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IMPROVING BREAST CANCER DETECTION USING DEEP LEARNING

Muhammad Wakil*[1], Nasir Khan[1], Muhammad Younas[1], Natasha[1]

[1]*Faculty of Computer Science & Information Technology, The Superior University Lahore, Pakistan*

*[1]waki.developer@gmail.com

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Corresponding Author: *
Muhammad Wakil

Abstract

Breast Cancer (BC) is one of the leading causes of mortality all over the world. By 2020, 10 million of them will have breast cancer; a disease that disproportionately that affects women around the globe and often leads to fatal outcomes. Cancer is ranked 4 th among the three leading causes of mortality globally with cervical, colorectal and brain tumors. In addition, it is projected that breast cancer incidences will increase by 70 percent in the next 20 years. Early and proper diagnosis of breast cancer forms part and parcel in enhancing its likelihood of detection, as well as raising its chances of survival, which is usually between 30-50% of patients. With the improved technology in healthcare, deep learning has become the solution of choice in the analysis of large volumes of X-ray, Magnetic Resonance Imaging , and computed tomography images. This paper is aimed at developing a deep learning model that can identify breast cancers and classify them correctly. Breast cancer may be categorized into eight different types of tumors, these include benign Adenosis and benign Fibroadenoma; benign Tumor; tumor of Lobular Region and malignant Mucous Cancer and malignant Papillary Cancers. Information was obtained in Kaggle repository to identify breast cancer and further classify it, and the evaluation metrics of proposed models were recall, precision, accuracy and F1 score. When it is developed and tested on preprocessed data in development validation and testing mode; accuracy (97.60 percent), recall (97.60 percent) and F1-Score scores showed the deep learning models were effective in precisely classifying breast cancers.

INTRODUCTION

One of the most prevalent cancers and second major cause of death among women in the globe is Breast Cancer. This is the second most common cancer in the world in 2002 after it rose by 1 million new diagnoses between 1999 and 2002.Unfortunately, even with advances in early detection technology and understanding about molecular causes behind its biology, over 30% of early-stage cases still recur several years later. Finding an effective yet nontoxic treatment requires understanding both molecular and clinical characteristics of the tumor in certain areas, and then researching them thoroughly. Breast cancer treatments typically include hormones, immunotherapy and chemotherapy treatments which are used adjuvant, transient or neoadjuvant forms; generally, these agents are effective against 90-95% major breast cancers and 50-60% of metastases at first; however, over time progression does happen; furthermore, resistance to treatment has become both predictable and unpredictable [7, 9].

Early diagnosis of BC is one of the most important parts of treatment, and imaging remains a powerful method to do just that. Imaging provides valuable information on patients who may have BC. Researchers discovered that certain imaging techniques, e.g., we can use Magnetic Resonance Imaging, mammography, Single Photon Emission Computed Tomography, Positron Emission Tomography (PET) and Computerized Tomography (CT) imaging technologies that will assist in detecting and monitoring the patients with BC in various stages. Furthermore, imaging techniques combined with biochemical biomarkers such as proteins, mRNAs, DNA or microRNAs could be utilized as new therapies and analytic tools in treating BC [12, 13 ,14].

Deep Learning , one form of Machine Learning (ML), bases its operation on how neurons in human brains process information. A distributed Lefschetz network's core components are artificial neurons - small nodes connected by weighted connections between each node - typically placed in layers. Recently, the advent of deep learning (DL) technology has spawned numerous areas of research to address complex issues or increase existing efficiency by taking advantage of cutting-edge technology. Examples of how DL can be utilized are speech recognition, machine translation and sentiment analysis as well as image recognition facial recognition signal processing and more [17].

Medical applications utilizing Deep Learning technology have seen tremendous success due to its ability to perform more accurate analyses than human professionals and deliver greater accuracy than human specialists. Google conducted an impressive study comparing its accuracy at diagnosing diabetic Retinopathy against human experts [2222]. Furthermore, transfer learning techniques are also increasingly used. Instead of creating an entire model just to tackle one task at once, transfer learning allows weights trained for one task to serve as starting points when creating another model [22223.].

Transfer learning offers many advantages over traditional methods, including faster training time and improved results. Alex Net, VGG ResNet and Xception CNN models are popular choices when using this form of transfer learning.

Transfer Learning can be implemented using two strategies. A first approach entails using an initial model pre-trained with weights from an ImageNet dataset as inputs for transfer learning.

Transfer learning technology and Xception neural networks were employed in this research study to accelerate learning of an identification model [6].

LITERATURE REVIEW

Artificial Intelligence, is currently being used Expert Systems and Neural Networks in treating Breast Cancer to increase screening precision. While most hospitals initially employed x-rays as diagnostic tools for BC diagnosis, recent years hospitals have begun switching over to mammography scans due to their ease of analysis through intelligent models and this has increased accuracy and efficiency when diagnosing BC.

Many strategies and models were proposed to increase accuracy in diagnosing BC, The authors of [3] and 18 have used Kaggle repository to gather their information to create a prediction model to determine whether a person is undergoing breast cancer and to make people aware or diagnosed with this condition. To provide an accurate model to predict breast cancer, comparisons of precision between each of random forest, SVM, Naive Bayes classification system, logistic regression and Naive Bayes logistic regression were carried out to provide a precise and accurate model that identified breast cancer at an accuracy ranging between 52.63 percent and 98.24 percent accuracy during these research studies.

These research studies use KNN models to address early and precise cancer screening procedures that doctors can employ in order to accurately distinguish whether cancer is malignant or benign. Their primary aim was to compare the outcomes of different supervised learning algorithms before combining these with voting as a technique of classification. Voting was used as a grouping method, since it could blend different models to increase precision when classifying individuals. All data were gathered at the University of Wisconsin. The 8th one reached 98.90 percent accuracy while [16] attained an accuracy rate of 97.60 percent, [17] reaching 97.13, and [10] hitting 99.9% accuracy while [27] reaching 98.10 percentage while % of [28] reaching 98.23 and % of [6] reaching 83.45%, respectively. Studies conducted since then ([15, 21, 29-30 31]), asserted the significance of early diagnosis and treatment to decrease mortality risk significantly, though breast cancer prognosis still poses risks of returning and spreading further. This research sought to determine the likelihood of breast cancer recurrence using various machine learning techniques such as (SVM). Furthermore, new methods were proposed by authors in order to increase accuracy with these algorithms. Patient information was gathered for cancer patients in UCI Machine Learning Repository for Wisconsin Dataset. This dataset features 35 attributes. They utilized Naive Bayes C4.5 decision Tree as well as SVM algorithms in this instance and tested their accuracy of predictions using them. Effective feature selection algorithms enabled them to increase accuracy by eliminating features of lower quality that were contributing less significantly. Associating them with classification could cause difficulties; using high quality attributes was instrumental in significantly improving accuracy for all algorithms.

There's something very satisfying in being a part of something bigger, something with meaning for you and for us as a collective whole. So don't just settle for average - strive for excellence with us. Study [4, 10, 11 24 25 26 and 32] developed a deep learning method using CNNs - which are specific types of feedforward networks placed other initial experiments based on deep learning technology to identify breast cancer mammography picture with BreaKHis, which is a community dataset. The procedure that is based on the removal of patches out of images to educate a convolutional neural network and apply the patches to the classification has been effective to screen mammograms.

Overall accuracy was satisfactory as an independent test set from Digital Database for Screening Mammography DDSM was classified with 0.88 percent performance rate (sensitivity = 86.2 per cent and specificity = 80.2 percent).

Research [1, 2, 5, and 6] sought to create methods of classifying cancers into distinct prognostic groups based on gene expression levels using artificial neural networks (ANNs). SRBCTs (small round blue cells) were chosen as models because of their four different diagnostic categories and associated diagnostic difficulties; all samples identified correctly while also highlighting those genes most relevant with each class; experiments revealed that new algorithms increased reliability as well as accuracy for classification; these new algorithms have an estimated accuracy level of over 99%!

A. Previous Studies Summary

Studies sought to establish whether an image contained breast cancer; while in this one the objective is categorizing eight kinds. A review was made of previous studies regarding factors like Machine Learning methods utilized and programming languages employed; most effective results; best method employed and sources of data utilized (Table I).

There have been various studies and recommendations proposed to combat breast cancer, each offering their own methods for detection and management. Certain studies employ imaging processing and computer system applications to examine breast shape changes; others focus on studying how breasts have changed over time. Studies have increased the efficacy of methods used to detect signs and symptoms of disease. These studies focused on the presence of cancerous breast tissue but none classified all eight types. This study will focus on classifying eight type of breast cancer, such as benign fibroadenoma, benign adenosis, benign tubular adenoma, benign phyllodes tumor and eight malignant types such as malignant mucinous carcinoma, papillary carcinoma malignant ductal carcinoma, and malignant lobular carcinoma.

TABLE I. An Overview of Previous Studies by Method, Best Method, Language, Remainder Results and Dataset Used

Reference	Methods Used	Best Methods	Language	Best Result	Data Provider
[1]	ANN	ANN	-	96.00	Private
[2]	ANN	ANN	Python	90.30	Kaggle
[3]	LR	LR	-	97.00	Wisconsin
[4]	CNN	CNN	Python	89.50	BreaKHis
[5]	ANN	ANN	-	99.00	Wisconsin
[6]	KNN	KNN	-	83.45	Wisconsin
[8]	KNN	KNN	-	98.90	FMC
[9]	CNN	CNN	Python	90.00	BreaKHis
[10]	CNN	CNN	Python	88.00	DDSM
[11]	SVM,LR	LR	Python	98.24	Kaggle
[12]	SVM	SVM	-	92.30	Wisconsin
[13]	SVM,KNN	KNN	-	99.90	Wisconsin
[14]	SVM,ANN	ANN	Python	94.00	DDSM
[15]	SVM,KNN	SVM	Minitab	98.10	Wisconsin

METHODOLOGY

This approach to study involves collecting data, prepping datasets for analysis and data splitting, building the proposed model and training it, then validating as illustrated in Fig 1.

Dataset

This was a data set, BreakHis (Breast Cancer Histopathological Image Classification), downloaded on Kaggle.com and contains 709 histologically-reconstructed breast cancer tissue images, 82 different patients, and multiple magnification lenses (40X 100X, 200X, 400X and 200X).

There were 2,480 benign as well as 5,429 malignant specimens that are 700X460 pixels 3 channel RGB 8 bit depth PNG formatted PNG files. It was manufactured along with P&D Laboratory-Pathological Anatomy and Cytopathology based in Parana Brazil.

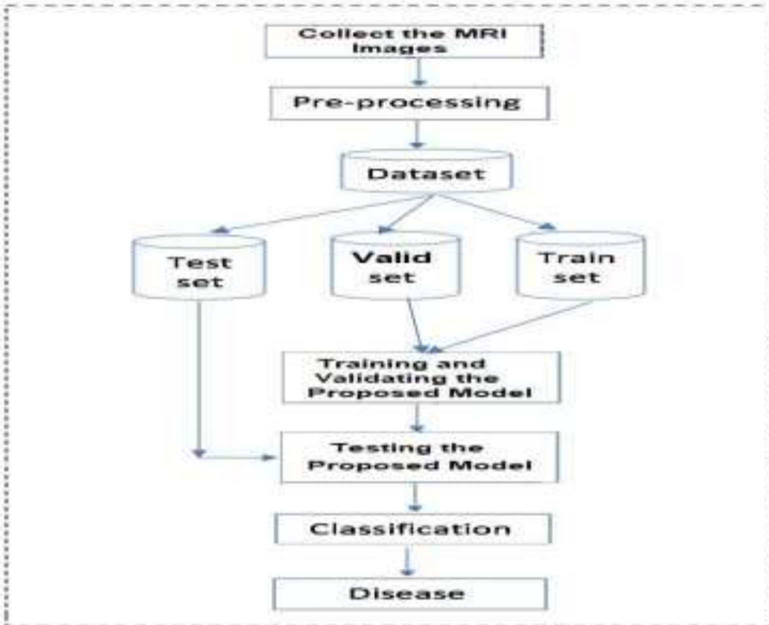

Fig. 1. Methodology Flowchart.

Data Perpetration
BreakHis contains many pictures; its original BreakHis dataset contained 7,909 images. Although this number may seem low, new methods exist that allow one to generate additional pictures for expanding this data set by employing Generative Adversarial Networks" (GANs). GANs use two neural nets fighting each other in order to generate fake images that appear genuine, making this technology very well known in image, speech and video generation [19, 20, 23, 23 and 23]. With the aid of GAN, our database was expanded from 1,000 images up to 10,000 with eight classes that each contain 1250 pictures (a sample is shown in Figure.2).

Data Splitting
The dataset is divided into three data sets for training, validating, and test purposes with an equal split ratio between these sets (60/20% respectively).

Proposed Model
An already trained Deep Learning model are called Xception was suggested as being refined for screening and classifying breast cancer. This pre-trained Deep Learning model stands out as being particularly accurate at recognizing 1000 natural images from ImageNet [1717].

Performance Measures A variety of renowned measures were employed in the development of the model proposed. Accuracy and Precision were represented as two separate metrics, while Recall represented three. F1 Score was then also represented three and four.

Accuracy = (TP + TN) / (TP+TN+FP+FN)

Precision = (TP / (TP+FP)

Recall = (TP / (TP+FN)

F1-score= 2x(Precision x Recall)/(Precision+Recall)

Where TP = True Positive, TN = True Negative

FP = False Positive, FN = False Negative

To make use of a model trained for a different dataset, it must be refined accordingly. Since there are only eight classes present in the current dataset, this requires that Xception model's top layer - known as its classifier - be removed and replaced with one specifically tailored for these eight classes, as shown in Figure 3.

Validating and Testing Model Training Modules

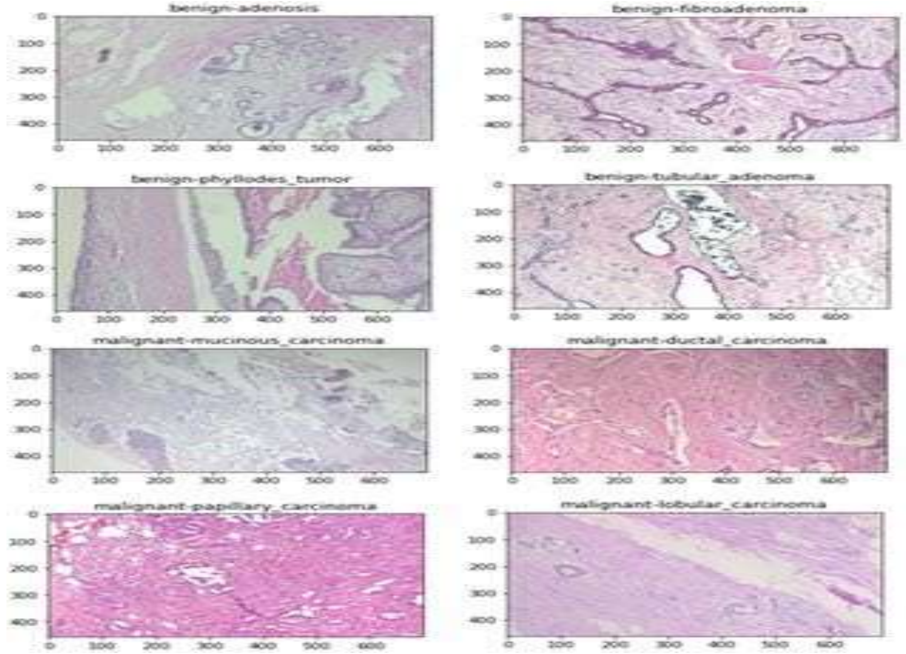

Fig. 2. Sample of the Dataset with its 8 Different Classes.

A training dataset that had been prepared was used to train the new customized Xception algorithm, and then it was cross-validated on 120 instances of its validation dataset. All the training attributes were used to solve overfitting problem: Learning rates (0.0001) (0.0001), Batch size (128), Optimizer Adam and data augmentation were utilized, which shows not only that there is a reduction in the training process but also that the xception model achieves accuracy and validation as shown in figures 4 and 5.

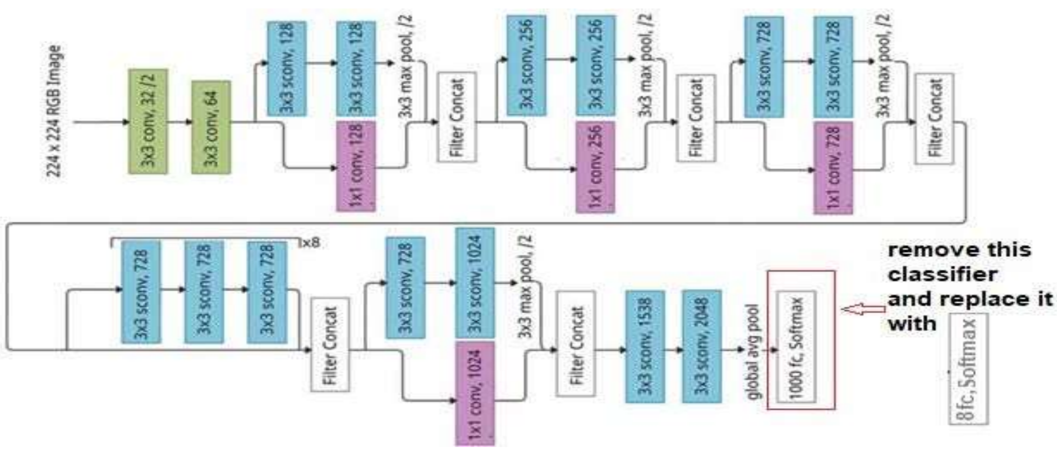

Fig. 3. Architecture of the Customized Xception Model.

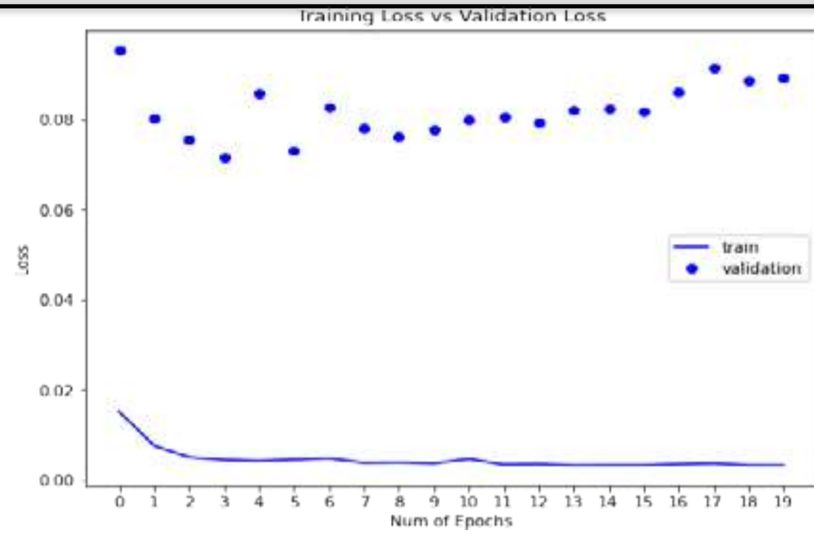

Fig. 4. Training and Validation Loss.

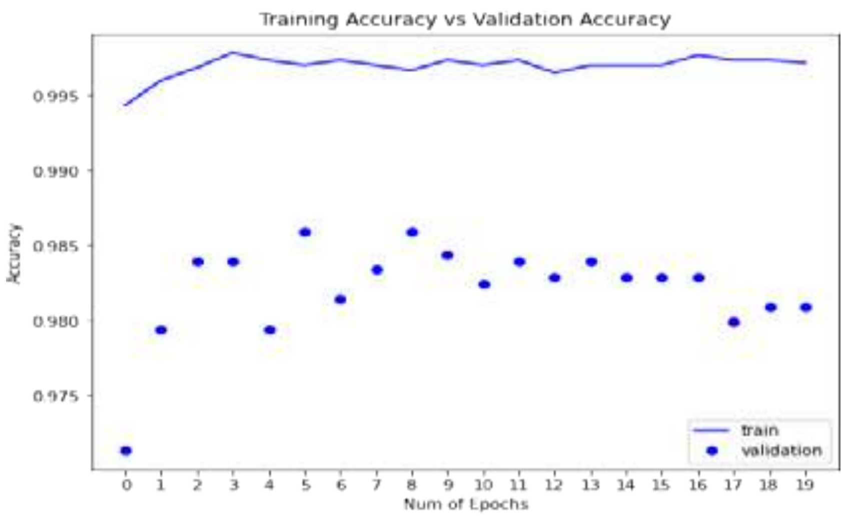

Fig. 5. Training and Validation Accuracy.

Once training was complete and validated, Xception model It was then put through rigorous tests using the testing dataset; various performance metrics were noted as part of this assessment process.

RESULT AND DISCUSSION

This model has achieved accuracy of training of 99.78% and accuracy for validating (98.59%) as well as testing (97.60%), custom tailored to meet training needs with loss rates between (0.00315) for training loss and validating loss (0.07326) and test loss (0.09518) depending on training duration of 2944 seconds and 5.32 seconds respectively for testing purposes.

Table II indicates the precision, recall, F1 Score and precision of each class in the dataset depending on eight classes that models are being used to classify including benign adenosis and benign fibroadenoma , benign phyllodes cancer, benign tubular adenoma , Malignant tumors of the lobular region by each class and malignant mucinous cancer , malignant papillary cancer, and malignant ductal cancer. The averages of customized models were Precision (97.60 percent), Recall (97.60 percent) and F1 Score (97.58 percent).

Figure 6. shows that every class in the database achieved 100% ROC Curve values as shown.

TABLE II. PRECISION OF EXCEPTIONS XCEPTION PRECISION, RECALL, F1-SCORE OF EACH CLASS IN THE DATASET.

Measure	BA	BF	BPT	BTA	MLC	MMC	MPC	MDC	Model AVG
Precision	98.20%	97.60%	99.01%	97.01%	94.34%	95.16%	96.62%	99.81%	98.60%
F1-Score	94.40%	94.21%	98.40%	93.20%	94.59%	96.46%	97.89%	98.60%	99.98%
Recall	98.60%	97.80%	97.80%	97.40%	95.00%	97.80%	96.40%	99.00%	98.60%

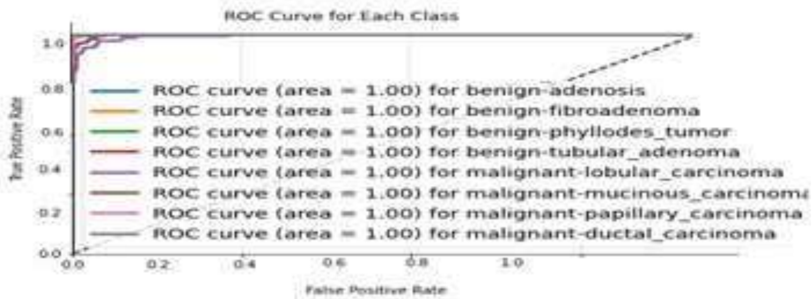

Fig. 6. ROC Curve for each Class in the Dataset.

CONCLUSION AND FUTURE WORK

Breast Cancer is one of the leading causes of death worldwide; over 10 million people died of cancer worldwide in 2020 alone. Breast Cancer can be devastating and deadly to women worldwide. As technology for healthcare continues to advance, deep learning and machine learning have become a staple of medical imaging processing. The purpose of this research project is to utilize deep learning algorithms for classifying Breast cancer cases. An Xception model was utilized and modified in order to fit a dataset with eight classes from Kaggle that was later supplemented by GAN. Training Validation, Testing and Training were combined and used to review customized Xception models before being tested and validated to achieve accuracy (97.60%) and recall (97.60%) as well as F1 Score (97.58%) of 100%.

Future experiments will include employing different ways of creating images, as well as testing out Xception's algorithm on newly made ones. Furthermore, other trained models will be evaluated against actual results for comparison.

REFERENCES

Westermann et al., "Classification and diagnostic prediction of pediatric cancers using gene expression profiling and artificial neural networks", *GBM Annual Fall meeting Halle 2020*, vol. 2020.

S. Joo, Y. Yang, W. Moon and H. Kim, "Computer-Aided Diagnosis of Solid Breast Nodules: Use of an Artificial Neural Network Based on Multiple Sonographic Features", IEEE Transactions on Medical Imaging, vol. 23, no. 10, pp. 1292-1300, 2021.

T. Kiyan and t. Yildirim, "breast cancer diagnosis using statistical neural networks", Istanbul university journal of electrical & electronics engineering, vol. 4, no. 2, 2021.

F. Spanhol, L. Oliveira, C. Petitjean and L. Heutte, "Breast cancer histopathological image classification using Convolutional Neural Networks", 2017.

H. Salem, G. Attiya, N. El-Fishawy. Early diagnosis of breast cancer by gene expression profiles. Pattern Analysis and Applications. Vol. 20, no. 2, pp. 567–578, 2017.

U. K. Kumar, M. B. S. Nikhil and K. Sumangali, "Prediction of breast cancer using voting classifier technique," 2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), 2017, pp. 108-114.

Albatish, I.M., Abu-Naser, S.S. Modeling and controlling smart traffic light system using a rule based system. Proceedings - 2019 International Conference on Promising Electronic Technologies, ICPET 2019, 2019,
pp. 55–60.

N. Ponraj, E. Jenifer., P. Poongodi, S. Manoharan. "Morphological operations for the mammogram image to increase the contrast for the efficient detection of breast cancer", European Journal of Scientific Research, (ISSN) 1450-216X, vol. 68, no.4, pp. 494-505, 2021.

Naser, S. S. A. JEE-Tutor: An intelligent tutoring system for java expressions evaluation. Information Technology Journal, 2008, Vol. 7, No. 3, 528-532.

B. Gayathri, C. Sumathi, T. Santhanam, "Breast cancer diagnosis using machine learning algorithm a survey". International Journal of Distributed and Parallel Systems, vol. 4, no. 3, pp. 39-50, 2017.

L. Shen, L. Margolies, J. Rothstein. Deep Learning to Improve Breast Cancer Detection on Screening Mammography. Sci Rep vol. 9, no.1, pp. 24-35, 2019.

World health organization https://www.who.int/.

Abu-Naser, S.S., El-Hissi H., Abu-Rass, M., & El-khozondar, N. An expert system for endocrine diagnosis and treatments using JESS. Journal of Artificial Intelligence, 2010, Vol. 3, No. 4, pp. 239-251.

Abu Naser, S.S. Evaluating the effectiveness of the CPP-Tutor, an intelligent tutoring system for students learning to program in C++. Journal of Applied Sciences Research, 2009, Vol. 5, No. 1, pp. 109-114.

A. F. Agarap. On breast cancer detection: an application of machine learning algorithms on the wisconsin diagnostic dataset. ArXiv, abs/1711.07831, 2018.

D. R. Pavithra, S. Preethi, & A. K. SriRakshitha. Breast Cancer Classification using the Supervised Learning Algorithms. 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1492-1498, 2021.

17. H. Asri, H. Mousannif, H. Moatassime, & T. Noël. Using Machine Learning Algorithms for Breast Cancer Risk Prediction and Diagnosis. ANT/SEIT, 2017.

A. M. Gonzalez-Angulo, F. Morales-Vasquez, G. N. Hortobagyi. Overview of resistance to systemic therapy in patients with breast cancer. Adv Exp Med Biol. 2017; vol. 608, pp. 1-22.

Saleh, A., Sukaik, R., Abu-Naser, S.S. Brain tumor classification using deep learning. Proceedings - 2020 International Conference on Assistive and Rehabilitation Technologies, iCareTech 2020, 2020, pp. 131–136,
9328072.

Arqawi, S., Atieh, K.A.F.T., Shobaki, M.J.A.L., Abu-Naser, S.S., Abu Abdulla, A.A.M. Integration of the dimensions of computerized health information systems and their role in improving administrative performance in Al-Shifa medical complex, Journal of Theoretical and Applied Information Technologythis link is disabled, 2020, Vol. 98, No. 6, pp. 1087–1119.

A. I. Pritom, M. A. R. Munshi, S. A. Sabab and S. Shihab, "Predicting breast cancer recurrence using effective classification and feature selection technique," 2016 19th International Conference on Computer and Information Technology (ICCIT), 2017, pp. 310-314.

A. Joshi, D. A. Mehta. Comparative Analysis of Various Machine Learning Techniques for Diagnosis of Breast Cancer. International Journal on Emerging Technologies, vol. 8, (NCETST-2017), pp. 522– 526, 2017.

A. D. Omondiagbe, V. Shanmugam, S. S. Amandeep. Machine Learning Classification Techniques for Breast Cancer Diagnosis, vol. 5, no. 3, 2019.

K.Wadkar, P. Pathak, N. Wagh. Breast cancer detection using Ann network and performance analysis with SVM. International journal of computer engineering and technology, vol. 10, no. 3, 2019, https://doi.org/10.34218/ijcet.10.3.2019.009

.M. TIWARI, R. Bharuka, P. Shah, R. Lokare. Breast Cancer Prediction Using Deep Learning and Machine Learning Techniques. SSRN Electronic Journal. Published. https://doi.org/10.2139/ssrn.3558786, 2020.

D. A. Ragab, M. Sharkas, S. Marshall, J. Ren. Breast cancer detection using deep convolutional neural networks and support vector machines. PeerJ, vol. 7, no. 6, pp. 20-31, 2019. https://doi.org/10.7717/peerj.6201.

M. F. Ak. A Comparative Analysis of Breast Cancer Detection and Diagnosis Using Data Visualization and Machine Learning Applications. Healthcare, vol. 8, no. 2, pp.1-11, 2020.

H. Mousannif, H. Asri, H. A. Moatassime, T. Noel. Using Machine Learning Algorithms for Breast Cancer Risk Prediction and Diagnosis. Procedia Computer Science, vol. 83, pp. 1064–1069, 2017.

R. MurtiRawat, S. Panchal, V. K. Singh and Y. Panchal. Breast Cancer Detection Using K-Nearest Neighbors, Logistic Regression and Ensemble Learning. International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 534-540, doi: 10.1109/ICESC48915.2020.9155783.

D. Selvathi and A. A. Poornila. Performance Analysis of Various Classifiers on Deep Learning Network for Breast Cancer Detection. International Conference on Signal Processing and Communication (ICSPC), pp. 359-363, IEEE 2017.

A. LG, E. AT. Using Three Machine Learning Techniques for Predicting Breast Cancer Recurrence. Journal of Health & Medical Informatics, vol. 04, no. 02.2018.

M. A. Naji, S. E. Filali, K. Aarika, E. H. Benlahmar, R. A. Abdelouhahid, O. Debauche. Machine Learning Algorithms for Breast Cancer Prediction and Diagnosis. Procedia Computer Science, vol. 191, pp. 487–492, 2021.