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Comparative analysis of classical machine learning and deep learning techniques for predicting benign-malignant breast cancer

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Abstract *:* Classical machine learning methods and deep learning techniques have been widely used for early detection of breast cancer. We do not know which method is best used to classify benign-malignant breast cancer. Therefore, the purpose of this research is to compare classical machine learning and deep learning techniques. The method we use to compare classical machine learning and deep learning techniques is first we take secondary data from the results of digital mammography X-ray photos, then we cropping with a size of 2 cm. then we count 90 features on mammography, 90 features are used as input variables from machine learning. For the CNN method we use 2 types of image sizes, namely full image and 2 cm cropping image, then we calculate the True Positive (TP), False Positive (FP), False Negative (FN), True Negative (TN), accuracy, sensitivity, specificity, precision, TPR and FPR values. Then the value is compared with existing machine learning algorithms such as Random Forest, Naïve Bayes, Decision Tree, K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), Support Vector Machine (SVM). The results obtained by Deep learning techniques with CNN cropping 2 cm algorithm has the best performance, accuracy, sensitivity, specificity, highest precision and lowest false positive and false negative compared to other methods such as Random Forest, Naïve Bayes, Decision Tree, KNN, ANN, SVM, CNN full image. Conclusion Deep learning techniques with CNN cropping 2 cm algorithm is best used to predict benign-malignant breast cancer.

Keywords: machine learning; deep learning; benign; malignant; breast cancer

1. Introduction

Breast cancer is one of the most common malignant diseases and the leading cause of death in women[1]–[4] . Many people die of breast cancer because of late treatment. By 2024, in the United States there will be 2,001,140 new cancer cases and 611,720 deaths[5] . For this reason, early detection of breast cancer is needed. Mammography is one of the most widely applied tools for early detection of breast cancer for non-solid breasts[6]–[8] , besides mammography, MRI is also widely applied for early detection of solid breast cancer[9]–[11] .
For teenage women under 40 years old ultrasonography is often used for early detection of breast cancer[12]–[14] . Many machine learning methods have been used for early breast cancer detection, including Random Forest[15]–[24] , Naïve Bayes[25]–[31] , Decision Tree[13], [32]–[34] , KNN[35]–[40] , ANN[41]–[44] , SVM[45]–[53] and deep learning such as CNN[54]–[62] . But no one knows which algorithm has the best performance among all machine learning and deep learning methods applied.

Many do not know that in digital mammography images there are 9 main features. In this research will be analyzed, what are the main features in mammography. Whether the 9 main features can be developed into 90 subfeatures. How to develop it. Can the 90 subfeatures be used as input variables for machine learning methods to detect benign-malignant. Which machine learning algorithm is best for detecting benign malingnant compared to deep learning CNN. This research is very important to be carried out to get the best algorithm from machine learning and deep learning in detecting benign-malignant breast cancer. Therefore, the purpose of this research is to compare machine learning and deep learning to predict benign-malignant breast cancer. The results of this study can help radiologists to diagnose breast cancer.

2. Methods

This research is a quantitative study, secondary data taken from the radiology installation of Sutomo doctor hospital from 2010 until now. there are 670 mammogram images, consisting of 342 benign, 328 malignant. Mammogram images are taken randomly, with a composition of 70% of mammogram images used for training while the remaining 30% of mammogram images are used for testing. In each mammogram image we get 90 features consisting of entropy1 to entropy10, contrast1 to contrast10, Angular second moment1 to Angular second

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moment10, Inverse difference moment1 to Inverse difference moment10, mean1 to mean10, deviation1 to deviation10, Entropy of hdiff1 to Entropy of hdiff10, Angular second moment of hdiff1 to Angular second moment of hdiff10 and Mean hdiff1 to Mean hdiff10. In this research we use 2 types of methods, namely classical machine learning methods (Random Forest, Naïve Bayes, Decission Tree, KNN, ANN, SVM) and deep learning techniques (CNN cropping 2 cm, CNN full image). Furthermore, this research will compare the values of TP, FP, FN, TN, accuracy, sensitivity, specificity, precision, TPR and FPR by using 2 types of classical machine learning methods and deep learning techniques methods. Then we also make a ROC graph to see the best performance of the two methods. The Research Flowchart of our research is shown in Figure 1.

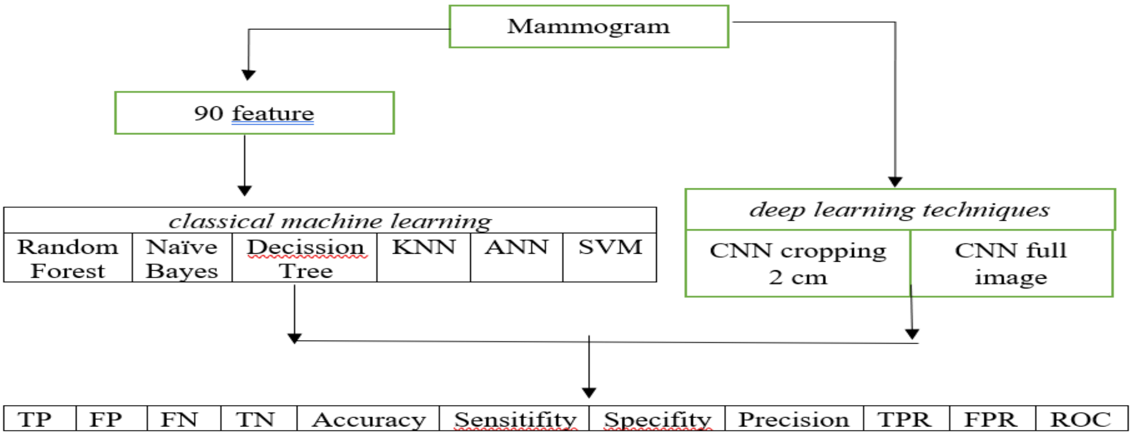

Fig.1. Research Flowchart

How to expand from 9 features to 90 subfeatures

First the mammogram is cropped with a size of 2 cm. Then the image is analyzed by calculating the number of occurrences of gray level pairs at a distance of 1 pixel as shown in Figure 2 and the number of occurrences of gray level pairs at a distance of 2 pixels as shown in Figure 3.

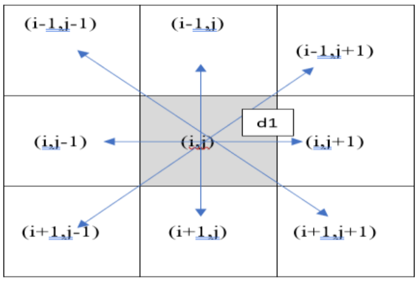

Fig.2. Gray level pairs at 1 pixel distance.

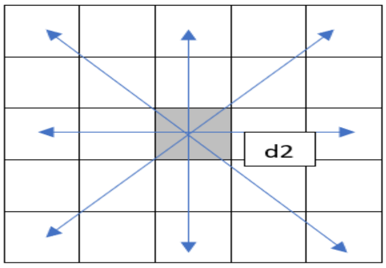

Fig.3. Gray level pairs at 2 pixel distance

And so on until the number of occurrences of gray level pairs at a distance of 10, as shown in Figure 4.

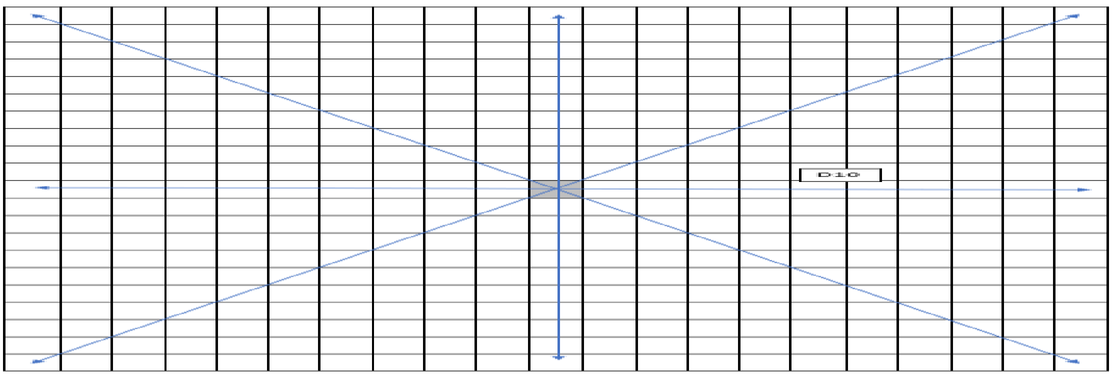

Fig.4. Gray level pairs at a distance of 10 pixels

From the ten distances between pixels, the number of gray level pairs from H(y1,y1,d1) to H(y255,y255, d10) is obtained, then the values of entropy, contrast, angular second moment, inverse difference moment, correlation, mean, deviation, entropy of hdiff, angular second moment of hdiff and mean hdiff are calculated using equations (1 to 11): [63], [64]

$$Entropy = -\sum_{yq=y1}^{yt}\sum_{yr=y1}^{yt}[H(yq,yr,d)]log[H(yq,yr,d)] \quad (1)$$

$$Contrast = \sum_{yq=y1}^{yt}\sum_{yr=y1}^{yt}(yq-yr)^2 H(yq,yr,d) \quad (2)$$

$$Anguler\ second\ moment = \sum_{yq=y1}^{yt}\sum_{yr=y1}^{yt}[H(yq,yr,d)]^2 \quad (3)$$

$$inverse\ difference\ moment = \sum_{yq=y1}^{yt}\sum_{yr=y1}^{yt}\left[\frac{H(yq,yr,d)}{1+(yq-yr)^2}\right] \quad (4)$$

$$correlation = \frac{\sum_{yq=y1}^{yt}\sum_{yr=y1}^{yt} y_q\, y_r H(y_q,y_r,d) - \mu H_m(y_q,d)\mu Hm(y_r,d)}{\sigma H_m(y_q,d)\sigma H_m(y_r,d)} \quad (5)$$

$$mean = \sum_{yq=y1}^{yt} y_q H_m(y_q,d) \quad (6)$$

$$deviation = \sqrt{\sum_{yq=y1}^{yt}\left[y_q - \sum_{yp=y1}^{yt} y_p\, H_m(y_p,d)\right]^2 H_m(y_q,d)} \quad (7)$$

$$H_{diff}(i,d) = \sum_{yq=|y_q-y_r|=i}^{yt}\sum_{yr=y1}^{yt} H(y_q,y_r,d) \quad (8)$$

$$entropy\ of\ hdiff = -\sum_{i=i1}^{it} H_{diff}(i,d)\log H_{diff}(i,d) \quad (9)$$

$$angular\ second\ moment\ (ASM) of\ hdiff(i,d) = \sum_{i=i_1}^{it}\left[H_{diff}(i,d)\right]^2 \quad (10)$$

$$mean\ H_{diff} = \sum_{i=i_1}^{it} i\ H_{diff}(i,d) \quad (11)$$

Where yq, yr, d are the gray-level value of pixel 'q', the gray-level value of pixel 'r' and the distance between pixel 'q' and pixel 'r', respectively. H(yq,yr,d) is the number of gray-level pairs of pixel 'q' and pixel 'r' at distance d.

3. Results

The comparison results of true positive, false positive, false negative, true negative, false positive rate and true positive rate of the 2 types of methods are as shown in Table 1.

Table 1. comparison of TP, FP, FN, TN, FPR and TPR values of various machine learning and deep learning methods.

	T.P	F.P	FN	TN	FPR	TPR
Random Forest	95	0	4	102	0.0	0.96
Naïve Bayes	98	90	1	12	0.88	0.98
Decission Tree	100	0	4	97	0.0	0.96
KNN	68	1	38	94	0.01	0.64
ANN	0	0	98	103	0.0	0.0
SVM	57	52	0	0	0.85	1.0
CNN cropping 2 cm	103	0	0	98	0	1.0
CNN full image	102	2	1	96	0.02	0.99

From Table 1, it can be seen that CNN cropping 2 cm has the largest TP, TN, and the lowest FP, FN, as well as having the best TPR and FPR values of TPR=1 and FPR=0. It can be concluded that CNN algorithm with 2 cm cropping has the best performance.

While the comparison value. Accuracy, Sensitivity, Specificity, and Precision of 2 types of methods such as table 2.

Table 2. Accuracy, Sensitivity, Specificity, and Precision Values of Each method

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%
Random Forest	98	96	100	100
Naïve Bayes	55	99	12	52

Decission Tree	98	96	100	100
KNN	81	64	99	99
ANN	51	0	100	Nan
SVM	56	100	15	52
CNN cropping 2 cm	100	100	100	100
CNN full image	99	99	98	98

From table 2, it can be seen that the CNN cropping algorithm of 2 cm has the best performance, because it has Accuracy, Sensitivity, Specificity, Precision values of all 100%.

A comparison of the ROC graphs of the 2 types of methods can be seen in Figure 5.

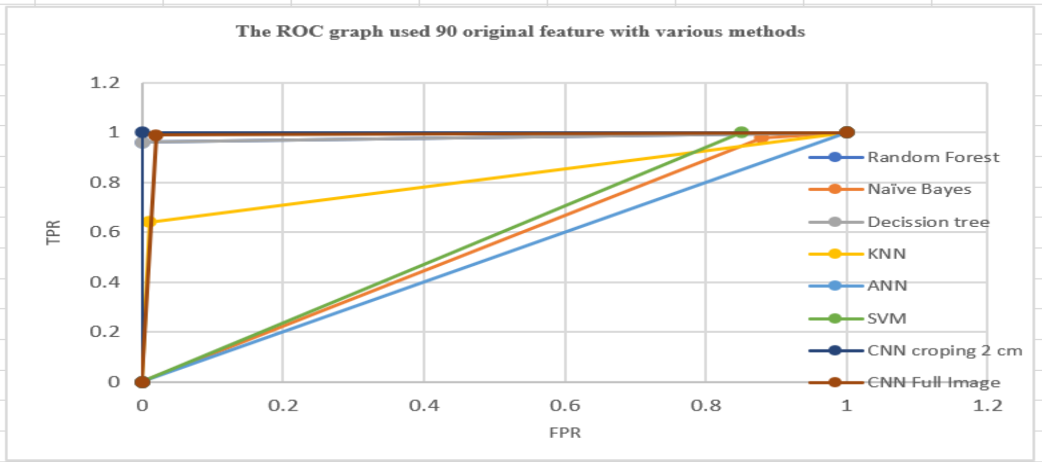

Fig.5. ROC graphs of the 2 types of methods.

From Figure 5, it can be seen that the CNN cropping algorithm of 2 cm has the best performance, as it has the highest ROC area.

A comparison of the accuracy values of the two methods is shown in Figure 6.

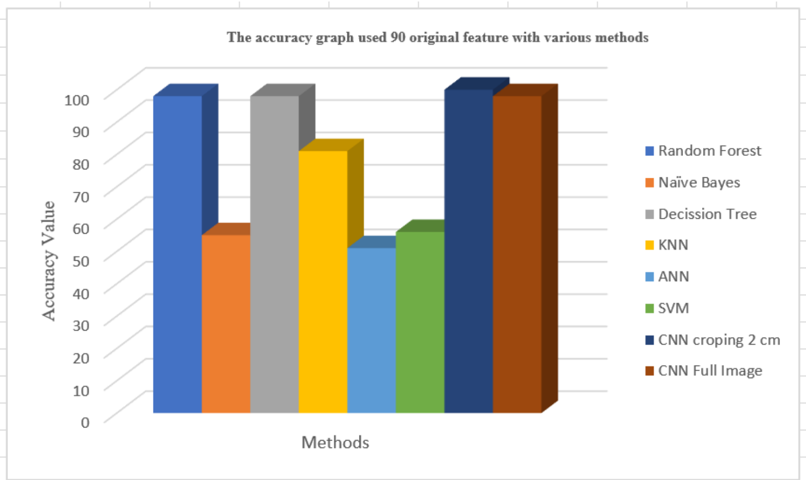

Fig.6. Comparison graph of accuracy values of 2 types of methods.

From Figure 6, it can be seen that the 2 cm CNN cropping has the highest accuracy of 100%.

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Comparison of the sensitivity values of the 2 types of methods as shown in Figure 7

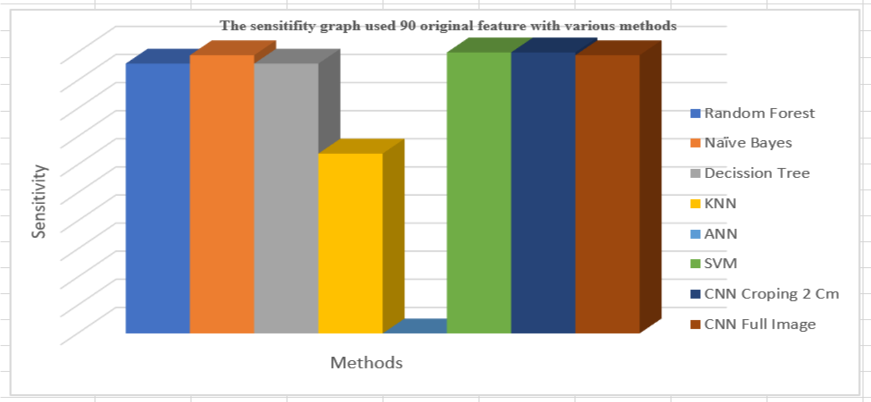

Fig.7. Comparison graph of sensitivity values of 2 types of methods.

From Figure 7, it can be seen that the SVM and CNN cropping algorithm of 2 cm has the highest sensitivity of 100%.

Comparison of the specificity values of the 2 types of methods as shown in Figure 8.

Figure 8 shows that the Random Forest, Decission Tree, ANN and CNN cropping 2 cm algorithms have the highest specificity.

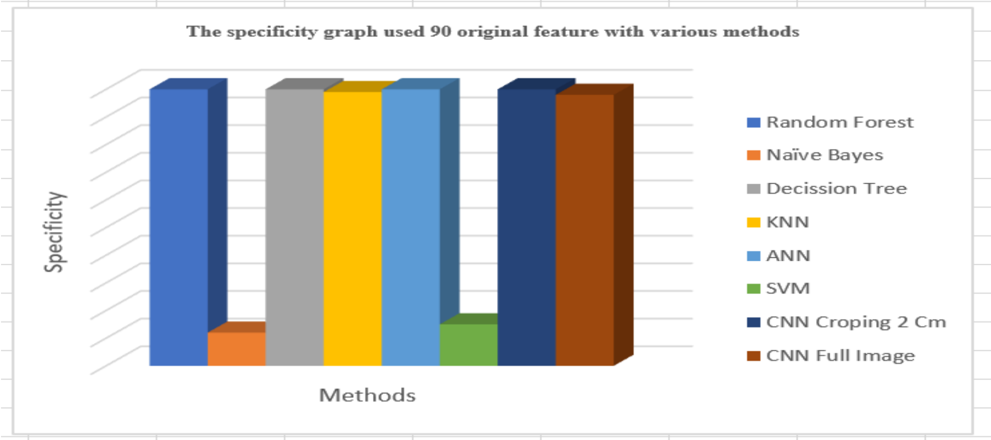

Fig.8. Comparison of specificity values of 2 types of methods

Comparison of the precision values of the two methods as shown in Figure 9.

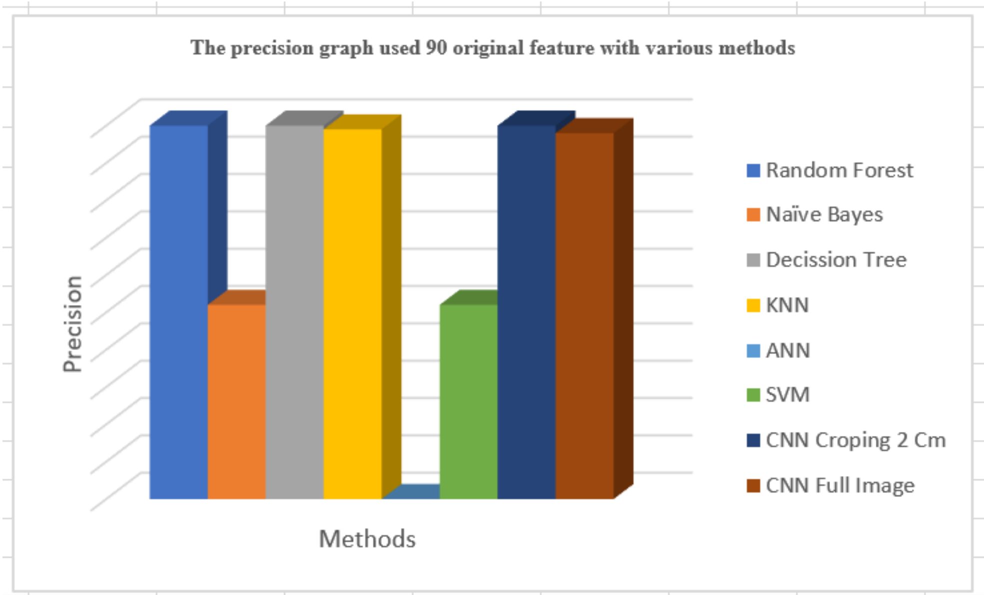

Fig.9. Comparison of precision values of 2 methods

From Figure 9, it can be seen that the Random Forest algorithm, Decission Tree, and CNN cropping 2 cm have the highest precision.

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Comparison of the true positive values of the 2 types of methods as shown in Figure 10

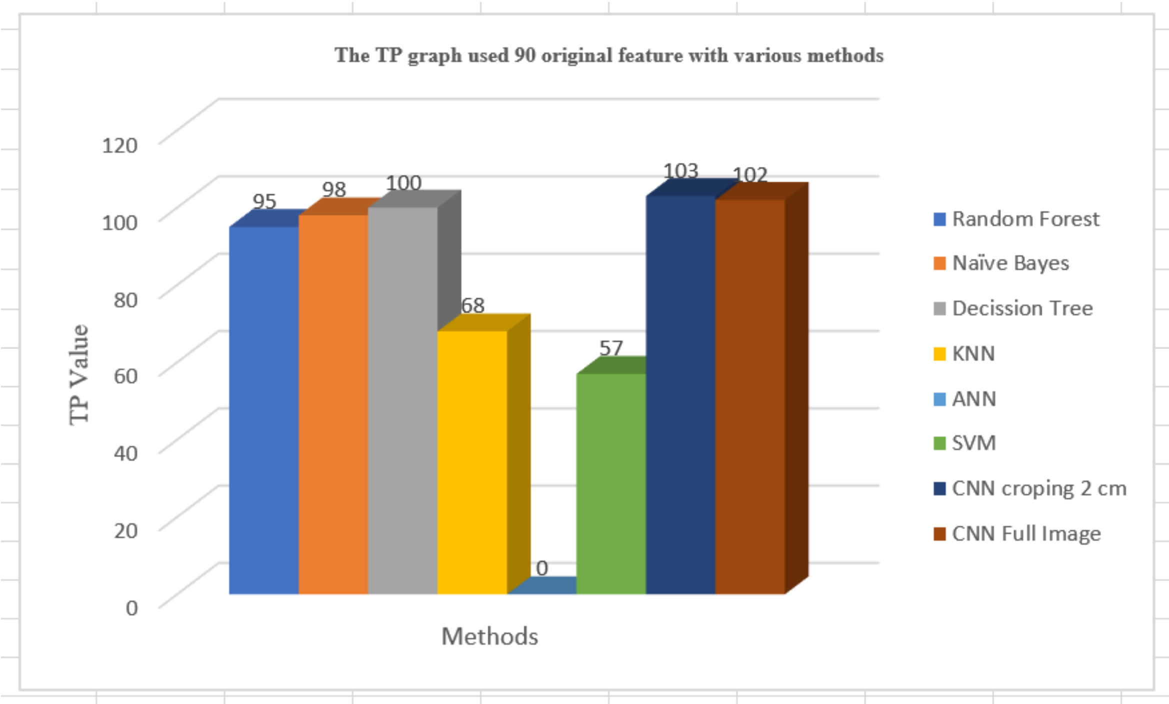

Fig.10. Comparison of true positive values of 2 types of methods

Figure 10 shows that the CNN cropping algorithm of 2 cm has the highest true positive.

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A comparison of the false positive values of the two methods is shown in Figure 11

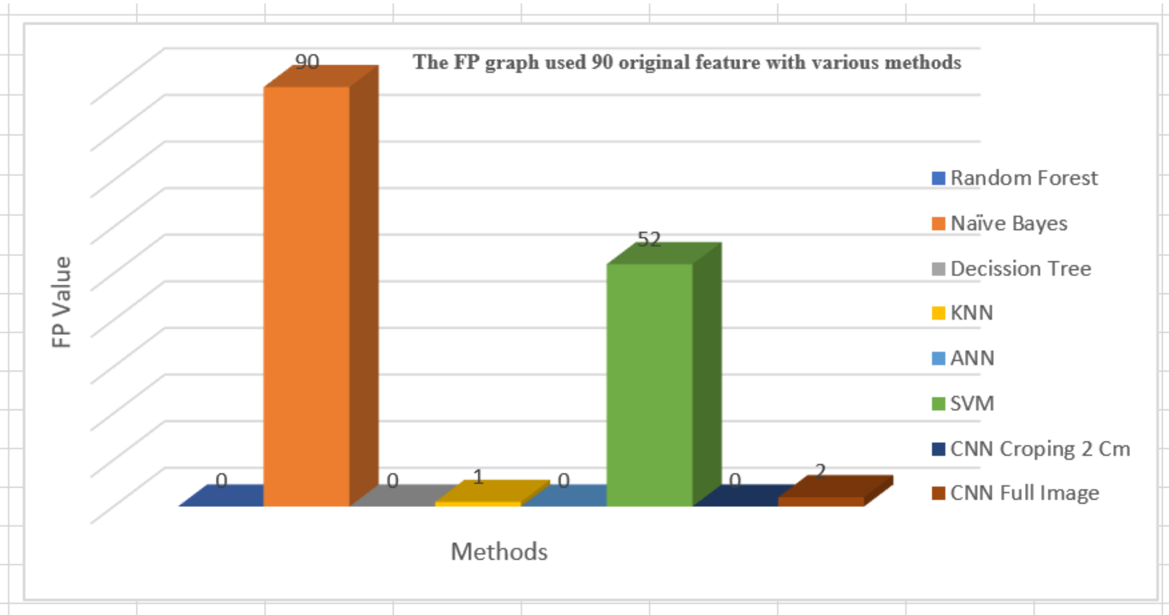

Fig.11. Comparison of false positive values of 2 types of methods

Figure 11 shows that the Random Forest, Decission Tree, ANN, CNN cropping 2 cm algorithm has the lowest false positive.

Comparison of the false negative values of the 2 types of methods as shown in Figure 12.

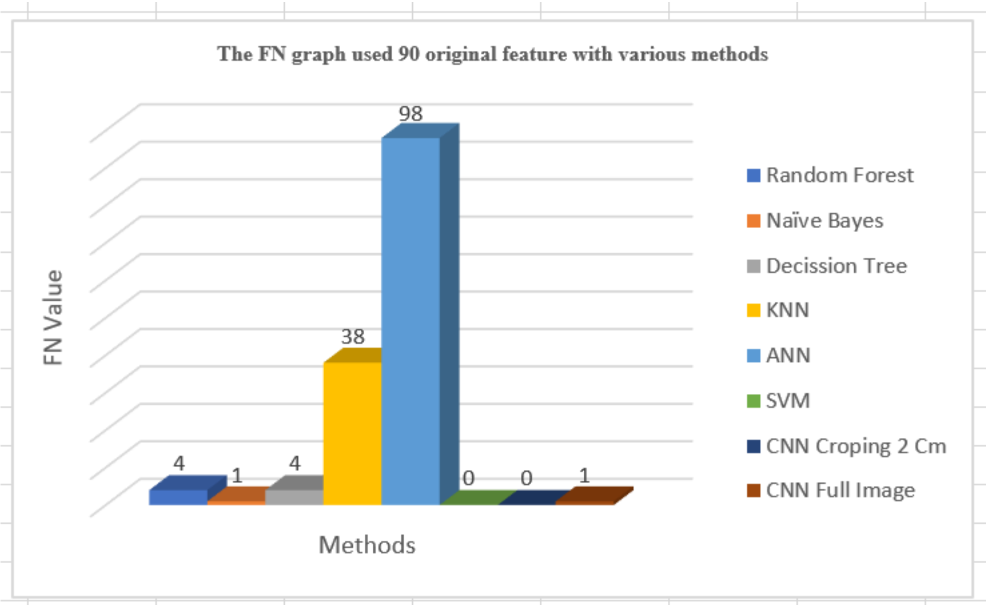

Fig.12. Comparison of false negative values of 2 types of methods

From Figure 12, it can be seen that the SVM algorithm, CNN cropping 2 cm has the lowest false negative.

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Comparison of the true negative values of the 2 types of methods as shown in Figure 13

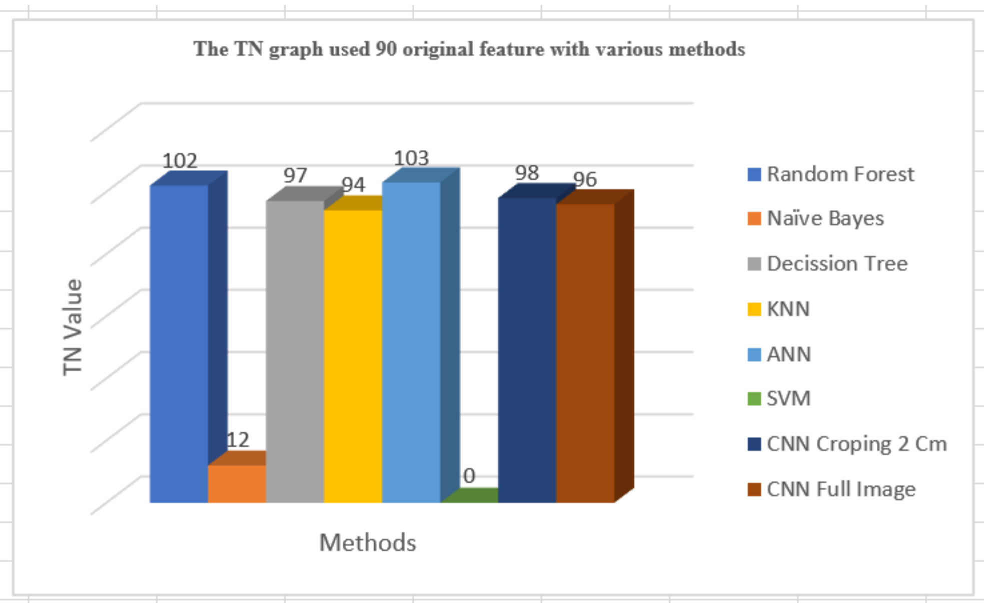

Fig.13. Comparison of true negative values of 2 types of methods

From Figure 13, it can be seen that the ANN algorithm has the highest true negative

Comparison of the true positive rate values of the two types of methods as shown in Figure 14.

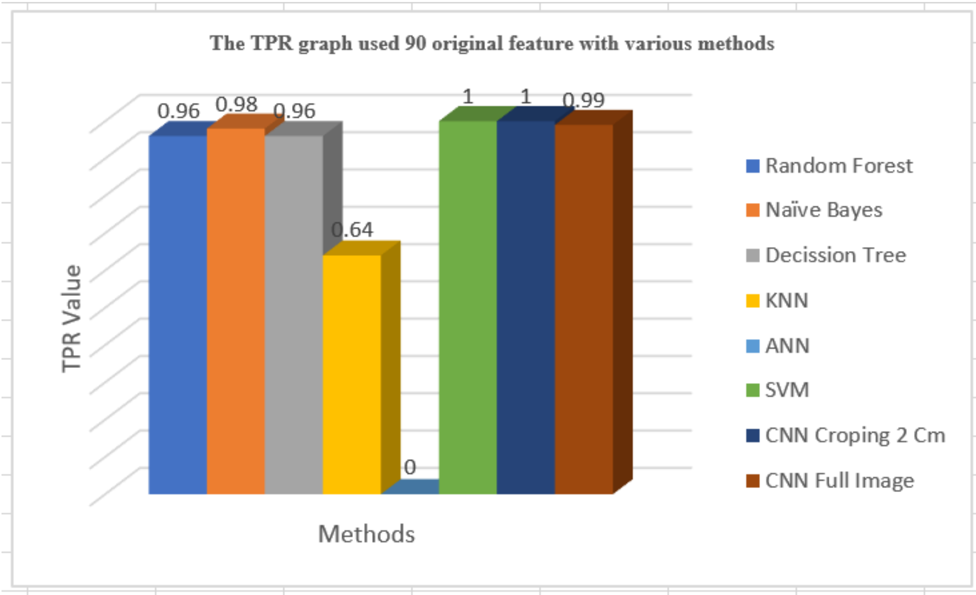

Fig.14. Comparison of true positive rate values of 2 types of methods

Figure 14 shows that the SVM algorithm, CNN cropping 2 cm has the highest true positive rate.

4. Discussions

Deep learning techniques with CNN cropping 2 cm algorithm has the best performance, highest accuracy, sensitivity, specificity, precision and the lowest false positive and false negative compared to other methods such as Random Forest, Naïve Bayes, Decission Tree, KNN, ANN, SVM, CNN full image. Why CNN cropping 2 cm is better than CNN full image, because CNN cropping 2 cm is focused on the suspicious mass (ROI) compared to CNN full image. In full image, there is a lot of bias because the background also affects. In classical machine learning methods (Random Forest, Naïve Bayes, Decission Tree, KNN, ANN, SVM) although we use 2 cm cropping, the value is still low compared to CNN cropping 2 cm, this is because we have not applied binary and bipolar data transformation. Our next research will use binary and bipolar data transformation in order to improve the performance of classical machine learning methods. Many methods have been done by other researchers to classify benign and malignant breast cancer such as table 3.

Table 3 methods that have been done by previous researchers

Study	Year	Method	Accuracy	Sensitivity (Recall)	Specificity
Kuljeet Singha et al.[65]	2023	Nested Ensemble Technique of Machine Learning	97.18	97.20	Not mentioned
Takeya Ahmed Taymour et al. [66]	2024	ultrasound shear wave elastography	94.40	94.40	94.40
Na Li et al. [67]	2024	Value of S-Detect combined with multimodal ultrasound	90.50	97.80	79.30
Eman Badawy et al. [68]	2023	AI	Not mentioned	93.64	Not mentioned
Amany Mohammed Hussein Zahran et al. [69]	2022	Diffusion-weighted MR imaging	90.90	96.60	80.00
Jyoti Kadadevarmath et al. [70]	2024	Improved Watershed Segmentation and DualNet Deep Learning	93.82	94.27	97.83
Petra Mürtz et al[71]	2022	Simplified intravoxel incoherent motion	93.70	Not mentioned	Not mentioned
Safak Kayikci et al. [72]	2023	Gated attentive multimodal deep learning	91.20	79.80	84.10

Ahad Alloqmani et al. [73]	2023	Deep Learning	97.36	Not mentioned	Not mentioned
Duo Zuo et al. [74]	2023	Machine learning-based models	97.10	94.70	97.60
Na Li et al. [75]	2023	Value of inversion imaging	84.20	86.10	81.50
Mahati Munikoti Srikantamurthy et al. [76]	2023	hybrid CNN-LSTM based transfer learning	99.00	Not mentioned	Not mentioned
Abdullah-Al Nahid et al. [77]	2022	machine learning algorithms	82.85	88.89	80.00
Soumya Sara Koshy et al. [78]	2022	deep learning techniques - A survey	90.00	Not mentioned	Not mentioned

5. Conclusions

The conclusion of this research shows that in the comparative analysis between Classical Machine Learning and Deep Learning Techniques to predict benign-malignant breast cancer, Convolutional Neural Network (CNN) algorithm with 2 cm cropping gives the best result. This indicates that deep learning approaches, especially CNN with image cropping strategy, are able to improve prediction accuracy compared to classical machine learning methods.

Classical machine learning algorithm methods such as Random Forest and Decission Tree are not much different from the CNN cropping 2 cm method, having an accuracy value of 98%, sensitivity of 96%, specifity, precision are both 100% with CNN cropping 2 cm. The value of accuracy, sensitivity, specificity, precision using classical machine learning methods can be improved by using binary and bipolar data transformation, then continued with the selection of significant data using the Anova statistical test.

Conflicts of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Author contributions

all authors have read and approved the manuscript

AANG: project design, data analysis, script writing; IGS: data analysis, IWS: data collection, PAN: Manuscript editing, data collection: AANF: machine learning program. AANB: deep learning program, KMA: machine learning program.

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