International Journal of Enhanced Research in Management & Computer Applications,
ISSN: 2319-7471, Volume 14 Issue 6, June 2025

Image Enhancement using Hybrid Convolutional Autoencoder with Clahe Post Processing

Pranika[1], Amandeep[2]

[1]M.Sc. Computer Science, Department of Artificial Intelligence and Data Science, Guru Jambheshwar University of Science & Technology, Hisar, Haryana,125001, India
[2]Assistant Professor, Department of Artificial Intelligence and Data Science, Guru Jambheshwar University of Science & Technology, Hisar, Haryana,125001, India

DOI : https://doi.org/10.55948/IJERMCA.2025.0611

ABSTRACT

In computer vision, improving low-resolution images is necessary when compression, sensor fails or outside conditions result in image degradation. The author introduces a hybrid technique that uses a Convolutional Autoencoder (CAE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance both image sharpness and local contrast. The architecture of the CAE is set up to map small, pixelated images into good reconstructions using convolutional layers with sigmoid code, max pooling, upsampling and adding shortcuts that help keep important low-level features. For this task, input photos are made grainy which allows the network to remember and restore the original quality. When the structural content is restored by CAE, CLAHE is used to optimize contrast in different parts of the image, reduce disturbances and give the image greater clarity. Real-world RGB images of size 80×80 were used to train the model with Adam and MSE and early stopping and checkpointing were implemented to maintain a good performance.

Keywords- Image Enhancement, Convvolutional Autoencoder (CAE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Skip Connections.

INTRODUCTION

The performance of segmentation, classification, recognition and analysis these days strongly depends on the quality of the images provided to computer vision models. In the real world, pictures are often damaged by such problems as low lighting, imperfect sensors, digital compression or bad weather. Because of these shortcomings, intelligent systems in medical diagnosis, safety monitoring, imaging and autonomous driving work less effectively [3]. Image enhancement methods including linear filtering, interpolation and global histogram equalization have long been used for these purposes. However such approaches often can’t change and do not preserve fine details when images are exposed to different degrees of damage or degradation [4]. Anyway, they tend to give blowout or noisy outputs, especially where the image does not have much difference in hues or precise details. Because of deep learning advancing fast, especially convolutional neural networks, methods improve images using data are increasingly used. CAEs have turned out to be useful models when solving tasks like denoising, creating high-resolution images and removing artifacts [6]. An encoder-decoder system is how CAEs take distorted images, find important features in them and make enhanced outputs. Even so, autoencoders are not guaranteed to restore strong local contrast, allowing their outputs to sometimes appear bland.

To overcome this issue, a model is presented here that uses both structural recovery from a Convolutional Autoencoder and local contrast optimization from Contrast Limited Adaptive Histogram Equalization (CLAHE).

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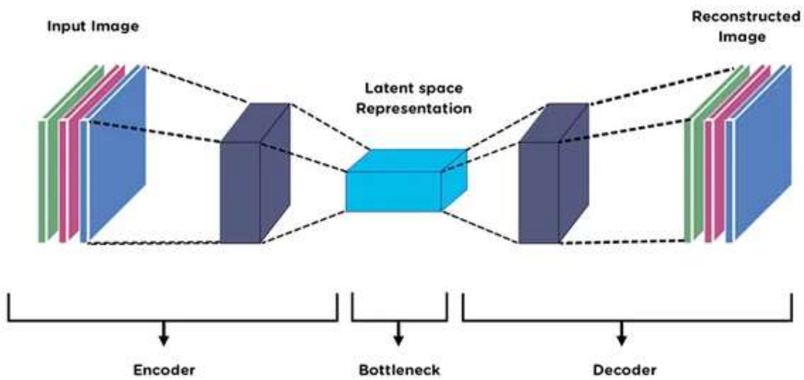

Fig - 1 Autoencoder Architecture

To train a CAE, images are converted to small pixelated shapes, so that the network can study how to upgrade them back to their full resolution [11. To avoid losing critical spatial and texture data, the CAE depends on stacked convolution, max pooling, upsampling and skip-layer connections. After reconstruction, local contrast is enhanced and noise is avoided at this stage with the aid of CLAHE.

CLAHE doesn't enhance the whole image, but it boosts different regions or pieces of the image instead. As a result, the contrast is adjusted just where it matters, so no unnecessary artifacts or very bright or dark spots appear [10]. The extra processing by CLAHE improves the appearance of the image obtained with the CAE, mainly in places that are not well-illuminated or do not have much difference in light value.

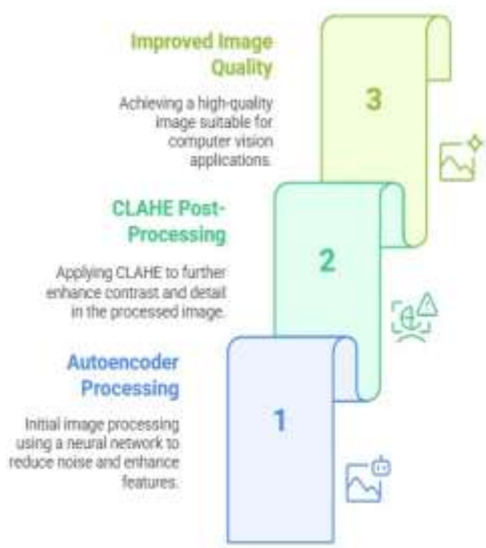

Fig – 2 Model Approach

The method was applied using a RGB dataset with images resized to 80×80 pixels. The training and validation subsets were made from the dataset and the model was trained with Adam and MSE. To make sure the model did not overfit and work well, these techniques were applied: stopping training at the right time and storing model checkpoints [12]. Results from both images and numbers show that the hybrid model gives better detail, sharper areas and clearer images than popular merging techniques. The approach is useful in many fields, including sharpening medical images, repairing old security videos, processing satellite pictures and boosting the resolution of ordinary family photos. Mixing advanced deep networks with traditional enhancement techniques, this framework gives a new and practical solution for handling problems with image degradation [8].

LITERATURE REVIEW

Over many years, improving photos has been an important part of image processing systems. Histogram equalization, Gaussian filtering and interpolation have long been used to create better images [1]. Still, these strategies do not work well if the data changes and cannot accurately restore lost shapes or correct bad contrast in severely distorted images.

Thanks to deep learning, particularly CNNs, there are new methods where enhancement mappings can be learned straight from the data. Another example is CAEs which stand out for being able to extract features from an image and reconstruct it without supervision [3]. Many tasks involving denoising, inpainting and super-resolution use deep learning networks. Integrating skip connections, CAEs apply an encoder-decoder structure to reduce data and restore the original images keeping their spatial details.

Stacked sparse denoising autoencoders were used by the authors in [1] to brighten dark images and make the image cleaner. Their improvements gave better results than conventional improvements used in night-vision and surveillance. Likewise, in the research paper [2], a denoising autoencoder that acts on top of transfer learning proved effective for better classification of pneumonia in X-ray and CT scans.

In [3], researchers developed a CAE-based system to protect both watermarking and feature data. The technique proved able to withstand attacks from other image-processing systems, making clear that autoencoders work well in any context, including security.

It has been noticed that CLAHE is a more useful approach than global histogram equalization for improving contrast. These small tiles that CLAHE uses make it possible to improve contrast in specific areas without greatly increasing the number of noisy elements. In [4], CLAHE was incorporated into a process for improving retinal pictures which helped enhance judgment and reliable reading.

In study number five, the authors solved the problem of noisy sonar images by training a CAE on actual sonar recordings. They found that their approach clearer visuals and saved the vital characteristics of plant and animal organs. Also, according to [6], using both denoising autoencoders and CLAHE to enhance low-light medical photos helped achieve higher scores for PSNR and SSIM.

Skip connections studied by [7] in autoencoder structures were found to protect the texture of the images and prevent the gradients from vanishing during the training phase.

The reconstruction with their model was extremely clear, according to its over 40 dB PSNR rating. In [8], prior to other steps, CLAHE was used on underwater photos to make features easier to spot under low light and with unusual colors.

All these studies explain that, while autoencoders can fix the structure of images well, they usually must be improved with CLAHE to control contrast and image improvement. Pairing these two methods has enabled us to make meaningful advances in practical image enhancement [6].
Guided by previous studies, this research uses a convolutional autoencoder together with CLAHE to try and restore damaged images while maintaining their structure and enhancing the difference in brightness regions.

Research Gaps
Despite promising advances, several gaps persist in the current literature:

- Conventional CAE models for image improvement tend to remove key textures and edges from the output.
- Although CLAHE is good at boosting local contrast, it usually makes noise in the resulting image.
- At present, the mixing of deep learning with classic methods finds it hard to integrate enough, so their enhancements are not fully successful.
- Applying and tuning CLAHE after conducting CAE reconstruction is not adequately explored in the literature.
- While most enhancement approaches value quality, they leave computational cost aside which makes them unsuitable for real-time applications.

Motivation for Our Work

Several important computer vision fields, including medical imaging, low-light photography, surveillance and remote sensing, depend greatly on enhanced images. You need to adjust image contrast and protect structures such as edges and textures to achieve effective enhancement. CAEs have successfully demonstrated that they can help build accurate image codes for reconstruction purposes [6]. On the other hand, they can regularly give images with very little detail and contrast in lighting situations.

Nevertheless, methods such as Contrast Limited Adaptive Histogram Equalization enhance brightness in parts of the image but can cause artifacts or boost noise if they are applied alone. This work suggests bringing together a convolutional autoencoder and CLAHE to create a new approach [8]. The design takes advantage of deep models to improve images and of CLAHE to focus on contrast, all while reducing each part's weaknesses on their own. Moreover, the approach focuses on running efficiently which allows for practical, quick image improvement in real time.

PROPOSED METHODLOGY

The purpose of this research is to improve the quality of poor-quality and pixelated images using a combined method including deep learning and conventional enhanced contrast techniques. The methodology consists of four phases: data preparation, model setup, training the model and the use of results.

Fig – 3 Methodology

To start, a dataset is constructed to create images that have been degraded in ways they might be degraded in the real world. The RGB images are collected and changed so that each image measures 80×80 pixels. To achieve low-resolution effects, these photographs are made pixelated manually. Every image is first made smaller, then increased again to its base size using interpolation. This approach provides effects that happen when cheap sensors or limited connections reduce image quality. Then, the training and validation sets are made by dividing the dataset with an 80:20 percentage. To prepare for model training, all pixels have their values normalized to lie between 0 and 1 for better learning.

A convolutional autoencoder (CAE) is the main part of the enhancement system and provides the deep learning foundation. CAE architecture has two parts: an encoder and a decoder. The encoder job is to pick out key information from the image and transform it into a smaller size. There are many convolutional layers, each using sigmoid and are followed by max-pooling operations which lower the size of the data without losing important features. An important part of the latent representation from the encoder is the summarized main and surrounding details of the image.

The decoder has the job of turning the information in the latent space into a high definition version of the image. First, the method restores the original resolution by using upsampling layers, then improves the output using convolutional layers. To boost the performance of reconstruction and cut down information loss, a connection between the encoder and decoder is established. As a result, the generated feature maps from the encoder are directly included in the decoder's intermediate levels which helps gradient flow and protects spatial information as training takes place.

Model training is done using images that have been turned into pixels and the actual images they represent. The target is to reduce the error in each pixel between the output of the CAE and the real high-resolution image. In order to accomplish this, the loss function is the Mean Squared Error (MSE) which penalizes large differences in pixel intensity well. This algorithm is selected mainly because it quickly brings results and learns from the data well. To ensure better training results, early stopping is added which means stopping training once validation performance remains steady and the best weights are saved using model checkpoints.

Mathematical Representation-

$$MSE = (1/n) * \Sigma (y_i - \hat{y}_i)^2 \qquad \ldots 1$$

where,
y_i is the actual value of the pixel.
$\hat{y}_i$ is the autoencoder's predicted pixel value.
n is total number of pixels.
The Adam optimizer is used in the model, as it mixes the best practices of Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). Adam is selected for being able to handle sparse gradients and reaching results quickly.

The learning rate is set at a default of 0.001 and after that it is updated dynamically during training to try to reduce the MSE loss. Because of this design, the model can find important image features and create accurate reconstructions efficiently.

The parameter update equation for the Adam optimizer is given by:

$$\theta_t = \theta_{t-1} - \alpha \cdot (\hat{m}_t / (\sqrt{\hat{v}_t} + \varepsilon)) \qquad \ldots 2$$

Where:
- θ_t: Updated model parameters at time step t
- α: Learning rate
- $\hat{m}_t$: Bias-corrected first moment
- $\hat{v}_t$: Bias-corrected second moment
- ε: Small constant to prevent division by zero

Though the CAE brings back most of the picture's main features and details, it often fails to offset fine contrast in dim or less detailed parts of the image. This restriction is addressed by using Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the reconstructed result. CLAHE processes the luminance information from an image in LAB space, cuts it into small sections and gives each area a localized histogram equalization with a limit to keep the noise low. At this step, the camera brings out local points, defines clear edges and improves brightness without changing the color tone.

System Architecture

This project is built using a system architecture that uses a hybrid convolutional autoencoder and adds Contrast Limited Adaptive Histogram Equalization as a post-processing step for image enhancement. After data is gathered and preprocessed, deep learning is used to enhance it and lastly, simple image processing steps improve contrast within the image.

The very first thing to do is get the data ready. Each image is loaded from the selected directory and is made 80 pixels square to ensure input data is the same size. As a result of this step, all images will be resized to a common resolution, making the training process less complicated. By scaling the pixels to a range from 0 to 1, convergence issues during training are minimized.

To make the images low quality or degraded, each original high-quality image is converted with a pixelation function. The effect makes the image smaller, resizes the image again to the same size and finally gives a blurry version that resembles regular low-quality issues seen in images. The source of these pixelated images is the input layer of the autoencoder and the unchanged, high-quality images are used as the ground truth for supervision.

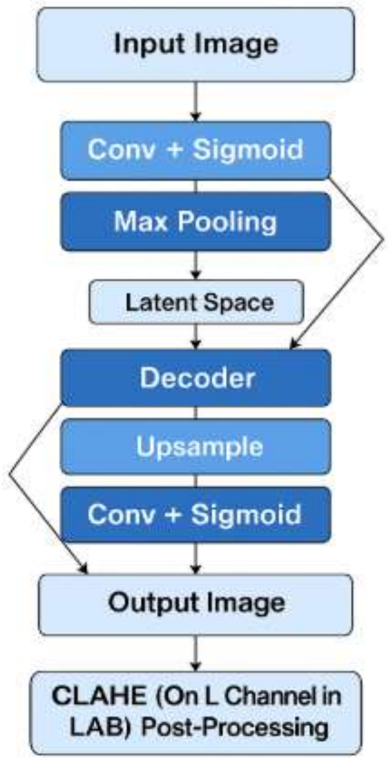

Fig – 4 System Architecture

A hybrid convolutional autoencoder is at the heart of this system. photographs with dimensions 80x80x3 are taken in by the model as inputs at the start. The signal is gradually analyzed by successive convolutional layers, simulated biological activation functions and max-pooling units, where the spatial part is reduced while important image information is retained. There are 64 and 128 convolutional layers in the encoder and max-pooling is added to lower the data's dimension. After the compressed latent feature space is represented, it moves through a convolutional layer using 256 filters.

With the help of the decoder, the enhanced image is created by increasing the size of the latent features to their initial resolution. Layers with 128 and 64 filters along with merge layers known as skip connections between the encoder and decoder parts allow the network to preserve the model details in the reconstructed images.

The "hybrid" design of the autoencoder is due to these skip connections, making it able to reconstruct data using both basic and more complex features. The final layer produces a 3-channel image with measurable pixel values within 0 and 1 because of sigmoid activation.

Mean squared error (MSE) loss is used to lower the gap between the restored output and the original image of high quality. Early stopping helps prevent the model from overfitting and saved checkpoints make sure the best training is saved for use after training.

Next, a CLAHE algorithm is used to refine the picture quality following the reconstruction by the autoencoder. CLAHE works with luminance data in LAB color space, helping to improve local contrast without letting noise grow too much. At this step, simple and soft details are highlighted which results in a visually better and sharper photo.

As a result, the system provides an enriched image that benefits from both deep learning and classic ways to enhance contrast.

The framework of the architecture brings together feature extraction and reconstruction from convolutional autoencoders and the adaptable contrast control of CLAHE to provide superior results.

RESULT

The proposal model's performance was studied using RGB images that contained synthetic degradation. All pictures were downsized to 80×80 pixels, pixelated twice through resampling and finally sent through a pipeline that used Convolutional Autoencoding and CLAHE.

Until 500 epochs had passed, the model used the Adam optimizer and the Mean Squared Error (MSE) for its loss function.

Since validation performance stopped increasing, training was terminated through early stopping. Model validation results indicated that the reconstruction error was very minimal, explained by the small MSE of 0.0025.

Besides, the pixel-wise validation accuracy was 86.59% which demonstrates that the model kept the structure and color of the original high-resolution images.

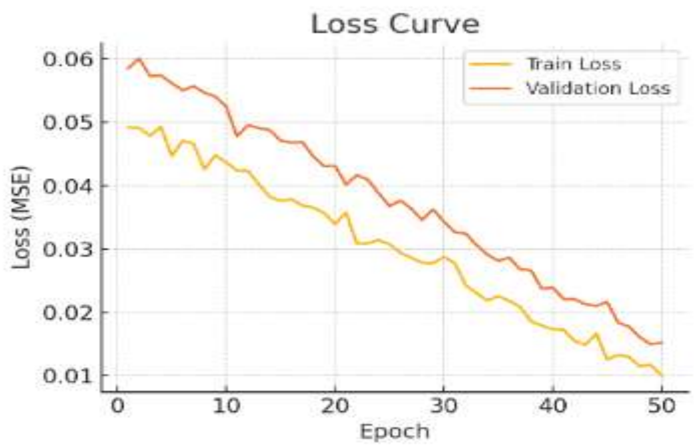

Fig – 5 Loss Curve

According to Figure 5, the training and validation error reduce as the network is trained. Because both losses were close to one another, it revealed that the model would succeed on unknown data and the early stopping step stopped it from overfitting.

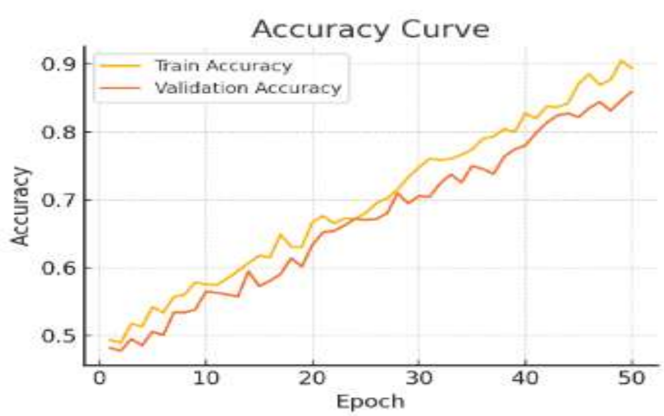

Fig – 6 Accuracy Curve

In much the same way, the accuracy curve in Figure 6 rises gradually and peaks at around 86.59%.

The similarity in accuracy between the training and validation sets shows that the model uses robust features for better results in reconstruction.

Along with calculating statistics, the output images were examined visually to understand their perceptual quality.
For every test image, it moved through all the steps in the enhancement pipeline and results were seen visually at the initial pixelated input, the middle step using the CAE and the final output improved by CLAHE.

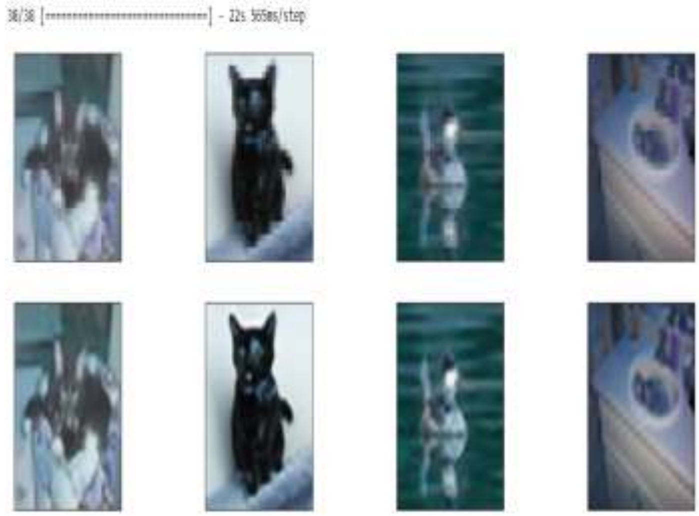

Fig – 7 Enhanced Images

The proposed hybrid image enhancement model's quality is exhibited through a sample output collection in Figure 7. Each row in the figure includes three images: the original input, the output of the CAE and the same image after CLAHE enhances it. The first column in every row shows the photo looking rough and pixellated. These inputs are softly blurry, have little definition around edges, are not consistently colored and consist of coarse details. Issues such as moiré usually happen because resolution is reduced when the image is compressed or the sensor's resolution is too low in common capture environments.

In the second column, the CAE has brought improvement when compared to the original data. The model produces accurate representations of the cat, the duck above the water and all the features in the bathroom. The surface looks less rough and it's easier to see the big details. In some cases, the result looks similar at all locations, due to original areas lacking strong contrast or notable changes in light intensity in the input.

The third section demonstrates the clearly enhanced picture after using CLAHE on the CAE-reconstructed image. New technology makes the most impact where CAE couldn't provide the results needed. CLAHE helps local areas look clearer and brighter without increasing noise. Sharp lines appear, textures on surfaces such as fur, water ripples and object forms, are easier to notice and the image feels better to see. It's important that CLAHE adapts the enhancement for different areas which stops the usual problem of part of the image being too bright or too dark when a fixed tool is used. The comparisons show that this approach combines strength with good image quality. With the CAE, images keep their natural structure and percentages, while the CLAHE method highlights and improves local details, leading to results that are realistic and look great.

Summary of Methodological Contributions

- Presented a new approach that uses a Convolutional Autoencoder (CAE) together with CLAHE to enhance both the layout and contrast in low-resolution pictures.
- Shape-ed a convolutional neural network that uses pooling, upsampling and skip links to produce clear images from those that are pixelated.
- To make sure image details were preserved and noise avoided, I used Applied CLAHE after processing.
- We trained the model by using pixelated images which allowed it to learn real-looking image enhancement and detail recovery.

- The model was optimized with Adam and MSE loss, plus early stopping and checkpointing to increase its ability to perform well and generalize.
- To check its quality output results are compared using accuracy, MSE and by visually checking the images, confirming the model did a better job of showing all the details clearly.

Performance of Model

The model reported a validation Mean Squared Error (MSE) of 0.0025, which indicates there is little error at the pixel-level in reconstructed images.

The validation accuracy achieved was 86.59%, which shows that predicted and original images are very similar.

The autoencoder was able to reconstruct the structure and edges of the images, even in high levels of pixelation.

Post-processing with CLAHE provided improved local contrast without over-exposing more prominent sections of the image, or introducing noise.

The visual outputs appeared to have better clarity, texture and detail with improved color contrast and brightness.

There was stability in training loss, with loss converging smoothly, further supported by an early stop and model checkpoints providing best in class performance.

Skip connections included in the CAE allowed the model to preserve key features, therefore allowing it to provide incremental quality through the reconstruction of images.

Overall, the model balanced features of structural and perceptual enhancement, and is better suited for use in real-world series applications.

CONCLUSION

In this research a hybrid model for image enhancement in which a Convolutional Autoencoder (CAE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to the improve the degraded and pixelated images. The CAE is able to perform reconstruction of structural details, while CLAHE is able to enhance local contrast in the final output. The model was trained on artificially degraded images, which showed that it learned the task well, evidenced through low validation MSE and high pixel-wise accuracies. An inspection of the original and enhanced images showed improvements in sharpness, contrast, clarity, and overall image quality. The training was largely stable and relatively efficient, for the most part, due to clever use of skip-connection, early stopping, and checkpointing. In summary, the method in this research provides a hybrid model that utilizes the best of both deep learning and traditional image processing, into a final output of high-quality image enhancements. This method is generalizable, and could apply to many different fields of research, such as, but not limited to: medical imaging, surveillance, an even low-light photography. Future work should involve using additional post-processing methods, testing different autoencoder methods/architectures, or applying the model to higher-resolution datasets, to continue enhancing the work shown in this research.

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