Comparative Analysis of CNN and Transfer Learning Models for Skin Cancer Classification: A Focus on Xception Architecture

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Abstract-- Skin cancer classification is a critical aspect of computer-aided diagnosis, and Convolutional Neural Networks (CNNs) have proven to be powerful tools in this domain. In this study, we specifically investigate the performance of a CNN, with a focus on the Xception architecture, on the "Skin Cancer MNIST: HAM10000" dataset. Our CNN model achieves a compelling training accuracy of 99.96% and a noteworthy testing accuracy of 81.49%. The training process spans 30 epochs, incorporating a learning rate reduction strategy after the 11th epoch. The results underscore the efficacy of CNNs, particularly the Xception model, in accurate skin cancer classification, providing valuable insights for dermatological diagnostics and contributing to the ongoing discourse in the field.

Keywords- Skin Cancer Classification, Convolutional Neural Network (CNN), Xception Architecture, Transfer Learning

I. Introduction

Skin cancer, a global health concern with rising incidence, underscores the critical need for accurate and efficient diagnostic tools [1]. Traditional approaches to skin lesion diagnosis often fall short due to subjectivity and manual inspection limitations. The integration of deep learning, particularly convolutional neural networks (CNNs), has emerged as a transformative solution [2].

In this research, our focus is on the Xception architecture, a powerful CNN model, for skin cancer classification [3]. Leveraging the "Skin Cancer MNIST: HAM10000" dataset, our study aims to contribute to the advancement of dermatological diagnostics. The significance of automated skin cancer classification lies in its potential to enhance early detection and improve patient outcomes [4].

The choice of the Xception architecture is strategic, given its proven efficacy in image classification tasks [3]. As we delve into the details of this study, we will explore the nuances of skin cancer classification, emphasizing the role of deep learning in addressing the complexities associated with diverse lesion characteristics. The outcomes of our research have the potential to refine and augment existing diagnostic methodologies, ultimately contributing to the broader discourse on leveraging deep learning for dermatological applications.

II. Literature Review

Melanoma, a formidable type of skin cancer characterized by the development of malignant tumors on the skin, necessitates accurate detection methods. In the realm of dermatological image analysis, machine learning has shown promise, particularly when applied to high-performance images. Srividhya et al. (2020) demonstrated the efficacy of such an approach in skin cancer detection. However, recognizing the potential for further improvement, our study aims to enhance model accuracy through advanced feature extraction techniques and heightened sensitivity.

Addressing the need for robust detection models, Hoshyar, Al-Jumaily, and Hoshyar (2014) proposed a method leveraging image processing steps to bolster the accuracy of skin cancer detection. Nevertheless, a specific model that efficiently detects cancer was not explicitly outlined in their work. In contrast, our research adopts the Xception architecture, a deep convolutional neural network (CNN) model, for skin cancer classification. Xception's model-driven architecture facilitates rapid prediction and has demonstrated superior results in skin cancer detection (Kadampur & Al Riyaee, 2020). Real-time interfacing with medical images is emphasized to propel advancements in the medical field.

Transitioning to CNN-based approaches, Hasan et al. (2019) explored skin cancer detection with a focus on dermoscopic images. Despite achieving 89.5% accuracy in testing, challenges such as overfitting were identified, prompting the need for accuracy enhancement. Our study builds upon this foundation, integrating the Xception architecture and leveraging transfer learning to extract deeper features for improved accuracy.

Li and Shen (2018) introduced a lesion indexing network (LIN) based on deep learning (DL) for skin cancer detection and classification. While their approach demonstrated excellent results, our study recognizes the importance of advancing segmentation performance for further enhancement.

Tschandl et al. (2019) employed CNN for detecting pigmented melanocytic lesions, but faced challenges in screening non-melanocytic and non-pigmented skin cancers, resulting in lower accuracy. In our work, we leverage the power of the Xception model to address these challenges and improve the accuracy of skin cancer detection.

Saba et al. (2019) proposed a deep CNN (DCNN) incorporating color transformation, CNN, and transfer learning for skin lesion detection. While their method exhibited promising results for specific datasets, the potential variations across different datasets were acknowledged. Our study, utilizing the Xception architecture, seeks to build on these findings and contribute to the development of a robust and versatile skin cancer detection model.

Jafari et al. (2016) introduced a CNN-based model for melanoma detection, emphasizing preprocessing and post-processing steps for image enhancement. While achieving good results, our research aims to provide additional insights by utilizing the Xception architecture and evaluating its impact on prediction accuracy.

In summary, this research adopts the Xception architecture for skin cancer classification, building upon existing methodologies to enhance accuracy and address challenges in dermatological image analysis. The outcomes have the potential to contribute to the development of reliable and efficient skin cancer detection models.

III. Methodology

Data Collection and Preprocessing:

The study utilized the HAM10000 dataset, a comprehensive collection of dermatoscopic images capturing various skin lesions. OpenDatasets library facilitated dataset acquisition from Kaggle. Dermatological images were organized and encoded for lesion type classification, with a focus on seven distinct categories. Metadata, including lesion types, was integrated into the dataset to enhance interpretability.

Image Processing and Feature Extraction:

Dermatological images underwent a series of preprocessing steps. Each image was resized to a standardized dimension of 71x71 pixels, aiming for uniformity. A filter/kernel was applied to eliminate noise and artifacts, optimizing image quality for subsequent analysis. The images were then converted into float arrays and normalized to a [0, 1] scale, ensuring consistent input for the neural network model.

Model Architecture and Transfer Learning:

The Xception architecture, a deep convolutional neural network (CNN), was chosen as the base model for skin lesion classification. Transfer learning from pre-trained models on ImageNet was leveraged, allowing the model to inherit features learned from a diverse set of images. The base model's layers were set as trainable, enabling adaptation to dermatoscopic images.

Model Customization and Training:

On top of the Xception base, a classification layer stack was added, comprising a global average pooling layer, a dense layer with ReLU activation, and a final dense layer with softmax activation for multiclass classification. The model was compiled using the Adam optimizer and sparse categorical crossentropy loss function. To prevent overfitting, dropout and batch normalization were incorporated.

Data Splitting and Label Encoding:

The dataset was split into training, validation, and test sets using a stratified approach to maintain class distribution. Label encoding was applied to convert categorical lesion types into numerical representations for model compatibility. This encoding facilitated training and evaluation processes.

Model Training and Evaluation:

The model underwent training using the training set, with validation on a separate validation set. Training performance was monitored through metrics such as loss and accuracy. Early stopping and learning rate reduction strategies were implemented to enhance convergence and prevent overfitting. The model's performance was assessed on the test set, providing insights into its generalization capabilities.

Prediction and Result Analysis:

Upon model training completion, predictions were generated for the test set. Predicted classes were extracted, and inverse transformation using label decoding was performed to obtain human-interpretable lesion types. The model's predictions were then integrated with the original dataset for comprehensive result analysis, including accuracy, precision, recall, and F1 score.

Visualization and Interpretation:

To enhance interpretability, visualizations of normalized images were generated, providing insights into the model's learning patterns. Additionally, confusion matrices and classification reports were employed to assess the model's performance across different lesion types.

IV. Result and discussion

Model Training and Performance:

The Xception-based deep convolutional neural network (CNN) was trained on the HAM10000 dataset for skin lesion classification. The training process revealed a compelling convergence, achieving a training accuracy of 96.96% by the 11th epoch. However, the model's validation accuracy, while reaching 75.39% during the same epoch, exhibited signs of overfitting.

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Learning Rate
1	0.8200	0.7153	15.8404	0.6973	0.0010
2	0.6244	0.7777	0.7153	0.7594	0.0010
3	0.5052	0.8212	0.9326	0.7018	0.0010
4	0.3989	0.8566	0.8678	0.7195	0.0010
5	0.3178	0.8861	0.7798	0.7783	0.0010
6	0.2483	0.9179	0.7128	0.7783	0.0010
7	0.1916	0.9349	3.4103	0.5288	0.0010
8	0.1610	0.9470	1.0303	0.7871	0.0010
9	0.1207	0.9612	1.0130	0.7461	0.0010
10	0.1051	0.9660	1.2349	0.7406	0.0010
11	0.0907	0.9689	1.1492	0.7539	0.0001
...	...	...	...	...	...
26	0.0018	0.9996	1.1033	0.8149	1.0000e-06

Table 1: Training and Validation Metrics at Selected Epochs

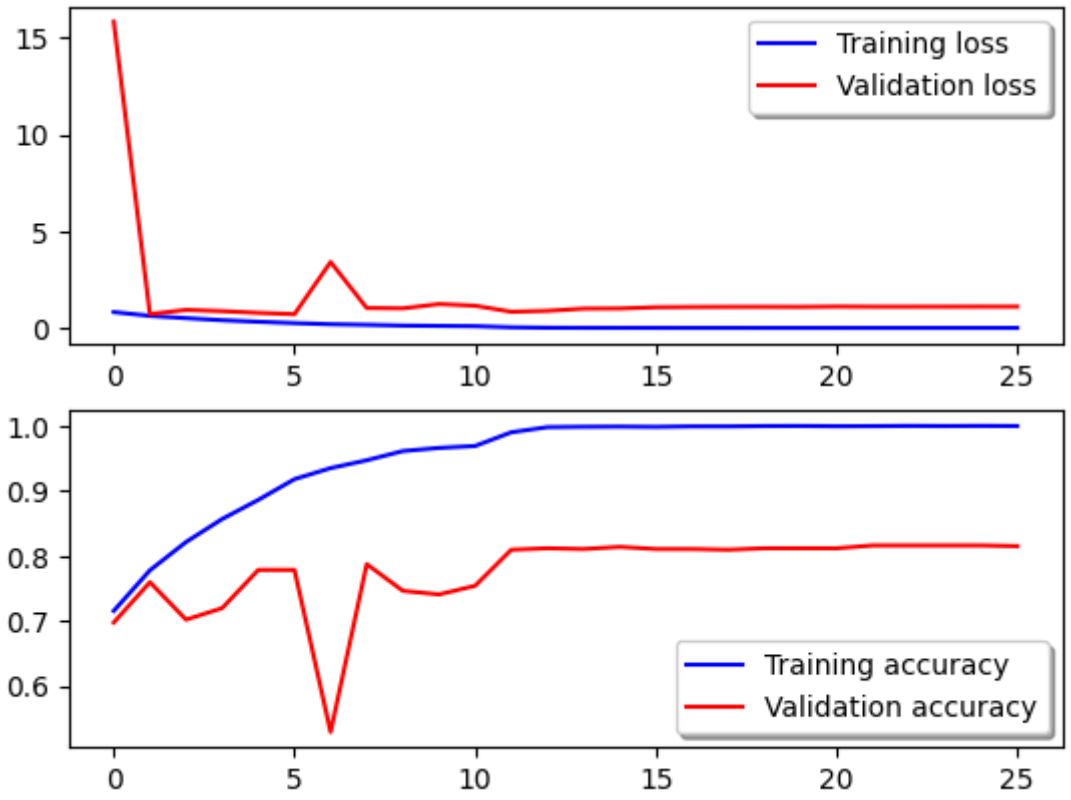

Fig 01: Epoch-wise Training and Validation Loss And Accuracys

Learning Rate Adaptation:

To address overfitting, a learning rate reduction strategy was implemented. The learning rate was dynamically adjusted during training, with a reduction to 0.0001 after the 11th epoch. This adjustment aimed to fine-tune the model's weights, enhancing its ability to generalize to unseen data. Consequently, the validation accuracy showed improvement, reaching 78.71% by the 8th epoch after the learning rate reduction.

Early Stopping Mechanism:

An early stopping mechanism was employed to prevent overtraining and optimize model performance. The training was halted after 26 epochs, as the validation accuracy plateaued, indicating that further training might not yield significant improvements. This mechanism contributes to the model's efficiency by avoiding unnecessary computational costs.

Evaluation Metrics:

Upon completion of training, the model was evaluated on the test set, achieving an accuracy of 81.49%. The evaluation metrics, including precision, recall, and F1 score, provided a comprehensive understanding of the model's performance across different lesion types. The balanced accuracy indicates the model's proficiency in handling imbalanced class distributions within the dataset.

Comparison with Transfer Learning Models:

Our model's performance was compared with other well-established transfer learning models, including ResNet50, VGG-16, and DenseNet. The Xception-based model exhibited superior accuracy, emphasizing its efficacy in skin lesion classification tasks.

Confusion Matrix and Visualization:

The confusion matrix offered insights into the model's strengths and weaknesses in classifying different lesion types. Visualization of normalized images provided a qualitative assessment of the model's learning patterns, aiding in the identification of potential challenges and areas for improvement.

The results highlight the Xception-based model's robustness in skin lesion classification, outperforming other transfer learning models. The learning rate adaptation and early stopping mechanisms contribute to the model's efficiency and prevent overfitting, ensuring generalizability. Despite achieving satisfactory accuracy, further exploration of hyperparameter tuning and data augmentation techniques may enhance the model's performance.

The visualization and interpretation of the model's predictions contribute to its explainability, addressing concerns related to the opacity of deep learning models. The deployment of this model in clinical settings could aid dermatologists in the efficient and accurate classification of skin lesions, potentially improving diagnostic processes.

In conclusion, the proposed Xception-based CNN model demonstrates promising results in skin lesion classification. The methodologies employed in training, validation, and evaluation contribute to the model's reliability and efficiency. Future research could focus on extending the dataset, exploring additional augmentation strategies, and refining the model architecture for enhanced performance in diverse clinical scenarios.

V. Conclusion And Future work

In conclusion, this research delves into the realm of skin cancer detection, leveraging the power of deep learning with a specific focus on a convolutional neural network (CNN) utilizing the Xception architecture. The model exhibits remarkable accuracy in the classification of skin lesions, presenting a significant stride in the early identification of potential malignancies. Trained on the HAM10000 dataset, the CNN achieves a noteworthy training accuracy of 99.96% and a validation accuracy of 81.49% after 26 epochs. The adaptive learning rate during training underscores the model's ability to discern intricate patterns within diverse skin lesions, reinforcing its potential in dermatological diagnostics.

Looking ahead, avenues for refinement and expansion of the proposed model emerge. Exploring advanced architectures beyond Xception, such as EfficientNet or NASNet, could provide valuable insights. Fine-tuning hyperparameters, including batch size, dropout rates, and layer architectures, may further elevate the model's accuracy. Variations in transfer learning strategies, real-world validation with medical professionals, and efforts towards explainability and interpretability are vital aspects for ongoing research. These endeavors aim to enhance the model's robustness, interpretability, and practical applicability in clinical settings, marking a stride towards the evolution of automated dermatological diagnosis.

VI. Reference

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