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Deep Learning for Lung Disease Classification: an Approach to the Analysis of Chest X-Ray

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ABSTRACT: In recent years, deep learning has been considered a potential way of detecting and classifying diseases from medical imaging. This study mainly focuses on using deep learning in the health sector by finding any anomalies present in the input image of chest X-rays. Based on the patterns present in the input image, it is classified into various categories of diseases. A large set of chest X-ray images were used in this study for training and testing the model that was created. Image re-sizing, class-wise normalization, and data augmentation were used as the Preprocessing pipeline, which helped enhance the accuracy and robustness of the model. During the creation of the model, many layers were used. This helps in creating a more accurate model. The model had a high level of accuracy and it could be used in clinical practice, making diagnoses based on lung disease. The results of the model are then evaluated with the help of confusion matrices and classification reports, which determine the precision and recall of this model. Therefore from this study, the significance of the application of deep learning in the health-care sector is evident.

KEYWORDS: Convolutional Neural Networks (CNN), Deep Learning, Lung Disease Detection, Bacterial Pneumonia, Corona Virus Disease (COVID-19), Tuberculosis, Viral Pneumonia, Medical Imaging, Data Augmentation, Chest X-ray Classification.

I. INTRODUCTION

The emergence of deep learning is one such highlight that has changed the dynamic in several fields, including medical image analysis. Chest X-rays are the most commonly used tool in diagnosis and provide crucial information on lung health which helps to diagnose a spectrum of pulmonary diseases. Yet, reading chest X-rays manually via visual inspection by radiologists is a time-consuming and unreliable process especially when diverting under the pressure of a high workload burden for quick diagnostics. For this purpose, it is required to have automated and accurate as well as efficient diagnostic tools.

When coming to the classification of images based on the patterns present in those images, the convolutional neural network has achieved a remarkable performance. CNNs can outperform traditional image processing techniques to give better accurate results by learning hierarchical feature representations from raw pixel data. This ability makes CNNs appropriate for medical image analysis because even subtle differences in the features of images can be exploited to arrive at a correct diagnosis.

The objective of this work is to examine the potential for classifying the images of chest X-rays into various categories [18] based on the common patterns that are present in the X-ray images of the same disease by using deep learning models. The purpose of this is to create a model that can aid radiologists by automatically doing some basic analysis work, thus shortening the diagnostic process and avoiding wrong decisions.

This Image set is in the form of a data set, which is used as an example for this study consisting of different chest X-ray images with clear labels corresponding to specific diseases. Model input with Preprocessing techniques such as image re-sizing, normalization, and data augmentation would be utilized to ensure that the model learns better from images thereby leading to a higher generalization ability. The CNN architecture will extract the deep features from a sequence of convolutional, pooling layers and then the densely connected layer can be used for final classification.

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In this paper, you will discover the approach to preprocess and build/train a CNN model and then evaluate its performance. This indicates the potential of the model in predicting classification on chest X-rays, thus demonstrating the importance of deep learning in the medical sector. This study attempts to provide some empirical evidence on this. This study focuses on developing a system, that helps in the faster diagnosis of the diseases of the people. By implementing this system, doctors will be able to help patients with the faster detection of diseases in the early stages. Implementing these kinds of systems avoids the room for human errors during diagnosis. The CNN model helps to get more accuracy in the result than any other method. This can be seen in this study as well.

Furthermore, future enhancements will focus on integrating advanced techniques such as transfer learning and ensemble methods to improve model performance. Transfer learning will enable various techniques, that will help to achieve some great impact in the classification model. In case of ensemble methods, it helps in improving the accuracy of the outcomes. The system should be then applied in the real-time systems. This would allow for real time evaluation and thus helps in faster diagnosis of these diseases.

II. RELATED WORK

Okeke et al. [1] (2019) went the opposite route and trained a CNN from scratch for pneumonia classification on chest X-ray images to avoid TL/handcrafted limitations. The way they have done this was helpful in interpretation and strengthening the clinical relevance of medical imaging. Limited availability of data had made them use a method called data augmentation thereby enhancing their model performance with accomplished notable validation accuracy.

Varshni et al [2] focused on utilizing pre-trained models for finding the presence of disease from the input image(X-ray). Then they used these models as feature extractors and trained them using different types of classifiers to differentiate between abnormal X-rays from normal. Their research stressed the utility of DenseNet-169 and an SVM classifier (especially with a limited number of expert radiologists).

Kundu et al. [3] For example, in 2021 has focused on creating a system, that detects pneumonia from the input image of the chest X-ray [20]. For this purpose, they have used three deep-learning models. The study effectively exhibited statistical and deep transfer learning on large-scale ensemble models.

El Asnaoui and Chawki [4] have focused on comparing several deep learning models to their COVID classification model. They have done this by identifying the pattern in the input images given to the model. They have utilized X-ray images for this. In this case, they compared VGG16, etc. with a data set of 6087 images.

Hammoudi et al. [5] (2020) have investigated how deep learning algorithms can be used to detect the presence of pneumonia in the lungs of a person. They have used an X-ray image of the chest as an input image for this purpose. Working on publicly available data sets, they tried out different architectures proved by tailored models that were over 84% accurate. The difference in each of these models was significant, especially for the InceptionResNetV2 model.

Xu et al. [6] have introduced CXNet-m1. This model uses a convolutional neural network. The presence of any variations in the X-ray image of the chest can be found using this model. However, the CXNet-m1 was able to overcome many issues compared to fine-tuning existing deep networks.

Abiyev and Ma'aitah [7] (2018) have focused on the usage of the CNN algorithm for finding any anomalies present in the input image that is given to the model. They have used a convolutional neural network for this purpose. The image of the X-ray of the chest was used as the input. In their study, they tested CNNs against various convolutional neural networks. The study demonstrates CSCN performance metrics in chest pathology classification by evaluating the accuracy, error rate, and processing time.

Sirazitdinov et al. [8], have conducted a study, in which they have proposed a model which is a combination of RetinaNet and R-CNN for finding the presence of any anomalies from the input image of chest X-ray [21]. This method helps in achieving high recall and validation on large clinical data sets. This idea helped in the development of the model in this project.

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In the study conducted by Chandra & Verma [9], they used an automated pneumonia detection method using machine learning. They have achieved much better results compared to conventional methods on the ChestX-ray14 data set with Logistic Regression and Multilayer Perceptron classifiers (95.63% and %94,39% accuracy respectively).

Chattopadhyay et al. [10] introduced a new pneumonia detection method on lung X-ray images that enhances DenseNet-201 with a two-stage algorithm for feature extraction and selection of features based on optimal sine cosine. In this study, They achieved accuracy and sensitivity above 90%, which indicates this approach is effective in improving diagnostic accuracy and efficiency.

Ukwuoma et al. [11] In 2024, designed a hybrid deep learning model combining ensemble pre-trained models and Transformer Encoder networks to improve accuracy for early pneumonia detection in chest X-rays as compared with previous binary classification or multiclassification techniques, performing best under both experiments. The model showed a large improvement over existing methods and improved the interpretability using heat maps, and saliency maps.

Hou and Gao [12] (2024) created a DCNN-based model that differentiates COVID-19 pneumonia from the remaining type via chest X-ray, which achieved 96% accuracy. This AI-based approach helped the radiologists by improving diagnostic precision.

These studies about the application of deep learning in the detection of diseases from input images have helped in the development of the model in this study.

III. METHODOLOGY

A. Data-set:

In this study, the data set that is used is from a public platform that contains various classes of diseases. In each of these classes, there are a wide variety of images of Chest X-rays. This diversity and volume of this data set are necessary to train and validate the CNN model so that it can separate positively through different lung diseases or nominal conditions.

Training Data-set:

This set of data is used to train the model. The number of images in various categories is as follows:

- Bacterial Pneumonia: 1,205 images
- Corona Virus Disease: 1,218 images
- Normal: 1,207 images
- Tuberculosis: 1,220 images
- Viral Pneumonia: 1,204 images

These images in the training data set help in training the model, using which it learns to identify key features of each condition. Having as many images per category helps in creating a strong generalized model that will identify disease patterns precisely.

Test Data-set:

By using this data set, the model checks whether the model classifies the images into correct categories or not. The number of images in each category is as follows :

- Bacterial Pneumonia: 403 images
- Corona Virus Disease: 407 images
- Normal: 404 images
- Tuberculosis: 408 images
- Viral Pneumonia: 403 images

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Therefore using the above data-set helps in evaluating the working of the model, that is, whether it is working accurately or not. When the model is working properly, then the accuracy of the model will be increased as a result.

B. Data Preprocessing

The Preprocessing of the image should be done properly before the model is trained with the data set. In this step, various techniques were used to improve the performance of the model. Because, when the Preprocessing steps are done correctly, then the model will be able to analyze the images correctly. They are described below:

Loading and Re-sizing: The grayscale images are loaded to avoid the complexity of color channels, where pixel intensities alone would be considered. For medical imaging tasks, grayscale images are a valuable choice because they hold enough data to classify diseases and therefore reduce computation costs. Then the image level is converted to a standard size of 48x48 pixels. The re-sizing operation guarantees consistent image dimensions on the data set and easy processing in model training.

Normalization: Normalizing is one of the important Preprocessing steps to normalize image pixel values. Normalizing scales down the value of the pixels into some range, which makes sure the model does not base its learning on one or two-pixel columns. Here in this study, the value of the pixels was divided by 255. This re-scaling process converts these pixel values in the given range so that it can also serve as input to our CNN model.

Data Augmentation: Data Augmentation techniques are applied for broadening and strengthening the training data set. It is a way to introduce variety into the training images which might help the model to be better generalized (less over-fitting) to unseen data.

Some of the popular augmentation methods consist of rotation, shift, flip images zoom, and shear. These transformations generate new training samples from different angles, orientations, and scales. The utilization of it will be more useful for adjusting a wide range of variations like image acquisition conditions. Especially, in medical tasks that suffer from less data. Data augmentation helps the CNN model learn robust features that are invariant to these variations by simulating realistic variations in input data.

These Preprocessing steps are necessary to ensure the correct depiction of the pattern from the input images. In such a way, the model will be able to classify the [16] input images into various categories without making more mistakes.

C. Model Architecture

This study has focused on classifying the image of X-ray into various diseases [17]. This study has utilized the deep learning technique for this classification. Bacterial Pneumonia, Corona Virus Disease, Tuberculosis(TB), Viral Pneumonia(VP), and Normal [19], where the classes of diseases to which the model classified the input image. Each layer plays a role in helping the model learn and recognize higher-level patterns within the images as they are fed through.

Model Initialization:

The model is created with a Sequential model, and it allows the creation of a linear stack of layers. This makes it easy to build deep models where you just add layers one by one.

First Convolutional Layer:

Convolutional Layer: This is the first layer of the model, that has about 64 filters sized with 5x5. It is a two-dimensional layer. This layer is then used to scan the input images (48x48 pixels, single channel) with these filters and thereby renders feature maps that enhance important features like edges & textures. The ReLU activation function is a function that helps the model identify complex patterns.

Max Pooling Layer: It's followed by a max-pool layer of size 5x5. The purpose of this layer is to reduce dimensions so that it all only takes a view (by retaining most crucial features) processing and further there will be very little risk of over-fitting.

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Second Convolutional Layer:
Convolutional Layers: The second set of layers contains two 2D convolutional layers, each having a depth of 64 and using size (3x3) filters. These layers after extracting feature maps, process them to extract more intricate features. The ReLU function also helps in capturing non-linear patterns of the model [13].

Average Pooling Layer: After the above-mentioned layer, comes this later, which has a pool size of 3x3 and strides of 2x2. This particular layer helps to average the values within the pool and thus helps the model to generalize better.

Third Convolutional Layer:
Convolutional Layers: The third pair of layers contains two 2D convolutional layers with each using 128 filters and a filter size, as already mentioned to be equal to (3X3) These layers will be able to learn even more complicated and abstract features from the images [14].

Average Pooling Layer: This particular layer with a 3x3 pool size is used to reduce the spatial dimensions in feature maps, but not by losing any important information.

Fully Connected Layers:
Flattening Layer: This helps in feeding a fully connected layer with a one-dimensional vector.

Dense Layer: This function uses 1024 neurons and the ReLU function This layer makes the model capable of learning complex features by combining low-level convolutional patches.

Dropout Layer: This layer is mainly added to prevent over-fitting - i.e., during the training step, the 20% of neurons is set to zero so that each neuron becomes robust.

Second Dense Layer: Another layer is added with some amount of neurons and ReLU activation, which is then followed by the second Dropout(Dropout rate=0.3).

The last output layer has some number of neurons which is equal to the five classes and the activation function here would be soft-max. The fifth layer is an output layer and generates a class probability accessibility map (CPAM) with 5 classes.

Compilation:
The model is then compiled due to its multi-class nature. The loss is minimized using the Adam optimizer, and accuracy is chosen as a metric to evaluate model performance.

The figure 1 (FIG. 1) displays the architecture of a sequential convolutional neural network (CNN) model. It includes multiple convolutional layers (Conv2D) with ReLU activation, followed by pooling layers for down-sampling.

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```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 44, 44, 64)        1664
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 20, 20, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 18, 18, 64)        36928
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 64)        36928
_________________________________________________________________
average_pooling2d_1 (Average (None, 7, 7, 64)          0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 5, 5, 128)         73856
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 3, 3, 128)         147584
_________________________________________________________________
average_pooling2d_2 (Average (None, 1, 1, 128)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              132096
_________________________________________________________________
dropout_1 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_2 (Dense)              (None, 1024)              1049600
_________________________________________________________________
dropout_2 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_3 (Dense)              (None, 5)                 5125
=================================================================
```

FIG. 1 MODEL ARCHITECTURE

Training Process:
Data Augmentation: ImageDataGenerator is used for augmentation. This serves to improve the diversity of the training data set without specifically adding new images.

Training: The training is done using the fit_generator. The model is trained, in in-order to help it understand a new input given to it. So, the model will be able to classify the [16] unknown input into the correct category. Number of epochs with which model is trained: 85, Number of batches:55. In this way, training the model with the correct amount of epochs and batches helps to increase the accuracy of the model.

Model Saving and Loading: If a pre-trained model(model1.h5) is there, then it is loaded. Otherwise, the model is trained from the start and saved upon completion [15].

IV. EXPERIMENTAL RESULTS

The model was trained on 85 epochs which had a training accuracy of around 94.21%. The model kept increasing its performance over both accuracy and loss during training, with a final training loss of 0.1427. The confusion matrix helped to see the performance of the model on different test data sets, which gave an idea about its classification credibility. The confusion matrix shown in Fig 3 explains it.

It successfully predicted, 123 out of the 403 test images as Bacterial Pneumonia. For COVID-19, the model accurately identified 212 out of the 407 test images with very low misclassifications which majorly goes to Viral Pneumonia. 206 out of 404 images were predicted correctly in case of the Normal class. In the case of Tuberculosis, the model predicted 213 out of 408 images correctly, with minimal confusion primarily with Viral Pneumonia. Whereas in the case of Viral Pneumonia, the model classified 189 out of 403 images correctly, though a significant number were misclassified as

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Bacterial Pneumonia.

The CNN model has a great predictive capacity to be used as an assistant diagnosis tool, which can classify X-ray images spread over various lung disease categories and it has high training accuracy simply because of its learning ability from data. The model achieved high accuracy through robust Preprocessing (re-sizing, normalization, and data augmentation, which increased diversity in training data). This made the model to perform so well. With the CNN layered architecture, The information from the images was extracted at different stages of the layer.

However, limitations of the model include significant misclassification between Bacterial Pneumonia vs. Normal and Bacterial vs. Viral Pneumonia which indicates that this idea will need some refinement for higher accuracy in clinical scenarios. It is also possible that a data imbalance could have affected this model's scores, as it has proved to be very powerful over the years.

The confusion matrix (FIG. 2) depicts the performance of the model by highlighting the number of correct and incorrect predictions across five classes. It shows that the model is highly accurate for class 1 and struggles with class 0 and class 4.

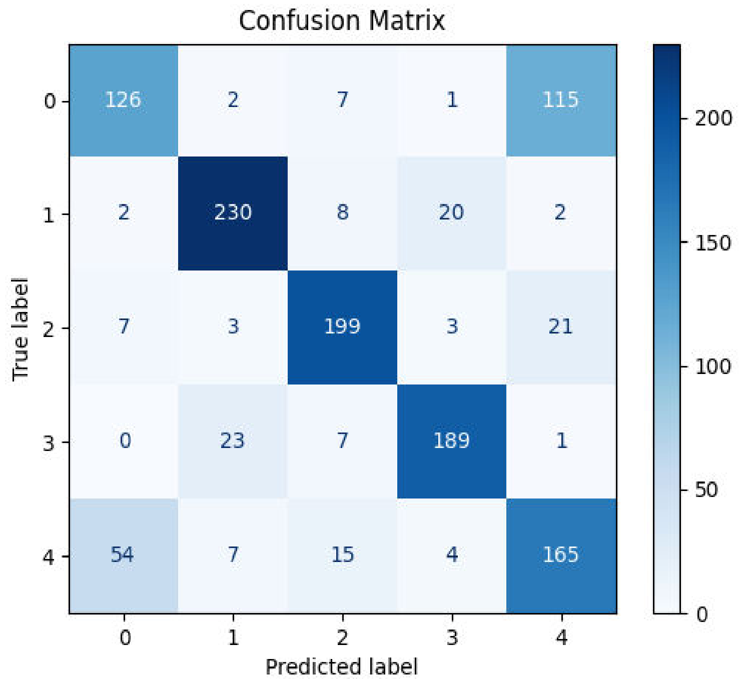

FIG. 2 CONFUSION MATRIX

The ROC curve (FIG. 3) illustrates the true positive rate versus the false positive rate for five different classes. Each curve's area under the ROC curve (AUC) indicates the model's discriminative ability, with values close to 1.0 signifying excellent performance.

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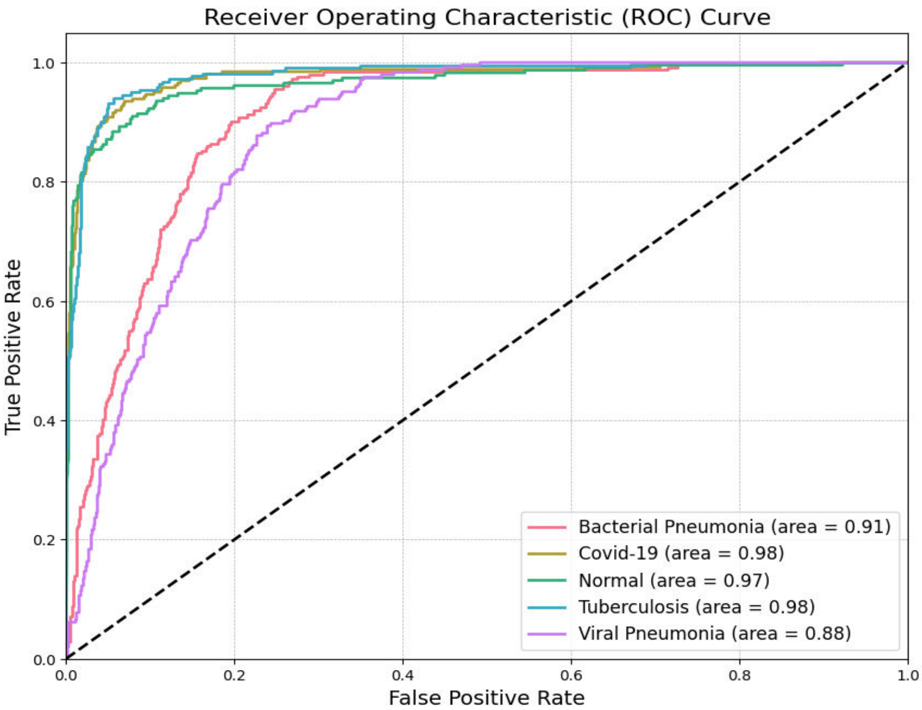

FIG. 3 ROC CURVE

V. CONCLUSION

This study aims to investigate the efficiency of CNNs for classifying the input image into one of the categories of diseases or classifying the image into the normal category. When combined with thorough data processing including image re-sizing, normalization, and data augmentation, a successful training of the CNN model resulted in an accurate recognition performance with robustness.

The multi-convolutional, pooling and fully connected layers of the model architecture were able to extract subtle features leading to accurate classifications. Applying data augmentation techniques was key in making the model more robust so that it would generalize to new and unseen images.

Confusion matrices and classification reports were used for the analysis of outcomes that reflect how well our model could be utilized as a diagnostic tool in medical imaging. This illustrates the value of deep learning in enabling the automation of this diagnostic step and freeing radiologists to make faster, more accurate clinical decisions. These recognition rates for different lung diseases are so high that the inclusion of AIs in the healthcare system cannot be ignored.

This work is part of a growing set focusing on applications for deep learning in medical diagnostics, which illustrates the promising role they can play in transforming health care. Assisting towards an accurate prediction and thus decreasing the workload of radiologists along with minimization of human error from one end to another ultimately resulting in an effective improvement in patient outcomes.

The next approach is to refine the model further, first by scaling the data with richer transcripts and clinical features before playing around CNN architectures or evaluation in real-world clinical settings. This is so that the model can learn through different medical images, and health and have a higher accuracy in detecting tasks. Because the model

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did not do any high-end techniques like Transfer Learning or Ensembles, this could boost performances especially when you look at a large number of data sets.

Finally, this paper just reaffirms the strong potential for CNN-based approaches to deliver additional benefits in medical imaging and exhibits that necessary research into broader parts of deep learning within health care has not been completed. Positive results of this research translate to innovation in AI-based diagnostic tools which revolutionize cost-effective means for efficient healthcare service.

VI. FUTURE ENHANCEMENT

This model model could be developed further in the future by expanding the classification model from the current set of diseases to a wide variety of diseases related to various parts of the body . Diseases like fungal infections, lung cancer and COPD along with all other respiratory conditions can also be added in the future. The utility and relevance of the model in clinical setting could be greatly improved by having diversified classification categories.

Furthermore, future enhancements will focus on integrating advanced techniques such as transfer learning and ensemble methods to improve model performance. Transfer learning will enable various techniques, that will help to achieve some great impact in the classification model. In case of ensemble methods, it helps in improving the accuracy of the outcomes.

The system should be then applied in the real-time systems. This would allow for real time evaluation and thus helps in faster diagnosis of these diseases. More work could then be done to optimize the model for edge devices and HIT systems in order to further streamline work-flow of care providers. It will also need improvements to make such interpretations of black box prediction models more interpretable. In the end, although it is a diagnostic system using X-ray images or another data-set by automatically using AI independently and rapidly to reduce time in hospitals on laboratory workers , if visualization tools are made showing substantial position causing of classifications of X-rays at ROI that could help radiologists understand how decisions were made by AIs then develop trust.

By implementing these types of enhancements, the project focus to enhance the reliability, accuracy of the project in the detection or classification of the X-ray images to various disease categories. Hence it helps the health-care sector for the fast detection of the diseases and help the patients to recover from it, cause the fast discovery of the diseases helps in the fast recovery of the disease. Thus this model will have a very good impact in the health-care sector
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