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An ensemble image augmentation approach to enhance granular parakeratosis dataset

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ABSTRACT

The study discusses the revolutionizing impact of deep convolutional neural network (CNN) techniques on medical image classification, particularly in identifying skin lesions. It addresses the challenge of limited datasets for granular parakeratosis (GP) and paraneoplastic pemphigus (PNP) by employing traditional and advanced ensemble data augmentation techniques. These techniques include geometric transformations, generative adversarial networks (GANs), Cutout, and keep augment. GP affects keratinization in the groin and other regions, while PNP is associated with malignancies. The study's relevance is enhanced by the shared imaging characteristics of the chosen conditions. By utilizing tools like U-net for segmentation, region props for feature extraction, and a support vector machine (SVM) 10-fold cross-validation model for classification, the study achieved impressive performance metrics, including 95% accuracy, 100% sensitivity, and 100% specificity when evaluated on the DermnetNZ skin lesion dataset. These findings underscore the effectiveness of augmentation in enhancing the precision of medical image classifiers and signify a substantial improvement over traditional method. Thus, the research showcases the critical role of data augmentation in overcoming data scarcity challenges and advances medical image analysis.

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1. INTRODUCTION

In recent days, automated skin disease diagnosis using machine learning is a challenging task. Though several researchers have adopted convolutional neural networks (CNNs) for this, their performance is hindered by the limited availability of datasets, which are essential for training robust classifiers. Additionally, certain skin diseases, such as granular parakeratosis (GP) and paraneoplastic pemphigus (PNP), present unique challenges due to their complex clinical presentations. Skin diseases encompass a wide range of conditions that can cause pain, discomfort, and aesthetic concerns [1]. Accurate diagnosis is crucial for effective management and therapy. GP is a benign skin disorder that presents as erythematous hyperpigmented, hyperkeratotic papules and plaques in skin folds [2]. Excessive use of topical agents and exposure to chemical irritants are linked to its onset. In contrast, PNP is a severe mucosal inflammatory condition associated with lymphoproliferative disorders [3]. PNP can lead to life-threatening complications.

Figure 1 shows the samples of GP and PNP. Recent advancements in machine learning, particularly deep learning methods such as CNNs, are revolutionizing the field of automated skin disease diagnosis [4]. However, publicly accessible skin lesion datasets are often small or unevenly distributed, posing challenges for training robust classifiers. To address these limitations, ensemble deep learning models and data augmentation techniques are employed [5]. Ensemble models integrate predictions from multiple models trained using diverse techniques, enhancing prediction accuracy. Data augmentation plays a crucial role by artificially expanding the dataset through transformations such as rotation, translation, mirroring, scaling, and flipping. These augmentations preserve the semantic meaning of the original images and have proven effective in achieving state-of-the-art results in melanoma classification studies [6]. But the pitfall is most of the researchers focus only on the melanoma disease.

Figure 1. Granular parakeratosis and paraneoplastic pemphigus samples

The primary objective of this study is to enrich the GP and PNP datasets using ensemble augmentation techniques, aiming for significant improvements in evaluation metrics. By employing these methodologies, this research aims to enhance the accuracy and reliability of automated diagnostic systems in dermatology, thereby facilitating more effective clinical interventions and improved patient outcomes.

The remaining text is organized as follows: section 2 reviews various augmentation approaches used by the researchers; section 3 provides a description of datasets and the augmentation approaches used by the proposed model; section 4 focuses on the proposed methodology; section 5 presents the results obtained for the proposed model and its comparison with state-of-the-art techniques.

2. LITERATURE REVIEW

Data augmentation techniques are commonly used by researchers to improve the reliability and adaptability of machine learning models, particularly in tasks like melanoma classification. These techniques include conventional methods such as resizing, rotating, inverting, and tilting images, as well as more advanced approaches like deep learning-based techniques and methods using generative adversarial networks (GANs). The literature outlines three main types of data augmentation: basic image manipulations [7], deep learning-based techniques, and advanced techniques such as cutout and hide-and-seek. These methods aim to address the shortage of labeled data by expanding the training dataset through geometric and intensity modifications of baseline images. Li and Wu [8] introduced dense fuse, which combines convolutional layers and uses dense blocks as encoders to extract deep features, and convolutional layers as a decoder to reconstruct the final fused image. Addition and L1-Norm strategies are utilized to combine features, showing the effectiveness of this architecture for infrared and visible image fusion tasks. The pitfall of this method is that only few evaluation metrics were considered. Zhang *et al.* [9] proposed an image fusion framework (IFCNN) based on CNNs, featuring convolutional layers for feature selection, fusion rules, and reconstruction. This model shows promising generalization potential but is limited to specific types of images. The deep learning-based fusion method of [10] optimizes fusion rule thresholds in shearlet transform. Though it demonstrates high efficiency across various input images, it achieves limited performance metrics. The work of [11] combined data augmentation with deep CNNs, achieving an impressive 89% classification rate using the Inception V4 architecture. However, they noted that the effectiveness of data augmentation varied, indicating room for improvement. Yu *et al.* [12] developed a fully convolutional residual network (FCRN) that incorporates residual learning to automate melanoma recognition and address overfitting. By using random and fixed rotation augmentation, they increased the number of skin images, achieving an 85.5% classification rate. This method highlighted the importance of robust augmentation techniques. Qin *et al.* [13] developed style-based GANs for data augmentation, achieving 95.2% accuracy on the ISIC 2018 dataset. Although this approach demonstrated potential, it highlighted the need for better feature extraction techniques. The work of [14] utilized a trained end-to-end

CNN to classify skin lesions into three categories: melanomas, seborrheic keratosis, and benign/nevus. Using the Inception V3 pre-trained architecture, they achieved a classification rate of 72.1%, indicating the challenges in achieving high accuracy in skin lesion classification. Table 1 provides a summary of the augmentation techniques used in the literature, highlighting their advantages and limitations.

Despite these advancements, many models still struggle with effective performance metrics. Single augmentation techniques, such as GANs, often fall short in handling data imbalance efficiently. The proposed model aims to address these challenges by combining traditional (geometric transformations) and advanced augmentation approaches (GAN methods and cutout (random erasing)) to manage smaller datasets and data imbalances more effectively [7].

Table 1. Overview of the augmentation techniques used in the literature

Ref	Method	Dataset	Performance metrics	Disadvantages
[15]	Rotation, flipping, shearing, and zooming	HAM10000 and ISIC 2019	94% recall score	Small data set
[16]	GAN based augmentation method	ISIC 2017	Accuracy - 99.38%	Unable to fine-tune its hyperparameters
[17]	Raman spectroscopy augmentation	RS dataset	Accuracy - 83%	Small sample set
[18]	Progressive growing of GAN	HAM10000	Accuracy - 70.1%	Not robust, inaccurate
[19]	Flips, skew-left-right	ISIC 2019 and PH2	Accuracy - 91%	Variable size filters

3. IMAGE AUGMENTATION

3.1. Augmentation techniques

Limited annotated medical images present a challenge for developing effective machine learning models in medical image analysis. Small datasets like MED-NODE, dermatology information system, and DermQuest highlight the need for larger datasets to improve CNN performance. Data augmentation is a key solution to this problem, as it involves making alterations to the original training set to generate new examples without altering the class characteristics. This process enhances generalization and model performance by expanding the dataset. Various techniques, such as feature-space, GAN-based, geometric-transformation-based, and advanced augmentation methods, can help address data imbalances and are crucial for the success of deep learning, especially with small datasets.

- Geometric augmentation enhances dataset diversity by altering the geometry of images without changing their labels or class information. This helps models learn general patterns rather than relying on specific poses or orientations. Common geometric augmentation techniques in deep learning include:
- Rotation (rotates image clockwise or counter clockwise), translation (shift image horizontally or vertically), scaling (resize images to larger or smaller versions), flipping (flips image horizontally or vertically), and cropping (removes parts of the image to create variations). These techniques enrich training data with diverse geometric variations, enhancing model performance in tasks like object classification, detection, and image segmentation. Two approaches can be used for geometric augmentation: dataset generation and in-place augmentation
  - Dataset generation: the process begins by obtaining the initial input image from the drive. Random transformations, such as translations, rotations, and other modifications, are then applied to the source image. After each transformation, the modified image is saved back to disk. This sequence of transforming and saving the image is repeated N times, resulting in the generation of numerous new images derived from the original, which are suitable for training purposes.
  - In-place augmentation: the image data generator receives a batch of input images. It then applies a random set of translations, rotations, and other transformations to every image in the batch. After that, the calling function receives the batch that was randomly modified.
- GANs are used in medical image analysis to augment data, create new images, and adapt the domain to enhance CNN performance [20]. GANs generate synthetic samples, increasing the available dataset when obtaining large amounts of true data is impractical or impossible.
- Feature-space augmentation
- This approach involves two methods: under sampling and oversampling.
- Under sampling: reducing samples from the majority class balances class distribution and improves the recognition of the minority class, but it may result in loss of valuable information.
  - Oversampling: generating additional samples from the minority class to match its representation with the majority class, creating a more balanced dataset.
- Cutout and keep augment
- In the training samples set, cutout removes random patches and substitutes zero values for the pixels in the deleted areas. This is achieved by masking off random sample locations using a square matrix of

constant weights. But, the drawback of region deletion techniques (cutout) is that more suitable regions cannot be chosen for deletion due to the random nature of the deletion process. It can sometimes result in the most useful features being removed, resulting in poor performance. The approach can be effectively used when combined with keep augment to ensure that images are augmented in a way that preserves the useful features.

Incorporating data augmentation techniques is essential for overcoming the challenges posed by limited annotated medical images. By employing ensemble traditional and advanced augmentation techniques, researchers can enhance dataset diversity, build network invariances, and improve generalization performance. This approach ensures that machine learning models are more resilient to real-world image variations, ultimately leading to better outcomes in medical image analysis.

3.2. Performance metrics

In medical image analysis, three critical metrics are used to evaluate the performance of segmentation and classification methods: accuracy, sensitivity, and specificity. These metrics provide a comprehensive understanding of how well a model is performing after data augmentation. The following equations specify the computation of these metrics [21]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Specificity = \frac{TN}{TN+FP}$$

Where TP indicates true positive, TN indicates true negative, FP indicates false positive, and FN indicates false negative

3.3. Datasets

Datasets are the cornerstone of machine learning. A dataset must be extensive enough to provide comprehensive training data and should be of high-quality and relevant to the task at hand. Three types of datasets are available: text (utilized in natural language processing tasks), image (computer vision tasks, such as the proposed model), and sensor (IoT and time-series applications). For the proposed model, image data is essential. The images are sourced from publicly available resources, such as DermnetNZ [22] and the DermIS database. These databases provide a rich collection of medical images that are critical for training robust machine learning models in dermatology.

4. METHOD

In the realm of medical image analysis, data augmentation is crucial for addressing limited annotated datasets. The Keras image data generator is widely used for this purpose, applying random transformations to create diverse versions of images. This process enhances the model's ability to generalize and accurately predict unseen data. The ensemble augmentation technique also prevents overfitting and improves accuracy. After feeding the original dataset into the model, the samples undergo the following transformations: flipping, rotation, shifting, zooming, and keep augment in accordance with the parameters shown below.

Key Parameters of image data generator in the proposed model:

- Horizontal flipping: OpenCV offers tools for flipping an image along its x- or y-axis, or even both. The cv2.flip method needs two inputs: the image to flip and a code/flag to decide the flip direction. To rotate the image vertically, around the x-axis, specify a flip code of 0. To rotate the image horizontally, around the y-axis, specify a flip code of 1.

```
cv2.flip(image, 1)
```

  - This transformation flips the image horizontally along the y-axis, creating a mirror image. This is crucial for models to recognize features irrespective of their orientation.
- Random rotation: to create the transformation matrix M that is necessary to rotate an image, use the cv2.getRotationMatrix2D() function. The warpAffine() function takes transformation matrices as parameters and returns the rotated image.

M1 = cv2.getRotationMatrix2D ((cols, rows), rand_num, 1)
image = cv2.warpAffine(image, M1, (cols,rows))

- Randomly rotating images ensures that the model learns to recognize objects from different angles. The `cv2.getRotationMatrix2D()` function creates the transformation matrix, while `cv2.warpAffine()` applies it.

– Shift: the parameters height_shift_range and width_shift_range allow the ImageDataGenerator class to shift an image vertically or horizontally, respectively. The proposed model takes 20% of width of the image and 20% of height of the image to shift

– Rotate: the rotation_range option of the image data generator class accepts an integer number that a user can employ to rotate images via any degree between 0 and 360 at random. In the proposed model, this option is set to 40 degrees, allowing the model to see the images from various rotated perspectives.

– Random zoom: zoom augmentation randomly zooms in or out of the image. A value smaller than 1 zoom in on an image. In contrast, any value greater than 1 zooms out the image. The zoom range is set to 0.2, meaning images are randomly zoomed in, providing a diverse set of training examples.

Advanced augmentation techniques

– Cutout: cutout takes 2 parameters. First specifies the number of patches to take out from an image and the second specifies the length of each patch.

– Keep augment: is an approach that identifies the most informative regions of an image using saliency map-based importance rankings of different areas. These regions are prioritized during subsequent augmentation processes to preserve their usefulness. In skin lesion dataset, the lesion region is given more importance than the non-lesion region. The saliency map of an image indicates what pixels in the image are important for network prediction. The proposed methodology first uses Keep Augment to extract lesion regions and then applies the cutout method to filter out the non-lesion areas.

Once the augmented image arrays are obtained, they are concatenated to the original training arrays which is then split into train and validation set. Following each epoch, the performance is validated using a validation dataset. Figure 2 illustrates how the proposed ensemble augmentation technique maximizes the performance of skin lesion classification. Thus, selection of this ensemble augmentation approach not only increases the dataset size but also maximizes the model's performance and ensures it can generalize well to new, unseen data, making it a powerful tool. This is illustrated in the following section.

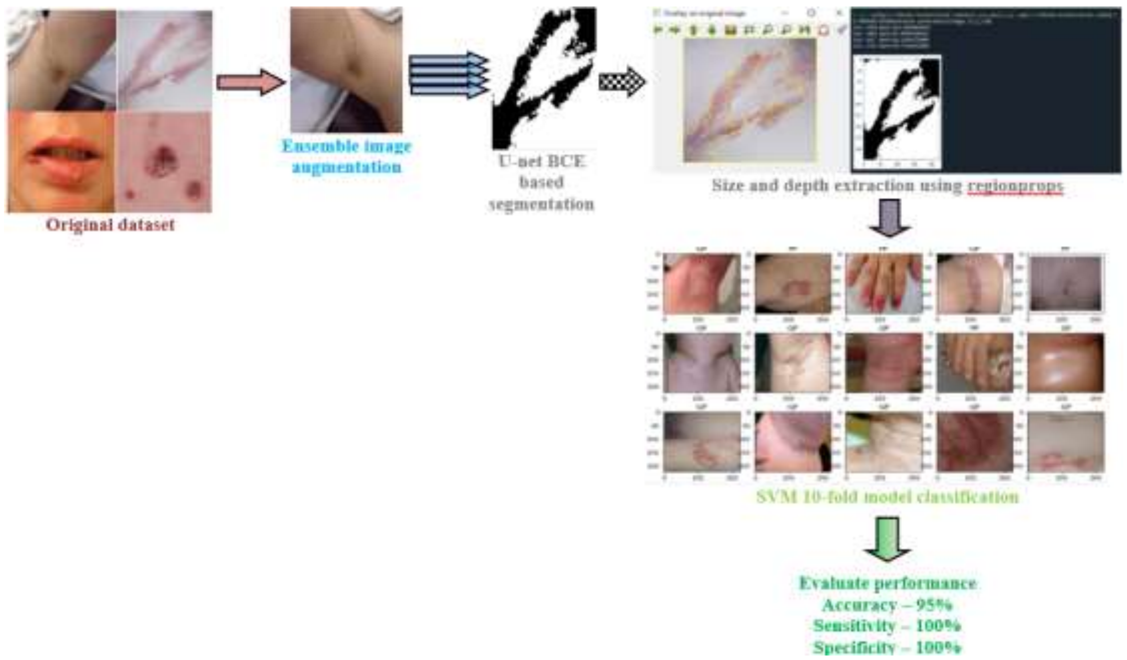

Figure 2. Flow of skin lesion classification with the proposed ensemble augmentation technique

5. RESULTS AND DISCUSSION

A model needs to be trained in advance in model-based image augmentation for creating augmented images. As a part of the implementation, prior to inputting the images into the networks, few of the augmentation strategies have been incorporated to boost the quantity of training images. The model applies various input strategies for training that transform the images from their original size after pre-processing to a suitable input size. Augmentation is solely aimed at boosting the dataset's image count, without any medical rationale. This offers a great advantage over the techniques that focus only on melanoma.

5.1. CNN input strategy

The proposed model starts by loading 224×224×3 sized .bmp color images from the data source. These images are then subjected to ensemble augmentation techniques such as flipping, rotating, shifting, cutout, and keepAugment resulting in a significantly larger dataset. The augmented dataset undergoes segmentation using U-net with binary cross-entropy (BCE) loss, size and depth are extracted using the regionprops module from skimage and classifies the lesions using support vector machine (SVM) with 10-fold cross-validation. Table 2 shows the count of updated dataset which shows a significant increase over the original set of images. Figure 3 depicts some examples of data augmentation phase allowing the model to be trained on more varied dataset leading to better performance see in Figures 3(a)-3(e).

The proposed research combines three types of augmentation, geometric (dataset generation, in-place augmentation), GAN-based augmentation, and advanced augmentation (cutout and keep augment) thereby generating ensemble model. Initially, the model normalizes input image to generate normalized data and then performs scaling, zooming, rotating horizontal flips, and cutout to augment the normalized data. In this step, the suitable parameters of each function are applied to generate new samples from the original dataset.

For geometric augmentation, this study makes use of rotation, shear, shift, zoom, and flip; Table 3 provides the description of geometric augmentation values. A total of 2 epochs with a batch size of 18 are run during GAN-based augmentation. The parameter values for the GAN-based augmentation are structured as shown in Table 4. Keep augment's saliency map makes use of normalization and windowing function to extract the lesion areas. Table 5 shows the parameters used in cutout implementation. Binary cross-entropy is used as the loss function for segmentation and hinge loss (serves as a better loss function for SVM 10-fold model) for the classification. The model uses Adam optimizer with a learning rate of 1e-4 since it speeds up the training process. ReLU serves as the activation function for all layers with the exception of the last layer, which employs a linear activation function. Since it mimics the implementation of an SVM classifier if added to the final layer of a CNN model, the final layer utilizes a linear activation function. Table 6 displays the appropriate values of the training model's parameters, including epoch, batch size, learning rate, loss functions, and optimizer. It might affect the model's performance if such parameters are not chosen properly.

Table 2. Comparison of original and augmented dataset count

	Original datasets	Augmented datasets
Granular parakeratosis	1505	75250
Paraneoplastic pemphigus	99	4950

(a) (b) (c) (d) (e)

Figure 3. Augmented dataset samples: (a) original, (b) zoom, (c) shift, (d) rotate, and (e) cutout

Table 3. Geometric augmentation values description

Augmentation techniques	Values
rotation_range	40
width_shift_range	0.2
height_shift_range	0.2
shear_range	0.2
zoom_range	0.2
horizontal_flip	True

Table 4. GAN-based values description

Parameters	Values
Conv2D	ReLU
Conv2D	ReLU
Flatten	
Dense-full connection	ReLU
Dense-output layer	Linear

Table 5. Cutout implementation parameters

Parameters	Values
Probability of performing cutout	0.5
Minimum value of erased region against input image	0.02
Maximum value of erased region against input image	0.4
Minimum aspect ratio of erased region	0.3
Maximum aspect ratio of erased region	3.33
Minimum value for erased area	0
Maximum value for erased area	255

Table 6. Training model parameters

Parameters	Values
Optimizer	Adam
Learning rate	1e-4
Batch size	18
Epochs	2
Loss	Binary cross entropy (segmentation) Hinge (classification)

Two kinds of experiments have been carried out with the given datasets. The first one is to evaluate the proposed method using original datasets without image augmentation. The second one is to evaluate the proposed method with augmented datasets. Table 7 shows classification accuracy, sensitivity, and specificity results from the original dataset and the proposed augmentation. The corresponding graphical representation of the classification result is shown in Figure 4. The numerical values of the table clearly indicate that the input dataset without augmentation or using a single augmentation technique provides very less performance but the proposed model's performance is drastically increased with the usage of ensemble augmentation.

Figure 4 demonstrates that sensitivity and specificity are improved with the augmented dataset, suggesting better true positive and true negative detection. The green bars (augmented dataset) show consistent improvement across all three metrics compared to the brown bars (original dataset) signifying that data augmentation has positively impacted the model's overall performance. There aren't many measurements that receive a perfect score for both sensitivity and specificity. However, the suggested model meets this requirement, demonstrating its superiority.

Table 7. Comparison of classification accuracy, sensitivity, and specificity results from the original dataset and the proposed augmentation

	SVM 10-fold performance without augmentation	SVM 10-fold performance with augmentation
Accuracy	85	95
Sensitivity	91	100
Specificity	89	100

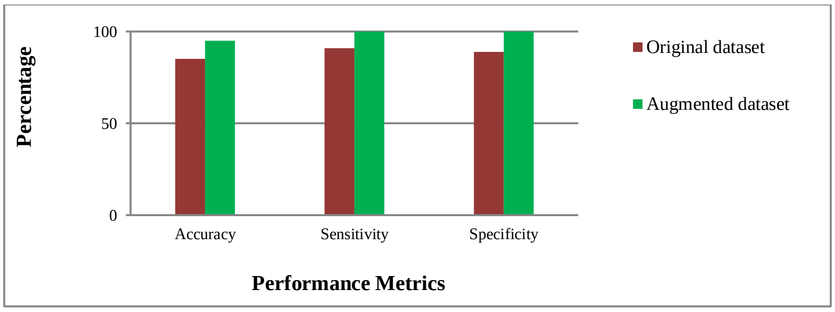

Figure 4. Graphical representation of the classification result for original and augmented dataset

5.2. Segmentation, feature extraction, and classification

The BCE-based U-net method is trained on the augmented parakeratosis and pemphigus lesions dataset and obtained better performance metrics on training set, test set, and validation set as described in our previous work [23]. The authors also have published their work related to feature extraction [24] which specifies that size and depth features can be extracted efficiently using partition clustering and regionprops technique. The work of classification [25] demonstrates that changing the last layer of CNN to linear activation function and incorporation of hinge loss function effectively implements the SVM classifier. The output of SVM classifier is fed into 10-fold cross validation model thereby increasing the performance metrics and this is considered to be superior compared to traditional techniques. The effectiveness of the proposed model was rigorously tested using datasets from DermIS and DermnetNZ. The results were compelling with accuracy: 95%, sensitivity: 100%, and specificity: 100%. These performance measures highlight the remarkable improvement in classification metrics when using the ensemble augmentation model compared to the original dataset. Table 8 illustrates the comparison of proposed methodology with the state-of-the art techniques including synthetic minority oversampling technique (SMOTE) augmentation [26], acral lentiginous melanoma (ALM) detection using CNN [27], and skin lesion detection via data augmentation and explainable AI [28]. Comparing the performance of the classifier after ensemble augmentation with all the techniques mentioned suggests it has a better performance.

Table 8. Comparison of proposed methodology and state-of-the art techniques

Ref	Accuracy	Sensitivity	Specificity
[26]	92.18	80.77	95.1
[27]	86.9	-	-
[28]	91.5	-	-
Proposed methodology	95	100	100

6. CONCLUSION

In the study focused on developing an effective deep neural network for skin lesion classification, the use of ensemble augmentation techniques proved to be crucial in expanding the volume of labeled images. The proposed model, which combined traditional and advanced augmentation methods, demonstrated a significant improvement in classification accuracy and robustness. The augmented dataset, combined with the original one, was processed through a comprehensive machine learning pipeline, resulting in a remarkable performance boost. Testing the model using datasets from DermIS and DermnetNZ showed that the ensemble augmentation model outperformed state-of-the-art techniques, achieving 95% accuracy, 100% sensitivity, and 100% specificity. The study concludes that implementing ensemble data augmentation significantly enhances skin lesion classification performance, setting a new benchmark and improving the reliability of medical image analysis but has a limited accuracy. The study recommends further research to enhance accuracy and explore the generalizability of these augmentation strategies in other domains.

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