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DEEP LEARNING APPROACHES FOR DIABETIC RETINOPATHY CLASSIFICATION: A COMPARATIVE ANALYSIS OF PRETRAINED MODELS

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Abstract: Diabetic Retinopathy (DR) is a prevalent retinal disease stemming from diabetes mellitus, often leading to irreversible vision impairment and blindness. Early detection of DR is essential for effective intervention and management. This paper explores the application of deep learning models for Diabetic Retinopathy (DR) classification, a critical concern in diabetes-related ocular complications leading to vision impairment. Leveraging the APTOS-2019 dataset from Aravind Eye Hospital, the study addresses DR severity through a multiclass classification approach, ranging from 2-Class detection to 5-Class categorization of disease presence and severity levels. EfficientNet B5 stands out as a top-performing model, demonstrating high accuracy in navigating the complexities of multiclass classification. This research offers valuable insights into the effectiveness of deep learning, particularly highlighting the diagnostic prowess of EfficientNet B5 in enhancing the accuracy of DR classification. The findings contribute to advancing automated screening systems for early DR detection and management, crucial for preventing irreversible vision impairment and blindness.
Keywords: Deep Learning, Multiclass Classification, Transfer Learning, Automated Screening Systems

I Introduction

Diabetic Retinopathy (DR) stands as a formidable retinal disease, primarily induced by diabetes mellitus, and it currently holds the unenviable distinction of being the leading cause of blindness on a global scale. This ocular complication is intricately woven into the fabric of diabetes, with the potential to inflict irreversible damage to the retina, ultimately compromising vision. In its early stages, Diabetic Retinopathy often operates in stealth, displaying minimal symptoms, if any. This asymptomatic nature poses a significant challenge as neural retinal damage and clinically imperceptible microvascular changes gradually unfold during this covert phase. The insidious progression of the disease in its initial stages underscores the critical importance of early detection and intervention.

Cause of Diabetic Retinopathy (DR): Diabetic Retinopathy (DR) evolves as a consequence of prolonged exposure to elevated levels of glucose in the bloodstream, a hallmark characteristic of diabetes mellitus[1][2]. Over time, this sustained hyperglycemia instigates a cascade of changes within the delicate retinal microvasculature, precipitating the development of DR. The primary mechanism underlying DR involves the progressive blockage of the tiny blood vessels that intricately nourish the retina. The relentless onslaught of excess sugar in the blood triggers a deleterious process, ultimately leading to the obstruction of these vital vessels, consequently cutting off the retina's blood supply.

In response to this compromised blood flow, the eye initiates a compensatory mechanism by attempting to generate new blood vessels. However, these newly formed vessels do not undergo proper development, exhibiting structural abnormalities. Notably, these aberrant vessels are characterized by a propensity to leak easily, disrupting the delicate equilibrium of the retinal microenvironment. In essence, the vascular changes induced by prolonged hyperglycemia, coupled with the unsuccessful attempts at neovascularization, collectively contribute to the pathogenesis of Diabetic Retinopathy[3][4][5]y. Understanding these intricate processes is paramount for developing effective preventive measures and interventions aimed at mitigating the impact of this leading cause of global blindness. This project delves into the realm of leveraging advanced technologies, specifically deep learning models, to address the complexities of Diabetic Retinopathy classification[6][7][8]. In the realm of classifying Diabetic Retinopathy (DR), a spectrum of deep learning models has emerged as pivotal tools. VGG19[9], ResNet50[10], EfficientNetB5[11], EfficientNetB7[12], InceptionV3[13],

and Xception[14] represent a selection of these models, each carrying its own set of advantages and limitations. This paper delves into a meticulous exploration to discern the most accurate and suitable model for the multiclass classification of DR grading.
The complexity of DR grading is approached through a multiclass classification framework, stratifying the severity into different categories. The classification is structured as follows: 2-Class for detecting the mere presence of the disease, 3-Class discerning between No DR, mild DR, and severe DR, 4-Class categorizing No DR, mild DR, moderate DR, and severe DR, and a more intricate 5-Class encompassing No DR, mild DR, moderate DR, severe DR, and Proliferative DR. Given the diverse nature of these DR grading classes, each model is scrutinized to decipher its efficacy in providing accurate classifications. This exploration aims to shed light on the nuanced strengths and weaknesses inherent in each model, ultimately guiding the selection of the most apt model for the task at hand. The ultimate goal is to contribute valuable insights to the ongoing efforts in utilizing deep learning for the precise and reliable classification of Diabetic Retinopathy

II Methodology

Implementation of Diabetic Retinopathy Classification : To address the challenge of diabetic retinopathy (DR) classification, we have meticulously executed a comprehensive implementation process. The stages involve preprocessing raw DR images, extracting features using Convolutional Neural Networks (CNNs), training a supervised learning model, and evaluating its performance.
Stage:1 Preprocessing: Image Pre-processing plays a pivotal role in enhancing the performance of deep learning models, particularly in the context of classifying diabetic retinopathy from fundus images. This section outlines the meticulous steps taken to prepare the training dataset for optimal model training and evaluation. A) **Resizing Images to 512 x 512:** To ensure uniformity and facilitate effective feature extraction, the training images, initially numbering 3662, undergo resizing to a standardized dimension of 512 x 512 pixels. This step is crucial for maintaining consistency across the dataset, enabling seamless model processing. B) **Dataset Splitting:** The resized dataset, comprising 2929 training images and 733 testing images, is strategically divided to create subsets for model training and evaluation. This split, allocating 80% of the data for training and 20% for testing, is essential for robust model assessment. C) **Grayscale Conversion and Circular Crop:** The images are transformed into grayscale to simplify processing and reduce computational complexity. Additionally, a circular cropping technique is applied to eliminate extraneous areas surrounding the fundus images. This circular crop ensures that the model focuses solely on the relevant retinal features, improving the model's ability to discern critical details. D) **Gaussian Blur Preprocessing:** To further enhance feature visibility and emphasize important structures within the circularly cropped images, a Gaussian blur preprocessing technique is employed. This step aids in reducing noise and highlighting relevant patterns, contributing to the overall interpretability of the images for the subsequent model. E) **ImageDataGenerators for Subsequent Split:** Leveraging the power of ImageDataGenerators, the training images, now enhanced through circular cropping and Gaussian blur, undergo an additional split. This fine-grained split results in 2344 images designated for training and 585 images for validation. This nuanced division allows for a robust evaluation of the model's generalization capabilities, ensuring it performs effectively on previously unseen data. By meticulously implementing these preprocessing steps, the dataset is primed for training deep learning models. The focus on resizing, circular cropping, grayscale conversion, Gaussian blur, and strategic data splitting collectively lays the foundation for a well-optimized and highly effective diabetic retinopathy classification model. Figure:1 shows the sample images of original dataset, these images are resized 200 x 200 , Figure:2 shows the images which undergo circular cropping, followed by the application of a Gaussian blur preprocessing technique. This step is crucial as Gaussian blurred images facilitate clearer visualization of the features within the image, enhancing the model's ability to discern and extract relevant patterns and information. Given the class imbalance, data augmentation has been implemented to address and rectify the uneven distribution of classes within the training dataset. This

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augmentation technique aims to create a more balanced representation of each class, thereby improving the model's ability to generalize across diverse instances and enhance overall performance(See Figure:3).

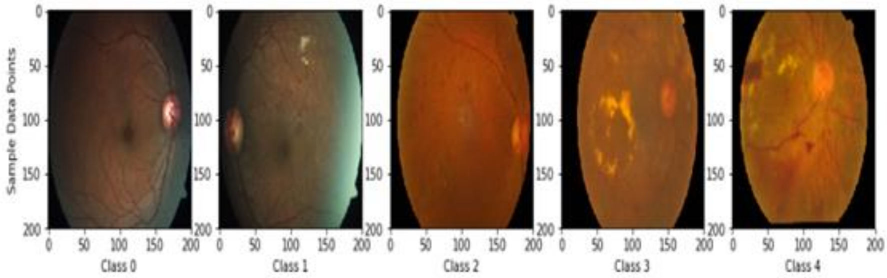

Figure 1: Sample Images from the Original Dataset

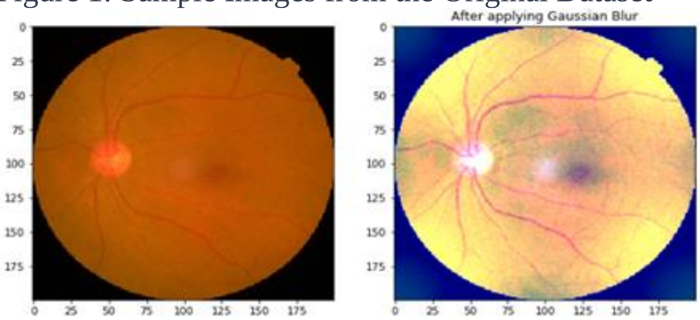

Figure 2: Images After Circular Crop and Gaussian Blur Preprocessing on Resized Images

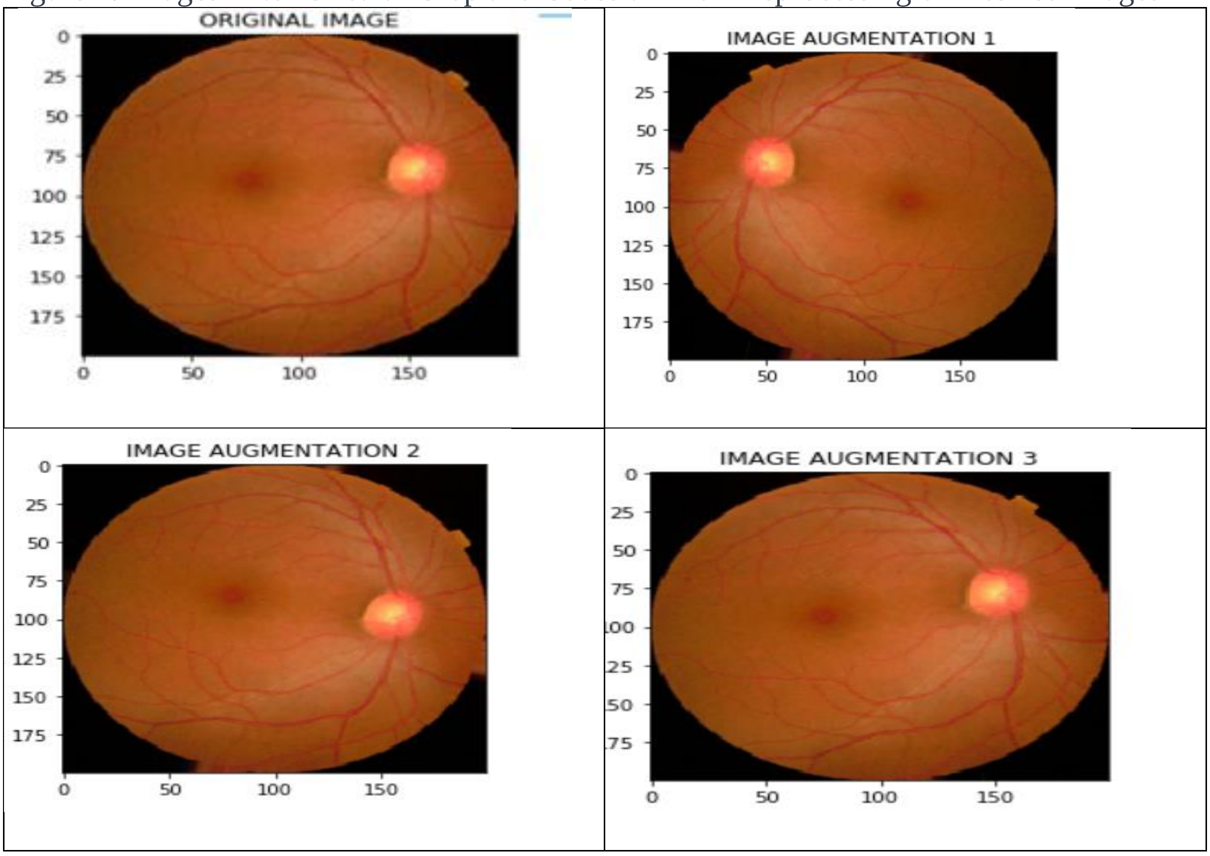

Figure 3: Images of Data Augmentation on Class Distribution in the Training Dataset

Stage:2 Feature Extraction using CNN: Features are extracted from the preprocessed images utilizing Convolutional Neural Networks (CNNs). CNNs are adept at capturing hierarchical representations within images, enabling the model to discern intricate patterns relevant to diabetic retinopathy.

Stage:3 Supervised Learning Model: A supervised learning model is trained to classify fundus images based on the extracted features. We explore a variety of pretrained models, each tailored to leverage the strengths of different architectures, to enhance the model's ability to discern and classify retinopathy severity.

Models Trained:

VGG16: VGG16, developed by the Visual Geometry Group at Oxford, is a renowned convolutional neural network (CNN) celebrated for its simplicity and efficacy in image classification. Featuring 16 layers, including 13 convolutional and three fully connected layers, VGG16 employs 3x3 filters followed by 2x2 max-pooling for feature extraction. Its deep representation learning capabilities, coupled with small filter sizes, make it adept at discerning intricate patterns in images. Pretrained on ImageNet, VGG16 is widely applied in transfer learning for diverse computer vision tasks. Despite its computational challenges, newer architectures like ResNet and EfficientNet have since emerged for improved efficiency. Nonetheless, VGG16 remains influential as a foundational model in the evolution of deep neural networks. Image resized to 320 x 320, using Imagenet weights, with a batch size of 8.

Xception: Xception is a high-performance convolutional neural network (CNN) architecture designed for image classification. Introduced by Google Research, Xception stands out for its exceptional performance and novel approach to convolutional layers. Unlike traditional CNNs, Xception replaces standard convolutional layers with depthwise separable convolutions, enabling better feature representation and reducing computational complexity. This architecture excels in capturing intricate patterns and is particularly efficient in tasks requiring large-scale image data. Pretrained on ImageNet, Xception often serves as a robust feature extractor in transfer learning applications. Its innovative design, which decouples spatial and channel-wise information, contributes to its effectiveness in various computer vision tasks, marking it as a notable advancement in deep learning architectures. Image resized to 320 x 320, using Imagenet weights, with a batch size of 8.

InceptionV3: InceptionV3 is a highly efficient convolutional neural network (CNN) architecture designed for image classification. Developed by Google, it is part of the Inception family of models. InceptionV3 is renowned for its advanced architecture, incorporating inception modules that allow for the extraction of multi-level features from input images. With 48 layers, including multiple convolutional and pooling layers, InceptionV3 excels at capturing diverse and complex patterns in images. The model has achieved significant success in large-scale image classification tasks and is pretrained on the ImageNet dataset. InceptionV3's modular design, featuring the innovative inception blocks, enhances its ability to process information at various scales, contributing to its effectiveness in diverse computer vision applications. Image resized to 320 x 320, using Imagenet weights.

ResNet50: ResNet50 is a powerful convolutional neural network (CNN) architecture renowned for its deep residual learning approach. Developed by Microsoft Research, ResNet50 consists of 50 layers and employs residual blocks to mitigate the challenges of training very deep networks. The unique residual connections enable the network to skip certain layers during training, preventing the vanishing gradient problem and facilitating the learning of more complex features. This architecture has excelled in image classification tasks, achieving state-of-the-art results. Pretrained on ImageNet, ResNet50 serves as a robust feature extractor for transfer learning in various computer vision applications due to its ability to effectively capture intricate patterns in images. Tested for three cases

1. Image resized to 320 x 320, using Imagenet weights, with a batch size of 8.
2. Image resized to 227 x 227, additional convolutional layer, batch size of 8.
3. Image resized to 320 x 320, removed existing convolutional layer, batch size of 8.

EfficientNetB5/B7: EfficientNetB5 is a high-performing convolutional neural network (CNN) architecture known for its efficiency in image classification tasks. Part of the EfficientNet family, it was developed by Google Research. EfficientNetB5 strikes a balance between accuracy and computational cost by optimizing model parameters and scaling network dimensions. With its innovative compound scaling approach, it efficiently captures complex patterns in images. Pretrained on ImageNet, EfficientNetB5 is often employed for transfer learning, showcasing its effectiveness across various computer vision applications. Its scalable design makes it particularly useful for tasks demanding robust feature extraction from large-scale image datasets. **EfficientNetB5:** Image resized to 320 x 320, using Imagenet weights, with a batch size of 8. **EfficientNetB7:** Image resized to 320 x 320, using Imagenet weights, with a batch size of 4.

III Results and Discussion

Dataset:

The Asia Pacific Tele-Ophthalmology Society (APTOS)-2019[15] dataset is a critical resource aimed at addressing the challenges of detecting and preventing eye diseases, particularly in rural areas where medical screening is challenging. This dataset is a collaborative effort with Aravind Eye Hospital in India, known for its commitment to providing eye care to underserved communities.The dataset comprises 3662 images for training, with a distribution across five distinct classes. Class-0 has 1805 images, class-1 contains 370 images, class-2 consists of 999 images, class-3 includes 193 images, and class-4 features 295 images. Additionally, there are 1928 validation images. The significance of this dataset lies in its diversity, with images varying in size, reflecting the real-world challenges faced during medical screenings. To facilitate model development and evaluation, the training dataset has been split into training and testing subsets. This division allocates 80% of the data (2929 images) for training and 20% (733 images) for testing. A notable aspect is the absence of class labels for the validation images, necessitating careful consideration during the experimental design. The dataset not only serves as a valuable benchmark for developing automated screening solutions but also aligns with the overarching goal of leveraging technology to enhance the efficiency of disease detection and diagnosis in remote and underserved regions.

Evaluation Measures:

The model's performance is rigorously evaluated using key metrics, including precision, recall, and accuracy. These metrics provide insights into the model's ability to correctly identify and classify instances of diabetic retinopathy, enabling a thorough assessment of its efficacy. Table 1 shows Training and Test Cohen's Kappa and Accuracy Comparison for Various Models This table provides a comprehensive comparison of the training and test Cohen's Kappa and accuracy metrics for different implemented models. The values offer insights into the performance of each model during the training phase as well as its ability to generalize to new data during testing. This comparative analysis aids in assessing the models' reliability, robustness, and overall effectiveness in addressing the classification task.

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Models	**Image size**	**Training Cohen's kappa**	**Training accuracy**	**Test Cohen's kappa**	**Test accuracy**	**Additional layers**	**Batch size**
RESTNET50	227x227	87.9	84.7	82.6	78	5 convolution layer	8
RESTNET50	320 x 320	82.6	81.5	81.4	78.7	removal of convolution layers	8
RESTNET50	320 x 320	89.7	84.5	82.6	79.7	same layers	8
EFFICIENTNETB5	320 x 320	92.8	88.7	88.4	81.2	same layers	8
EFFICIENTNETB7	320 x 320	92.6	89.1	87.5	80.8	3 convolution layer	4
VGG19	320 x 320	88.8	83.4	87.2	81.7	Same layers	8
XCEPTION	320X320	91.4	87.1	84.4	79.3	Same layers	8
INCEPTIONV3	320x320	92.5	87.8	86.4	80.9	2 convolution layer	8

Table 1: Training and Test Cohen's Kappa and Accuracy Comparison for Various Models

The Figure shows the Training and Test Cohen's Kappa Comparison graph. This illustrates the performance of different deep learning models in terms of Cohen's Kappa on both the training and test datasets. Cohen's Kappa is a statistical measure of inter-rater agreement, commonly used to assess the reliability of classification models. The X-axis represents the models, including ResNet50, EfficientNetB5, EfficientNetB7, VGG19, Xception, and InceptionV3. The Y-axis shows the accuracy values of Cohen's Kappa, ranging from no agreement beyond chance, and 1 represents perfect agreement.

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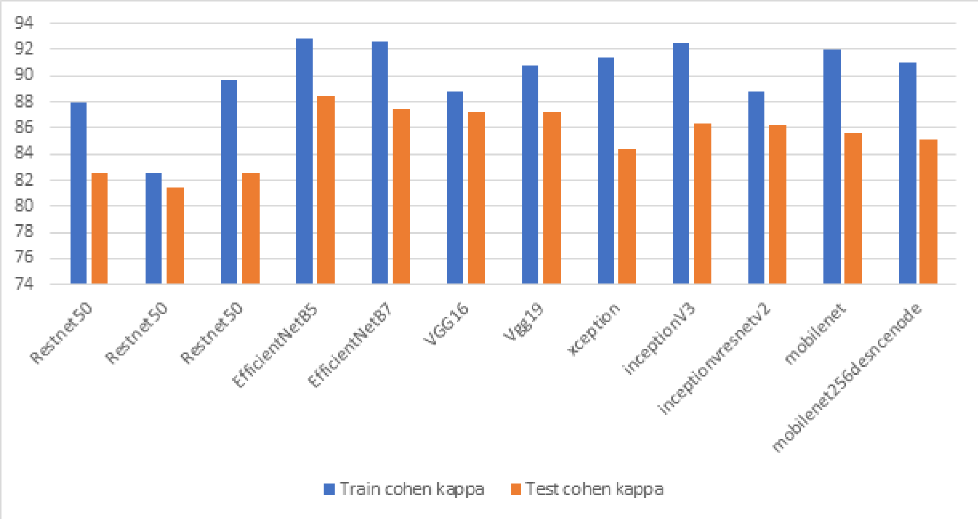

Figure:4 Training and Test Cohen's Kappa Comparison graph.

This Figure shows the comparison of training and test accuracy across diverse deep learning models. The X-axis enumerates the different models, while the Y-axis signifies the corresponding accuracy values. The blue lines represent the accuracy achieved during the training phase, offering a glimpse into the models' learning capabilities. In contrast, the orange lines showcase accuracy on the test dataset, reflecting the models' proficiency in generalizing to new, unseen data. This research offers valuable insights into the effectiveness of deep learning, particularly highlighting the diagnostic prowess of EfficientNet B5 in enhancing the accuracy of DR classification. The findings contribute to advancing automated screening systems for early DR detection and management, crucial for preventing irreversible vision impairment and blindness.

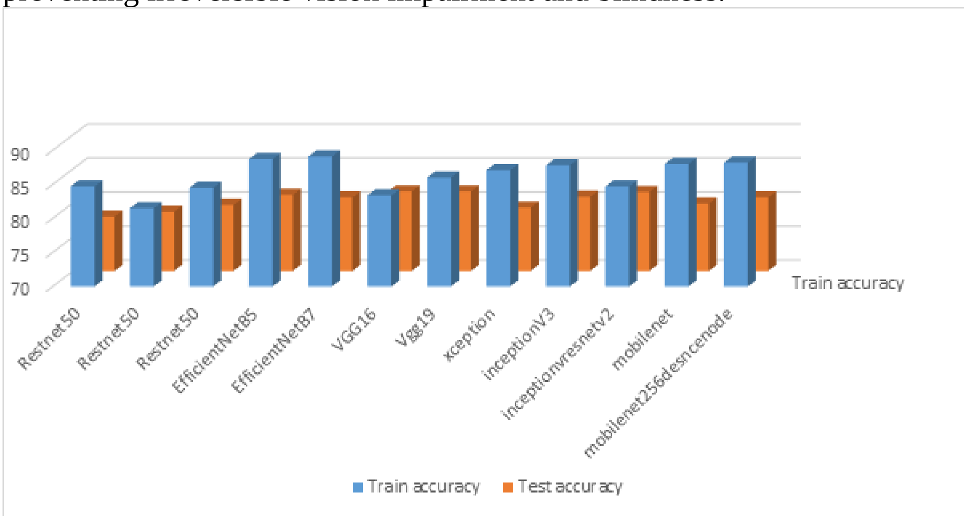

Figure:5 Comparison of training and test accuracy across diverse deep learning models.

IV Conclusion

In conclusion, this research underscores the critical role of deep learning in addressing the multiclass classification challenges posed by Diabetic Retinopathy. The utilization of the APTOS-2019 dataset from Aravind Eye Hospital allowed for a nuanced examination of DR severity levels, enabling the classification into distinct classes. EfficientNet B5's exceptional accuracy in handling the multiclass problem highlights its potential as a robust tool for DR diagnosis. The findings encourage further exploration of deep learning models in ophthalmology, paving the way for more accurate and efficient automated screening systems. This study contributes to the ongoing efforts to leverage technology for early detection and management of Diabetic Retinopathy, particularly in resource-constrained healthcare environments.

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