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Detection of Breast Cancer through Histopathological Images using Deep Learning

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Abstract
One of the most prevalent occurrences of cancer amongst women is that of the breast cancer. The occurrence of this cancer in the female body leads to the impairment of various mental and physical related health issues. A large amount of complexities are however related to the presence of this disease which majorly includes the processing of images and its detection through image processing techniques. In addition to image processing techniques; various deep learning and transfer learning based techniques and algorithms can also be used in order to determine the same. For the purpose of implementation of the proposed research study; the author of the paper tends to utilize the Kaggle dataset which comprises of detailed information of breast cancer images which are obtained using the histopathological process. The dataset comprises of 800 cancer images and 250 healthy images which are undetermined with tumor. The entire process of defining the image takes place through the normalization technique using the concepts of histogram. Further, the author proposes to implement the working theory of CNN as a deep learning algorithm and Dense-Net-121 as transfer learning based algorithm. The transfer learning based algorithm however uses a pre-trained model to implement the same and further hyper-parameter tuning is also performed so that higher values of accuracy and precision can be obtained.

Keywords
D cancer, deep learning, DenseNet, histopathological, radiation.

1. Introduction

A high frequency of malignant tumor with respect to breast cancer is observed in women worldwide. It is also considered to be as the most widely occurring form of cancer and tends to occur in women with respective age group. As per a study in [1] a total count of 2.8 million women experienced breast cancer in 2020 and with due to the reports a prediction of 3.6 million is expected to be reached by 2030. For the process of detecting the disease early, various technologies and methodologies are used. Few of them include MRI, solography and mammography. The implementation usage of mammography is widely observed in order to detect the presence of cancer cells in breast tissues. Another process of radiation is also widely accepted in order to detect the same. The process of radiation is observed to be an enhanced form of cancer detection which is a scanning process and may cause genetic mutation. However, on the other hand; false positive results may also be produced due to the usage of the same. Hence, the most reliable form of detection is considered to be biopsy which is used to analyze sample tissues of the breasts using microscopic analysis. As per authors in [2]; they define the branch of histopathology to be a broad study of various biological tissues that might result into production of cancer cells and hence can be identified under the microscope. However, the process of histological scans must be carried out through an expert or the on-field physician. This process also helps to detect and distinguish various cancers which can be categorized as malign and benign. However, another method which can be used to distinguish the *same*; utilizes the conceptual working theory of computer aided diagnosis (CAD). This form of technology tends to focus on the applications of various deep learning and transfer learning based methods by taking hold of various histopathology pictures of the diseased tissue. The radiologist further works on it and divides the images of the cells and the tissues that tends to depict the occurrence of the disease within.

Through the usage and implementation of deep learning algorithms; various techniques such as that of CNN and ANN can be employed. The advantage of using such techniques is the evolution and the usage of multiple layers so that in depth extraction of information can occur. This further enables transfer of information from one layer to another and tends to predict the disease in a much accurate manner. The entire information is therefore transferred from one layer to another and the information is thus gradient in nature until it reaches the last layer. The last layer comprises of information which has thus been extracted from previous layers and therefore tends to generate the output in an efficient manner. Various algorithms and models such as that of CNN, ResNeT and DenseNeT are used. However, all the models tend to accumulate the results and therefore combine and produce a unified output. An advantage of using such models is that the network becomes pre-trained in nature and the working model is therefore more accurate in terms of predicting the final output of the model. In addition to this; if such algorithms and methodologies tend to use image processing techniques; then the overall concept of over-fitting is also delayed to a larger extent. This makes the images thus produced to evolve in a refined resolution and prevents the issues of over-fitting.

However, the working concept of the presented research study includes the implementation of CNN as the algorithm along with the conceptual working of DenseNet. This process allows the algorithm to correctly identify the negative and positive cases of breast cancer and therefore allows the algorithm to predict the instances accurately. In addition to this; the usage of transfer learning model helps to train the entire algorithm in a pre-defined manner so that the obtained accuracy can evolve in better ways.

However, in the final stage; the findings and diagnosis as presented by the doctor tends to remain the most trusted one. Therefore after the completion of the process using deep learning algorithm the final satisfaction of the patient comes from the diagnosis done by the doctor. Hence the primary objective of the research study thus presented allows the author to scout for more domains in which the elimination of the doctor can be performed in an overall manner so that the entire process of disease detection can be performed by the machine in an accurate manner. Therefore; the author of the proposed study implements the theory of CNN combined with DenseNet in order to achieve the objective of the research study.

2. Related Works

Various research works has been observed in the field of detecting breast cancer amongst women. Researchers have used the conceptual working theory of machine learning algorithms, deep learning algorithms an transfer learning techniques. The diagnosis of the same is hugely expected to be done using ultrasound images and tolls of mammography. However, with the evolution in artificial intelligence technologies; fine-tuning of hyper parameters is observed in this field so that efficient diagnosis of the same can be done at the right stage. Once the appropriate data is collected; the image of the data undergoes the process of fine tuning using various methodologies. Few of them are listed below.

A. Implementation of Deep Learning Algorithms:

The evolution of deep learning has occurred through the on-going process of machine learning wherein various algorithms are iteratively used for medical purposes so that proper diagnosis of the disease can be made. It has also been widely observed that the adoption of machine learning algorithms has been done in the medical field so that accurate analysis of the images can be done and further predictions of the disease can be made. In a research work proposed by authors in [3] they summarized the entire stages of image processing technique through the usage of deep learning models. This included the implementation and theory of CNN, RNN and ANN. The study also comprised on the Python packages thus used to implement the proposed model. It was observed that through the usage of Python as the programming language; the overall memory and storage of the model was optimized which resulted into generation of better outputs. The research work also compared various existing models of deep learning algorithms such as those of ANN with respect to CNN. A major comparison was done on the basis of layers which were included in the algorithms. The basic difference amongst the models thus used was the number of parameters and the involved layers. More number of layers produced and generated higher and optimized results; whereas lesser number of layers was observed to undergo the issues of over-fitting. An overall summary of various algorithms was observed wherein it was concluded that the usage of deep learning algorithm enhanced the comprehensive accuracy of the system model. Another research work conducted by authors in [4] they exclusively worked on the complex structures of the Dense Network. A deep iterative nature of the DenseNet was observed in the working of the model. Larger number of layers was also involved. Apart from this various other sigmoid functions were also employed in the processing of the same. A pathological image data was applied to the DenseNet and the workflow mechanism was taken into consideration. A deep iterative network was implemented in order to train the images obtained from the cancer dataset. In the next stage; various layers thus involved were also fine-tuned so that training of the cancer dataset could be made. A comprehensive and iterative network was achieved in the research study; wherein the cancer images of the female patients was collected and further used to predict the occurrence of breast cancer. The issues of over-fitting were thus resolved through the usage of Refine Net and eight layers of the connectivity network were used to enhance and optimize the results.

Authors in [5] implemented the deep learning approach in order to classify various images which were to be utilized in the medical sector. A heavy trained network was used by the authors so that relative features could be extracted and multi-training of the respective model can be done on the images which were thus obtained from the repository. The dataset thus contained of 850 sample images from cancer patients which were to be predicted by the model thus built. A supervised method of learning was used and the labels were thus given to the images and further training of the dataset was done. The usage of supervised learning enhanced the prediction mechanism of the model so that better detection accuracy could be formed. In this research the authors implemented the multi training concept so that appropriate labeling of cancer detection could be done. A supervised method of gradient boosting was thus used and the classification accuracy of the model. The author used the implementation of gradient boosting as the algorithm in order to classify the same. In addition to this; the author also used the conceptual working theory of ResNet v2 and compared it with the implementation of CNN as a whole. On comparison it was observed that due to heavy layers in CNN; the model outperformed ResNet v2. This concluded the fact that the usage of CNN enhanced the precision factors which were thus responsible to generate better outcome through the usage of deep learning algorithms.

Authors in [6] classified various stages of breast cancer amongst women by using the mammography charts from the images thus obtained from the dataset. A back propagation network was used in order to perform the research with 100 nodes thus involved in the detection process. With the layers of the network in the pre-trained model; the classifiers which were used enabled the diagnosis process to occur in a suitable manner. With more number of nodes and layers involved; the optimization results achieved higher levels of accuracy. The CCN architecture was able to generate an overall accuracy of 72percent. On the other hand; the author also implemented the working concept of ResNet as the detection model for diagnosis of breast cancer. It was observed that due to less number of layers and nodes involved; the algorithm did not match with the level of accuracy thus generated.

In another study performed by authors in [7]; they implemented the classification of breast cancer patients using the histopathological images thus obtained from the respective dataset. This dataset comprised of four different forms and categories of magnification images which were to be trained on the CNN model using various hyper-parameters. ANN algorithm was taken into consideration and a comparative analysis of the same was also conducted. In the research further; the author also used the implementation of DenseNet as the algorithm so that three techniques could be used in order to validate the entire working process. All the three models were trained so as to achieve higher levels of accuracy.

B. Image Processing Technique

The image processing technique is one of the most widely occurring methods which are used in the medical analysis of various diseases. The diagnosis of cells that causes breast cancer in the female body helps in the detection of the illness in the early stage. For this to occur; the cancer cells must be obtained from the histopathological images and further processing must begin. In such a scenario; the technique of normalization plays a vital role which is used to eliminate the overall contrast in the histopathological image and its related intensity. Authors in [8] studied this process of normalization in order to perform the image processing technique using the concepts of unsupervised learning. For this purpose; a stain-vector method was also adopted. In addition to this; the author also made use of neural networks so that the process of classification could be performed. The stain-vector method generated an overall accuracy of 70percent. Whereas on the other hand; the process of normalization was observed to generate more accuracy since it involved the implementation of CNN as the neural network. Due to the involvement of additional layers in the CNN the overall impact created on the prediction model was achieved to be higher.

In another research work performed by authors in [9] the authors evaluated the predicted system model by proposing a de-convolution model using blind and color method based on the Bayesian technique of disease diagnosis. The algorithm began by detecting the outliers from the histopathological images thus obtained from the dataset. In the next stage; a color based vector matrix is determined so that the background vectors could be removed. This made the detection process of cancer cells a much faster and robust method in comparison to the technique authors offered in [7]. A different segmentation technique was therefore observed using this process of color vector based matrix. In a different study conducted by authors in [10]; they proposed a similar work to that of [9]; however, the authors here proposed the implementation of supervised learning techniques with a combination of transfer learning algorithms. A total of six algorithms including ResNet, DenseNet, Inception Net, CNN, Naives Bayes and SVM were used to diagnose the occurrence of breast cancer amongst women. A similar method of image segmentation was achieved through the usage of histopathological images and high levels of accuracy were thus obtained with much reduced false positive rates. In another research work proposed by authors in [11]; they implemented a convolutional network based on neural complexities of the system model by using deep learning concepts. The usage of CNN contributed to enhance the overall accuracy of the system model by extracting only the relevant features of the image dataset thus obtained. All the images achieved the levels of sharpening the image edges and sides which resulted into generation of better results. In addition to this; a detailed study on image augmentation was also done using mammography of breast tissues. In the next stage, a histogram was created with bimodal intensity. Usage of this method allowed the author to increase the overall region of interest of the image and therefore enhance the overall prediction result that could probably be generated by the model.

C. Transfer Learning Technique

For the purpose of medical analysis in the medical field; the role of classification plays an important role. This is done so that the respective disease can be categorized as either disease positive or negative. Another important aspect to this is the usage of CNN as the neural networking algorithm. This is done so that the diagnosis can be carried out in an effective manner. However, for these purpose large amounts of dataset is required in the medical domain. With smaller datasets an error of false positive results is expected to be generated. This is also observed due to patient privacy since they appear to preserve their sensitive data. As a result of which transfer learning is used for the same purpose so that appropriate diagnosis of the disease can be made by detecting the cells that leads to breast cancer. In a research study conducted by authors in [12] used the concepts of transfer learning in order to classify breast cancer images obtained from Kaggle repository. The repository comprised of 250 healthy images of the patients followed by 180 infectious images of breast cancer patients. The authors made use of DenseNet as the transfer learning based model. In the next stage; the author performed a comparative analysis with respect to DenseNet and ResNet. It was observed that the implementation of ResNet generated higher results and produced optimized accuracy with accurate precisions. The cancer images were in colored images which were further converted in gray scale and further categorized. Due to the usage and implementation of transfer learning the networking model was heavily pre-trained with 1000 classes of the image. In the later stages; the DenseNet also made use parameters that allowed the authors to increase the resolution of the image dataset. Due to heavily trained model of the DenseNet; the implementation achieved higher results of accuracy with minimalized false positive rates. A sigmoid function was also used so as to eliminate the issues of over-fitting. The author perfumed an overall comparative analysis so that an efficient comparison between DenseNet and ResNet could be performed. In another research work [13] the authors used the concepts of Inception Net to analyse and diagnose the presence of cancer cells in the female body. For this purpose; they obtained the dataset

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from the Kaggle repository. The repository had two csv files with over 2596 files of positive breast cancer patients. The overall accuracy achieved by the authors was 87.63percent.

3. Methodologies Used

The diagnosis of cancer detection through the usage of mammography is a very commonly used technique. Apart from this; the conduction of a breast biopsy appears to be a more prices and accurate method that could detect the occurrence of the same. However, the second method requires long hours of time followed by a medical expert who could manually check and verify the entire process being conducted. For this purpose; various pathologists and doctors come together and tend to evaluate the histopathological process of defining the image. The preparation of this image however, requires a series of steps to be followed such as that image segmentation, collection of images and fixing the ratio and resolution of the cells those results into cancer. As a result of which the process of breast biopsy is determined to be performed under a microscope making the process a time consuming task. Hence, the implementation and execution of deep learning algorithms followed by transfer learning algorithms is a combined process. This technique has been widely adopted by many research scholars for the same purpose. The usage of CNN in the medical field appears to be advantageous due to the presence of multiple layers in the networking model. In addition to this the concept of neurons and the process of back propagation helps the algorithm to avoid the issues of over-fitting.

A Data Understanding

Due to a limitation of dataset not being available; serves a problem to the running algorithms since they require larger datasets to generate accurate results. This dataset comprises only two available kernels, encompassing a total of 7909 images across four magnifications: 40X, 100X, 200X, and 400X. Table 1 elucidates the distribution of images based on magnification levels and the two distinct classes. In Figure 1, malignant and benign images across all magnifications from the dataset are depicted. For instance, "40X B" denotes a benign image at 40X magnification, while "40X M" signifies a malignant image at 40X magnification. Subsequently, these images are partitioned into training, testing, and validation folders, maintaining an 80:10:10 ratio, as outlined in Table 1. The dataset consists of 5439 malignant and 2480 benign images, all three-dimensional with dimensions of 460 by 700 pixels. The subsequent section details the various steps involved in preparing the data, taking into account these aspects of the image dataset.

Table1: Distribution of the image as per the resolution

Pixel	Benign	Malignant
40X	Train: 500 Valid: 62 Test: 63	Train: 1140 Valid: 93 Test: 96
100X	Train: 526 Valid: 69 Test: 64	Train: 1500 Valid: 95 Test: 93
200X	Train: 420 Valid: 32 Test: 56	Train: 1263 Valid: 98 Test: 86
400X	Train: 526 Valid: 62 Test: 36	Train: 1560 Valid: 36 Test: 86

B Normalization of the Image

Enhancing the quality of medical images is crucial for aiding pathologists in disease detection and diagnosis when employing automated deep learning models. In reference to [13], the Histogram Equalization method is utilized for image enhancement based on mean and variance, aiming to enhance the image's contrast and brightness without compromising crucial details. In the context of this research, the Histogram Equalization method is applied to histopathological image data to improve contrast and brightness. Histopathological images, vital for microscopic examination, often undergo staining processes that make interpretation challenging. Image normalization is implemented to heighten image contrast, thereby enhancing the accuracy and performance of the deep learning model. Figure 1 visually illustrates the impact of histogram normalization on one of the benign histopathological image types.

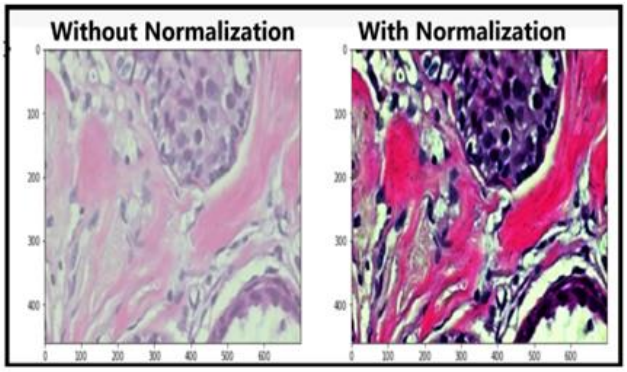

Figure 1: Effect of normalization

C Augmentation of Data

Following the normalization of images, an up-sampling process is implemented before feeding them into the CNN-based DenseNet model through transfer learning. Building upon the methodology outlined in [14], this study incorporates basic augmentation techniques such as scaling, Gaussian blurring, and Gaussian noise. Morphological augmentation includes horizontal and vertical mirroring, 90-degree and 180-degree rotations, as well as scaling by a factor of 0.5 to 1.0. In this research, the number of benign images is augmented to align with the count of malignant images. Specifically, a 90-degree rotation and a batch size of 32 are employed for augmentation. During the input phase of the classification model, runtime augmentation is performed by fine-tuning various parameters, as detailed in the evaluation section. Table 2 provides an overview of the number of benign histopathological images at all magnifications before and after up-sampling. Additionally, Table 2 elucidates the hyper-parameters utilized, along with their corresponding tuned values, to select the most suitable parameters for the classifiers.

Table 2: Distribution of image resolution

Parameters	Values obtained
Rotation of the image	50,60,120,170
Width shift	0.3
Height shift	0.2
Zoom	0.9,0.6
Target	224*128*64*32
Color	RGB
Size of the batch	128,64,32
Horizontal flip	True

D Proposed System

A Convolutional Neural Network (CNN) is composed of Transition layers, Dense blocks, and Convolutional layers, forming a sequence of neural networks designed for feature extraction. To facilitate the circulation of features at different levels, the CNN concatenates all features from preceding layers. The architecture of the CNN, as outlined in [14], comprises five main layers. The Convolutional layer is employed to capture local information from the input, utilizing filters to compute the dot product of their weights with the input image region. Following this, the Batch Normalization layer regulates the output from the previous layer before passing it to the next activation layer [15]. Normalization in the gradient process aids in balancing weights within the network. The Rectified Linear Unit (ReLU) serves as an activation function in the CNN, accelerating its execution. As the CNN deepens the complexity of extracted features increases. To reduce the feature map size, a MaxPooling layer is incorporated. Each fully connected layer's neurons connect with the preceding layer to calculate the class count. The output layer incorporates a Softmax or sigmoid function for classification purposes. This comprehensive architecture enables the CNN to effectively extract features and make predictions in various applications.

In this research study, the transfer learning approach is employed, utilizing the DenseNet-121 model. This model, depicted consists of 121 layers and leverages pre-trained weights from Imagenet. As illustrated in the figure, Dense layers are relatively narrow, and classification is performed based on the knowledge encapsulated in the pre-trained weights. This approach allows for the learning of intricate image patterns from a limited number of parameters, reducing computation time, as highlighted in [15]. It delineates the output layers, convolutional layers used in each dense block, and transition block, shedding light on the structural components of the model. This transfer learning strategy enables the model to benefit from the wealth of knowledge encoded in pre-trained weights, enhancing its performance with a smaller training dataset.

4. Results

This section provides a comprehensive analysis of two models and the optimization of various parameters to achieve optimal performance. In this research study, two models are applied to the histopathological image dataset obtained from Kaggle, with a specific emphasis on utilizing DenseNet-121 as a novel approach for this dataset. The evaluation process involves calculating the loss and accuracy for both training and validation data per epoch for each model. Plots depicting accuracy and loss during training and validation are generated. Test accuracy is computed based on predictions and test data. Furthermore, confusion matrices are calculated for each model to determine true positive and true negative values. The ensuing experiments detailed below focus on elucidating the increased accuracy and elevated values of true negatives, both crucial factors in medical diagnosis. Precision (Specificity) is also computed as a function of true negative and false positive values. In alignment with the insights, fine-tuning is carried out by adjusting different parameters in the model, and the subsequent impact on accuracy is observed throughout the experiments. This

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comprehensive analysis aims to provide valuable insights into the performance of the models and their applicability to medical diagnosis.

The primary objective of this research study is to enhance the accuracy and precision values for cancer detection. The preprocessing step of image normalization notably increased the average accuracy for both models, with a more pronounced effect observed in the DenseNet-121 model. Hyper-parameter tuning proved effective in boosting the accuracy of both the CNN and transfer learning models. Remarkably, the DenseNet-121 transfer learning model achieved the highest accuracy at 88.03%. However, it is noteworthy that its accuracy tends to decrease when trained on a large dataset featuring mixed magnifications. Figure 2 presents the configuration metrics for 100X image data with a size of 128 by 128 using the CNN model. In this figure, '0' denotes benign cases, and '1' denotes malignant cases. The confusion matrix reveals a true negative value of 119 out of 144 malignant cases and a true positive value of 20 out of 65 benign cases, resulting in a sensitivity of 30% and a specificity (precision) of 82.63%. It's important to note that further improvement in accuracy and sensitivity may be achievable by training the model on a larger number of epochs. However, due to hardware limitations, this experiment was conducted with a restricted number of epochs.

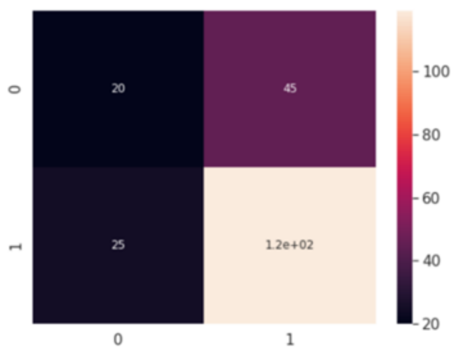

Figure 2: Confusion Matrix

5. Conclusions and Future Works

This research successfully implemented a CNN-based deep learning model for the detection of breast cancer in histopathological images, achieving a notable accuracy of 90.9% in identifying cancerous cases. The study concludes that images captured at 100X and 200X magnifications yield higher accuracy in diagnostic assessments. As a result, the research suggests that incorporating 100X and 200X magnification images in biopsy results can enhance diagnostic precision in clinical applications. The application of the histogram normalization method played a crucial role in increasing the precision value to an impressive 99.28%, concurrently reducing execution time. This underscores the potential of the CNN model for quick and accurate cancer detection in histopathological image data. To address over-fitting issues during training, the research utilized histogram normalization, image augmentation, and fine-tuning techniques. Looking forward, future endeavors could explore the application of stain normalization to histopathological images before classification, further refining the model's robustness. Additionally, the adoption of cross-validation techniques, as suggested in [15], may be considered to enhance the performance of the CNN network in subsequent studies. The research employed a transfer learning-based DenseNet-121 model to analyze individual magnification image data. After fine-tuning, DenseNet-121 achieved an impressive accuracy of 88.3%, surpassing the state-of-the-art results. The study concludes that utilizing ImageNet pre-trained weights and a Sigmoid output activation function is optimal for this particular image dataset. In the context of transfer learning, the model performed exceptionally well with 128 by 128 images incorporating a 90-degree rotation, exhibiting superior accuracy. However, for cancer detection precision, 224 by 224 images outperformed other configurations. The incorporation of the class weight parameter during model execution notably increased the true negative value in the confusion metrics, as depicted in Figure 8. Despite the remarkable achievement of correctly identifying cancerous cases with a precision of 99.28%, the experiment faced challenges in accurately detecting non-cancerous cases. The model demonstrated higher suitability for detecting cancerous cases than for identifying non-cancerous cases, suggesting areas for potential improvement in future iterations of the research.

In future work, enhancing the sensitivity of the model could involve exploring and tuning additional parameters. Trying various transfer learning-based models on the image data may provide insights into alternative architectures that could potentially improve performance. Experimenting with different numbers of epochs and employing diverse image enhancement processes could be valuable for fine-tuning the model for optimal results. To extend the study, feature extraction using transfer learning could be conducted. Extracted features could then be subjected to further classification using a CNN model. This approach may offer a more intricate and nuanced analysis, potentially improving the model's ability to discern subtle patterns in the histopathological images. The exploration of these

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avenues could contribute to refining the model's sensitivity and overall performance in detecting cancerous cases.

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