# Breast Cancer Classification Using Deep Learning

Jasmir
Intelligent System Research Group
Computer Enginnering STIKOM
Dinamika Bangsa
Jambi, Indonesia
ijay_jasmir@yahoo.com

Siti Nurmaini
Intelligence System Research Group
Faculty Of Computer Science
Sriwijaya University
Palembang Indonesia
sitinurmaini@gmail.com

Reza Firsandaya Malik
Faculty Of Computer Science Sriwijaya University
Palembang, Indonesia
rezafm@unsri.ac.id

Dodo Zaenal Abidin
Intelligent System Research Group
Computer Engineering
STIKOM Dinamika Bangsa Jambi, Indonesia
dikdodoza@gmail.com

Ahmad Zarkasi
Intelligent System Research Group
Faculty of Computer Science
Sriwijaya University
Palembang, Indonesia
zarkasi98@gmail.com

Yesi Novaria Kunang
Intelligent System Research Group
Bina Darma University
Palembang, Indonesia
yesinovariakunang@binadarma.ac.id

Firdaus
Intelligent System Research Group
Faculty Of Computer Science Sriwijaya University
Palembang, Indonesia
virdauz@gmail.com

*Abstract*— Breast cancer has been identified as the most widespread cancer amongst women and also the major cause of female cancer death all over the world. In this paper, we build the classification model of a person who is exposed to breast cancer based on recurrences-event and no-recurrences event. This classification using datasets from the University of Medicine Center, Institute Of Oncology, Ljublijana, Yugoslavia of the 286 datasets consist 2 classes, 201 No-Recurrences-Events classes, 85 Recurrences-events classes and 10 attributes including classes. The algorithm used for breast cancer classification is the Multilayer Perceptron algorithm with the accuracy level of 96.5% and high evaluation is 69.93% in 8-fold cross validation from 10-fold cross validation.

***Keywords— breast cancer, deep learning, multilayer perceptron, classification***

## I. INTRODUCTION

Breast cancer is one of the most deadly deceases affecting women worldwide. This deceases is the leading cause of cancer death. Breast cancer examination is includes categories such as cancer category or not, recurrent-event or no-recurrent-event, and benign or malignant. [1] [2][3]

In giving results, an anatomical pathologist must calculate what the anatomic pathology laboratory has produced. Doctor's calculations are not timely due to the verdict of a breast cancer patient. Therefore, it motivates the use of methods that can be used by computers.[4]

The use of computer science method is deep learning. In recent years deep learning has attracted wide attention in the field of classification. The classification algorithm in medical needs is still highly relied upon, especially if it is associated with deep learning [5]. The use of deep learning classification applications has been widely applied, and has proved to be a powerful method to face of complex problems [6]

Some researches about breast cancer using various methods have been done. Alexander W. Forsyth et al 2018 using Natural Languange Processing method, in this study NLP and machine learning method are used to extract symptoms of breast cancer, conclusions from this study demonstrate the potential of machine learning to collect, track and analyze the symptoms experienced by cancer patients during chemotherapy. The final model achieved precision of 0.82, 0.86, and 0.99 and recall of 0.56, 0.69, and 1.00 for positive, negative, and neutral symptom labels, respectively. The most common positive symptoms were pain, fatigue, and nausea. Machine based labeling of 103,564 sentences took two minutes [7]

Ahmed M. Abdel-Zaher, et al 2015 using Deep Belief Network to detecting breast cancer based on DBN unsupervised pre-training phase followed by a supervised back propagation neural network phase (DBN-NN). This technique was tested on the Wisconsin Breast Cancer Dataset (WBCD). The classifier complex gives an accuracy of 99.68% indicating promising results over previously-published studies. The proposed system provides an effective classification model for breast cancer. [8]

Hiba Chougrad, et al 2018 using Convolutional Neural Network. In this paper, they developed a Computer-aided Diagnosis (CAD) system based on deep Convolutional Neural Networks (CNN). The developed framework could predict and provide the correct diagnosis for 98.23% of the images from MIAS, 97.35% from DDSM 95.50% for INbreast and 96.67% for BCDR. The results obtained demonstrate that the proposed framework is performant and can indeed be used to predict if the mass lesions are benign or malignant. [9]

978-1-5386-5721-8/18/$31.00 ©2018 IEEE

Harikumar Rajaguru were researching about classification of risk breast cancer using Bayesian Linear Discriminant Analysis. Dataset from Department of Oncology of Sri Kuppuswamy Naidu Hospital, Coimbatore, India. The results show that an average classification accuracy of about 83.45% is reported when Bayesian Linear Discriminant Classifier is utilized**.** [10]

Murat Karabatak using naïve bayes to research breast cancer. Dataset from Wisconsin breast cancer database University of Wisconsin-Madison Hospitals. Based on the conducted experiments, the applied weighted NB obtained 99.11% sensitivity, 98.25% specificity and 98.54% the accuracy values respectively. [11]

S.A Mujarad has done research on breast cancer by using multilayer perceptron and 3-fold cross validation. Data were obtained from 46 patients who had been diagnosed with a carcinoma or benign breast tumor. But Mujarad discusses the predicted development of breast cancer from a data set and four biomarkers. The four biomarkers are DNA ploidy, cell cycle distribution (GOG lig2M), steroid receptors (ERlPR) and S-phase fraction (SPF). The highest accuracy result is in SPF that is 65.21% [12]

Guided by Mujarad's research that predicts breast cancer using multilayer perceptron with predictive accuracy values of 65.21%. We see the opportunity to conduct further research, namely by increasing the value of accuracy by classifying using one of the deep learning methods, namely multilayer perceptron because Multilayer perceptron has been widely used, and has proven to be a method capable of dealing with complex problems [13]

Therefore, based on some of the above studies we tried to discuss other types of breast cancer and other datasets. In this paper, we build a classification model utilizing the dataset from Medical Center University, Institute Of Oncology, Ljublijana, Yugoslavia to evaluate and classify recurrent and no-recurrent breast cancer types using multilayer perceptron, weka 3.8 and 10-fold cross validation evaluations. This model can be used to help the medical parties to determine the types of recurrent and no-recurrent breast cancer.

The remainder of this paper is organized as follows. In Section II, we briefly discuss methods. In Subsection B of Section II, we do the preprocessing. In Subsection C section II we focus on the Multilayer Perceptron. The performance evaluation methods are explained in Subsection D Section II. Section III are process classification using multilayer perceptron. Section IV are Evaluation. The conclusion and suggestions for future research are summarized in Section V.

## II. METHOD

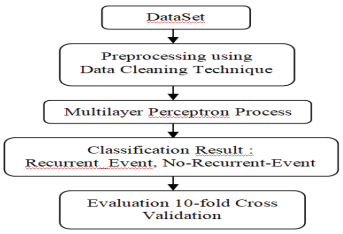


Fig.1 The flow of classification Process

### A. Dataset

The data were obtained from data centers of Medical Center University, Institute Of Oncology, Ljublijana, Yugoslavia with 286 data and 10 attributes of Age, Menopause, Tumor-Size, nv-nodes, Node-Caps, Deg-malig, Breast, Breast-Quad , Irradiate and Class.[14]

### B. Preprocessing

The available dataset is random and there is no data label yet, so the initial stage of preprocessing is to make improvements by sorting and labeling data and explaining the types of processes that process raw data to prepare for other process procedures. In this dataset there is still incomplete data or missing value denoted by the "?" [15]. Thus, data refinement is required by using data cleaning technique to fill missing values on the dataset by handling using the average attribute values of all samples residing in the same class.

### C. Multilayer Perceptron Proses

The main focus of the presented work is the application of multilayer perceptron (MLP) for breast cancer classification. The MLP is consisted of simple neurons named perceptron. As refer to neuron weights in input nodes and generating the output by employing nonlinear activation mathematical function, linear combination will be formed by perceptron through computation of an output neuron from multiple real valued inputs. [16]. The computation can be expressed as Eq. (1).

$$y = \varphi(\sum_{i=1}^{n} w_i x_i + b) = \varphi(\boldsymbol{w}^T \boldsymbol{x} + b), \quad (1)$$

where x is the vector of inputs, w denotes the vector of weights, ˆ represents the activation function, and *b* denotes the bias and.

The MLP architecture is a layered feedforward neural network, in which the nonlinear elements (neurons) are arranged in successive layers, and the information flows unidirectionally, from input layer to output layer, through the hidden layer(s). Nodes from one layer are connected (using interconnections or links) to all nodes in the adjacent layer(s), but no lateral connection between nodes within one layer, or feedback connection is possible. The number of input and output units depends on the representations of the input and the output objects, respectively. The hidden layer(s) is(are) an important parameter(s) in the network. The MLPs with an arbitrary number of hidden units have been shown to be universal approximators for continuous maps to implement any function. [13]

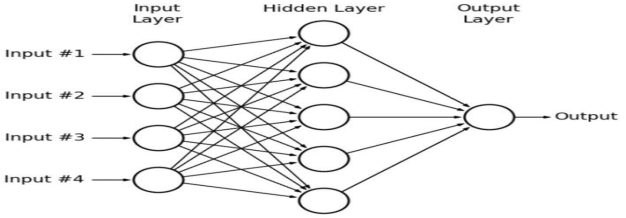


Fig. 2 Schematic of three-layered feedforward neural network, with one input layer, one hidden layer, and one output layer.

### D. *Classification Result*

To identify breast cancer, the most popular Neural Network (NN) model – general multilayer perceptron (MLP) with back propagation learning rule is used [17]. The first layer is the input layer that receives input vectors. Last layer is called output layer; layers in between first and last ones are called hidden layers. Each neuron in the hidden layer and output layer receives output vectors from the previous layer to evaluate the weighted sum and to achieve the output vectors by the activation functions of the neurons. The main goal of a classifier system using NN is to recognize an unknown pattern based on some deterministic or statistical measurements.

### E. *Evaluation*

Evaluation phase using 10-fold Cross Validation which is one technique to assess the accuracy of a model built on the dataset. Model making aims to predict the dataset. The data used in the model development process is called training data, while the data to be used to validate the model is called data testing. In this technique the dataset is divided into 10 partitions randomly. Then a number of 10 experiments were conducted, each experiment using the 10th partition data as data testing and utilizing the rest of the other partition as training data. Classification and Evaluation using Weka 38 applications.

## III. RESULT

The result of the arff data structure of the 286 datasets used consisted of 2 classes, 201 classes of No-Recurrence-Events and 85 for the Recurrence-Events class. The following is a table of training data to be used for calculating Multilayer Perceptron. There are 10 attributes: Age, Menopause, Tumor-Size, nv-nodes, Node-Caps, Deg-malig, Breast, Breast-Quad, Irradiate and class.

Tabel-1 Table Training Data

| A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|
| No | Age | Menopause | Tumor-Size | Inv-Nodes | Node-Caps | Deg-Malig | Breast | Breast-Quad | Irradiat | Class |
| 1 | '40-49' | 'premeno' | '15-19' | '0-2' | 'yes' | '3' | 'right' | 'left_up' | 'no' | 'recurrence-events' |
| 2 | '50-59' | 'ge40' | '15-19' | '0-2' | 'no' | '1' | 'right' | 'central' | 'no' | 'no-recurrence-events' |
| 3 | '50-59' | 'ge40' | '35-39' | '0-2' | 'no' | '2' | 'left' | 'left_low' | 'no' | 'recurrence-events' |
| 4 | '40-49' | 'premeno' | '35-39' | '0-2' | 'yes' | '3' | 'right' | 'left_low' | 'yes' | 'no-recurrence-events' |
| 5 | '40-49' | 'premeno' | '30-34' | '3-5' | 'yes' | '2' | 'left' | 'right_up' | 'no' | 'recurrence-events' |
| 6 | '50-59' | 'premeno' | '25-29' | '3-5' | 'no' | '2' | 'right' | 'left_up' | 'yes' | 'no-recurrence-events' |
| 7 | '50-59' | 'ge40' | '40-44' | '0-2' | 'no' | '3' | 'left' | 'left_up' | 'no' | 'no-recurrence-events' |
| 8 | '40-49' | 'premeno' | '10-14' | '0-2' | 'no' | '2' | 'left' | 'left_up' | 'no' | 'no-recurrence-events' |
| 9 | '40-49' | 'premeno' | '0-4' | '0-2' | 'no' | '2' | 'right' | 'right_low' | 'no' | 'no-recurrence-events' |
| 10 | '40-49' | 'ge40' | '40-44' | '15-17' | 'yes' | '2' | 'right' | 'left_up' | 'yes' | 'no-recurrence-events' |
| 11 | '50-59' | 'premeno' | '25-29' | '0-2' | 'no' | '2' | 'left' | 'left_low' | 'no' | 'no-recurrence-events' |
| .. | .. | .. | .. | .. | .. | .. | .. | .. | .. | .. |
| .. | .. | .. | .. | .. | .. | .. | .. | .. | .. | .. |
| 284 | '30-39' | 'premeno' | '30-34' | '6-8' | 'yes' | '2' | 'right' | 'right_up' | 'no' | 'no-recurrence-events' |
| 285 | '50-59' | 'premeno' | '15-19' | '0-2' | 'no' | '2' | 'right' | 'left_low' | 'no' | 'no-recurrence-events' |
| 286 | '50-59' | 'ge40' | '40-44' | '0-2' | 'no' | '3' | 'left' | 'right_up' | 'no' | 'no-recurrence-events' |

The data testing used is taken randomly from training data. Here are 9 data testing that will be used for the calculation of Multilayer Perceptron

Table 2. Table Testing Data

| No | Age | Menopause | Tumor-Size | Inv-Nodes | Node-Caps | Deg-Malig | Breast | Breast-Quad | Irradiat | Class |
|---|---|---|---|---|---|---|---|---|---|---|
| 8 | '40-49' | 'premeno' | 10-14' | '0-2' | 'no' | '2' | 'left' | 'left_up' | 'no' | ? |
| 27 | '50-59' | 'ge40' | '10-14' | '0-2' | 'no' | '2' | 'right' | 'left_low' | 'no' | ? |
| 38 | '60-69' | 'ge40' | '45-49' | '6-8' | 'yes' | '3' | 'left' | 'central' | 'no' | ? |
| 118 | '60-69' | 'ge40' | '10-14' | '0-2' | 'no' | '1' | 'left' | 'left_up' | 'no' | ? |
| 140 | '50-59' | 'premeno' | '30-34' | '0-2' | 'no' | '1' | 'left' | 'central' | 'no' | ? |
| 157 | '30-39' | 'premeno' | '30-34' | '0-2' | 'no' | '2' | 'left' | 'left_up' | 'no' | ? |
| 166 | '50-59' | 'ge40' | '30-34' | '6-8' | 'yes' | '2' | 'left' | 'right_low' | 'yes' | ? |
| 225 | '30-39' | 'premeno' | '20-24' | '0-2' | 'no' | '3' | 'left' | 'left_up' | 'yes' | ? |
| 237 | '30-39' | 'lt40' | '15-19' | '0-2' | 'no' | '3' | 'right' | 'left_up' | 'no' | ? |

The designed MLP in this study consists of an input layer and one hidden layer with variable number of nodes depending on the number of input markers and an output layer WIth one neuron. The network is fed with different combination of markers in each nm to investigate the predictive significance of each marker. Hence, the number of input neurons is defined by the number of markers and the number of hidden neurons is optimized for each marker combination. The network is then trained using Multilayer Perceptron Algorithm and validated with k-fold cross validation.

The following picture is a screenshot of the multilayer perceptron training process with weka app

```
=== Evaluation on training set ===

Time taken to test model on training data: 0.01 seconds

=== Summary ===

Correctly Classified Instances         276               96.5035 %
Incorrectly Classified Instances        10                3.4965 %
Kappa statistic                          0.9157
Mean absolute error                      0.0482
Root mean squared error                  0.1567
Relative absolute error                 11.5332 %
Root relative squared error             34.2946 %
Total Number of Instances              286

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0.980     0.071     0.970     0.980     0.975     0.916     0.980     0.986     no-recurrence-event
                 0.929     0.020     0.952     0.929     0.940     0.916     0.980     0.978     recurrence-events
Weighted Avg.    0.965     0.056     0.965     0.965     0.965     0.916     0.980     0.984

=== Confusion Matrix ===

   a   b   <-- classified as
 197   4 |   a = no-recurrence-events
   6  79 |   b = recurrence-events
```

Fig 3. Snapshot of the data training process using Weka

Here is a graph of the end result of the classification consisting of the class "no-recurrences-events" and class "recurrences-events".

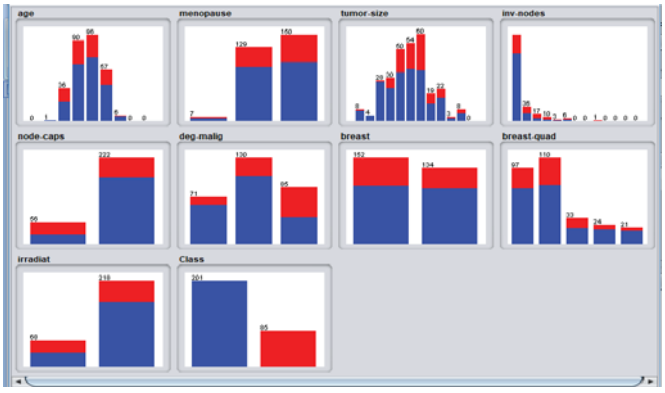


Fig 4. Graph of all attribute dataset

## IV. EVALUATION USING 10-FOLD CROSS VALIDATION

The following is a snapshot of the 10-Fold Cross Validation process, just process 8th, process 9th and process 10th using Weka 3.8 app.

### 1. Output of 8/10-*Fold Cross Validation*

In Figure 5 the system has successfully performed the 8th evaluation by using 10-fold cross validation of the breast-cancer.arff data and using multilayer perceptron algorithm calculation of 69.9301%.

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         200               69.9301 %
Incorrectly Classified Instances        86               30.0699 %
Kappa statistic                          0.2652
Mean absolute error                      0.3079
Root mean squared error                  0.5008
Relative absolute error                 73.5835 %
Root relative squared error            109.5748 %
Total Number of Instances              286

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0.801    0.541    0.778      0.801    0.789      0.266    0.665     0.792     no-recurrence-events
                 0.459    0.199    0.494      0.459    0.476      0.266    0.665     0.532     recurrence-events
Weighted Avg.    0.699    0.439    0.693      0.699    0.696      0.266    0.665     0.715

=== Confusion Matrix ===

   a   b   <-- classified as
 161  40 |   a = no-recurrence-events
  46  39 |   b = recurrence-events
```

Fig 5 Output 8-*Fold Cross Validation*

### 2. Output of 9/10-*Fold Cross Validation*

In Figure 6 the system has successfully performed the 9th evaluation by using 10-fold cross validation of the breast-cancer.arff data and using multilayer perceptron algorithm calculation of 69.2308%.

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         198               69.2308 %
Incorrectly Classified Instances        88               30.7692 %
Kappa statistic                          0.2429
Mean absolute error                      0.3317
Root mean squared error                  0.525
Relative absolute error                 79.2691 %
Root relative squared error            114.8586 %
Total Number of Instances              286

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0.801    0.565    0.770      0.801    0.785      0.243    0.634     0.788     no-recurrence-events
                 0.435    0.199    0.481      0.435    0.457      0.243    0.634     0.489     recurrence-events
Weighted Avg.    0.692    0.456    0.684      0.692    0.688      0.243    0.634     0.699

=== Confusion Matrix ===

   a   b   <-- classified as
 161  40 |   a = no-recurrence-events
  48  37 |   b = recurrence-events
```

Fig 6 Output 2/10-*Fold Cross Validation*

### 3. Output of 10/10-*Fold Cross Validation*

In Figure 7 the system has successfully performed the last evaluation by using 10-fold cross validation of the breast-cancer.arff data and using multilayer perceptron algorithm calculation of 64.6853%

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         185               64.6853 %
Incorrectly Classified Instances       101               35.3147 %
Kappa statistic                          0.1575
Mean absolute error                      0.3552
Root mean squared error                  0.5423
Relative absolute error                 84.8811 %
Root relative squared error            118.654  %
Total Number of Instances              286

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0.746    0.588    0.750      0.746    0.748      0.158    0.623     0.790     no-recurrence-events
                 0.412    0.254    0.407      0.412    0.409      0.158    0.623     0.410     recurrence-events
Weighted Avg.    0.647    0.489    0.648      0.647    0.647      0.158    0.623     0.677

=== Confusion Matrix ===

   a   b   <-- classified as
 150  51 |   a = no-recurrence-events
  50  35 |   b = recurrence-events
```

Fig 7 Output 10-*Fold Cross Validation*

For more details, the accuracy value of each process k-fold cross validation can be seen in the following table

Table 3. Summary process from 2 to 10-fold-Cross-Validation

| Number process | Accuracy % |
|---|---|
| 2 | 65.7343 |
| 3 | 66.7832 |
| 4 | 65.7343 |
| 5 | 66.7832 |
| 6 | 65.7343 |
| 7 | 65.7343 |
| 8 | 69.9301 |
| 9 | 69.2308 |
| 10 | 64.6853 |

## V. CONCLUSION

We have developed a evaluation model to determine breast cancer recurrent and no-recurrent using multilayer perceptron. The accuracy of classifying recurrent and no-recurrent is 96.5% and high evaluation is 69.93% in 8-fold cross validation from 10-fold cross validation. It can be increased by increasing the dataset as here we have taken into account measurement of mass-circularity in the data-set and from statistical analysis we found that this quantitative measurement leads to transparency in our conclusion

For future research, we will create an automatic diagnosis and classification model for other disorders such as epilepsy, cardiac arrhythmias, diabetic retinopathy, brain disorders, mental disorders etc. Furthermore, we will implement cloud computing that can be applied in the medical field to make it useful for the medical community and can expand this idea to Android-based mobile devices that can help patients to get their diagnostic results quickly.

## REFERENCES

[1] C. Avaznia and S. H. Naghavi, “Breast Cancer Classification Using Covariance Description in Riemannian Geometry,” pp. 110–113, 2017.

[2] F. A. Spanhol, L. S. Oliveira, C. Petitjean, and L. Heutte, “A Dataset for Breast Cancer Histopathological Image Classification,” vol. 9294, no. c, pp. 1–8, 2015.

[3] K. Discovery, "A breast cancer risk classification model based on the features selected by novel F-score index for the imbalanced multi-feature dataset," pp. 2–7, 2016.
[4] H. Nasser, M. King, H. K. Rosenberg, A. Rosen, E. Wilck, and W. L. Simpson, "Anatomy and pathology of the canal of Nuck," *Clin. Imaging*, vol. 51, no. 11, 2017, pp. 83–92, 2018.
[5] B. Pan, Z. Shi, and X. Xu, "MugNet : Deep learning for hyperspectral image classification using limited samples," *ISPRS J. Photogramm. Remote Sens.*, 2017.
[6] H. Mohsen and A. M. Salem, "Classification using Deep Learning Neural," *Futur. Comput. Informatics J.*, 2018.
[7] A. W. Forsyth *et al.*, "Machine Learning Methods to Extract Documentation of Breast Cancer Symptoms from Electronic Health Records," *J. Pain Symptom Manage.*, 2018.
[8] A. M. Abdel-zaher and A. M. Eldeib, "Breast Cancer Classification Using Deep Belief Networks," *Expert Syst. Appl.*, 2015.
[9] H. Chougrad, H. Zouaki, and O. Alheyane, "Deep Convolutional Neural Networks for Breast Cancer Screening," *Comput. Methods Programs Biomed.*, 2018.
[10] H. Rajaguru and S. K. Prabhakar, "Bayesian Linear Discriminant Analysis for Breast Cancer Classification," no. Icces, pp. 266–269, 2017.
[11] M. Karabatak, "A new classifier for breast cancer detection based on Naïve Bayesian," *MEASUREMENT*, vol. 72, pp. 32–36, 2015.
[12] S. A. Mojarad, W. L. Woo, and G. V Sherbet, "Breast Cancer Prediction and Cross Validation Using Multilayer Perceptron Neural Networks," pp. 760–764, 2010.
[13] F. F. Ting and K. S. Sim, "Self-regulated Multilayer Perceptron Neural Network for Breast Cancer Classification."
[14] "UciDataSET.pdf." .
[15] D. Henry, "Filter hashtag context through an original data cleaning method," *Procedia Comput. Sci.*, vol. 130, pp. 464–471, 2018.
[16] A. Ella, H. M. Moftah, A. Taher, and M. Shoman, "MRI breast cancer diagnosis hybrid approach using adaptive ant-based segmentation and multilayer perceptron neural networks classifier," *Appl. Soft Comput. J.*, vol. 14, pp. 62–71, 2014.
[17] S. Chatterjee, A. K. Ray, and R. Karim, "Classification of Malignant Tumors Using Multiple Sonographic Features," pp. 252–256, 2011.

978-1-5386-5721-8/18/$31.00 ©2018 IEEE