Improving the Breast Cancer Image Classification using Autoencoders and CNN

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Abstract - Breast cancer is the most common disease among female rather than male, affecting 2.1 million women every year. Globally more than 70,000 women die from breast cancer every year. Deep learning architectures such as Convolution neural networks are mostly used for image classification. They fit well in classifying breast cancer images also. Several feature extraction mechanism have been already available. The CNN is also used for the feature extraction and for the image classification. For improving the classification accuracy, the Convolution auto encoders are used to extract the features and the output of the auto encoders are fed into the Convolution neural network. The objective of the work is to improve the classification accuracy by combining the feature extraction mechanism such as auto encoders along with the Convolution neural network for various types of breast cancer images like Histology images, Mammogram images and Sonogram images.

Keywords: Convolution neural networks, auto encoders, histology, sonograms, mammograms

1 Introduction

Globally, cancer is considered as the dangerous diseases.. Cancer is the unlimited cell growth all over the body. There are different types of cancer, some of them are lung cancer, liver cancer and breast cancer. There are several screening tests and preliminary diagnosis of cancer, the definitive diagnosis is made by analyzing a biopsy sample of the suspicious tissue. The general signs and symptoms can be observed in patients with various cancers: loss of weight, Giddiness, irregular bleeding, recurrent cough or change in voice and fever. Generally, the cancer is found out mostly by the biopsy results and it helps in determining the stages of the cancer. Cancer can be categorized into 5 stages – 0 to 4. The different stages of cancer will be determined by the doctor based on the biopsy result and the symptoms of the patient. The treatments for the cancer are chemotherapy, radiation therapy and surgery. The prognosis of cancer ranges from excellent to poor. It depends on the stages of the cancer.

A. Convolution Neural Network

For picture categorization and recognition, the Convolution Neural Network (CNN) is utilised. The input of CNN is taken as an image, the input will be manipulated, and assigns to one of several categories. Every image will be processed using a sequence of convolution layers with filters (Kernals), pooling, fully connected layers (FC), and Softmax to categorise the values ranging from 0 to 1 [1]. The several layers in CNN are explained as follows:

a) Convolution Layer: The convolutional layer will compute the output of neurons connected to particular regions in the input by computing a dot product between their weights and a small region in the input volume to which they are connected. As a result of the reduction in area, this could result in an increase

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in volume. While using pictures, connecting neurons to every neurons is a cumbersome job in high dimensional inputs. In order to connect neurons it should be connected to the tiny portion of the input volume [1].

b) Pooling: This layer is placed after the Convolution layer. The main purpose of having this layer is to reduce the spatial size of the given input and also reduces the parameters and computations in the network. This particular layer controls the overfitting issue.

c) Fully Connected Layer: Neural networks take in data and transform it through a number of layers that are hidden from view (a single vector).The individual hidden layer is consists of group of neurons, every neuron is fully connected in the previous layer and each of which functions independently and without sharing any connections. The "output layer" refers to the last fully connected layer.

d) Activation function: In tens or flow, the activation functions provide different types of nonlinearities for use in neural networks. These include smooth nonlinearities (sigmoid, tanh, relu, softplus, and softsign), and dropout.

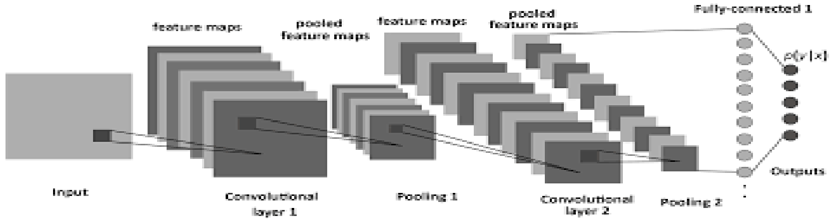


Fig1: CNN Architecture

B. AUTOENCODER:

A neural network with only one hidden layer is known as an auto-encoder. To perform compression, the hidden layer will have smaller units than the input layer ,and then to rebuild the input by reversing the compression process. The total units in the hidden layer are found by the compression level. Auto-encoders are used before convolution layer to optimize and preprocess image so that information which contains no significant weight age can be eliminated to help in computation complex processing.

Different types of Auto encoder are listed as follows

1. De noising Auto encoder: De noising auto encoders produce a flawed duplicate of the data by adding noise. This prevents auto encoders from simply replicating the input to the output without learning about the data's characteristics. While practising, these auto encoders accept a partially corrupted input and reconstruct the original undistorted input. To neutralise the extra noise, the model learns a vector field to transfer the input data to a lower dimension multiplier that describes the natural data.

2. Sparse Auto encoder: Nodes concealed in sparse auto encoders are larger than input nodes. They can still find key data features. The obscurity of a node matches the activation point of a generic, sparse auto encoder. A sparsity limitation is applied to the buried layer. This is to prevent data from being transferred from the output sheet into the input sheet. Sparsity can be achieved during the training phase by adding more terms to the loss function, either by comparing the probability distribution of the hidden unit activations with a low desirable value, or by manually making zero. The stacking of sparse auto encoders within deep neural networks was used in some of the most effective AIs in the 2010s.

3. A deep auto encoder is made up of two symmetrical deep belief networks (DBNs), it consists of two layers, the first layer consists of four or five shallow layers providing the encoding half of the net and the other with restricted Boltzmann machines (RBNs), the building blocks of DBNs.

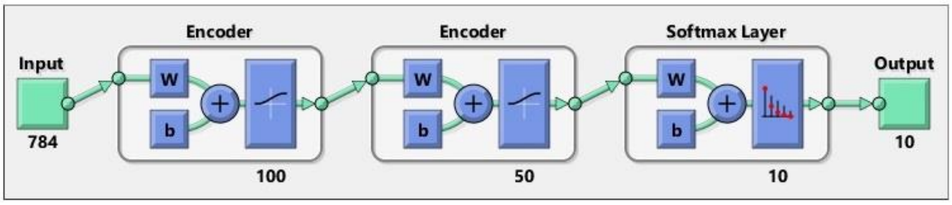


Fig.2 An Example of the Encoding portion of an auto encoder

After training the network as an AE, the decoding part of the network is ignored and the output of the deepest hidden layer is given into the classifier layer.

4. Convolutional Auto encoder: To exploit this observation, The Convolution Operator is used by Convolutionary Auto encoders. They learn how to decode the input into a series of simple signals,then attempt to recreate their input by changing the image's geometry or reflectance. They are the most advanced techniques for learning convolutional filters without supervision. These filters can be applied to any input once they have been trained to extract features. The features can then be applied to any task that requires a concise representation of the input, such as classification.

2 Related Work

Sara, Peyman et al proposed to identify his to pathological biopsy images using the Deep Learning Network Ensemble. The scientist, along with the Convolutional Neural Networks (CNN), used the Computer Aided-Detection (CAD) to assist in the identification of any abnormality. The author has suggested the automatic binary classification approach using a deep learning algorithm for the histology images ensemble. The proposed model consists VGG19, MobileNet, and DenseNet, which are pretrained. The multi model is used for the extraction and representation of features. Once the functions are removed, the classification process is fed into the multi-layer perceptron classifier. The four datasets used in the paper which are publicly available are ICIAR, BreakHis, Patch Cameleon and Bioimaging. The role extraction is performed using the transfer learning principle. Transfer learning has advantages such as accelerating network convergence, lowering computational power, and improving network performance. The architecture of the three path ensemble is used to improve the accuracy of the classification. The InceptionV3, InceptionresNetV2, Xception, ResNet50, MobileNetV2 and DenseNet201, VGG19 and VGG16) have different combinations of hyperparameters including, optimizer, learning rate, weight initialization, batch size, dropout rate to achieve the best possible detection output for breast cancer. The final completely interconnected layers of every CNN architecture are combined to create the final feature vector. The combination allows more detailed features to be captured. So a more reliable precision can be obtained. The three architectures are used for abstraction and depiction of features. The combination of different functions leads to a better performance in generalization than a single classifier. The accuracy, recall and F1-score are the assessment parameters used in the paper. The proposed model provides the best estimates for the four separate datasets with a precision of 98.13 percent, 95.00 percent, 94.64 percent and 83.10 percent. The proposed approach in this paper gave a poor performance due to the clarity in Bio-imaging dataset. This is because the Bioimaging dataset is not broad enough to capture the high level deep learning models features and differentiate classes [1].

Using the CNN method, Sumaiya Dabeer, Maha, and Saiful addressed the Cancer classification using histopathological images. The tasks of image processing adapt CNN for the automated extraction of a feature. CNN is often used for the segmentation of images and processing of medical data. The author has suggested 2 layers: Convolutional layers and Pooling layers. During the classification process, it calculates the loss and updates the weights of the hidden layer. Accuracy standard derived from numerous state-of-the-art experimental setups. Precise confirmation is enhanced. There is a significant improvement in precision and recall. This method is very useful because it is fully automated with this device. In this paper, the assessment metrics are accuracy, recall, f1-score and help. The data is initially pre-processed by resizing and reshaping and then fed into the layers of Convolution and pooling. After that, the functions are collected and then given to the fully connected layers as an input. The dataset is taken from the BreakHis database, which was compiled between January 2014 to December 2014 from the survey carried out by P&D Lab, Brazil. The surgical (open) biopsy (SOB) technique uses the breast tissues as samples. The result shows 93 percent accuracy. The author has described the future scope that for improving the classification accuracy, the features can be extracted with the aid of autoencoders and then the extracted features are provided as input to the convolution neural network [2].

Riu et al. looked at a publication that used hybrid deep neural networks to classify the breast cancer. Convolutional Neural Networks are a deep learning technology that is often used to recognise photos and extract visual attributes, according to the author. The author tackled picture classification by dividing the input into small patches, then using CNN to identify each patch, and then combining the results of patch classification, such as majority vote. Additionally, CNN is employed as a feature extraction approach to extract the features, and then the output of the entire histopathology pictures is rendered using a machine learning classification algorithm such as Support Vector Machine. The author has proposed a method that extracts multi-level features and incorporates the advantages of the neural network CNN and Recurrent neural network (RNN) by maintaining the short-term and long-term spatial correlations between patches. The pathology images are divided into the small patches. The author had reported that the average accuracy obtained for the four classification methods is 91.3 percent which outperforms all other existing methods. The image dataset consists of 3771 high-resolution images (2048 to 1536 pixels) and stained breast pathological images of annotated hematoxylin and eosin (H&E). The author has addressed the following steps, the data increase and the processing of images are carried out in the first stage. The H&E staining is done to standardize the pathological images. For each picture, the paper had established about 50 random color increases. In the second step, the patch-wise method called Google's Inception-V3, the CNN architecture is trained to top-five accuracy at 93.33 percent on the 2014 ImageNet's 1000 object classes. For the two main reasons, the author had suggested the Inception-V3, firstly, The Inception-V3 network uses factorised inception modules, which allow it to choose appropriate kernel sizes for the convolution layers and learn low-level features and high-level features with bigger conversions. The advantages of Innovation in the second stage include computational efficiency and low parameter, and it could be used in high-resolution scenarios. The image-wise process is the third phase, and the author suggests that in this system, the RNN be used to decrease the contextual information of features that are connected to the top of the CNN feature extractor to have the final image. Patch functions are captured by the CNN, whereas short-term and long-term patch dependencies are captured by the RNN. In the study, exactness and precision are employed as measures. The long-term bidirectional memory network (BLSTM) is employed for classification. An LSTM extension. According to the author, deep learning can adapt to the use of the attention system. The author suggests a novel hybrid model that blends hybrid convolutional and recurrent deep neural networks. Through an RNN, the proposed technique evaluates both long and short term spatial correlations between patches. According to the author, the employment of the attention mechanism in deep learning can be used to improve performance. [3].

Using the Convolutional Neural Networks, Phu et al addressed the classification of breast cancer by multiclass. The author has proposed using deep learning to extract features from the dataset, without using any extractors to build features. The Convolution neural networks are used in image processing, speech recognition and classification. The BreakHis dataset is used in this paper which includes 7909 Histopathological images with benign subclasses and malignant subclasses respectively. Four separate magnifications make up the image dataset. The convolutional layer is used to measure the output of the neurons attached to input regions. The weights associated with the input are called the kernel or filter. In the Convolutional Neural Networks, the author has suggested different setups that include, input layer, Convolutional layers, ReLu layers, and pooling layers. The instruction data set is broken down into 90% and the test data set is broken down into 10%. The author used Keras and Python frameworks to construct the classification model. The paper addressed the final result for the maximum validation accuracy of 73.68 percent the number of epochs is 32. This leads to the lowest loss of validity. The degree of precision can be increased by investigating the different classification methods and optimizing the parameters [4]

SanaUlah, Naveed et al suggested the deep learning system for classifying breast cancer. With the pre-trained CNN architectures, the author has explored the feature selection techniques. Mostly based on the network of Google, the Visual Geometry Grouping Network and the Residual Network combined with the learning of transition. In this paper, the definition of average pooling classification is used. The transfer learning and fine-tuning of attributes are shared throughout the three CNN designs (GoogLeNet, VGGNet, and ResNet). These three CNN architectures were trained using sample images from the ImageNet data collection, and transfer learning was used. This allows the architecture to learn common features from different data sets without requiring additional training. The number of features extracted are integrated for categorization of malignant and benign cells into the final layer utilising average pooling classification. The dataset utilised in this paper is a conventional benchmark dataset, while the other is being created locally at the LRH hospital in Peshwar, Pakistan. For both datasets, data augmentation techniques such as rotation, scaling, translations, and colour processing are used. There are approximately 8000 photos in the data collection. 6000 photographs are for training, and 2000 images are for testing. The proposed system is trained separately on three different CNN architectures, and then the learning data is transferred into the combined feature extraction using transfer learning. The classification accuracy of Googlenet is 93.5 percent, VGGNet is around 94.15 percent, and ResNet is around 94.35 percent, while the proposed system is around 97.52 percent. For testing, the author separated the data sets into three categories: 90%:10%,80%: 20% and 70%:30% correspondingly. In comparison to all present architectures, the author found that the proposed architecture provides the most precision. Precision, recall, F1 score, and accuracy were among the variables examined in the study. The average accuracy of the various training and testing breakups is compared to the accuracy of the three different present systems and the proposed technique. Out of all the alternative architectures, the author has concluded that the presented design is the most accurate. [5].

Anika et al proposed the Clinical, data and WSI dataset for the prediction. The author has built the unsupervised encoding method Multimodal patient data in a generic representation of features which is independent of data form or process. Patients with similar characteristics tend to form a cluster, and unsupervised patient encodings are predictive with a wide variety of useful clinical variables. These feature representations serve as an combined multi-modal patient details, allowing machine learning models to be compared and contrasted with patients in a sequential order. Thus, in a number of contexts, these encodings could be of vital use, ranging from prognosis prediction to treatment recommendation. On 20 TCGA cancer sites, the proposed method achieved C-index of 0.784. The proposed method achieves high accuracy, reducing the attributes and information from cancer types to overcome data scarcity. The author has implemented CNN for learning the unsupervised learning between clinical data, gene data and image dataset. The author has used only one image dataset for the prediction and used CNN for the classification approach [6].

Chuang Zhu et al suggested using several compact CNNs to identify breast cancer. The author has suggested several CNN architectures that have a branch of the local and global model. The stronger representation is achieved by local elections and two branch information combining, and the proposed Squeeze-Excitation-Pruning (SEP) block is also fed into the hybrid model to replace the redundant channels. The model that is being suggested would reduce overfitting and produce better precision. The BreakHis and the Breast Cancer Histology (BACH) drawn from the two datasets used in this article. To extract the stains in the histopathology images in the dataset, the author has used the staining tool. Data incrimination and shearing transformation methods are used to prevent overfitting. The channel pruning technique used to delete the pattern redundancies. The pruning of channels has the following steps:pre-training, weight computing of channels, pruning of channels, retraining and compressed function. The weights are determined using the SEP block which is embedded. Using the Caffe deep learning system provided by Berkley Learning and Vision Center, classification is carried out. The evaluation criteria performed in the paper are Patient Ratings, the global patient recognition rate, the recognition rate of image level, Positive predictive value and Kappa. The author concluded that the proposed algorithm has better accuracy in classification compared to other existing methods, the proposed method has a local and global branch. For the simple diagnosis, the proposed model was very useful to the pathologists. The future work is that the channel pruning strategy will be utilised in tandem with other standard compression methods in the workplace, such as Dynamic Network Surgery (DNS), to provide higher precision with the same model size and provide improved accuracy. [7].

Yuqian Li et al addressed that the classification is performed using pictures from the Histology. In this paper, the Convolutional neural networks are used for the analysis of the histology pictures. Classification is based on the three normal, malignant and benign categories. The two types of patches with different sizes from breast cancer histology images by a sliding window mechanism for preserving essential information include cell and tissue-level features, and then train two CNNs as feature extractors respectively. Use the feature extractors to extract smaller and larger points, and measure the final feature of the entire image to prepare for classification. P-norm pooling removes the picture finishing functionality. The image-wise classification is enhanced by removing from the breast histology images smaller patches and larger patches to include cell-level and tissue-level properties. The author discriminated against the cluster algorithm and CNN with 128 x128 pixel patches. SVM is used for the final grading of images. The dataset is composed of high resolution 2048 x 1536 pixels and H&E Stained breast cancer histology images from the 2015 Bioimaging breast histology classification competition. Precision, recall and F-Score are the success parameters used in this paper. The author described the image classification and recommended the following steps. The initial step is to use the sampling technique to remove the contiguous 128x128 pixel overlapping patches and 512x512 pixel patches with the 50 percent overlap of the test images. In the second step, the Rest-Net 50 cluster is used to fine-tune by 128x128 pixel patches, is prone to patches that are more discriminative The network is used to anticipate smaller patches and to select patches that have a higher likelihood of categorization than a predetermined threshold. The third step is to feed the extracted patches and selected patches corresponding to each test image into RestNet 50-512 and ResNet 50 clusters to get the group of dimensional features of 2048. The fourth step is to use the 3 norm pooling method to calculate the final attribute of each picture and to use the Support Vector Machine (SVM) to make a final classification. The method suggested is 95 percent more effective than the current system, which is only 85 percent [8].

In all above methods, the Convolution Neural Network (CNN) is used for image classification and feature extraction. The dataset used in all the above method is of only one image dataset. Whereas, in this paper, multimodal image classification is performed by using different image datasets. In order to improve the accuracy, the autoencoder is implemented. The classification accuracy is improved in such way that the output of the CNN classification is given as an input to the autoencoder.

III. Proposed System

In order to improve the classification accuracy, the feature extraction method called autoencoder is implemented. The image dataset is fed into the autoencoder and the output of the autoencoder is fed into the input of the Convolution Neural Network (CNN). The autoencoder takes the relevant features from the given image as an input and the classification accuracy is monitored.

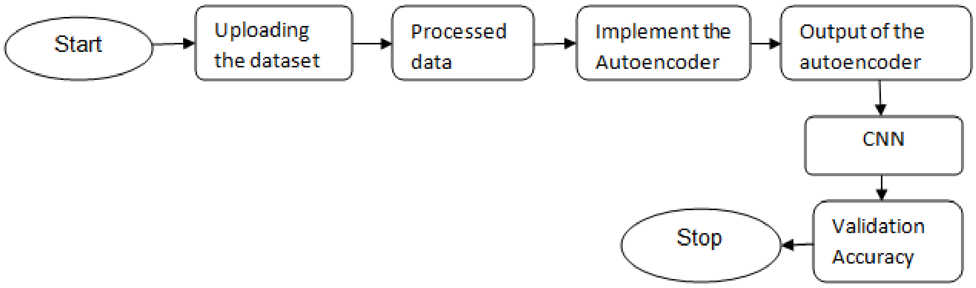


Fig 3 Flow diagram for auto encoder implementation

In the above figure, the dataset is taken from various sources, the dataset is preprocessed, after preprocessing it is implemented using autoencoder, the output of the autoencoder is given as an input to the CNN and the accuracy is checked.

A. Datasets*:*

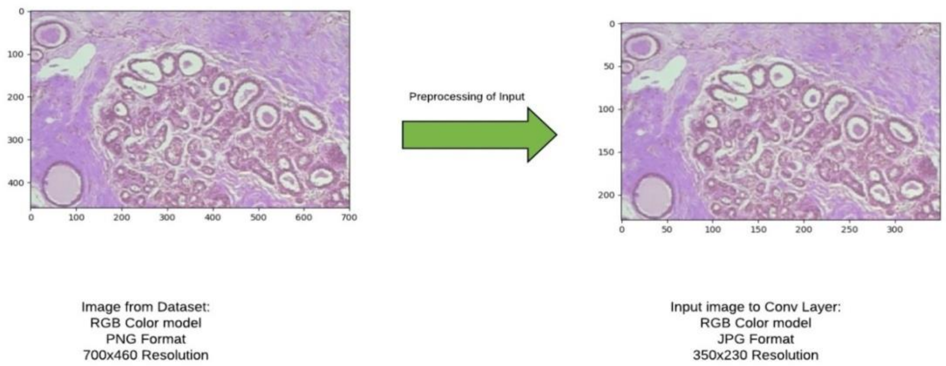
Histopathological image dataset: The Breast Cancer Histopathological Image Classification (BreakHis) is made up of 7,909 microscopic images of breast tumour tissue taken from 82 people. and magnified at various magnifications..There are 2,480 benign and 5,429 malignant samples in the database (700X460 pixels, 3-channel RGB, 8-bit depth in each channel, PNG format). In most cases, benign tumours are deemed harmless because they grow slowly and stay localised. The term "malignant tumour" refers to a tumour that can infiltrate and destroy nearby structures (locally invasive) as well as spread to distant areas (metastasize) and cause mortality.

Mammogram image dataset: The Mammogram images are taken from Mammogram Image Analysis Society (MIAS). It consists of 322 images of both benign and Malignant classes. The image were in the form of .pgm format.

Ultrasound image dataset: The data collected from the women of ages between 25 and 75 years old. The data was collected in the year 2018. The number of female patients are 600. The dataset consists of 780 images with an average image size of 500x500 pixels. The image are in the .png format. The images are divided into three classes: Benign, Malignant and Normal.

B. Image Preprocessing:

The deep learning algorithm is implemented by first processing the images in the dataset. The Open CV library in Python is used to accomplish this. This stage removes duplication from the input data, which adds to the network's computational complexity while providing no substantial increases in results. Because both dimensions are decreased by a factor of two, the aspect ratio of the original image is kept, resulting in an image that is 1/4rth of its original size.



C. Feature Extractiong Using CNN

Raw pixels of an image do not provide meaningful features to the classifier through which it may learn, therefore, a CNN is used to extract prominent features from the data. This network consists of 2 types of layers:

1. Convolutional Layers
2. Pooling Layers

The details of the network are illustrated in the given table followed by its visual representation:

Table 1 Parameters of CNN

Layer #	1	2	3	4
Type	Convo lution	Pooling	Convo lution	Pooling
Channel	256	-	256	-
Filter size	3x3	-	3x3	-
Pooling size	-	2x2	-	2x2
Activation	ReLu	-	ReLu	-

D. Autoencoder:

The details of the autoencoder are illustrated in the given table followed by its visual representation:

Table 2 Parameters of Encoding and decoding

Layer #	1	2	3	4
Type	Convo lution	pooling	Convo lution	pooling
Channel	16	-	8	-
Filter size	3x3	-	3x3	-
Pooling size	-	2x2	-	2x2
Activation	ReLu	-	ReLu	-

3 Experimental Results

The three different image dataset is considered for the analysis. Initially, all the 7909 histology images are fed as an input into the Convolution Neural Network and the classification accuracy is monitored. For the experimenting purposes, all the three image datasets (Histology, Mammogram and Sonogram) with the count of 500 images are taken for consideration (250 - benign and 250 – Malignant images). Initially, all 500 images from different datasets are implemented using CNN.

A. EXPERIMENTAL SETUP IN GOOGLE COLAB

The following steps need to be followed:

Step:1 The user should have google account to work in the google colab

Step:2 Create a dedicated development folder

Step:3 Create a snippets notebook: After creating the development folder it can automatically sync to the google drive. In order make the drive accessible to the network the following commands need to be used.from google.colab import drive
from pathlib import Pathdrive.mount("/content/drive", force_remount=True)

Python environment to find the scripts:

base = Path('/content/drive/My Drive/fastai_course2/')
sys.path.append(str(base))

As, the proposed methodology, all the three image datasets are implemented using CNN, and the output of the CNN is given as an input to the Convolution autoencoder, and the classification accuracy is monitored. The Classification accuracy implemented using autoencoder gave better accuracy compared to CNN. The Convolution neural network extracts irrelevant features from the input image, whereas, the autoencoder extracts the specific features from the image, and thereby, the classification accuracy is increased.

The number of epochs is considered as 500 for all the image dataset. The epochs is set by the user based on the hardware and software requirement.

Table 3 Image classification using CNN and Autoencoder

S.No	Image type	Number of images	Number of Epochs	Feature Extraction	Accuracy
1.	Histology	7909	500	Implemented using CNN	77%
2.	Histology	7909	500	Autoencoder	90%
5.	Ultrasound	500	500	Implemented using CNN	80.4%

6.	Ultrasound	500	500	Autoencoder	82%
7.	Mammogram	500	500	Implemented using CNN	78.6%
8.	Mammogram	500	500	Autoencoder	81%

From table 4.1, it is inferred that using the Convolution autoencoder, the classification accuracy is improved for all the image datasets. Histology dataset has more images and with CNN, the accuracy was 77%, when it is implemented with autoencoders it is around 90%. Similarly, for the ultrasound images implemented over CNN, the accuracy is 80.4%, when it is implemented with autoencoders it is around 82%. The mammogram images implemented over CNN, the accuracy was 78.6%, when it is implemented with autoencoders it is around 81%.

4 Future Work

The future work mainly based on the development of certain features which may or not be incorporated in the existing system they are remodeling the Neural network to perform better. To design a user-friendly GUI to provide ease to non-programmer users, use of more than 1 GPU for implementing a more complex network and the ability to train longer and smarter. The other feature extraction method such as transfer learning can also be used.

Conclusion

One of the key advantages of deep learning over prior neural nets and machine-learning algorithms is its ability to infer new characteristics from a small collection of features in a training set. That is, it will look for and find more characteristics that are similar to the ones currently recognised. Deep learning's capacity to build features without being explicitly taught means that depending on these networks can save data scientists months of labour. It also means that data scientists can work with more complicated feature sets than machine learning techniques would allow.

The main aim of the work was to design a deep neural network with convolution autoencoders that performs the task of detecting breast cancer and achieves results with accuracy that proves to be challenging to the existing work.

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