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MRI Brain Tumor Classification using Optimized APSO-LLRBFNN

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ABSTRACT: One of the most prevalent kinds of brain cancers are brain tumors. In this study, we suggest a fresh and effective machine learning technique for classifying brain tumors. The proposed method combines image segmentation, classification, and feature extraction into one framework. The suggested Particle Swam Optimization PSO and Adaptive Particle Swam Optimization with Local Linear Radial Basis Function Neural Network APSO-LLRBFNN models were assessed using Support Vector Machine (SVM), and Learning Management Systems LMS-LLRBFNN classifier approaches. The results show that the proposed method has a high rate, as seen by the numerical findings of 98.93% with computational time 12.23 secs, which is more than other existing methods.

KEYWORDS: LLRBFNN, FAST FUZZY C-MEAN, APSO, PSO, ABC

I. INTRODUCTION

Extracting the tumor's footprint from MRI scans is merely one hurdle in the complex diagnostic landscape faced by radiologists and healthcare professionals. For the first study phase, two models—the PSO-LLRBFNN and the APSO-LLRBFNN—are described in detail to detect and categorize brain tumors. The wavelet transform was used in this study to improve the efficiency of the feature extraction and MR image segmentation procedures. The suggested PSO and APSO-LLRBFNN model were assessed using support vector machine (SVM), machine learning, and LMS-LLRBFNN classifier approaches [2,22,23,24]. The study concentrated on certain processes, including feature extraction, where relevant features are considered. In the subsequent phase, For the classification job, the characteristics are loaded into the proposed PSO-LLRBFNN model. The third phase entails comparing the results of a classification problem using the SVM and LMS LLRBFNN machine learning algorithms.

Compared to the machine learning method based on LLRBFNN and SVM, it is found that the proposed model requires less processing time [2,22,23,24]. The results of the recommended model outperform those of the classification findings. When it comes to precisely and expertly interpreting MRI brain images.

This paper's primary contribution is,

- Machine learning (ML) classification methods were used to differentiate between cancer and healthy cells.
- Discussed applying AI methods like SVM to identify cancer tumor cells based on their optimum features, extracted from segmented images.
- Finally, applied our APSO-LLRBFNN classifier is an efficient model that, unlike existing methodologies can quickly distinguish between cancer cells and healthy cells based on features collected from MRI cell images.

In the upcoming Section 2 will discuss similar related work and its consistent discussion. Section 3 will cover research methodology and flow using machine-learning approaches to identify and categorize brain tumor malignancy at its early stages. In Section 4, Results, discussion, and finally conclusion of the research will be discussed.

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II. RELATED WORK

There have been several research using various approaches in the field of brain tumor detection and classification. According to T. Sathies, Kumar et al. [1] used SVM Classifier and artificial neural networks to detect and classify cancers based on MR images.

Brain tumor segmentation is fully automated by using encoder-decoder based convolutional neural networks, as reported by Raghu, S. et al. [2]. The UNet deep neural network, which employs semantic segmentation to separate malignancies from brain The focus of this study is MRI pictures. Cocosco presented a method for automatically classifying brain tissues using a Multi-Layer Perceptron Network into categories of normal and pathological., C. A. et al. [3] and colleagues. S. Bauer and colleagues [4] examined a range of tumor segmentation techniques and underlined how crucial precise segmentation is for analysis and diagnosis.

Sauwen, N et al. [5] focused on detecting relevant tumor substructures to enhance diagnosis and treatment planning. Neha Rani et al. [6] employed statistical analysis and backprop neural networks for tumor detection, achieving high accuracy and reduced consumption time. Sanghamitra T. Kamble et al. [7] highlighted the efficiency of Kmeans clustering for tumor segmentation. Weidong Ji et al. [8] discussed the principles and applications of Radial Basis Function networks. M. Masroor Ahmed et al. [9] proposed a method combining image enhancement and clustering for automatic tumor segmentation.

Piyush M. Patel et al. [10] and associates developed an adaptive clustering method to enhance tumor segmentation. An approach for tumor identification based on K-Means clustering was presented by Malathi R et al. [11] and associates. Nimeesha K M et al. [12] and colleagues in their work highlighted the benefits of using KMeans over FuzzyCMeans clustering algorithms for tumor identification. Brain abnormalities and cancers were detected and classified using median filtering, GLCM, and ANFIS by G. Santhosh Krishnan et al. [13] and colleagues. For the purpose of medical image segmentation, V. Sagar Anil Kumar et al. [14] presented an effective K-Means clustering approach.

Yudong Zhang et al. [15] used wavelet-energy and support vector machines to create an automated abnormal brain detection system. A technique for figuring out the data center of an RBFNN and training network weights was presented by Mingwen Zheng et al. [16]. For image segmentation, Eman Abdel-Maksoud et al. [17] integrated fuzzy C-means with K-Means clustering. An innovative RBFNN with significantly delocalized neuronal receptive fields was presented by P. Maffezzoni et al. [18]. An initial cluster centers selection technique for RBFNN performance improvement was proposed by Yiping Jiao et al. [19]. An approach based on clustering was presented by Antonios D et al. [20] to train RBFNN of the Gaussian type.

In general, current methods concentrate on segmentation, extraction of features, or classification on their own, with little feature extraction and poor tumor detection accuracy. This research will combine physiologically inspired wavelet processing with HybridK-Means, FuzzyCMeans, and RBFN to increase the diagnostic precision of brain cancer detection and classification.

III. METHODODOLOGY

3.1 Data Preparation

The normalized feature table is accessible. The Gray Level Co-occurrence Matrix feature extraction approach was used to extract features, as Zhang X, et al. [21] pointed out. A total of 3000 photos were used in the experiment; 150 were used for training and 100 for assessment.

The characteristics, energy, skewness, and variance versus kurtosis, all provided unique values that were essential for differentiating between benign and malignant tumors, according to the analysis. For classification, these features were then fed into the suggested HybridRBFNN method. The efficacy of the Fast fuzzy c-means, KNN, and FuzzyCmeans algorithms in differentiating between benign and malignant tumors was also evaluated using the same data. MRI datasets have been gathered from the public Alzheimer's disease Neuroimaging Initiative (ADNI) database [23,24] and the architecture of Harvard Medical School. For training and testing purposes, a total of 3000 MRI pictures, both normal and pathological, were used. The MRI images will be processed to create a grayscale image, create a template, compute a correlation, locate tumor location, segment brain tumors, and provide training as shown in Table 3.1.

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Table 3.1 Features for Analysis

Img	S.Dev	Avg	uncertainty	variability	asymmetry	tiredness	vitality
Im-1	0.0673	0.0055	0.0503	0.0002	0.433552	0.21474	0.04086
Im-2	0.1661	0.0447	0.2637	0.0045	0.859782	0.55365	0.32505
Im-3	0.1811	0.0598	0.3126	0.0058	0.565064	0.32323	0.43472
Im-4	0.1813	0.0598	0.3272	0.0057	0.565062	0.32324	0.43473
Im-5	0.1403	0.0293	0.1913	0.0032	0.440844	0.30206	0.21344
Im-6	0.1535	0.0365	0.2267	0.0033	0.754416	0.52533	0.26582
Im-7	0.1616	0.0568	0.3152	0.0032	0.491598	0.34038	0.41323
Im-8	0.1122	0.0177	0.1128	0.0022	0.214917	0.10528	0.12935
Im-9	0.1124	0.0179	0.1228	0.0033	0.214919	0.10587	0.12937
Im-10	0.0612	0.0044	0.0396	0.0003	0.470328	0.15567	0.0308
Im-11	0.1468	0.0323	0.2053	0.0032	0.90197	0.84225	0.23357
Im-12	0.0424	0.001	0.0206	0.0002	0.428482	0.13516	0.0143
Im-13	0.0838	0.0087	0.0712	0.0004	0.575784	0.24066	0.06214
Im-14	0.1113	0.0168	0.1234	0.0012	0.441103	0.21942	0.12248
Im-15	0.0421	0.0018	0.0202	0.0002	0.344872	0.13664	0.01406

In the proposed study, characteristics like entropy, energy, standard deviation, autocorrelation, mean, and variance are retrieved from MR image data. The two most significant features among them are variance and entropy. As a result, various picture signals are clustered using these values. The Hybrid Fuzzy C Means RBFN technique is then used to cluster and classify 200 feature vectors. For the purposes of training and classification, 300 photos were used. [22-24] For clustering optimization, the RBFNN model with PSO training took about 11.21453 seconds. The model's classification accuracy was calculated and summarized in Table 3.2. MATLAB R2017a was used to measure the computational time.

Table 3.2 RBFNN version classification accuracy

Framework	Data set size	Processing time	Accuracy of Classification
LMS-RBFNN	300	18.21272	95.1
PSO-RBFNN	300	12. 21533	97.8
RBFNN-ABC	**300**	**12.213146**	**98.12**
KNN	300	38.32524	81.2
KMEANS	300	30.21433	86.1
FuzzyCMeans	300	25.23232	91.4
FastFuzzyC Means	300	22.12242	94.7

3.2 The Optimized APSO-LLRBFNN model for classification to improve the classification process

3.2.1 Adaptive Particle Swarm Optimization (APSO)

- **Particle Swarm Optimization (PSO)** is a popular optimization technique based on the social behavior of birds or fish. It involves particles moving through the solution space to find optimal or near-optimal solutions.
- **Adaptive PSO (APSO)** enhances PSO by dynamically adjusting the learning parameters (inertia weight, cognitive, and social components) based on the particles' current performance and exploration/exploitation needs.
- This adaptation leads to more efficient convergence towards optimal parameters of the model, avoiding local minima and speeding up the learning process.

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3.2.2 Locally Linear Radial Basis Function Neural Network (LLRBFNN)

- The **RBFNN** is a type of neural network that uses radial basis functions as activation functions. It is effective in classification tasks due to its ability to model complex nonlinear mappings.
- The **Locally Linear RBF (LLRBF)** is a variant where the linear mapping is applied locally to the clusters formed by radial basis functions. This allows for better generalization and more flexible decision boundaries, particularly in high-dimensional data.
- LLRBFNN adapts well to both linear and non-linear separable data, making it a strong choice for various classification problems.

3.2.3 Optimized APSO-LLRBFNN Framework

- **Initialization:** Start by initializing the parameters of the LLRBFNN, including the number of neurons, centers, widths, and weights.
- **APSO Optimization:** APSO is used to optimize the centers and widths of the radial basis functions and the weights of the locally linear output layer.
- **Fitness Evaluation:** At each iteration, evaluate the fitness (i.e., the classification accuracy or loss function) of each particle (solution) in the swarm. This involves using the current set of parameters to train the LLRBFNN on the classification task and assessing the model's performance.
- **Adaptive Updates:** Update the position and velocity of particles based on the current fitness, adjusting the balance between exploration (global search) and exploitation (local search).
- **Termination:** The process continues until a stopping criterion is met, such as a maximum number of iterations or a satisfactory classification accuracy.

3.3 Steps for Implementing Optimized APSO-LLRBFNN

3.3.1 Preprocessing

- Normalize/standardize the input data.
- Split the data into training and testing sets.

3.3.2 APSO Initialization

- Initialize a swarm of particles where each particle represents a potential solution (set of parameters for the LLRBFNN).
- Randomly initialize the particle positions and velocities.

3.3.3 LLRBFNN Training

- For each particle, train an LLRBFNN using its current parameters (centers, widths, and weights).
- Evaluate the model's classification performance on the training set.

3.3.4 APSO Update

- Adaptively adjust the learning rates and update particle positions and velocities to search for better parameter sets.
- Consider both individual particle success and the overall swarm's best performance.

3.3.5 Iterative Optimization

- Repeat the APSO optimization process, adjusting parameters at each iteration, and retraining the LLRBFNN.
- Monitor the classification accuracy or other performance metrics on the validation set.

3.3.6 Final Model Selection

Once the optimization converges, select the best set of parameters found by APSO.

- Test the optimized LLRBFNN on the unseen test set to evaluate its classification performance.

3.4 Proposed LLRBFNN-APSO model

The suggested LLRBFNN-APSO classification model is shown in Fig. 3.1. The APSO algorithm updates the weights.

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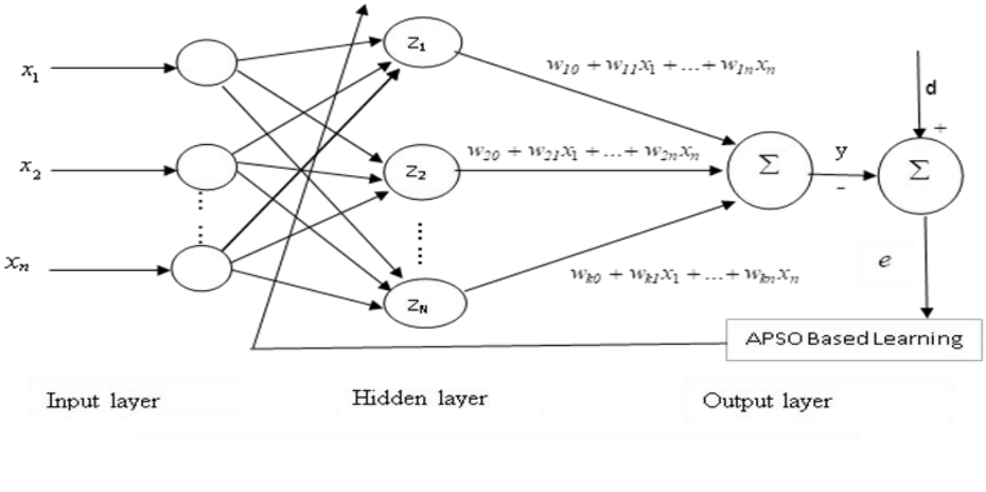

Fig. 3.1 Radial Basis Function Neural Network Enhanced by APSO Algorithm

3.5 Research Workflow

The image's features are extracted using the wavelet transform, and the suggested APSO LLRBFNN model uses these features as input for the classification task. The research work flow shown in Fig.3.2.

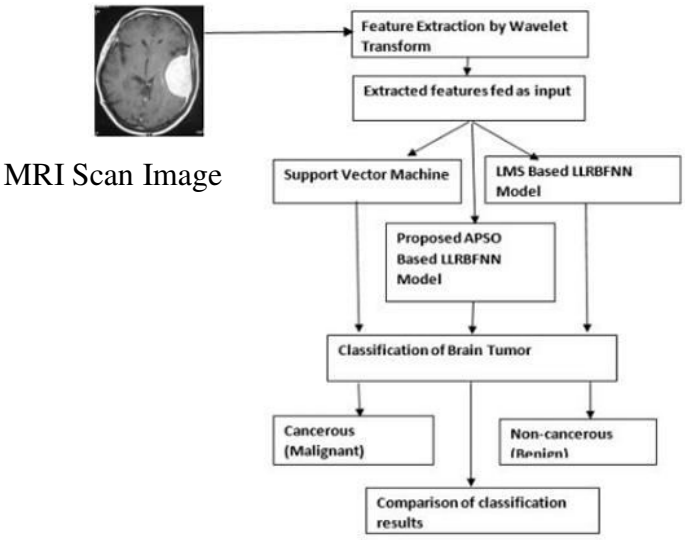

Fig. 3.2 Flow diagram of the proposed research work

Wavelet Transform-Based Feature Extraction Features that were extracted and fed into a support vector machine Comparison of classification results for brain tumors classified as non-cancerous (Renien) and cancerous (Malignant) using the LMS Based LLRBFNN Model and the Proposed APSO Based LLRBFNN Model. The model, which assumes the function of the hidden and output layers of the traditional RBFNN, replaces weights in the LLRBFNN model [22]. You can use input or hidden nodes interchangeably. By assigning local linear weights to hidden nodes for computation and iteratively training random weights, LLRBFNN improves pattern classification while reducing the overall number of network nodes. PSO [23,24] and LLRBFNN model weights are optimized via APSO algorithms, and the outcomes are contrasted. The input data points serve as features in this model, and the Gaussian functions in the hidden units are represented by the variables Z1, Z2... Z_n. Using the (Eq.1) A Gaussian kernel. It is known what the n^{th} hidden cell layer's activation function is.

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$$Z_n(x) = e^{\left(\frac{-\|x-v_i(n)\|^2}{2\sigma_n^2}\right)} \quad (1)$$

Where σ_n^2 is the activation function's smoothness parameter controlled. The function center and the inputs, as well as the hidden node's center, and shows the Euclidean distance between them. The (Eq.2) objective function's goal is to reduce errors, and the MSE is provided.

$$MSE(e) = \frac{1}{N}\sum_{n=1}^{N}(d_n - y_n)^2 \quad (2)$$

Where the required vector is denoted by "d".
The PSO and APSO approaches are used to optimize the weights of this network once they are originally set to zero.

3.6 APSO's weight optimization method

Conventional PSO usually makes use of both the individual best and the current global best. While chance can also contribute to solution variety, the inclusion of the individual best tries to increase such diversity. Consequently, unless the optimization issue is extremely nonlinear and multimodal, there might not be a compelling case for using the individual best. A streamlined strategy that can hasten convergence is to use only the best available worldwide. As consequently, the velocity vector is produced using Accelerated Particle Swarm Optimization (APSO) utilizing a more straightforward (Eq. 3). [22, 23, 24].

$$v_i^{t+1} = v_i^t + \alpha \in_n + \beta\left[g^* - x_i^t\right] \quad (3)$$

Where $\in_n$ is drawn from a normal distribution (0, 1) [23]
N (0, 1) to replace the second term. (Eq.4) the position update is then simply [23, 24].

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

The (Eq.5) further enhance convergence; we can express the location update in a single step.

$$x_i^{t+1} = (1-\beta)x_i^t + \beta g^* + \alpha \in_n \quad (5)$$

This streamlined approach produces convergence rates that are similar. For most applications, β=0.1∼0.7 and α=0.1L∼0.5L, are adequate, where L is each variable's scale. Interestingly, velocity is not included in Equation. (5), which removes the requirement for velocity vector initialization and greatly simplifies APSO. Unlike many other PSO variations, APSO has a simple mechanism and uses just two parameters. Reducing unpredictability as iterations go on is another way to improve APSO. (Eqs.6,7) are monotonically decreasing function.

$$\alpha = \alpha_0 e^{-\gamma t} \quad (6)$$

$$\alpha = \alpha_0 \gamma^t, \qquad (0 < \gamma < 1) \quad (7)$$

Where γ, the randomness parameter's initial value, roughly falls between 0.5 and 1. In this case, 0<<10<γ<1 is the control parameter, where t is the quantity of time steps, or iterations, [23]. The interval [0, maxtmax], where maxtmax represents the maximum number of repetitions, contains the value t.

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IV. RESULTS AND DISCUSSIONS

Using the LMS-based LLRBFNN model as well as the PSO-based LLRBFNN model, we retrieved the features and tested them. Comparison results shown in Table 4.1.

Table 4.1 Accuracy Percentage of the LLRBFNNMODEL

framework	dataset size	Processing time	Accuracy of Classification
LLRBFNN - LMS	3000	18.453675	96.3
LLRBFNN - PSO	3000	10.213452	98.5
SVM	3000	23.345235	92.7
RBFNN-LMS	3000	20.216235	84.5
RBFNN-PSO	3000	19.873591	90.4

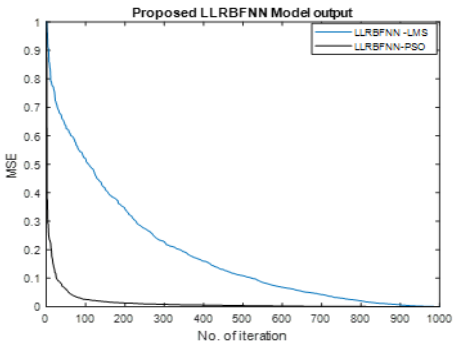

Fig. 4.1 With the LLRBFNN Model, mean square error

Fifty of the two hundred photos were utilized for testing, while the other fifty were used for training. According to the findings, optimizing the model LLRBFNN with LMS training took about 800 steps, whereas optimizing the model LLRBFNN with PSO training took about 200 iterations. It was also shown that LLRBFNN with PSO training takes 9.213453 seconds to compute, but LLRBFNN with LMS takes 17.453676 seconds shown in Fig.4.1. Based on the model's output, the MATLAB R2017a program was used to calculate the computational time and accuracy percentage. To calculate errors, the recovered features were supplied into the SPO-LLRBFNN, APSO-RBFN, PSO-RBFN, and proposed APSO LLRBFNN models. The model that is recommended is this one. In contrast to the current classification models, our study used less processing time. The proposed model has a classification accuracy of 98.92% since we modified the APSO weight of the LLRBFNN model and used the Enhanced Fuzzy C Means algorithm for center selection.

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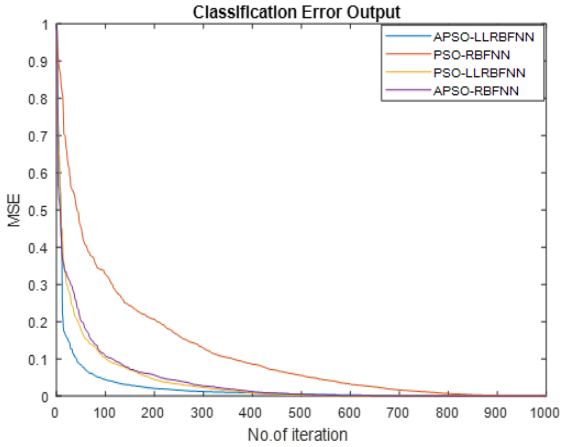

Fig. 4.2 Mean square error using LLRBFNN Model

As the Fig.4.2 illustrates, the proposed APSO LLRBFNN model converges in roughly 360 iterations. The PSO-LLRBFNN model, on the other hand, requires 410 iterations to converge. Conversely, the APSO-RBFNN and PSO-RBFNN models converge after around 900 and 550 iterations, respectively. Comparison results were illustrated in Table 4.2.

Table. 4.2 A table of classification accuracy using APSO=LLRBFNN

framework	dataset size	Processing time	Accuracy of Classification
PSO-LLRBFNN	1000	9.213451	98.72
APSO-LLRBFNN	**1000**	**12.23422**	**98.93**
LMS-RBFNN	1000	22.31612	83.52
PSO-RBFNN	1000	18.873591	89.23
APSO-RBFNN	1000	16.34526	95.22

By combining different machine learning techniques for feature extraction, image segmentation, and the classification of two types of tumors, the research seeks to increase the accuracy of tumor classification. For tumor detection, the proposed LLRBFNN model exhibits promise in assisting clinical diagnosis and freeing radiologists from a tedious task. The main objective is to automatically detect and classify tumors using LLRBFNN in conjunction with LMS and PSO training. After segmenting the images and extracting the features using a wavelet transform, eight features are considered for classification. LLRBFNN APSO and LMS training works better than conventional SVM approaches, showing better classification accuracy and faster calculation times.

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V. CONCLUSION

This research work offers a new and efficient machine learning method for brain tumor classification. The suggested approach combines picture segmentation, classification, and feature extraction into one framework. The combined method makes use of the advantages of each step: image segmentation separates the tumor territory, feature extraction finds pertinent features in the MRI scans, and classification classifies the type of tumor. With more accuracy and

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quicker processing times than SVM, this all-encompassing technology outperforms the competition. Patients and medical professionals alike stand to gain greatly from the enhanced accuracy provided by LLRBFNN model, which is based on APSO. Moreover, the system modified to improve accuracy by these characteristics with the extraction of more data from each frame. Prepare to examine the similarities and differences between various machine-learning methods shortly. The suggested method has a high rate, as seen by the numerical findings of 98.93% with computational time 12.23 secs, which is more than other existing methods. This research investigates a more future work may examine how well this model performs in multi-tumor classification settings and whether it can be used to different MRI datasets.

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