Flatten (Flatten)          (None, 1600)          0      |
_________________________________________________________________
LSTM (LSTM)                 (None, 128)           885248
_________________________________________________________________
Dense_1 (Dense)               (None, 64)            8256
_________________________________________________________________
Dropout (Dropout)             (None, 64)            0
_________________________________________________________________
Output (Dense)              (None, 3)             195
=================================================================
Total params: 967,491
Trainable params : 967,491
Non-trainable params : 0
```

Figure 7: LSTM model with patch embedding and positional encoding.
Source: Authors, (2025).

III.4.2. PATCHES EMBEDDING + Bidirectional LSTM

In our second combination we have applied a Bidirectional LSTM for the classification step. It is particularly advantageous in the context of breast cancer detection, as it allows the relationships between patches to be captured in both directions (forward and backward). This improves contextual understanding, particularly useful for subtle anomalies and complex dependencies in imaging data. (figure 8)

```
_________________________________________________________________
Layer (type)              Output Shape          Param #
=================================================================
Sequence_Input (InputLayer)     [(None, None, 64, 64, 1)] 0
_________________________________________________________________
TimeDistributed_Patch_Embedding  (None, None, 1600)      73792
_________________________________________________________________
| Patch_Embedding_Model        |
|  Conv2D_1 (Conv2D)          (None, 64, 64, 32)      320    |
|  MaxPooling2D_1 (MaxPooling2D)(None, 32, 32, 32)      0      |
|  Conv2D_2 (Conv2D)          (None, 32, 32, 64)      18496  |
|  MaxPooling2D_2 (MaxPooling2D)(None, 16, 16, 64)      0      |
|  Flatten (Flatten)          (None, 1600)          0      |
_________________________________________________________________
Bidirectional_LSTM (Bidirectional  (None, 256)          1802240
_________________________________________________________________
Dense_1 (Dense)               (None, 64)            16448
_________________________________________________________________
Dropout (Dropout)             (None, 64)            0
_________________________________________________________________
Output (Dense)              (None, 3)             195
=================================================================
Total params: 1,896,675
Trainable params: 1,896,675
Non-trainable params: 0
```

Figure 8**:** Breast Cancer Detection Model With BiLSTM.
Source: Authors, (2025).

III.5 FULLY CONNECTED LAYERS FOR CLASSIFICATION

After the RNN model analyzes the spatial relationships in an image, it combines the outputs from different patches to make a global prediction. This is done using Fully Connected Layers that take the summarized information from the RNN to create a final classification. The model uses several dense layers with ReLU activation functions to improve these predictions. The final layer applies a Softmax activation function, allowing the model to clearly show the probability that the image represents malignant cancer.

III.6 VALIDATION AND LEARNING MODEL

A rigorous training and validation phase is essential to ensure the model's performance. The dataset is divided into three parts: a training set to adjust the model weights, a validation set to evaluate performance during training, and a test set toz assess final performance. Based on the targeted classes, an appropriate loss function, such as Categorical Cross entropy, is employed. Optimization is carried out using algorithms like Adam or Stochastic Gradient Descent (SGD), which adjust the model parameters to minimize the loss.

IV. RESULTS AND DISCUSSIONS

To present the results of the two RNN models mentioned (Breast Cancer Detection Model with BiLSTM and LSTM with Patch Embedding) on the CBIS-DDMS dataset, we used the evaluation metrics (Recall, Precision, F-measure, Accuracy, Error). Experiments may vary according to the parameters (Learning rate, Batch size, Number of units in the LSTM/BiLSTM layers, Dropout %, Number of epochs. All the obtained results and configuration of parameters are illustrated in detail in the tables 1 and 2.

Table 1: Result of breast cancer detection using our solution with **simple LSTM RNN** model for the classification and variation of parameters (learning rate, batch size, LSTM UNIT, DropOut, Recall , Precision, Accuracy, Error).

Learning Rate	Batch Size	LSTM UNIT	Dropout	Recall	Precision	F-measure	Accuracy	Error
0.001	32	256	0.3	0.91	0.89	0.90	0.92	0.08
0.001	64	256	0.5	0.88	0.87	0.87	0.90	0.10
0.0005	32	128	0.3	0.93	0.91	0.92	0.93	0.07
0.001	32	128	0.3	0.89	0.88	0.88	0.91	0.09
0.001	64	128	0.5	0.87	0.86	0.86	0.89	0.11
0.0005	32	256	0.3	0.91	0.90	0.91	0.92	0.08
0.001	16	256	0.3	0.92	0.90	0.91	0.94	0.06
0.0005	16	128	0.3	0.88	0.87	0.87	0.90	0.10
0.0001	64	256	0.5	0.93	0.92	0.92	0.94	0.06
0.0001	64	128	0.5	0.86	0.85	0.85	0.88	0.12

Source: Authors, (2025).

Table 2: Result of breast cancer detection using our solution with bidirectionnel-LSTM RNN model for the classification and variation of parameters (learning rate, batch size, LSTM UNIT, DropOut, Recall , Precision, Accuracy, Error)

Learning Rate	Batch Size	LSTM UNIT	Dropout	Recall	Precision	F-measure	Accuracy	Error
0.001	32	128	0.3	0.88	0.86	0.87	0.89	0.11
0.001	64	128	0.5	0.86	0.84	0.85	0.88	0.12
0.0005	32	128	0.3	0.90	0.88	0.89	0.91	0.09
0.0005	64	128	0.3	0.89	0.87	0.88	0.90	0.10
0.0001	32	128	0.3	0.91	0.90	0.91	0.92	0.08
0.001	16	256	0.3	0.87	0.85	0.86	0.88	0.12
0.001	32	256	0.5	0.85	0.83	0.84	0.87	0.13
0.0005	64	256	0.3	0.88	0.86	0.87	0.89	0.11
0.0001	32	256	0.3	0.90	0.89	0.89	0.91	0.09
0.0001	64	256	0.5	0.88	0.87	0.87	0.89	0.11

Source: Authors, (2025).

This study explored the impact of key hyperparameters on model performance, including learning rates ranging from 0.0001 to 0.001 to analyze their effect on convergence, batch sizes of 16, 32, and 64, as well as LSTM units with varying complexities of 128 and 256. Dropout was also utilized to regulate overfitting and improve generalization.

The results indicate that BiLSTM models tend to outperform standard LSTM models in metrics such as recall and F-measure, although they require higher computational resources. Conversely, the LSTM model with Patch Embedding achieves slightly lower performance but remains more efficient due to its lighter parameter footprint. For optimal configurations, recall and precision stabilize around 0.88, with a balanced F-measure ranging between 0.87 and 0.91, suggesting consistent performance across all classes. The accuracy reaches up to 0.92, showcasing the model’s strong predictive capabilities on the tested data.

These findings highlight how hyperparameter variations influence the precision and robustness of the model. If specific analyses, additional parameters, or further refinements are required, they can be tailored to meet particular objectives or resource constraints.

COMPARATIVE STUDY

To give our result more reference in literature we have conduct a comparaison with existed techniques in literature such as vgg16, VGG19, Inception V3, MobileNET, DensNet201, ResNEt101, ResNet152,[22] GoogleNet[23]

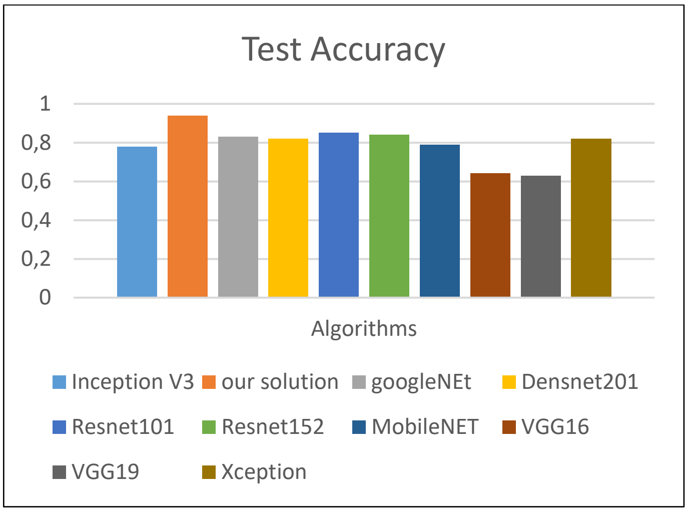


Figure 9: comparative study between our solution and existed solution in literature for breast cancer detection.
Source: Authors, (2025).

After analyzing the results in figure 9, We remark clearly that our model achieves an exceptional test accuracy close to 1.0, significantly outperforming other state-of-the-art architectures like Inception V3, Resnet101, Xception, GoogleNet, MobileNet, and VGG variants. This remarkable performance can be attributed to the innovative design of our pipeline. The UNET-Resnet50 architecture excels in segmentation tasks, enabling precise localization of regions of interest within medical images. By breaking down images into patches and embedding them, we ensure that local features are captured effectively while maintaining computational efficiency. The inclusion of a bidirectional LSTM further enhances the model's ability to analyze sequential dependencies and contextual information across patches, which is particularly valuable in understanding the spatial structure of tumors. Finally, the DenseNet-based classification layer aggregates these features to make robust predictions, benefiting from DenseNet's ability to preserve feature richness through dense connections.

In contrast, other architectures like Inception V3, Resnet101, and Xception, while powerful, may lack the specialized design needed for the nuances of breast cancer detection. Models such as GoogleNet and Densenet201 exhibit moderate performance but do not match the tailored approach of our pipeline. Simpler architectures like VGG16 and VGG19, known for their shallow designs, struggle to capture the complexity of medical images. MobileNet, optimized for lightweight applications, sacrifices depth and detail, making it less suitable for high-stakes tasks like cancer detection.

Several factors contribute to the superior performance of our solution. The UNET-Resnet50 segmentation step ensures accurate identification of suspicious regions, providing a strong foundation for subsequent analysis. Patch embedding allows the model to focus on localized features while reducing computational overhead, ensuring scalability. The bidirectional LSTM adds temporal and contextual understanding, enabling the model to interpret relationships between different parts of the image. DenseNet's dense connectivity pattern ensures efficient feature propagation and reuse, enhancing classification accuracy. Additionally, the pipeline likely benefits from pre-training on large-scale medical datasets, fine-tuning on domain-specific data, and rigorous optimization techniques such as advanced learning rate scheduling and regularization methods.

V. CONCLUSIONS

In this study, we developed an effective framework for breast cancer detection by combining patch embedding with feature extraction using a pretrained ResNet-50 model and sequential analysis through LSTM networks. Our approach demonstrated robust classification performance, achieving a high accuracy of 94% with optimized hyperparameters. These results emphasize the potential of integrating deep learning techniques for precise and automated breast cancer diagnostics. Furthermore, the use of patch embedding allowed for localized feature analysis, enhancing the system's ability to detect patterns indicative of malignancies.

Despite the promising outcomes, challenges remain, such as the computational cost associated with training deep learning models on large-scale datasets and the potential need for domain-specific dataset augmentation to address imbalances. Future work will focus on optimizing the framework further by exploring lightweight architectures and reducing computational overhead. Additionally, integrating explainable AI (XAI) techniques could enhance the interpretability of predictions, making the system more applicable in clinical settings.

Expanding the dataset diversity, including different imaging modalities and demographic factors, will also be prioritized to improve the generalizability of the model. Moreover, real-world validation through clinical trials will be crucial to ensure the reliability and practical utility of the proposed system for early and accurate breast cancer detection.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: hadj ahmed bouarara
Methodology: hadj ahmed bouarara
Investigation: hadj ahmed bouarara and kadda benyahia.
Discussion of results: hadj ahmed bouarara
Writing – Original Draft: hadj ahmed bouarara
Writing – Review and Editing: hadj ahmed bouarara and kadda benyahia.
Resources: hadj ahmed bouarara .
Supervision: kadda benyahia.
Approval of the final text: kadda benyahia.

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