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CVBN: Early Diagnosis of Breast Cancer Detection using Transfer Learning

[1]M. Subha, [2]Dr.P. Srimanchari,

[1]Ph.D Research Scholar, Department of Computer Science, Erode Arts and Science College(Autonomous), Erode-09. Tamil Nadu, India.

[2]Assistant Professor, Department of Computer Science, Erode Arts and Science College (Autonomous), Erode-09, Tamil Nadu, India

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Abstract:

One of the most common cancers afflicting women worldwide, breast cancer is characterized by uncontrolled cell growth in the breast tissue. Early detection and diagnosis are crucial for effective treatment and increased patient survival rates. Treatment results and patient survival rates are greatly improved by detecting breast cancer early. The optimal architecture for cancer prediction was suggested by this study as cascaded VGG19 with Bidirectional Long Short-Term Memory (CVBN). The VGG19 model is used to extract high-level characteristics from mammography pictures; it has been pre-trained on large image datasets. The Bi-LSTM network takes these characteristics and processes them, improving the model's prediction accuracy by capturing complex patterns and temporal correlations. The CVBN design outperforms conventional approaches on a large breast cancer dataset, proving its higher accuracy, sensitivity, and specificity. By enhancing feature extraction and segmentation, this integrated strategy successfully tackles the complexity and unpredictability of mammographic pictures, providing a potential tool for accurate and early identification of breast cancer.

Keywords: Breast cancer, Bi-LSTM, Early detection, VGG19, Transfer learning

I. Introduction

There are a number of subtypes and characteristics associated with each of the two main forms of breast cancer, carcinoma and non-carcinoma. There are two main categories of carcinoma: benign and normal [1]. The term "beneign" describes a little alteration in the structure of the breast that does not meet the criteria for cancer and, in the majority of instances, does not pose any health risks [2]. Additional carcinoma kinds include in-situ and invasive varieties [3]. While certain types of breast cancer, known as invasive carcinoma, spread to other organs, others, called in-situ or non-invasive, stay within the mammary ductal-lobular system and don't spread. With prompt diagnosis, in-situ carcinomas can be resected and even cured [4]. The first step in diagnosing breast cancer is palpation, which is a self-assessment. Subsequently, during routine checks, ultrasound imaging and mammography can be used [5]. One of the most dependable ways to diagnose breast cancer is with a needle biopsy, which is performed when there is a chance of malignant tissue growth [6]. Histologists examine tissues under a microscope to determine their microscopic structure and components [7]. Histological examination of breast tissue helps distinguish between the aforementioned cancers [8]. Hematoxylin and Eosin (H&E) staining is done on tissues before they are examined visually [9]. The nuclei (purple) and cytoplasm structure are more prominently seen on the tissue slide after staining [10].

Tragically, a large number of women who are diagnosed with breast cancer lose their battles against the illness year [11]. Early detection can reduce breast cancer death rates and enhance therapeutic effectiveness [12]. Research into digital pathology's potential as a fast and accurate means of breast cancer diagnosis is an encouraging field of study [13]. It has recently become possible to automate the diagnosis of breast cancer using deep learning. Deep learning is able to take on new problems with less specialised hardware and a smaller data set than normal because to transfer learning [14]. This is why deep transfer learning is being touted as a way to make breast cancer prediction models more accurate and precise [15]. The ease with which Fast AI can include transfer learning models makes it a popular deep learning tool [16]. Feature extraction from high-dimensional image data is a breeze using Sqeezenet's deep neural network due to its tiny size and great efficacy [17-20].

The main contribution of the paper is

- Prediction using CVBN

The rest of the article as follows In Section 2, a number of writers discuss different approaches of detecting breast cancer. On display in Section 3 is the CVBN method. The investigation's findings are summarised in Section 4. A discussion of the outcome and potential future research discussed with Section 5.

1.1 Motivation of the paper

Our research is to tackle the pressing need for early detection of breast cancer, a prevalent and sometimes deadly illness affecting women worldwide. This study employs deep learning and transfer learning, specifically via the novel CVBN architecture, to enhance the precision of breast cancer prediction. Compared to previous methods, the CVBN architecture achieves better sensitivity, specificity, and accuracy thanks to its use of Bi-LSTM for temporal dependency capture and VGG19 for robust feature extraction from mammography images.

II. Background study

Ahmad, H. M. et al. [1]these authors research details the implementation of a transfer learning system for the purpose of breast cancer histopathology picture type categorization. We improved upon the authors' 66.7 percent classification accuracy by modifying three pre-trained networks: AlexNet, GoogleNet, and ResNet. The updated networks now reach an impressive 85 percent accuracy. Computing time and a short training set are no longer problems thanks to this method.

Alhussan, A. et al. [3] these authors introduced a system that can automatically categorise breast cancer patients. An innovative optimisation strategy for better breast cancer case categorization has been devised by researchers using the ABER optimisation algorithm. Data augmentation, AlexNet-based feature extraction via transfer learning, and CNN optimisation for classification make up the three stages of the suggested method.

Alzubaidi, L. et al. [5] these authors research model is a hybrid of two ideas: residual connections and parallel convolutions with varying filter sizes. Improved feature representation and feature combination at different levels are significant properties of our model's structural architecture. Using transfer learning within the same domain, we have proposed a technique to address the problem of insufficient training pictures.

Chaudhury, S. et al. [7] these authors research provide the most recent results from IDC's texture classification experiments, which employed transfer learning with super convergence. In order to better explain and demonstrate how neural networks generate choices, the study also takes into account an easily deployable DL model and network graphics. Squeeze Net, a little model (4.8 MB), is used to demonstrate the outcomes. Several data augmentation methods, such as structure-preserving colour normalisation, were used to enhance the results.

Dutta, S. et al. [9] Care must be used while dealing with breast cancer since it is a serious condition. Patients' lives can be greatly improved by detecting this condition at an early stage. The study's overarching goal is to ascertain the likelihood of being impacted by breast cancer illness and to identify the practicability of using past medical information.

Guan, S., & Loew, M.[11] A delicate approach is required when dealing with the serious illness that is breast cancer. Early diagnosis of this condition is crucial for patient survival. Finding out how likely it is that you would be impacted by breast cancer illness and if it is feasible to use prior medical information are the two main goals of this research. A model based on stacked GRU-LSTM layers was designed and built in this research using deep learning techniques.

Tan, Y. et al. [17] Feature extraction from several participant settings, rather than a centralised learning facility, was proposed as a method for breast cancer picture classification in this research. To train the model to be fully data decentralised, without sharing any data across hospitals, a collection of international medical imaging centres and hospitals worked together in the centralised environment.

2.1 problem definition

Breast cancer, which affects many women throughout the globe, begins with the uncontrolled growth of cells in the breast tissue. Discovery must occur quickly if we are to improve patient survival rates and guarantee successful therapy. Using the CVBN architecture, which stands for Cascaded VGG19 with Bidirectional Long Short-Term Memory, this work aims to address the issue of early breast cancer detection. This novel approach employs pre-trained VGG19 to extract intricate information from mammography images. Next, we use Bi-LSTM to pick up on recurring patterns and correlations throughout time. Results from tests on many breast cancer datasets show that the CVBN architecture is more accurate, sensitive, and specific than conventional methods.

III. Materials and methods

In this section, the proposed method focuses on utilizing a cascaded VGG19 with Bi-LSTM architecture, termed CVBN, for enhancing the accuracy of image processing tasks. The VGG19 model is employed initially to extract high-level features from input images, capturing intricate details effectively.

3.1 Dataset collection

The dataset collected from mendeley repository https://data.mendeley.com/datasets/ywsbh3ndr8/2 is a substantial resource for the early diagnosis of breast cancer. With a size of 786MB, it comprises a collection of image files in PNG format and is organized as a semi-supervised dataset. This dataset is specifically categorized into two types of classes: benign masses and malignant masses.

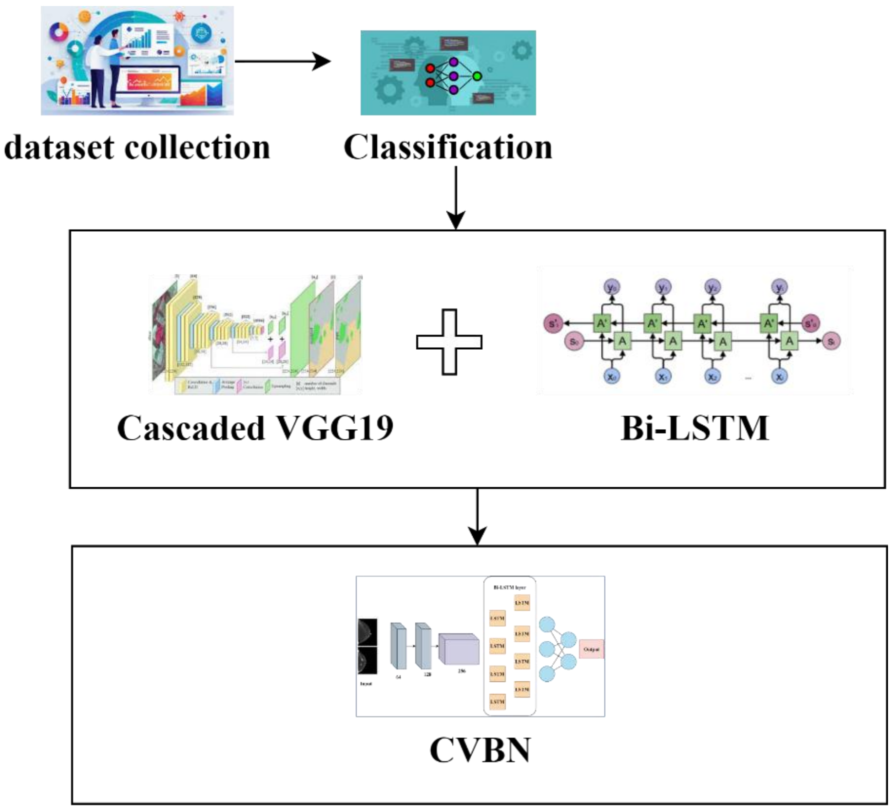

Figure 1: CVBN workflow architecture

3.2 Breast Cancer Prediction using cascaded VGG19 with Bi-LSTM

3.2.1 CascadedVGG19

The cascaded VGG19 convolutional neural network (CNN) is used as a strong feature extractor in the cascaded VGG19 method. Its 19-layer deep design allows it to collect complex visual information from pictures referred by Alhussan, A. et al. (2023). The learnt weights of VGG19, which were pre-trained on big datasets like ImageNet, provide a strong basis for identifying typical patterns. Layers like Bi-LSTM networks or fully connected layers are used to further refine and improve the extracted features in the cascaded configuration, which uses the output from VGG19's final convolutional layer. In medical imaging applications, such as identifying benign from malignant breast lumps, the model's capacity to correctly categorise complicated image data is enhanced by capturing both spatial and temporal correlations.

Figure 2 shows that thecascaded VGG19 architecture, which is composed of 19 layers of CNNs, is an effective tool for insect classification because it can extract complicated information from insect photos. CascadedVGG19 stands out in the detection and identification of different insect species by gradually producing abstract representations via pooling and convolutional layers. The power of the

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model to account for differences in insect size, orientation, and contextual surroundings is enhanced by its depth, leading to improved classification accuracy. To enhance computing performance, decrease data dimensionality, and add non-linearity, the design incorporates Max pooling and ReLU activation layers. The last set of fully connected layers uses a softmax activation function to produce output layers that calculate probability for different groups of insects. Because of its processing power and suitability for complicated picture recognition tasks, cascadedVGG19 is a popular choice in entomology and agriculture. It has a significant impact on the precision of insect identification, the efficacy of pest management, and our understanding of the environment. The importance of the first convolutional layers in collecting basic features like forms and edges is seen in the detailed cascadedVGG19 architecture illustration. With this understanding, we can trace the model's input-output data flow from the beginning. With its hierarchical structure, cascadedVGG19 is able to distinguish intricate insect traits, highlighting its crucial role in insect taxonomy.

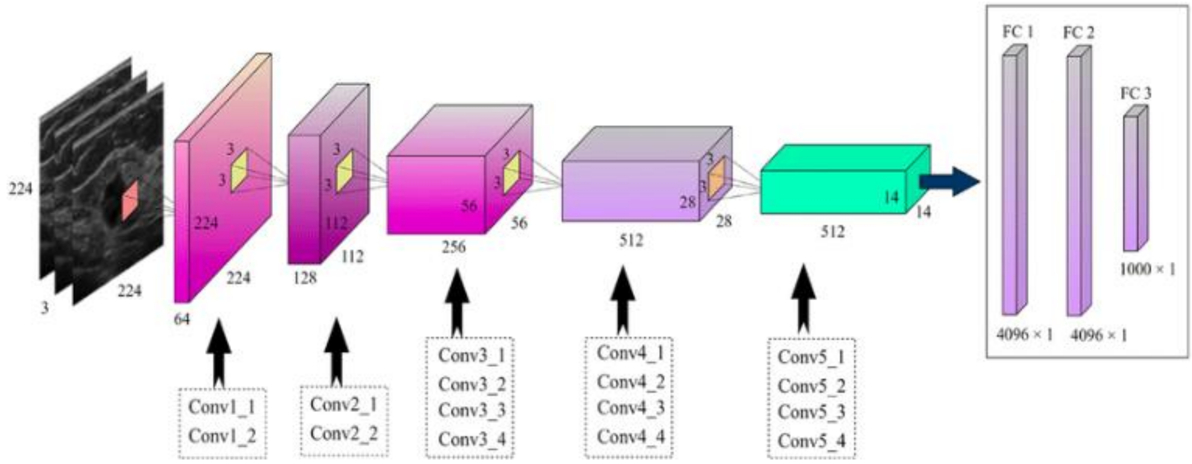

Figure 2: Cascaded VGG19

3.2.2 Bi-LSTM

An enhanced kind of recurrent neural network (RNN) called the Bidirectional Long Short-Term Memory (Bi-LSTM) network is intended to extract context and long-range relationships from sequential input. Bi-LSTM networks, as described by Dutta, S. et al. (2020), process data in both forward and backward directions, in contrast to typical LSTMs, which only process input data in one way. By using both past and future context, this bidirectional method helps the model identify patterns and relationships in the data.

We have taken into account a standard SISO wireless communication system. At the input of the receiver, the distorted signal is shown as

$y = Hx + n$ ------------- (1)

in where H is the channel's impulse response and n is the quantity of additive white Gaussian noise (AWGN). For channel computation, we suggested a Bi LSTM-based design. Hx is the output notation for the simplest linear deep learning model. The letters w stand for the weights. The inputs with the format are used to configure the model. The LSTM architecture can be shown in Figure 1. Many think$n$ the gate structure can alter the cell state by adding or removing data. Each of its three gates—an input, a forget, and an output—are essential to it.

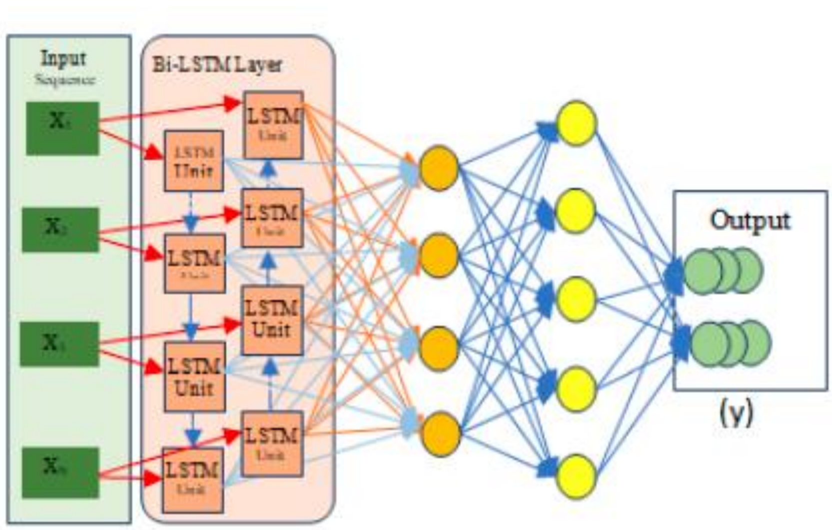

Figure 3: Bidirectional LSTM architecture.

Two Long Short-Term Memory (LSTM) layers placed side by side form a bidirectional LSTM design, as seen in Figure 3. In order to train one layer of an LSTM, the input sequence is fed forward. Training a second LSTM layer in the opposite way requires the input sequence to be supplied in the opposite order. Both directions of the model's training employ the input sequence of size 256. The simulated training data's actual and imaginary components are included in these input sequences. We fed the first layer the original, unaltered sequence of 256 elements, and the second layer a duplicate of the original, but in reversed form.

It is believed that the LSTM neural network can fix RNNs' vanishing gradient problem when dealing with lengthy sequence data. One way to depict the LSTM four gates is as

$f_t = \sigma(w_f x_t + R_f h_{t-1} + b_f$----------- (2)

$g_t = tanh\left(W_g x_t + R_o h_{t-1} + b_g\right)$------------ (3)

$i_t = \sigma(W_o x_t + R_o h_{t-1} + b_i)$----------- (4)

$o_t = \sigma(W_o x_t + R_o h_{t-1} + b_o)$------------ (5)

In the present input state xt, the weight matrices areW_o, and the bias terms are b_f, b_g, b_i, and b_o.To determine the network's present and future state, c_t, one can use

$c_t = f_t \times c_{t-1} + i_t \times g_t$------------- (6)

And the output yt of the network is

$y_t = h_t = o_t \times tanh(c_t)$------------ (7)

Where, ct-1 represents the previous long-term state.

3.2.3 CVBN

By combining the strengths of VGG19's CNN for feature extraction with Bi-LSTM's sophisticated temporal pattern recognition, the cascaded VGG19 with Bi-LSTM model achieves exceptional results. At first, the 19-layer deep architecture of the VGG19 model captures complex visual details and patterns in input pictures by extracting high-level spatial data. The Bi-LSTM network takes in the extracted features and uses them to analyse the data in both directions, identifying linkages and temporal correlations in the feature sequence. The model's capacity to detect nuanced data changes is improved by this bidirectional processing, which allows it to remember context from both previous and future states. By combining VGG19 with Bi-LSTM, a strong framework is created. This framework is capable of accurately classifying complicated pictures, such as those showing breast lumps that are either benign or malignant. As a consequence, diagnostic accuracy and reliability are enhanced for the early diagnosis of breast cancer.

When compared to more conventional RNNs and feedforward neural networks, recurrent hidden layers with their recurrent connections and dedicated memory blocks provide superior performance when modelling sequence data. The network's temporal state is stored at each time step by memory cells with self-connections in memory structures. Further, the gates, which are multiplication units, allow information to flow into the memory cell (via the input gate) and out of the cell (through the output gate). In order to understand the precise timing of the outputs, the LSTM design makes use of "peephole" connections.

Figure 1 depicts the layout of the LSTM network. From repeatedly calculating the output sequence from time step t= 1 to T, the following mathematical phrases are used:

$i_t = \sigma[(W_{ix} \times x_t) + (W_{ir} \times r_{t-1}) + (W_{ic} \times c_{t-1}) + b_i]$ -------- (8)

$f_t = \sigma\left[\left(W_{fx} \times x_t\right) + \left(W_{fr} \times r_{t-1}\right) + (W_{cr} \times c_{t-1}) + b_i\right]$ ----------- (9)

Those are the weight matrices denoted by W. For instance, the input gate to input weight matrix is represented as W_{ix}. In the present input statex_t, the weight matrices are W_o, and the bias terms are b_f, b_g, b_i, and b_o.To determine the network's present and future state, c_t, one can use

$r_t = o_t.\tanh(c_t)$ ------------- (10)

$y_t = \emptyset\left(W_{yr} \times r_t + b_y\right)$ ---------------- (11)

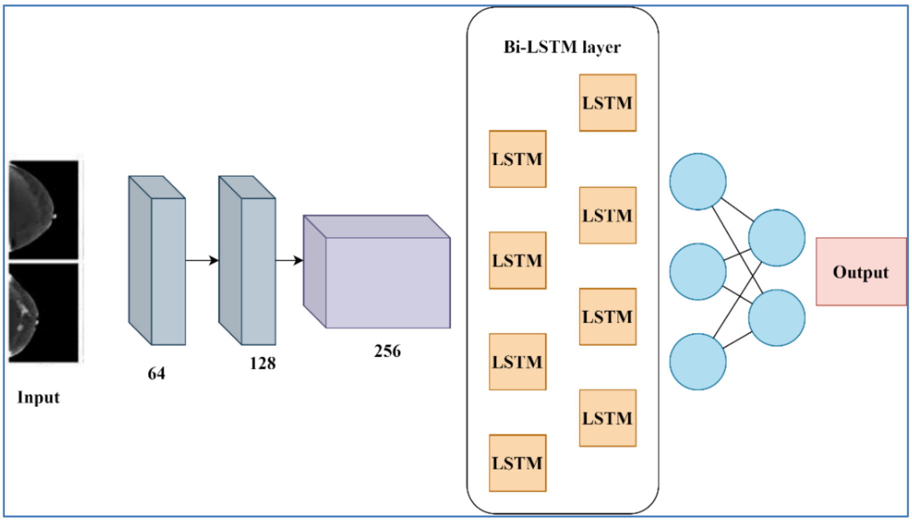

Figure 4: CVBN architecture

Despite RNNs' benefit of encoding input dependencies, they experience a condition of inflating and disappearing against their gradient when dealing with lengthy data sequences. Utilizing Bi-RNN allows for even more gains than LSTM and RNN, which are limited to utilizing data from the preceding context. Figure 1 shows that the Bi-LSTM, which can handle data from two sources concurrently, is the product of merging the Bi-RNN and the LSTM. In addition to LSTM's feedback features for the layer below, the Bi-LSTM can handle data that relies on long-range connections.

Algorithm 1: CVBN

Input:

Mammogram images or other breast cancer diagnostic images.

Typically, these are grayscale or RGB images with specific dimensions.

Steps:

Feature Extraction using VGG19:

- Utilize the pre-trained VGG19 model to extract high-level spatial features from input images.
- VGG19 captures intricate visual details and patterns through its deep convolutional layers.

Feature Representation:

- The output features from VGG19 represent a high-dimensional representation of the input images.

Bidirectional Long Short-Term Memory (Bi-LSTM) Processing:

- Input the extracted features into the Bi-LSTM network.
- Bi-LSTM processes these features bidirectionally, capturing temporal dependencies within the sequence of features.
- The LSTM cells in Bi-LSTM maintain memory over long sequences, enhancing the model's ability to understand and utilize sequential information effectively.

Temporal Context Integration:

- The integration of Bi-LSTM allows the model to retain context from both past and future states, enhancing its capability to discern subtle differences and patterns within the data.

Output:

Output predictions based on the processed features and temporal dependencies captured by the Bi-LSTM network.

IV. Results and discussion

In this section, the results and discussion highlight the performance outcomes and insights derived from applying the proposed CVBN method. The section begins with an analysis of key metrics such as accuracy, precision, recall, F-measure, Mean Squared Error (MSE), and PSNR.

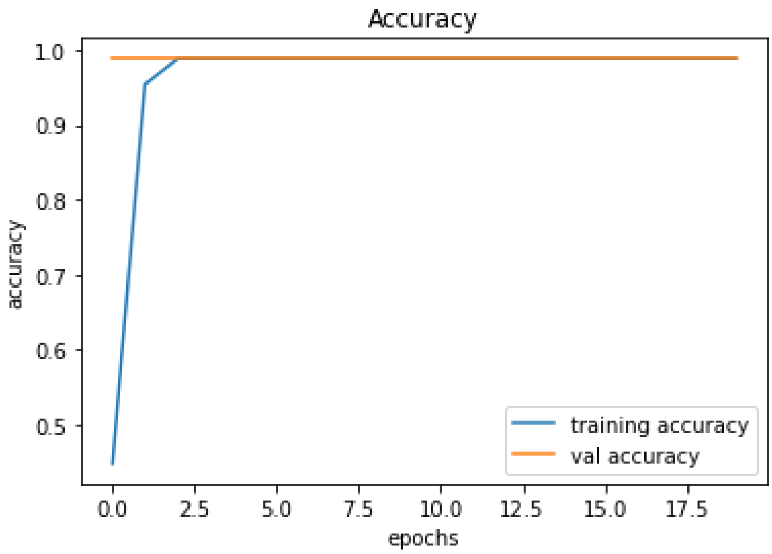

Figure 5: Training accuracy value comparison chart

A comparison chart of training accuracy values is shown in figure 5. Values for precision are shown on the y-axis and epochs are shown on the x-axis.

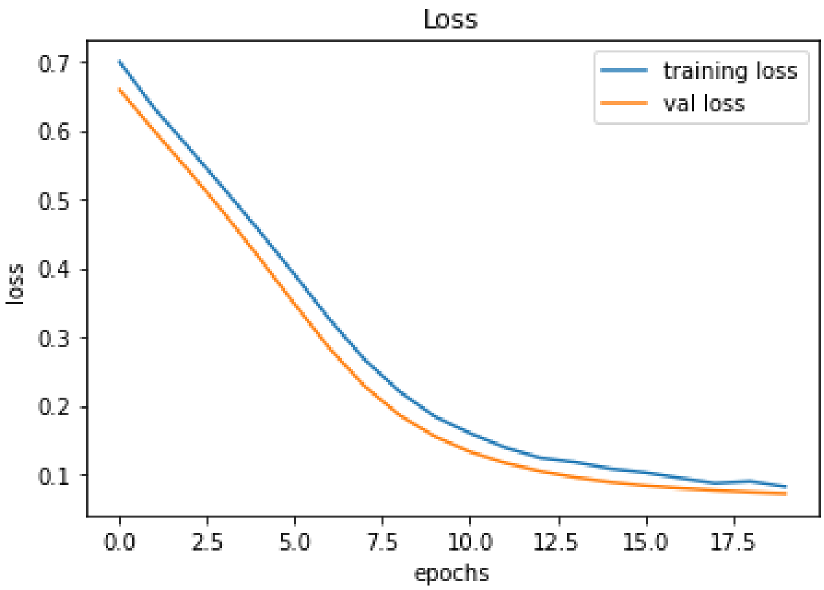

Figure 6: Training loss value comparison chart

Figure 6 displays a chart comparing training loss values. Loss values are shown on the y-axis and epochs are shown on the x-axis.

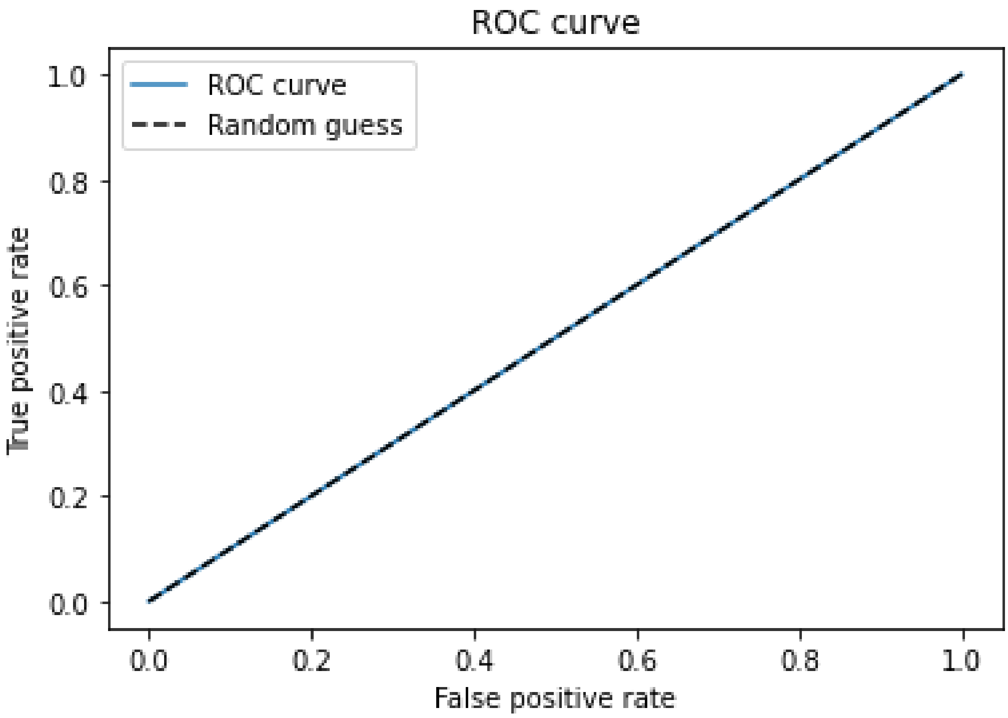

Figure 7: ROC curve

The ROC curve is shown in Figure 7. The false positive rate is shown on the x-axis, while the actual positive rate is shown on the y-axis.

Table 1: Classification performance metrics comparison table

	MIAS			**INbreast**			**DDSM**		
Methods	**VGG19**	**Bi-LSTM**	**CVBN**	**VGG19**	**Bi-LSTM**	**CVBN**	**VGG19**	**Bi-LSTM**	**CVBN**
Accuracy	96.42	96.57	96.89	97.00	97.11	97.65	97.89	98.01	98.79
Precision	96.32	96.55	96.95	97.01	97.31	97.52	97.95	98.21	98.79
Recall	95.33	96.50	96.99	97.11	97.25	97.89	98.85	99.61	100
F-measure	95.02	95.31	96.36	98.36	99.01	99.24	99.02	99.21	99.39

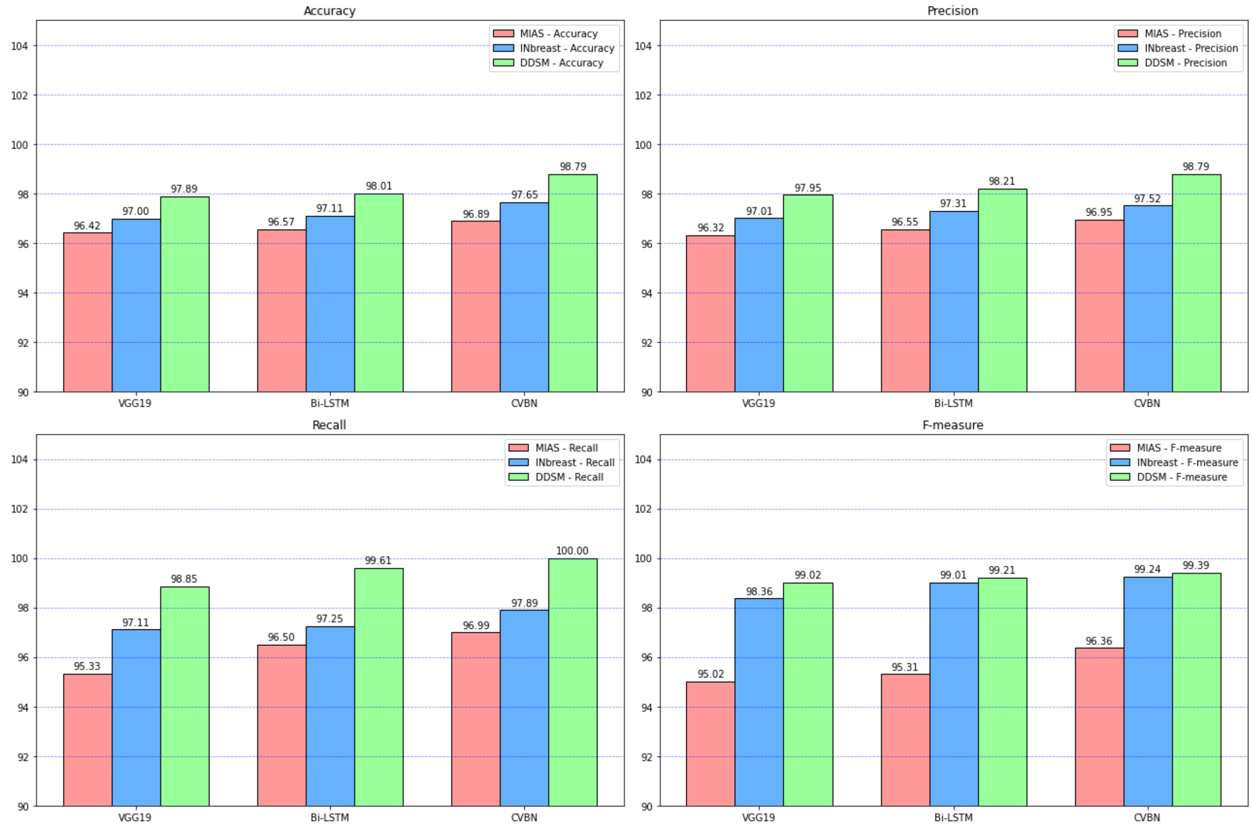

Figure 8: Classification performance metrics comparison chart

The table 1 and figure 8 shows performance metrics for VGG19, Bi-LSTM, and CVBN models across MIAS, INbreast, and DDSM datasets demonstrate notable differences in their accuracy, precision, recall, and F-measure values. In terms of accuracy, CVBN consistently outperforms the other models, achieving 96.89% on MIAS, 97.65% on INbreast, and 98.79% on DDSM. Precision values for CVBN are similarly high, with 96.95%, 97.52%, and 98.79% for the respective datasets. Recall values also show CVBN's superiority, with perfect recall of 100% on DDSM, 97.89% on INbreast, and 96.99% on MIAS. The F-measure scores highlight CVBN's balanced performance, scoring 96.36% on MIAS, 99.24% on INbreast, and 99.39% on DDSM. Bi-LSTM also performs well, especially on the DDSM dataset, with an accuracy of 98.01%, precision of 98.21%, recall of 99.61%, and an F-measure of 99.21%. VGG19, while slightly lower, still shows strong performance, particularly on the DDSM dataset, with an accuracy of 97.89%, precision of 97.95%, recall of 98.85%, and an F-measure of 99.02%. These results clearly indicate that CVBN is the most effective model across all datasets, excelling in all evaluated metrics and demonstrating its robustness in accurately detecting and classifying breast cancer images.

Table 2: MSE and PSNR value comparison table

Methods	**MSE**	**PSNR**
VGG19	0.017	17.32
Bi-LSTM	0.014	18.01
CVBN	0.012	19.13

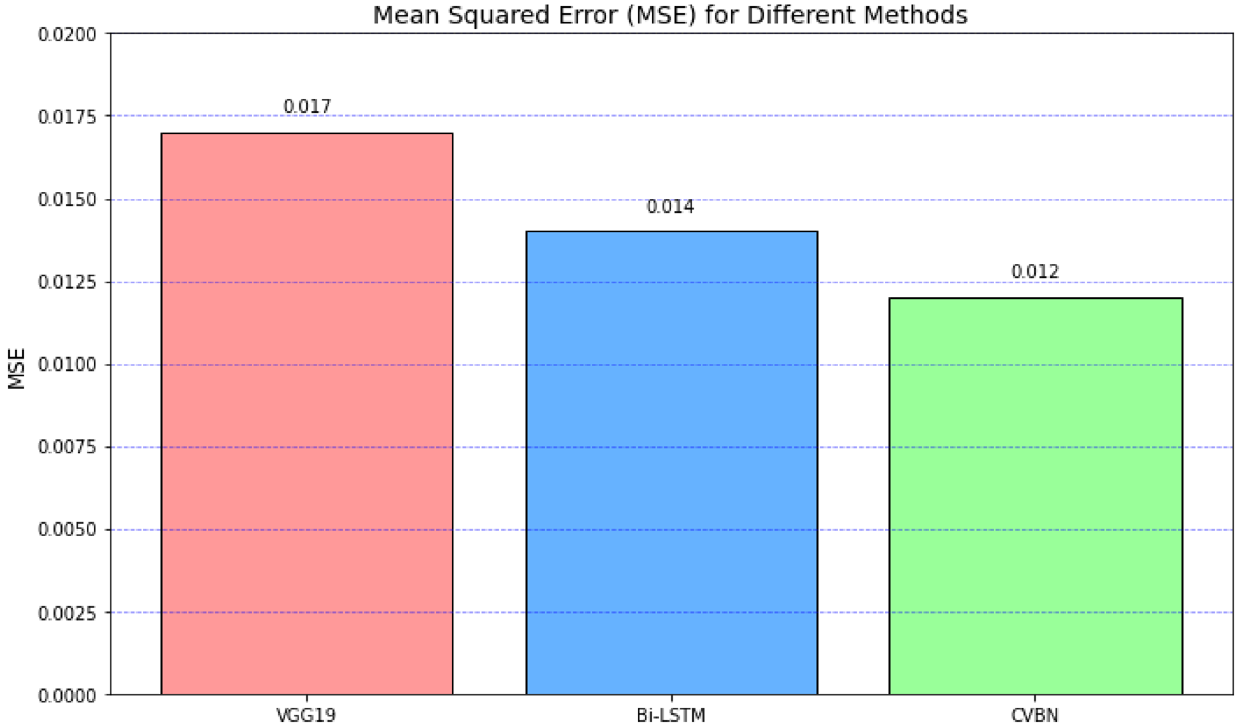

Figure 9: MSE value comparison chart

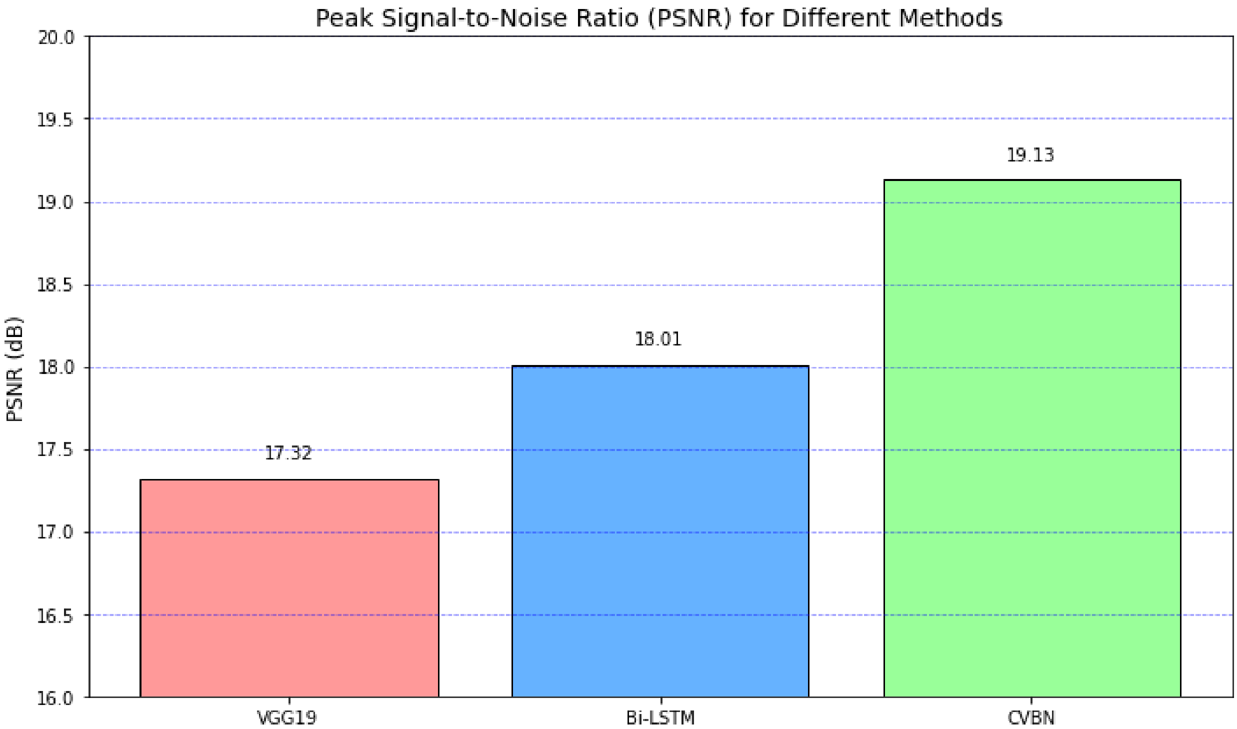

Figure 10: PSNR value comparison chart

The table 2 and figure 9, 10 shows Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) metrics provide insights into the image processing capabilities of VGG19, Bi-LSTM, and CVBN models. VGG19 exhibits the highest MSE of 0.017 and the lowest PSNR of 17.32 dB, indicating relatively higher image reconstruction errors and lower quality in image representation compared to the other models. Bi-LSTM shows a notable improvement with reduced MSE of 0.014 and enhanced PSNR of 18.01 dB, suggesting better image fidelity and lower reconstruction errors than VGG19. CVBN outperforms both models with the lowest MSE of 0.012 and the highest PSNR of 19.13 dB, indicating superior image reconstruction quality and minimal distortion, highlighting its effectiveness in maintaining image fidelity. These results underscore CVBN's superiority in image processing tasks, demonstrating its capability to achieve higher image quality and accuracy compared to traditional CNN and LSTM-based approaches.

V. Conclusion

The CVBN architecture represents a significant advancement in the early detection of breast cancer, utilizing state-of-the-art techniques in deep learning and image segmentation. By integrating the cascaded VGG19 model with Bidirectional Long Short-Term Memory (Bi-LSTM) networks and U-Net segmentation, this research demonstrates substantial improvements in predictive accuracy, sensitivity, and specificity on breast cancer datasets. The enhanced feature extraction and precise tumor localization capabilities of CVBN underscore its potential as a robust tool for improving diagnostic outcomes and patient care. Future studies should continue to refine and validate this approach across diverse datasets, aiming to further optimize its performance and clinical applicability in early breast cancer detection.

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