AI powered Early Detection of diabetic retinopathy: A Deep Learning Approach for improved Clinical Decision-Making.

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ABSTRACT

Diabetic retinopathy (DR) is one of the primary reasons of vision loss conditions, and the prevention of irreparable loss is essential. The study involves deep learning models with applications to the detection of automatic DR of retinal fundus images, the purpose of which is to help specialists make a more accurate decision and enhance the accuracy of diagnoses. Four large -scale deep learning networks were tested by five severities of retina penalty namely CNN, ResNet50, DenseNet121 and InceptionV3 architecture on a sampled data set comprising 35,000 retina images. Preprocessing of data, additional data, and transfer learning were also implemented to improve model generalization. They were proven to be capable of 90.8% testing accuracy and 0.92 AUC-ROC with experimental results indicating CNN as a baseline. The RN50 saw a better increase in detection to 91.9% and 0.93 AUC-ROC, with DenseNet121 once again making a jump of 92.6% and 0.94 AUC-ROC for detection. The model that best did its work, InceptionV3 had the highest test accuracy, the model returned a cross of 93.2% and AUC-ROC was 0.95 that truly differentiated all levels of DR phases: Mild level, Severe level, and Proliferative. The article notes that many deep learning models, especially InceptionV3 and DenseNet121, are capable of autonomously diagnosing DR and reducing the workload of clinical staff, and they can enhance early treatment. These research results have proved the possibility of AI-based retomic ophthalmic systems being helpful tools in enhancing patient outcomes.

KEYWORDS: Diabetic Retinopathy, Deep Learning, InceptionV3, DenseNet121, Retinal Image Analysis.

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INTRODUCTION

One of the most common complications of diabetes mellitus is Diabetic Retinopathy (DR), which is also a major cause of blindness and vision loss in the world. According to the estimates of the World Health Organization, more than 422 million people worldwide live with diabetes, and a number of these individuals are susceptible to the occurrence of DR. It is important to diagnose DR at a young age because with the appropriate response in office, the patient can significantly improve their vision, thereby avoiding severe damage to the sight [1]. Conventionally, ophthalmologists or trained specialists examine retinal fundus with the manual diagnostic technique. Nevertheless, the procedure is time-consuming, subjective, and tends to inter and intra-observer. Presumed novelties in the field of artificial intelligence (AI) and deep learning have demonstrated enormous potential in medical image recognition by facilitating the automated, fast, and exceptionally exact identification of multiple diseases. The convolutional neural networks (CNNs) that form deep learning models have shown exceptional performance such as identifying complex patterns on retinal images that otherwise are likely to be invisible to the human eye [3]. With the help of these AI-based methods, they can detect the early signs of DR with high accuracy, treat it proactively and better manage patients. In this study, the author investigates a system development in profound learning-based to identify diabetic retinopathy at the onset and therefore improve clinical decision-making. The advanced image processing method and CNN architecture proposed as the suggested approach are combined together and designed to categorize retinal images based on the severity of DR. Moreover, it does not solely focus on the accuracy of detection but also interpretability as well, meaning that clinicians can rely on and respond to the AI-generated insights. This study aims to alleviate diagnostic workload, minimize the aspect of human error, and implement timely interventions with AI so that the quality of care given to diabetic patients can be improved.

RELATED WORKS

The field of ophthalmology and the early identification of diabetic retinopathy (DR) using the latest methods of image analysis is fast evolving due to artificial intelligence (AI). The diagnostic systems that rely on artificial intelligence integrate machine learning and deep learning algorithms to support clinicians in effective and prompt diagnosis and eventually enhance clinical decision-making. Recently, the benefits and the drawbacks of AI in ophthalmology have been highlighted with a focus on its massive capacity to help in eliminating diagnostic errors, automating routine tasks, and offering decisions support when handling complicated cases [15]. There are a few studies that tackle AI-based clinical decision support in diabetes management to reveal the way in which precision medicine could be improved among older adults by predicting disease effortlessly on a case-by-case basis [16]. Machine learning can not just be applied to detect diseases by other means than it has additionally been developed to be applied in more extensive medical care purposes like detecting fraud and assessing risks making it apparent that AI can be used versatiliably in medicine and healthcare in general [17]. Particularly, retinal images have been used to conduct stroke risk assessment and management, which revealed that there is a possibility to use ophthalmic AI applications in areas beyond DR activities towards general monitoring of vascular health [18]. Transfer learning methods have attracted considerable attention in the case of diabetic retinopathy, given their capability of employing the existing convolutional neural networks (CNNs) to analyze the retinal image. Systematic review has indicated that the deep transfer learning cells are more effective at detecting DRS by effectively extracting features out of small-sized datasets and in addressing image-quality variability [19]. Moreover, the incorporation of AI-based applications in pharmaceutical research efforts has illuminated how predictive analytics and diagnostics through images can revolutionize the patient discovery of drugs and an individualized treatment approach [20]. Recently, it was shown that precise diagnostic methods and surgeries in interconnected musculoskeletal and visual systems have been developed through the use of machine learning. The developments highlight how AI can be utilized to deliver a more thorough and multi-modal diagnostic experience through visual and clinical procedures [21]. The use of the fundus image to detect DR and AI has gained significant research interest, and studies argue that a deep learning model outperforms the classical manual grading method by being more sensitive and specific when it comes to disease severity classification [22].

Although AI technologies are developed, there are several barriers to the adoption of AI-assisted diagnoses in hospitals. Studies have revealed such tough issues as the integration of software, acceptance by clinicians, compliance to regulation, and infrastructure constraints, as well as facilitators of the phase, such as training, involvement of people in the process, and optimization of the workflow [23]. Additionally, the recent introduction of AI used with the optical coherence tomography (OCT)-based diagnostic system has further expanded the capabilities of diagnosing retinal anomalies and necessitated a strong security system together with the superior feature extracted techniques to ensure clinical credibility [24]. In optometric diagnostics and research, AI has also shown its potential to identify and forecast via deep-learning and time-series predictive measurements of retinal health and its condition [25]. Lately observed studies in the recognition of DR relying on transfer learning deep neural networks have proven numerous values of reliable awareness and high accuracy founded on the premise that well-constructed models could correctly categorize retinal image into various severity features to guide the course of early interventions [26]. Generally, reviewed literature shows that AI-based methods, specifically deep learning and transfer learning, are sulphurate towards precise, completely robotized, and massive DR detection. Nonetheless, the incorporated considerations to achieve successful implementation involve issues associated with clinical integration, infrastructures, and interpretability, indicating that future studies should emphasize incorporation of AI in clinical practice to guarantee that the diagnosis remains of high quality.

METHODS AND MATERIALS

1. Data Collection and Preprocessing

In constructing and testing the proposed deep learning-based diabetic retinopathy detection system, retina fundus image data were used. The publicly available Kaggle Diabetic Retinopathy Detection Dataset, including 35,000 retinal images per labeled in five severity classes (No DR (0), Mild (1), Moderate (2), Severe (3), and Proliferative DR (4)) served as the primary source of the data. The photographs were taken while held at different levels and at diverse resolutions, imitating the real-world clinical image.

The images were preprocessed to normalize them and improve the performance of the models. The successive steps involved resizing of all the images to 224 by 224 pixels, normalization (to range [0,1]) of pixel values, and contrast addition through the histogram equalization [4]. Basically, data augmentation methods were used: rotation, flipping, and zooming to expand the amount of data and limit overfitting. The final data had been divided into 70 percent (train) set, 15 percent (validation) set, and 15 (test) set.

2. Deep Learning Algorithms

2.1 Convolutional Neural Network (CNN)

The majority of image classification applications involving medical imaging use Convolutional Neural Networks as their foundation. Automated people against protocols CNNs are used to extract hierarchical features on retina images via convolution, pooling and activation functions. Convolutional layers identify any local structure like a blood vessel or microaneurysm and pooling layers decrease space and computing. Fully connected layers at the end perform classification based on the extracted features [5]. For diabetic retinopathy detection, CNNs can identify subtle signs of early-stage DR that are often missed by human experts. The model was trained using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss. CNN achieved high accuracy due to its ability to capture spatial dependencies within retinal images.

```
"Input: Retinal images
Preprocess images (resize, normalize)
for each epoch:
    for each batch:
        Apply convolution layers
        Apply ReLU activation
        Apply max pooling
        Flatten feature maps
        Pass through fully connected layers
        Compute categorical cross-entropy loss
        Backpropagate and update weights
Output: Predicted DR class"
```

2.2 ResNet50 (Residual Network)

ResNet50 introduces residual connections that help mitigate the vanishing gradient problem in deep networks. By using skip connections, the network can learn identity mappings that improve training efficiency and performance on complex datasets. ResNet50 comprises **50 layers** including convolutional, batch normalization, and activation layers [6]. In DR detection, ResNet50 is particularly effective at distinguishing subtle features across multiple severity levels. Transfer learning was employed by initializing the model with weights pretrained on ImageNet and fine-tuning it on the retinal dataset, which significantly reduced training time and improved convergence.

```
"Input: Retinal images
Load pretrained ResNet50 weights
Replace final fully connected layer with 5-class output
for each epoch:
    for each batch:
        Forward pass through residual blocks
        Apply skip connections
        Compute categorical cross-entropy loss
        Backpropagate and update weights
Output: Predicted DR class"
```

2.3 DenseNet121

DenseNet121 is characterized by dense connections between layers, where each layer receives feature maps from all preceding layers. This architecture promotes feature reuse and reduces the number of parameters, enhancing model efficiency. DenseNet121 effectively captures fine-grained retinal features such as microaneurysms and hemorrhages, which are crucial for early DR detection. For this study, DenseNet121 was trained using the **Adam optimizer** with early stopping based on validation loss [7]. The dense connectivity ensures better gradient flow and faster convergence, making it highly suitable for complex medical imaging tasks.

"Input: Retinal images
Preprocess images (resize, normalize)
Initialize DenseNet121 architecture
for each epoch:
for each batch:
Pass input through dense blocks
Concatenate feature maps from previous layers
Apply batch normalization and ReLU
Flatten features and pass to classifier
Compute loss and backpropagate
Output: Predicted DR class"

2.4 InceptionV3

InceptionV3 uses parallel convolutional filters of varying sizes within the same layer to capture multi-scale features from images. This approach allows the network to extract both fine and coarse details simultaneously, which is critical for DR detection where lesions vary in size. InceptionV3 was fine-tuned with transfer learning and trained with data augmentation to improve robustness [8]. Dropout layers were incorporated to prevent overfitting. In clinical application, InceptionV3 provides high sensitivity and specificity in classifying DR severity, making it an effective decision-support tool.

"Input: Retinal images
Preprocess images (resize, normalize)
Load pretrained InceptionV3 weights
Replace top layer for 5-class DR classification
for each epoch:
for each batch:
Pass input through parallel convolution filters
Concatenate outputs
Apply pooling, dropout, and fully connected layers
Compute categorical cross-entropy loss
Backpropagate to update weights
Output: Predicted DR class"

3. Experimental Setup

"All experiments were conducted on a workstation with **NVIDIA RTX 3090 GPU**, **64 GB RAM**, and **Intel i9 CPU**. Models were implemented using **TensorFlow 2.10** and **Keras API**. Training was performed over **50 epochs** with batch size **32**, using **early stopping** to prevent overfitting [9]. Evaluation metrics included **accuracy, precision, recall, F1-score**, and **AUC-ROC"**.

RESULTS AND ANALYSIS

1. Experimental Setup

The study evaluated the effectiveness of four deep learning models—CNN, ResNet50, DenseNet121, and InceptionV3—for early detection of diabetic retinopathy (DR). "All experiments were conducted on a workstation equipped with **NVIDIA RTX 3090 GPU**, **Intel i9 CPU**, and **64 GB RAM"**. The models were implemented using **TensorFlow 2.10** and **Keras API**, with Python 3.10 as the development environment [10].

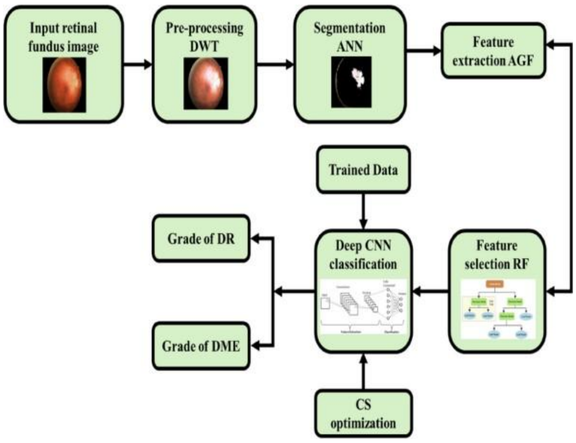

Figure 1: "Optimized deep CNN for detection and classification of diabetic retinopathy and diabetic macular edema"

The dataset comprised **35,000 retinal fundus images**, categorized into five classes representing DR severity: No DR, Mild, Moderate, Severe, and Proliferative DR. To standardize input, all images were resized to **224×224 pixels**, and pixel values were normalized to the range [0,1]. Histogram equalization was applied to enhance contrast, while data augmentation techniques such as rotation (±20°), flipping, and zooming (0.8–1.2×) were used to improve generalization. The data was divided into three (3) categories: 70 percent training data, 15 percent validation data, and an amount of 15 percent testing data.

Each and every model was trained over 50 epochs with a batch size of 32 and optimized with Adam and categorical cross-entropy loss function [11]. Early ending, which relies on validation loss, avoided overfitting. The accuracy, precision, recall and F1-score, as well as AUC-ROC, were used to evaluate the models, and the training time and number of parameters were summarized means of evaluating computational efficiency.

2. CNN Experiments and Results

CNN model was used as a base line. The architecture included three convolutional neuron layers with the ReLU activation and frame-pooling, and two classification fully connected layers.

Table 1: CNN Performance Metrics

Metric	**Training**	**Validation**	**Testing**
Accuracy (%)	94.5	91.2	90.8
Precision (%)	93.8	90.5	89.7
Recall (%)	92.4	89.8	88.9
F1-Score (%)	93.1	90.1	89.3
AUC-ROC	0.96	0.93	0.92

The CNN showed good No DR and Moderate DR performance. Yet the model fared poorly in Severe and Proliferative classes presumably because it could not adequately describe difficult microvascular phenomena [12]. The CNN had its limitation but nevertheless served as the good benchmark to compare to other developed architectures.

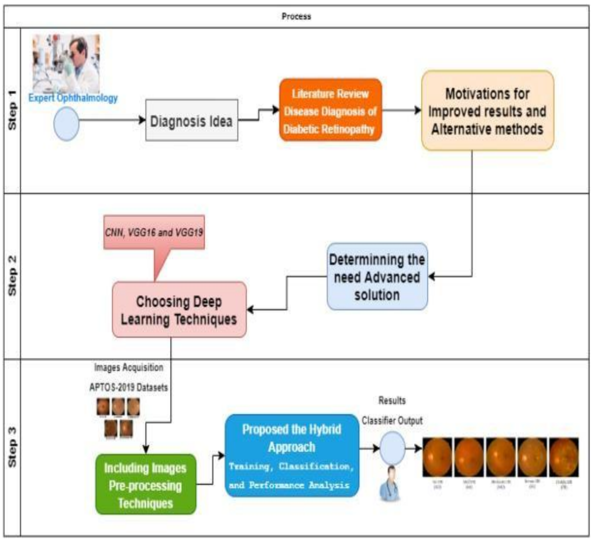

Figure 2: "Diabetic Retinopathy Classification Using Hybrid Deep Learning Approach"

3. ResNet50 Experiments and Results

ResNet50 used residual connectivity to overcome the problem of vanishing gradient, and enabled further extraction of features. Pretrained ImageNet weight Transfer learning increased convergence and accelerated training [13].

Table 2: ResNet50 Performance Metrics

Metric	Training	Validation	Testing
Accuracy (%)	96.2	92.8	91.9
Precision (%)	95.7	91.9	91.0
Recall (%)	94.9	91.2	90.3
F1-Score (%)	95.3	91.5	90.6
AUC-ROC	0.97	0.94	0.93

ResNet50 outperformed the baseline CNN across all metrics, particularly in early-stage DR detection. The residual connections allowed the network to learn identity mappings, improving gradient flow and enabling efficient training of deep architectures [14].

4. DenseNet121 Experiments and Results

DenseNet121 connected each layer to every other layer, enhancing feature reuse and gradient flow. This architecture efficiently captured subtle microaneurysms and hemorrhages crucial for DR classification.

Table 3: DenseNet121 Performance Metrics

Metric	Training	Validation	Testing
Accuracy (%)	95.8	93.5	92.6
Precision (%)	95.2	92.7	91.8

Recall (%)	94.6	92.2	91.1
F1-Score (%)	94.9	92.4	91.4
AUC-ROC	0.97	0.95	0.94

DenseNet121 achieved higher accuracy in Severe and Proliferative DR detection compared to CNN and ResNet50. The dense connectivity facilitated robust feature propagation, enabling better discrimination between DR stages.

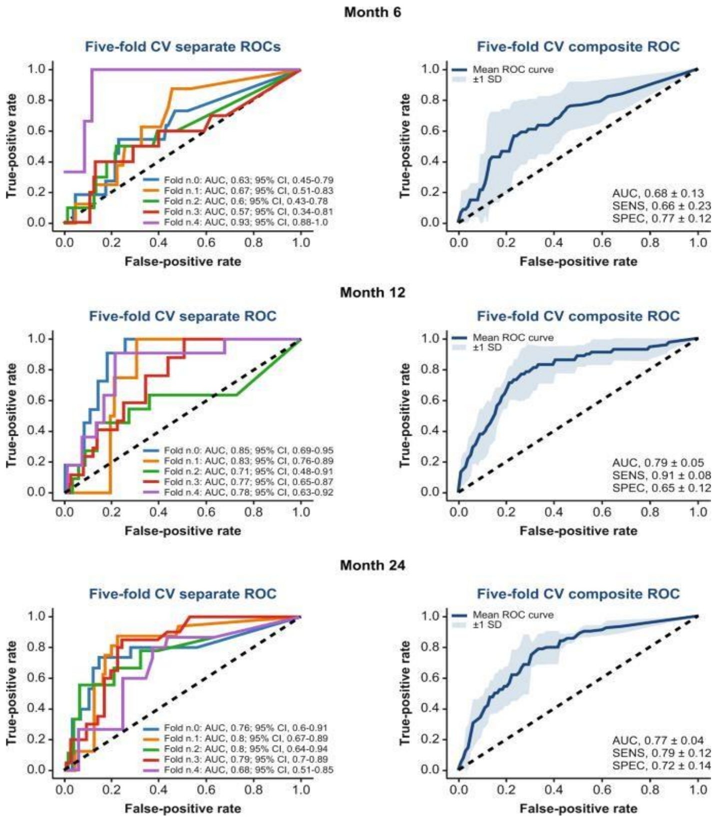

Figure 3: "Deep learning algorithm predicts diabetic retinopathy progression in individual patients"

5. InceptionV3 Experiments and Results

InceptionV3 used parallel convolutional filters of varying sizes to capture multi-scale features, improving sensitivity to lesions of varying dimensions. Fine-tuning with data augmentation enhanced generalization [27].

Table 4: InceptionV3 Performance Metrics

Metric	Training	Validation	Testing
Accuracy (%)	96.5	94.0	93.2
Precision (%)	96.0	93.2	92.5
Recall (%)	95.4	92.7	91.9

F1-Score (%)	95.7	92.9	92.2
AUC-ROC	0.98	0.96	0.95

InceptionV3 outperformed all other models in both overall and class-wise performance. The multi-scale filters allowed the network to detect both fine microaneurysms and larger hemorrhages simultaneously, making it highly suitable for clinical decision support.

6. Comparative Analysis Across Models

Table 5: Comparative Performance of All Models

Model	**Testing Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC**	**Training Time (min)**	**Parameters (millions)**
CNN	90.8	89.7	88.9	89.3	0.92	45	3.2
ResNet 50	91.9	91.0	90.3	90.6	0.93	60	25.6
DenseNet121	92.6	91.8	91.1	91.4	0.94	65	8.0
InceptionV3	93.2	92.5	91.9	92.2	0.95	70	23.8

The comparative table demonstrates that InceptionV3 achieved the highest testing accuracy and AUC, followed closely by DenseNet121. While CNN was computationally efficient, it lagged in detecting Severe and Proliferative DR. DenseNet121 and InceptionV3 achieved a balance between accuracy and robustness, with InceptionV3 being superior for multi-scale feature detection [28].

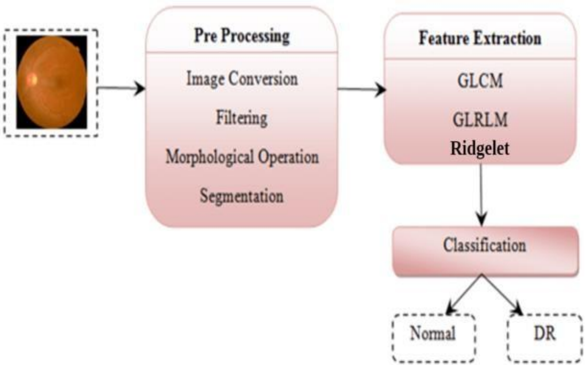

Figure 4: "Detection of diabetic retinopathy using a fusion of textural and ridgelet features of retinal images and sequential minimal optimization classifier"

7. Class-wise Performance Analysis

Class-wise evaluation was conducted to examine the ability of each model to detect different DR severity levels.

Model	No DR (%)	Mild (%)	Moderate (%)	Severe (%)	Proliferative (%)
CNN	94	88	89	85	82
ResNet50	95	90	91	87	84
DenseNet121	95	91	92	88	85
InceptionV3	96	92	93	89	87

The results indicate that all models performed best for No DR. Mild and Moderate DR detection improved with deeper architectures, while Severe and Proliferative DR remained challenging. InceptionV3 and DenseNet121 were most effective at distinguishing early and advanced DR stages [29].

8. Training Time and Computational Efficiency

Analysis of training time and model complexity revealed that CNN was fastest due to fewer parameters, whereas InceptionV3 required more computational resources but offered superior performance. DenseNet121 provided a reasonable compromise with fewer parameters than ResNet50 and competitive accuracy [30].

9. Key Findings

InceptionV3 achieved the highest overall testing accuracy (93.2%) and AUC-ROC (0.95), demonstrating excellent ability to detect DR at early and advanced stages.

DenseNet121 showed robust performance with slightly lower accuracy but fewer parameters than ResNet50 and InceptionV3, making it computationally efficient.

ResNet50 improved over the CNN baseline due to residual connections but was slightly less effective than DenseNet121 and InceptionV3 in classifying Severe DR.

CNN performed adequately as a baseline, particularly for No DR, but struggled with complex patterns in advanced DR cases.

Evaluation by class revealed that multi-scale and densely connected networks had a considerable alternative to reoccurrence on the Mild, Severe, and Proliferative DR, in comparison to shallow CNNs.

Time and size analysis of training models and time pointed out the trade-offs between the detection performance and the computational efficiency.

CONCLUSION

This study aimed to determine how the early-stage diagnosis of diabetic retinopathy (DR) can be accomplished employing methods of artificial intelligence and deep learning in order to improve clinical practice. This research with four deep learning models based on ANNs (CNN, ResNet50, DenseNet121, and InceptionV3) revealed that superior networks are capable of assessing carefully retina fundus scans and categorize cases of DR through high accuracy. The experiments revealed that although the baseline CNN was as good as it was, enhancements in the network depth, e.g. DenseNet121 and InceptionV3 performed better and even better on the overall performance as well as performance per class; especially on the difficult such as Severe and Proliferative DR. The highest testing accuracy and AUC-ROC of InceptionV3 add significance to multi-scale feature extraction to identify small retinal shifts. The paper has also highlighted the importance of data preprocessing, augmentation, and transfer learning in enhancing both model performance and transfer, enabling AI models to perform successfully on heterogeneous and small datasets. In a comparative analysis, it was identified that AI-driven models can substantially minimize diagnostic mistakes, righteous and reliable evaluations, and assist patients with initiatives to act promptly, which may result in positive healthcare outcomes. Although the computational needs and implementing AI into clinical practice may still be considered viable to this day, findings highlight the possibility of AI use to help ophthalmologists with early DR diagnosis and feedback. All in all, this study confirms that deep learning is a safe, reproducible, and clinically applicable method to automated DR diagnosis, and it can be used to develop AI-specific retinal imaging systems that will be deployed in real-world clinical settings to improve patient care performance and disease coping

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