Hybrid Machine and Deep Learning in Brain Tumor MRI Analysis

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***Abstract*—This research examines ensemble machine and deep learning techniques for brain tumor classification from Magnetic Resonance Imaging (MRI). It analyzes most recent advances that combines convolutional neural networks with traditional machine learning classifiers illustrating their performance in achieving classification accuracies spanning from 95% to over 99%. The review covers core elements including brain tumor types, standardized datasets and performance evaluation metrics. Considerable findings indicate that the feature fusion approaches integrating deep learning representations with custom radiomic features consistently yield the best results. However challenges which include computational complexity, limited dataset and clinical validation requirements remain critical obstacle to widespread adoption and this paper concludes by identifying research directions for developing more efficient, interpretable and clinically deployable brain tumor classification systems to support diagnostic decision making in healthcare settings.**

***Index Terms*—Brain Tumor Classification, Magnetic Resonance Imaging, Deep Learning, Machine Learning, Hybrid Models, Medical Image Analysis, Convolutional Neural Networks, Computer-Aided Diagnosis**

I. INTRODUCTION

A. Motivation

The accurate classification of brain tumors from MRI scans is vital for determining appropriate treatment strategies and improving patient outcomes, however manual diagnosis by radiologists faces different challenges of subjectivity, time constraints and increasing workload. Recent advances in Artificial Intelligence specifically combination of both machine learning and deep learning offer promising solutions to augment clinical decision making. These automated systems can provide rapid, consistent and quantitative assessments to support healthcare professionals. This review examines the current state of hybrid techniques to provide researchers and clinicians with comprehensive understanding of this rapidly evolving field and its potential for clinical integration.

B. Challenges in Traditional Diagnosis

Classical brain tumor diagnosis from MRI scans encounter multiple limitations however manual interpretation by radiologists suffers from subjectivity and inter observer variability leading to inconsistent diagnoses. This method is time consuming, creating workflow bottlenecks as imaging volumes increase and tumor complexity with variations in size, shape and irregular boundaries further complicates accurate classification as these challenges are exacerbated by specialist shortages and diagnostic fatigue underscoring the need for automated decision support system.

C. Paper Organization

The layout of this paper is organized as follows. Section II gives concise background on brain tumor and essential role of artificial intelligence in medical imaging. Section III provides thorough academic review of machine learning and deep learning techniques utilized for brain tumor classification. Section IV describes experimental analysis and results and Section V concludes the paper with summary of findings and future perspectives.

II. BACKGROUND

A. Overview of Brain Tumors

Brain tumors depicts non-uniform group of diseases each with seperate origins, malignancy level and imaging characteristics and the most common brain tumors are **meningiomas**, **gliomas** and **pituitary tumors**.

- **Meningiomas** come from meninges which act as layers of tissue that cover brain and are often benign and they are usually well circumscribed and demonstrate dural tails on contrast enhanced MRI.
- **Gliomas** originates from glial cells e.g. astrocytes and oligodendrocytes and they are often malignant infiltrating the surrounding brain tissue which makes their boundaries irregular.
- **Pituitary tumors** grows in pituitary gland at base of the brain which are distinct location that often leads to characteristic endocrine symptoms.

Precise classification of brain tumor types is one of the most important for clinical management as illustrated in Figure 1 and these tumors exhibit distinct morphological features across different MRI planes axial, coronal and sagittal which form basis for diagnostic differentiation [1]. Automated classification systems aim to learn and distinguish these subtle radiological markers to assist in early and precise diagnosis.

B. AI in Medical Imaging

The inclusion of Artificial Intelligence in medical imaging has revolutionized the diagnostic workflows from manual

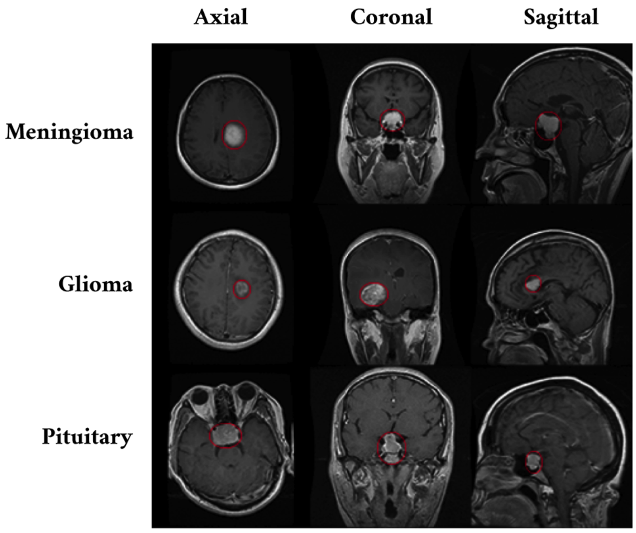

Fig. 1: Magnetic resonance imaging views of common brain tumors (Meningioma, Glioma, Pituitary) across three anatomical planes: axial, coronal, and sagittal. The red outline indicates the tumor boundaries. Adapted from Badža and Barjaktarović [1].

interpretation toward automated systems. Traditional machine learning approaches mostly rely on custom feature extraction and classifiers like SVM but they were limited by feature quality. Deep learning particularly CNNs revolutionized the field by automating feature extraction from raw pixel data achieving superior performance for complex tasks like tumor detection however pure deep learning models face criticism as black boxes require large datasets and may overlook clinical knowledge. Combined techniques have appeared to bridge this gap combining CNN based feature extraction with machine learning classifiers or fusing deep and handcrafted features. These method goal is to develop systems that are accurate, efficient, generalizable and clinically interpretable [2], [3], [4].

C. Workflow for Brain Tumor Classification

The classical process for programmed brain tumor classification from MRI scan follow systematic flow as illustrated in Figure 2 however the process start with input of raw medical images which first undergo preprocessing stages including noise removal, skull stripping and image enhancement to improve data quality. The configuration perform feature extraction using deep learning model to learn representations or traditional method to extract custom features such as texture, shape and size characteristics and after that the extracted features are then fed into classification algorithms either machine learning classifiers or deep learning networks to categorize the tumor type. Finally the system outputs the classification result typically identifying the scan as glioma, meningioma, pituitary tumor or no-tumor completing the diagnostic pipeline.

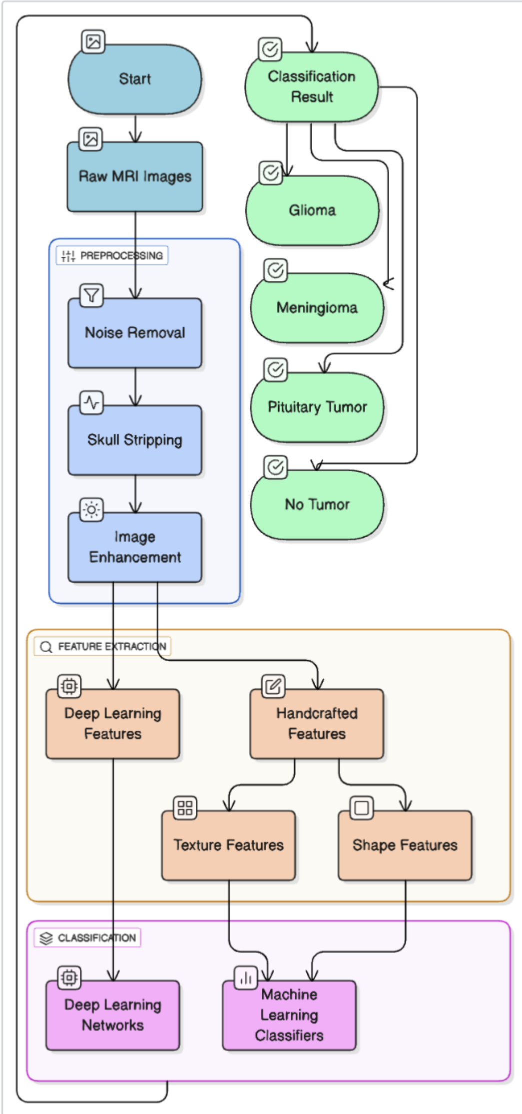

Fig. 2: Workflow for brain tumor classification

III. Literature Review

Seyed Matin Malakouti. [5] developed brain tumor classification system using machine learning and transfer learning on MRI images and they achieved 95.7% accuracy with Light Gradient Boosting Machine on numerical dataset and 99.3% accuracy using modified GoogLeNet model on 3,762 MRI images however the key limitations include computational cost of deep learning and performance dependency on specific algorithm components. Sandhiya. [3] developed deep learning system which is used to classify brain tumors from MRI images into four categories. Using two datasets their model achieved high accuracies of 97.97% and 98.21% and their methodology fused features from pretrained models like Inception V3 and DenseNet201 with custom radiomic features classifying tumors with Particle Swarm Optimized Kernel Extreme Learning Machine (PSO-KELM). A key limitation they addressed in existing work was dependence on complex preprocessing and convolutional feature extraction alone. Simo. [6] developed two step deep learning model to first detect and then classify brain tumors from MRI images. Using Kaggle dataset of 7,023 images they built Fully Convolutional Neural Network and found the Nesterov momentum optimizer performed best achieving final accuracy of 95%. A key limitation they identified was model's performance being constrained by limited quantity and occasional poor quality of available MRI images. Agarwal et al. [7] developed composite system for brain tumor classification and their two phase approach first enhances image contrast using the ODTWCHE technique and then classifies tumors using fine tuned Inception V3 network. They achieved accuracy of 98.89% on the Figshare dataset outperforming models like AlexNet and VGG-16. A key limitation is model potential inability to adapt to new circumstances not seen in its training data.

Remzan et al. [8] developed deep learning system for brain tumor classification using RadImageNet model and ensemble learning and their best model combining feature from ResNet-50 and DenseNet121 achieved 97.71% accuracy on dataset of 7,023 images. A core limitation is medical datasets often lack diversity, hindering model generalizability. Bhimavarapu et al. [9] also develop system using improved Fuzzy C-Means algorithm for segmentation and Enhanced Extreme Learning Machine for classification. Their model achieved high accuracies of 98.47% and 99.42% on Figshare and Kaggle datasets. A key limitation is model computational complexity and challenge of segmenting tumors accurately due to imaging artifacts. AG et al. [10] developed brain tumor classification system by fusing ResNet101 model with Channel-wise Attention Mechanism (CWAM). Their model achieved state of the art accuracy of 99.83% on Kaggle dataset of 7,023 MRI images. The system uses deep features refined by the CWAM module to prioritize relevant data channels. A key limitation is the model's increased computational complexity and memory demands due to attention modules. Ilani et al. [11] developed hybrid deep learning system for brain tumor classification. Their U-Net model achieved the highest accuracy of 98.56% on Figshare dataset and demonstrated strong generalizability with 96.01% accuracy in cross dataset validation. A key limitation is model dependence on large accurately labeled datasets.

Saboor et al [12] developed deep learning model for brain tumor classification using Attention Gated Recurrent Unit model and their method which integrate attention mechanism with GRU network achieved high accuracy of 99.32% on augmented dataset of MRI images. The model strength is ability to capture sequential patterns and spatial information with in MRI scans. A noted limitation is that the model's high computational complexity and memory requirements which result in longer training times. Shoaib et al [13] developed brain tumor classification system by integrating pretrained CNN models with machine learning classifiers and PCA. Their strategy achieved 100% accuracy on one dataset and 98% on another using DenseNet201 with SVM,MLP the authors noted that perfect scores raise concerns about potential overfitting, highlighting the need for validation on more diverse datasets.

Batah et al [14] developed system which is used to classify tumors by evaluating six machine learning algorithm on dataset of 15,000 MR images from Kaggle and their K-Nearest Neighbors and Neural Network models achieved the highest accuracies of 98.5% and 98.4% and the study primary limitation is the need for validation with real world clinical data which is used to confirm the model effectiveness and generalizability outside the research dataset. Filvantorkaman et al [15] develop deep learning system for brain tumor classification using custom 26-layer CNN and fine-tuned VGG16 and Xception models. Their approach achieved accuracies up to 100% on the Harvard Medical dataset and 98.57% on the Br35H dataset. A key limitation they identified was overfitting in their initial Deep CNN model which they addressed by incorporating techniques like Global Average Pooling to improve generalization, particularly on smaller datasets. Gencer et al [4] developed hybrid model for brain tumor classification using EfficientNetB0 for feature extraction and Quantum Genetic algorithm for feature selection and lastly they achieved accuracies of 98.36% and 98.25% on two MRI datasets and key limitation is the computational complexity of the QGA.

Sadr et al [16] developed deep learning model for brain tumor classification achieving high accuracies of 97.27% with custom 26-layer Deep CNN on Figshare dataset and up to 98.57% and 100% using fine tuned VGG16 and Xception models on Br35H, Harvard Medical datasets and they utilized three datasets Figshare, Br35H and Harvard Medical comprising thousands of MRI images and their approach utlizes deep convolutional neural networks to automatically extract features eliminating the need for manual feature engineering. A key limitation noted was the issue of overfitting with their custom Deep CNN model on smaller datasets, which they addressed by incorporating transfer learning and Global Average Pooling layers to improve generalization. Ali et al [17] developed system to classify brain tumors from MRI scans using a Co-Evolutionary Genetic Algorithm (CEGA) to automatically optimize the hyperparameters of two deep learning models, EfficientNetB3 and DenseNet121. Their approach tested on a Kaggle dataset, achieved high accuracies of 99.39% and 99.01% respectively without data augmentation, but a key limitation is its unproven performance on other diverse medical datasets.

Ishfaq et al [18] developed system using custom CNN, Inception-v4 and EfficientNet-B4 models which is used to classify brain tumor from MRI scans into ten categories and they used public Kaggle dataset achieving high accuracies up to 99.76% however a key limitation is that the dataset may not

TABLE I: Summary of Brain Tumor Classification Studies Using Hybrid Machine and Deep Learning Techniques

Study	Dataset	Models	Features	Accuracy	Limitation
[5]	3,762 MRI	Light GBM, GoogLeNet	CNN features	95.7%	High computational cost
[3]	Benchmarks	InceptionV3, DenseNet201	CNN + Handcrafted fusion	98.0%	Complex preprocessing
[6]	7,023 MRI	F-CNN	Deep features	95.0%	Limited data quality/quantity
[7]	Figshare	InceptionV3	Deep features	98.9%	Limited generalization
[8]	7,023 MRI	ResNet-50, DenseNet121	Deep features	97.7%	Limited dataset diversity
[9]	Custom	Enhanced ELM	Segmented features	99.4%	High computational complexity
[10]	7,023 MRI	ResNet101 + CWAM	Attention-based deep	99.8%	High memory demand
[11]	Figshare	U-Net based	Deep features	98.6%	Protocol variability
[12]	Custom	A-GRU	Sequential + spatial	99.3%	High computational complexity
[13]	Multiple	DenseNet201 + SVM/MLP	CNN + PCA features	98-100%	Potential overfitting
[14]	15,000 MRI	KNN, Neural Network	Image features	98.5%	Needs clinical validation
[15]	Custom	CNN Ensemble	Deep features	98-100%	Overfitting issues
[4]	MRI	EfficientNetB0 + QGA	Optimized deep features	98.3%	High computational complexity
[16]	Figshare	VGG16, Xception, Deep CNN	Deep features	97-100%	Overfitting on small datasets
[17]	MRI	EfficientNetB3, DenseNet121	Optimized deep features	99.0-99.4%	Unproven generalization
[18]	Kaggle	Inception-v4, EfficientNet-B4	Deep features	99.8%	Limited clinical diversity
[19]	3,000+ MRI	MobileNetV2, DenseNet-201	Deep features	96.5%	Model comparison only
[20]	MRI	DenseNet + Attention	Enhanced deep features	99.7-99.9%	High computational cost

Abbreviations:GBM: Gradient Boosting Machine; **F-CNN**: Fully Convolutional Neural Network; **ELM**: Extreme Learning Machine; **CWAM**: Channel-wise Attention Mechanism; **A-GRU**: Attention Gated Recurrent Unit; **SVM**: Support Vector Machine; **MLP**: Multi-Layer Perceptron; **KNN**: K-Nearest Neighbors; **QGA**: Quantum Genetic Algorithm; **PCA**: Principal Component Analysis.

fully represent real world clinical diversity, requiring further validation. Mijwil et al [19] aimed to find the most suitable deep learning architecture for classifying brain tumors from MRI images. The author compared four different CNN models DenseNet-201, Inception-V1, AlexNet and MobileNetV2 on dataset of over 3,000 MRI images from Kaggle. The results showed that MobileNetV2 was the most effective model achieving accuracy of 96.5% along with precision of 98.2%, sensitivity of 96.6% and an F1-score of 97.4%. Amir et al [20] developed automated system to classify brain tumors from MRI scans using two public datasets e.g. Figshare and BraTS2020. Their method combined image enhancement, U-Net segmentation, DenseNet feature extraction with attention mechanisms and ensemble classifier. The system achieved very high accuracy 99.67% and 99.94% but has limitations including high computational cost and need for broader clinical testing.

A. Popular Datasets

The implementation and validation of brain tumor classification model depend on standardized dataset and one of the most used resources is Kaggle Brain Tumor MRI Dataset [21] used by numerous studies [5], [13], [14], [18], [19]. This collection contains over 7,000 MRI scans categorized into four differnet classes glioma, meningioma, pituitary tumors and no tumor. The dataset popularity originates from its extensive size, balanced class distribution and classified structure which collectively facilitate training of data intensive deep learning model without requiring extensive data curation however another is Figshare MRI Dataset [22] utilized in various studies like [7], [9], [11]. This collection provide T1 weighted contrast enhanced MRI scancs across the same four tumor categories and it standardized imaging protocols and clinical relevance make it valuable for evaluating both segmentation accuracy and classification performance under consistent conditions. For binary tumor detection tasks Br35H dataset [15], [16] gives substantial image volume organized as tumor versus non tumor while the Harvard Medical School Whole Brain Atlas [23], [15], [16] offers diverse clinical scans from various conditions and populations making it invaluable for testing model generalizability and real world applicability. The use of these datasets across multiple studies has established crucial common ground for performance evaluation which accelerated the progress in automated brain tumor classification systems.

IV. Experimental Analysis

A. Dataset Description and Preprocessing

The practical analysis was conducted using publicly available Brain Tumor MRI Dataset from Kaggle [21] which contains T1 weighted contrast enhanced MRI scans which are organized into four distinct categories glioma, meningioma, pituitary tumor and no tumor. All MRI scans faced standardized preprocessing to ensure its consistency and improve model performance and preprocessing pipeline included three main steps. First resizing: all images were resized to standard 100×100 pixels using bilinear interpolation to maintain computational efficiency while preserving essential features:

$$I_{\text{resized}} = \text{resize}(I_{\text{original}}, (100, 100)) \tag{1}$$

Second, color space conversion: images were converted from BGR to RGB color space to maintain the compatibility with standard computer vision libraries:

$$I_{\text{RGB}} = \text{cv2.cvtColor}(I_{\text{BGR}}, \text{COLOR\_BGR2RGB}) \tag{2}$$

Third, normalization: pixel values were normalized to the range [0, 1] to improve training stability:

$$I_{\text{normalized}} = \frac{I}{255.0} \tag{3}$$

The dataset exhibited relatively balanced class distribution which helps mitigate potential bias in model training and evaluation.

B. Feature Extraction Methodology

In order to capture both texture and color characteristics of brain MRI scans we utilizes two feature extraction techniques e.g. Histogram of Oriented Gradients (HOG) for texture analysis and Color Histograms for color distribution analysis. The HOG feature descriptor describes local shape information by analyzing the distribution of gradient orientations. For image $I(x, y)$, the gradient magnitude $G(x, y)$ and orientation $\theta(x, y)$ are computed as:

$$G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2}, \tag{4}$$

$$\theta(x, y) = \arctan\left(\frac{G_y(x, y)}{G_x(x, y)}\right) \tag{5}$$

where G_x and G_y represent horizontal and vertical gradients respectively. The HOG parameters used were: 9 orientation bins, 16×16 pixels per cell, and 2×2 cells per block resulting in 1,764-dimensional feature vector. Color histograms capture distribution of pixel intensities in each RGB channel. For image with B bins per channel, the normalized combined feature vector is:

$$H_{\text{combined}} = \left[\frac{H_R}{\sum H_R + \epsilon}, \frac{H_G}{\sum H_G + \epsilon}, \frac{H_B}{\sum H_B + \epsilon}\right] \tag{6}$$

We used $B = 32$ bins per channel resulting in 96-dimensional feature vector, with $\epsilon = 10^{-7}$ to prevent division by zero. The final feature representation was obtained by concatenating both feature vectors:

$$F_{\text{final}} = [F_{\text{HOG}}, F_{\text{color}}] \tag{7}$$

This method merge strengths of both texture and color information providing comprehensive feature set for effective brain tumor classification.

C. Model Architecture and Implementation

We employed Support Vector Machines with three kernel functions for brain tumor classification:

1) **Linear Kernel:** Simple dot product between features
2) **Polynomial Kernel:** Non linear polynomial transformations
3) **RBF Kernel:** Distance based similarity decay

To tackle imbalance class weighted SVM was used where parameters were adjusted based on class frequencies and models were trained using scikit learn with default parameters on combined HOG and color histogram features optimizing decision boundaries.

D. Experimental Results and Analysis

The practical results demonstrate the performance of three SVM kernels on brain tumor classification. Table II depicts comparison of all evaluation metrics across different kernels providing observation into model performance at both macro and class specific levels while Table III provides detailed class wise performance metrics. Evaluation of Tables II and III shows that the polynomial kernel achieved performance with highest test accuracy (94.28%), F1-score (0.94) and AUC scores across all tumor types and it demonstrated better generalization with smallest train test gap (-0.05) and consistently outperformed other kernels in class wise F1-scores while linear kernel was fastest (159.74s) polynomial kernel offered optimal balance with minimal computational increase (168.94s) for substantial accuracy gains and it cearly reduced glioma meningioma misclassifications from 61/42 to 37/16 cases. The polynomial kernel is therefore the optimal choice for brain tumor classification.

V. Conclusion

This review has analyzed the current landscape of hybrid machine and deep learning techniques for brain tumor classification from MRI scans. The analysis of recent advancements reveals that the hybrid approaches consistently achieve high classification accuracies typically ranging from 95% to over 99% across various datasets. The combination of both deep learning feature extraction capabilities with traditional machine learning robustness and interpretability has proven particularly effective in addressing complex challenges of medical image analysis. Several key trends emerge from this review. First, the fusion of CNN extracted deep features with custom radiomic features significantly enhance classification performance as evidenced by studies achieving accuracies above 98%. Second, attention mechanisms and ensemble methods has shown success in improving model focus and generalization. Third, consistent use of standardized datasets like Kaggle and Figshare has enabled meaningful comparisons and accelerated progress in the field however significant challenges remain computational complexity, potential overfitting, limited dataset diversity and the need for clinical validation represent persistent limitations. Future research should focus on the developing more computationally efficient architectures enhancing model interpretability for clinical adoption improving generalization across diverse patient populations and imaging protocols and conducting rigorous real world validation studies. The integration of multi modal data and development of standardized evaluation frameworks will be crucial for translating these technical advances into clinically diagnostic tools that can effectively support healthcare professionals in improving patient outcomes.

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TABLE II: Comprehensive Performance Analysis of SVM Kernels for Brain Tumor Classification

Kernel	Accuracy Metrics				Macro Avg			Class AUC			Efficiency		
	Train	Test	Gap	Best F1	Prec	Rec	F1	Glioma	Menin.	Pit.	Time(s)	Speed	Rank
Linear	0.92	0.85	-0.07	0.95	0.84	0.84	0.84	0.96	0.92	0.99	159.74	Fast	2
Poly	0.99	0.94	-0.05	0.99	0.94	0.94	0.94	0.99	0.98	1.00	168.94	Fast	1
RBF	0.93	0.87	-0.05	0.97	0.87	0.87	0.86	0.97	0.93	0.99	236.35	Slow	3

TABLE III: Class-wise Performance Metrics for SVM Kernels

Kernel	Glioma (P/R/F1)			Meningioma (P/R/F1)			No Tumor (P/R/F1)			Pituitary (P/R/F1)		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Linear	0.81	0.77	0.79	0.73	0.71	0.72	0.93	0.97	0.95	0.91	0.93	0.92
Poly	0.93	0.86	0.90	0.87	0.91	0.89	0.99	0.99	0.99	0.97	0.99	0.98
RBF	0.86	0.83	0.84	0.81	0.69	0.74	0.93	0.97	0.95	0.87	0.98	0.92

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