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Research Article

Breast Cancer Detection using Convolutional Autoencoder with Hybrid Deep Learning Model

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Abstract:

The most deadly cancer among women in world is Breast cancer (BC). The early identification of malignancy helps in the disease diagnosis and it can help strongly to enhance the survival rate. With the rapid development of modern medical science and technology, medical image classification has become a more and more challenging problem. However, in most traditional classification methods, image feature extraction is difficult, and the accuracy of classifier needs to be improved. Therefore, this paper proposes a high-accuracy medical image classification method based on Deep Learning (DL) which is called Convolutional Neural Network (CNN). This research focused to create a hybrid DL model with a single test that subjected at inference and even adopted VGG16 as Autoencoder for Transfer Learning (TL) that performs an image analysis task such as segmentation and even set as an adaptor for pre training the model. The VGG16 is used to train from the source dataset and perform as the adaptors that have been optimized at the testing stage using a single test subject for effective computation. Therefore, this study has been used CNN with Bi-Long Short Term Memory (Bi-LSTM) method to extract features from Ultrasound Images of Breast for cancer detection database that involves images to benign as well as malignant breast tumors for performing analysis of the unsupervised images. The evaluated results showed that accuracy of VGG16 with CNN-Bi-LSTM has high accuracy as 98.24% indicates hybrid DL with VGG16 models have appropriate in detection and classification of the breast cancers precisely.

1. Introduction

Breast cancer is one of the major causes of death in women around the world. According to the American cancer society, 41,760 women and more than 500 men died from breast cancer recently1. Breast cancer occurs in four main types: normal, benign, in-situ carcinoma and invasive carcinoma [1]. A benign tumor involves a minor change in the breast structure. It is not harmful and does not classify as a harmful cancer. In cases of in-situ carcinoma, the cancer is only in the mammary duct lobule system and does not affect other organs. This type is not dangerous and can be treated if diagnosed early. Invasive carcinoma is considered to be the most dangerous type of breast cancer, as it an spread to all other organs. . According to WHO, 627,000 women died from the breast cancer in 2018. Breast cancer is the main problem that spreads everywhere in the world but mostly found in United State of America. There are four types of breast cancer. First type of cancer is Ductal Carcinoma in Situ that found in the coating of breast milk ducts and it is pre-stage breast cancer. Second type of breast cancer is most popular disease and contains upto 70-80% diagnosis. Third type of breast cancer is Inflammatory breast cancer which is forcefully and quickly developing breast cancer in this disease cells penetrate the skin and lymph vessels of the breast. The fourth type of breast cancer is Metastatic breast cancer which is spreads to other parts of the body. According to global health statistics, breast cancer is women's most frequently diagnosed cancer. It accounts for many cancer-related deaths worldwide [2]. The mortality rates associated with breast cancer underscore the critical need for effective detection and diagnosis methods [3]. Early detection is crucial in improving patient outcomes and reducing mortality rates. Therefore, developing accurate and efficient breast cancer detection approaches is paramount in medical research. The breast cancer can be detected using several methods including X-ray mammography, ultrasound (US), Computed Tomography (CT), Portion Emission Tomography (PET), Magnetic Resonance Imaging (MRI) and breast temperature measurement. Usually, the golden standard is a pathological diagnosis for BC detection. For detecting BC, mammography is the most promising method among other methods and radiologists frequently preferred this method [4].

Ultrasound is relatively affordable with a lower price point among the portable units. This makes ultrasound a widely accessible, non-ionizing method for imaging studies, including underserved populations in developing countries [5,6]. Breast ultrasound is also utilized as an adjunct to x-ray mammography in certain cases, particularly the dense breast. Given these advantages, an intensive effort has been made to improve breast ultrasound using computer-assisted analyses over recent decades. The challenge of addressing increasing cases of breast cancer has motivated widening and intensification of research in the domain. This is necessary considering that fact that breast cancer case count is racing up the ladder as it now currently being rated the second cause of death after cardiovascular diseases [7]. The use of deep learning methods has been widely applied to addressing the problem of early detection of the disease. This approach has demonstrated outstanding performance in reporting impressive classification accuracy and also synthesization of data for supporting the training of the models. However, the use of the deep learning models has often been limited to single modality of breast cancer imaging. Studies which have addressed abnormality classification on single modality have often considered magnetic resonance imaging (MRI), digital mammography, and ultrasound technology [8,9]. In recent years, further developments in artificial intelligence (AI) have broadened the types of breast cancer analyses. Previous studies utilizing machine learning approaches, such as support vector machine (SVM) and random forest have output breast classifications of benign or malignant. These typically include feature extraction and selection, and their performance and running time rely on the efficiency of this step. Thus, machine learning approaches for breasts traditionally extracted simple texture or morphological features from log-compressed B-mode images. However, how to optimize feature extraction and selection remains unclear yet critical for performance. To address this feature dependency on performance and time-consuming processes, deep learning algorithms have been recently applied to breast cancer detection not only in classification but also in lesion segmentation [10,11]. Deep learning can advantageously extract data-driven and self-optimized feature maps from input images, and thus feature detection and selection are unnecessary. However, many approaches require large training sets to produce accurate diagnostic classifications, and collecting a large number of patient ultrasound data is challenging [12]. Moreover, due to the computational complexity of deep learning, there are limitations to the size and type of ultrasound signal inputs. Specifically, data is commonly processed (including log-compression and speckle reduction) before input to the algorithms. The raw ultrasound signals are not utilized, which limits classification performance. Therefore, new approaches which utilize the raw ultrasound signals while exploiting the advantages of deep learning and machine learning. The basic AE is an auto-associative neural network, and it derives from the multi-layer perceptron, which attempts to reproduce its input, i.e., the target output is the input. The AE network can convert an input vector into a code vector using a set of recognition weights. Then, a set of generative weights are used to convert the code vector into an approximate reconstruction of the input vector. We can use the basic AE as a building block to train deep networks. The autoencoder can be seen as a three-layer network (input layer, hidden layer, and output layer), including an encoder and a decoder. The encoder maps the input data of the high-dimensional space to the encoding of the low-dimensional space to achieve data compression and the decoder decompresses the input data to achieve recurrence. The decoder is usually eliminated and the encoder model is retained after completing the training phase to extract the input data features [13]. In this paper, hybrid deep learning architecture-based systems are modeled and proposed, and their performances on the spectral data are analyzed to provide a robust model for improved accuracy for BC prediction and classification by employing Raman spectral data. Several deep learning hybrid models are discussed in this explorative research work to find the effectiveness of increased prediction accuracy and learning efficiency of the deep learning hybrid models.

2. Literature Review

This section reviews previous research on breast cancer detection using CNNs as feature extractors.

Some studies have used CNNs to extract features, which are then fed into a classifier to make a final prediction about the label of an image. The basic idea behind a CNN is to extract high-level features from an image using a series of convolutional, pooling and fully connected layers. These layers work together to identify and extract the most important information from the image, leading to more accurate classification and detection. This section summarizes recent developments and advances in breast cancer detection, particularly in the use of standard CNN architecture and methods to improve its performance. The focus is on presenting existing work related to the method proposed in this work.

Choudhary et al [14] proposed a novel approach for histopathological image classification using a deep CNN-based transfer learning method with structured filter pruning. The approach aimed to reduce the runtime resource requirements of the trained deep learning models while maintaining and even improving their accuracy. The method starts by removing less important filters from the convolutional layers, then trains the remaining experiments on the histopathological image dataset using different models along with three important pre-trained CNNs, VGG19, ResNet34 and ResNet50; with the VGG19 model, the VGG19 model achieved 91.25% accuracy, the ResNet34 model achieved 91.80% accuracy and the ResNet50 model achieved 92.07% accuracy. Abdolahi et al [15] presented two deep learning techniques for classifying IDC in histopathology images. In the first approach, a simple CNN (called the base model) is trained. In the second method, the VGG-16 model is used for feature extraction, fine-tuning and classification of breast disease images. The base model accuracy for automatic classification of IDC terms is 85%. Othman et al [16] propose a deep learning model using CNNs to detect liver tumors from CT scans. They use hybrid models based on DeeplapV3 pre-trained with ResNet-50 and VGG-16, ResNet-50 V2 and U-Net with LSTM for liver tumor detection and segmentation. Experimental results show that the first method achieves high accuracy. Ibrahim et al [17] presented a new combination of DL models based on CNNs for liver tumor detection using CT scans. They used DeeplapV3 + ResNet-50 and VGG-16 + ResNet-50 V2 + U-Net++ methods, which achieved high accuracy in the detection of liver tumors. Yu [18] developed a CNN model for automatically diagnosing Invasive Ductal Carcinoma (IDC). The model consisted of multiple 2D-convolutional layers and max-pooling layers, producing a dichotomous output of IDC or non-IDC. The model achieved satisfactory performance on a dataset of 162 patients, with an accuracy of 88% and an Area Under Curve (AUC) score of 95%, showcasing its potential in automating IDC diagnosis. It presents public general pre-trained word embeddings as input features and employs a hybrid dilation convolution structure and the attention mechanism to improve the two networks. The model achieved a reasonable F1 score of 73.72% on the JNLPBA corpus and is the first to adopt the hybrid structure that combines CNN with BLSTM in BNER [19]. This studies the use of a novel neural network architecture for biomedical named entity recognition (BNER), which involves extracting chemical names from biomedical texts to support research. The proposed system uses bidirectional long short-term memory (BLSTM), dynamic recurrent neural network (RNN), and conditional random field (CRF) with character and word level embedding as the only features [20]. This research discusses the importance of NLP technology in the medical field, particularly in event extraction from electronic medical records. The focus of the article is on tumor-related medical event extraction, the method is tested on the CCKS2020 dataset and achieves an F1 value of 73.52 [21]. This research proposes a CAE2 to support unsupervised image feature learning for nodules using unlabeled data. This proposed structure adds a reconstruction input for the convolution operation. The procedure of the convolutional conversion from the input on feature maps to the output is called the convolutional decoder. Then, the output values are reconstructed using the inverse convolutional operation, which is called a convolutional encoder. Moreover, using the standard unsupervised greedy training for AE, the parameters of the encoder and decoder operation can be calculated [22]. In this study, we used an autoencoder that integrates a bidirectional Long Short Term Memory (BiLSTM) layer with a Maximal Overlap Discrete Wavelet Transform (MODWT) layer. This configuration aimed to detect anomalies in Lamb wave signals propagating through a composite structure. Our deep learning approach was trained on 720 raw baseline signals covering 36 different stimulus-sensor pathways. The proposed method is validated using unseen datasets consisting of 72 randomly selected signals. One of the key strengths of our approach is that it can work directly with raw oscilloscope signals, thus eliminating the need for extensive data preparation. To determine the effectiveness of our method, we compare the validation accuracy with a pure LSTM-based deep model and a 1D Convolutional Neural Network (CNN) model. The results reveal that our proposed method performs admirably. To detect anomalies, we added damaged signals to the trained coder model and set thresholds derived from the error generated by the model on the underlying signals [23].

3. Research Methodology

This research focus on improving the classification accuracy for better detection of BC that can be done through the feature extraction method named CAE which is implemented with hybrid model of CNN with BiLSTM. The pre-trained output of the CAE has fed the picture dataset is used as an input for fine-tuned CNN-BiLSTM architecture. The classification accuracy is achieved using the CAE's assistance in identifying the important features from the input images that are accessible.

3.1 Data Collection

The data collected at baseline include breast ultrasound images among women in ages between 25 and 75 years old. This data was collected in 2018. The number of patients is 600 female patients. The dataset consists of 780 images with an average

a) *b)*

Figure 1. *a) Ultrasound image for Benign and b) Ultrasound image for Malignant*

image size of 500*500 pixels. The images are in PNG format. The ground truth images are presented with original images. The images are categorized into three classes, which are normal, benign, and malignant. Figure 1a illustrate the ultrasound image for benign patient of BC available in the dataset and similarly the 1b illustrate the ultrasound image for malignant patient of BC considered in the dataset. Moreover, the overall architecture of predicting BC using CAE with CNN-BiLSTM model. Hence, the architecture of BC prediction using CAE with CNN-BiLSTM model is shown in figure 2

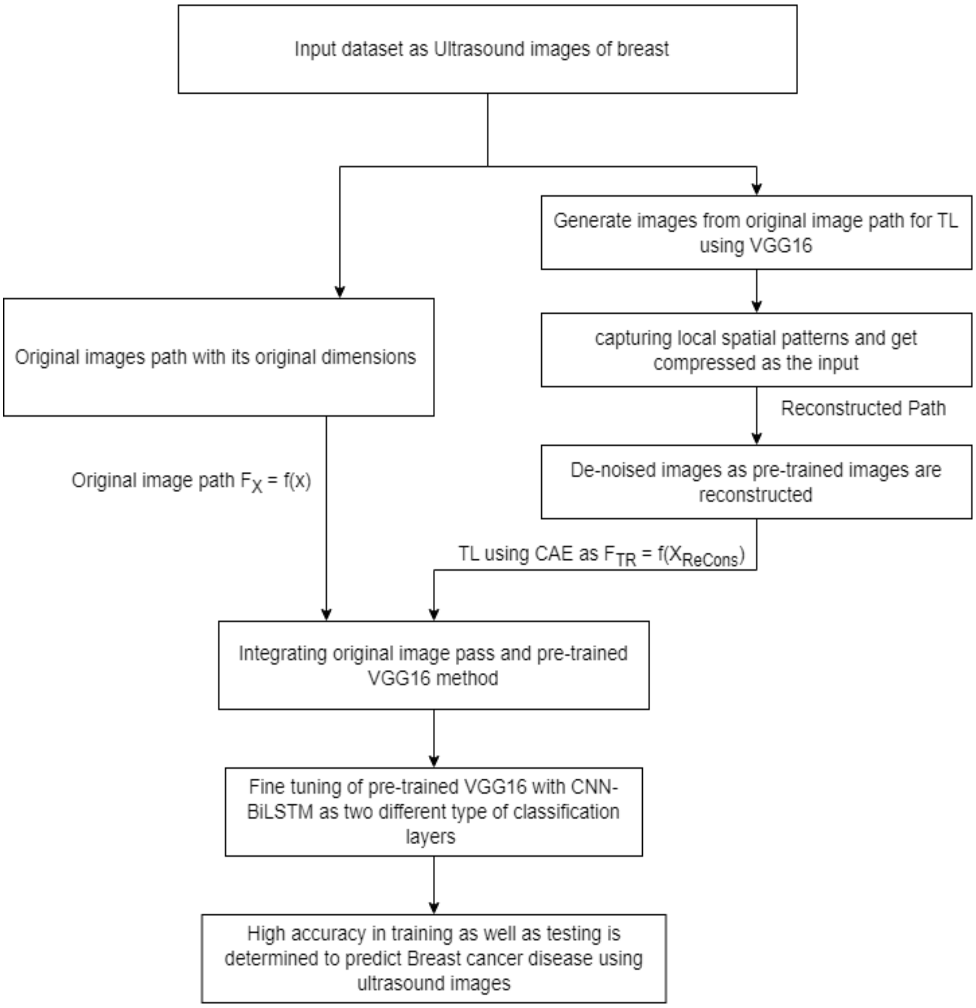

***Figure 2**. Architecture of predicting BC using CAE with CNN-BiLSTM*

3.2 Data Preprocessing

The dataset is stored in three distinct files containing three distinct kinds of images. Image Data Generator is used for prepping training and validation data, including rescaling, rotation range, and fill mode as "nearest." The train data generator has 1148 pictures with two classes, while the validation data generator has 545 images with two classes. These are the two types of data generators. The rotation range produces a picture that is randomly rotated by up to 15 degrees, while the rescaling function helps with pixel value rescaling. The closest accessible pixel is utilized to fill in the missing pixels using the fill mode.

3.3 Working of VGG16 as AE

In this experiment, the proposed approaches based on VGG16 as AE and Multi-Depth VGG AE. Indeed, the use the AE as supervised learning to perform segmenting the image for this mechanism. The VGG16 AE Network with VGG16 model as the encoder part for the first approach by using Pooling and Convolution layers. This process allows to decrease the size of the input data then, it get replaced with the fully connected layers as a latent space. This reconstruction process increases the size of the latent space representation to bring it back to its input dimensions by using Upsampling and Convolution layers which are known as transposed VGG16 architecture. In the Compressed VGG Auto-Encoder approaches, we stacked Convolution and Pooling layers in the Encoder parts for down-sampling the input images, and in the Decoder part we have placed Convolution and Upsampling layers for up-sampling the images in latent space. In fact, the hidden layers are in multi-depth. In such a way that the number of layers will be reduced, i.e. the VGG16 Auto-Encoder model will be compressed to VGG12 and VGG10. Finally we train the whole models from scratch with Teselas dataset. General approaches VGG16 Auto-Encoder and Multi-Depth VGG Auto-Encoder architecture can be visualizing in Figure3.

3.4 Working of CNN-BiLSTM Technique

The hybrid CNN-BiLSTM technique consists of stacked two one-dimensional convolutional layers (64 filters each, with a filter size of 3) to filter the input signal. The results of these convolutions were then passed to a one-dimensional MaxPooling layer (pooling size of 2, no strides and “valid” padding), in order to down-sample the feature maps, reduce the dimensionality, extract only the relevant information and in general make the network more robust.

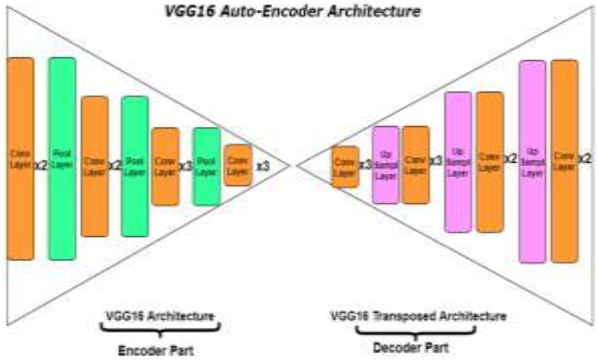

Figure 3. *Structure layers of the approach model based VGG16 Auto-Encoder*

Notice that we only halved the dimensionality, applying a modest pooling size of 2. Applying a pooling layer after (usually two or more) convolutional layers in order to filter the relevant information while also making the network easier to train is a standard procedure in CNNs. We then flattened the down-sampled results into a vector of neurons, and we provided it as a sequence to three-layer stacked Bidirectional LSTMs (BiLSTMs), each one, respectively, with 200, 100 and 50 units. A BiLSTM cell can be simply thought of as made of two LSTMs: one reading the input sequence forward and the other reading it backwards, before concatenating both interpretations. Doing so increases the amount of information available to the model because it provides more context and, while so far it has been typically applied for Natural Language Processing tasks, it recently proved to be very useful also for time series forecasting. Finally, the output of the BiLSTM submodel is followed by a fully connected (FC) layer of 25 neurons to interpret its outcomes. We then stacked the output layer, which was again a fully connected one, this time made by 12 neurons (when we wanted to forecast the next 12 months) or just a single neuron (when we performed single-step forecasting).

3.5 BiLSTM Working Principle

LSTMs are part of the recurrent neural networks (RNN) family, which are neural networks that are constructed to deal with sequential data by sharing their internal weights across the sequence. LSTM addresses the problem of the vanishing error gradient and captures long term dependencies by using its gates to manage the error gradient. The Mathematical representation of LSTM can be shown in equation 1.

$$h_r = f\left(W_h \cdot x_t + U_h \cdot h_{\{t-1\}} + b_h\right) \qquad (1)$$

Where,
x_t = Current feature embedding

W_h and U_h = feature weight matrix
b_h = Bias of the feature
$f(\ )$ = Non-linear function
Generally, the model consider tanh and ht as the basic hidden state whereas the input gate, forgot gate and output gate is shown in equation 2 to equation 6.

$$f_t = \sigma\left(W_f \cdot x_t + U_f \cdot h_{\{t-1\}} + b_f\right) \qquad (2)$$

$$i_t = \sigma\left(W_i \cdot x_t + U_i \cdot h_{\{t-1\}} + b_i\right) \qquad (3)$$

$$o_t = \sigma\left(W_o \cdot x_t + U_o \cdot h_{\{t-1\}} + b_o\right) \qquad (4)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot tanh(W_c \cdot x_t + U_c \cdot h_{t-1} + b_c) \quad (5)$$

$$h_t = o_t \cdot tanh(c_t) \qquad (6)$$

Here ft is called the input gate, ft the forget gate, ct the memory cell, σ the sigmoid function and o the Hadamard product. By itself, the forget gate decides which previous information to forget, while the input gate controls which new information to store in the memory cell. Finally, the output gate decides how much information in the internal memory cell should be released. These gate units help an LSTM model to remember important information over multiple time steps. One drawback of LSTM is that it does not adequately take into account post-word information as the sentence is only read in one direction; forward. To solve this problem, we use two LSTMs with their outputs combined together, known as bidirectional LSTM.
One LSTM reads the sentence forward and the other LSTM reads it backwards. We combine the hidden states of each LSTM after processing their respective final words, technically BiLSTM implements two separate LSTM units, one for the forward direction and one for the backward direction.
The two secret states h_t^forward and h_t^backward from these LSTM units are merged into a final secret state: h_t^BiLSTM is shown in equation 7.

$$h_t^{BiLSTM} = h_t^{forward} \oplus h_t^{backward} \qquad (7)$$

Where,
$\oplus$ = concatenation operator.
However, the learning model is based on LSTM for semantic relationship classification and found that BiLSTM can discover richer semantic information and make full use of contextual information than LSTM. The utilization of BiLSTM is to obtain high-level semantic information features from feature embedding and completes image mapping relationship classification.

4. Results and Discussion

For an experimental research, the high performance server have equipped with i7 Intel Core DMI2 CPU, 100GB of free space, 12GB RAM, as well as Quadro K600 GPU was employed. Ubuntu 18.04.3 LST is the Operating System (OS) that was used to run the aforementioned GPU during the image dataset training process. The loss function and optimizer is used for proposed model with adam as well as binary cross entropy. The VGG16 model is pretrained using imagenet weights and resized the shapes into 224x224x3 which get imported from the module of keras applications. The constructor of the VGG16 as AE takes three primary arguments are input_shape, weight and include_top. The network can process a wide range of input sizes by weight constructor represented the threshold weight with respect to initiated model like include_top, which involves a classifier with dense connections at the network top as well as input_shape represents the shape of image tensor. This study involves consists of 9016 images involved with the size of 24x224x3 pixel and evaluation is done through two different metrics namely accuracy and loss. Table 1 is training and testing images of breast cancer dataset.

Table 1. *Training and testing images of breast cancer dataset*

Breast cancer dataset	Cancer status	Count of the Images	Overall Images for experiment	
			Training	Validating
Breast Cancer images	Benign	4574	4074	500
	Malignant	4442	4042	400

This research majorly focuses for involving VGG16 instead of considering hyperparameter with huge number and the VGG16 goal is to provide convolution layers with 3 x 3 filter using a three stalk with maxpooling each as well as frequent utilization of the similar padding to 2 x 2 convolution layer filter with each maxpool to two stalks. Thus, the arrangement has sequenced based on convolution layer monitored through one layer of max pool to each stalk frequently done by the whole architecture. Finally, it consists of BiLSTM technique before 2 FC layers as dense layer subsequently a softmax for output. The 16 layers over VGG16 involves 16 layers through weights as AE has improved the accuracy of model in detecting BC precisely. The proposed hybrid model as CNN-BiLSTM with VGG16 has define the classification of Benign and Malignant. Figures 4 and 5 show the associated training and validation accuracy a as well as model loss. The figure 4 have illustrated the CNN-BiLSTM with VGG16 model accuracy in which the training accuracy for 6 epoch as well as maintaining the incremental accuracy from 83.63% to 99.08%. In validation accuracy, the drastic change in accuracy and finally obtained with 98.24%. As the epochs increases the accuracy increases and slight decreases, whereas finally training accuracy is higher with 99.08% than testing accuracy is 98.24%. Figure 5 has illustrated the model loss in training is from 0.4049 to 0.0362 and in the validation loss is 0.2369 to 0.0606 which is lesser than training since the model initially has not learn better. When the epoch get increases, there is a reduction in loss from 0.4049 to 0.0362 which liable in defining transfer learning have been occurred for minimizing the loss. Similarly in validation loss curve, the value of loss get minimized from 0.2369 to 0.0606. Thus, the model has trained in the best mode for classifying the model with 99.08% accuracy and validation with 98.24% accuracy. The suggested CNN with VGG16 model defines the classification of Benign and Malignant, whereas Figures 6 and 7 show the associated model loss as well as training and validation accuracy. The figure 6 have illustrated the CNN-VGG16 model accuracy in which the training accuracy became steady after 32 epochs as well as maintaining the incremental accuracy from 92.68% to 96.17%. In validation accuracy, the drastic change in accuracy and finally obtained with 86.24%. As the epochs increases the accuracy increases and slight decreases, whereas finally training accuracy is higher with 96.17% than testing accuracy is 86.24%. Figure 7 has illustrated the model loss in training is from 0.6414 to 0.1123 and in the validation loss is 0.4279 to 0.3710 which is lesser than training since the model initially has not learn better. When the epoch get increases, there is a reduction in loss from 0.6414 to 0.1123 which liable in defining transfer learning have been occurred for minimizing the loss. Similarly in validation loss curve, the value of loss get minimized from 0.4279 to 0.3710. Thus, the model has trained in the best mode for classifying the model with 96.17% accuracy.

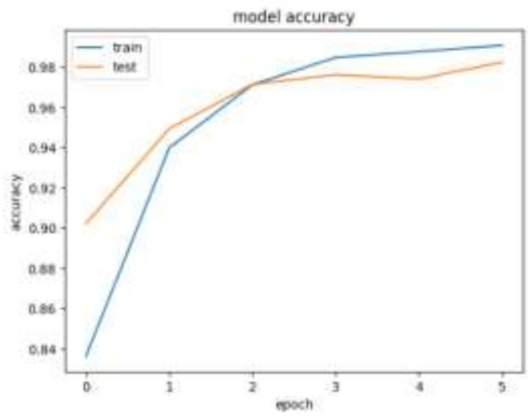

Figure 4. *Comparison of model accuracy for VGG16 with CNN-BiLSTM method*

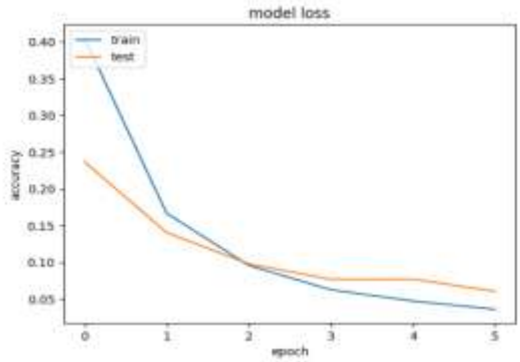

Figure 5. *Comparison of model loss for VGG16 with CNN-BiLSTM method*

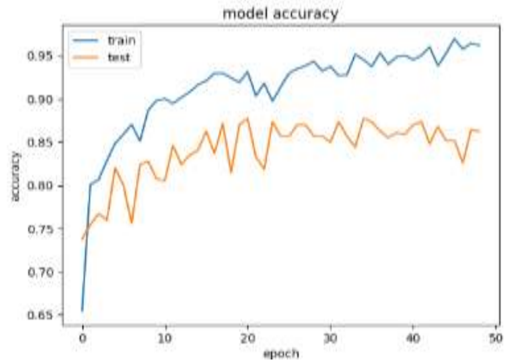

Figure 6. *Comparison of model accuracy for CAE using CNN-VGG16 method*

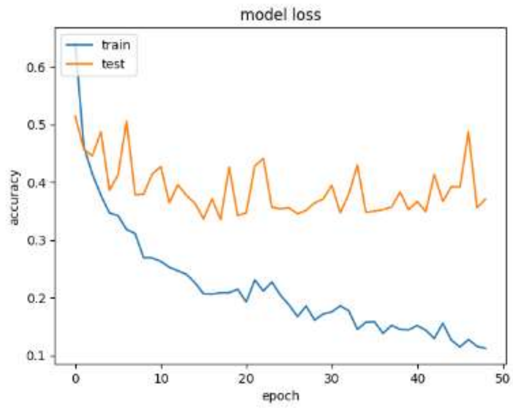

Figure 7. *Loss curve for CAE with CNN-VGG16 method*

Table 2 illustrate the evaluation metrics for CAE with VGG16 based CNN and CAE with VGG16 based CNN in which accuracy and loss is determined through training and testing module. Figure 8 illustrates the accuracy model in training for VGG16 with CNN-BiLSTM is 99.08% which is comparatively higher than CAE with CNN-VGG16 and CAE with CNN-VGG19 is 96.17% and 94.25%. Moreover, VGG16 with CNN-BiLSTM has generated high accuracy in training as well as testing module. Similarly, the testing model involves VGG16 with CNN-BiLSTM is 98.24% comparatively higher than CAE with CNN-VGG16 and CAE with CNN-VGG19 is 86.24% and 85.69%. Figure 9 illustrates the model loss in training for

Table 2. *Evaluation metrics for various AE with DL method*

Evaluation Metrics	Model description	Training	Testing
Accuracy	CAE with VGG19 based CNN	94.25	85.69
	CAE with VGG16 based CNN	96.17	86.24
	VGG16 with CNN-BiLSTM	99.08	98.24
Loss	CAE with VGG19 based CNN	0.1676	0.3695
	CAE with VGG16 based CNN	0.1123	0.3710
	VGG16 with CNN-BiLSTM	0.0362	0.0606

VGG16 with CNN-BiLSTM is 0.0362 which is comparatively lesser than CAE with CNN-VGG16 and CAE with CNN-VGG19 is 0.1123 and 0.1676. Moreover, VGG16 with CNN-BiLSTM has generated least loss in training as well as testing module. Similarly, the testing model involves VGG16 with CNN-BiLSTM is 0.0606 comparatively lesser than CAE with CNN-VGG16 and CAE with CNN-VGG19 is 0.371 and 0.3695.

5. Conclusion

To enhance AE using VGG16 with hybrid CNN-RNN performance for image classification tasks. This experimental research has suggest the study to use VGG16 as a universal unsupervised learning in feature extraction technique for building robust as well as compressed representations of features. In image classification models, the used CNN-BiLSTM models with VGG16 are typically taken into consideration. This study has indirectly determined that TL based method has leads to the best performance using VGG16 with CNN-BiLSTM results comparing with other CAE with CNN-VGG16 and CAE with CNN-VGG19 image classification models. In contrast, this method determined the proposed method has ability for improving the VGG16 with CNN-BiLSTM for

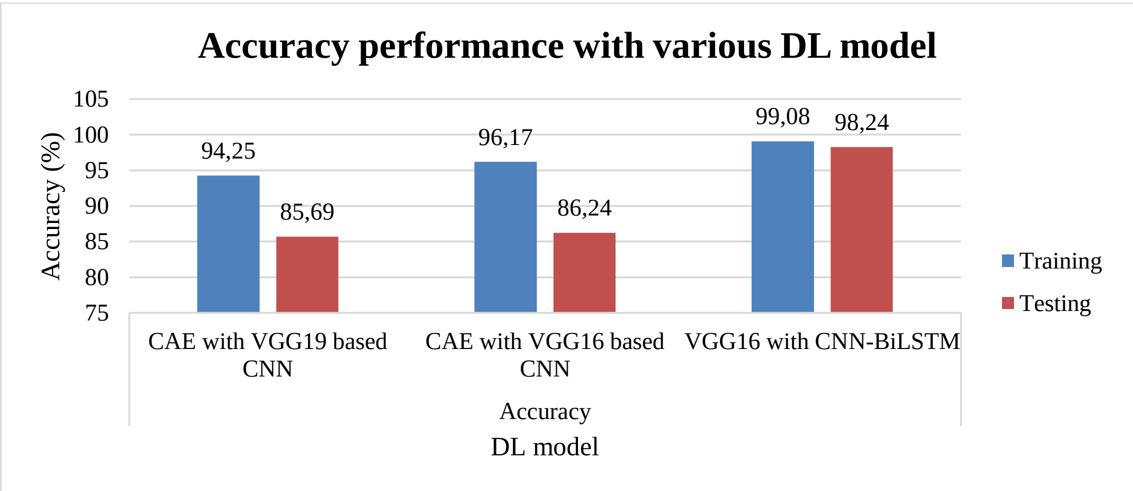

Figure 8. *Accuracy comparison of various AE with CNN-VGG method*

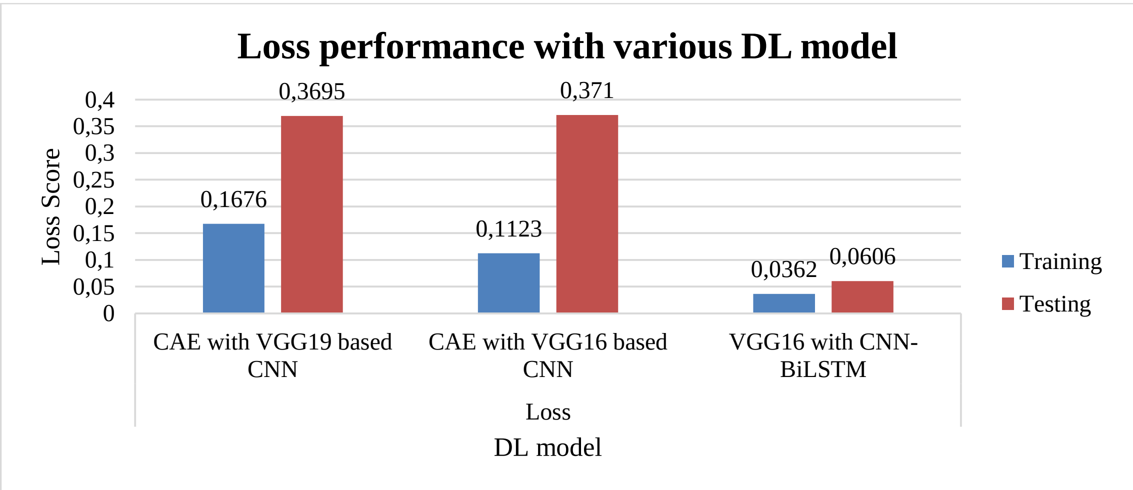

Figure 9. *Loss comparison of various AE with CNN-VGG method*

image classification models consists of sufficient layer in CNN model selection for leading the reliable and robust experimental results. Thus, the prediction of BC detection is high accuracy in VGG16 with CNN-BiLSTM is 98.24% is comparatively higher than CAE with CNN-VGG16 and CAE with CNN-VGG16.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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