Breast Cancer Prediction Using Artificial Neural Network

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Abstract

in this study, we have developed an artificial neural network that will help determine if patient have breast cancer. Artificial neural network have been used effectively in detection and treatment of several dangerous diseases, helping in early diagnosis and treatment, thus increasing the patient's chance of survival. The system starts by collecting an image dataset, which was pre-processed by converting this images into an array of binary digits. Image Augmentation was performed on the images so as to avoid the problem of imbalance in the dataset. An artificial Neural Network algorithm is used for training our proposed model to detect breast cancer. After preprocessing, the model was built with a total of 178 input neurons, output layers which will detect if the patient have no Breast Cancer or the patience have a Breast Cancer which can further be categorized into any of the two stages which are Benign stage, Malignant stage,. The model was trained using a Artificial Neural Network with 9 numbers of epoch, and gave an accurate result of about 98.87% accuracy at an epoch number of 8.

Keywords: *Breast cancer, Artificial neural network*

1.0 Introduction

Medical imaging analysis is crucial in detecting abnormalities in several organs of the body, including blood cancer, skin cancer, breast cancer, brain tumors, lung cancer, and retinal cancer. (Saba et.al, 2019). The organ defect usually leads to rapid tumor growth, which is the leading cause of death worldwide (Bray *et.al*, 2018). Breast cancer which is a major concern that is plaguing the modern world is the leading cause of cancer mortality in woman in Nigeria and the world at large which has been a major public health problem. Early detection and treatment of breast cancer is and can mitigate the side effect and improve the chances of survival. While detection of breast cancer has been associated with larger tumour size, increased involvement of the lymph nodes and organ metastases (Kononenko *et.al,* 2016). The classification of Breast Cancer data can be useful to predict the outcome of some diseases or discover the genetic behavior of tumors (Vikas & Saurabh, 2014).

Mammograms, breast ultrasounds, and breast MRIs are currently used to diagnose breast cancer. These procedures are costly, and they may offer health hazards to people with benign tumors. As a result, a safer alternative is desired, which can automatically detect the existence of breast cancer and make recommendation to patient. Artificial Neural Network (ANN) which is part of machine learning has the potentials to provide such solutions and has been used previously to detect existence of breast cancer, however there is still need to improve on the accuracy of previous studies, which has necessitate this study.

Artificial Neural Network are computing systems vaguely inspired by the biological neural networks that constitute animal brains. Such systems learn to perform tasks by considering examples, generally without being programmed with task-specific rules. This paper will cover the detection and diagnosis of breast cancer using Artificial Neural Network by collecting and analyzing a breast cancer dataset.

2.0 RELATED WORKS

Many innovative systems for detecting breast cancer have been created as medical science has progressed. The following is a review of the research in this area;

Hu *et al., (*1994) proposed a technique to classify cancer using supervised and unsupervised learning methods .In supervised learning, a single hidden layer feed forward NN with back-propagation training is applied for error minimization. Various activation functions such as sigmoid, sinusoid and Gaussian are tested to establish different network configurations. In unsupervised learning, fuzzy and non-fuzzy and c-means clustering methods were used, with 80% classification accuracy. Won *et al.,* (20003) presented a technique using ensemble of neural network classifiers studied from negatively correlated characteristics to accurately categorize cancer and it estimates the functioning of the proposed technique with using three benchmark datasets. Experimental performance proves the ensemble classifier with negatively correlated characteristics provides best recognition rate on these benchmark datasets. However, patients were classified with accuracy of 83%. Xu *et al.,* (2005) presented A hybrid method of probabilistic neural network (PNN) and discrete binary version of Particle swarm optimization. PSO is basically used for optimal selection of genes and dimensionality reduction. Feed forward neural network is used to implement neural network configurations. This method is efficiently experimented on large B-cell lymphoma dataset with 80% classification accuracy. Ziaei *et al.,* (2007) introduced a new method for prediction of cancer with the help of perceptron network. This network is tested on diffuse large B-cell lymphoma (DLBCL) database. They observed 4026 genes based on their ranking, which is calculated according to their signal to noise ratios. A threshold value is obtained and those genes are removed whose ratios were less than the threshold value. Perceptron network is applied as a classifier. Thus, patients were classified with accuracy of 93%. Hiro *et al., (*2007) proposed an innovative hybrid method of projective Adaptive Resonance Theory (ART) and boosted fuzzy classifier with SWEEP operator method for detection of cancer classes. They employed this method to microarray data of acute leukemia and brain tumor. Tumor is accurately classified over the classification rate of 90%. They combined wrapper and filter approaches for applying these methods to gene expression microarray data of leukemia and central nervous system tumor.

Chau et.al, (2009) proposed the use of bagging with C4.5 algorithm, bagging with Naïve Bayes algorithm to diagnose the heart disease of a patient . (about 86% accuracy). S.Vijayarani et al., (2010) analyzed the performance of different classification function techniques in data mining for predicting the breast cancer from the breast cancer disease dataset. The classification function algorithms is used and tested in this work. The performance factors used for analyzing the efficiency of algorithms are clustering accuracy and error rate. The result illustrates shows Logistics classification function efficiency is better than multilayer perception and sequential minimal optimization, with a classification rate of 89% accuracy. T Joshi *et al.,* (2010) a brain tumor identification and detection system is recommended by. Here, MRI images of several cancer patients are analyzed by using neural network. Various image processing techniques like image segmentation, morphological functions, histogram equalization, image enrichment and feature extraction are applied on those MRI images. Neuro fuzzy classifier is used for detection of brain tumor cells. This experiment provides good classification accuracy with Neuro fuzzy classifier with about 87% accuracy. P. Rajeswari (2011) presented a technique for identification of tumor cells. Support Vector Machine (SVM) and FNN (Fuzzy Neural Network) are used in the classification problem. Liver cancer data set is used for testing the proposed technique .The experimental results indicate that the proposed technique has the ability to classify the cancer cells appreciably when it is compared with the conventional methods of cancer classification was 95.75% accurate throughout testing. Various ranking techniques are described in this paper for discriminatory selection of genes. Barnali sahu *et al.,* (2011) proposed a novel feature selection approach for the classification of high dimensional cancer microarray data, gene ranking is carried out using filtering technique such as signal-to-noise ratio (SNR) score and optimization technique as Particle swarm Optimization (PSO) is used for dimensionality reduction. Support vector machine (SVM), k-nearest neighbor (kNN) and Probabilistic Neural Network (PNN) are used as classifiers (about 90% accuracy). Dong-Sheg et.al, (2014) proposed a new decision tree based ensemble method combined with feature selection method backward elimination strategy with bagging to find the structure activity relationships in the area of chemo metrics related to pharmaceutical industry. Senapati et al., (2014) proposed a hybrid system for the detection of breast cancer using KPSO and RLS for RBFNN. The centers, as well as variances of RBFNN, are adjusted using K-particle swarm optimization and adjusted using back-propagation. The classification accuracy achieved by RBFNNKPSO and RBFNN-extended Kalman filter is 97.85% and 96.4235%, respectively, whereas the coverage time is 8.38 s and 4.27 s, respectively.

Bellaachi et al. (2016) adopted naive Bayes, decision tree and back-propagation neural network to predict the survivability in breast cancer patients. Although they reached good results (about 90% accuracy), their results were not significant due to the fact that they divided the data set to two groups; one for the patients who survived more than 5 years and the other for those patients who died before 5 years. Hasan et al., (2016) developed a mathematical model for the prediction of breast cancer based on the symbolic regression of Multigene Genetic Programming. The ten-fold technique is used to avoid over fitting here. The stopping criteria for the model were generated but the generation level did not reach zero. The highest accuracy obtained by the model is 99.28% with 99.26% precision.

Ali *et al., (*2020) proposed a supervised pattern classification model is known as SVM which is engaged as an algorithm (training algorithm) to learn classification and regression imperative for collected information. The motivation behind this procedure is to isolate information until a hyperplane with high minimum distance is found. (about 90% accuracy),.Yuchun et al., (2008). This technique is a combination of granular computing, fuzzy clustering and statistical learning. Recursive feature elimination algorithm is also used in this approach. This algorithm eliminates unnecessary and noisy genes and selects only informative genes among thousands of genes. FG-SVM approach performs 96% accurately with three different open database sets. Azar et al., (2012) used decision tree variations to develop a technique for predicting breast cancer. A single decision tree, a boosted decision tree, and a decision tree forest are all modalities utilized in this approach (DTF).To arrive at a judgment, a data set must first be trained, followed by testing. In the training phase, there were 97.07 percent and 98.83 percent accuracy results produced by SDT and BDT, respectively, indicating that BDT performed better. Decision tree forest was 97.51% accurate, whereas SDT was 95.75% accurate throughout testing. Ten-fold cross-validation was used to train the dataset. Sakri et al. (2018); utilized a feature selection method called particle swarm optimization (PSO) in conjunction with machine learning algorithms K-NNs, Naive Bayes (NB), and the reduced error pruning (REP) tree to improve the accuracy value. According to their study, Saudi Arabian women's breast cancer is one of its main issues. According to their findings, this disease primarily affects women over the age of 46. They have acquired 70%, 76%, and 66% accuracy for NB, REP, and K-NN, respectively. Jahjharia et al., (2016) proposed decision tree algorithms for breast cancer diagnosis. The WEKA platform simulated the most popular decision tree algorithms, CART and C4.5, using MATLAB and python. The CART implemented in Python had the most fantastic accuracy (97.4%) and sensitivity (98.9%). The CART implemented in MATLAB had the highest specificity (95.3%), while the CART and C4.5 simulated in WEKA both had the lowest specificity (95.3%). Sakri et al. (2018) used the WBCD dataset to test four phase-based data processing methods. They published a study that compared classification without a feature selection technique to category with a feature selection method. For NB, RepTree, and K-NNs, they achieved 70 percent, 76.3 percent, and 66.3 percent accuracy, respectively. They utilized the Weka tool to do their data analysis. They discovered four characteristics that are optimal for this classification job after using PSO. They achieved accuracy values of 81.3%, 80%, and 75%for NB, RepTree, and K-NNs using PSO, respectively.

Table1: Summary of Research Work Discussed

Authors	**Methods**	**Drawbacks**
Hong-Hee Won, et al.,(2003)	Neural Network Ensemble	Unexplained functioning of the network. The network is reduced to certain value of the error on the sample means that the training has completed. This does not give us optimum result.
RuiXu, et al., (2005)	Probabilistic neural network (PNN)	PNN are slower than multilayer perceptron networks at classifying new cases. PNN require more memory space to store model.
L. Ziaei, et al., (2007)	Perceptron network	The output values of a perceptron can take only one of two values (0 or 1) due to the hard limit transfer

		function. Perceptron can only classify linearly separable sets of vectors.
Hiro Takahashi, et al., (2007)	Adaptive Resonance Theory (ART) and boosted fuzzy	ART networks are inconsistent (fuzzy) as they depend upon the order in which training data or upon the learning rate.
My Chau Tu, et al., (2009)	C4.5 algorithm, bagging with Naïve Bayes algorithm	The c4.5 algorithm suffers from over fitting; poor attribute split technique, inability to handle continuous valued and missing valued attributes with high learning cost
P Rajeswari, G. et al., (2011)	Support Vector Machine (SVM).	SVM choose an optimal kernel for SVM for best classification, In case of large number of features, an over fitting may occur Long training time for large dataset.
Hasan MK, et al., (2016)	Multigene genetic programming	Requires less information about the problem, but designing an objective function and getting the representation and operators right can be difficult
Rashid NBA, et al., (2018)	particle swarm optimization (PSO) in conjunction with machine learning algorithms K-NNs, Naive Bayes (NB)	The disadvantages of particle swarm optimization (PSO) algorithm are that it is easy to fall into local optimum in high-dimensional space and has a low convergence rate in the iterative process.

3.0 MATERIALS AND METHODS

3.1 Dataset Description

The breast cancer dataset was acquired from the University of California Irvine (UCI) machine learning repository. There are 699 instances in this dataset, and the cases are classified as benign or malignant depending on their severity. Four hundred fiftyeight of these instances (65.50%) are mild, whereas two hundred forty-one (34.50%) are malignant. The class in the dataset is divided into two groups: two for the mild case and four for the malignant case, where two represent the soft case, and four represents the malignant case. To determine if a cell is benign or malignant, This system uses a Breast cancer Histopathology image dataset was used which contains a total number of 3368 scan images of the breast for the classification of Breast Cancer. The images were process using Image Data Generator in rescaling the image by 1/255.

3.2 Data Pre-processing

Data pre-processing is the first step in filling in the gaps left by missing data, detecting and eliminating outliers, and resolving self-contradiction problems. In the dataset, there are 16 missing values for characteristics that are not present. The mean takes the place of the missing attributes for that class. Additionally, the dataset is subjected to random selection to ensure that the data is adequately circulated. After data pre-processing, the dataset was divided into the training and testing phase. The training phase is used to extract the features from the dataset, and the testing phase is used to evaluate how the suitable model performs when it comes to predicting from the dataset. Each component of the dataset is split into two parts, Training and Testing.

Training and Testing Phase

The training phase extracts the features from the dataset and the testing phase is used to determine how the appropriate model behaves for prediction. The dataset is divided into two, from the divided dataset, 70% of the dataset is used for training the model, while 30% of the dataset is used for testing.

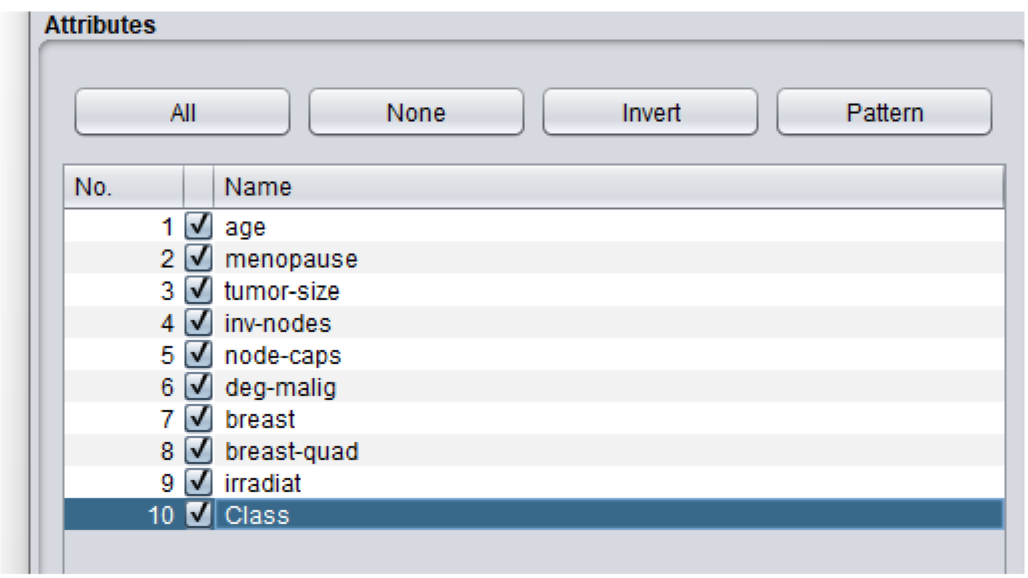


Fig1A; Attributes of the dataset

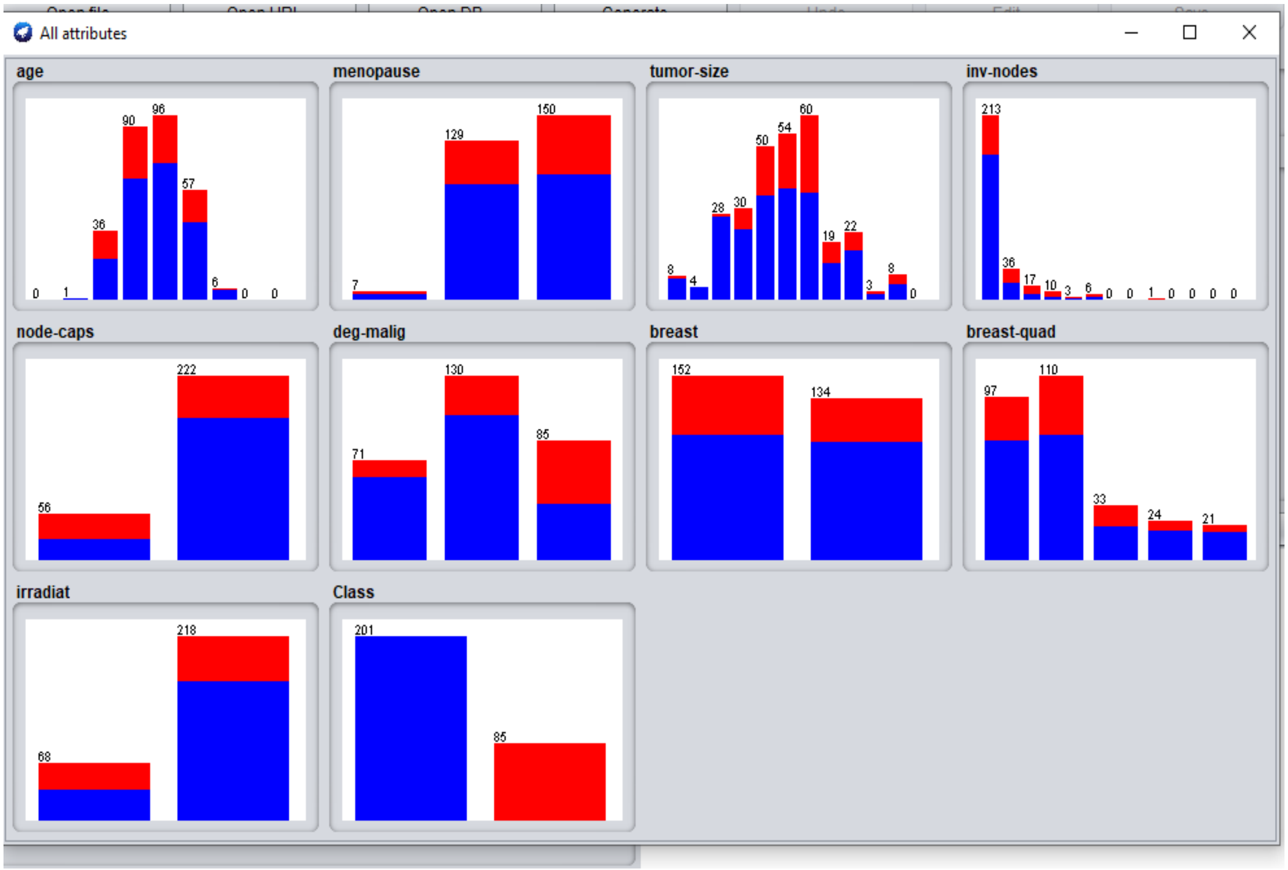


Fig 1B ; showing individual attributes of the dataset

3.3 Artificial Neural Network

The Artificial Neural Networks is a model which functions like human brain's nervous system that has an enormous number of nodes associated with each other. ANNs have extraordinary advancement in classifying and diagnosing in the initial stages and have an achievement in breast cancer. A model ANN is developed from a lot of layers primarily: input, hidden and output layer (Figure 1)

ANNs Layers are made out of neurons which are interconnected to each other and contain activation function used for the purpose of showcasing a change which is non-linear to reinforce the ability of expressions for non-linear data. Input layer has to accept input data and will be transmitting the information to a concealed layer, that is engaged in progression of the info and to provide the training outputs for the output layer which demonstrates the classification results. All things considered, contingent upon the issue explanation. During the way towards training, ANN might consist of long causal chains for computational stages.

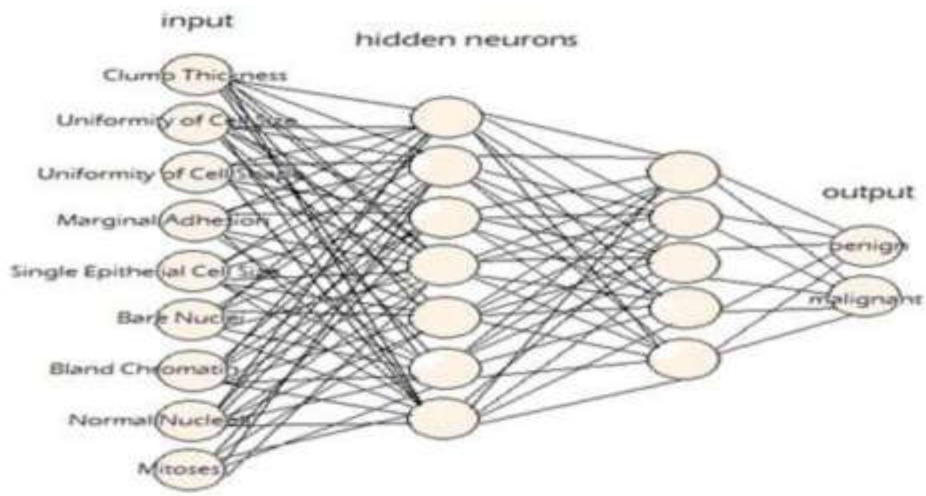


Fig3A; A straightforward case the way in which ANN is prepared to foresee the indicative result from 9 inputs and two hidden layers.

3.4 SYSTEM ARCHITECTURE

Breast cancer detection will be based on scanned images. This images will be collected from a breast cancer histology dataset. This system starts by acquiring this image dataset, pre-process this image dataset, and train an Artificial Neural Network algorithm on the stated dataset. The trained model will be scored based on accuracy and saved.

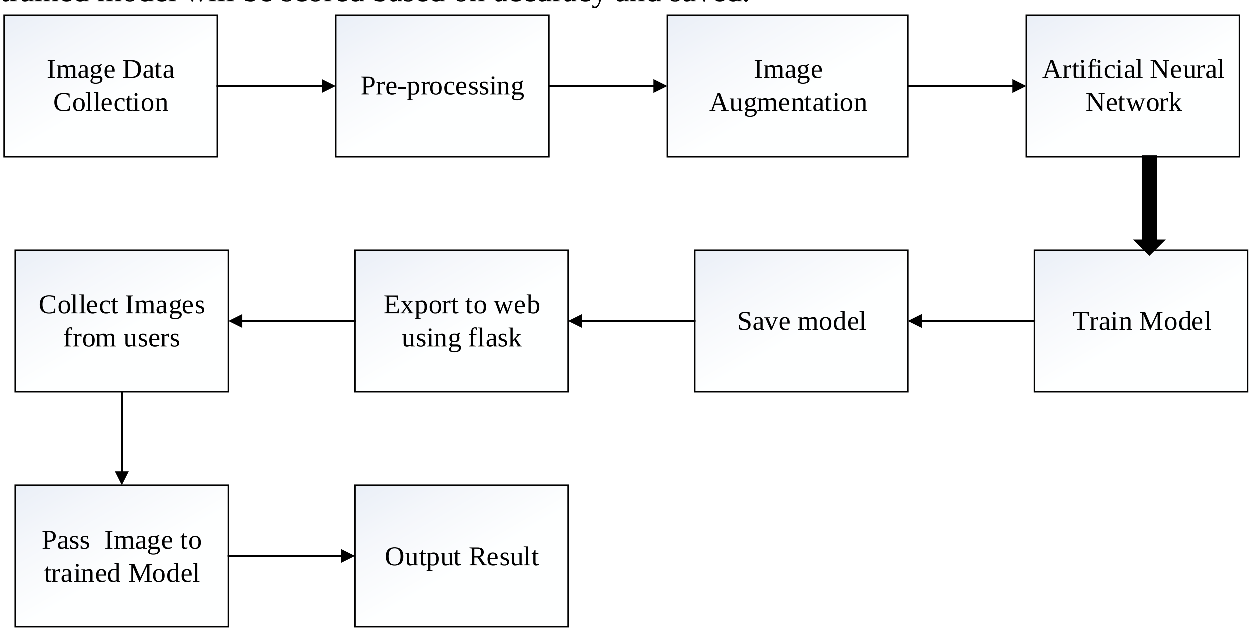


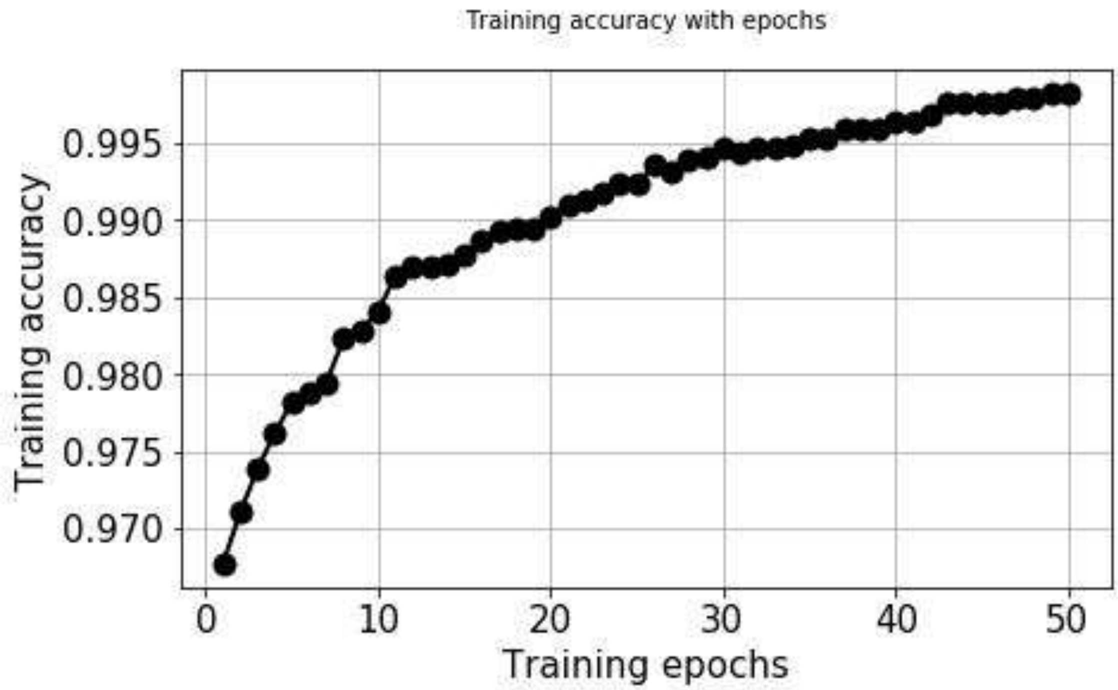
Fig3B; System architecture.

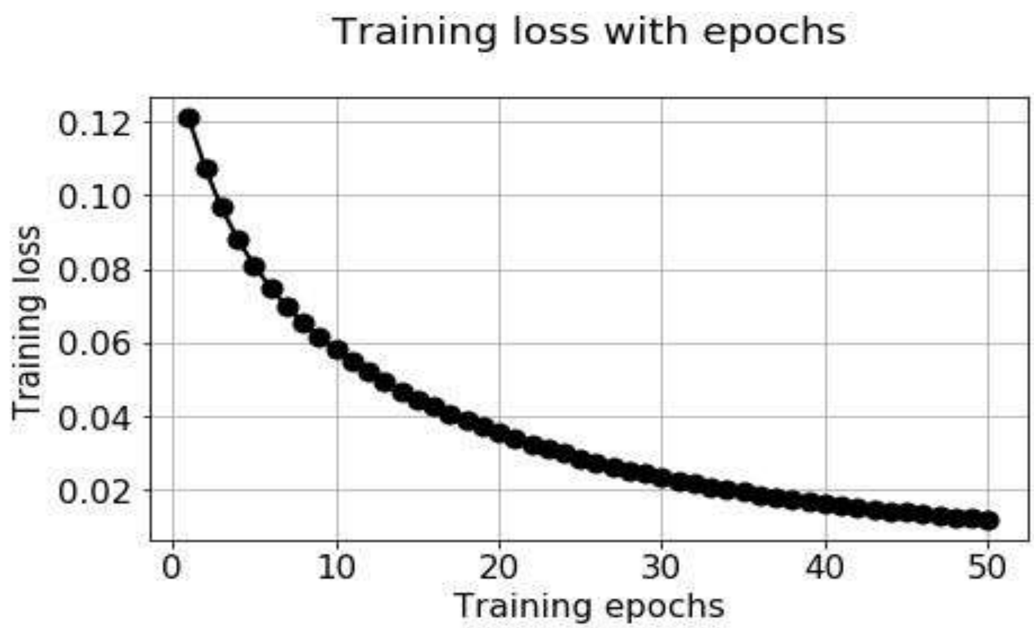
The system starts by collecting an image dataset, the dataset will be pre-processed by converting this images into binary digits that will be hold as array. Image Augmentation will be performed on the images so as to avoid imbalance problem. An artificial Neural Network algorithm will be used for training our proposed model to detect breast cancer. The model will be saved and exported to web using python flask to build a mini diagnosis system to collect scanned breast cancer images and pass it to the exported model for classification.

4.0 RESULTS

```
Epoch 1/50
3900/3900 [==============================] - 1s 233us/step - loss: 0.1210 - acc: 0.9677
Epoch 2/50
3900/3900 [==============================] - 1s 230us/step - loss: 0.1074 - acc: 0.9710
Epoch 3/50
3900/3900 [==============================] - 1s 230us/step - loss: 0.0967 - acc: 0.9738
Epoch 4/50
3900/3900 [==============================] - 1s 233us/step - loss: 0.0881 - acc: 0.9762
Epoch 5/50
3900/3900 [==============================] - 1s 232us/step - loss: 0.0810 - acc: 0.9782
Epoch 6/50
3900/3900 [==============================] - 1s 230us/step - loss: 0.0750 - acc: 0.9787
Epoch 7/50
3900/3900 [==============================] - 1s 233us/step - loss: 0.0697 - acc: 0.9795
Epoch 8/50
3900/3900 [==============================] - 1s 229us/step - loss: 0.0655 - acc: 0.9823
Epoch 9/50
3900/3900 [==============================] - 1s 231us/step - loss: 0.0615 - acc: 0.9828
Epoch 10/50
3900/3900 [==============================] - 1s 235us/step - loss: 0.0580 - acc: 0.9841
Epoch 11/50
3900/3900 [==============================] - 1s 242us/step - loss: 0.0548 - acc: 0.9864
Epoch 12/50
3900/3900 [==============================] - 1s 244us/step - loss: 0.0519 - acc: 0.9869
Epoch 13/50
3900/3900 [==============================] - 1s 240us/step - loss: 0.0493 - acc: 0.9869
Epoch 14/50
3900/3900 [==============================] - 1s 238us/step - loss: 0.0469 - acc: 0.9872
Epoch 15/50
3900/3900 [==============================] - 1s 250us/step - loss: 0.0446 - acc: 0.9877
Epoch 16/50
3900/3900 [==============================] - 1s 300us/step - loss: 0.0425 - acc: 0.9887
```

Fig4.Showing model training





5.0 Discussion

The system starts by collecting an image dataset, the dataset will be pre-processed by converting this images into binary digits that will be hold as array. Image Augmentation will be performed on the images so as to avoid imbalance problem. An artificial Neural Network algorithm will be used for training our proposed model to detect breast cancer. The model will be saved and exported to web using python flask to build a mini diagnosis system to collect scanned breast cancer images and pass it to the exported model for classification. The images were read from directory using the flow_from_directory(). The images were further resized to 200 x 200 following a batch size of 128. After preprocessing, the model was built with a total of 178 input neurons, five hidden layers and two output layers which will detect if the patient have no Breast Cancer or the patience have a Breast Cancer which can further be categorized into any of the two stages which are Benign stage, Malignant stage,. The model was trained using a Artificial Neural Network with 9 numbers of epoch. Artificial Neural Network gave an accurate result of about 98.87% accuracy at an epoch number of 8. The saved model was deployed to web for easy diagnosis and classification of breast cancer histopathology using python flask.

5.1 CONCLUSION

A machine learning technique for breast cancer prediction was presented in this research. In the field of medicine, conducting a medical diagnostic process is extremely costly and time-consuming. Machine learning techniques may be employed as a clinical assistant to diagnose breast cancer, according to the system's recommendations, which will be highly advantageous for new doctors of a physician in the field. In the case of a misdiagnosis. The model created by ANN is more consistent than any other method previously stated, and it can be used to predict the future has the potential to significantly improve breast cancer prediction. We can deduce from the research findings that Machine learning approaches can diagnose the disease with high accuracy automatically. This study presents an Artificial neural network algorithm for the detection of breast cancer. This study could be extended by building a smart android application for diagnosis of breast cancer hsitopathology . Below are related areas which are not treated in this work. They are as follows:

i. Using of Feed Forward Neural Network algorithm for detecting of breast cancer histopathology.
ii. Recurrent Neural Network

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