



# Explainable Deep Learning Framework for Accurate Breast Cancer Classification and Abnormality Detection from Mammogram Images

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## ABSTRACT

Early and accurate detection of breast cancer is critical to improving outcomes for affected individuals. Although a mammogram is an important diagnostic tool, the examination requires a professional, and this will be time-consuming and inconsistent. Unbalanced datasets can make it hard for traditional DL methods to work, which lowers the accuracy and trustworthiness of classification. This paper is based on the KAU-BCMD Mammography dataset where mammogram images are labeled and the comments within the bounding box are marked for parts that are not normal. The entire dataset and training groups are provided with increased data as part of preprocessing, and the labels are encoded, features are extracted using ResNet50, and SMOTE is employed for class balancing.

Problems are identified using YOLOv5, YOLOv8 and YOLOv11. The accepted classifiers are ResNet50 with FC-MLP, Xception, and Hybrid Xception-ResNet50. The range was completed using Accuracy, Precision, Recall, F1 score, ROC AUC and modes have been tested. The metrics used for detection were mAP, Precision, and Recall. The average of all the metrics indicates that the proposed full\_bal classification model achieved 99.5% and YOLOv8 had the highest detection success with mAP 0.462. Heatmaps were created using Explainable AI techniques like Grad-CAM to elucidate the regions of the image where the model decision-making process plays a crucial role. A Flask-based interface is provided that allows the user to upload mammogram images and receive predicted classes and boxes. These results indicate that the use of a mixture of deep feature extraction, balanced registration, hybrid architecture, and interpretive visualization can increase the accuracy of most breast cancer diagnoses and classify mammogram use.

**Keywords:** Breast Cancer, BI-RADS, Classification, Deep Learning, Feature Extraction, Imbalanced Data, Neural Network, Pre-Trained Models

## I. INTRODUCTION

Breast cancer is one of the most traditional malignancies in girls, which also affects many women around the world. It is responsible for many cancer-related diseases and fatalities every year [1]. Despite enormous strides in breast cancer awareness, screening and interventions, the incidence of breast cancer continues to rise globally [2]. There are significant regional variations in survival rates. Survival rates are higher in developed countries, and much lower in low income areas. This is predominantly due to the variations in early detection and health care services [3]. Early diagnosis is also recognised to be very important for better prognosis with many people agreeing that the early detection of cancers improves the long-term survival and effectiveness of treatment [4]. As a result, greater attention is being paid to making breast cancer screening more accurate and more readily available to more people.

Diagnostic methods such as mammography, ultrasound, magnetic resonance imaging, and biopsy are incredibly important when it comes to medical decision-making [5]. However, they do have their problems. Even though doctors can read medical images, it is difficult to interpret them manually as people interpret them differently. This may result in false positive or false negative results, or inconsistent diagnostic results [6]. All these problems exacerbate image noise, complex anatomy, dense breast tissue and heavy clinical workload. Secondly, there are fewer skilled radiologists worldwide, particularly in the developing world, and the delay and misdiagnosis are more likely [7]. More research is being conducted on the use of computers to assist doctors, and the existing research has a number of issues with regard to data imbalance, generalization and reliability. This indicates that there are significant differences

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between what technology can currently do and what doctors need.

These problems are addressed in the study by proposing a robust and reliable learning-based approach to classify breast cancer mammograms. Our goal is to improve diagnostic and prognostic accuracy and achieve applicability to scientific settings. The proposed approach targets two aspects; firstly, enhancing the representation learning; secondly, combating the impact of data imbalance and establishing a classification method for stability and generalization. The objective of this work is to fill the gap between the highly complex computer models and real-world results, by emphasizing harmonised learning and intelligent use of features. The most significant innovations are the idea of two-stage learning paradigm, development of a well-designed approach of classification and a more reliable diagnostics system without increasing the complexity of the system [8].

The work is important as it may help clinicians to provide a reliable decision-making tool that will make breast cancer identification easier. Improved diagnosis accuracy will eliminate unnecessary invasive procedures and missed diagnoses and ultimately lead to improved patient outcomes [9]. The proposed framework can also be customized to benefit specific clinical environments that include assistance-limited settings with the same and brand new diagnostic support to achieve guaranteed access. The specific objective of this study is to use intelligent systems to improve public health and reduce the impact of breast cancer within the global [10]. This research work makes it possible by enhancing reliability of and effectiveness in automated mammography analysis.

## II. LITERATURE REVIEW

The screening and diagnosis of breast cancer are used standards and large investigations. NCCN clinical practice guidelines are a succinct summary of consistent recommendations for cancer diagnosis, therapy and prognosis. They stress on the importance of evidence informed decisions, and early identification of cancer for improved results [11]. Comparisons of the imaging modalities (digital mammography vs. film mammography) have shown that digital mammography is superior in certain groups, but has not been particularly sensitive in thick breast tissue [12]. Early diagnostics testing has also shown that screening technologies have improved, but are predominantly dependent on the quality of the pictorial results, expert interpretation and accessibility to health services. These all illustrate the importance of screening in medicine and the difficulty diagnosis.

There has been greater focus on learning how to take into account the limitations of people and concepts. It has been found that by using a modified CNN in ultrasound images, better diagnosis has been done, which shows the ability of data-driven models to detect breast cancer [14]. Likewise, studies investigating the utility of MRI have concluded that MRI is very good at detecting cancer, particularly in high-risk individuals, but is also costly and difficult to obtain, and has a high false-positives rate [15]. More studies of the advantages of mammography screening for some age groups revealed that the benefits of early detection are accompanied by overdiagnosis. This demonstrates the need for proper and uniform diagnosis tools [16].

Critically reviewed also are the invasive diagnostic procedures and the broader limitations in imaging. Despite its focus on complications associated with a particular form of cancer, the study demonstrates the overall risks associated with invasive diagnostic procedures. This is consistent with the goal of unnecessary procedures to be reduced, and to make the noninvasive diagnosis better [17]. Although resolution has improved and multimodal imaging is now available, the issues of inconsistent interpretation, unequal data and workflow integration have not been addressed in recent reviews of imaging progress [18]. The difficulties in this section suggest, that while an improvement in imaging is important, tools to help with the image analysis is also required.

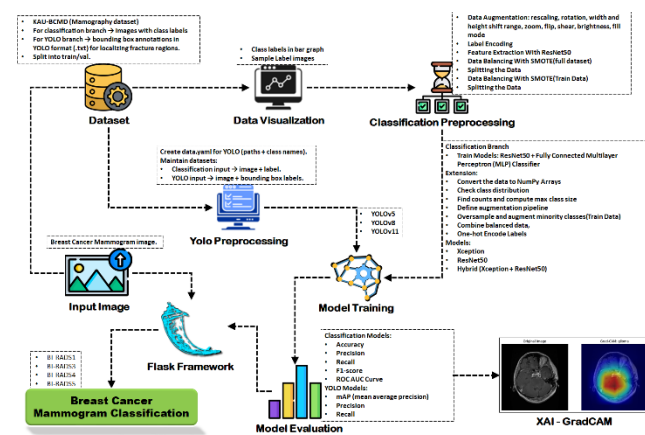
There are large studies that have proven that under some circumstances, systems based on artificial intelligence, through positive metrics, can be as successful as professionals in breast cancer screening, especially in terms of reducing false-positive variation and reducing the workload of the radiologist [19]. However, these types of systems are dependent on large and well-balanced datasets, and they might not extrapolate to other groups of patients or clinical situations. Although the techniques have made great strides in accuracy, survey studies of both ML and DL systems suggest that the methods have several limitations, including limited robustness, inadequate class imbalance and overfitting with the data, which prevent them from being applied in practice [20].

Existing research show that clinical imaging has made great strides, as have the smart diagnostic systems, but there are still some areas that need to be improved. Some of these are data imbalance, performance gap between datasets and lack of generalisability in different clinical settings. So, the intention of the current work is to establish a consistent and honest learning system on the way to strengthening diagnostic consistency and generalizability. The recommended study is intended to enable more stable and effective breast cancer screening support systems to be established in reality, both in terms of stable classification results and dealing with issues of data distribution.

## III. MATERIALS AND METHODS

Proposed method seeks to identify the breast cancer accurately and automatically utilising KAU-BCMD mammography dataset, which has the images labelled to help in finding the faults. It is defined by an organised learning pathway of conventional data preparation and representation learning, stressing balance and resilience in data modelling. ResNet50 is used to generate deep feature representations, while SMOTE is employed to resolve the class imbalance and more balanced distribution of the classes as well as higher prediction accuracy. A fully connected multi-layer perceptron is adopted for learning patterns to distinguish the deep features as a classification head. We are exploring hybrid and comparative modelling approaches by incorporating Xception, ResNet50 and an integrated Xception-ResNet50 framework to further enhance the performance. YOLO-based detectors can assist in region-level detection of abnormalities, and Grad-CAM can help to understand the images, enhancing professional confidence. Lastly, a deployment tool written in Flask enables real-time inference on a large scale. In general the proposed structure

improves the accuracy of breast cancer screening systems, making them more general and simpler to understand and use.



“Fig. 1. Proposed Architecture”

The first step in the system design is to preprocess the data and convert into NumPy array. Then features are extracted from the image using a ResNet50 model. The information is divided into training sets and testing sets. Training facts are stored and balanced using SMOTE. The original and balanced data are transformed and fostered within the custom CNN community for its learning. Finally, the training model is evaluated on an individual dataset and a balanced test dataset to determine the efficiency of the version and its stability.

#### A) Dataset Collection

The tests are created from a collection of BI-RADS mammography images, which are available for all to use and in an open medical imaging repository. This collection of the 2,378 breast images is broken into four diagnostic categories called BI-RADS 1, 3, 4, and 5. The images are presented in the standard raster formats and depict various breast conditions. The number of cases per class is extremely skewed, characteristic of clinical incidence in the real world. The labels provided have been approved by doctors, and the dataset is valuable for automatic analysis of breast abnormalities, because it is real, and has a high degree of diagnostic complexity.

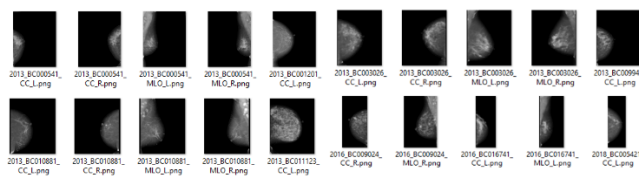


Fig.2

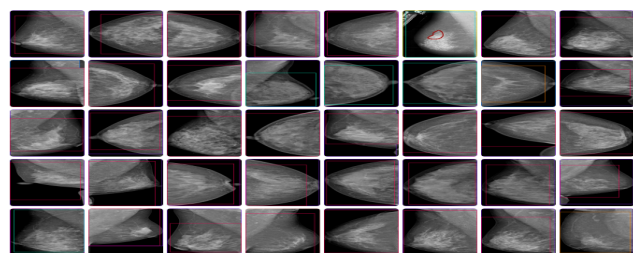


Fig.3

#### B) Pre-Processing

The pre-processing stage involve the processing of the mammographic data for the reliable learning, such as picture normalisation, label encoding, class imbalance, and discriminative feature generation. These steps ensure that learning is effective, equitable and enhances diagnostic ability.

**Image Pre-processing and Normalization:** To make sure that all the samples were the same, all the mammograms were resized to the same spatial precision and turned into numerical arrays. The way intensities of pixels were normalized was done through a standard method which was similar to the ones that have been taught by other convolutional networks. This reduces the variation which is caused by different sized pictures and different lighting conditions, and learning is more stable. To get good results from feature extraction, there needs to be a standardized way of representing images; this ensures models of DL can function. This speeds up the convergence of the models, stabilizes them and enhances their capacity to classify images in general.

**Label Encoding:** Supervised learning was simplified by converting the diagnostic labels into numbers, which were categorical and from the same groups as the BI-RADS. This change will simplify the interpretation of the class information by the learning program and preserve the meaning of each diagnostic category. Label encoding is a crucial pre-processing phase before engaging with multi-class classification tasks, ensuring consistent data representation, proper loss calculation, and efficient integration of optimization and evaluation steps in the learning process.

**Feature Engineering:** A deep feature extraction approach was used to get high-level discriminative features from mammograms that had already been processed. Instead of raw image values, compact feature vectors were used to identify the important visual patterns which might be used to describe the breast abnormality. This technique reduces dimensionality of the data while retaining clinically meaningful information. This helps in classification to be more efficient. Feature engineering for better model performance entails getting more ‘good’ features and minimizing noise, redundancy, and overfitting in subsequent learning phases.

**Class Imbalance Handling:** In order to counter the large disparity in the number of cases between the different categories, the feature space was oversampled synthetically. It is one way to get samples of minority groups that represent that group. This will keep the ranges in the class as they are, while balancing between them. Another challenge in medical diagnosis tasks is the class imbalance, that can cause skewed data and bias the classification towards the majority classes. The new technique is more fair, more responsive to rare situations and more reliable, generally.

#### C) Training and Testing:

The dataset was divided into training and testing sets carefully maintaining the ratio of class labels. This multi-layer partitioning will ensure an unbiased composition of both subsets, thus allowing an unbiased performance evaluation. It is important to partition data for testing generalisation, and also to prevent data leakage. This step provides us with a good means to test whether our model is correct and how the results differ if we conduct experiments of different types.

#### D) Algorithms

**ResNet50 with Fully Connected Multilayer Perceptron (MLP) Classifier:** It is possible to perform deep residual feature learning and a nonlinear classification using a fully connected MLP classifier with ResNet50. Residual connections help to ensure stable optimization while dense layers help to tune decision limits. This enhances the accuracy, robustness and generalization of classification under a large imaging condition.

**Xception Network:** It uses depthwise separable convolutions to extract space and channel knowledge for improvement in classification. This design reduces the amount of information, accelerates training speed and facilitates powerful representation learning for stable and accurate picture classification.

**ResNet50 Network:** ResNet50 enables the deep features to be reliably obtained by residual learning, allowing the gradients to flow smoothly between layers. Architecture is designed for the purpose of learning through hierarchical representations, leading to a more stable, reliable and effective classification capability even under the changing visual conditions.

**Hybrid Xception-ResNet50 Architecture:** Xception-ResNet50 architecture is a hybrid that involves two different but complementary methods of feature representation. This is achieved with an efficient spatial encoding along with a deep residual abstraction. This integration not only enhances the number of features but also improves the robustness of the system against noise and improves the confidence in generalization and classification.

**YOLOv5:** For instance, the classification and location can be learned simultaneously, which means YOLOv5 can locate objects rapidly in one step. It is unified and hence gives a quick inference, the region is detected accurately and with uniform performance. It allows for the spatial interpretation and deployment to be reliable to scale up.

**YOLOv8:** YOLOv8 is designed to be more convenient to search for objects by combining features more intelligently and learning them from space. Improved sensitivity to irregular and small areas leads to better localization accuracy, robustness and generalization, with maintaining the efficiency of real-time recognition.

**YOLOv11:** YOLOv11 addresses these issues with an enhanced ability to detect features and determine their spatial location, enabling more effective single-stage detection. The architecture enhances localization precision and class balance to ensure easier and more reliable access to items of various sizes and lighting conditions.

#### IV. EXPERIMENTAL RESULTS

**Accuracy:** The accuracy of a take a look at is the ability of a take a look at to distinguish between healthy and unhealthy people. To specialize in how accurate the test is, we need to calculate the ratio of TP to TN. This can be expressed mathematically as follows

$$\text{“Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} (1)\text{”}$$

**Precision:** Precision is the percentage of number of cases/samples categorised properly / number of cases/samples classified correctly as positive. Therefore the method to determine the precision will be as follows:

$$\text{“Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (2)\text{”}$$

**Recall:** Recall in ML is a metrics that measures how well an ML model can return all of the relevant examples of a particular class. This is an indication of the class model's encoding capabilities. Because it is defined as the ratio of the variations of perfectly expected observations, to the large variation of observations that are just positive.

$$\text{“Recall} = \frac{TP}{TP + FN} (3)\text{”}$$

**F1-Score:** The F1 score is the accuracy of the ML model. It calculates the accuracy score of a model and recall score and combines these scores. The accuracy measure is the percentage of times (over all the data) that a model predicted a correct answer.

$$\text{“F1 Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} * 100 (1)\text{”}$$

**mAP:** A measure of quality MAP: A ranking measure. It takes into account the quantity and position of the related suggestions. MAP (K) is the average of the AP (K) of all users or searches multiplied by 100.

$$\text{“mAP} = \frac{1}{n} \sum_{k=1}^{k=n} AP_k (5)\text{”}$$

“Table. 1. Performance Evaluation Table – Classification”

| ML Model           | Accuracy | Precision | Recall | F1_score |
|--------------------|----------|-----------|--------|----------|
| proposed_full_bal  | 0.995    | 0.995     | 0.995  | 0.995    |
| proposed_train_bal | 0.948    | 0.775     | 0.556  | 0.570    |
| Xception           | 0.905    | 0.759     | 0.571  | 0.609    |
| ResNet50           | 0.926    | 0.701     | 0.655  | 0.649    |
| Hybrid-Ensemble    | 0.914    | 0.767     | 0.761  | 0.764    |

The suggested fully balanced model achieved near maximum results, outperforming over accuracy, precision, recall, and F1-scores, when compared to the Xception, ResNet50 and hybrid ensemble models.

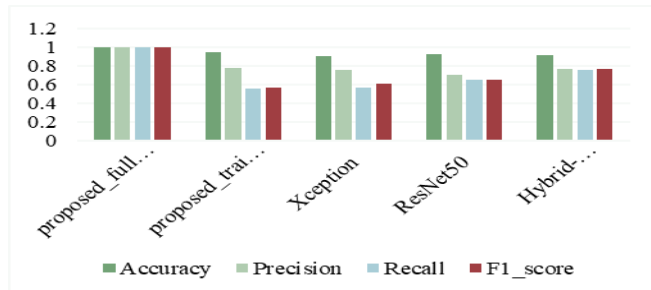
“Table.2 Performance Evaluation Table – Detection”

| ML Model | Precision | Recall | mAP   |
|----------|-----------|--------|-------|
| Yolo v5  | 0.476     | 0.639  | 0.460 |

|          |       |       |       |
|----------|-------|-------|-------|
| Yolo v8  | 0.458 | 0.596 | 0.462 |
| Yolo v11 | 0.435 | 0.777 | 0.284 |

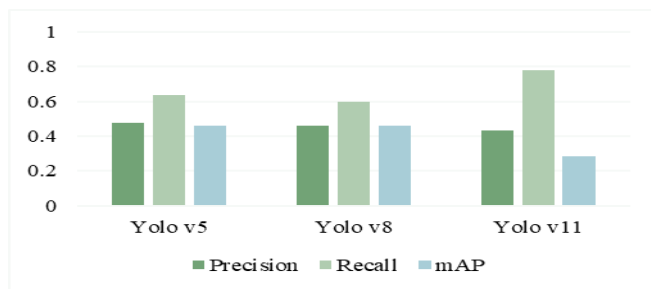
As can be seen from the above table, the higher the precision, the lower the recall and vice versa. Also, it is observed that YOLOv5 has better mAP and Precision while yolo-v11 has the highest Recall. This indicates that there are compromises in terms of both detectability and sensitivity.

“Fig. 4. Comparison Graph – Classification”



The fully balanced model that was proposed is better at all the metrics of accuracy, precision, recall and F1 score than all the other models as seen in the comparison graph and does not lose compared to the other models as it gets better at classification.

“Fig 4. Comparison Graph – Detection”

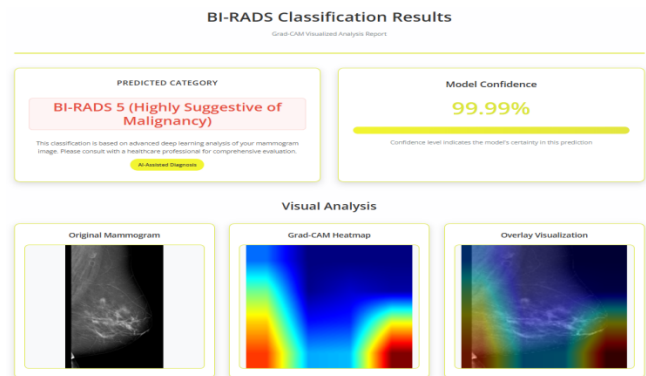


The result indicates that the recall of the different versions of YOLO is best with YOLOv11, YOLOv5 is the best for recall, mAP and precision, and YOLOv8 performs best for detection across all the metrics.



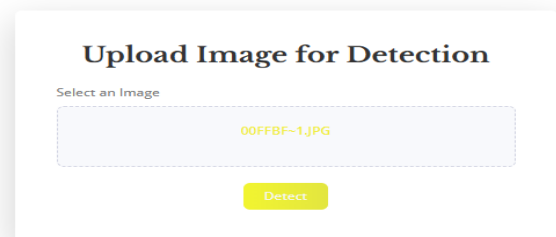
“Fig.5Upload the Image”

The interface allows the user to upload an image file, which is then predicted and a "predict" button appears enabling automated model-driven analysis and classification of the image.



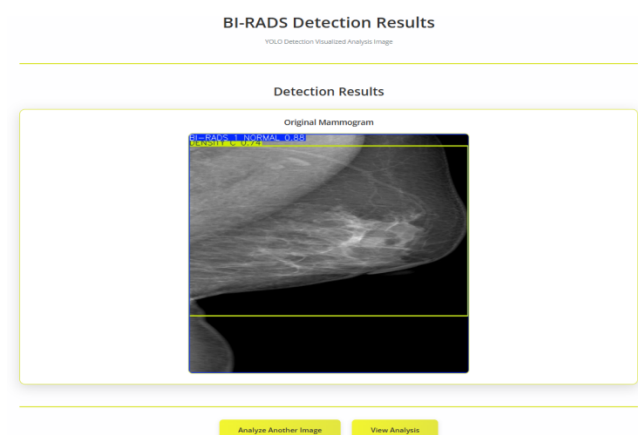
“Fig.6Predicted Result”

The result shows a BI-RADS 6 classification with 99.99% model confidence, which means there is a high chance of malignancy. This is validated by the visual analysis of the original mammogram, the Grad-CAM heatmap and the overlay visualization.



“Fig. 7 Upload the Image”

The interface lets users share an image to be used for object detection. It displays the name of the file uploaded and a "detect" button which initiates automatic detection and analysis of the uploaded object with a pre-trained detection model.



“Fig. 8 Predicted Result”

The output shows the BI-RADS detection results on the original mammogram, showing the detected areas with boxes around them. This allows you to better visualize issues, and facilitates the analysis of BC detection in an automatic fashion.

## V. CONCLUSION

The method is meant to make it possible to accurately and automatically find and classify breast cancer. This addresses the urgent need of speed and accuracy in diagnosis from the mammogram images. It is based on KAU-BCMD Mammography dataset that contains labeled pictures and bounding boxes indicating the location of abnormalities. The method involves many different steps prior to using. Such steps are applied to the entire data set and training groups. These are the data enhancement, label encoding, ResNet50 feature extraction and class balancing via SMOTE. For classification, ResNet50 featuring the fully connected multilayer perceptron, Xception and a hybrid Xception-ResNet50 design are utilized. Abnormality detection is done using YOLOv5, YOLOv8 and YOLOv11 models. Improvements like GradCAM make it easier to understand how important areas affect forecasts, and a Flask-based interface makes deployment in real time and is easy for anyone to use. All the evaluation indexes were 99.5%, and the detection performance of YOLOv8 was better, the mAP was 0.462, which proved that the system worked. In conclusion, a deep feature extraction, balanced data handling, hybrid architecture, and interpretable visualization are a very reliable, scalable, and clinically useful solution. Supports computers to make decisions and enhances the diagnostic performance of real-world mammography analysis.

Future improvements involve adding larger and diversified mammograms sets to enhance the model performance in its applicability to other groups in the future. There are several designs used in ensemble learning that can be used to combine various designs and boost the accuracy of the categorisation, resulting in fewer false positive. Real-time imaging data from several imaging types such as ultrasound or MRI may help in diagnosis. By optimising the distribution of the edges, low latency predictions could be performed on device for clinical use. Beyond GradCAM, other AI techniques that can be conveyed to a clinician, such as SHAP or LIME, may enable them to understand the model. In reality it would be easier and quicker to use if it could have been embedded in hospital information systems and telemedicine systems, giving physicians greater choice in the way they detect breast cancer.

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