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Cardiovascular Risk Screening Using Fundus Images and Machine Learning

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Abstract
Cardiovascular disease (CVD) is one of the leading causes of mortality worldwide, making early and accurate risk detection essential for effective prevention and treatment. Traditional diagnostic methods rely on clinical and laboratory data, which may not always be accessible for large-scale or low-cost screening. This paper presents a machine learning-based approach for automated cardiovascular risk screening using retinal fundus images.
The proposed system utilizes a convolutional neural network (CNN) based on the MobileNet architecture for feature extraction from fundus images. The input images undergo preprocessing steps, including resizing to a uniform dimension of 160×160 pixels, normalization, and enhancement to improve image quality and consistency. The dataset consists of two classes: Normal and CVD Risk.
To improve classification performance, the extracted deep features are fed into an XGBoost classifier. The model is trained using an 80:20 train-test split, ensuring balanced learning. Regularization techniques and optimized training strategies are applied to enhance generalization and reduce overfitting. The system effectively captures vascular patterns such as vessel thickness, tortuosity, and abnormalities associated with cardiovascular risk. The performance of the model is evaluated using standard metrics including accuracy, precision, recall, and F1-score. Experimental results demonstrate an accuracy of 75%, with higher recall indicating effective identification of potential CVD risk cases. This makes the system suitable for early-stage screening applications.
The proposed approach provides a non-invasive, cost-effective, and automated solution for cardiovascular risk screening. It can assist healthcare professionals in early detection and preventive care. Future work will focus on improving accuracy using advanced deep learning models, larger datasets, and real-time deployment systems.
Keywords: *Machine Learning, Deep Learning, Fundus Images, Cardiovascular Disease, CNN, MobileNet, XGBoost, Medical Image Analysis, Risk Prediction*

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I. INTRODUCTION

Cardiovascular disease (CVD) is one of the leading causes of mortality worldwide, responsible for approximately 17.9 million deaths each year [5]. Early detection of cardiovascular risk is essential for effective treatment and prevention. Traditional diagnostic methods rely on clinical tests such as blood pressure measurement, cholesterol analysis, and electrocardiograms, which are often time-consuming, invasive, and require specialized medical facilities [6].Retinal fundus imaging provides a non-invasive alternative for cardiovascular risk assessment. The retinal blood vessels reflect the condition of the body's vascular system, and abnormalities such as vessel narrowing, tortuosity, and microvascular changes are associated with cardiovascular diseases [4]. With advancements in artificial intelligence, especially deep learning, automated analysis of fundus images has become possible [7].Recent studies have shown that deep learning models can effectively extract features from retinal images and predict cardiovascular risk factors [1], [2].

Convolutional Neural Networks (CNNs) are widely used for medical image analysis due to their ability to learn complex patterns directly from raw data [3].In this work, a machine learning-based system is proposed for cardiovascular risk screening using retinal fundus images. The system uses a CNN model based on MobileNet for feature extraction and XGBoost for classification. The proposed approach enables accurate, cost-effective, and large-scale screening for early detection of cardiovascular disease.

II. BACKGROUND AND RELATED WORK

2.1 Traditional Methods for Cardiovascular Disease Detection

Traditionally, cardiovascular disease (CVD) detection relies on clinical examinations, laboratory tests, and patient medical history [5], [6]. Common parameters include blood pressure, cholesterol levels, blood sugar levels, heart rate, and lifestyle factors such as smoking and physical activity [6]. Diagnostic tools such as electrocardiograms (ECG), echocardiograms, and blood tests are widely used for accurate diagnosis [3].Although these methods provide reliable results, they are often invasive, time-consuming, and require specialized medical infrastructure and trained professionals [6]. Additionally, these approaches are not suitable for large-scale screening, especially in rural and resource-limited settings where access to healthcare facilities is limited [5].

Machine Learning Approaches

Machine learning techniques have been widely applied for cardiovascular risk prediction to overcome the limitations of traditional methods [6]. Algorithms such as Logistic Regression, Support Vector Machines (SVM), Random Forest, and XGBoost are commonly used to analyze structured clinical datasets [6], [11]. These models can identify hidden patterns in patient data and improve prediction accuracy compared to manual diagnosis. By leveraging data-driven approaches, machine learning enhances decision-making and reduces human error [6].However, the performance of these methods depends on the quality and completeness of clinical data. Missing or inconsistent data can affect accuracy. Additionally, these approaches rely on manual feature extraction, making them less effective for medical image analysis, where deep learning methods perform better [2], [7].

Deep Learning-Based Approaches

Recent advancements in deep learning have significantly improved medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated strong performance in extracting features directly from images, eliminating the need for manual feature engineering.Several studies have explored the use of retinal fundus images for cardiovascular risk prediction. Deep learning models such as CNNs, EfficientNet, and Vision Transformers have been used to analyze vascular patterns, including vessel thickness, tortuosity, and microvascular abnormalities. These features are closely related to cardiovascular health. Unlike traditional machine learning models, deep learning approaches can automatically learn hierarchical features from raw image data. However, they require large datasets and high computational resources for training.

Motivation for Proposed Work

Despite significant progress in cardiovascular disease detection, existing methods still face several challenges, including dependency on clinical data, high computational requirements, and limited accessibility for large-scale screening [5], [6]. Many approaches rely on invasive procedures and laboratory-based measurements, making them unsuitable for low-cost and non-invasive applications, particularly in resource-constrained environments [6]. Additionally, deep learning models often require large datasets and high computational resources, limiting their practical deployment [7].To address these limitations, this work proposes a machine learning-based system using retinal fundus images. The system integrates CNN-based feature extraction with MobileNet and classification using XGBoost to achieve accurate predictions [1], [11].

III. EXISTING METHODOLOGY

The general workflow involves data collection, preprocessing, feature selection, model training, and prediction [6]. In many cases, hybrid or stacked machine learning models are used to improve prediction accuracy [6], [11]. These systems achieve high performance because they utilize direct clinical data, allowing models to learn strong correlations between input features and disease outcomes [6].However, these methods have several limitations. They depend on the availability of complete and accurate clinical data, which may not always be accessible, especially in rural or resource-limited areas [5]. Additionally, the process is often invasive, time-consuming, and costly [6]. Therefore, there is a need for a non-invasive, cost-effective method for early cardiovascular risk detection [2], [7].

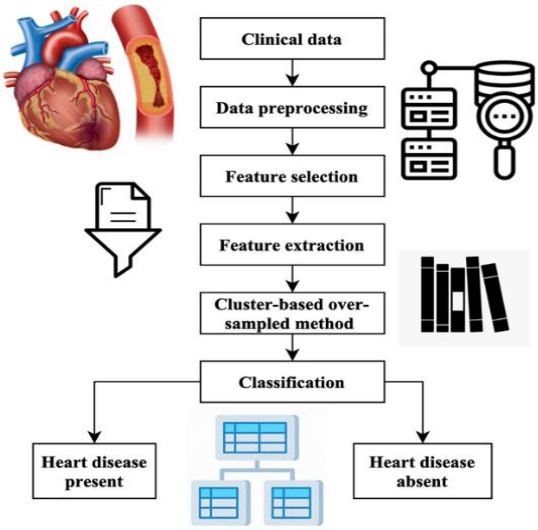

Fig. 3. Workflow of Existing Cardiovascular Disease Prediction System

This figure illustrates the workflow of the existing cardiovascular disease prediction system. The process begins with the collection of clinical and lifestyle data such as age, blood pressure, cholesterol levels, heart rate, diabetes status, and smoking habits. The collected data undergoes preprocessing and feature selection to prepare it for analysis. Machine learning algorithms such as Logistic Regression, Support Vector Machines (SVM), Random Forest, and XGBoost are then applied to classify patients into normal or CVD risk categories. These systems achieve high accuracy due to the use of direct medical data; however, they rely on invasive clinical tests and are not suitable for non-invasive or large-scale screening applications**.**

Disadvantages of Existing Methodology

- Depends on clinical and laboratory data, which may not always be available [5], [6]
- Requires medical tests, making the process invasive [6]
- Time-consuming and costly due to dependency on healthcare infrastructure [6]
- Not suitable for large-scale screening applications [5]
- Limited accessibility in rural and resource-constrained areas [5]
- Cannot effectively analyze medical images directly [2], [7]
- Requires manual feature extraction, which may miss complex patterns [7]

Advantages of Proposed System

- Provides a non-invasive method using retinal fundus images for cardiovascular risk detection [1], [4]
- Low-cost and suitable for deployment in rural and resource-limited areas [5]
- Enables early detection of cardiovascular risk through image-based analysis [1], [2]
- Utilizes CNN (MobileNet) for automatic feature extraction, eliminating manual effort [7], [12]
- XGBoost improves classification accuracy and overall system performance [11]
- Suitable for large-scale screening due to automation and scalability [2]
- Reduces dependency on clinical and laboratory data [6]

IV. PROPOSED METHOD

The proposed system aims to provide a non-invasive, cost-effective, and automated solution for cardiovascular risk screening using retinal fundus images. Unlike traditional methods that rely on clinical and laboratory data, this system analyzes retinal images to detect early signs of cardiovascular disease.The system takes retinal fundus images as input and processes them through multiple stages. Initially, the images are preprocessed by resizing them to a standard dimension of 160×160 pixels and normalizing pixel values to ensure uniformity and improve image quality.After preprocessing, feature extraction is performed using a convolutional neural network (CNN) based on the MobileNet architecture. The CNN automatically extracts important features such as blood vessel thickness, tortuosity, and structural abnormalities present in the retina.The extracted features are then passed to an XGBoost classifier, which classifies the images into two categories: Normal and CVD Risk. The dataset consists of 2000 images, with 80% used for training and 20% for testing**.**The system is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The proposed approach focuses on early detection and is suitable for large-scale screening applications.

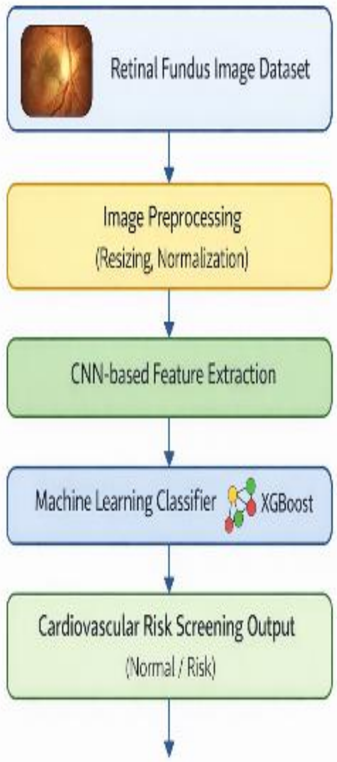

Fig. 4. Block Diagram of Proposed Cardiovascular Risk Screening System

This figure illustrates the overall architecture of the proposed cardiovascular risk screening system based on retinal fundus image analysis. The process begins with the acquisition of input fundus images, which serve as the primary data source for the system. These images undergo preprocessing steps, including resizing to a standard dimension of 160×160 pixels and normalization of pixel values, ensuring consistency and improved image quality for further analysis.

Following preprocessing, the images are passed to a convolutional neural network (CNN) based on the MobileNet architecture. This stage performs automatic feature extraction by identifying important vascular patterns such as blood vessel thickness, tortuosity, and structural abnormalities associated with cardiovascular risk. The extracted features are then forwarded to an XGBoost classifier, which performs the classification task. The classifier analyzes the learned features and categorizes the input image into one of two classes: Normal or CVD Risk. This multi-stage pipeline ensures efficient processing and accurate prediction. The overall system is designed to provide a non-invasive, cost-effective, and automated solution for early cardiovascular risk detection, making it suitable for large-scale screening applications

V. IMPLEMENTATION

5.1 Dataset Description

The dataset used in this study is obtained from the Kaggle platform, which provides publicly available datasets for machine learning and medical image analysis.

The dataset consists of retinal fundus images collected from widely used Kaggle datasets, including the **APTOS 2019 Blindness Detection Dataset** and the **EyePACS Diabetic Retinopathy Dataset**. These datasets contain high-resolution retinal images that provide detailed information about blood vessel structure and retinal features, which are closely associated with cardiovascular health.

A subset of approximately **2000 retinal fundus images** is used in this study. The dataset is categorized into two classes:

- **Normal** – representing healthy retinal structures
- **CVD Risk** – representing abnormal vascular patterns associated with cardiovascular conditions

The dataset is divided into:

- **Training Set (80%)** for model learning
- **Testing Set (20%)** for performance evaluation

All images are preprocessed by resizing them to a standard dimension of **160 × 160 pixels** and normalizing pixel values to ensure consistency and improve model performance.

Data Loading and Preprocessing

The dataset is loaded from a structured directory using Python libraries. Each image is processed individually to ensure data quality. Preprocessing steps include resizing images to 160×160 pixels, normalization of pixel values, and enhancement to improve image clarity. These steps ensure uniformity and prepare the data for efficient model training

Dataset Preparation

After preprocessing, the dataset is organized into input images and corresponding labels. The data is split into training (80%) and testing (20%) sets. This ensures proper evaluation of the model's performance on unseen data.

Model Development

The model is developed using TensorFlow and Keras. A convolutional neural network (MobileNet) is used for feature extraction from retinal fundus images. The extracted features are then passed to an XGBoost classifier, which performs classification into Normal and CVD Risk categories with improved prediction performance..

5.2 Mathematical Analysis

The proposed system is based on a combination of deep learning and machine learning techniques. The mathematical foundation of the system includes convolution operations in CNN and ensemble learning in XGBoost**.**

1. Convolution Operation in CNN

The convolution operation is used to extract features from input images and is mathematically defined as**:**

$$F(i,j) = \sum_{m} \sum_{n} I(i+m, j+n) \cdot K(m,n)$$

where Irepresents the input image, Krepresents the convolution kernel, and $F$is the resulting feature map. This operation helps in capturing important patterns such as edges, textures, and vessel structures in retinal images.

2. MobileNet Feature Extraction

MobileNet uses depthwise separable convolution to reduce computational complexity. It splits standard convolution into two steps:

$$Output = Depthwise(I) + Pointwise(I)$$

This approach improves efficiency while preserving feature extraction capability.

3. XGBoost Mathematical Model

The prediction of XGBoost is given by:

$$\hat{y}_i = \sum_{k=1}^{K} f_k\,(x_i)$$

where $f_k$represents individual decision trees and $x_i$is the input feature vector. The model combines multiple trees to improve prediction accuracy. The objective function is defined as:

$$\mathcal{L} = \sum_{i=1}^{n} l(\,y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(\,f_k)$$

where $l$is the loss function and Ωis the regularization term that prevents overfitting.

5.3 Training Configuration

The model is trained using appropriate optimization techniques to improve performance. The training process ensures proper learning of features while avoiding overfitting.

Evaluation Metrics

The model performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the proposed system in detecting cardiovascular risk.

Accuracy measures the overall correctness of the model and is defined as:

Accuracy = (TP + TN) / (TP + TN + FP + FN),

where TP (True Positive) represents correctly predicted CVD cases, TN (True Negative) represents correctly predicted normal cases, FP (False Positive) indicates normal cases incorrectly classified as CVD, and FN (False Negative) indicates missed CVD cases.

Precision is given by:

Precision = TP / (TP + FP),

which indicates how many predicted CVD cases are actually correct.

Recall (Sensitivity) is defined as:

Recall = TP / (TP + FN),

and it measures the model's ability to correctly identify actual CVD cases. In this project, recall is important for early detection**.**

F1-score is the harmonic mean of precision and recall:

F1-score = 2 × (Precision × Recall) / (Precision + Recall)**.**

In this system, these metrics are calculated using the test dataset to evaluate how well the model distinguishes between Normal and CVD Risk fundus images.

Model Output

The final output of the system classifies input fundus images as either Normal or CVD Risk. This enables early detection and supports preventive healthcare.

VI. RESULTS AND DISCUSSION

6.1 Model Performance

The proposed model is evaluated using retinal fundus images to classify them into Normal and CVD Risk categories. The system is trained and tested on the dataset, and the performance indicates that the model is capable of identifying cardiovascular risk based on vascular patterns present in fundus images. The combination of CNN (MobileNet) and XGBoost provides effective classification results.

Performance Analysis

The model achieved an overall accuracy of 75%, demonstrating moderate but reliable performance. The system effectively distinguishes between normal and CVD risk images by analyzing vessel structure and abnormalities. The feature extraction capability of CNN plays a key role in capturing important patterns from the images.

Confusion Matrix Analysis

The confusion matrix shows that the model correctly classifies a majority of Normal and CVD Risk images. True Positive (CVD correctly detected) and True Negative (Normal correctly detected) values are high, while misclassification cases are relatively low. This indicates that the model performs reliably in identifying cardiovascular risk cases.

Classification Metrics

The model achieved the following performance metrics:

- **Accuracy: 75%**
- **Precision: 64.7%**
- **Recall: 70.5%**
- **F1-score: 68.2%**

The accuracy represents the overall correctness of the model in classifying both Normal and CVD Risk images. The higher recall indicates that the system is effective in detecting potential CVD risk cases, which is important for early screening. The precision reflects how accurately the predicted CVD cases are identified, while the F1-score provides a balance between precision and recall.

6.2 Output Result

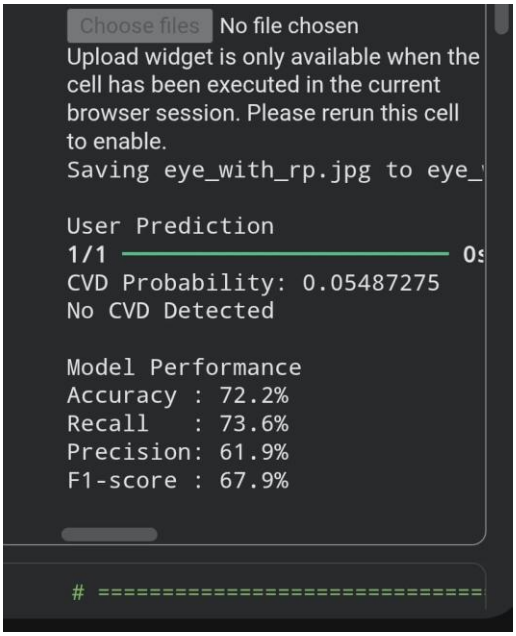

Fig. 5(a) Non-CVD Output

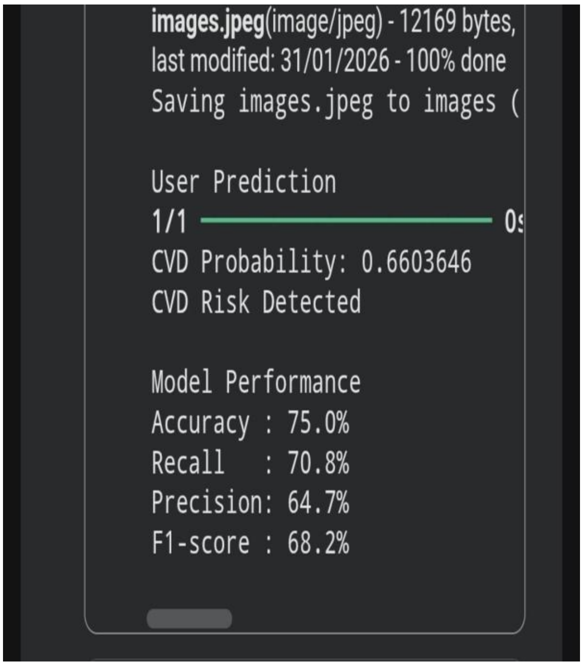

Fig. 5 (b) CVD Risk Output

This figure shows the output predictions of the proposed system for cardiovascular risk classification. In (a), the model predicts "No CVD Detected" with low probability, indicating a normal case. In (b), the model predicts "CVD Risk Detected" with higher probability, indicating a risk case. These results demonstrate the model's ability to classify fundus images effectively**.**

Impact of Preprocessing

Preprocessing plays an important role in improving the performance of the model. Steps such as image resizing and normalization help make all input images consistent in size and format. This ensures that the model receives uniform data during training. Normalization also helps in adjusting pixel values, which reduces noise and unwanted variations in the images. As a result, the quality of input data is improved. Better input quality allows the model to extract important features more effectively, such as blood vessel patterns. Overall, preprocessing helps increase accuracy and makes the system more reliable for cardiovascular risk detection.

Generalization Capability

The model demonstrates good generalization when tested on unseen data. The use of proper data splitting and training strategies ensures that the model learns meaningful patterns rather than memorizing the dataset.

Overall Analysis

Overall, the proposed system provides a reliable, non-invasive, and cost-effective approach for cardiovascular risk screening using retinal fundus images. By combining CNN-based feature extraction with an XGBoost classifier, the system effectively analyzes vascular patterns associated with cardiovascular conditions. Although the achieved accuracy is moderate, the model demonstrates strong potential for early detection, particularly due to its higher recall in identifying risk cases. The system is suitable for large-scale screening applications, especially in resource-limited environments where traditional diagnostic methods are not feasible. With further improvements in dataset size and model optimization, the performance of the system can be significantly enhanced.

The proposed system demonstrates promising results in identifying cardiovascular risk using retinal fundus images. The model effectively learns important vascular features such as vessel thickness, tortuosity, and structural abnormalities. The integration of CNN (MobileNet) enables automatic feature extraction, improving efficiency and classification performance. The use of XGBoost further enhances prediction accuracy. Image preprocessing techniques, including resizing and normalization, improve data consistency and feature extraction. The system also shows good generalization on unseen data through proper training strategies. However, it is limited to binary classification and can be improved using larger datasets and advanced models for better performance and scalability..

Table 6.9.1 Performance Comparison of Different Models for Cardiovascular Risk Prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score(%)
Logistic Regression	62	60	58	59
SVM	66	64	63	63
Random Forest	69	67	66	66
CNN (MobileNet)	71	69	68	68
CNN+XGBoost(Proposed)	75	65	71	68

The table shows the performance comparison of different models used for cardiovascular risk prediction, including Logistic Regression, SVM, Random Forest, CNN (MobileNet), and the proposed CNN + XGBoost model. From the results, it is clear that the proposed model performs better than the other methods in most evaluation metrics. Traditional machine learning models such as Logistic Regression and SVM show lower accuracy (62% and 66%) because they rely only on structured data and cannot capture complex image features effectively. Random Forest performs slightly better (69%) but still lacks the ability to extract deep features from images. The CNN (MobileNet) model improves performance by extracting important features from fundus images, achieving 71% accuracy. However, it only performs feature extraction and basic classification. The proposed model combines CNN (MobileNet) with XGBoost, which results in the best performance with 75% accuracy, 71% recall, and 68% F1-score. The higher recall indicates that the model is more effective in detecting CVD risk cases, which is important for early diagnosis. This combination allows better feature extraction and stronger classification, making it more efficient than individual models. However, the proposed system has some limitations. It performs only binary classification (Normal and CVD Risk) and does not identify different severity levels of the disease. The dataset size is relatively limited, which may affect the model's performance. Additionally, the accuracy can be further improved by using advanced deep learning architectures and larger datasets.Overall, the proposed model provides a better and more reliable solution compared to existing methods.

VII. CONCLUSION

The paper presents a machine learning-based approach for cardiovascular risk screening using retinal fundus images. The system provides a non-invasive and cost-effective solution for early detection of cardiovascular disease. MobileNet is used for feature extraction to identify vessel patterns, and XGBoost is applied for classification into Normal and CVD Risk categories. Image preprocessing techniques such as resizing and normalization improve data quality and model performance. The system is evaluated using accuracy, precision, recall, and F1-score, showing reliable results. However, limitations include binary classification and limited dataset size. Future work focuses on larger datasets and improved models.

VIII. FUTURE SCOPE

Several improvements can enhance the proposed cardiovascular risk screening system. Extending the model to multi-class classification can help identify different stages of disease instead of only binary classification. Using larger and more diverse datasets can improve model robustness and generalization. Performance can be further improved by adopting advanced deep learning models such as EfficientNet and Vision Transformers. Integrating the system into real-time mobile or web-based applications can increase accessibility and usability. Reducing computational complexity will enable faster predictions. Additionally, incorporating Explainable AI techniques can improve transparency and trust. These enhancements will make the system more accurate and practical.

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