International Journal of Sciences: Basic and Applied Research (IJSBAR)

ISSN 2307-4531
(Print & Online)

https://gssrr.org/index.php/JournalOfBasicAndApplied/index

Detection and Diagnosis of Breast Cancer Using an Ensemble Statistical Learning Method

Alio Boubacar Goga[a*], Chaibou Kadri[b], Ibrahim Sidi Zakari[c], Harouna Naroua[d]

[a,b,c,d]*Département de Mathématiques et Informatique, Faculté des Sciences et Techniques, Université Abdou Moumouni, Niamey, Niger*

[a]*Email: gogaalioboubacar@gmail.com* , [b]*Email: kadrichaibou73@gmail.com*

[c]*Email: sidizakariibrahim@gmail.com*, [d]*Email: hnaroua@yahoo.com*

Abstract

Breast cancer is a malignant tumor that originates in the cells of the breast. It is the second leading cause of women's death, after lung cancer. Moreover, the availability of medical data facilitates the development of related Artificial Intelligence Systems (AIS)**.** The diagnosis (or classification) of breast cancer is a delicate task, which requires efficient and robust classifiers. However, classical classification methods (in which a single basic classifier (estimator)) are generally confronted with the "bias-variance" dilemma. This, very often, affects seriously their efficiency and robustness. In this article, to mitigate this problem, we propose a new learning model called Triple-Stacking. This technique is composed of three (3) methods of statistical learning (Logistic Regression, Voting and Stacking) and a meta-learner (Decision Stump). The proposed model outperformed the existing ones on two different databases: Breast Cancer Wisconsin Original Data Set and Breast Cancer Wisconsin Diagnostic Data Set, with accuracies of 99.57% and 99.64%, respectively.

Keywords: Artificial Intelligence; Breast Cancer; Ensemble Method; Statistical Learning; Triple-Stacking.

Received: 3/30/2023
Accepted: 4/29/2023
Published: 5/22/2023

----

* Corresponding author.

1. Introduction

Breast cancer is a disease in which the cells in the breast tissue change and divide uncontrollably, usually resulting to a mass. The majority of breast cancers start in the lobules (mammary glands) or in the ducts that connect the lobules to the nipple [1, 2]. If not diagnosed early, it can lead to death. Breast cancer can be divided into two (2) categories: benign (non-dangerous) and cancerous (malignant). Benign tumors grow quite slowly, do not invade adjacent tissues and do not spread to different parts of the body [1, 3]. Moreover, it is the second leading cause of women's death, after lung cancer [2, 4]. It was also observed that the survival rate of this disease is strongly influenced by the malignant stage during diagnosis. Therefore, early detection is necessary to give legitimate treatment to patients with this scourge and to reduce the rate of sadness and mortality [5].

There are several techniques that can be used to distinguish benign breast lesions from malignant lesions that will continue to infiltrate other organs. Intelligent automatic prediction systems based on statistical learning could improve cancer diagnostic ability and reduce diagnostic errors [6]. Among these statistical methods, the best known and most used nowadays are artificial neural networks (although there are different architectures, we can mention deep learning which is considered as a form of artificial neural network (ANN)), support vector machines and logistic regression. The introduction of statistical learning techniques into the process of medical analysis of breast cancer has been shown to have many advantages. It increases diagnostic accuracy, reduces costs and human resources [7]. With the traditional statistical methods, one must first come up with a model, test it, and then come up with another model. This process is repeated until a sufficiently accurate model is obtained. However, an ANN is trained on data by a learning mechanism that acts on the constituents of the network to best perform the desired task [8]. The use of support vector machines (SVMs) in medical X-ray processing allows a large number of variables to be classified in a non-linear fashion. The separation of variables is achieved with maximum margin using transformation functions (or kernels) which are used to transform the data and choose resulted support vectors. The algorithm must be trained on an initial set of patients (data) to determine these support vectors, which will then be used on other patients (data) with unknown fates [9].

The classification of breast cancer is a difficult task, which requires efficient and robust classifiers. However, classical classification techniques, which consist in considering a single basic estimator (classifier), are generally confronted with the "bias-variance" dilemma, which often seriously affects their efficiency and robustness. To solve this problem, we propose an ensemble technique called Triple-Stacking composed of three (3) methods of machine learning (Logistic Regression, Voting and Stacking) and a meta-learner (Decision Stump) allowing to combine the basic-learners predictions into a prediction final .

Our objective is to evaluate the performance of the proposed method in terms of accuracy, precision, recall and F1-Score on a breast cancer diagnosis (classification) problem.

The rest of this paper is organized as follows. Section 2 is about related works. Section 3 presents the architecture of Triple-Stacking. Section 4 presents the obtained results and the discussion. Finally, section 5 concludes the document.

2. Review Of Statistical Learning Techniques

Although there are many statistical learning techniques that can be used to process medical images, we will give only a brief review on the techniques that are commonly used in breast cancer detection.

In [10], breast cancer was detected by using two electronic noses (ENs) to analyze breath and urine samples, namely the MK4 and the Cyranose 320 models. The model obtained, i.e. the artificial neural network based on the analysis carried out by the MK4 and the Cyranose 320, was able to classify breast cancer patients with an average accuracy of over 95%. Using discrete Haar wavelets, Reference [11] have earlier proposed a method based on the representation of images. Introduced into artificial neural networks, the images are classified using two classifiers, namely the Neural Network Back Propagation (NNBP) with a precision of 59.02% and the Radial Basis Function Network (RBFN) with a precision of 70.49%. Based on an artificial neural network, Reference [12] have also proposed a computational model which is capable of detecting the presence or the absence of abnormalities on a mammogram. The model obtained was proved to be highly performant in the detection of breast cancer on a mammogram with a correct recognition rate of 91.66%.

Reference [5] presented the convolutional neural network improvement algorithm for breast cancer classification (CNNI-BCC). Indeed, the sensitivity of the convolutional neural networks (CNN) to radiological images prompted the authors to improve CNN. To detect and classify into malignant, benign and normal categories, the CNNI-BCC method uses feature-based data extension algorithms (FWDA), convolutional neural network-based classification (CNNBS) and interactive detection-based lesion locator (IDBLL). This model can be incorporated into wearable devices, such as smartphones. CNNI-BCC achieved an accuracy of 90.50%. In order to alleviate the lack of early detection of breast cancer, Reference [13] also proposed a cancer detection approach based on convolutional neural networks (CNN). This technique can simultaneously locate and classify the mass as benign or malignant on a mammographic image. Ultimately, the model was trained and evaluated via mammographic images and achieved an accuracy of 91.86%.

In [4], statistical learning algorithms such as Support Vector Machine (SVM), decision trees (C4.5), Naive Bayes (NB) and K-Nearest Neighbours (K-NN) have been used to classify and predict breast cancer. The authors compared the performance of these algorithms using Wisconsin breast cancer from the UCI machine learning benchmark. They were able to show that SVM has the highest accuracy (97.13%) and the lowest error rate (2%).

Ensemble classification techniques have attracted considerable interest in breast cancer research, as they help to achieve more accurate diagnosis, prognosis and treatment within relatively short time [14]. In order to improve classification algorithms for early diagnosis of breast cancer, Reference [6] proposed a new hybrid ensemble technique called nested ensemble (NE). This new approach is used to create an accurate automatic prediction model that can classify patients into benign and malignant categories. Furthermore, it allows several ensemble methods to be applied at the same time with the aim of improving the performance of the prediction system. The final classifier is constructed by combining the results of the generated classifiers. The authors created four (4) nested two (2) layers classifiers based on voting and stacking techniques. The proposed model (SV-Naïve Bayes-3-MetaClassifiers) achieved an accuracy of 98.07%.

3. Proposed Breast Cancer Classification Model

In this section, we tested many architectural models on the Wisconsin Breast Cancer Database (BD1) to improve the best ensemble algorithm for this study. Next, we used 10-fold cross-validation to divide each dataset into ten (10) subsets. With the aim of optimizing the best ensemble learning method including Stacking, Voting, AdaBoostM1, Bagging and LogitBoost, we used BD1 extracted from the UCI repository [15]. Finally, we tested the improved model on another breast cancer database (BD2).

3.1. Description of the breast cancer database (DB1)

The database (BD1) used contains 699 clinical cases. Patients are characterized by 11 attributes, 9 of which represent clinical cases. The following table shows information about these attributes.

Table 1: Patient characteristics

N°	Attributes	Definitions
1	Sample code number	Patient identifier
2	Clump Thickness	1-10
3	Uniformity of Cell Size	1-10
4	Uniformity of Cell Shape	1-10
5	Marginal Membership	1-10
6	Single Epithelial Cell Size	1-10
7	Bare Nuclei	1-10
8	Bland Chromatin	1-10
9	Normal Nucleoli	1-10
10	Mitoses	1-10
11	Class	Benign or Malignant

3.2. Evaluation Measures

We consider the following evaluation criteria:

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \times 100 \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (3)$$

$$F1 - Score = \frac{2\times(Precision\times Recall)}{(Precision+Recall)} \quad (4)$$

where:

- Accuracy is the ratio of the correctly classified samples (examples) to the total number of presented samples (examples) .
- Precision is the ratio of the number of true positives (TP) to the sum of true positives (TP) and false positives (FP). A value of 1 expresses that all samples classified as positive were actually positive.
- A Recall of 1 means all positive samples were found.
- F-Measure: this quantity makes it possible to group the performance of the classifier (for a given class) into a single number.

For a given class, a classifier and a sample, four cases can arise:

- The sample is of this class, and the classifier was not mistaken: it is a true positive (TP);
- The sample is of this class, but the classifier predicts that, it is false: it is a false negative (FN);
- The sample is not of this class, but the classifier assigns it anyway: it is a false positive (FP);
- The sample is not of this class, and the classifier does not place it in this class either: it is a true negative (TN).

3.3. Proposed model

The table 2 below shows the components of some tested models :

Table 2: Examples of some tested architectures

Models	**Classifiers**	**Meta-Classifiers**
Stacking	SMO, Multilayer Perceptron (MP)	C4.5
Stacking	SMO, Multilayer Perceptron (MP)	Decision Stump
Voting	SMO, MP	
AdaBoostM1		Decision Stump
Bagging		Decision Stump
LogitBoost		Decision Stump

According to our simulations, the ensemble stacking method obtained the best performance, so it will be optimized in order to create a robust model for the binary classification of breast cancer (normal and abnormal patient). We used Decision Stump as Meta-Classifier . To improve the performance of the classifier, we applied the k-cross validation technique (k=10) because the dataset used is small. Below are the components of the proposed method (Triple-Stacking):

Table 3: The components of Triple-Stacking

Proposed model	**Classifiers**	**Meta-Classifier**
Triple-Stacking	Logistic Regression, Vote and Stacking	Decision Stump

We have tested many architectural models in order to choose the best of them. Figure 1 shows the architecture of the proposed model:

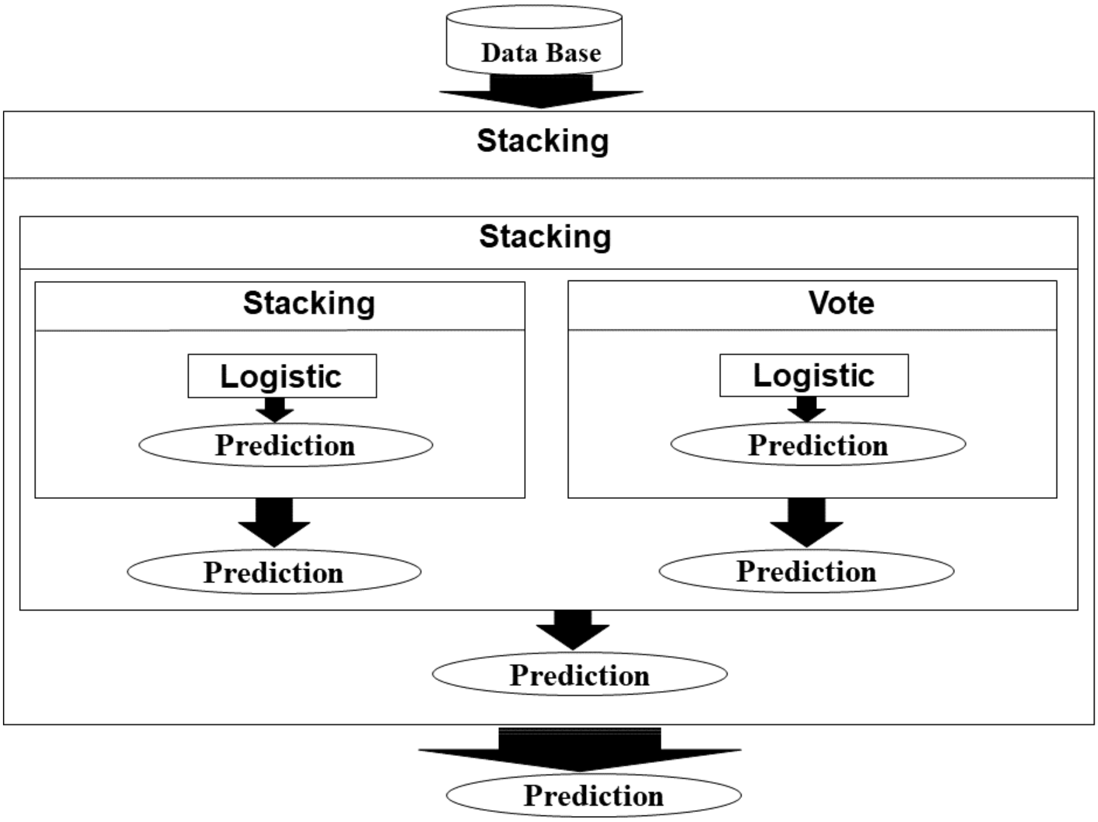

Figure 1: Triple-Stacking

In order to improve the early classification of breast cancer, we proposed a new ensemble method called Triple-Stacking. This technique combines two learning methods, namely stacking and voting (each of these models uses logistic regression as a weak learner). Finally, for each combination of predictions, we used Stacking and Decision Stump as the Meta-Classifier.

4. Results and Discussion

This part presents the results of the proposed model on two (2) different breast cancer datasets. Ensemble techniques are methods of combining two (2) or more models to design a single effective model. Since our problem falls into the category of statistical classification problems, some error measurement parameters were evaluated. Table 4 shows the confusion matrix and Table 5 shows the performance of Triple-Stacking.

Table 4: Confusion Matrix

456	2
1	240

Here is the meaning of the different values of the confusion matrix or error matrix of Table 4:

- True positive (TP) = 456; which means that 456 positive class data points were correctly classified by the model.

- True Negative (TN) = 240; which means that 240 negative class data points were correctly classified by the model.
- False Positive (FP) = 2; which means that 2 negative class data points were incorrectly classified as belonging to the positive class by the model.
- False negative (FN) = 1; which means that 1 positive class data points was incorrectly classified as belonging to the negative class by the model.

Table 5 shows the accuracy, precision, recall, and F-measure of the proposed model:

Table 5: Performance of the Triple -Stacking method on the BD1

Performance parameters	Triple-Stacking
Accuracy	99.57%
Precision	99.56%
Recall	99.78%
F-Measure	99.67%

In order to verify the robustness of the model (Triple-Stacking), it was evaluated on another breast cancer database (**BD2**) extracted from the UCI repository [16]. This dataset describes the characteristics of the cell nuclei present in the image. It contains 569 clinical cases. Here is the information from this dataset:

- Number of instances: 569
- Number of attributes: 32 (ID, diagnostic, 30 actual-valued input characteristics)
- Breakdown of classes: 357 benign, 212 malignant

Table 6 shows the accuracy, precision, recall and F-measure of the proposed model on the **BD2** breast cancer database**.**

Table 6: Performance of the Triple-Stacking method on BD2

Proposed Model	Triple-Stacking
Accuracy	99.64%
Precision	100%
Recall	99.44%
F-Measure	99.71%

Tables 5 and 6 show that the proposed model performs well on the two (2) breast cancer databases (**DB1** and **DB2**). According to this study, it can be concluded that the proposed model (Triple-Stacking) is robust.

Our study presents a new approach to ensemble learning. To obtain a better accuracy for breast cancer classification, we used three (3) machine learning (or statistical learning) methods: Logistic Regression, Voting and Stacking. Here are the essential steps of Triple Stacking:

- The first block of Stacking is composed of a single set method called Stacking. This block uses Decision Stump as meta-classifier.
- The second block of Stacking is composed of two (2) ensemble techniques (Stacking and Voting). For this block, the ensemble algorithms each use a single classifier, in particular Logistic Regression. Additionally, the Stacking sub of Stacking in the second block uses Decision Stump as a meta-learner. This block uses Decision Stump as a meta-classifier in order to combine the predictions from Stacking and Vote.

In this research, we tested several ensemble classifiers in order to choose and optimize the best technique among several Artificial Intelligence algorithms namely Stacking, Vote, AdaBoostM1, Bagging, LogitBoost, Support Vector Machine (SMO), Artificial Neural Network (ANN), Decision Tree (C4.5) and others. We chose to optimize Stacking for the classification of breast cancer.

We conducted the experiments on two (2) data sets (Breast Cancer Wisconsin Original Data Set and Breast Cancer Wisconsin Diagnostic Data Set) and the 10-fold cross-validation technique is used for the evaluation of the proposed model (Triple-Stacking).

Table 7 shows the accuracies obtained by the proposed method (Triple-Stacking) and other techniques from the literature, on two (2) databases.

Table 7: Comparative study between Triple-Stacking and the techniques from our literature review

	BD1	**BD2**
[17]	99.02%	-------
[18]	97.51%	-------
[19]	96.71%	-------
[20]	97.36%	-------
[21]	98.57%	-------
[22]	99.2%	-------
[23]	-------	97.7%
[24]	-------	99.42%
[25]	-------	99.03%
[6]	-------	98.07%
[26]	-------	98.40%
Triple-Stacking (Proposed method)	99.57%	99.64%

We compared our technique with the existing machine learning methods (literature review) in terms of Accuracy. Results demonstrate that Triple-Stacking outperforms existing ensemble techniques (Stacking, Vote, AdaBoostM1, Bagging and LogitBoost) and state-of-the-art methods in this study (SVM, …).

Triple-Stacking achieved an Accuracy of 99.57% on the first dataset (DB1 Breast Cancer Wisconsin Original) and 99.64% on the second dataset (DB2 Breast Cancer Wisconsin Diagnostic).

The formation of Triple-Stacking takes time compared to other existing models including Stacking. It has not been tested for multi-class classification and this model is tested on small database sizes. The accuracy of our model comes from the combination of existing models like Stacking (this method combines several classifiers using the Stacking method) [27], the Vote (forms various basic models and predicts based on the aggregation of results of each basic model) [28] and Logistic Regression (models the probability of an event occurring by making the logit function of the event a linear combination of one or more independent variables. Therefore, the Logistic Regression model is set up to ensure that whatever estimate of risk we get, it will always be some number between 0 and 1) [29, 30].

5. Conclusion

This article has shown the importance of combining statistical learning methods in order to diagnose (or classify) breast cancer. This work also consists in evaluating ensemble learning techniques on two breast cancer datasets . These techniques made it possible to classify breast cancer into two (2) classes (malignant and benign) using two (2) databases (DB1 and DB2). The model obtained (Triple-Stacking) achieved an accuracy of 99.57% on the first dataset (DB1) and 99.64% on the second dataset (DB2). Ultimately, the obtained results surpassed the state of the art.

Our future work focuses on:

- Image processing, in particular mammographic images.
- The development of a complex deep learning model applied to mammographic images to classify normal (benign tumor) and abnormal (malignant tumor) patients.
- The deployment of the Triple-Stacking model to facilitate the diagnosis of breast cancer for healthcare professionals.

References

[1] Essam H. Houssein, Marwa M. Emam, Abdelmgeid A. Ali, Ponnuthurai Nagaratnam Suganthan. “Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review”. Expert Systems With Applications, vol. 167, pp. 1-49, 2021.
https://www.sciencedirect.com/science/article/pii/S0957417420309015

[2] American Cancer Society. Atlanta: American Cancer Society, Inc. 2019.

[3] Mohammed A. Al-masni, Mugahed A. Al-antari, Jeong-min Park, Geon Gi, Tae-Yeon Kim, Patricio Rivera, Edwin Valarezo, Mun-Taek Choi, Seung-Moo Han,Tae-Seong Kim. “Simultaneous Detection and ClassiÞcation of Breast Masses in Digital Mammograms via a Deep Learning YOLO-based CAD System”. Computer Methods and Programs in Biomedicine, vol. 157, pp. 85-94, 2018. https://www.sciencedirect.com/science/article/pii/S0169260717314980

[4] Hiba Asri, Hajar Mousannif, Hassan Al Moatassime, Thomas Noel. “Using Machine Learning Algorithms for breast Cancer Risk Prediction and Diagnosis”. Procedia Computer Science, vol. 83, pp. 1064-1069, 2016. https://www.sciencedirect.com/science/article/pii/S1877050916302575

[5] Fung Ting, Yen Jun Tan, Kok Swee Sim. “Convolutional Neural Network Improvement for Breast Cancer Classification”. Expert Systems With Applications, vol. 120, pp. 103-115, 2019.
https://www.sciencedirect.com/science/article/pii/S0957417418307280

[6] Moloud Abdar, Mariam Zomorodi-Moghadam, Xujuan Zhou, Raj Gururajan, Xiaohui Tao, Prabal D Barua, Rashmi Gururajan. “A new nested ensemble technique for automated diagnosis of breast cancer”. Pattern Recognition Letters, vol. 132, pp. 123-131, 2020. https://www.sciencedirect.com/science/article/pii/S0167865518308766

[7] Lingxi Peng, Wenbin Chen, Wubai Zhou, Fufang Li, Jin Yang, Jiandong Zhang. “An immune-inspired semi-supervised algorithm for breast cancer diagnosis”. Computer Methods and Programs in Biomedicine, vol 134, pp. 259-265, 2016. https://www.sciencedirect.com/science/article/pii/S016926071530359X

[8] Manel Zribi, Younes Boujelbene. “Les réseaux de neurones un outil de sélection de variables : Le cas des facteurs de risque de la maladie du cancer du sein” . Éthique et économique, 9(1), 2012.

[9] J.-E. Bibault, A. Burgun, P. Giraud. “Intelligence artificielle appliquée à la radiothérapie”. Cancer/Radiothérapie, vol. 21, pp. 239-243, 2017.
https://www.sciencedirect.com/science/article/pii/S1278321817300537

[10] Or Herman-Saffar, Zvi Boger, Shai Libson, David Lieberman, Raphael Gonen, Yehuda Zeiri. “Early non-invasive detection of breast cancer using exhaled breath and urine analysis”. Computers in Biology and Medicine, vol. 96, pp. 227-232, 2018. https://www.sciencedirect.com/science/article/pii/S0010482518300775

[11] Sertan Kaymak, Abdulkader Helwan, Dilber Uzun. “Breast cancer image classification using artificial neural networks”. Procedia Computer Science, vol 120, pp. 126-131, 2017. https://www.sciencedirect.com/science/article/pii/S1877050917324298

[12] M. Boukhobza And M. Mimi. “Détection automatique de la présence d’anomalie sur une mammographie par réseau de neurones artificiels”. Courrier du Savoir, vol. 13, pp.103-108, 2012.

[13] Simon Hadush Nrea, Yaecob Girmay Gezahegn, Abiot Sinamo Boltena, Gebrekirstos Hagos. "Breast cancer detection using convolutional neural networks", 2020.

[14] Mohamed Hosni, Ibtissam Abnane, Ali Idri, Juan M. Carrillo de Gea, José Luis Fernández Alemán. "Reviewing ensemble classification methods in breast cancer, Computer Methods and Programs in Biomedicine", 2019.

[15] Breast Cancer Wisconsin (Original) Data Set (BD1).
https://archive.ics.uci.edu/ml//Breast+Cancer+Wisconsin+%28Original%29

[16] Breast Cancer Wisconsin (Diagnostic) Data Set (BD2).
https://archive.ics.uci.edu/ml//Breast+Cancer+Wisconsin+%28Diagnostic%29

[17] Sulyman Age Abdulkareema, Zainab Olorunbukademi Abdulkareem. "An Evaluation of the Wisconsin Breast Cancer Dataset using Ensemble Classifiers and RFE Feature Selection Technique". International Journal of Sciences: Basic and Applied Research (IJSBAR),Volume 55, No 2, pp 67-80, 2021.

[18] M. Amrane, S. Oukid, I. Gagaoua and T. Ensarİ. "Breast cancer classification using machine learning". 2018 Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT), pp. 1-4. 2018.

[19] S. K. Sarkar and A. Nag. "Identifying patients at risk of breast cancer through decision trees". International Journal of Advanced Research in Computer Science, vol. 8, no. 8, pp. 88–91, 2017.

[20] V. Chaurasia, S. Pal, and B. Tiwari. "Prediction of benign and malignant breast cancer using data mining techniques". Journal of Algorithms & Computational Technology, vol. 12, no. 2, pp. 119–126, 2018.

[21] M. M. Islam, M. R. Haque, H. Iqbal, M. M. Hasan, M. Hasan, and M. N. Kabir. "Breast cancer prediction: a comparative study using machine learning techniques". SN Computer Science, vol. 1, no. 5, pp. 1–14, 2020.

[22] Egwom, O.J., Hassan, M., Tanimu, J.J., Hamada, M., Ogar, O.M. "An LDA–SVM Machine Learning Model for Breast Cancer Classification". Biomedinformatics, vol. 2, pp. 345–358, 2022.

[23] Walid Theib Mohammad, Ronza Teete, Heyam Al-Aaraj, Yousef Saleh Yousef Rubbai, Majd Mowafaq Arabyat. "Diagnosis of Breast Cancer Pathology on the Wisconsin Dataset with the Help of Data Mining Classification and Clustering Techniques". Applied Bionics and Biomechanics, 2022.

[24] Adel S. Assiri, Saima Nazir, Sergio A. "Velastin. Breast Tumor Classification Using an Ensemble Machine Learning Method". J. Imaging ,2020.

[25] Abdur Rasool, Chayut Bunterngchit, Luo Tiejian, Md. Ruhul Islam, Qiang Qu, Qingshan Jiang. “Improved Machine Learning-Based Predictive Models for Breast Cancer Diagnosis”. nt. J. Environ. Res. Public Health, 2022.

[26] MUAWIA. A. ELSADIG. “ENSEMBLE CLASSIFIER FOR BREAST CANCER DETECTION”. Journal of Theoretical and Applied Information Technology, vol. 100, pp. 3278-3287, 2022. http://www.jatit.org/volumes/Vol100No10/11Vol100No10.pdf

[27] David H. Wolpert. “Stacked generalization”. Neural Networks, vol. 5, pp. 241-259, 1992. https://www.sciencedirect.com/science/article/abs/pii/S0893608005800231.

[28] Ludmila I. Kuncheva (2004, July 2). Combining Pattern Classifiers: Methods and Algorithms. John Wiley and Sons, Inc.. Available : http://www.ccas.ru/voron/download/books/machlearn/kuncheva04combining.pdf [May 5, 2022].

[29] le Cessie, S., van Houwelingen, J.C. “Ridge Estimators in Logistic Regression”. Applied Statistics, Vol. 41, pp. 191-201, 1992.

[30] David G. Kleinbaum, Mitchel Klein (2010, July 1). Logistic Regression: A Self-Learning Text. (3nd edition). Springer.