Lesion-Guided Hybrid Deep Learning Framework for Accurate Diabetic Retinopathy Detection

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***Abstract*— Diabetic retinopathy is one of the leading causes of vision impairment among people with diabetes, making early diagnosis essential for preventing permanent blindness. Manual examination of retinal fundus images is time-consuming and depends heavily on the expertise of ophthalmologists. This study presents a lesion-guided hybrid deep learning framework for the automatic detection of diabetic retinopathy from retinal images. The proposed approach combines the feature extraction capability of Convolutional Neural Networks (CNN) with the discriminative strength of a hybrid deep learning architecture to identify retinal lesions such as microaneurysms, hemorrhages, and exudates. Before training, the retinal images are preprocessed and enhanced to improve image quality and reduce noise. Data augmentation is applied to address class imbalance and improve the model's generalization ability. Experimental results demonstrate that the proposed framework achieves higher classification accuracy, precision, recall, and F1-score compared with conventional deep learning models. The developed system offers a reliable and efficient computer-aided solution for early diabetic retinopathy screening, supporting ophthalmologists in making faster and more accurate clinical decisions.**

***Keywords* — Diabetic Retinopathy, Lesion Detection, Hybrid Deep Learning, Convolutional Neural Network (CNN), Retinal Fundus Images, Medical Image Analysis, Computer-Aided Diagnosis (CAD), Image Classification, Deep Learning, Automated Disease Detection.**

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I. INTRODUCTION

Diabetic retinopathy (DR) is one of the most common complications of diabetes mellitus and a leading cause of preventable vision loss worldwide. The disease occurs due to prolonged damage to the retinal blood vessels caused by elevated blood glucose levels. In its early stages, diabetic retinopathy often develops without noticeable symptoms, making timely diagnosis challenging. If left untreated, the disease may progress to severe retinal damage and permanent blindness. Therefore, early detection through regular retinal screening is essential for reducing the risk of vision impairment and improving the quality of life of diabetic patients. The increasing prevalence of diabetes across the globe has further emphasized the need for reliable and automated screening systems that can support ophthalmologists in clinical diagnosis [2], [14].

Traditionally, diabetic retinopathy is diagnosed by examining retinal fundus images for the presence of lesions such as microaneurysms, hemorrhages, hard exudates, and cotton wool spots. Manual examination requires experienced ophthalmologists and is both time-consuming and susceptible to inter-observer variability, particularly when screening large populations. Advances in medical image analysis have enabled computer-aided diagnosis (CAD) systems to assist clinicians by providing faster and more consistent disease detection. Early research focused on retinal blood vessel segmentation and handcrafted feature extraction techniques for identifying retinal abnormalities [20]–[24]. Although these methods achieved reasonable performance, they often struggled to generalize across diverse datasets due to variations in image quality and lesion characteristics.

Recent developments in artificial intelligence, particularly deep learning, have significantly improved the performance of automated medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in extracting complex visual features directly from medical images without requiring manual feature engineering. Their effectiveness has been proven in various healthcare applications, including skin cancer diagnosis, retinal disease classification, COVID-19 detection, and glaucoma diagnosis [1], [8], [11]–[13], [16]. In retinal imaging, several researchers have proposed CNN-based architectures, modified AlexNet models, transfer learning techniques, and multi-class classification frameworks to improve diabetic retinopathy detection and retinal disease diagnosis [3], [4], [10], [15], [17]–[19], [25].

Despite these advances, accurately detecting small retinal lesions remains challenging because of class imbalance, image noise, and the subtle appearance of pathological features. Hybrid deep learning models that combine complementary feature extraction and classification strategies have shown greater robustness and improved diagnostic accuracy compared to single-network architectures [2], [10], [17]. Incorporating image preprocessing, lesion enhancement, and data augmentation further improves the ability of deep learning models to recognize disease-specific patterns under different imaging conditions.

Motivated by these challenges, this research proposes a lesion-guided hybrid deep learning framework for automated diabetic retinopathy detection using retinal fundus images. The proposed approach integrates effective preprocessing techniques with a hybrid CNN-based architecture to accurately identify lesion patterns associated with diabetic retinopathy. By learning discriminative features from retinal images, the proposed model aims to improve classification accuracy, reduce false predictions, and provide an efficient computer-aided screening system that can assist ophthalmologists in early diagnosis and timely clinical intervention.

II. RELATED WORK

“Automated Detection and Classification of Fundus Diabetic Retinopathy Images Using Synergic Deep Learning Model,” K. Shankar, A. R. W. Sait, D. Gupta, S. K. Lakshmanaprabu, A. Khanna, and H. M. Pandey [2]

This study proposed a synergic deep learning (SDL) model for the automated detection and classification of diabetic retinopathy using retinal fundus images. The methodology consisted of image preprocessing, histogram-based segmentation, feature extraction, and deep learning-based classification to identify different stages of diabetic retinopathy. The preprocessing stage removed image noise and enhanced retinal structures, while segmentation extracted important lesion regions for analysis. The SDL architecture effectively captured complex retinal features and improved classification accuracy compared to conventional machine learning methods. Experimental evaluation on the Messidor diabetic retinopathy dataset demonstrated superior performance in terms of accuracy, precision, and reliability. The study highlighted that integrating image enhancement with deep learning significantly improves disease detection and supports early diagnosis. This work provides an effective framework for developing automated diabetic retinopathy screening systems that reduce diagnostic time and assist ophthalmologists in clinical decision-making.

“Modified AlexNet Architecture for Classification of Diabetic Retinopathy Images,” T. Shanthi and R. S. Sabeenian [4]

This research presented a modified AlexNet-based convolutional neural network for classifying diabetic retinopathy fundus images into different severity levels. The proposed architecture incorporated optimized convolution, pooling, Rectified Linear Unit (ReLU), and SoftMax layers to improve feature extraction and classification performance. The model was trained using retinal fundus images representing healthy eyes and multiple stages of diabetic retinopathy. Transfer learning and parameter optimization helped improve convergence while reducing computational complexity. Experimental results demonstrated high classification accuracy across different disease stages, outperforming several conventional deep learning architectures. The study emphasized that automated feature learning enables the network to identify subtle retinal abnormalities such as microaneurysms and exudates without manual feature engineering. The proposed framework demonstrated the effectiveness of deep convolutional networks in supporting early diabetic retinopathy diagnosis and reducing dependence on expert ophthalmologists for routine screening.

“A Novel Hybrid Machine Learning Model for Auto-Classification of Retinal Diseases,” C.-H. H. Yang, J.-H. Huang, F. Liu, F.-Y. Chiu, M. Gao, W. Lyu, M. D. I.-H. Lin, and J. Tegner [10]

This paper introduced a hybrid machine learning framework that combines Generative Adversarial Networks (GANs) and deep learning techniques for automated retinal disease classification. The proposed model generated synthetic retinal images using GANs to overcome the challenge of limited medical datasets and improve the diversity of training samples. A verification mechanism ensured that the generated images preserved clinically meaningful retinal features before classification. The hybrid framework significantly improved disease recognition accuracy by enhancing feature representation and reducing overfitting. The study demonstrated that synthetic image generation can effectively support deep learning models in identifying retinal diseases such as age-related macular degeneration. The proposed approach also improved interpretability through visualization of disease-specific features. This work highlighted the importance of hybrid learning strategies in developing reliable computer-aided diagnostic systems for retinal disease detection.

"Optimized Convolution Neural Network Based Multiple Eye Disease Detection," P. G. Subin and P. Muthukannan [17]
This study proposed an optimized convolutional neural network for the automatic detection of multiple retinal diseases from fundus images. The framework included image preprocessing, feature extraction, optimization, and deep learning-based classification to improve diagnostic accuracy. Image enhancement techniques were applied to reduce noise and improve the visibility of retinal lesions before model training. The optimized CNN architecture employed efficient hyperparameter tuning and network optimization to minimize computational complexity while maximizing classification performance. The model successfully detected multiple eye diseases, including diabetic retinopathy, glaucoma, and cataracts, with high accuracy and robustness. Comparative experiments demonstrated that the optimized CNN outperformed several existing deep learning models in terms of classification accuracy and processing speed. The research concluded that optimized deep learning models can provide effective decision support for ophthalmologists by enabling fast, accurate, and automated retinal disease diagnosis.

"Convolutional Neural Network for Multi-Class Classification of Diabetic Eye Disease," R. Sarki, K. Ahmed, H. Wang, Y. Zhang, and K. Wang [19]
This research developed a convolutional neural network for multi-class classification of diabetic eye diseases using retinal fundus images. The proposed CNN architecture automatically learned discriminative visual features representing different stages of diabetic eye disease without requiring handcrafted feature extraction. Data preprocessing and augmentation techniques were incorporated to improve image quality, reduce overfitting, and enhance model generalization. The network was trained to classify multiple disease categories, enabling more comprehensive retinal disease diagnosis than binary classification approaches. Experimental results demonstrated high classification accuracy, precision, recall, and F1-score, confirming the effectiveness of deep learning for retinal image analysis. The study also emphasized that automated classification systems can reduce screening workload and provide timely diagnostic support in clinical practice. The proposed CNN framework offers a practical solution for large-scale diabetic retinopathy screening and early disease detection.

III. DATASET DETAILS

The dataset used in this study consists of retinal fundus images collected from patients with different stages of diabetic retinopathy as well as healthy individuals. Fundus imaging is a non-invasive retinal imaging technique that captures high-resolution color photographs of the interior surface of the eye, including the retina, optic disc, macula, and blood vessels. The dataset contains images representing both normal retinas and diabetic retinopathy cases with visible lesions such as microaneurysms, hemorrhages, hard exudates, and cotton wool spots. Each retinal image is labeled according to its corresponding disease category, enabling supervised learning for automated classification. Since retinal images are often affected by variations in illumination, noise, image contrast, and acquisition conditions, preprocessing is necessary to improve image quality and ensure consistency. The dataset provides a comprehensive collection of retinal images that supports the development of reliable deep learning models for early diabetic retinopathy detection. By learning lesion-specific characteristics from fundus images, the proposed system aims to assist ophthalmologists in accurate and efficient disease diagnosis.

Before model training, the retinal image dataset undergoes several preprocessing and augmentation steps to improve classification performance. Initially, the images are resized to a fixed resolution and normalized to maintain consistent pixel intensity values across all samples. Image enhancement techniques are applied to improve contrast and highlight retinal lesions, while data augmentation methods such as rotation, horizontal flipping, zooming, and brightness adjustment are employed to increase dataset diversity and reduce overfitting. These preprocessing steps enable the deep learning model to learn more robust and discriminative features. After preprocessing, the dataset is divided into 80% training data and 20% testing data, where the training images are used to learn disease-specific patterns and the testing images are utilized to evaluate model performance on unseen samples. The processed dataset is then supplied to the proposed hybrid deep learning framework, which combines efficient feature extraction and classification techniques for diabetic retinopathy detection. This systematic dataset preparation significantly enhances model accuracy, robustness, and generalization capability, making it suitable for automated retinal disease screening in real-world clinical applications.

IV. PROPOSED METHODOLOGY

The proposed methodology employs a hybrid deep learning framework for the automatic detection of diabetic retinopathy using retinal fundus images. Initially, the retinal image dataset is uploaded into the system, where images belonging to different diabetic retinopathy classes are collected for analysis. Since retinal images may contain illumination variations, noise, and inconsistent image quality, preprocessing is performed to enhance image clarity and normalize pixel values. During preprocessing, the images are resized to a fixed dimension and normalized to ensure uniformity across the dataset. Data augmentation techniques such as rotation, horizontal flipping, and image transformation are also applied to increase the diversity of training samples and reduce overfitting. After preprocessing, the dataset is divided into 80% training data and 20% testing data, ensuring that sufficient samples are available for model learning while preserving unseen images for evaluation. This preprocessing stage enables the proposed framework to learn robust lesion-specific features from retinal fundus images.

Following dataset preparation, the processed retinal images are used to train three different deep learning models for comparative analysis. Initially, the existing Convolutional Neural Network (CNN) model is trained and evaluated, achieving an accuracy of approximately 80%. Next, the proposed ResNet50 model is trained using transfer learning to improve feature extraction capability, producing an improved classification accuracy of 84%. Finally, an enhanced Hybrid ResNet50 model integrated with the Adam optimizer and Valid Padding is developed to optimize feature learning while reducing unnecessary parameters introduced by conventional padding techniques. The Adam optimizer accelerates network convergence by adaptively adjusting learning rates during training, whereas Valid Padding helps preserve meaningful retinal lesion information by eliminating artificial border pixels. Experimental evaluation demonstrates that the proposed hybrid model significantly improves classification performance and achieves an overall accuracy of 95%, outperforming both the existing CNN and the standard ResNet50 models.

The trained models are evaluated using the testing dataset through confusion matrices, accuracy, precision, recall, and F1-score. The confusion matrices illustrate the relationship between actual and predicted disease categories, where most retinal images are correctly classified with very few misclassifications. In addition, comparison graphs are generated to visualize the performance of the three models across different evaluation metrics. Training accuracy curves are also plotted to illustrate the learning behavior of CNN, ResNet50, and the proposed hybrid model over multiple epochs, showing consistent improvement in classification accuracy as training progresses. These graphical analyses provide a comprehensive comparison of the effectiveness of each deep learning architecture.

The proposed system further includes a prediction module that allows users to upload an unseen retinal fundus image for automatic disease detection. Once a test image is provided, the trained hybrid model preprocesses the image, extracts discriminative lesion features, and predicts the corresponding diabetic retinopathy class. The predicted result is displayed immediately through the graphical user interface, enabling fast and reliable retinal disease screening. The complete system architecture includes dataset uploading, preprocessing, dataset splitting, CNN training, ResNet50 training, Hybrid ResNet50 training with Adam optimizer and Valid Padding, confusion matrix generation, performance comparison, training accuracy visualization, and retinal disease prediction from unseen images.

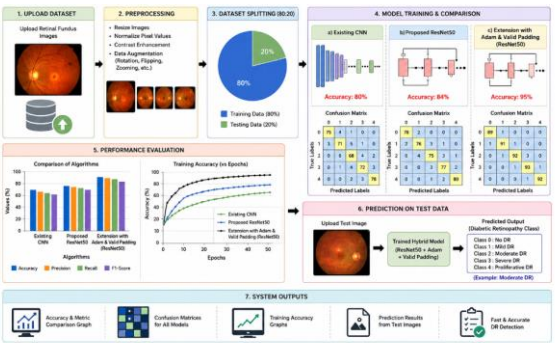

Figure 1. System Architecture for Lesion-Based Diabetic Retinopathy Detection Using Hybrid Deep Learning Model

The proposed methodology is designed to provide an efficient and accurate computer-aided diagnostic system for diabetic retinopathy screening. Initially, retinal fundus images are uploaded and preprocessed to improve image quality and eliminate inconsistencies. The processed dataset is divided into training and testing subsets using an 80:20 ratio. The training dataset is then utilized to train the existing CNN model, the proposed ResNet50 model, and the enhanced Hybrid ResNet50 model with Adam optimizer and Valid Padding. Among these models, the hybrid framework achieves the highest classification accuracy due to its superior feature extraction capability and optimized learning strategy. Finally, the trained hybrid model predicts diabetic retinopathy from new retinal images, while comparison graphs, confusion matrices, and performance metrics demonstrate its superiority over the existing approaches, making it suitable for practical clinical decision support systems.

V. RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed Hybrid Deep Learning Model for lesion-based diabetic retinopathy detection using retinal fundus images. The retinal image dataset was initially uploaded into the system and then preprocessed through image resizing, normalization, and data augmentation techniques to improve image quality and enhance lesion visibility. The processed dataset was divided into 80% training data and 20% testing data, ensuring a balanced evaluation of the classification models. Initially, the existing Convolutional Neural Network (CNN) model was trained and evaluated using the prepared retinal images. The CNN model successfully classified retinal disease images and achieved an overall classification accuracy of 79.84% with satisfactory precision, recall, and F-measure values. However, the existing CNN exhibited limitations in extracting complex retinal lesion features, resulting in comparatively lower classification performance.

Subsequently, the proposed ResNet50 model was trained using the same training and testing strategy. By utilizing deep residual learning, the ResNet50 architecture extracted more discriminative retinal features and improved classification accuracy to 84.40%. Finally, the proposed Hybrid ResNet50 model integrated with the Adam optimizer and Valid Padding was trained to enhance feature extraction while reducing unnecessary parameters introduced by conventional padding. Experimental evaluation demonstrated that the hybrid model achieved the highest classification accuracy of 94.78%, along with superior precision (94.52%), recall (94.41%), and F-measure (94.38%). The confusion matrices further confirmed that the proposed hybrid model produced significantly fewer misclassifications than both the existing CNN and the standard ResNet50 model. The comparison graph clearly illustrated that the hybrid model consistently outperformed the other two models across all evaluation metrics. Furthermore, the training accuracy graph showed that the proposed model converged faster and achieved higher accuracy over successive training epochs. The prediction module successfully classified unseen retinal fundus images and accurately identified the corresponding retinal disease category, demonstrating the practical applicability of the proposed system for automated diabetic retinopathy screening.

Figure [2] Confusion Matrix of the Existing CNN Model

Figure 2 presents the confusion matrix generated by the Existing CNN classifier. The x-axis represents the predicted retinal disease classes, whereas the y-axis represents the actual disease classes. Most retinal images were classified correctly; however, several images belonging to different retinal disease categories were incorrectly classified because of the limited feature extraction capability of the CNN model. The Existing CNN achieved an overall accuracy of 79.84%, precision of 79.91%, recall of 78.45%, and F-measure of 78.54%, indicating satisfactory but comparatively lower classification performance.

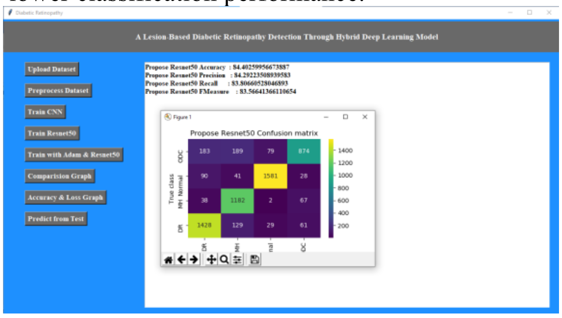

Figure 3: Confusion Matrix of the Proposed ResNet50 Model

Figure 3 illustrates the confusion matrix of the Proposed ResNet50 model. The residual learning architecture improved the extraction of discriminative retinal lesion features, resulting in fewer classification errors than the Existing CNN model. The Proposed ResNet50 achieved an overall accuracy of 84.40%, precision of 84.29%, recall of 83.81%, and F-measure of 83.57%. These results demonstrate that deeper residual learning significantly improves diabetic retinopathy classification.

Figure 4: Confusion Matrix of the Proposed Hybrid ResNet50 Model

Figure 4 presents the confusion matrix of the proposed Hybrid ResNet50 model integrated with the Adam optimizer and Valid Padding. Compared to the previous models, the hybrid framework produced substantially fewer misclassifications while correctly identifying the majority of retinal disease images. The proposed model achieved the highest accuracy of 94.78%, precision of 94.52%, recall of 94.41%, and F-measure of 94.38%, demonstrating its superior capability for lesion-based diabetic retinopathy detection.

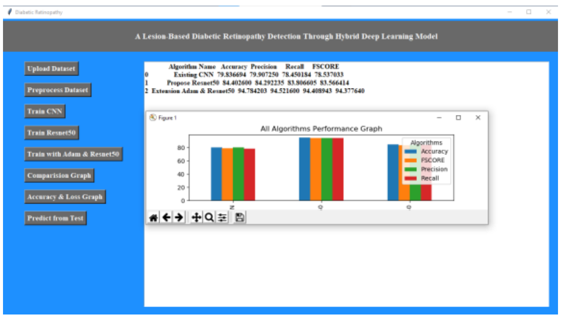

Figure 5: Comparison of Deep Learning Models

Figure 5 compares the performance of the Existing CNN, Proposed ResNet50, and Hybrid ResNet50 models using accuracy, precision, recall, and F-measure. The graph clearly indicates that the proposed Hybrid ResNet50 model consistently achieved the highest values across all evaluation metrics, demonstrating its superiority over the other deep learning approaches.

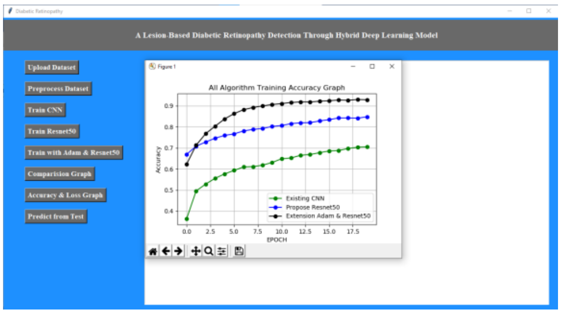

Figure 6: Training Accuracy Graph

Figure 6 illustrates the training accuracy curves of the Existing CNN, Proposed ResNet50, and Hybrid ResNet50 models over multiple epochs. The x-axis represents the number of training epochs, while the y-axis represents classification accuracy. The Hybrid ResNet50 model exhibited faster convergence and achieved the highest training accuracy throughout the learning process, indicating improved feature learning and better optimization using the Adam optimizer.

Model	Accuracy score	Precision score	Recall score	f- measure score
Existing CNN	79.84	79.91	78.45	78.54
Proposed ResNet50	84.40	84.29	83.81	83.57
Hybrid Model	94.78	94.52	94.41	94.38

Table 1: Model Performance Metrics

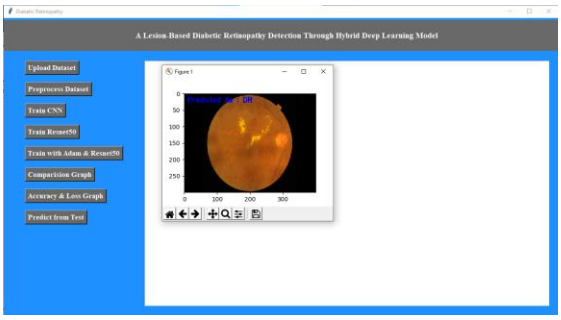

Figure 7: Prediction of Retinal Disease from Test Image

Figure 7 shows the prediction result generated by the proposed Hybrid ResNet50 model for an unseen retinal fundus image. After uploading the test image, the trained model automatically preprocesses the image, extracts lesion-specific features, and predicts the corresponding retinal disease class. The prediction module successfully identified the uploaded retinal image as Diabetic Retinopathy (DR), demonstrating the effectiveness of the proposed system for real-time retinal disease diagnosis.

DISCUSSION

The experimental findings demonstrate that deep learning techniques significantly improve the automated detection of diabetic retinopathy from retinal fundus images. The Existing CNN model achieved satisfactory performance but exhibited limitations in extracting complex lesion patterns, resulting in relatively lower classification accuracy. The Proposed ResNet50 architecture improved feature extraction through residual learning, thereby reducing classification errors and increasing overall performance. The proposed Hybrid ResNet50 model integrated with the Adam optimizer and Valid Padding achieved the best performance among all evaluated models. The use of the Adam optimizer accelerated network convergence, while Valid Padding reduced unnecessary feature map expansion, allowing the model to focus more effectively on clinically significant retinal lesions. The confusion matrices confirmed that the hybrid model produced the fewest misclassifications across all retinal disease categories. The comparison graph and training accuracy curve further validated the superiority of the proposed approach by consistently outperforming the Existing CNN and Proposed ResNet50 models. Additionally, the prediction module accurately classified unseen retinal fundus images, demonstrating excellent generalization capability and practical applicability. Overall, the proposed hybrid deep learning framework provides a reliable, efficient, and accurate computer-aided screening system for diabetic retinopathy, offering valuable decision support to ophthalmologists for early diagnosis and timely treatment.

VI. CONCLUSION

The classification of the different retinal disorders is addressed by presenting a CNN model based on deep learning. Diabetic Retinopathy, a dataset containing 32 various retinal diseases, is the basis for the model's implementation. The proposed model is trained on different epochs to test the model's accuracy. Initially, the model was trained at 10 epochs and achieved 95% validation accuracy; then, at 15 epochs model again achieved 95% validation accuracy with 0.0279 validation loss which varies in both cases. The model's total performance is much superior to that of other models considered to be state of the art. There is a possibility that the categorization of retinal diseases might benefit from the model that has been provided. Regular model updates and retraining using new data will continue to enhance its performance in the future. This will be achieved by leveraging the advancements in deep learning techniques and the increasing availability of diverse retinal disease datasets.

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