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Transformed image features can improve machine learning performance for detecting benign-malignant of breast cancer

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Abstract: Breast cancer is a commonly diagnosed disease in women. This research aimed to create a transformed image features can improve machine learning performance for detecting benign-malignant of breast cancer.This research was quantitative research. Data was taken from the radiology installation at Doctor Sutomo Hospital from 2010 until now, where there were 670 data, consisting of 342 benign and 328 malignant. The data was distributed randomly; 70% was used for training, while the remaining 30% was used for testing. Every mammography had nine features: Entropy, Entropy of hdiff, contrast, Angular second moment, Angular second moment of hdiff Inverse difference moment, mean, Mean hdiff, and deviation. This research developed each feature into ten sub-features, namely Entropy at a distance of 1 pixel to Entropy at a distance of 10 pixels, and so on until the mean Hdiff at a distance of 10 pixels. Thus, the total features used in this research were 90 features. This research used three types of transformation, namely original, binary transformation, and bipolar transformation. Besides, this research also used three types of methods, namely 90 features, average, and optimization. Furthermore, this research sought the best performance based on the widest ROC graph, highest accuracy, and lowest false negative rate. In addition, this research also sought the best types of transformation and methods. Models with optimization types with binary and bipolar transformations had the highest positive true values. Models with optimization types with binary and bipolar transformations both had the lowest false negative values. The average type model with bipolar transformation had the highest accuracy value, followed by binary transformation. Models with optimization types with binary and bipolar transformations both had the highest ROC area. Based on the three methods and three transformations proposed, it was found that the optimization method and types of binary and bipolar transformations had the best performance.

Keywords: *Machine Learning, Breast Cancer, Benign, Malignant, Mammography, transformation data***.**

1. Introduction

Breast cancer is a commonly diagnosed disease in women and accounts for nearly one in four cancer cases [1]–[4]. Cancer is the second cause of death worldwide and has been identified as a dangerous disease [5]–[7]. Breast cancer is the most frequently diagnosed cancer in women globally and the fourth leading cause of female cancer-related deaths in Japan [8], [9]. Breast cancer is one of the most prominent heterogeneous and leading causes of death in women worldwide [10], [11]. Breast cancer is one of the top five causes of cancer-related deaths [12].

Many patients have a poor prognosis due to late treatment. Since 1960 there has been a 66% increase in global cancer death reported by the International Agency for Research on Cancer (IARC) [13]. A total of 144,524 women were diagnosed with primary ductal carcinoma in situ (DCIS), with an average age at diagnosis of 57.4 years and 1540 breast cancer deaths in the group [14]. In 2018, million new cases of cancer were diagnosed. The most common was lung cancer (2.09 million cases), followed by breast cancer (2.09 million cases) and prostate (1.28 million cases) [15].

In 2022, 1,918,030 new cancer cases and 609,360 deaths due to cancer in the United States [16]. In 2024, 2,001,140 new cancer cases and 611,720 deaths in the United States [17].

Therefore, breast cancer screening is significant. Mammography is the most commonly used screening tool for breast cancer [18]–[23]. According to Kosmia Loizidou (2023), mammografi is the most effective tool for screening breast cancer [5], [24]–[26]. Early detection by mammography screening can increase the survival of breast cancer patients [27]. Magnetic Resonance Imaging in recent years has become a useful tool to support the diagnosis of preoperative intraductal spread of breast cancer [28]–[32]. According to Xuemin Liu (2021), MicroRNA-155 (mir-155) can serve as a diagnostic biomarker for breast cancer [33].

Many methods have been developed for the early detection of breast cancer. Ioannis Sechopoulos (2021) developed machine learning for breast cancer screening

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using digital mammography [34]. Suvarna Vani (2022) developed an artificial intelligence to detect and classify Invasive Ductal Carcinoma [35]. Bita Asadi (2023) developed Deep Learning to detect breast cancer [36]. Yash Amethiya (2022) developed machine learning and biosensors for the early detection of breast cancer [37]. Imran Ul Haq (2022) developed deep learning for breast cancer screening [38].

Machine learning is currently being developed for breast cancer screening. Richard Adam (2023) used Deep learning for breast cancer detection with MRI [39]. Kimberlee (2023) used a machine learning model to predict the increased risk of ductal carcinoma in situ (DCIS) surgery for invasive cancer [40]. Wei-Chung Shia (2021) used machine learning to classify malignant tumors on breast ultrasound [41]. Vincent Peter (2021) used machine learning to detect early breast cancer recurrence [42]. Zahra Maghsoodzadeh Sarvestani (2023) used machine learning for cation diagnosis of breast microcalcification on mammogram images [43].

Machine learning can process data quickly and efficiently, identify patterns, and accurately predict the risk of disease. However, many do not know that binary or bipolar data transformation can improve machine learning performance. For this reason, this research aimed to create a transformed image features can improve machine learning performance for detecting benign-malignant of breast cancer. This research is fundamental to carry out, considering that the breast cancer death rate is increasing every year.

2. Materials and Methods

This research was quantitative research. Data was taken from the radiology installation at Doctor Sutomo Hospital from 2010 until now. There were 670 data, consisting of 342 benign and 328 malignant. The data was distributed randomly; 70% was used for training, while the remaining 30% was used for testing. Every mammography had nine features: Entropy, contrast, Angular second moment, Inverse difference moment, mean, deviation, Entropy of hdiff, Angular second moment of hdiff, and Mean hdiff, as shown in Figure 2. This research developed each feature into ten sub-features: Entropy at a distance of 1 pixel to Entropy at a distance of 10 pixels, and so on until the mean Hdiff at a distance of 10 pixels. Thus, the total features used in this research were 90, as shown in Figure 3. This research used three types of transformation, namely original, binary transformation, and bipolar transformation. Besides, this research also used three types of methods, namely 90 features, average, and optimization. Furthermore, this research sought the best performance based on the ROC graph, the highest accuracy, and the lowest false negative rate. In addition, this research also sought the best types of transformation and methods. What is meant by average was taking the average of each feature. What is meant by optimization was taking significant features with a significant value < 0.05 using the ANOVA test. Then, this research compared TP, FP, FN, TN, accuracy, sensitivity, specificity, precision, TPR, and FPR values using three types of data, namely original data, binary transformation data, and bipolar transformation data, as shown in Table 1, Table 2, and Figure 4 to Figure 10. From Table 1, Table 2, Figure 5, and Figure 6, this research concluded the method had the highest accuracy value and the lowest false negative. Furthermore, this research also made a ROC graph to see the best performance of this research-proposed method, as shown in Figure 11. The research flowchart from this research is as shown in Figure 1.

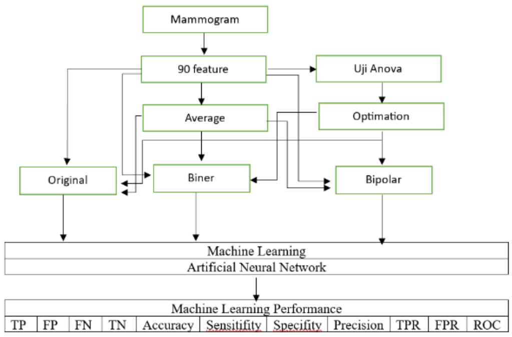

Fig. 1. Research Flowchart

3. Results and Discussions

3.1 Result

The calculation results of TP, FP, FN, and TN values for each transformation can be seen in Table 1.

Table 1. TP, FP, FN, and TN Values from Each Transformation

		T.P	F.P	FN	TN
90 Features	Original	0	0	98	103
	Binary	89	0	9	103
	Bipolar	98	4	0	99
Average	Original	19	8	79	95
	Binary	98	4	0	99
	Bipolar	97	1	1	102
Optimization	Original	68	43	30	60
	Binary	98	4	0	99
	Bipolar	98	3	0	100

The calculation results of the Accuracy, Sensitivity, Specificity, and Precision values for each transformation can be seen in Table 2

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

		Accuracy	Sensitivity	Specificity	Precision	TPR	FPR
90 Features	Original	0.51	0.00	1.00	nan	0.00	0.00
	Binary	0.96	0.90	1.00	1.00	0.91	0.00
	Bipolar	0.98	1.00	0.96	0.96	1.00	0.04
Average	Original	0.57	0.19	0.92	0.70	0.19	0.08
	Binary	0.98	1.00	0.96	0.96	1,00	0.04
	Bipolar	0.99	0.99	0.99	0.98	0.99	0.01
Optimization	Original	0.63	0.69	0.58	0.61	0.69	0.42
	Binary	0.98	1.00	0.96	0.96	1.00	0.04
	Bipolar	0.98	1.00	0.97	0.97	1.00	0.03

Data visualization of nine features contained in digital mammography is shown in Figure 2.

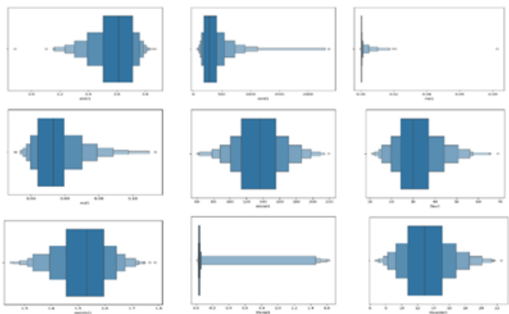

Fig. 2. Visualization of Digital Mammography Data

Histogram of 90 features from digital mammogram as shown in Figure 3

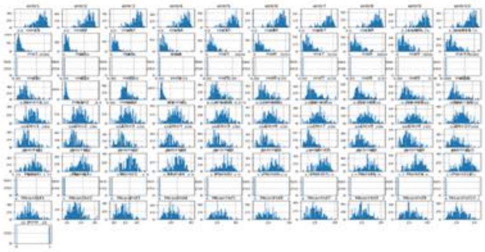

Fig. 3. Histogram of Features Contained in Digital Mammography

The model with 90 feature types with bipolar transformation had the highest true positive value, followed by binary transformation. The average type model with binary transformation had the highest true positive value, followed by bipolar transformation. Models with optimization types with binary and bipolar transformations both had the highest positive true values, as seen in Figure 4.

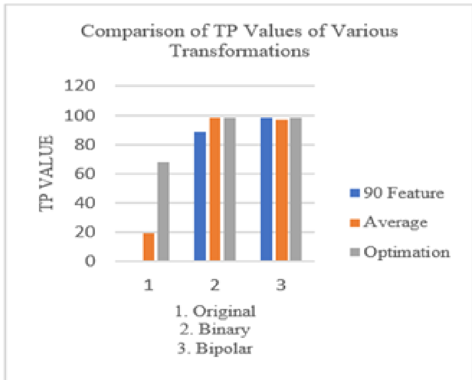

Fig. 4. Comparison of True Positive Values of Various Transformations

The model with 90 feature types with bipolar transformation had the lowest false negative value, followed by binary transformation. The average type model with binary transformation had the lowest false negative value, followed by bipolar transformation. Models with optimization types with binary and bipolar transformations both had the lowest false negative values, as seen in Figure 5

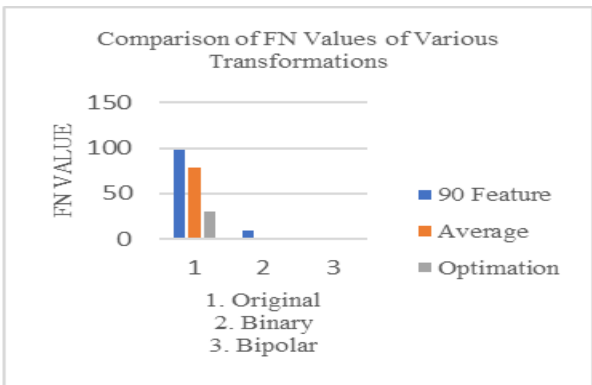

Fig. 5. Comparison of False Negative Values of Various Transformations

The model with 90 feature types with bipolar transformation had the highest accuracy value followed by binary transformation. The average type model with bipolar transformation had the highest accuracy value, followed by binary transformation. The model with optimization type with bipolar transformation had the highest accuracy value, followed by binary transformation, as seen in Figure 6.

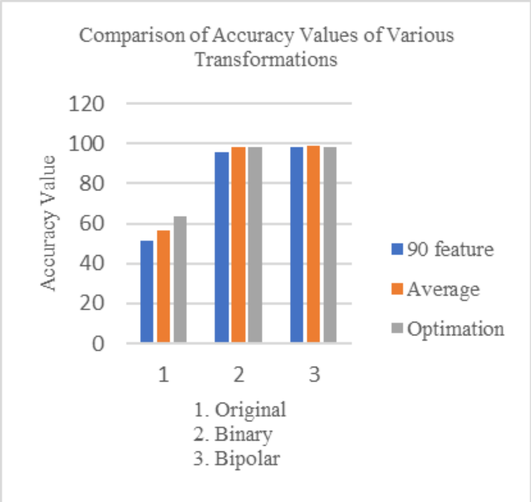

Fig. 6. Comparison of Accuracy Values of Various Transformations

Binary and bipolar data transformations could increase the sensitivity value, the average, and optimization data types, which had the same sensitivity value with binary and bipolar transformations. However, the 90 feature data types had a different sensitivity value between binary and bipolar transformations. The sensitivity value of bipolar transformation with 90 feature data types was higher than binary transformation with 90 feature data types, as shown in Figure 7.

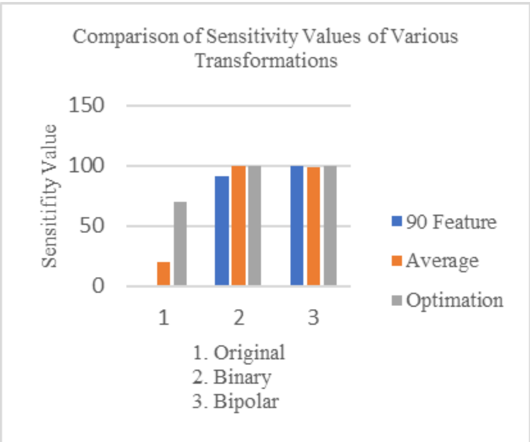

Fig. 7. Comparison of Sensitivity Values of Various Transformations

Binary and bipolar data transformations could increase the specificity value, the average, and optimization data types, which had the same specificity value with binary and bipolar transformations. However, the 90 feature data types had a different specificity value between binary and bipolar transformations. The specificity value of bipolar transformation with 90 feature data types was lower than binary transformation with 90 feature data types, as shown in Figure 8

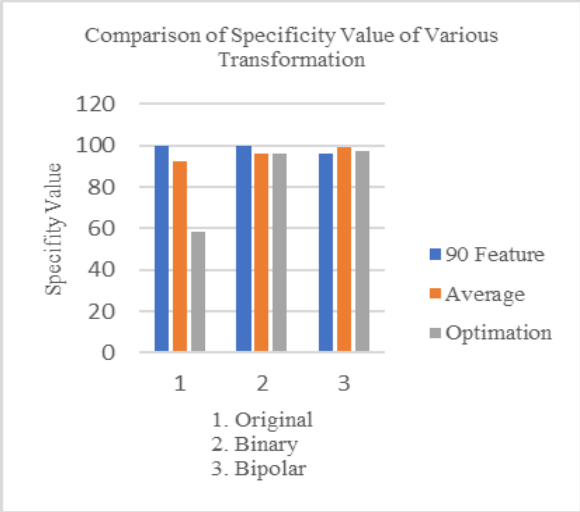

Fig. 8. Comparison of Specificity Values of Various Transformations

Binary and bipolar data transformation could increase the precision value, the average data type, and optimization, which had the same precision value with binary and bipolar transformations. However, the 90 feature data types had a different precision value between binary and bipolar transformations. The precision value of bipolar transformation with 90 feature data types was lower than binary transformation with 90 feature data types, as shown in Figure 9

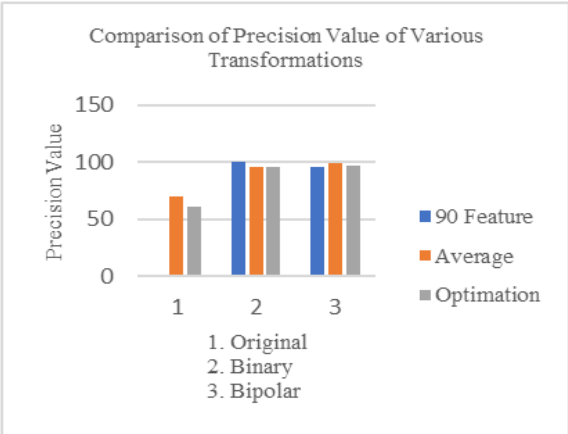

Fig. 9. Comparison of Precision Values of Various Transformations

Binary and bipolar data transformation could increase the True Positive Rate value, the average, and optimization data types, which had the same True Positive Rate value as binary and bipolar transformations. However, the 90 feature data types had a different True Positive Rate value between binary and bipolar transformations. The True Positive Rate value of bipolar transformation with 90 feature data types was higher than binary transformation with 90 feature data types, as shown in Figure 10.

The model with 90 feature types with bipolar transformation had the highest ROC area, followed by binary transformation. The average type model with binary transformation had the highest ROC area, followed by bipolar transformation. Models with optimization types with binary and bipolar transformations both had the highest ROC area, as seen in Figure 11.

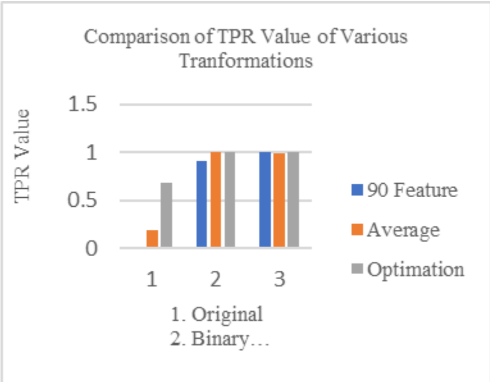

Fig. 10. Comparion of TPR Value of Various Transformation

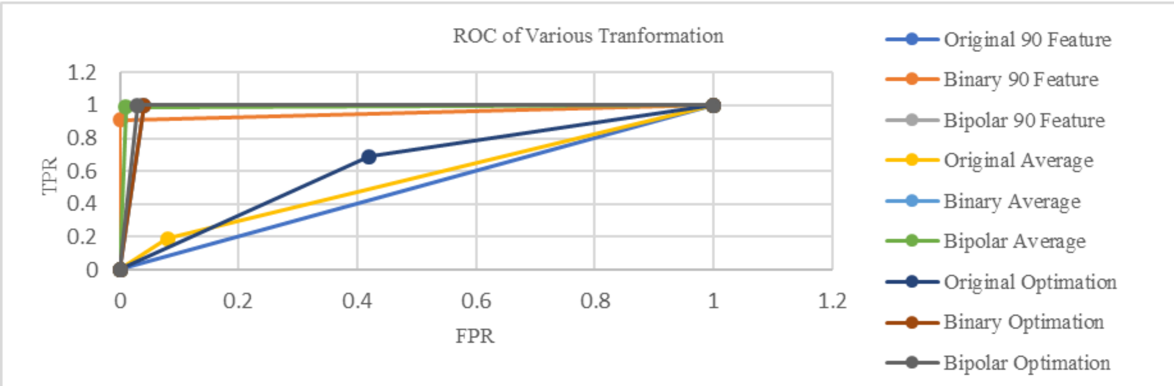

Fig. 11. ROC Graph of Various Transformations

3.2. Discussions

Binary and bipolar data transformations could increase true positive values, accuracy, sensitivity, specificity, precision, and true positive rate. Binary and bipolar data transformations could reduce false negative values. Machine learning performance could be improved by transforming data, both binary transformation and bipolar data transformation. The feature type should use the average feature type or the optimization feature type. Literature studies showed that a comparison of specificity, sensitivity, and accuracy values with other sophisticated methods can be seen in Table 3.

Table 3. Summary of Performance Results of Other Advanced Methods

Study	Year	Method	Accuracy	Sensitivity	Specificity
Demirler S¸ ims¸ir et.al [44]	2021	Dual-Layer Spectral CT	-	0.966	0.917
Chen et al. [45]	2023	Artificial Intelligence	0.778	0.921	0.671
Osman et al. [46]	2020	Adjusted Quick Shift Phase	Not mentioned	0.795	0.979
El Houby et al. [47]	2021	Convolutional Neural Networks	0.965	0.965	0.965

Abdolahi et al [48]	2020	Artificial Intelligence	0.85	Not mentioned	Not mentioned
Nelson et al. [49]	2023	Star-Convex Polygon	0.876	Not mentioned	Not mentioned
Eroglu et al. [50]	2021	Convolutional Neural Networks	0.956	Not mentioned	Not mentioned
Deepa et al [51]	2022	Convolutional Neural Network Models	0.945	Not mentioned	Not mentioned
Wu et al. [52]	2022	Deep Learning Fusion Models	0.877	0.861	Not mentioned
Kawattikul et al. [53]	2022	Conventional Handcrafted Feature and Deep-Learning Technique	Not mentioned	0.82	0.85
Liew et al[54]	2021	XGBoost-Based Algorithm	0.97	Not mentioned	Not mentioned
Shia et al. [41].	2021	Support Vector Machine and Pre-Trained Deep Residual Network Model.	Not mentioned	0.943	0.932
Rahman et al. [55]	2022	Multi-Scale Feature Fusion	0.992	Not mentioned	Not mentioned
Song et al. [56]	2022	Deep Multi-View Fusion	0.850	0.957	0.716
Webb et al. [57]	2021	Deep Learning-Based	Not mentioned	0.826	0.993
Leong et al. [58]	2022	Deep Convolutional Neural Networks	0.999	0.999	1,000
Haq et al. [38]	2022	Feature fusion and Ensemble Learning-Based CNN Model	0.994	0.995	0.994
Joseph et al. [59]	2022	Handcrafted Features and Deep Neural Networks	0.979	Not mentioned	Not mentioned
Assari et al. [60]	2022	Deep Residual Learning-Based	0.917	0.898	0.938
Yuchao Zheng et al. [61]	2023	Transfer Learning and Ensemble Learning	0.989	Not mentioned	Not mentioned
Caballo et al. [62]	2020	Deep learning-Based	0.92	Not mentioned	Not mentioned
Chaudhury et al. [63]	2023	Fast AI Technique and Squeezenet Architecture Sushovan	0.903	Not mentioned	Not mentioned
Huang et al. [64]	2021	Convolutional Neural Networks (CNN), AlexNet, DenseNet, and ShuffleNet	0.955; 0.997; 0.978	Not mentioned	Not mentioned

Akinnuwesi et al. [65]	2020	Support Vector Machines	0.976	0.952	1.00
Kadry et al. [66]	2023	Pre-Trained Deep Learning Schemes	0.955	Not mentioned	Not mentioned
Khan et al. [67]	2022	Deep Neural Network MultiNet	0.99	Not mentioned	Not mentioned
Aljuaid et al. [68]	2022	Deep Neural Networks and Transfer Learning	0.978	0.976	0.973
Asadi et al. [36]	2023	Deep Learning Network ResNet50	0.986	0.986	Not mentioned
Bo-Wei Han et al [69]	2021	cfDNA-based nucleosome	Not mentioned	Not mentioned	Not mentioned
Rijthoven et al [70]	2021	HookNet	Not mentioned	Not mentioned	Not mentioned
Proposed	2024	Data Transformation	0.990	0.989	0.990

4. Conclusions

Machine learning was important in the breast cancer detection process. This research used three ways to see the best performance of machine learning in detecting breast cancer. This research looked at the widest ROC graph, which had the highest accuracy and the lowest false negative values. Based on the three types of data models analyzed, only binary and bipolar transformations showed an improvement in machine learning performance. Not all features in mammography could improve machine learning performance, and only averaged and optimized features could improve machine learning performance. This research contributed to providing knowledge about the use of feature averaging and optimization with binary or bipolar transformations to improve machine learning performance.

List of abbreviations

KNN : K-Nearest Neighbor

ANN : Artificial Neural Networks

SVM : Support Vector Machine

TN : Predicted to be benign actually benign

T.P : Predicted to be malignant, actually malignant

F.P : Predicted to be malignant but actually benign

FN : Predicted to be benign actually malignant

FPR : False Positive Rate

TPR : True Positive Rate

ROC : Receiver Operating Characteristics

Consent for publication

Not applicable.

Availability of data and materials

Data taken from Installation Radiology Doctor Sutomo Hospital from 2010 until now where there are 670 data consisting of 342 benign and 328 malignant.

Competing interests

The authors declare that they have no competing interests

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Author Contributions

All authors have read and approved the manuscript,

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

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