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# Optimized ELM with CNN depending on DSC for Brain Lesion Segmentation in ISLES 2015

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**Abstract**

Brain lesion detection has an important role for human health care. People with Alzheimer's or traumatic brain injuries have lesions in the brain area. In this research, brain lesions were detected by the use of extreme learning based on deep learning. To improve the Extreme Learning Machine and increase accuracy. The Fully Connected Layer was replaced with an Extreme Learning Machine. The weights of Convolutional Layer and First Layer of extreme learning Machine Optimized with Imperialist Competitive algorithm. The ISLES 2015 dataset is used to calculate the accuracy of the proposed method. The results show that the value of DSC (Dice Similarity Coefficient) is near 91.3%

**Keywords:** Brain lesion detection, Deep learning, Convolutional Neural Network, Extreme learning Machine, Dice Similarity Coefficient.

## * Introduction

Brain lesions created by head trauma or MS disease. Diagnosis of injured places is challenging task. In the MS disease, immune system attacks to myelin sheath, and caused to brain dysfunction. At the result it was created permanent destruction of brain tissue. Automated diagnosis of these are very helpful for physicians. This destruction has different signs. In this study it was used deep learning of neural network. There are different algorithms for deep learning training such as ADAM, NADAM that is based on descending gradient algorithm and improves the convergence speed changes with weight factor assign. Extreme learning machine has fast convergence speed. Use of this property in all layers that totally related to neural network cause to speed and accuracy increase in the deep learning training. For training, the CNN layer improves with use of Imperialist competition algorithm. The demand for computer-aided detection of brain lesions using volumetric magnetic resonance imaging (MRI) is driven by the need for rapid and automated diagnosis of neurological illnesses. The template-matching technique is effective for automatically localising brain lesions. However, it is still difficult to determine the ideal template size that maximises the similarity between the template and the lesion. Processing big MRI volumes using three-dimensional (3D) templates leads to an increase in algorithm complexity and the need for more computational resources. Therefore, it is necessary to decrease the computational complexity of template matching. This research presents a mathematical framework that suggests a method for calculating the normalised cross-correlation coefficient (NCCC) as a measure of similarity between an MRI volume and an assumed 3D Gaussian template. The proposed method has a linear time complexity.

The difficulty of the O(amaxN) approach is lower than the typical fast Fourier transform (FFT) based approach, which has a complexity of O(amaxN logN). Here, N represents the number of voxels in the image, and amax represents the number of tested template radii. In addition, they presented a mathematical model to accurately determine the ideal template radius for each voxel in the image and calculate the normalised cross-correlation coefficient (NCCC) using the location-specific optimal radius. This method reduces the level of intricacy to O(N). The methodologies were assessed using a single synthetic and two authentic multiple-sclerosis datasets. Their results in lesion detection were evaluated in comparison to FFT and a cutting-edge lesion prediction system. Their trials effectively demonstrate the effectiveness of the suggested methods for detecting brain lesions, and their performance is comparable to existing techniques [1]. It was done different works for diagnosis of lesion or Tumors with use of neural network. In 2016, Yue Deng et al introduced fuzzy deep learning neural network [2]. Their method was based on input data transformation to fuzzy data for deep learning of neural network. With use of this method, it was improved the accuracy percent.

In 2016, Hongyoon choi et al studied the use of deep learning neural network for detection of grey matter in medulla oblongata. They used from 2 CNN classification for diagnosis and recovery of these places [3]. Their method was based on brain image classification.

In 2016, Daniele Rav et al predicted health condition of patients with use of deep learning [4]. They used different methods for this matter such as deep learning, Boltzmann machine and extreme learning of neural network based on belief.

In 2016 J. Ngiam et al studied deep learning of neural network with use of several types of neural networks with several implementations. [2]. their method show that use of some implementation methods improved final response in noise and image detection. In 2011 Jiquan Ngiam et al studied how created deep learning and introduced it as one detector for diagnosis. [6]

Deep learning has become the favoured method for tackling many predictive analytics tasks in recent years. Recurrent neural networks (RNN) are frequently employed for sequence prediction tasks due to their ability to effectively leverage sequential information, where the output is influenced by previous computations. Nevertheless, the dependencies of the calculation exist in the latent domain, which may not be suitable for certain applications that require anticipating a sequence of step-wise transformations. This series depends entirely on the previous calculation in the visible domain. The researchers propose that a fusion of convolutional neural networks (CNN) and stacked autoencoders (SAE) can proficiently acquire a sequence of operations that nonlinearly transform an input shape or distribution into a target shape or distribution with identical support. The paradigm has diverse applications, such as robotic path planning, sequential decision-making in games, and discovering material processing methods to create specific microstructures. One such instance that demonstrates the practical use of the framework is the manipulation of fluid deformations in a microfluidic channel through the strategic arrangement of a series of pillars. Gaining understanding about a complex topological transition has significant implications for the rapid advancement in material science and biomedical applications [7].Obstacle detection is a crucial challenge for robotic systems, particularly for autonomous systems operating at high speeds in uncertain environments. Scene depth estimate is commonly accomplished using multiple methods. For effective detection of fast motion, it is necessary to have a detection range that is sufficiently long to ensure safe avoidance and path planning. Current methodologies occasionally depend on presumptions on vehicle movement, thereby limiting their practicality or operating solely within specific parameters. The authors' tests have proven that the Deep Q Network (DQN) approach has intrinsic limitations when applied to designing a path in situations with multiple problems. Constructing the reward function can be a challenge, and identifying favourable experience transitions within experience replay might be arduous. The authors propose an improved iteration of Double DQN (DDQN) to tackle the issue by integrating principles from A* and Rapidly-Exploring Random Tree (RRT). In order to increase the variety of experiences in the replay, the robot's initialization is modified in each training cycle using the Rapidly-exploring Random Tree (RRT) technique. Moreover, the compensation for the unfilled positions is specifically customised to accelerate the acquisition of knowledge, in line with the definition of position cost in the A* algorithm. The empirical results of the simulation validate the efficacy of the improved Double Deep Q-Network (DDQN). The robot is able to successfully acquire the skills of obstacle avoidance and optimal path planning, which are not feasible with DQN or DDQN alone [8].

This study presents a novel attention mechanism that use keypoints to enhance visual identification in still images. Deep Convolutional Neural Networks (CNNs) have demonstrated remarkable effectiveness in image identification challenges that involve distinct categories. Nevertheless, their capacity to precisely distinguish minor variations in meticulous modifications is relatively diminished. The authors presented a complete Convolutional Neural Network (CNN) model that incorporates a unique attention mechanism to effectively capture important elements that link small variations. This method utilises the detection of semantic regions (SRs) and their spatial distributions to capture the spatial arrangements in images. It has been proven to be essential for accurately capturing subtle differences in images. The identification of these SRs is automated through the grouping of significant spots noticed in a given image. The effectiveness of these systematic reviews (SRs) for image identification is evaluated using a unique and intentional procedure that gives priority to the most relevant areas of the image for a certain task. This methodology can be used for both traditional and detailed picture recognition tasks without requiring the utilisation of manually annotated regions, such as bounding boxes for body parts or objects, for the purposes of training and prediction. Additionally, the suggested attention mechanism, which is driven by important points, can be seamlessly included into the current CNN models. The framework is assessed on six distinct benchmark datasets. The model surpasses the most advanced methods by a significant margin when tested on various datasets, including Distracted Driver V1 (Accuracy: 3.39%), Distracted Driver V2 (Accuracy: 6.58%), Stanford-40 Actions (mean Average Precision: 2.15%), People Playing Musical Instruments (mean Average Precision: 16.05%), Food-101 (Accuracy: 6.30%), and Caltech-256 (Accuracy: 2.59%) [9].

*** Materials and Methods**

ISLES 2015 is the used data base for this research. There are some learning algorithms for CNN training, such as ADAM and NADAM. In this study, ICA was used for its high speed. Also, some phases of ICA were changed.

Among several types of neural networks, the CNN structure is one of the best neural networks that scientists recently noticed for diagnosis and detection.

The aim of CNN designation is accurate implementation of this type of network and its relationship and links with the visual section of the brain for modelling of systems, which its task is automated with efficient properties, image learning in total neural structure and also omission of probable redundancy. Deep learning includes Relu, Max pooling and convolution layers.

The 2D convolution structure is shown in figure 1. In the picture, it is divided into equal squares and each square times into a convolution matrix.

1- $Conv_2 = \sum_{i=1}^{n} W_i * X_i$

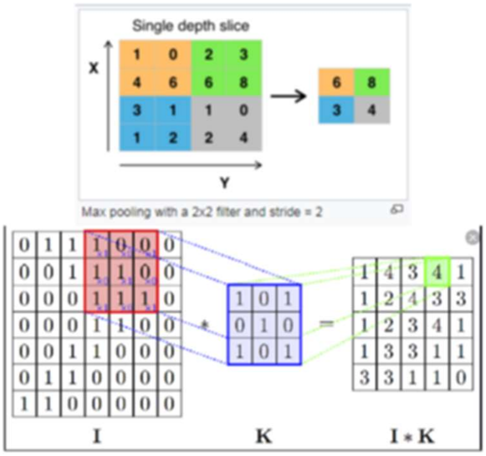


**Figure 1: The multiplication of 2D convolution**

In the Max Pooling layer input, the picture is divided into squares and you choose the maximum value of that square. In Figure 1, an example of Max pooling is presented.

The Relu Function is used for its high speed and data reduction. Also, there is a Semi Relu function that is similar to the Relu function. The equations of these two functions are presented below.

2- $Relu(x) = \begin{cases} x & ,x \geq 0 \\ 0 & ,x < 0 \end{cases}$

3- $SemiRelu(x) = \begin{cases} x & ,x \geq 0 \\ x/a & ,x < 0 \end{cases}$

In semi Relu function, if x is negative, the value of x is reduced by dividing into a.

The ICA algorithm, like many evolutionary algorithms, uses modeling of behaviors of countries for development. In implementing the Imperialist competition algorithm, it used revolutionary and conquest functions.

Semi-code related to the Imperialist competition algorithm: -

1- Select several random points and create an initial empire.

2- If there is any country in one empire that has lower cost from a imperialists, change their places.

3- Calculate the total cost of one empire.

4- Select the weakest empire and give it the highest possession possibility.

5- Remove weak empires.

6- If there remains one empire, stop, and otherwise go to 2.

This algorithm begins with the random population and the creation of the initial empire and is replicated with policy attraction and imperialist competition.

ELM is a generalization of a radial neural network and supports vector machines. Its neural network structure is similar to the feed forwarded neural network ANN, with the difference is that the learning method is different and its learning time is lower. ELM has a higher speed of learning than the Back Propagation neural network with a descending gradient algorithm.

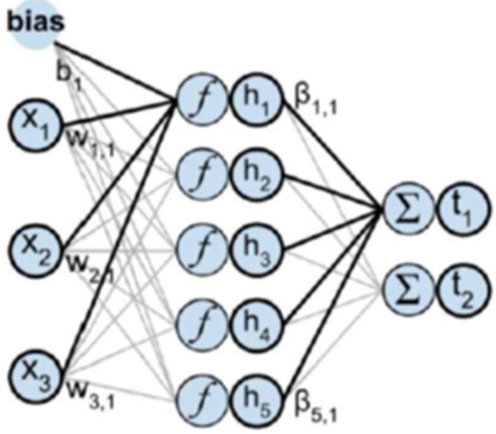


**Figure 2: The structure of ELM**

The weights of input and hidden layers are random. The purpose is weight changes between hidden and output layers provided that there is minimal input errors for learning data. The general equation is shown in below.

$3 - \ Minimize : \sum_{i=1}^{N} ||\beta * f(\alpha * x_i + b) - t_i||$

Where $x_i$and $t_i$ are training data and desired output respectively. The $\alpha$ is weight coefficient of input and hidden layer and $\beta$ is weight coefficient of hidden and output layer.

With notice to that the above equation is matrix, output calculated as

$4 - \ \beta = t_i * inv(f(\alpha * xi + b))$

Where INV shows the inverse matrix. With notice that is asymmetric, for the calculation of its inverse, it was the moore-penrose method that is a method for asymmetric matrices. In figure 2, it shows the structure of ELM.

For implementation, the first convolution layer was implemented, then the max pooling layer and the next Relu layer were implemented. The full connected layer is a detection layer that, in this article, was used ELM that has several instances of patients.

Each instance includes 512 scans in 3D and each scan is 512*512 in size. Slices begins from below the neck and continues to above the head. Each slice includes 512*512, which is a grey scale. The suffix for pictures is "ini".

The learning implemented in this study is supervisory. According to each picture, there is one file with 512 slices and its size is 512*512. For lesion sections the label is one else is zero.

the implementations include convolution layer 13*13 and each picture 512*512 divided to square a 16*16 size. So that all of the learning instances from each slice is converted to 1024 instances.

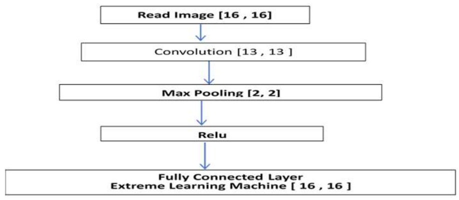


**Figure 3: CNN structure with 13*13 convolution layer and 16*16 input.**

In figure 3, the implemented structure is presented. For finding the optimized weights, several algorithms we could use and here the Imperialist competition algorithm was used for improvement of the convolution matrix. For training CNN, the ISLES 2015 dataset is used. Each data is a nifty type with 512*512*512 slices for each person. The evaluation method is K-Fold (5).

*** Results and Discussion**

In this paper, the data is divided into 5 parts and each time one part is used for testing and others for training. The DSC (Dice Similarity Coefficient), precision and accuracy is selected for evaluating the proposed methods.

$$5-\ Precision=\frac{TP}{TP+FP}$$
$$6-\ DSC=\frac{2*TP}{2*TP+FN+F}$$
$$7-\ Accuracy=\frac{TP+TN}{TP+TN+FN+FP}$$

Where: -

1- TP (True Positives): Correctly detected lesion pixels (the overlap between prediction and ground truth).

2- FP (False Positives): Pixels wrongly predicted as lesion (prediction says lesion, ground truth says no lesion).

3- FN (False Negatives): Pixels missed as lesion (ground truth says lesion, prediction says no lesion).

Accuracy, precision and DSC formulae are presented above for evaluation of convolution matrix that are designed with ICA. There are several algorithms such as ADAMs, NADAMS for training. In this research, due to the high speed of ICA and Extreme Learning Machine, the CNN can be optimized faster. There is no need for training a fully connected layer and just Convolution Layer trained with ICA.

**Table 1: The Convolution Neural Network Layers.**

| number of layer | Layer | characteristics |
|---|---|---|
| 1 | Image Input | 16*16 |
| 2 | Convolution | 13*13 |
| 3 | Max pooling | 2*2 |
| 4 | Relu | - |
| 5 | Fully Connected | Extreme Learning Machine |
| 6 | Soft Max | |

The fitness function in the CNN algorithm is equal to DSC with K-Fold (5). The 20% of the data used for testing and 80% is used for training. With the setting of the convolution matrix, the DSC value was increased to maximum value.

$$8-\ Fitness(X_i)=\frac{2*TP}{2*TP+FN+FP}$$

Implementation was done on the computer with CPU Intel Core-i7 4790K. The RAM Is 16GB. The used number of images in the dataset consist of brain MRI scans of 28 people with lesion disease. For every man there are 192 slices. The number of data for learning is 5376 images with 192*192. The total number of 16*16 images is 774144 samples.

We noticed that in the above structure there were 196 parameters of CNN Layer.

The country, the replication of 10, 80, 50 numbers are considered. For calculation of fitness function in each country, all weights move to the country with the highest accuracy. The numbers of neurons in the hidden layer are equal to 4096 neurons. The input of ELM is 1*196 and its output is 16*16.

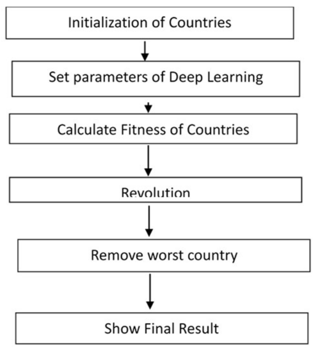

**Figure 4: Imperialist Competition algorithm flowchart for calculation of convolution matrix**

Optimization results are shown in figures 5, 6, 7, 8, 9, 10. The total number of countries is 10, 20, and 50 countries. At each step, one country was removed.

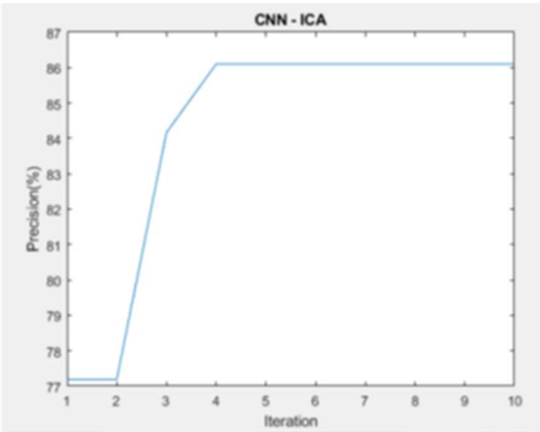


**Figure 5: Precision with K-Fold (5) and 10 countries on ISLES 2015**

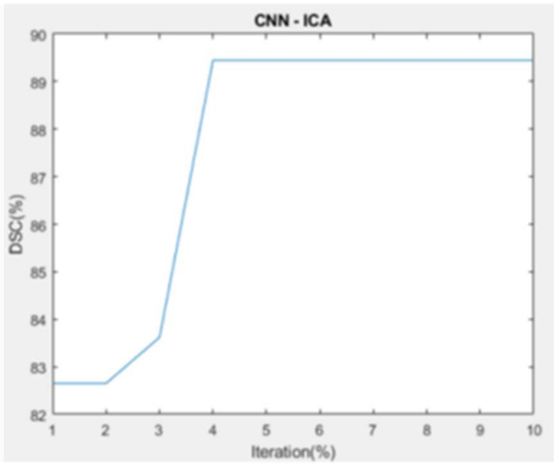


**Figure 6: DSC with K-Fold (5) and 10 countries on ISLES 2015**

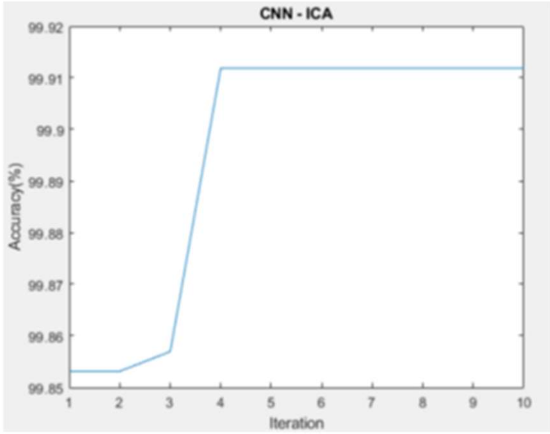


**Figure 7: Accuracy with K-Fold (5) and 10 countries on ISLES 2015**

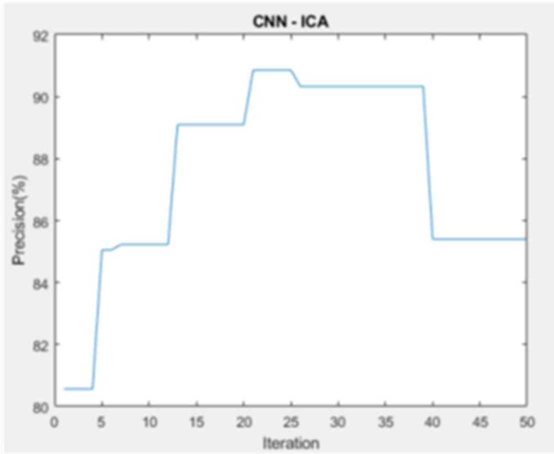


**Figure 8: Precision with K-Fold (5) and 50 countries on ISLES 2015**

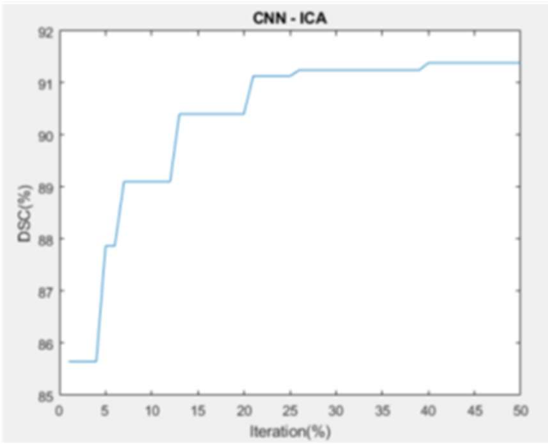


**Figure 9: DSC with K-Fold (5) and 50 countries on ISLES 2015**

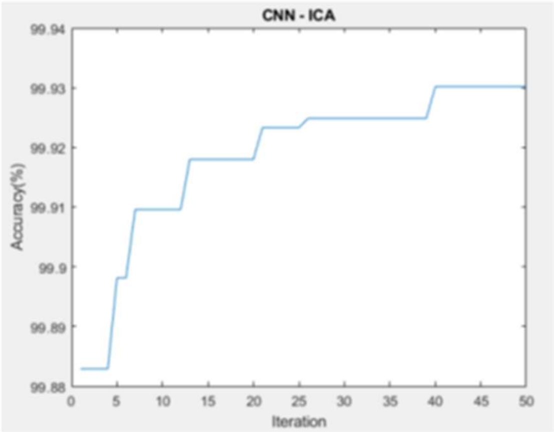


**Figure 10: Accuracy with K-Fold (5) and 50 countries.**

The results for training the best CNN are presented in tables 2, 3. With the increase in the number of countries, precision and DSC have increased. Also, the learning time is presented in table 2.

**Table 2: The results for data with K-Fold (5 on ISLES 2015**

| Training Time (minutes) | Precision (%) | Accuracy (%) | DSC (%) | Number of Imperialist |
|---|---|---|---|---|
| 118 | 85.92 | 99.91 | 89.02 | 10 |
| 528 | 88.04 | 99.93 | 91.12 | 20 |
| 3217 | 85.40 | 99.93 | 91.39 | 50 |
| | | | 49% | FCN[12] |
| - | - | - | 68% | MultiRes U-Net [10] |
| - | - | - | 51% | Multi-scale U-Net [11] |

According to Table 2, the proposed method has higher accuracy and precision and DSC.It was seen that with the increase in tested data discrepancy with learning data, the precision was reduced.

**Table 3: The results with K-Fold (5) on ISLES 2015**

| TN | TP | FN | FP | Number of Imperialist |
|---|---|---|---|---|
| 260926 | 977 | 81 | 160 | 10 |
| 260948 | 1001 | 59 | 136 | 20 |
| 260990 | 971 | 17 | 166 | 50 |

In figure 11-15, the results for the test slice are presented. The image index is 100, 122, 184, 185, and 179.


**Figure 11: The result of diagnosis for picture number 180**


**Figure 12: The result of diagnosis for picture number 182**


**Figure 13: The result of diagnosis for picture number 184**


**Figure 14: The result of diagnosis for picture number 185**


**Figure 15: The result of diagnosis for picture number 190**

## * Conclusions

In this article, we implemented deep learning with training of Imperialist completion algorithm and Extreme Learning Machine. We suggest that the results of this article are used in health care centres. Also, with an increase in training data, the results will be more accurate.

This research presents an innovative method for detecting brain lesions through the optimisation of an Extreme Learning Machine (ELM) utilising Convolutional Neural Networks (CNN) based on Dice Similarity Coefficient (DSC), accuracy, and precision. The traditional fully connected layer was substituted with an Extreme Learning Machine (ELM), and the weights of the convolutional layer and the first layer of the ELM were optimised using Independent Component Analysis (ICA) to improve model performance. The proposed method was assessed utilising the ISLES 2015 dataset through a 15-fold cross-validation technique.

Experimental results indicated that the model attained a Dice Similarity Coefficient (DSC) of roughly 91.3%, underscoring its efficacy in segmenting brain lesions. The assessment of performance indicators, including precision, validated the robustness and dependability of the proposed method, demonstrating significant enhancements over baseline deep learning systems.

The amalgamation of ELM with a CNN architecture offers a feasible and effective approach for detecting brain lesions, with prospective uses in clinical diagnosis and medical decision support systems. Future attempts will concentrate on augmenting the system to incorporate larger and more varied datasets, in addition to investigating its applicability to various medical imaging modalities.

Because of the heavy computation process, GPU usage is suggested.

Data Availability

All data available on request.

Conflicts of Interest

There is no conflict of interest regarding the publication of this paper."

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