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Detecting the stages of Breast Cancer using CNN

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Abstract: Breast cancer is the type of cancer that is originates in cells of breast. Breast cancer can occur in both men and women, but it is far more common in women. Breast cancer detection is critical for early diagnosis and treatment. Mammography is the most known and effective process to detect early signs of breast cancer. Convolutional Neural Networks (CNNs) have emerged as powerful tools for mammogram image analysis due to their ability to automatically learn and extract relevant features from complex data. This study explores the application of CNNs for detecting and classifying the stages of breast cancer from mammographic images. By employing a deep learning framework, we trained a CNN Pre-train model like EfficientNet B4, Inception V4 model on a labeled dataset of mammograms, where the images were preprocessed to enhance feature extraction. The model's performance was evaluated using metrics such as accuracy, sensitivity, specificity, and the area under the ROC curve (AUC). Results demonstrated that the CNN achieved high accuracy in distinguishing between different stages of breast cancer, highlighting its potential as an effective diagnostic aid. Further improvements and validations with larger datasets are necessary to enhance the model's robustness and generalizability. This approach promises to support radiologists in making more accurate and timely diagnoses, ultimately improving patient outcomes.

Keywords: Breast cancer, Convolutional Neural Networks (CNNs), mammogram images, CNN Pre-train model like EfficientNet B4, Inception V4 model

I. INTRODUCTION

Breast cancer is the disease which the cell of breast grows out of the control. Breast cancer is a commonly diagnosed disease in women. It occurs when cells in the breast grow and divide uncontrollably, forming a tumor. The detection and staging of breast cancer are critical components in the effective management and treatment of the disease, significantly influencing patient prognosis and survival rates. Mostly it can occur in women and rarely in men. It is the most common invasive cancer in women and is one of the main causes of their death.

Detecting Stages of breast cancer using Convolutional Neural Networks (CNNs) involves utilizing deep learning techniques to analyses mammogram image. Convolutional Neural Networks (CNNs) are highly effective for breast cancer detection using mammograms, images. Mammogram images are images of the breast used to detect and diagnose breast cancer. They are crucial for early detection, potentially improving treatment outcomes. Mammogram images display breast tissue, calcifications, and masses.

For this work we develop pre trained model such as Inception V4, EfficientNet B4 model, which has been trained on large datasets, including mammogram image. Inception V4 and EfficientNet model has learned to recognize patterns and features in mammogram images related to breast cancer. This pre-trained model helps to analyses mammogram images and identify potential signs of breast cancer without training it from scratch. EfficientNetB4 is an improved version of a type of computer vision model. It is a type of convolutional neural network that has faster training speed and better parameter efficiency than previous models. It is designed to be good at recognizing and understanding images. Inception V4 Model is a convolutional neural network (CNN)architecture designed for image classification tasks. It's a deep learning model that has been pretrained on a large dataset. These modules were designed to solve the problem of computational expense, as well as overfitting, among other issues. When applied to breast cancer, it can analyze mammogram image to assist in identifying patterns or features indicative of cancerous or non-cancerous conditions.

II. EXISTING SYSTEM

According to latest update, Convolutional Neural Networks (CNN’s) have shown promising results in detecting breast cancer from mammogram image. This deep learning models excel in image recognition tasks. Researchers and developers continue to refine CNN architectures and training methodologies to enhance accuracy and efficiency in breast cancer detection. They have used pre-trained models such as VGG16, mobile net, Inception V3, DenseNet and so on. The combination of CNN architecture and pre-trained models contributes to more accurate and efficient breast cancer diagnosis.

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Abdel and Eldieb [7] Deep belief network (DBN) was used for the data set, and a stunning 94.68% accuracy was achieved. DBN travels in an uncontrolled manner. Using BPNN and the Levenberg-Marquardt learning function, this system was created. where the DBN route is used to initialize the load of nodes. The system outperforms existing classifiers and offers results that are adequate. Deep learning dramatically increases precision while reducing error rates to a minimum. Jhajhari et al. [8] provided a prototype for classifying breast tumor that used a feed-forward based neural network to categorize the data and a component analysis technique known as PCA, principal component analysis, to extract some characteristics from the dataset. Data is divided by a splitting percentage for training and testing data to get the desired outcome. They used a least SVM machine to analyze a WDBC (Wisconsin Diagnostic Breast Cancer) dataset (LSSVM). This system used a validation approach to achieve accuracy of 98.53%...

Ghosh et al. [9] proposed a technique for classifying breast cancer based on neuro-fuzzy analysis. These data sets were also used to assess the effectiveness of the procedure. A multi-layer perceptron is then used to categorize the data. The objective is finally achieved via inducing defuzzification.

III. PROPOSED SYSTEM

A Convolutional Neural Network (CNN) for staging breast cancer typically involves image analysis to classify tumors into different stages. It utilizes image data, like mammograms to classify cancer stages. The stages usually include early stages (I and II) and advanced stages (III and IV). For this project we use pre-trained models such as EfficientNet B4 and Inception V4 model. The goal is to assist healthcare professionals in accurate and timely diagnosis, enabling appropriate treatment strategies for patients at various stages of breast cancer.

Dataset

A well-arranged dataset is an indispensable requirement to produce a functional and study method for the identification of breast cancer. Dataset in use for this paper was acquired from Kaggle. Dataset was acquired from a trusted medical source with little to no bias. It was assumed that the data set was normalized. Breast cancer is generally categorization into five main stages, ranging from 0 to 4. In this work we have divide the Dataset into 80% Training and 20% Validation, for training we have consider 2001 images and Validation 502 images which is in the PNG format image.

Convolution Neural Network (CNN)

A convolutional neural network (CNN) is the type of artificial neural network used for image recognition and processing, due to its ability to recognize the patterns in the image.

Basic Architecture of CNN

Data Preprocessing: Images are enhanced and normalized to improve quality and consistency. Techniques like resizing and augmentation are used to prepare the data for analysis.

Convolutional Layers: These layers apply filters to the input images to detect important features like edges, textures, and patterns that are indicative of cancerous tissues.

Kernal size: The kernel size typically varies depending on the architecture and specific application. Common kernel sizes used in CNNs for image classification tasks, including breast cancer detection, Kernal size for this project is 3x3.

Max Pooling: It is a technique commonly used for feature extraction and dimensionality reduction. It's not specifically used for detecting stages of breast cancer but rather for extracting the most important features from the input data.

Fully Connected Layers: These layers connect every neuron in one layer to every neuron in the next layer, providing a global understanding of the input data.

Activation Functions: ReLU introduces non-linearity, ReLU: (Rectified Linear Unit): ReLU is used as an activation function. It introduces non-linearity by replacing all negative values in the input with zero, while leaving positive values unchanged. ReLU is defined as \(f(x) = \max (0, x) \).and dropout prevents overfitting by ignoring random neurons during training.

Dropout: Dropout is a regularization technique used for breast cancer detection, to prevent overfitting and it is typically used to increase the performance of the deep learning task on the unseen dataset. Dropout prevents overfitting by ignoring random neurons during training.

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Output Layer: Typically uses a SoftMax function to provide probabilities for each class.
SoftMax: SoftMax is an activation function typically used in the output layer. It converts the output scores of the network into probabilities.

IV. PROPOSED METHODOLOGY

4.1 Data Acquisition and Preprocessing
Collect mammogram images of breast cancer patients with labelled stages (e.g., I, II, III, IV).

4.2 Image Preprocessing: Apply image enhancement techniques like contrast limited adaptive histogram equalization to improve image quality. Resize images to a standard size compatible with the chosen CNN models.

4.3 Normalization: Transforming features to a common scale, making them comparable and suitable for analysis. Commonly used methods include.

4.4 Min-max scaling: It scales and transforms numeric features to a specific range, typically between 0 and 1.

4.5 Batch Size: The batch size refers to the number of samples processed in one iteration during training.

V. MODEL SELECTION AND TRAINING

5.1 EfficientNet B4: This model offers a good balance between accuracy and computational efficiency, making it suitable for resource-constrained environments.

5.2 Inception V4: This model excels in image recognition tasks and has demonstrated promising results in medical image analysis.

5.3 Transfer Learning: Utilize pre-trained versions of EfficientNet B4 and Inception V4 on large datasets like ImageNet, Kaggle and fine-tune them for breast cancer stage classification.

5.4 Train-Test Split: Divide the preprocessed data into training, validation, and testing sets.

VI. HYPERMETER TUNING

It involves adjusting parameters related to training, such as learning rate, batch size, Dropout, Image

6.1 Learning Rate: The learning rate in hyperparameter tuning controls the step size during model training, affecting how quickly or slowly the model learns and converges to an optimal solution.

6.2 Batch Size: Batch size in hyperparameter tuning determines how many training examples are processed together in one iteration during model training. It affects the speed and efficiency of training and can impact the model's performance and convergence.

6.3 Dropout: It involves temporarily removing a certain proportion of neurons during training iterations to prevent overfitting in neural networks. Experiment with dropout rates between 0.2 and 0.5 to prevent overfitting.

6.4 Image Resolution: Image resolution in hyperparameter tuning refers to the dimensions (width and height) of the images used for training a model. The model's performance may vary based on the resolution of the input images.

VII. MODEL EVALUATION

Evaluate the trained models on the test set using metrics like accuracy, precision, recall, F1-score, receiver operating characteristic (ROC) curve, and area under the ROC curve (AUC). Compare the performance of Efficient Net B4 and Inception V4 to identify the most suitable model for breast cancer stage detection.

7.1 ROC: ROC (Receiver Operating Characteristic) is the graphical representation of the performance in binary classification model. The ROC curve and AUC curve plots the true positive rate (sensitivity) against the false positive rate (1 - specificity) for different threshold values.

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7.2 AUC: AUC (Area Under the Curve) is a metric in binary classification that quantifies the model's performance. It measures the area under the Receiver Operating Characteristic (ROC) curve, summarizing the model's ability to distinguish between classes. A higher AUC value, closer to 1, indicates better performance, while 0.5 suggests random guessing.

7.3 Training and validation accuracy: Training accuracy measures how well the model performs on the training data it was trained on, while validation accuracy measures its performance on unseen validation data.

7.4 Training and validation loss: Training loss indicates how well the model is fitting the training data during training whereas, Validation loss measures the performance of the model on a separate validation dataset, which it hasn't seen during training.

VIII. RESULT ANALYSIS OF EFFICIENTNET B4 AND INCEPTION V4 MODEL

The proposed model has been implemented with python using Jupyter notebook and dataset are used to test the performance parameter. Initially model is trained using few images.

8. EFFICIENTNET B4 MODEL

TABEL 8.1 MODEL SUMMERY OF EFFICIENTNET B4 MODEL

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 126, 126, 32)      896

 max_pooling2d (MaxPooling2  (None, 63, 63, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 61, 61, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 30, 30, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 28, 28, 128)       73856

 max_pooling2d_2 (MaxPoolin  (None, 14, 14, 128)       0
 g2D)

 conv2d_3 (Conv2D)           (None, 12, 12, 256)       295168

 max_pooling2d_3 (MaxPoolin  (None, 6, 6, 256)         0
 g2D)

 flatten (Flatten)           (None, 9216)              0

 dense (Dense)               (None, 512)               4719104

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 5)                 2565

=================================================================
Total params: 5110085 (19.49 MB)
Trainable params: 5110085 (19.49 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
Train Accuracy: 0.7541229128837585
Validation Accuracy: 0.8306772708892822
```

Tabel 8.1 Shows the performance of model summary of EfficientNet b4
Train Accuracy: 0.75 and Validation Accuracy : 0.83

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8.2 CLASSIFICATION REPORT:

The classification report provides a summary of key classification metrics for each class in a classification problem. The metrics included in a classification report are precision, recall, F1-score, and support.Here's how each metric is calculated:

1. PRECISION: Precision measures the ratio of correctly predictedpositive observations to the total predicted positives. It is calculated using the formula: Precision = TP / (TP + FP)

2.RECALL: Recall measures the ratio of correctly predicted positive observations to the all observations in actual class. It is calculated using the formula: Recall = TP / (TP + FN)

3. F1-SCORE:The F1-score is a harmonic mean of the precision and recall. It provides a balance between the precision and recall. It is calculated using the formula: F1-score = 2 * (Precision * Recall) / (Precision + Recall)

4. SUPPORT: The support is the number of actual occurrences of the class in the specified dataset. . It is calculated using the formula: Support = TP+FN

TABEL 8.2 CLASSIFICATION REPORT

Training Classification Report:

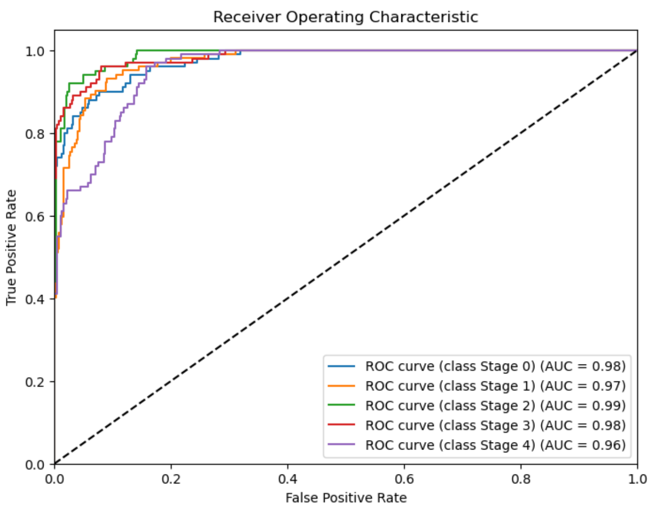
	precision	recall	f1-score	support
0	0.90	0.80	0.84	400
1	0.81	0.87	0.84	400
2	0.85	0.84	0.85	400
3	0.90	0.86	0.88	401
4	0.78	0.85	0.81	400
accuracy			0.84	2001
macro avg	0.85	0.84	0.84	2001
weighted avg	0.85	0.84	0.84	2001

Validation Classification Report:

	precision	recall	f1-score	support
0	0.93	0.79	0.85	100
1	0.80	0.81	0.81	102
2	0.84	0.89	0.86	100
3	0.88	0.86	0.87	100
4	0.73	0.80	0.77	100
accuracy			0.83	502
macro avg	0.84	0.83	0.83	502
weighted avg	0.84	0.83	0.83	502

Tabel 8.2 shows the Performance of the classification report of EfficientNet B4 Model of each stages

TABEL 8.3 ROC CURVE OF EFFICIENTNET B4 MODEL



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Tabel 8.3 shows the performance of ROC Curve for each particular stages in EfficientNet B4 model
Stage 0 (AUC)= 0.98
Stage 1(AUC)= 0.97
Stage 2(AUC)= 0.99
Stage 3(AUC)= 0.98
Stage 4 (AUC)= 0.96

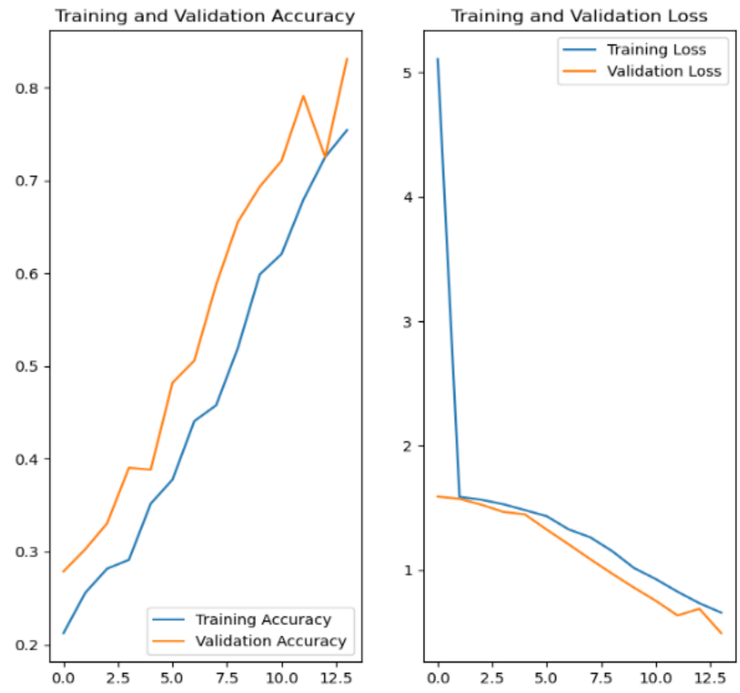
TABEL 8.4 GRAPH OF ACCURACY AND LOSS

```
 mixed10 (Concatenate)          (None, 8, 8, 2048)         0          ['activation_273[0][0]',
                                                                       'mixed9_1[0][0]',
                                                                       'concatenate_5[0][0]',
                                                                       'activation_281[0][0]']

 global_average_pooling2d_2  (None, 2048)              0          ['mixed10[0][0]']
  (GlobalAveragePooling2D)

 dense_6 (Dense)             (None, 1024)              2098176    ['global_average_pooling2d_2[0
                                                                  ][0]']

 dense_7 (Dense)             (None, 5)                 5125       ['dense_6[0][0]']

==================================================================================================
Total params: 23906085 (91.19 MB)
Trainable params: 2103301 (8.02 MB)
```

Tabel 8.4 shows the Performance of Accuracy and loss of training and validation. As Accuracy of Training and validation increases, loss of Training and validation decreases.

8.5 INCEPTION V4 MODEL

TABEL8.5 MODEL SUMMARY OF INCEPTION V4 MODEL



Tabel 8.5 shows the performance of model summary of Inception V4 model.

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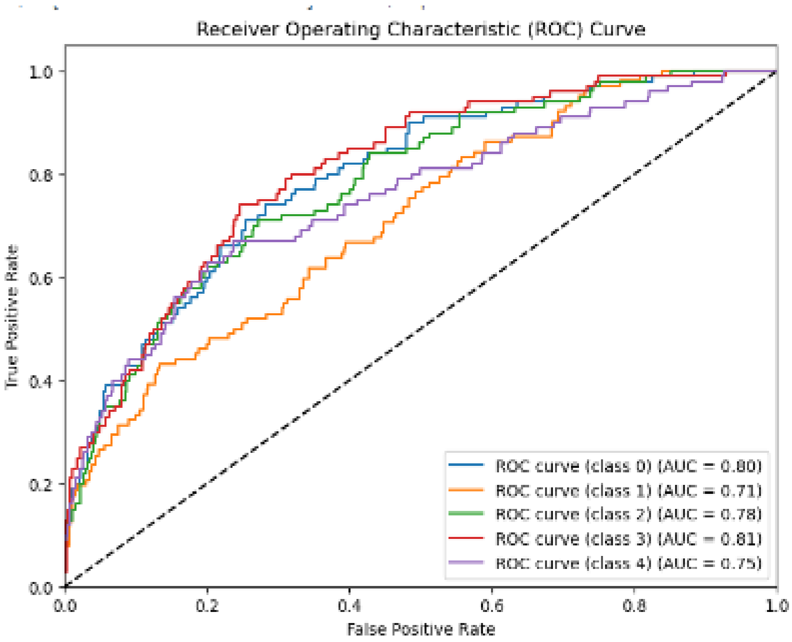
TABEL 8.6 CLASSIFICATION REPORT OF INCEPTION V4 MODEL



Tabel 8.6 shows the performance of classification report for each stage in Inception v4

TABEL 8.7 ROC CURVE OF INCEPTION V4 MODEL

	precision	recall	f1-score	support
Stage 0	0.75	0.09	0.16	100
Stage 1	0.25	0.91	0.40	102
Stage 2	0.58	0.32	0.41	100
Stage 3	0.62	0.24	0.35	100
Stage 4	0.74	0.23	0.35	100
accuracy			0.36	502
macro avg	0.59	0.36	0.33	502
weighted avg	0.59	0.36	0.33	502

Tabel 8.7 shows the performance of ROC Curve for each particular stage in Inception V4 model

Stage 0 (AUC)= 0.80
Stage 1(AUC)= 0.71
Stage 2(AUC)= 0.78
Stage 3(AUC)= 0.81
Stage 4(AUC)=0.75

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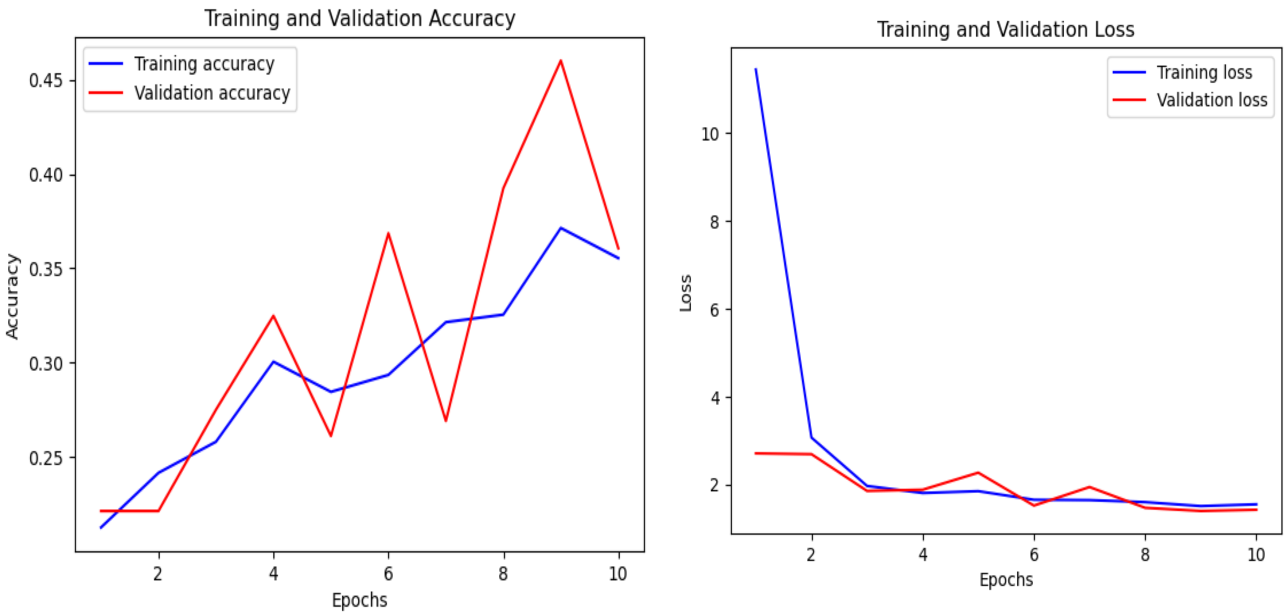
TABEL 8.8 GRAPH OF ACCURACY AND LOSS



Tabel 8.8 shows the Performance of Accuracy and loss of training and validation. As Accuracy of Training and validation increases, loss of Training and validation decreases.

IX. CONCLUSION

Detecting the stages of breast cancer using Convolutional Neural Networks (CNNs) has shown significant promise in improving diagnostic accuracy and efficiency. CNNs, with their ability to automatically extract and learn features from mammogram images, can differentiate between various stages of breast cancer more effectively than traditional methods.

The application of CNNs can lead to earlier and more precise detection, potentially improving patient outcomes and reducing the burden on healthcare professionals. Detecting breast cancer using Convolutional Neural Networks (CNNs) offers high accuracy and efficiency, surpassing traditional methods and aiding early diagnosis. CNNs models hold great potential for enhancing breast cancer detection and improving patient outcomes. EfficientNet B4 Model shows 99% overall ROC and Inception V4 Model is nearly 81% overall ROC. Hence EficientNet B4 Model shows the performance with higher Accuracy compared to Inception V4 model.

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