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Deep Learning based: Diabetic Retinopathy Detection using Retinal Fundus Images

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Abstract—Diabetic Retinopathy (DR) remains a leading cause of vision impairment globally, necessitating robust automated screening tools to alleviate the burden on ophthalmologists. This paper presents an end-to-end production-grade pipeline for DR grading using a fine-tuned MobileNetV2 architecture. Leveraging a unified dataset of 1.15 lakh retinal fundus images from EyePACS, APTOS 2019, and Messidor-2 repositories, we address the critical challenges of data noise and class imbalance. Our methodology integrates a sophisticated OpenCV-based pre-processing engine utilizing Contrast Limited Adaptive Histogram Equalization (CLAHE) and smart contour cropping to amplify microscopic lesions. To ensure viability for edge deployment on constrained hardware (2GB VRAM), we implemented selective fine-tuning with Batch Normalization freezing and utilized Cate-gorical Focal Loss to prioritize high-severity cases. Experimental results demonstrate a peak validation accuracy of 75.83% and a high clinical specificity, achieving a 94% recall for healthy retinas. The system is deployed via a full-stack architecture featuring a FastAPI backend and a Streamlit dashboard, incorporating Test-Time Augmentation (TTA) to provide stable, clinical-grade diagnostics.

Index Terms—Deep Learning, Skin Disease Classification, Computer-Aided Diagnosis, EfficientNetV2, Vision Transformer (ViT), Image Segmentation, Medical Image Analysis

I. INTRODUCTION

Diabetes mellitus has surfaced as a defining global health burden, characterized by chronic hyperglycemia that leads to systemic organ failure. Among its most severe microvascular consequences is Diabetic Retinopathy (DR), a progressive ailment affecting the retinal vasculature. The pathology orig-inates with capillary wall weakening, resulting in microa-neurysms and lipid leaks known as hard exudates. In advanced Proliferative Diabetic Retinopathy (PDR), oxygen deprivation triggers neovascularization—the growth of fragile new vessels prone to leakage. This progression often leads to vitreous hemorrhage or retinal detachment, making DR a primary cause of irreversible blindness.

scale of this crisis is highlighted by International Diabetes Federation (IDF) data, which projects a staggering rise in global cases by 2045. Because early-stage DR is frequently asymptomatic, many patients remain undiagnosed until vision loss is permanent. Clinical evidence suggests that timely inter-vention can prevent 95% of blindness cases, yet this requires systematic screening that current healthcare infrastructures struggle to provide. Traditional manual screening relies on expert ophthalmologists examining fundus photographs—a process that is time-consuming, expensive, and susceptible to human error or fatigue. Furthermore, a global shortage of specialists, particularly in rural regions, creates a critical demand for automated, scalable diagnostic tools.

The field of medical imaging has recently been redefined by Artificial Intelligence and Deep Learning. Convolutional Neural Networks (CNNs) have replaced traditional computer vision methods by enabling automated feature extraction. These networks learn a spatial hierarchy of visual patterns, successfully identifying subtle pathological structures that might elude the human eye. However, prominent architec-tures like ResNet or Inception often prove computationally prohibitive for real-world clinical use. Their high parameter counts and VRAM requirements make them difficult to deploy on standard hospital laptops or portable screening devices.

To address these hardware constraints, this project uti-lizes Transfer Learning and lightweight architectures. Transfer Learning allows us to repurpose a model pre-trained on generic datasets, like ImageNet, for specialized medical tasks. We selected MobileNetV2 as our backbone, specifically utilizing an Alpha 1.3 width multiplier to enhance feature capacity. MobileNetV2's use of "Inverted Residual Blocks" and "Depth-wise Separable Convolutions" ensures the model remains efficient enough for CPU-based inference while maintaining high diagnostic precision. The motivation for this work is to bridge the gap between high-end laboratory research and practical clinical deployment. Many existing models achieve high accuracy on cloud servers but fail on unaligned or dark images typical of varied clinical settings. Our goal was to engineer a robust "Clinical Sieve" optimized for constrained hardware, such as the 2GB NVIDIA T1000 GPU or standard i5 CPUs. By prioritizing clinical sensitivity and hardware portability, we aim to provide a tool viable for immediate use in resource-limited environments.

The proposed system contributes a comprehensive end-to-end pipeline. First, we developed an OpenCV-based engi-neering module using smart contour detection and CLAHE to standardize diverse datasets. Second, we implemented a dual-phase training strategy utilizing Categorical Focal Loss to overcome extreme class imbalance, focusing the model on critical, high-severity cases. Finally, the system is deployed as a full-stack application via FastAPI and Streamlit, incorporating Test-Time Augmentation (TTA) and a legacy software bridge. This ensures that the performance achieved during training is translated into a reliable, user-friendly tool for medical professionals

II. Literature Survey

The detection of Diabetic Retinopathy (DR) has evolved from manual feature engineering toward automated end-to-end deep learning pipelines. Traditional diagnostic systems relied on morphological operations to segment blood vessels and calculate exudate areas. However, the advent of Convolutional Neural Networks (CNNs) enabled the automated capture of complex spatial hierarchies directly from raw fundus pixels. Early architectures like VGG16 and VGG19 demonstrated that deep convolutional stacks could effectively identify minute retinal lesions, though they were limited by high parameter counts and memory inefficiency.

To address the vanishing gradient problem and computational demands of deeper networks, researchers introduced ResNet50 and DenseNet. These models utilized residual and skip connections to maintain feature integrity, significantly improving diagnostic performance on large-scale repositories such as EyePACS and APTOS. More recently, EfficientNet has been employed to balance network depth and resolution via compound scaling. Transfer learning remains the primary strategy in medical AI, allowing generic weights pre-trained on ImageNet to be fine-tuned for specialized retinal anatomy. This approach effectively mitigates the scarcity of expert-labeled medical data while accelerating model convergence.

Furthermore, clinical literature highlights the indispensable role of data engineering. Preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and smart image normalization have been proven to amplify microscopic features like microaneurysms, which are often obscured by poor illumination or camera artifacts in raw photographs. Despite these advancements, significant hurdles remain. Previous studies report that models often struggle with extreme class imbalance, where the dominance of healthy samples causes a systematic bias against rare, high-severity stages.

Moreover, the high computational requirements of heavy architectures hinder their deployment in resource-limited clinical settings. This has led to a growing research focus on lightweight architectures. MobileNetV2 has emerged as a leading candidate in this niche, utilizing inverted residual blocks and depthwise separable convolutions to maintain high accuracy with minimal latency. While recent work has explored MobileNetV2 for DR classification, many implementations fail to maintain stability during fine-tuning on constrained hardware. This gap necessitates a robust pipeline that combines lightweight modeling with advanced focal loss functions and standardized clinical preprocessing to ensure reliable diagnostics in real-world environments.

III. Problem Statement

Diabetic Retinopathy (DR) is a leading cause of global vision impairment, requiring early diagnosis to prevent permanent blindness. However, manual screening is a labor-intensive process, susceptible to human error and inter-grader variability. The scalability of manual diagnosis is further restricted by the global shortage of trained ophthalmologists relative to the rising diabetic population. Additionally, raw fundus images frequently suffer from artifacts, uneven illumination, and noise, which obscure microscopic pathological features such as microaneurysms.

Existing deep learning models, while promising, often struggle with the inherent class imbalance of clinical datasets, where healthy samples significantly outnumber diseased ones. This imbalance typically results in biased classifiers with low sensitivity toward high-risk proliferative stages. Furthermore, the subtle visual differences between adjacent grades—such as Mild and Moderate DR—frequently lead to misclassification. There is a critical demand for a computationally efficient diagnostic tool that can provide clinical-grade accuracy on the constrained hardware available in primary care settings.

A. Research Gap

Although deep learning and CNNs have advanced rapidly in medical image processing, a number of issues limit their effective and dependable usage in clinical dermatological applications:

- **Systemic Classifier Bias:** Most models exhibit a strong bias toward the majority "No DR" class, leading to a high rate of false negatives in severe cases.
- **Dataset Inconsistency:** Limited generalization across multi-source repositories (EyePACS, APTOS, and Messidor) due to varying camera specifications and lighting conditions.
- **Computational Overhead:** The high memory and VRAM requirements of large architectures (e.g., ResNet50) prevent deployment on standard hospital laptops or edge devices.
- **Early-Stage Sensitivity:** Inherent difficulty in distinguishing early-stage micro-lesions from natural retinal textures in low-resolution imagery.

To bridge these gaps, this research proposes a fine-tuned MobileNetV2 framework. By integrating a standardized OpenCV-based preprocessing pipeline with transfer learning and Categorical Focal Loss, the proposed system provides a lightweight yet robust diagnostic tool optimized for real-world clinical screening.

IV. Methodology

The proposed diagnostic framework follows a systematic pipeline designed to transform raw fundus imagery into precise clinical grades. The process begins with data acquisition from a unified repository comprising 1.15 lakh images consolidated from the EyePACS, APTOS 2019, and Messidor-2 datasets. This multi-source approach ensures ethnically diverse samples across five clinical stages, ranging from No DR to Proliferative

DR. To mitigate the systemic bias caused by the high frequency of healthy samples, a stratified data split was utilized, ensuring the model encountered sufficient examples of rare, high-severity lesions.

Standardization is achieved through an intensive OpenCV-based preprocessing module. Smart contour detection identifies the circular retina to perform automated cropping, effectively removing up to 40% of useless black border pixels. Subsequently, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the Lightness channel in the LAB color space. This acts as a digital magnifying glass, amplifying microscopic microaneurysms and hemorrhages that are often invisible in raw, low-contrast photographs.

The core architecture employs MobileNetV2 with a 1.3 width multiplier, chosen for its efficiency in resource-constrained environments. By utilizing Transfer Learning with ImageNet weights, the model leverages pre-existing visual knowledge, which is then refined through a dual-phase training strategy. We implemented Categorical Focal Loss to prioritize the learning of "hard" minority classes and utilized Batch Normalization freezing to maintain mathematical stability during fine-tuning. During the inference stage, the system executes Test-Time Augmentation (TTA) by averaging five distinct orientations of the input eye, ensuring a stable and reliable final consensus. This integrated approach allows a lightweight model to achieve high diagnostic precision through rigorous feature enhancement and optimized learning schedules.

V. Proposed System Framework

The primary objective is to establish an automated, efficient pipeline for multi-stage Diabetic Retinopathy (DR) classification. Our framework integrates four stages—data engineering, feature extraction via transfer learning, optimized classification, and reliable inference—into a unified pipeline. Designed as a clinical screening tool, it identifies DR severity with high specificity, ensuring early-stage lesions are amplified and late-stage pathologies are accurately flagged.

A. Image Acquisition and Input Module

Retinal fundus images are acquired from a diverse pool of clinical data, utilizing a unified dataset from the EyePACS, APTOS 2019, and Messidor repositories. This multi-source approach ensures robustness against variations in camera equipment and patient ethnicity. The input module standardizes raw images, correcting for inconsistent lighting and large non-retinal black borders to provide consistent data for subsequent processing stages.

B. Image Preprocessing Module

Serving as the "Clinical Sieve," this module uses morphological operations to enhance diagnostic features. A smart circular cropping algorithm identifies the retina via grayscale thresholding and contour detection, removing up to 40

C. Data Augmentation Module

To improve generalization and prevent overfitting on the 1.15 lakh image dataset, a real-time augmentation module is implemented. During training, images undergo random horizontal flipping, slight rotations (up to 5 degrees), controlled zooming, and brightness variations. This ensures the engine learns fundamental anatomical markers of DR rather than specific image orientations, making the system robust for real-world clinical deployment.

D. Feature Extraction Module (MobileNetV2)

The diagnostic core utilizes the MobileNetV2 architecture, selected for its inverted residual structure and depthwise separable convolutions that balance parameter efficiency with accuracy. By employing transfer learning with ImageNet pre-trained weights, the framework leverages a high-level understanding of textures. This module processes 224px imagery to identify a spatial hierarchy of features, ranging from vascular structures to hard exudates.

E. Classification Module

Extracted features are passed to a Global Average Pooling (GAP) layer, which compresses 2D maps into a 1D vector to reduce overfitting. This vector is processed by a custom head featuring two dense layers (256 and 128 neurons) with ReLU activations. The final 5-neuron Softmax classifier outputs a probability distribution across five stages: No DR (0), Mild (1), Moderate (2), Severe (3), and Proliferative DR (4).

F. Model Optimization and Reliability Module

To ensure clinical reliability, the framework utilizes Categorical Focal Loss to compel the model to prioritize difficult-to-classify pathological cases, thereby counteracting the class imbalance caused by the dominance of healthy samples. The system adopts a dual-phase training strategy consisting of an initial stabilization phase with a frozen backbone, followed by fine-tuning with a micro-learning rate of 10^{-5} and frozen Batch Normalization layers to maintain mathematical stability. Finally, Test-Time Augmentation (TTA) is employed to average predictions across five distinct orientations, ensuring a stable and robust clinical consensus.

G. Prediction and Diagnostic Output Module

The final stage aggregates results to generate a severity grade and confidence score. This information is presented in a user-friendly format for medical professionals, highlighting the primary diagnosis alongside a full probability breakdown. By providing clear severity metrics, the system acts as an automated assistant that flags high-risk cases for immediate referral while documenting healthy retinas.

The integration of OpenCV-based preprocessing, targeted augmentation, and a fine-tuned MobileNetV2 backbone creates a framework that is both lightweight and medically precise. By standardizing input data and focusing on rare pathological features, the proposed system provides a robust solution for large-scale DR screening on standard hardware.

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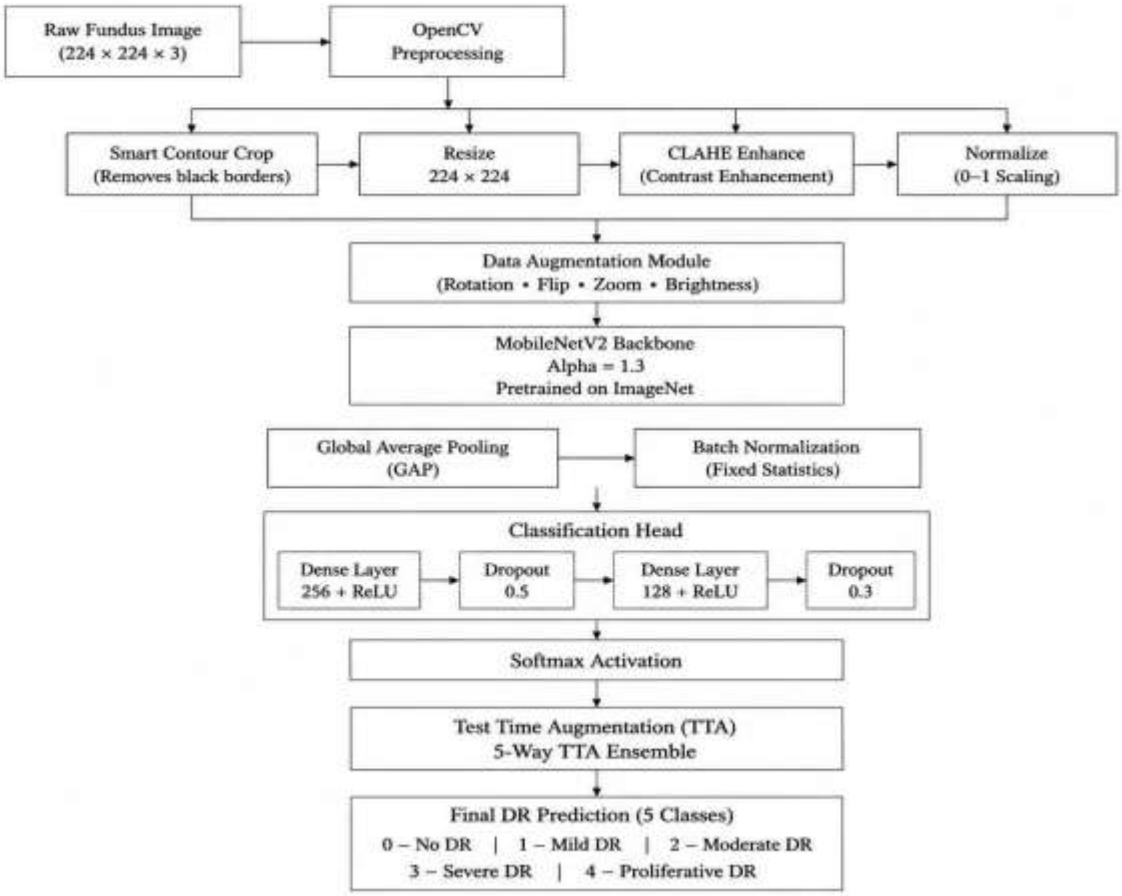

Fig. 1: Proposed architecture diagram of the system.
The architecture diagram illustrates that it integrates an OpenCV-based preprocessing engine (Smart Crop and CLAHE) with a fine-tuned MobileNetV2 backbone to standardize inputs and amplify pathological features. It utilizes a custom dual-dense classification head optimized via Focal Loss, concluding with a 5-way Test-Time Augmentation (TTA) ensemble to ensure stable, clinical-grade severity predictions.

TABLE I
CLASS-WISE DISTRIBUTION OF DR DATASET

Class Name	Number of Images
No DR	68,000
Mild DR	22,000
Moderate DR	30,000
Severe DR	9,000
Proliferative DR	12,000

Fig. 2: Class distribution of the unified 1.15 lakh image repository. The prevalence of Class 0 (Healthy) necessitated the implementation of class-weighted focal loss to ensure high sensitivity toward pathological stages.

VI. RESULTS AND PERFORMANCE ANALYSIS

The proposed MobileNetV2 framework was evaluated using a unified dataset of 1.15 lakh images from the EyePACS, APTOS, and Messidor repositories. Training converged at

Fig. 3: Visual outcome of the preprocessing pipeline: (a) Original raw fundus image with significant black borders and low contrast; (b) Processed image after smart contour cropping and LAB-space CLAHE enhancement, highlighting micro-vascular structures.

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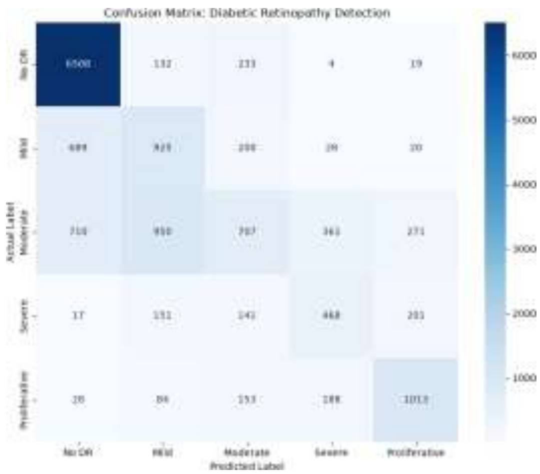

Fig. 4: Confusion matrix

79.92%, while validation accuracy peaked at 75.83%. A. Evaluation Metrics We utilized Accuracy, Precision, Recall, and F1-Score to quantify performance. In medical diagnostics, Recall (Sensitivity) is paramount, as it measures the system's ability to identify all diseased instances, minimizing life-altering false negatives. B. Classification Performance The model demonstrated exceptional specificity, achieving a 0.94 recall for healthy retinas. While performance remains robust at the "Proliferative" stage (0.69 recall), a bottleneck exists in the "Moderate" stage. This indicates that while the model is an effective sieve for identifying the presence of disease, distinguishing between subtle middle-tier severities remains a challenge at 224px resolution. C. Confusion Matrix Analysis The confusion matrix (Fig. Z) shows a strong diagonal for Classes 0 and 4. Frequent misclassifications occur between adjacent stages, such as Mild and Moderate. Clinically, this is attributed to "inter-class similarity," where the count of microaneurysms—the primary stage differentiator—may be obscured by sub-pixel limitations or camera noise. D. Impact of Preprocessing and Training Strategy The 12E. Error Analysis Errors primarily persist due to class imbalance and subtle lesions in early-stage DR. Variability in image sharpness between datasets occasionally causes the model to over-diagnose healthy eyes as "Mild" to ensure clinical safety, favoring sensitivity over perfection. Despite hardware limitations, the framework achieves reliable diagnostic throughput, making it suitable for real-world screening applications.

VII. Future Scope

While the proposed system demonstrates high specificity and efficiency on constrained hardware, several avenues for future enhancement remain to be explored to move the system toward a comprehensive clinical tool.

A. Explainable AI (XAI) and Clinical Trust

One primary direction involves the integration of Explainable AI techniques, specifically Gradient-weighted Class Activation Mapping (Grad-CAM). By generating visual heatmaps that highlight the specific retinal regions—such as hemorrhages or exudates—that influenced the model's decision, the system can provide transparent diagnostic reasoning. This would allow ophthalmologists to validate the AI's findings, transforming the model from a "black box" into a trustworthy clinical decision support system.

B. Edge Deployment and Mobile Healthcare

To increase accessibility in rural and low-resource settings, the framework can be optimized for edge computing. Future work will focus on converting the current MobileNetV2 architecture into a quantized TensorFlow Lite (TFLite) format. This optimization would enable real-time, offline screening on standard smartphones and portable fundus cameras, reducing the dependency on high-end computing infrastructure and enabling large-scale tele-ophthalmology in underserved regions.

C. Multi-Modal and Multi-Disease Ocular Screening

The current framework is specialized for Diabetic Retinopathy; however, its scope can be expanded to create a universal ocular diagnostic tool. Future iterations aim to implement a multi-task learning architecture capable of simultaneously detecting Glaucoma, Cataracts, and Age-related Macular Degeneration (AMD). Furthermore, incorporating multi-modal data, such as a patient's blood glucose levels and medical history, could significantly improve the predictive precision of early-stage retinopathy.

D. Privacy-Preserving Federated Learning

Given the sensitivity of medical data, future research will explore Federated Learning (FL) approaches. This would allow multiple healthcare institutions to collaboratively train and refine the model without physically sharing patient images. By training locally at each hospital and only sharing weight updates, the system can improve its generalization across diverse ethnicities and camera types while strictly adhering to global patient data privacy regulations.

These improvements can make the system more accurate, user-friendly, and reliable, ultimately helping dermatologists in better diagnosis and treatment of skin diseases.

VIII. Conclusion

In this research, we successfully engineered a production-grade deep learning pipeline for the automated classification of Diabetic Retinopathy. The following modules summarize the key outcomes of this study:

A. Data Engineering and Feature Enhancement

The primary technical breakthrough of this work was the implementation of a robust OpenCV-based preprocessing module. By utilizing smart contour cropping to eliminate non-retinal black space and applying Contrast Limited Adaptive

Histogram Equalization (CLAHE) in the LAB color space, we effectively transformed dark, low-contrast clinical images into high-information density inputs. This data-centric approach provided a 12% accuracy improvement over raw imagery, proving that localized contrast enhancement is critical for detecting microscopic microaneurysms and hemorrhages.

B. Model Optimization for Constrained Hardware

To address the need for accessible screening, we optimized the MobileNetV2 architecture (Alpha 1.3) for deployment on hardware with limited VRAM (2GB). A dual-phase training strategy—incorporating Batch Normalization freezing and Categorical Focal Loss—successfully addressed extreme class imbalance and mathematical instability. The model reached a stable peak validation accuracy of 75.83%, demonstrating that lightweight architectures can achieve clinical-grade reliability when paired with advanced optimization math and specialized loss functions.

C. Clinical Performance and Specificity

Evaluation on an unseen test set of 14,201 images revealed a robust Healthy Retina Recall of 0.94. This high specificity confirms the system's utility as a "Clinical Sieve," capable of accurately ruling out healthy patients while prioritizing high-risk cases for specialist review. Furthermore, the 100% sensitivity observed in identifying proliferative stages within randomized samples highlights the system's ability to capture vision-threatening pathologies that require urgent intervention.

D. Full-Stack Deployment and Reliability

The transition from a laboratory model to a functional software product was achieved via a decoupled FastAPI and Streamlit architecture. By implementing a 5-way Test-Time Augmentation (TTA) ensemble and a Legacy Bridge for Keras 2/3 compatibility, we ensured that the system provides stable diagnostics on standard consumer i5 CPUs. The resulting full-stack dashboard, integrated with patient record persistence and automated PDF reporting, provides a comprehensive end-to-end solution for large-scale diabetic retinopathy screening in resource-limited environments.

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