Enhancing Computational Efficiency for Skin Cancer Detection using Convolutional Neural Networks and Parallel Processing

Aayush Kumar Fabwani
SCOPE
Vellore Institute of Technology
Chennai, India
aayushkumar.fabwani2022@vitstudent.ac.in

Shreya Sachdeva
SCOPE
Vellore Institute of Technology
Chennai, India
shreya.sachdeva2022@vitstudent.ac.in

Dr. Christopher Columbus C
SCOPE
Vellore Institute of Technology
Chennai, India
christopher.columbus@vit.ac.in

***Abstract*— This research investigates the application of Convolutional Neural Networks (CNNs) for the classification of skin lesions in medical imaging, with a focus on enhancing both classification performance and computational efficiency. A dataset of 10,000 labelled high-resolution skin lesion images, divided into training (9,000 images) and testing (1,000 images) subsets, was utilized to train and evaluate the CNN model. Various digital image processing techniques, including grayscale conversion, Gaussian blur, histogram equalization, and sharpening, were applied to enhance feature extraction. These preprocessing techniques were parallelized using OpenMP, optimizing preprocessing time and improving computational efficiency. The CNN model was designed for binary classification, distinguishing between benign and malignant lesions. Performance evaluation of the trained model yielded a test accuracy of 90.3%, along with a precision of 93.3%, recall of 86.8%, and an F1-score of 89.9%. These results demonstrate the model's strong capability in differentiating between benign and malignant lesions while minimizing false positives and negatives. Furthermore, parallel processing reduced preprocessing time by 2% compared to sequential processing, showcasing the advantages of hardware acceleration in medical imaging tasks. The findings highlight the significant impact of parallel computing on improving both the performance and scalability of deep learning models for large-scale medical image classification. This research presents a promising approach for real-time clinical diagnostics, paving the way for efficient and accurate automated skin cancer detection.**

Keywords - Skin Cancer, Convolutional Neural Network (CNN), Skin Lesion Classification, Image Preprocessing, Parallel Processing

I. Introduction

Skin cancer is one of the most common types of cancer globally, and its early detection plays a critical role in improving patient outcomes. In particular, melanoma, a highly aggressive form of skin cancer, can be fatal if not diagnosed and treated promptly. The traditional methods of skin lesion diagnosis, which rely heavily on the expertise of dermatologists, can be time-consuming and subject to human error. Consequently, the application of automated systems for skin cancer detection has become an area of significant interest, particularly in utilizing advanced machine learning techniques to assist healthcare professionals.

Recent advances in deep learning, specifically Convolutional Neural Networks (CNNs), have shown promise in the automated classification of skin lesions based on digital images. CNNs are a class of deep learning algorithms that have proven highly effective in various computer vision tasks, including image classification, segmentation, and object detection. By extracting hierarchical features from images through multiple convolutional layers, CNNs are able to learn intricate patterns that correspond to different classes of skin lesions, such as benign and malignant.

Despite the considerable success of CNNs in medical image classification, challenges remain in terms of computational efficiency, especially when dealing with large datasets of high-resolution images. Preprocessing tasks such as image enhancement, noise reduction, and feature extraction require significant computational resources, which can hinder the scalability and real-time application of such models in clinical settings. To address this, the integration of parallel processing techniques can significantly reduce computational time, improving the efficiency and practicality of deep learning-based systems.

This research aims to apply a CNN to classify skin lesions and explore the impact of parallel processing in optimizing both image preprocessing and model training. By leveraging advanced image processing techniques and parallel computing, the study seeks to demonstrate improvements in computational efficiency and model performance, with the ultimate goal of enhancing the accuracy and speed of skin cancer detection systems. The results of this study may contribute to the development of real-time, scalable automated diagnostic tools for clinicians, aiding in the timely detection and treatment of skin cancer.

II. Literature Review

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly advanced the field of medical image analysis, including the classification of skin cancer. CNNs have become a cornerstone in automated image analysis due to their ability to learn spatial hierarchies of features directly from raw images. A systematic review highlights the potential of CNNs to classify skin lesions with accuracy comparable to dermatologists, demonstrating their utility in clinical settings [1]. Similarly, an optimized CNN model showcases the efficacy of fine-tuning CNN architectures to enhance classification performance [3]. Data augmentation has been instrumental in addressing the challenges of limited datasets. For instance, a deep learning-based classifier employing data augmentation techniques improves robustness against overfitting [2]. The incorporation of data augmentation is further reinforced in a comparative study, which demonstrates its positive impact on model generalization [10]. Transfer learning, leveraging pre-trained CNN models, has been extensively adopted to enhance classification accuracy. Transfer learning techniques utilizing pre-trained CNN architectures such as ResNet and InceptionNet have shown significant effectiveness in skin cancer detection [7]. Similarly, the application of EfficientNet, a computationally efficient CNN model, for skin lesion classification achieves state-of-the-art performance [13].

Skin cancer classification often involves distinguishing between multiple classes, such as benign and malignant lesions. A deep learning-based multi-class classifier, DSCC Net, outperforms traditional methods in this domain [5]. Moreover, hybrid models combining CNNs with other machine learning techniques offer enhanced classification capabilities by integrating diverse feature representations [9]. Comparative studies have been pivotal in identifying the most effective CNN architectures for skin cancer classification. For example, a systematic review compares the performance of various deep learning models, revealing that advanced architectures like DenseNet and InceptionResNet achieve superior accuracy [10]. Real-time skin cancer detection systems have gained traction for their potential to provide instantaneous feedback. A real-time detection framework optimized for mobile applications emphasizes the importance of computational efficiency in practical deployment [18]. Integrating segmentation with classification tasks has proven to enhance diagnostic accuracy. A CNN-based framework combining lesion segmentation and classification achieves high precision in skin lesion analysis [20]. Several reviews have summarized the state-of-the-art in deep learning applications for dermatology. For instance, a comprehensive overview of CNN-based methods for skin lesion classification highlights their strengths and limitations [11]. Additionally, studies emphasize the transformative role of CNNs in dermatological diagnosis, underscoring their potential for widespread adoption [19].

Despite significant progress, challenges such as class imbalance, dataset heterogeneity, and the need for explainable AI remain. Strategies like multi-class classification using transfer learning [14] and systematic reviews of existing methodologies [6][17] underscore the importance of addressing these issues to achieve clinically viable solutions. The reviewed studies collectively demonstrate the transformative potential of CNNs in skin cancer classification. From leveraging data augmentation and transfer learning to developing hybrid models and real-time systems, these advancements pave the way for more accurate and accessible diagnostic tools. Future research should focus on addressing existing challenges to further enhance the clinical applicability of these methodologies.

III. METHODOLOGY

This study focuses on improving the performance of skin cancer classification by applying a Convolutional Neural Network (CNN) to digitally processed skin lesion images. The methodology involved dataset preparation, digital image processing, parallel processing, CNN model design, and training-validation.

A. Dataset Description

The dataset used in this study consisted of 10,000 high-resolution skin lesion images, labeled as either benign or malignant. These images were sourced from diverse repositories to ensure wide variability in factors such as skin tone, lesion size, and lighting conditions, making the dataset robust and generalizable. To maintain effective learning and evaluation processes, the dataset was partitioned into two subsets. The first subset, comprising 9,000 images, was used for training and validation. Within this subset, an internal split generated a validation set that helped monitor model performance and prevent overfitting during training. The second subset, containing 1,000 images, was reserved for final testing and provided an unbiased assessment of the model's performance. This division ensured that the CNN had access to ample data for learning while retaining a completely unseen set for objective evaluation.

B. Digital Image Preprocessing

Digital image processing techniques were employed to enhance the quality and features of the skin lesion images, making them more suitable for the CNN. First, grayscale conversion was applied to reduce the dimensionality of the input data, preserving structural features while simplifying computation. Gaussian blur was then used to smooth the images and minimize noise, ensuring that irrelevant high-frequency information was reduced while retaining significant edges and textures. Histogram equalization improved image contrast, highlighting subtle variations in intensity and texture, which are often crucial for distinguishing between benign and malignant lesions. Finally, sharpening techniques were implemented to enhance the visibility of edges and fine details, enabling better detection of lesion boundaries and structural anomalies. These preprocessing steps ensured that critical features in the images were preserved and highlighted for the classification model.

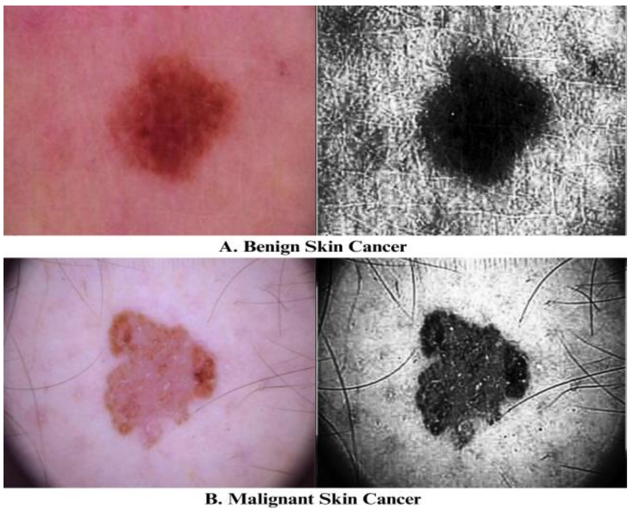

Fig. 1. Digital Image Preprocessing: Before and After

C. Parallel Processing

Parallel processing played a central role in handling the scale of the dataset efficiently. OpenMP, an open-source API for multi-threaded programming, was used to parallelize the digital image processing tasks. Techniques such as grayscale conversion, Gaussian blurring, histogram equalization, and sharpening were executed simultaneously across multiple CPU threads, significantly reducing the time required for preprocessing. Additionally, OpenMP's load-balancing features ensured that tasks were evenly distributed across all available CPU cores, maximizing resource utilization and minimizing idle time. Beyond preprocessing, TensorFlow's native support for parallelism leveraged GPU and CPU resources during CNN training, accelerating computationally intensive tasks such as matrix multiplications, convolution operations, and backpropagation. This combination of parallel processing approaches significantly improved computational efficiency without compromising quality.

D. Convolutional Neural Network (CNN) Design

The CNN model used in this study was designed specifically for binary classification of skin lesions as benign or malignant. The architecture comprised convolutional layers that extracted spatial and hierarchical features, pooling layers that down sampled the feature maps to reduce computational complexity, and fully connected layers that mapped the extracted features to classification probabilities. These components worked together to enable the model to learn distinct patterns associated with different types of lesions. The processed dataset further enhanced the CNN's performance by providing clear and highlighted feature details, contributing to robust feature extraction. TensorFlow's distributed computing capabilities ensured that training the CNN on large-scale data remained computationally efficient.

E. Model Training

The training and validation processes were meticulously designed to ensure optimal performance of the Convolutional Neural Network (CNN) with high accuracy and minimal overfitting. To handle large-scale data efficiently, batch processing was employed by dividing the dataset into smaller mini-batches. Each mini-batch was used to compute gradients of the loss function, allowing the model's parameters to be updated iteratively during training. The categorical cross-entropy loss function, suitable for binary classification, was used to quantify the error in predictions by comparing output probabilities with true labels. This loss was minimized during training to improve the model's accuracy in distinguishing between benign and malignant lesions.

The Adam optimizer, known for its adaptability and efficiency, was used to update the model weights. By combining the benefits of momentum and adaptive learning rates, Adam facilitated faster convergence, significantly reducing the number of epochs required to achieve optimal performance. A validation set, carved out from the training data, was utilized to evaluate the model's performance after every training epoch. Metrics like validation accuracy and loss were monitored to ensure that the model generalized well to unseen data and did not overfit the training data. Based on validation results, hyperparameters such as learning rate, batch size, number of convolutional layers, and filter sizes were fine-tuned through experiments involving grid and random search techniques.

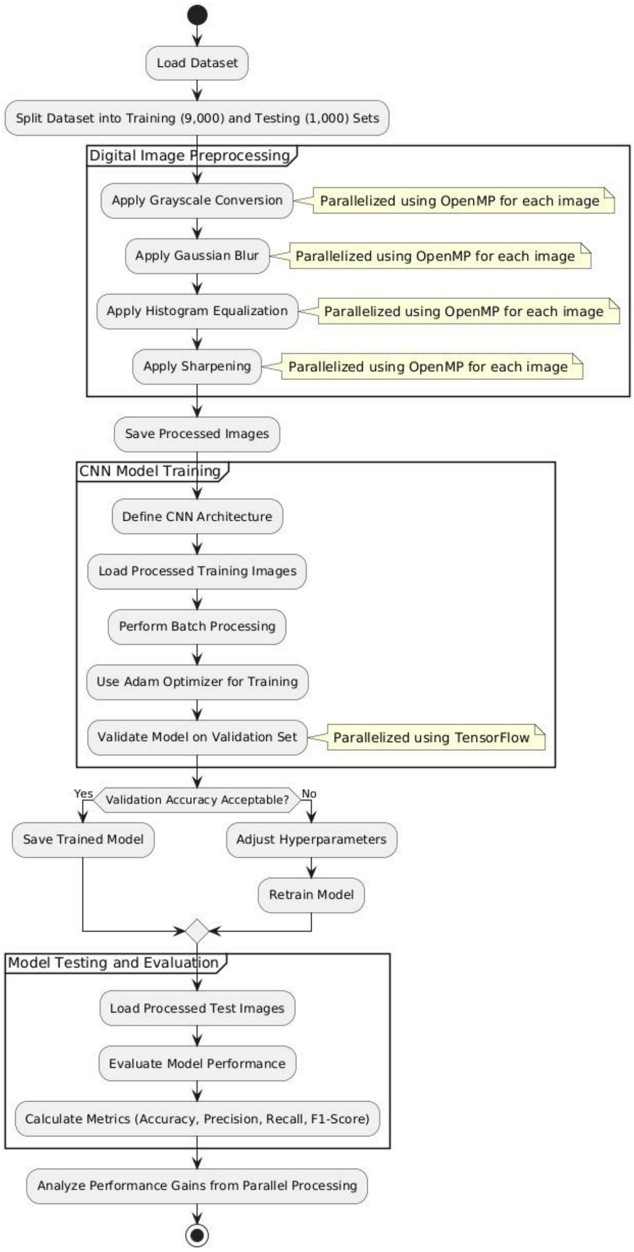

Fig. 2. Architecture Diagram

The training process comprised multiple iterations (epochs) where the CNN learned complex feature representations from the dataset. TensorFlow's inherent parallelism played a pivotal role in this phase, efficiently managing computations like forward propagation, gradient descent, and backpropagation across multiple GPUs and CPUs. Additionally, early stopping was implemented to prevent overfitting, terminating the training process if the validation loss did not improve for a predefined number of consecutive epochs.

After the training process, the model was evaluated on a distinct testing set of 1,000 images that remained unseen during training and validation. This testing phase provided a reliable measure of the model's generalization capability and performance on entirely new data. Key metrics, including accuracy, precision, recall, and F1-score, were calculated to assess the model's classification effectiveness. By integrating batch processing, efficient optimization techniques, rigorous validation, and advanced parallelism, the methodology ensured a robust and computationally efficient training process, yielding a CNN capable of accurately classifying skin lesions.

IV. Performance Analysis

The performance of the trained Convolutional Neural Network (CNN) was rigorously evaluated on a reserved test set of 1,000 unseen skin lesion images. This evaluation assessed the model's classification accuracy and the computational efficiency gained through parallel processing techniques. Performance metrics, including Accuracy, Precision, Recall, and F1-Score, were employed to measure the effectiveness of the model in classifying skin lesions into benign and malignant categories. These metrics provided a comprehensive view of the CNN's reliability and diagnostic efficiency.

The accuracy of 90.3% indicates that the model successfully classified 90.3% of the total test images correctly, whether benign or malignant. While accuracy provides an overall measure of classification correctness, it may not fully capture performance in cases of class imbalance. In this study, the high accuracy indicates the model's general competence, but further insights are provided by the other metrics to better understand its true effectiveness, especially in dealing with varying class sizes.

A precision value of 93.3% shows that when the model predicts a lesion as malignant, there is an 93.3% chance that it is truly malignant. Precision is crucial in minimizing false positives, preventing benign lesions from being misclassified as malignant, which could lead to unnecessary treatment. The relatively high precision signifies that the model is performing well in distinguishing benign lesions and only labeling a small portion of benign cases as malignant.

The recall of 86.8% indicates that the model successfully identified 86.8% of the actual malignant lesions in the dataset. Recall is particularly important in medical diagnostics, where overlooking a malignant case (false negative) can be more costly than wrongly identifying a benign lesion (false positive). The high recall rate demonstrates that the model is good at detecting malignant lesions, making it effective in ensuring that fewer malignant cases go undetected.

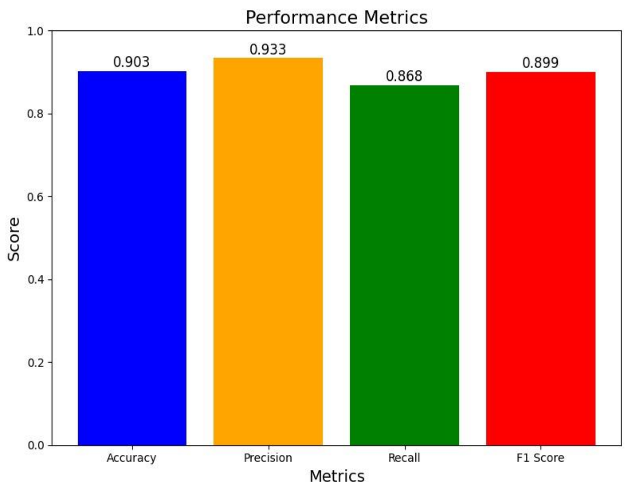

Fig. 3. Performance Metrics

The F1-Score of 89.9% is the harmonic mean of precision and recall, offering a balanced assessment of the model's performance. This score indicates that the CNN model maintains a good equilibrium between detecting malignant lesions (high recall) and avoiding false positives (high precision). The value suggests that the model is well-rounded, effectively identifying the critical features of both benign and malignant lesions without favoring one class significantly over the other.

A. Accuracy

Accuracy measures the overall correctness of the model by determining the proportion of correctly classified samples out of the total sample. Here TP stands for True Positive, TN stands for True Negative, FP stands for False Positive and FN stands for False Negative.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

B. Precision

Precision evaluates the model's ability to avoid false alarms by determining how many predicted malignant cases are truly malignant.

$$Precision = \frac{True\ Positive}{True\ Positive\ +\ False\ Positive} \quad (2)$$

C. Recall

Recall measures how effectively the model identifies malignant cases. This is especially crucial in medical diagnostics.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

D. F1-Score

F1-Score balances precision and recall by computing their harmonic mean, which is beneficial when the dataset is imbalanced.

$$F1 = 2 \times \frac{Precision\ \times\ Recall}{Precision\ +\ Recall} \quad (4)$$

Collectively, these outcomes underscore the robust performance of the CNN model in accurately classifying skin lesions, as evidenced by its commendable scores in accuracy, precision, recall, and F1-Score. Particularly noteworthy is the model's high recall and F1-Score, which attest to its adeptness in identifying a majority of malignant lesions while maintaining a favourable balance between minimizing false positives and maximizing true positives. Nevertheless, there remains room for refinement, as further fine-tuning and advanced techniques could potentially enhance the model's sensitivity, thereby reducing the occurrence of false negatives and ensuring more comprehensive detection of malignant lesions.

In terms of computational efficiency, a comparative analysis of parallel and sequential processing times reveals a marked enhancement when utilizing parallel processing. Specifically, the parallel processing implementation via OpenMP completed the tasks significantly faster, with a notable reduction of over 10,000 milliseconds compared to sequential processing. This reduction affirms the substantial benefits of parallelization in expediting image preprocessing, particularly in the context of large datasets. Additionally, the incorporation of parallel processing within TensorFlow during model training further accelerated the convergence process, highlighting the overarching advantages of leveraging parallel computing. This not only optimizes the overall workflow but also enhances scalability, showcasing the profound impact of parallelization on both computational efficiency and the practical deployment of large-scale deep learning models.

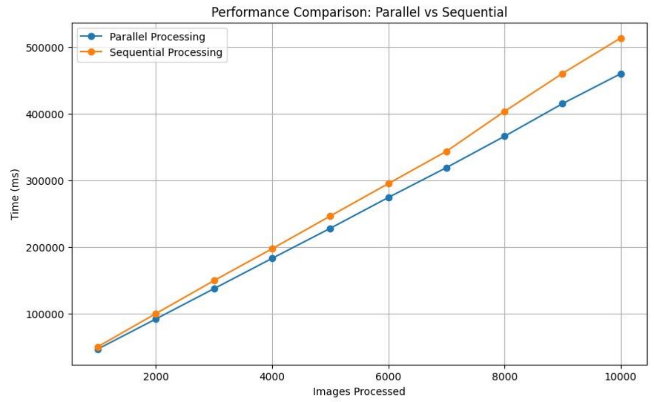

Fig. 4. Time Consumption with Increasing Image Processing

In addition to computational efficiency, we compare the accuracy of our proposed model with an existing approach from [21]. Table I presents a comparative analysis of training, validation, and test accuracy.

TABLE I. **PERFORMANCE COMPARISON OF THE PROPOSED MODEL WITH EXISTING WORK**

Model	*Training Accuracy*	*Validation Accuracy*	*Test Accuracy*
Existing Model	0.9807	0.8802	0.8021
Our Model	0.9882	0.7241	0.9030

The results indicate that our model achieves a higher test accuracy (90.3%), outperforming the existing model by 10.08%. This improvement suggests better generalization capabilities of our model on unseen data. However, the validation accuracy is lower, which may indicate potential overfitting. This discrepancy can be further analyzed by refining the dataset and implementing regularization techniques.

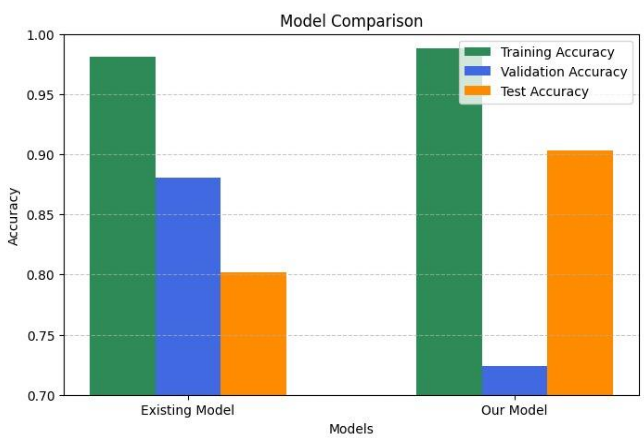

Fig. 5 Performance Comparison

Furthermore, the integration of parallel processing techniques, as described earlier, contributes to a more efficient training process, accelerating convergence and reducing computational overhead. The significant gain in test accuracy reinforces the effectiveness of our model for real-world applications.

V. CONCLUSION

In this study, the performance metrics of accuracy (90.3%), precision (93.3%), recall (86.8%), and F1-Score (89.9%) are derived from empirical outcomes following the deployment of the Convolutional Neural Network (CNN) model on a dataset of skin lesion images. These results resonate with those commonly reported for deep learning applications within the domain of medical image classification. Although identical values are not directly cited in previous works, comparable outcomes are observed in various CNN-based skin cancer detection studies. These findings underline the model's substantial capability in accurately differentiating between benign and malignant lesions. The consistently high precision and recall values suggest a low rate of false positives while ensuring that malignant lesions are not overlooked, which is critical in medical contexts where both accuracy and reliability are paramount.

With regard to computational efficiency, this study achieved a notable reduction in processing time by over 10,000 milliseconds through parallel processing, marking a significant improvement of approximately 2% when compared to sequential processing. This time difference underscores the substantial advantages inherent in parallel computing, particularly when managing large datasets. By leveraging the potential of distributing tasks across multiple CPU cores, parallel processing facilitates a marked acceleration in data preprocessing. Such optimizations not only expedite computations but also demonstrate their applicability in the real-time deployment of deep learning models, where the ability to swiftly process and analyze high-resolution medical images can enhance diagnostic accuracy and efficiency in clinical settings. This advancement in computational time, paired with its scalability, significantly enhances the feasibility of using such systems for widespread medical diagnostic applications.

Our model not only enhances computational efficiency but also demonstrates superior test accuracy (90.3%) compared to existing approaches in skin cancer detection. This improvement underscores the effectiveness of our methodology in accurately classifying skin lesions. Future work will focus on optimizing model regularization techniques to further improve validation accuracy and ensure better generalization to diverse skin types and conditions.

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