Breast Cancer Detection Using Machine Learning

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***Abstract* - Breast cancer (BC) is the second most common type of cancer in women that results in death, and it has a relatively high mortality rate. Early detection will lessen its impact. Early discovery of BC may motivate patients to receive quick surgical therapy, which will significantly improve the prognosis and likelihood of recovery. Therefore, it is essential to develop a system that enables the healthcare sector to rapidly and effectively detect breast cancer. Due to its benefits in modelling a vital feature detection from complicated BC datasets, machine learning (ML) is frequently utilised in the categorization of breast cancer (BC) pattern. In this research, we propose an ensemble of classifiers-based systems for the automatic diagnosis and prognosis of BC. Breast tumours, bloody nipple discharge, and changes in nipple or breast texture are all signs of breast cancer. Depending on the stage, breast cancer treatment options include surgery, hormone replacement therapy, chemotherapy, and radiation. Creating a machine learning model to categorise breast cancer as benign or malignant is the goal of this study. Logistic regression, decision trees, and random forests are all components of the technique utilised for the model. We got the best accuracy from SVM (Support Vector Machine) i.e. 97.36%.**

Index Terms - ML- Machine Learning, BC- Breast Cancer, AI- Artificial Intelligence, SVM- Support Vector Machine, WCRF- World Cancer Research Fund International.

I. Introduction

One of the most dangerous and common tumours in women, breast cancer kills a lot of women all over the world. In the world, breast cancer accounts for 6.6% of cancer-related fatalities and 8.4% of cancer diagnoses, according to a World Health Organization (WHO) report [1]. According to the Saudi Health Council [2], breast cancer accounted for 15.9% of all reported malignancies among Saudi citizens and 28.7% of all reported cancers among women of all ages. Women with dense breasts are more likely to develop breast cancer, and there is a correlation between age and breast density, with younger women having dense breasts than older women [3]. The Breast Imaging Data and Reporting System was created by the American College of Radiology (BI-RADS). The four BI-RADS assessment categories are shown in Table 1. Screening mammography is still viewed and interpreted manually under the guidance of a radiologist, despite recent advancements in computer vision. However, radiologists find it challenging to accurately manage the vast volume of screening pictures.

Table 1: BI- RADS Assessment Categories [4]

BI-RADS CATEGORY	BREAST DENSITY	RISK OF CANCER
BI-RADS I	Almost entirely fatty	(0-25)%
BI-RADS II	Some fibro glandular tissue	(26-50)%
BI-RADS III	Heterogeneously dense	(51-75)%
BI-RADS IV	Extremely Dense	(76-100)%

Modern methods have recently been employed by medical imaging experts to address issues with breast cancer analysis [4]. Numerous studies have been conducted on the automatic detection of breast cancer. According to the World Health Organization, BC accounts for about one in every four newly diagnosed cancer cases and is the most common malignancy in women. Only 1.7 million new instances of cancer were reported in 2012, according to the World Cancer Research Fund International (WCRF). Early detection of BC can greatly increase the odds of survival despite its high occurrence and even the absence of early indications [5]. Patients diagnosed with stage I or stage II BC have a five-year survival rate of 80 to 90 percent, whereas those with stage III or stage IV BC have a survival rate of only 24 percent, according to the WCRF. It follows that accurate classification of benign tumors is necessary to motivate patients to seek the right treatment and receive a better prognosis. As a result, a lot of study into the diagnosis of BC concentrates on precisely classifying people as benign or malignant. The BC Wisconsin diagnostic and prognosis dataset has been used to test a variety of machine learning (ML) methods and neural network (NN) techniques. Researchers have provided numerous ML approaches for the classification problem in earlier studies. We provide a thorough explanation of the various classification algorithms utilised to categorise BC in this study. We primarily concentrate on support vector machines (SVM) based on conventional machine learning (ML), k-nearest neighbour (KNN), decision tree (DT), and artificial neural network (ANN) methods based on deep learning (DL).

II. LITERATURE WORK

In recent years, a number of automated methods for classifying breast cancer have appeared; these systems employ various methodologies. The classification of breast cancer requires the extraction of discriminating traits, followed by classification. The next paragraphs address cutting-edge techniques for staging breast cancer that have been put forth. A two-stage patch classification method for mammography was proposed by Whitaker et al. [10] using the texture descriptors "Histogram of Oriented Texture (HOT)" and "Pass Band Discrete Cosine Transform (PB-DCT)." Mammogram patches are categorised as normal or abnormal in the initial stage. Support vector machines (SVMs) are used in the second step to categorise abnormal mammographic areas as benign or malignant. A texture-based approach was created by Jothilakshmi and Raaza [1] to distinguish between cancerous and benign tissue using multiple SVMs, with features extracted using "grey-level co-occurrence matrices" (GLCM). A novel method for separating benign from malignant breast tumours was put forward in [1]. The method transforms the two-dimensional mammographic outlines of breast masses into a one-dimensional signature. Nearest neighbour algorithms classify the data by identifying its closest neighbours in a multidimensional feature space with known examples of a training dataset. The forecasting effectiveness increases with improved dimension ratios for the closest neighbours. Both methods, the Manhattan distance and the Euclidean distance, were looked at this time because the outcomes of this algorithm depend on how the distance between the data is calculated. A supervised learning method for categorising, forecasting, and spotting outliers is called SVM. Because they only require a small subset of training points on support vectors, they are inexpensive and efficient, especially in high-dimensional areas.

III. METHODOLOGY

The technique for an ensemble of ML classifiers is presented in this section. Four separate ML models make up this architecture. They are piled before undergoing additional training together. The SVM model is employed for the result after training.

A. PROPOSED APPROACH

In this article, we develop a classification framework using an ensemble of SVM, LR, NB, and DT, four ML-based classifiers. Predictions from an ensemble model are layered, concatenated, and then supplied to the ANN model for the outcome. The next part also provides a brief explanation of each algorithm employed in our investigation. The suggested model's steps are outlined below in brief:

On a training dataset, we employed classifiers based on machine learning. The K-fold technique extracts the most frequent result from these classifiers in the subsequent phase. We combined the output of machine learning classifiers in the third stage. As a result, the new training dataset was simplified. In this step, the fresh dataset is fed into the built-in SVM. Results and outputs' evaluation was done.

B.SUPPORT VECTOR MACHINE

SVM is a supervised machine learning method that chooses a moderate number of samples, known as support vectors, and constructs a linear discriminant function. The limitation of linear bounds was resolved by SVM. SVM can be thought of as a two-class data set that can be linearly partitioned to display a maximum hyperplane margin. After choosing the proper mapping, the new samples are linearly fitted or seem linearly separable in the high-level plane. The SVM looks for the hyperplane that minimises the distance between two groups and offers the greatest advantages.

C. LOGISTIC REGRESSION

The posterior probability of K groups over linear roles in x is replicated to build the LR technique, making sure to keep the posterior probabilities equal to one and within the range [0, 1]. LR can be described in terms of log probabilities or logit shifts K-1. Although the odds ratio uses the final group as the denominator, the choice of the denominator is ambiguous because the numbers are distributed equally. When $K = 2$, the style is straightforward because there is just one linear role. This method is frequently employed in biostatic jobs that need repeated binary replies

IV. EXISTING WORK

In the past, researchers have employed mammography pictures as well as those from other imaging modalities like ultrasound and MRI to diagnose breast cancer using machine learning approaches like decision trees, random forests, and neural networks. As additional variables for prediction, some studies have also included patient data like age, family history, and genetics.

V. RESEARCH GAP

Despite the excellent accuracy rates mentioned in certain research, there are restrictions on the models' generalizability and interpretability. For breast cancer screening to become more accurate and accessible, there is a need for ongoing research in this field. By utilising a variety of regression algorithms and examining the model performance, our work intends to fill this research gap.

VI. PROPOSED WORK

Based on our mission statement, we will create machine learning models for the early diagnosis of breast cancer utilising logistic regression, decision trees, and random forest techniques. Being able to compare the outcomes of these three separate algorithms to ascertain which one performs the best in terms of accuracy, precision, recall, and F1-score makes our proposed study unique.

MODULES:

Cleaning and preparing the dataset for model training and testing is known as data preprocessing.
Model development: Training the models on the dataset using logistic regression, decision trees, and random forest techniques. Metrics like accuracy, precision, recall, and F1-score can be used to assess the performance of the models.
Results and discussion: The results are presented, the conclusions are discussed, and the performances of the three algorithms are contrasted.

STEPS:

1. Gathering patient and breast cancer data in a dataset and cleaning and preparing the dataset
2. Creating training and testing sets from the dataset.
3. Using the training dataset, train models for logistic regression, decision trees, and random forests.
4. Using the test dataset to run the models.
5. Assessing the models' performance using a range of evaluation indicators.
6. Presenting the findings, talking about further studies, and contrasting the outcomes of the five algorithms

The overall goal of our proposed effort is to increase the reliability and usability of breast cancer diagnosis by evaluating the performance of five distinct algorithms and comparing their results.

VII. PREVIOUS RESEARCH

Breast cancer is a condition in which cancerous cells proliferate in the breast tissues. A tumour is a collection of unhealthy tissue. Breast tumours can be classified as "benign" (non-cancerous) or "malignant" (cancerous). The basic building blocks of the breast or other tissue-containing body parts, cells, are where cancer begins. Sometimes, the process of cell division goes wrong, causing new cells to form or injured or old cells to stop dying when the body doesn't need them. A medical expert skilled in the detection of breast disease, which is frequently an indication of breast cancer, should then keep an eye on any new breast, lump, or breast alterations. There is currently no cure for malignant tumours. To reduce cancer-related fatalities and improve patients' quality of life, early breast cancer screening is essential
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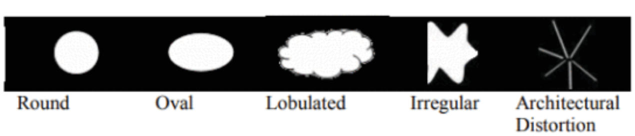

Fig. 1. Shape of Breast Mass [1]

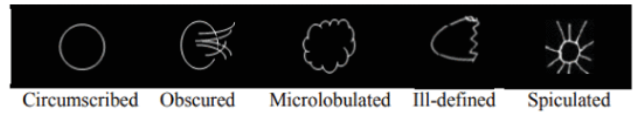

Fig. 2. Edges of Breast Mass [1]

Female sex, age, heredity, and having thick breasts are the most common and well-known risk factors for breast cancer. The amount of the unique tissues that make up a woman's breasts and how they appear on a mammography are both depicted by the term "breast density." Women with dense breasts are more likely to get breast cancer, and there is a correlation between breast densities and age, with younger women having dense breasts than older women. We have listed down the table consisting the previous research work conducted in the past 2 years:

Table 2:

S. No.	Title of the paper	Journal Name, Publisher Name, Year of Publication and Volume & Issue Number (only SCI)	Author Name	Problem addressed/ Problem Statement	Methods/Technologies used	Author Contribution	Shortcoming/ Assumption Made
1	An Automatic Detection of Breast Cancer Diagnosis and Prognosis Based on Machine Learning Using Ensemble of Classifiers	IEEE Access (Vol 10), IEEE, 12 May 2022, *Funding Agency:* Technology Development Program of MSS, National Research Foundation of Korea (NRF)	Usman Naseem, Junaid Rashid, Liaqat Ali, Jungeun Kim, Qazi Emad Ul Haq, Mazhar Javed Awan, Muhammad Imran	Providing the ML model such that it would have great accuracy with a new approach rather than following the other state-of-the-art methods	#.A classification framework was created using an ensemble of the machine learning classifiers SVM, LR, NB, and DT.	· Presented an ensemble of machine learning-based methods for breast cancer diagnosis and prognosis.	The performance of the classifiers could vary depending on the specific hyperparameter values chosen. It may be beneficial to perform a hyperparameter search in order to find the optimal values for each classifier.
2.	A Review on Recent Progress in Thermal Imaging and Deep Learning Approaches for Breast Cancer Detection	IEEE Access (Volume: 8), IEEE, 22 June 2020, *Funding Agency:* Ministry of Education and Culture of the Republic of Indonesia under 2020 Doctoral Research Grant and by Ministry of Research, Technology, and Higher Education of the Republic of Indonesia under 2019 World Class Professor (WCP) Programme	Khairul Munadi,Biswajeet Pradhan, Maimun Syukri, Roslidar Roslidar, Aulia Rahman, Rusdha Muharar, Muhammad Rizky Syahputra, Fitri Arnia	Finding out such ways to diagnose Breast Cancer that do not have any physical contact with body such as Thermography, using NN models to increase it accuracy in prediction of breast cancer thermogram classification	Using thermography for visualisation and quantification, facilitating risk-free detection of breast cancer	A summary of breast thermography's potential to detect cancer, including information on the dataset of breast thermograms..	Improved breast thermogram categorization must be the goal of future research. In order to do this, representative datasets, high-quality ROIs, high-quality kernel assignments, and lightweight CNN models must be used.

3.	Deeply-Supervised Networks With Threshold Loss for Cancer Detection in Automated Breast Ultrasound	IEEE Transactions on Medical Imaging (Volume: 39, Issue: 4, April 2020) *Funding Agency:*National Natural Science Foundation of China, Medical Science and Technology Foundation of Guangdong Province, Natural Science Foundation of SZIJ	Yi Wang, Na Wang, Min Xu, Junxiong Yu, Chenchen Qin, Xiao Luo, Xin Yang, Tianfu Wang, Anhua Li, and Dong Ni	Improve the network architecture for automatic cancer detection in ABUS, in order to accelerate the reviewing and meanwhile to obtain high detection sensitivity with low false positives	efficiently using multi-layer features to increase the detection sensitivity with a densely deep supervision method.	A more effective network design. To systematically combine multi-scale contextual information and increase the detection sensitivity for tiny lesions, we use 3D dilated convolutions.	fatty masses and cystic lesions would be mistaken for malignant tumours.
4.	Deep Learning Assisted Efficient AdaBoost Algorithm for Breast Cancer Detection and Early Diagnosis	Published in**:** IEEE Access(Volume: 8) Date of Publication**:** 08 May 2020 Funding Agency***:***10.13039/501100012151-Sanming Project of Medicine in Shenzhen (Grant Number: SZSM201811073)	Jing Zheng, Denan Lin, Zhongjun Gao, Shuang Wang, Mingjie He, And Jipeng Fan	The improvement of the prediction of tumour prognosis and the improvement of a deeper classification of results in breast cancer detection	Deep Learning assisted Efficient Adaboost Algorithm (DLA-EABA) for breast cancer detection has been proposed.	Proposed the deep learning assisted efficient Adaboost algorithm for breast cancer detection and early diagnosis	More testing is required and the model is tedious and extremely time consuming.

5.	Spectral Capacitively Coupled Electrical Resistivity Tomography for Breast Cancer Detection	Published in: IEEE Access (Volume: 8) Date of Publication: 11 March 2020 Funding Agency: 10.13039/501100000835-University of Bath Catherine and Raoul Hughes	Gege Ma and Manuchehr Soleimani	An alternative for traditional EIT medical use is proposed	This work focuses on the introduction and the evaluation of a spectral capacitively-coupled electrical resistivity tomography (CCERT) for breast cancer diagnosis.	The author introduces a new type of contactless measurement modality (CCERT) with the multi-frequency method for breast cancer imaging.	The frequency-difference imaging produced by the the CCERT method is affected by skin effects and fringing effects in the laboratory environment, which can influence the signal strength and accuracy of the reconstructed conductivity spectra.
6.	Breast Cancer Detection using Multimodal Time Series Features from Ultrasound Shear Wave Absolute Vibro-Elastography	Published in: IEEE Journal of Biomedical and Health Informatics (Volume: 26, Issue: 2, February 2022) Date of Publication: 10 August 2021 Funding Agency: University of British Columbia Clinical Canadian Institutes of Health Research	Yanan Shao, Hoda S. Hashemi, Paula Gordon, Linda Warren, Jane Wang, Fellow, IEEE, Robert Rohling, Fellow, IEEE, and Septimiu Salcudean, Fellow, IEEE	The goal is to ascertain whether S-WAVE can distinguish between benign and malignant breast tissue abnormalities.	In S-WAVE, a controlled shaker is used to excite the tissue in steady-state at different frequencies, and subsequent US RF data frames are captured in a time series. The placenta, prostate, and breast have all been studied using the S-WAVE imaging technology.	The dataset of about 40 patients is being studied and then acted upon with random forest classification techniques.	As the tissue motion is 3D rather than 2D, the 2D S-WAVE data modality employed in the study could lead to inaccuracies in determining quantitative elasticity.
7.	Enhancement of Penetration of Millimetre Waves by Field Focusing Applied to Breast Cancer Detection	Published in: IEEE Transactions on Biomedical Engineering (Volume: 68, Issue: 3, March 2021) Date of Publication: 04 August 2020	Ioannis Iliopoulos, Simona Di Meo, Marco Pasian, Maxim Zhadobov, Philippe Pouliguen, Patrick Potier, Luca Perregrini, Ronan Sauleau, and Mauro Ettorre.	The potentialities of improving the penetration of millimetre waves for breast cancer imaging are explored here.	A field focusing technique based on a convex optimization method. Field propagation inside the breast model.	A focusing technique based on convex optimization has been used here to increase the penetration in breast cancer imaging scenarios at millimetre waves.	No particular shortcomings were detected.

8.	Deep Neural Networks Improve Radiologists' Performance in Breast Cancer Screening	N. Wu *et al.*, "Deep Neural Networks Improve Radiologists' Performance in Breast Cancer Screening," in *IEEE Transactions on Medical Imaging*, vol. 39, no. 4, pp. 1184-1194, April 2020	Nan Wu; Jason Phang; Jungkyu Park; Yiqiu Shen; Zhe Huang; Masha Zorin	They offer a deep convolutional neural network trained on over 2,00000 exams for the classification of breast cancer screening exams (over 1000000 images). When put to the test on the screening population, their network successfully predicts the existence of breast cancer with an AUC of 0.895.	Pretraining the network is useful for improving the performance of the models, as demonstrated by an evaluation employing a task with a similar objective but a noisier result (screening BI-RADS classification).	Show that it is possible to train and test the network using more than 1,000,000 high-resolution mammograms, which is a very sizable data set for medical imaging and not just for breast cancer screening.	Although multicenter studies have shown that modern CAD applications do not increase radiologists' diagnostic ability, radiologists frequently utilise traditional computer-aided detection (CAD) in mammography to help with picture interpretation.
9.	A Novel Hybrid K-Means and GMM Machine Learning Model for Breast Cancer Detection	P. E. Jebarani, N. Umadevi, H. Dang and M. Pomplun, "A Novel Hybrid K-Means and GMM Machine Learning Model for Breast Cancer Detection," in *IEEE Access*, vol. 9, pp. 146153-146162, 2021	P. Esther Jebarani; N. Umadevi; Hien Dang; Marc Pomplun	This study demonstrates the methodology's adaptability by combining cutting-edge segmentation techniques with machine learning techniques, two emerging fields of study.	By suggesting a new parameter for assessing the performance of K-means and a Gaussian mixture model (GMM), this research significantly advances the field. On breast cancer, a hybrid mix of segmentation and detection was used.	A hybrid technique for detecting breast cancer is part of the novel notion in this work, and multivariate analysis is used to raise the suggested system's prediction rate.	It is a difficult challenge in research to identify the tumour mass by segmenting the region of interest. Therefore, automated methods and early detection technologies must work together to help radiologists correctly identify breast cancers.
10.	Part Mitosis: A Partially Supervised Deep Learning Framework for Mitosis Detection in Breast Cancer Histopathology Images	M. Sebai, T. Wang and S. A. Al-Fadhli, "PartMitosis: A Partially Supervised Deep Learning Framework for Mitosis Detection in Breast Cancer Histopathology Images," in *IEEE Access*, vol. 8, pp. 45133-45147, 2020	Meriem Sebai; Tianjiang Wang; Saad Ali Al-Fadhli	Using a partially supervised deep learning framework, the goal of this paper is to build a technique for the automatic recognition of mitotic patterns from breast cancer histology slides.	Based on two parallel deep fully convolutional networks, we propose an unique partially supervised framework. With the use of a weight transfer function, one of them is trained using weak labels and the other using strong labels.	It is quite difficult to identify hand-crafted traits that can effectively distinguish mitoses from imitators due to the diversity of the morphologies of the mitosis and the strong similarity between mitotic and non-mitotic cells.	The weighted sum of the weak segmentation branch predictions and the strong segmentation branch predictions represents the final detection findings.

IX. EXPERIMENTAL RESULTS

Standard Scalar

```
########## Standard Scaler ######################


Model 1 -> Logistic regression :
              precision    recall  f1-score   support

           0       0.96      0.97      0.96        67
           1       0.96      0.94      0.95        47

    accuracy                           0.96       114
   macro avg       0.96      0.95      0.95       114
weighted avg       0.96      0.96      0.96       114

Accuracy :  0.956140350877193

Model 2 -> Decision tree :
              precision    recall  f1-score   support

           0       0.95      0.93      0.94        67
           1       0.90      0.94      0.92        47

    accuracy                           0.93       114
   macro avg       0.93      0.93      0.93       114
weighted avg       0.93      0.93      0.93       114

Accuracy :  0.9298245614035088
```

Fig. 3. Standard Scalar Output From the Code

```
Model 3 -> Random forest :
              precision    recall  f1-score   support

           0       0.97      0.99      0.98        67
           1       0.98      0.96      0.97        47

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114

Accuracy :  0.9736842105263158

Model 4 -> Ridge logistic regression (Ridge Classifier) :
              precision    recall  f1-score   support

           0       0.92      1.00      0.96        67
           1       1.00      0.87      0.93        47

    accuracy                           0.95       114
   macro avg       0.96      0.94      0.94       114
weighted avg       0.95      0.95      0.95       114

Accuracy :  0.9473684210526315

Model 5 -> Support Vector Classifier :
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        67
           1       1.00      0.96      0.98        47

    accuracy                           0.98       114
   macro avg       0.99      0.98      0.98       114
weighted avg       0.98      0.98      0.98       114

Accuracy :  0.9824561403508771
```

Fig. 4. Random Forest, Ridge Logistic Regression, Support Vector Classifier Output and Accuracy Output.

Min Max Scalar

```
########## Minmax Scaler   ######################


Model 1 -> Logistic regression :
              precision    recall  f1-score   support

           0       0.94      1.00      0.97        67
           1       1.00      0.91      0.96        47

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114

Accuracy :  0.9649122807017544

Model 2 -> Decision tree :
              precision    recall  f1-score   support

           0       0.95      0.93      0.94        67
           1       0.90      0.94      0.92        47

    accuracy                           0.93       114
   macro avg       0.93      0.93      0.93       114
weighted avg       0.93      0.93      0.93       114

Accuracy :  0.9298245614035088
```

Fig.5. Minmax Scalar Output From the Code

```
Model 3 -> Random forest :
              precision    recall  f1-score   support

           0       0.97      0.99      0.98        67
           1       0.98      0.96      0.97        47

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114

Accuracy :  0.9736842105263158

Model 4 -> Ridge logistic regression (Ridge Classifier)
              precision    recall  f1-score   support

           0       0.93      1.00      0.96        67
           1       1.00      0.89      0.94        47

    accuracy                           0.96       114
   macro avg       0.97      0.95      0.95       114
weighted avg       0.96      0.96      0.96       114

Accuracy :  0.956140350877193

Model 5 -> Support Vector Classifier :
              precision    recall  f1-score   support

           0       0.97      0.99      0.98        67
           1       0.98      0.96      0.97        47

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114

Accuracy :  0.9736842105263158
```

Fig 6. Logistic Regression, Decision Tree Output and Accuracy

X. CONCLUSION

Based on our issue statement, we are attempting to create machine learning models for the early diagnosis of breast cancer utilising decision trees, logistic regression, and random forest methods. The successes of our model include the accuracy of all classifier functions, which is generally on and above 93% (one model even attained the accuracy of 98%), as well as the usability of our model, which is very user-friendly and far less complicated than previous work.

We now accept.csv files for the Future Enhancements section of the input, although mammogram images are also an option.

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