Classification of Breast Ultrasound Images: An Analysis Using Machine Intelligent Based Approach

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ABSTRACT

Purpose: *Breast Cancer (BC) is considered as one of the most dangerous diseases, especially in women. The survivability of the patient is a challenging task if the breast cancer is in severe stage. It is very much essential for the early classification of breast ultrasound images (BUIs) into several categories such as benign (BN), malignant (MG) and normal (NL), etc. so that preventive measures can be taken accordingly at the earliest.*

Approach: *In this work, a machine intelligent (MI) based approach is proposed for the classification of BUIs into the BN, MG and NL types. The proposed approach is focused on the stacking (hybridization) of Logistic Regression (LRG), Support Vector Machine (SVMN), Random Forest (RFS) and Neural Network (NNT) methods to carry out such classification. The proposed method is compared with other machine learning (ML) based methods such as LRG, SVMN, RFS, NNT, Decision Tree (DTR), AdaBoost (ADB), Naïve Bayes (NBY), K-Nearest Neighbor (KNNH) and Stochastic Gradient Descent (SGDC) for performance analysis.*

Result: *The proposed method and other ML based methods have been implemented using Python based Orange 3.26.0. In this work, 750 TLDIs having 250 numbers of each type such as BN, MG and NL are taken from the Kaggle source. The performance of all the methods is assessed using the performance parameters such as classification accuracy (CA), F1, Precision (PR) and Recall (RC). From the results, it is found that the proposed method is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGD.*

Originality: *In this work, a MI based approach is proposed by focusing on the stacking of LRG, SVMN, RFS and NNT methods to carry out the classification of BUIs into several types such as BN, MG and NL. The proposed approach performs better in terms of CA, F1, PR and RC as compared to LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC methods.*

Paper Type: *Conceptual Research.*

Keywords: Breast Ultrasound Image, Machine Learning, Classification Accuracy, F1, Precision, Recall

1. INTRODUCTION :

BC is considered as a major concern mainly for women throughout the globe. It is recognized as one of the very dangerous diseases due to lesser medicinal facilities. The survivability of the concerned patient is a very challenging task if the BC is in severe stage. It is very much essential for the early classification of BUIs [1-17] into several categories such as BN, MG and NL, etc. so that the diagnosis process can be initiated accordingly at the earliest in order to make attempt for increasing the survivability of the patient.

ML [18-23] can be considered as a solution for the classification of BUIs into several categories. The ML based methods can be broadly classified as supervised and unsupervised. The supervised ML [19, 20, 22] based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, etc. play a significant role to accomplish the classification mechanism. However, each ML based method is not capable of providing better classification results in several situations. The performance of each ML based method varies from one scenario to another scenario. So, it is a very challenging task to perform the classification mechanism accurately in different scenarios. Therefore, there is a need for some enhanced methods to carry out the categorization mechanism in a better way.

In this work, the main focus is given to the classification of BUIs into several categories such as BN, MG and NL [24] in a better way. Here, a MI [1-23] based approach is proposed to carry out the classification of BUIs into several types. This approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out such classification. The proposed method is able to perform better in terms of CA, F1, PR and RC than LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC methods. Here, the proposed work tries to provide better classification results than other methods.

The contributions in this work are mentioned as follows.

(1) In this work, a MI based approach is proposed for the classification of BUIs into BN, MG and NL types.

(2) The proposed approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out such classification mechanisms.

(3) The proposed method is compared with other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC in terms of CA, F1, PR and RC for performance analysis.

(4) The Simulation of this work is accomplished using python based Orange 3.26.0.

(5) From the results, it is found that the proposed method is capable of providing better classification results than other ML based methods in this scenario.

The rest of this work is presented as follows. Section 2 to Section 7 describes the related works, the objective of the work, methodology, results and discussion, recommendation and conclusion respectively.

2. RELATED WORKS :

Many research works have been accomplished related to the BUIs processing and analysis [1-17]. Some of the works are mentioned as follows. Shin et al. [1] concentrated on the localization and categorization of BUIs by focusing on joint weakly as well as semi supervised deep learning (DL) mechanisms. Ding et al. [2] focused on the categorization of BUIs on the basis of the multiple instance learning processes. Xie et al. [3] concentrated on the classification as well as segmentation of BUIs using convolutional NNT. Liao et al. [4] focused on the recognition of BUIs with the help of segmentation and DL based mechanisms. Masud et al. [5] emphasized on the recognition of BC with the help of pre-trained convolutional NNT by analyzing the ultrasound images. Jabeen et al. [6] emphasized on the probability based optimal DL feature fusion process for the categorization of BC. Huang et al. [7] concentrated on the fuzzy DL based network as well as breast anatomy constraints for the semantic categorization of BUIs. Mishra et al. [8] focused on an ML –Radiomics based process for the classification of breast ultrasound tumor. Zhuang et al. [9] concentrated on the classification of breast ultrasound tumor images with the help of an adaptive multi model spatial feature fusion process. Nguyen et al. [10] focused on the NetV2 and shallow NNT architectures for the categorization of BUIs. Luo et al. [11] focused on the classification of breast ultrasound tumor images using segmentation information with an attention integration process. Satoh et al. [12] emphasized on DL mechanism for the categorization of images in dedicated breast positron emission tomography. The review of some articles related to BUIs categorization is mentioned in Table 1.

Table 1: Review of some articles related to BUIs classification   Source: [1-8]

S. No	Field of Research	Focus	Outcome	Reference
1	Image Processing	DL	Categorization of BUIs	Shin et al. (2018). [1]
2	Image Processing	Multiple instance learning	Categorization of BUIs	Ding et al. (2012). [2]

3	Image Processing	Convolutional NNT	Categorization and segmentation of BUIs	Xie et al. (2018). [3]
4	Image Processing	DL	Recognition of BUIs	Liao et al. (2019). [4]
5	Image Processing	Convolutional NNT	Recognition of BC	Masud et al. (2021). [5]
6	Image Processing	DL	Categorization of BC	Jabeen et al. (2022). [6]
7	Image Processing	DL	Categorization of BUIs	Huang et al. (2021). [7]
8	Image Processing	ML	Categorization of breast ultrasound tumor	Mishra et al. (2021). [8]

3. RESEARCH GAP :

From the literature survey, it is observed that a single method may not be efficient enough to accomplish the classification process of BUIs in all scenarios. A method which is working well in a scenario may not perform well in other scenarios. So, accurate classification of BUIs into several categories by applying different methods is a challenging task. So, there is a need for the development of enhanced methods to carry out the categorization mechanism in a better way to solve the mentioned issues.

4. RESEARCH AGENDA :

The main focus of the research agenda is mentioned as follows.
(1) To apply different existing ML based methods for the categorization of BUIs into several types.
(2) To propose a MI based method to accomplish such a categorization process in a better way as compared to other methods.
(3) To analyze the performance of all the methods in terms of CA, F1, PR and RC.

5. OBJECTIVE :

The key objective of this work is presented as follows:
(1) To propose a MI based method by focusing on stacking mechanisms for the classification of BUIs into BN, MG and NL types in a better way
(2) To compare the proposed method with other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC in terms of CA, F1, PR and RC.

6. METHODOLOGY :

In this work, a MI [1-23] based approach is proposed for the classification of BUIs [24] into BN, MG and NL types. The proposed approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out such classification. The proposed method is compared with other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC in terms of CA, F1, PR and RC for performance analysis. The methodology is described in Fig. 1.
At first, the BUIs are imported to Orange 3.26.0 [25] through the Import Images option. Afterwards, the image embedding (IED) process is accomplished on the BUIs to extract the essential features such as height, width, etc. For IED, several embedders such as SqueezeNet, Inception v3, DeepLoc, etc. can be used. In this work, SqueezeNet (local) embedder is considered for processing. After the completion of the IED process, test and score computation will be performed by considering the ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and the proposed method to find out the CA, F1, PR and RC values in units. The test and score computation can be performed by considering cross validation (CRV) as well as random sampling mechanisms. In this work, the CRV process is focused. The CRV process can be carried out by recognizing the number of folds (NF) as 2, 3, 5, 10, 20, etc. But, in this work, the NF value is considered as 5 to accomplish the classification mechanism.

In this work, the parameter setup for each method is described as follows. For LRG, the regularization type can be considered as Lasso (L1) and Ridge (L2). İn this work, Ridge (L2) is considered for processing. The strength value (SV) for this work is considered as per equation (1).

SV=1 ------ (1)

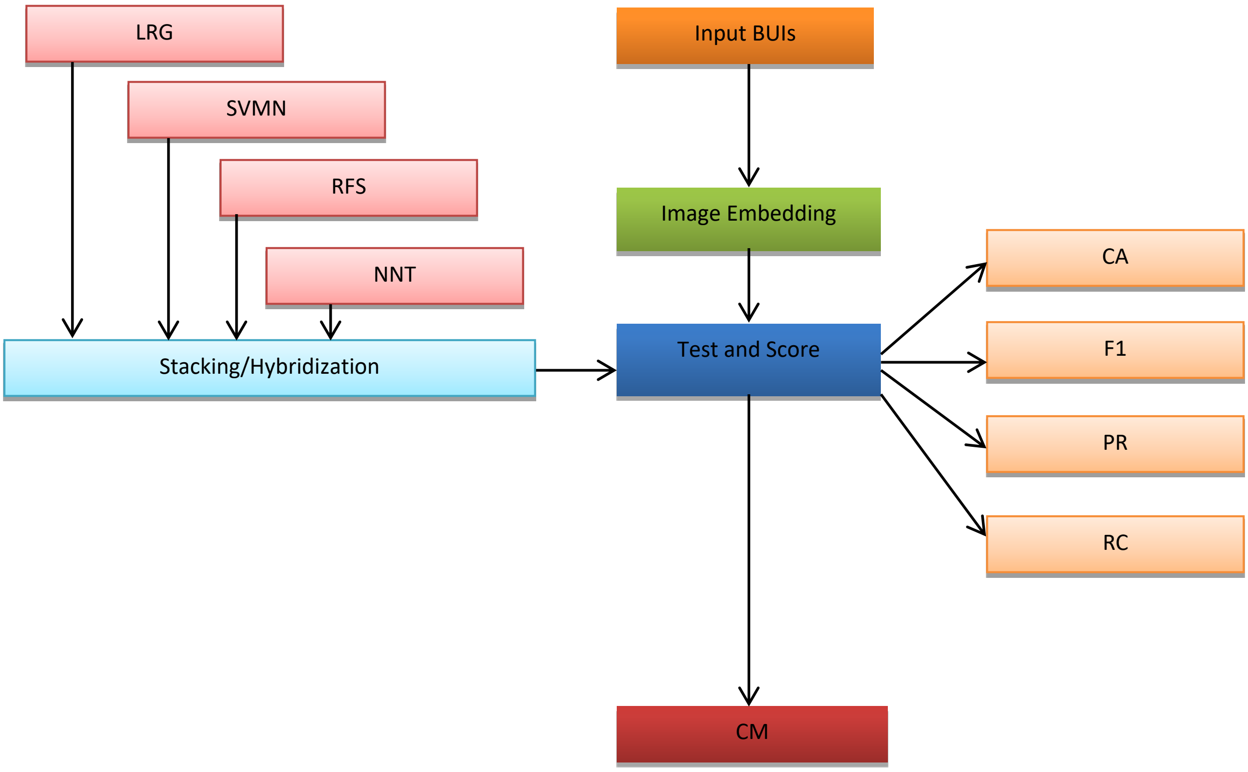


Fig. 1: Methodology [25]

For SVMN, the kernel can be considered as Linear, Polynomial, RBF and Sigmoid. In this work, the kernel is considered as a radial basis function and the iteration limit is taken as 100. Here, the numerical tolerance (NTL) value is taken for processing as per equation (2).

NTL=0.0010 ------ (2)

In this work, for RFS the number of trees (NBTR) considered for processing is mentioned in equation (3).

NBTR=50 ------- (3)

For NNT, the activation function can be considered as ReLu, Logistic, tanh, etc. The solver can be considered as Adam, SGDC, L-BFGS-B, etc. In this work, the activation function is considered as ReLu and the solver is considered as Adam with the maximal number of iterations as 100. The neurons (NR) in hidden layers and regularization (RE) value are considered in this work as per equation (4) and equation (5) respectively.

NR=200 ------ (4)

RE=0.0001 ------ (5)

For DTR, the maximum tree depth (MTDPT) is considered as per equation (6) with the minimum number of instances in leaves as 4.

MTDPT=100 ----- (6)

For KNNH, the metric can be considered as Euclidean, Manhattan, Chebyshev and Mahalanobis and the weight(WT) can be considered as distance (ds) and uniform (u). In this work, for KNNH weight value is mentioned in equation (7) by considering the number of neighbors as 10 and the metric as Manhattan.

WT=ds ------ (7)

At the test and score computation , the CA, F1, PR and RC values (in units) are computed. Then, the confusion matrix (CM) representation can be carried out. The CM can be represented by considering the number of instances, proportion of predicted and proportion of actual values. However, in this work, the number of instances is considered for processing. The methodology used in this work for the classification of BUIIs into BS, EB, LB, LM, SLS, TMV, TYLCV and HL types is described in Algorithm 1.

Algorithm 1: BUI Classification
Input: BUIs
Output: BN, MG and NL Type

Step 1: Start
Step 2: Input BUIs
Step 3: IED (BUIs)
Step 4: Test and Score (LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC, Proposed Method)
Step 5: Compute CA, F1, PR and RC by applying LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and Proposed Method
Step 6: Create (CM) for each method to analyze the classification results
Step 7: Stop

7. RESULTS AND DISCUSSION :

The simulation of this work is accomplished using Python based Orange 3.26.0 [25]. In this work, 750 different sizes BUIs having 250 numbers of each type such as BN, MG and NL are taken from the source [24].The Orange workflow setup diagram is mentioned in Fig. 2. The sample representation of BN, MG and NL types are mentioned in Fig. 3 to Fig. 5 respectively. The BUIs are processed using several ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and the proposed method when the NF value is recognized as 5. The performance of all the methods is accessed using performance parameters such as CA, F1, PR and RC which are described as follows.

- **CA:** It refers to the rate of correct classification. It is represented in equation (8) by considering the number of corrected predictions (CP) and the total number of input samples (IS).

$$\textbf{CA} = CP / IS \qquad ---- \qquad (8)$$

- **F1:** It is the harmonic mean of PR and RC. It is mentioned in equation (9).

$$\textbf{F1} = 2 * (PR * RC) / (PR + RC) \qquad ------ \qquad (9)$$

- **PR:** It is represented in equation (10) by considering the true positives (TP) and false positives (FP).

$$\textbf{PR} = TP / (TP+FP) \qquad ----- \qquad (10)$$

- **RC:** It is represented in equation (11) by considering the TP and false negatives (FN).

$$\textbf{RC} = TP / (TP+FN) \qquad ----- \qquad (11)$$

The classification results are better when the CA,F1, PR and RC values are higher. Table 2 describes the CA, F1, PR and RC computed values (in units) of the proposed method and other methods. Fig. 6 to Fig. 9 represents the comparison results of all methods graphically in terms of CA, F1, PR and RC respectively. This work is also focused on CM representation. The CM represents the actual and predicted values by showing the number of instances for each of these methods. The CM representation for LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and the proposed method are mentioned in Fig. 10 to Fig. 19 respectively. In CM, the actual values are represented using light blue color and the predicted values are represented using light pink color.

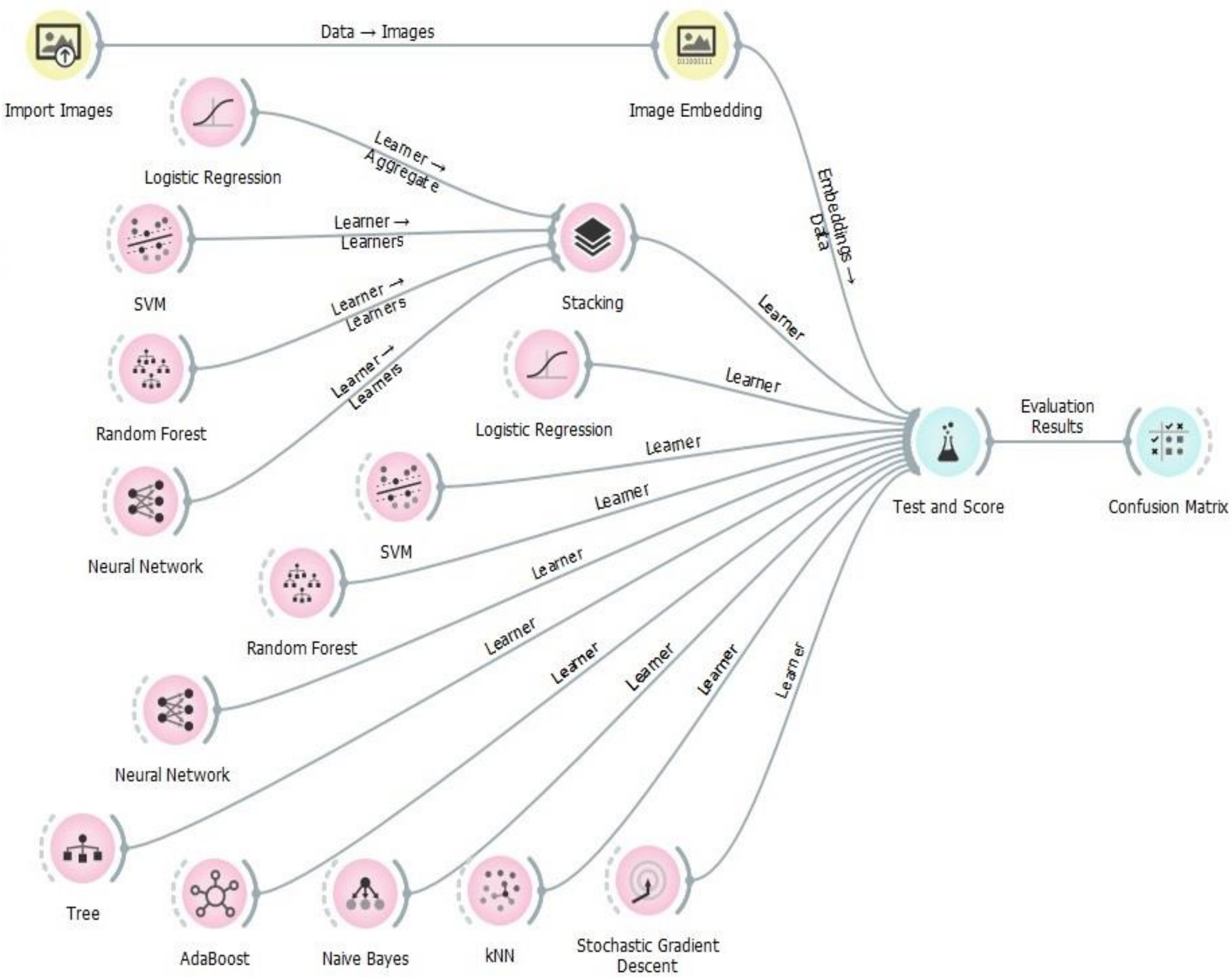


Fig. 2: Orange workflow setup diagram [25]

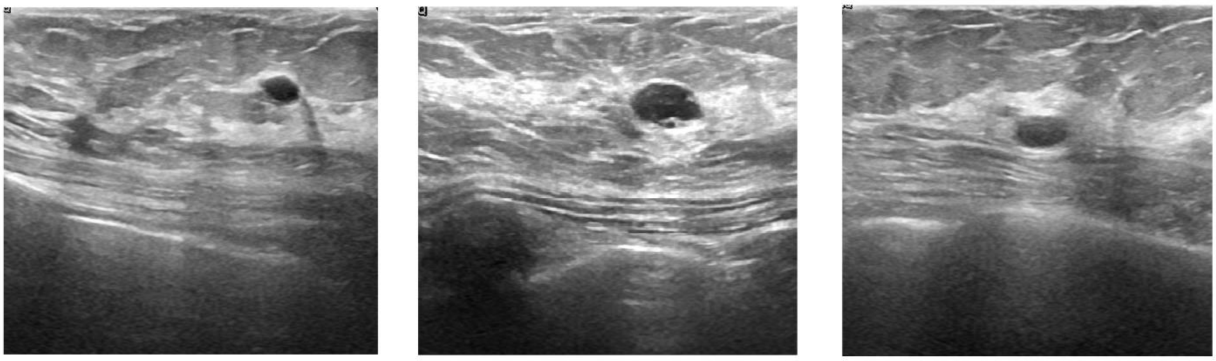
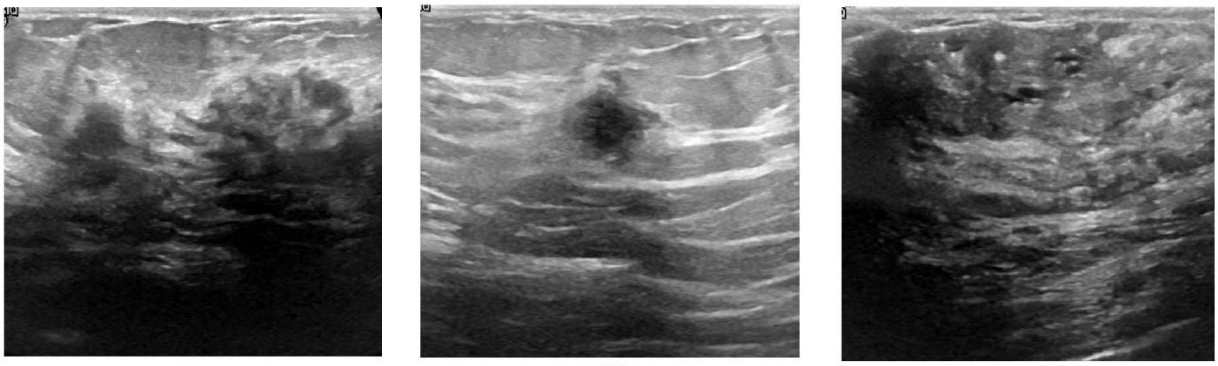
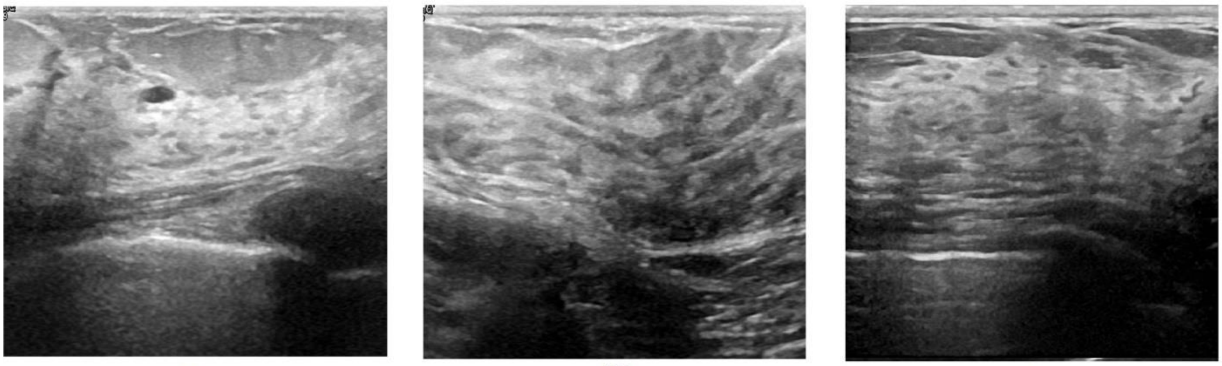


Fig. 3: Sample depiction of BN type [24]



(1) (2) (3)

Fig. 4: Sample depiction of MG type [24]



(1) (2) (3)

Fig. 5: Sample depiction of NL type [24]

Table 2: Comparison of the proposed method with other MI based methods [25]

Method	CA	F1	PR	RC
LRG	0.916	0.916	0.916	0.916
SVMN	0.917	0.917	0.919	0.917
RFS	0.896	0.896	0.897	0.896
NNT	0.939	0.939	0.939	0.939
DTR	0.821	0.821	0.821	0.821
ADB	0.824	0.824	0.825	0.824
NBY	0.736	0.739	0.825	0.736
KNNH	0.904	0.903	0.908	0.904
SGDC	0.915	0.914	0.915	0.915
Proposed Method	0.941	0.941	0.941	0.941

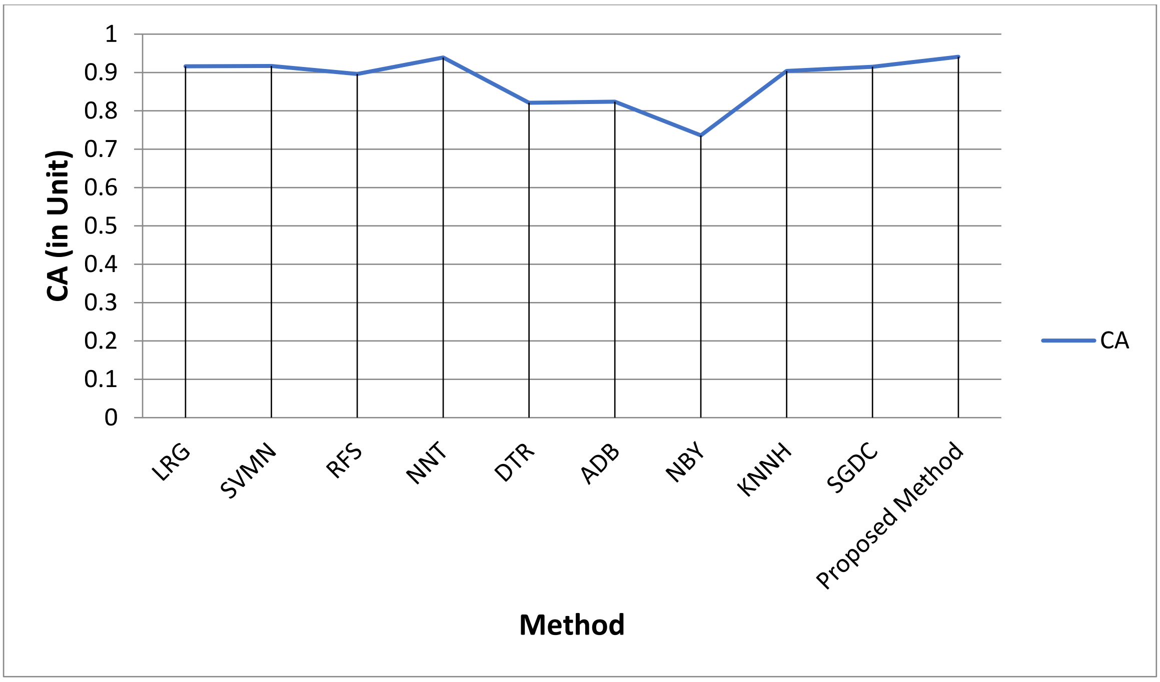


Fig. 6: Comparison results representation of all methods in terms of CA [25]

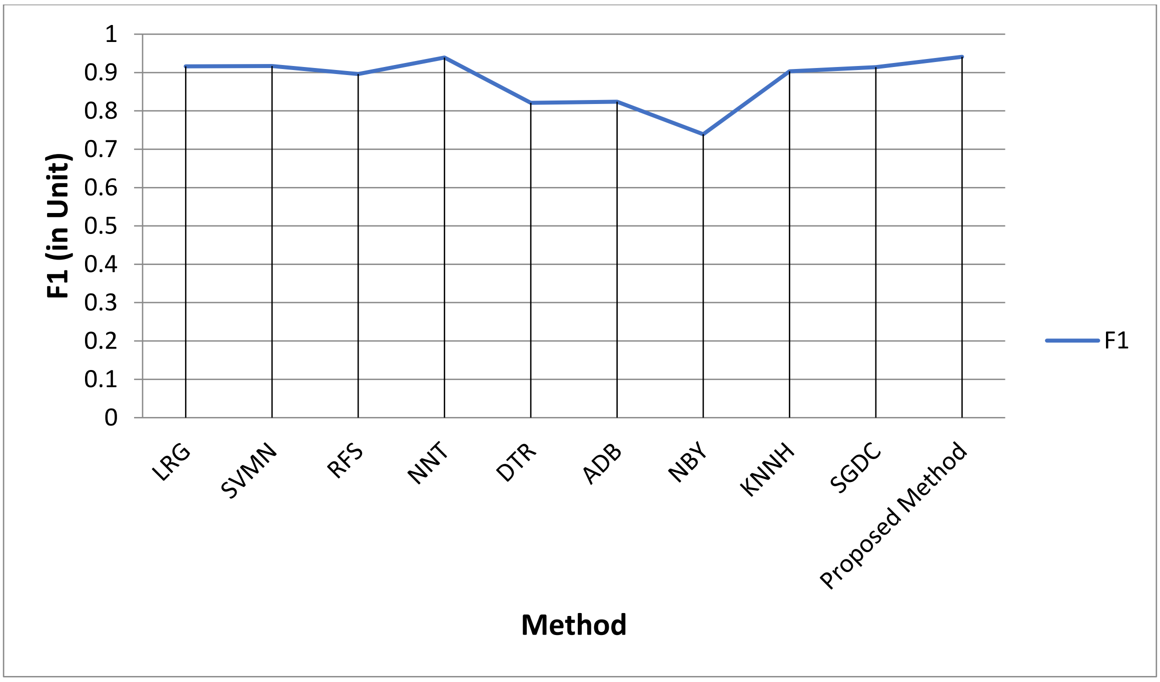


Fig. 7: Comparison results representation of all methods in terms of F1 [25]

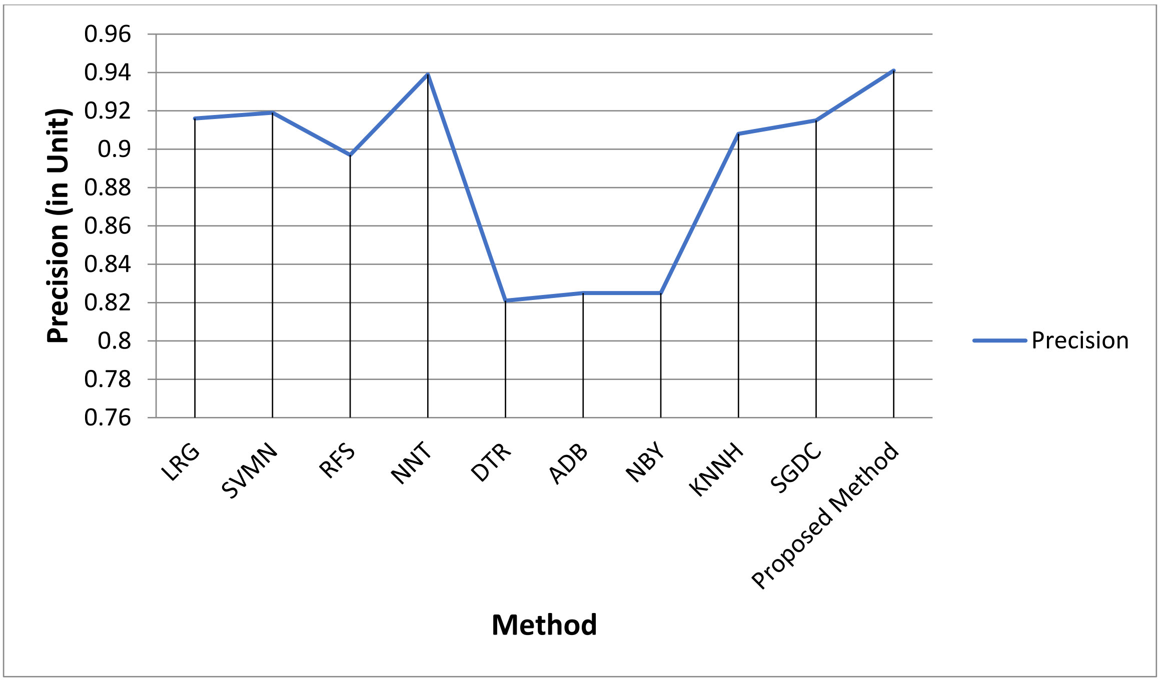


Fig. 8: Comparison results representation of all methods in terms of PR [25]

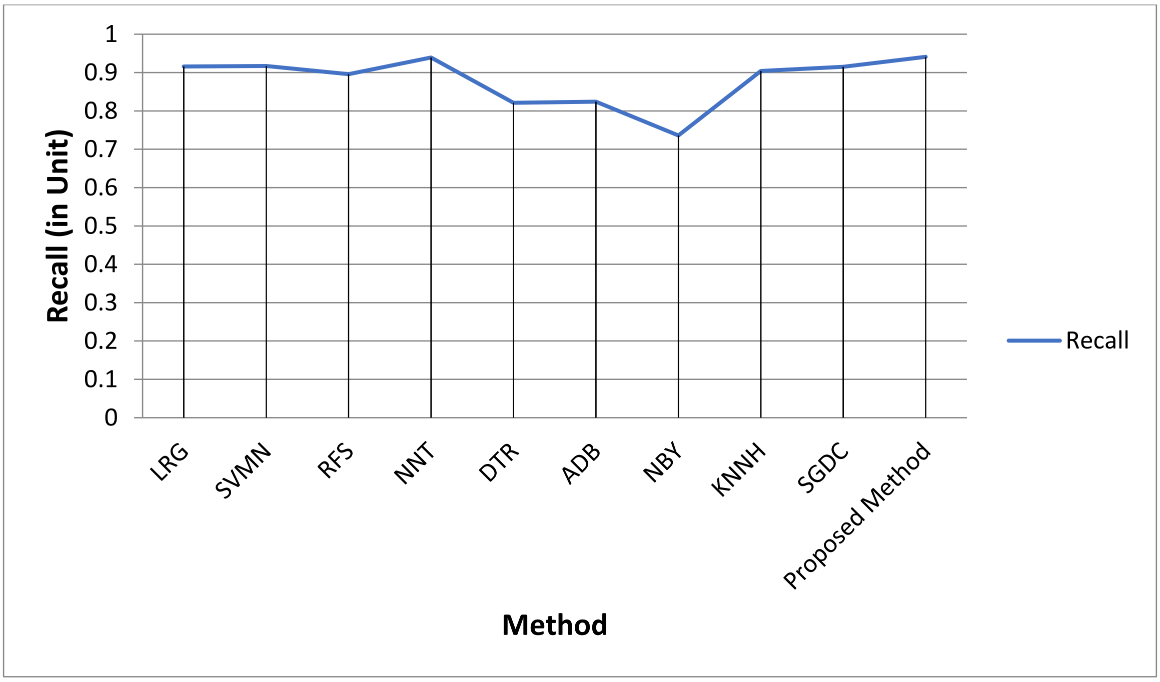


Fig. 9: Comparison results representation of all methods in terms of RC [25]

		Predicted			
		Benign	Malignant	Normal	Σ
Actual	Benign	226	19	5	250
	Malignant	15	225	10	250
	Normal	6	8	236	250
	Σ	247	252	251	750

Fig. 10: CM of LRG [25]

		Predicted			
		Benign	Malignant	Normal	Σ
Actual	Benign	219	20	11	250
	Malignant	9	227	14	250
	Normal	2	6	242	250
	Σ	230	253	267	750

Fig. 11: CM of SVMN [25]

		Predicted			
		Benign	Malignant	Normal	Σ
Actual	Benign	214	26	10	250
	Malignant	17	221	12	250
	Normal	3	10	237	250
	Σ	234	257	259	750

Fig. 12: CM of RFS [25]

		Predicted			
		Benign	Malignant	Normal	Σ
Actual	Benign	232	15	3	250
	Malignant	9	231	10	250
	Normal	3	6	241	250
	Σ	244	252	254	750

Fig. 13: CM of NNT [25]

		Predicted			
		Benign	Malignant	Normal	Σ
Actual	Benign	200	35	15	250
	Malignant	39	195	16	250
	Normal	15	14	221	250
	Σ	254	244	252	750

Fig. 14: CM of DTR [25]

		Predicted			
		Benign	Malignant	Normal	Σ
Actual	Benign	201	36	13	250
	Malignant	33	201	16	250
	Normal	11	23	216	250
	Σ	245	260	245	750

Fig. 15: CM of ADB [25]

		Predicted			
		Benign	Malignant	Normal	Σ
Actual	Benign	184	66	0	250
	Malignant	12	235	3	250
	Normal	1	116	133	250
	Σ	197	417	136	750

Fig. 16: CM of NBY [25]

Actual \ Predicted	Benign	Malignant	Normal	Σ
Benign	207	29	14	250
Malignant	6	225	19	250
Normal	2	2	246	250
Σ	215	256	279	750

Fig. 17: CM of KNNH [25]

Actual \ Predicted	Benign	Malignant	Normal	Σ
Benign	225	16	9	250
Malignant	15	221	14	250
Normal	3	7	240	250
Σ	243	244	263	750

Fig. 18: CM of SGDC [25]

Actual \ Predicted	Benign	Malignant	Normal	Σ
Benign	235	13	2	250
Malignant	12	228	10	250
Normal	2	5	243	250
Σ	249	246	255	750

Fig. 19: CM of Proposed Method [25]

From Table 2 and Fig. 6 to Fig. 19, it is observed that LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.916, 0.917, 0.896, 0.939, 0.821, 0.824, 0.736, 0.904, 0.915 and 0.941 CA values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.916, 0.917, 0.896, 0.939, 0.821, 0.824, 0.739, 0.903, 0.914 and 0.941 F1 values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.916, 0.919, 0.897, 0.939, 0.821, 0.825, 0.825, 0.908, 0.915 and 0.941 PR values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.916, 0.917, 0.896, 0.939, 0.821, 0.824, 0.736, 0.904, 0.915 and 0.941 RC values (in unit) respectively. So, the proposed method is capable of providing better classification results as compared to LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC methods and it is having 0.941 CA, F1, PR and RC values in units. However, the NBY method is not capable of providing better categorization results than other methods and it is having 0.736, 0.739, 0.825 and 0.736 CA, F1, PR and RC values in units respectively. The decreasing order of performance of these methods is proposed method, NNT, SVMN, LRG, SGDC, KNNH, RFS, ADB, DTR and NBY.

8. RECOMMENDATIONS :

This work can be extended to develop improved methods to carry out the classification of BUIs and other types of images in terms of higher CA, F1, PR and RC. This work can also be extended to process and analyze the classification results of BUIs and other types of images by applying DL based methods.

9. CONCLUSION :

This paper proposed a MI based approach for the classification of BUIs into BN, MG and NL types. The proposed approach is focused on the stacking of LRG, SVMN, RFS and NNT methods to carry out the classification of BUIs into such categories. From the results, it is found that the proposed method is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC. The CA, F1, PR and RC values in units using the proposed method are computed as 0.941 which is higher as compared to other methods. However, in this scenario, the NBY method is unable to perform better than other methods. The CA, F1, PR and RC values in units using the NBY method are computed as 0.736, 0.739, 0.825 and 0.736 respectively which are lower than other methods in this scenario. This approach can help the researchers to carry out the image classification mechanism in a better way for several applications.

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