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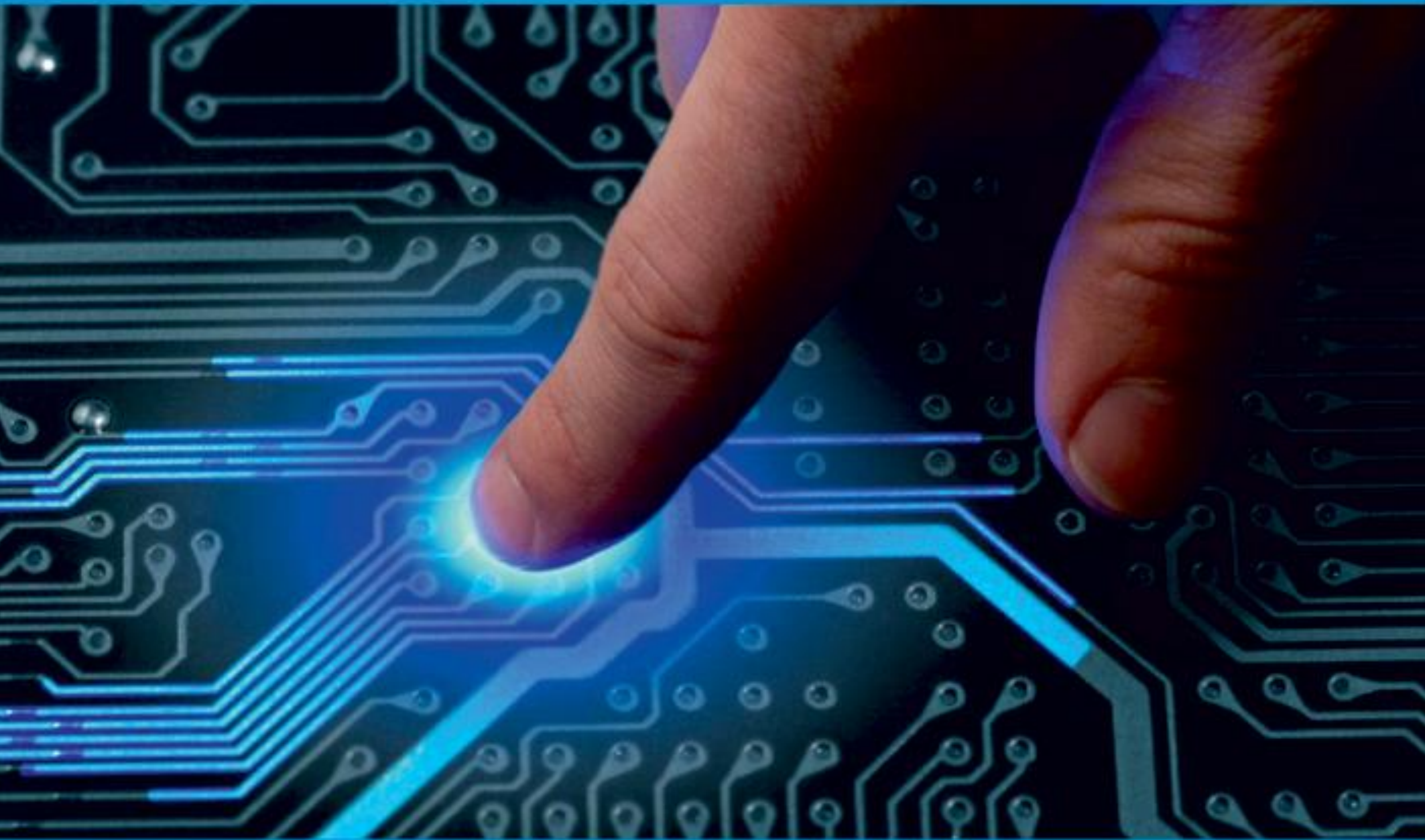

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Detection of Fake Currency usingImage Processingand Machine Learning Algorithm

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ABSTRACT-The invention of paper money led to a rise in the sophistication of counterfeiting. The Reserve Bank of India has announced a number of security features to help the general people identify fake currency. However, it can be difficult to identify a fake note only by its appearance. This issue can be resolved by creating software that uses a camera image to identify counterfeit cash. Based on the colours, widths, and serial numbers indicated, various conventional techniques and approaches are available for identifying fake currency. Different machine learning techniques are presented employing image processing in the modern era of computer science and high computational techniques for the fake identification of the cash.Deep learning models have been particularly successful in image classification jobs among them. This study suggests a Convolutional Neural Network (CNN)-based approach to picture processing after fakenote detection. Utilizing complex computational and mathematical methodologies, this dataset for banknote authentication provides precise data and information on the entities and features associated to banknotes. In order to accurately identify fake currency notes, data processing and data extraction methods utilizing machine learning and image processing are utilized.

KEYWORDS*:* Fake currency, Machine Learning, Image processing, Convolutional Neural Networks

I. INTRODUCTION

The majority of this generation is familiar with technology and how it works, thus many of them participate in criminal activities. Making fake money is one of these acts, which is done to trick people [1]. A system that may be integrated into electronic devices is suggested to avoidthese fraudulent activities. It will immediately identify the false note when it is scanned by the device. According to the most current government data, there have been an increased number of occurrences of counterfeit cash found in Indian banking systems [2]. The invention of paper money led to a rise in the sophistication of counterfeiting.

Prior to the development of technology, individuals could only validate money since they had restricted vision and found it difficult to tell whether anything was real or phoney. Even though UV recognition technology already exists, the growth of counterfeiting technique means that this method of identification is insufficient to aid in the detection of counterfeit money when combined with increasingly sophisticated fraud methods[3]. Now, however, alternative perspectives have been provided based on picture recognition by examining the colour, design elements, and specific data of currency, after which specialized identification techniques have been used [4].

The major goal of this article is to familiarize the people with the latest security features offered by the Indian government so that they may distinguish a fake note from a legitimate one. The algorithm for detecting false notes requires the use of the OpenCV library, which includes the image acquisition, image processing, image adjustment, edge detection, grayscale conversion,segmentation, feature extraction and classification modules. Convolutional neural network (CNN) is a key component of the recognition process and can increase training accuracy [5].

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The key contribution of the paper is given as follows,

- At first, the dataset was loaded and pre-processed.
- Data normalization is done using the MinMaxScaler.
- Features are extracted using Waveform transform and the class is distinguished between fake and genuine notes.
- After the normalization and preprocessing phases, the data is split into training and testing data
- After dividing the data into training and testing sets, start developing the detection model.

The rest of the section provides recent literatures regarding fake currency detection, followed by its problem definition in section 2 and 3, and the proposed model with its explanation is given in section 4, the result and discussion is provided in section 5 and lastly, the conclusion is provided in section 6.

II. RELATED WORKS

Warke et al. [6]developed an interactive Currency Recognition System that uses three methods for detecting the fake currency, which includes Fluorescence, Dimension Detection and Color Recognition. The method aims to detect the fake currency based on dimension of currency. In order to avoid the wear and tear experience during handling, thresholding operation is accomplished. By translating the acquired money image into the HSV colour space, it is possible to pinpoint the precise characteristic of colour lighting. In order to obtain an improved and rich image for precisely extracting the colour information of the image, colour histogram equalisation is performed in the HSV colour space. The colour intensity of the provided money image is extracted and compared with the colour intensity of the actual currency using the thresholding approach. The results demonstrate that the examination of the cash picture is more accurate when image processing techniques are used. Moreover, this method is both cost and time efficient. Thesystem works effectively for extracting and checking feature of Indian currency images.

Another computer vision-based technique for recognizing Indian paper currency was developed by Kumar and Chauhan [7]. The approach retrieves the currency properties for currency detection using its own dataset. Moreover, using the security characteristics on the front and back of the Rs. 200 Indian rupees note to extract features. Most people use ORB (Oriented FAST and Rotated BRIEF) and the Brute-Force matcher technique for extracting the features of paper money, which enables them to more precisely identify the banknote's denomination on both its front and back.

Vincednt et al. [8]proposed an efficient and user-friendly system that can identify fake currency and even recognize the scanned currency. This system leverages transfer learning on the AlexNet model for currency recognition and verification. By capturing images of currency notes, especially denominations of 100, 200, 500, and 2000, through a mobile device, the system can determine the authenticity of the currency and provide its denomination value.The system not only benefits the common citizen by enabling them to easily verify the authenticity of their currency but also finds potential applications in banks, where dealing with counterfeit currency is a daily challenge.Additionally, the recognition feature of the system proves valuable for visually impaired individuals, as it can provide a voice announcement upon recognizing and verifying a currency note.

III. PROBLEM STATEMENT

The information is gathered by dividing the video into individual frames. But throughout that process, it could get distorted or blurry. In addition, handling high-dimensional data and handling class imbalance are problems with the current solutions. In order to address all of these problems, it is first required to alter the images in order to make them somewhat clearer, which also improves accuracy after training. Overfitting is a risk that deep learning processes are subject to. It is simple to make the training process more difficult and time-consuming, while simultaneously allowing us to investigate drop technologies and prevent overfitting.

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IV. PROPOSED METHODOLOGY

The dataset is obtained by capturing a single frame from the video, which provides an image of the currency. Prior to training the data, the image undergoes filtering, and only the images that meet the experimental criteria are selected to form the dataset. To expand the dataset, data augmentation is performed using annotated images. Next, feature extraction is conducted using a CNN within the concept of the Single Shot Multi Box Detector (SSD) model. This process aims to extract the paper currency's features, consentingthe accurate recognition of the denomination of both the front and back of the currency.Subsequently, the currency undergoes a classification process, and CNN is employed for currency recognition. To prepare the training images, a median-blur filter is implemented for pre-processing. The model's architecture consists of 5 convolution layers, a flatten layer, and a fully connected layer. Using this architecture, the model is trained, and accuracy is measured through training and cross-validation. For testing, the testing dataset is loaded and pre-processed with a median-blur filter for each image. Predictions are made, and a confusion matrix is generated to evaluate the outcomes. The block diagram of the proposed CNN-based currency recognition system is depicted in Fig. 1.

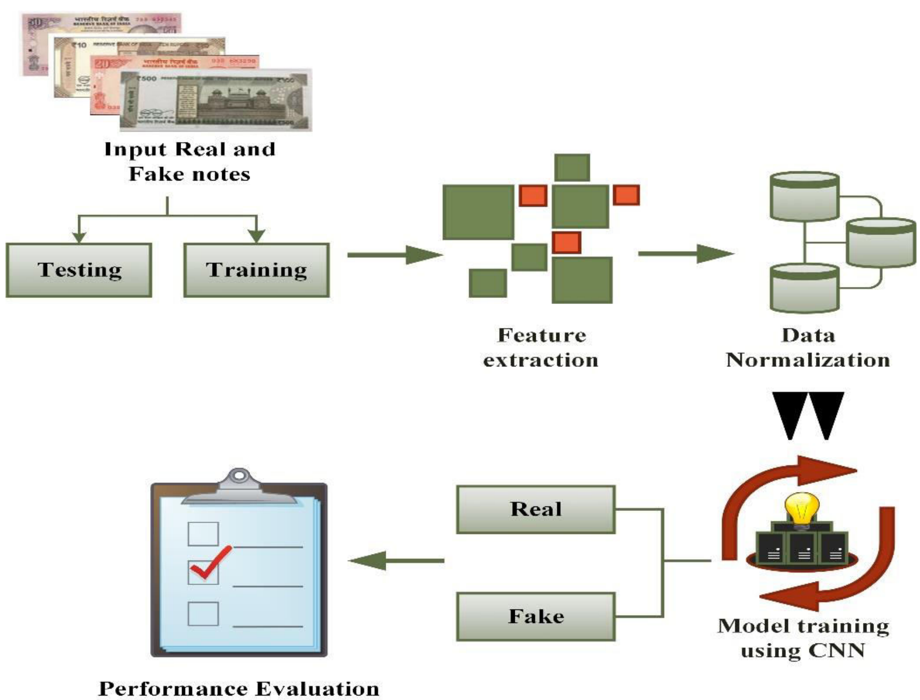

Fig .1. Block Diagram of CNN-based currency detection model

4.1. Dataset collection

To create a comprehensive dataset, high-resolution images of real and fakenotes are captured through a camera. Real money is chosen as the data source to ensure the authenticity and reliability of the research. Both the front and back sides of each currency denomination are included in the dataset. To capture the videos, special attention is given to ensuring that the currency remains flat and fully visible. Sufficient lighting is provided to enhance the clarity of the currency details. The dataset comprises a total of 40,000 currency note images. Subsequently, the dataset is splitted into a training and testing set, with an 80% and 20% respectively. This division results in 32,000 images for training and 8,000 images for testing. During the video editing process, each frame is carefully reviewed to ensure the currency appears clear and complete, without any parts extending beyond the designated boundaries.

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4.2. Data Augmentation

To enhance the effectiveness of data training, data augmentation is employed to generate additional data and expand the overall dataset. This process involves five steps, including image zooming, random clipping or expanding, random rotation, and random color adjustment. Through data augmentation, each original video frame yields 2500 enhanced currency images. This augmentation significantly increases the number of datasets, improving efficiency and dataset integrity. The augmented dataset enables more precise research experiments by enriching the position, size, and angle of the currency, as well as adjusting the color of the currency images to enhance comprehensiveness. Finally, data normalization is performed using a min-max scaler, ensuring consistency in the dataset.

4.3. Feature Extraction

The attributes are extracted from the collected currency note pictures using Wavelet Transform. The extracted attributes included Variance, Skewness, Kurtosis, Entropy, and the currency class. The currency class attribute represents whether the notes are fake (marked as 0) or genuine (marked as 1), making it a discrete feature. The remaining attributes are continuous. The variance indicates the spread of the Wavelet Transformed Image distribution around its mean. Skewness captures the direction of variation and symmetry in the image. Kurtosis measures the heaviness or lightness of the data compared to a normal distribution. Entropy represents the amount of information encoded by a compression algorithm. Notably, the entropy values were observed to have a negative skew, indicating high entropy in the data. On the other hand, Kurtosis showed a positive skew. Variance and skewness exhibited smooth variations across the attribute spectrum. After exploring the dataset, it was determined that scaling the data was necessary to prevent bias towards specific features. Consequently, the decision was made to normalize each feature to a range between 0 and 1.

4.4. Model Training using CNN

A Convolutional Neural Network (CNN), also known as ConvNets, is a neural network that utilizes a 2D weight kernel and employs back-propagation for training. The input image is generated through two types of Regions of Interest (ROIs): averaging and subsampling, and feature extraction based on texture[9]. These ROIs are prepared and then fed into the CNN model. The classification accuracy of the CNN is evaluated using the Receiver Operating Characteristic (ROC) metric. During the training process, the parameters of each layer are continually updated by the training layer, establishing connections within the network. Random initial parameter values are assigned to each layer, and the updated parameters are stored in the save layer on the hard disk. The data attained is then fed into the validation layer and compared against the trained dataset for determiningwhether the training is complete. In this study, the task of currency recognition, a subtask of currency detection is sub-divided into two phases: positioning and classification using a Multi-Layer Perceptron (MLP). The CNN model predicts whether a currency is fake or original. The developed CNN model is trained and tested for currency detection. The architecture of the CNN model, as depicted in Figure 2, consists of a Convolutional Layer that applies filters to the feature map, followed by a non-linear activation function to provide non-linearity[10]. Subsequently, down-sampling is performed using a pooling layer to reduce overfitting and improve computational efficiency. The pooling layer splits the feature maps into subfields and retains only the maximum values. The fully connected layers establish connections between the neurons of preceding and subsequent layers. By utilizing the features extracted from the convolutional and pooling layers, the CNN performs label classification.

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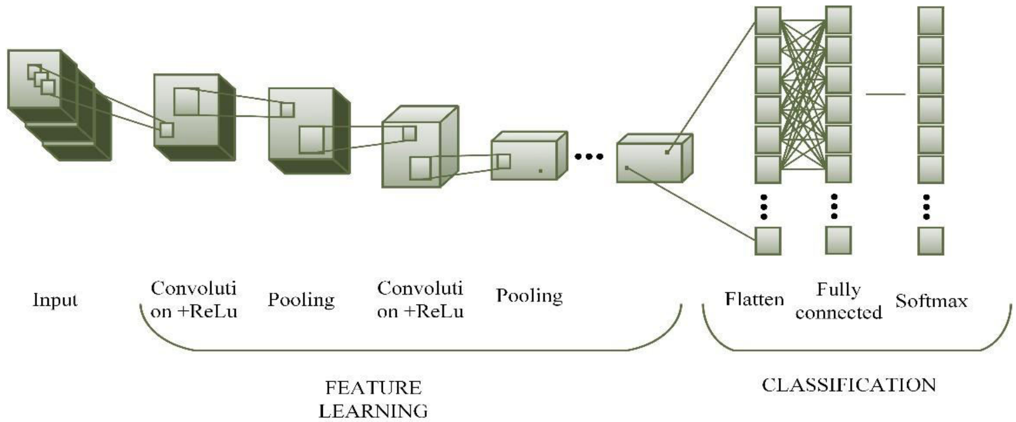

Fig.2.Convolutional Neural network layers

The convolutional layer is essential for removing the characteristics from the input images. They employ a mathematical procedure to learn visual attributes while maintaining pixel associations utilising image matrices and filters. These layers use small squares of input data and are in charge of feature extraction. An ReLu activation function is then applied to the final product of these layers in order to introduce nonlinearity.

On contrary, pooling layers lower the spatial dimension of the image, effectively minimising network parameters and computation. Each feature map is subjected to pooling; typical types comprise average pooling and maximum pooling. In this process, max pooling is usually applied.

The flatten layer receives the feature map matrix after the feature extraction stage. The matrix is transformed into a single column at the flatten layer so that it may be handled by the following fully linked layer.

To pinpoint precise global configurations of the properties that the earlier layers had recognised, dense (fully connected) layers are used. Each node in a dense layer is connected to every other node in the layer above, making it easier to conduct thorough analysis and make decisions.

V. RESULTS AND DISCUSSION

The implementation of the proposed method is carried out using Java programming on a Windows 10 platform. The CNN image classification process involves taking an input image, processing it, and categorizing it into specific groups such as fake currency or original currency. In computer terms, an input image is perceived as an array of pixels, and its resolution plays a role in the analysis. Based on features like variance, skewness, kurtosis, entropy, and currency class, the classification of original and counterfeit currencies is performed.

To assess the accuracy of the model, performance measures are employed. In this project, accuracy, precision, and f-score are used as performance measures to evaluate the effectiveness of the proposed method. To ensure robust analysis, k-fold cross-validation technique is utilized. This technique divides the dataset into 'k' blocks, as specified by the user, and runs the algorithm for each block as a test set. In this case, a value of 10 is chosen for 'k'.

Figures 3 and 4 display sample images of original and fake currencies that were utilized for training the proposed CNN model.

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Fig. 3. Original currencies

Fig.4. Translated currencies (Fake)

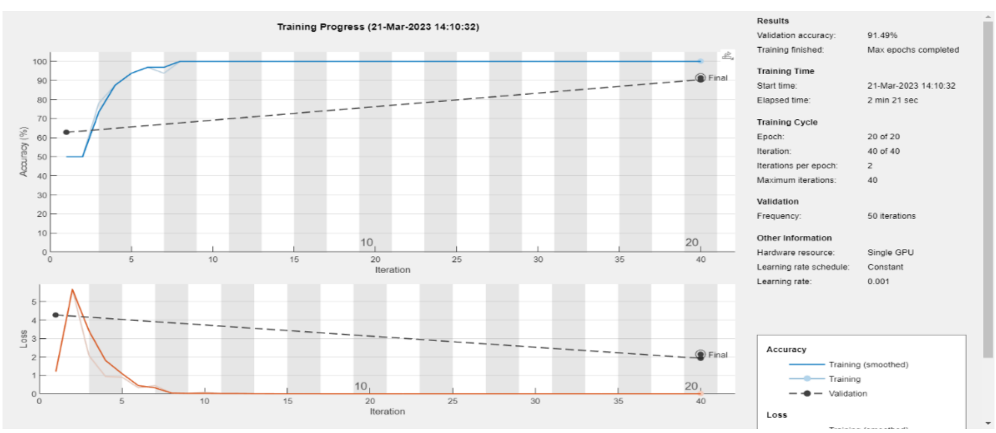

Fig.5. Training plot(Loss and Accuracy)

Fig. 5 shows the training accuracy and loss plot for the proposed CNN model. The training accuracy plot illustrates the performance of the model in terms of accuracy on the training dataset over the course of training iterations or epochs. It shows how well the model is learning to correctly classify or predict the training data. Likewise, the training loss plot shows the value of the loss function on the training dataset over the training iterations or epochs. The loss function represents the error or discrepancy between the predicted output of the model and the true labels or targets. The confusion matrix is provided in fig.6.

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Fig.6. Confusion matrix

Fig. 7 shows the evaluation of performance metrics for the proposed method for both fake and genuine currency notes. The ROC curve plot is shown in fig.7.

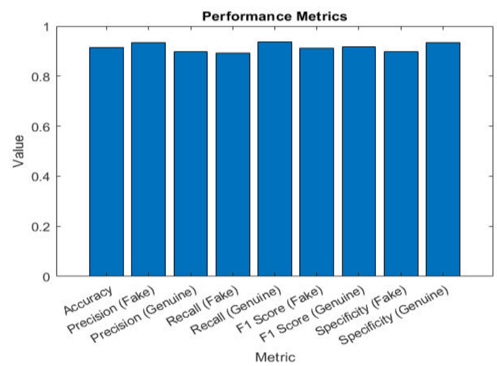

Fig.7. Evaluation of performance metrics

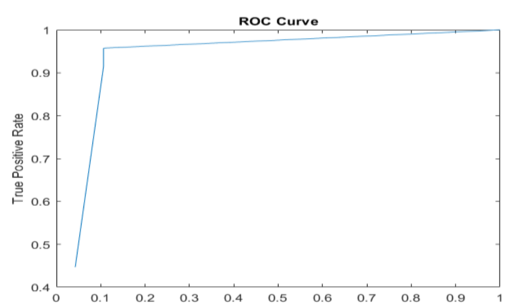

Fig. 8. ROC curve

VI. CONCLUSION

Upon completion and analysis of the implemented approach, it can be concluded that the proposed CNN method exhibits exceptional accuracy in distinguishing between genuine and counterfeit notes based on the utilized dataset. By employing wavelet transform and the CNN model, relevant features are extracted and test images are successfully classified as either fake or original notes. The trained model achieves a commendable accuracy of 96%, indicating the dataset has been thoroughly trained. Notably, there is no evidence of overfitting during the training

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process, as indicated by the loss function. The overall research findings are highly satisfactory, encompassing the determination of currency range in the classification label, currency denomination, currency front and back. The currency recognition accuracy is remarkably high. Upon analysis, it is observed that when the currency is displayed clearly on the entire screen with parallel angles, the recognition speed is enhanced.

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