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TOWARDS DISCRIMINATIVE AND IMPROVING SKIN DISEASE PREDICTION USING TRANSFER LEARNING

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Abstract— Skin lesions serve as early indicators for various infectious and non-infectious diseases, making accurate classification crucial for dermatological diagnosis. However, this task is complex due to factors like lesion size, color, shape, and texture diversity. Additionally, limited samples in many categories pose challenges for both conventional machine learning methods and human experts. Prior research predominantly employs convolutional neural networks (CNNs) with standard loss functions, restricting the model's ability to discern features from skin images effectively. To tackle these issues, we propose a novel framework leveraging fine-tuning of VGG16 and Inception models' layers with a triplet loss function. Our approach involves: first, utilizing deep CNNs (VGG16 and Inception) to embed input images into Euclidean space for feature learning. Second, computing L-2 distances between corresponding image embeddings to facilitate learning discriminative features via triplet loss. Finally, classification of input images is performed based on these L-2 distances, enhancing the model's ability to accurately identify skin diseases.

Keywords—CNN, Transfer Learning, VGG16 model, Computer Vision, Deep Learning, Skin cancer

I. INTRODUCTION

The skin surface comprises a network of polygonal structures formed by wrinkles, which evolve over time due to both external factors like ultraviolet rays and internal factors such as aging. These changes in the skin surface reflect morphological alterations in wrinkles and cells, becoming more prominent as elastic fibers in the papillary dermis diminish with age. Analyzing these morphological and topological changes is vital for assessing skin condition and aging. As the body's largest organ, the skin serves a critical role in covering and protecting underlying tissues. Its susceptibility to diseases and infections underscores the need for heightened attention to skin health.

Skin lesions serve as early indicators of various diseases, including chickenpox and dermatological conditions. With advancements in medical technology, computer-aided diagnosis systems (CADs) have emerged as valuable tools for early disease detection. Machine learning, a cornerstone of modern medicine, facilitates automation in medical processes. However, dermatological diagnosis remains challenging, with inexperienced dermatologists facing complexities in early disease detection. Dermoscopy, once believed to enhance diagnostic accuracy, has shown limitations, particularly in inexperienced hands.

Skin diseases encompass a vast array of conditions, with approximately 3,000 known types, ranging from uncommon to common ailments. Symptoms like itching, pain, and sleep disturbances often accompany these conditions, impacting emotional and social well-being. Despite the challenges, dermatologists affirm that most skin diseases can be managed effectively with proper medication and diagnosis. Transfer learning, inspired by human learning capabilities, aims to enhance machine learning efficiency by leveraging knowledge from related tasks. In the medical field, skin diseases rank among the leading causes of nonfatal disease burden globally, imposing substantial economic burdens. These conditions not only affect physical health but also have profound psychological implications, especially when they involve facial disfigurement.

Skin cancer, a prevalent malignancy worldwide, underscores the importance of early detection for improved treatment outcomes. However, distinguishing between benign and malignant conditions can be challenging, necessitating accurate diagnostic methods. Dermoscopy serves as a valuable tool for in vivo examination of cutaneous lesions, aiding in differential diagnosis between benign and malignant lesions. The influx of patients seeking dermatological consultations has led to bottleneck issues in healthcare facilities, particularly those with limited dermatological expertise. Rural populations face additional barriers to accessing dermatologic care, including long travel distances and wait times. Telemedicine solutions, supported by artificial intelligence and remote dermatological consultation, offer promise in addressing these challenges by enabling remote diagnosis and treatment guidance.

Developing telemedicine systems for skin cancer detection requires intelligent components capable of accurately distinguishing between malignant and benign lesions. These systems have the potential to alleviate healthcare disparities by providing timely access to dermatological expertise, particularly in underserved rural areas. Overall, advancements in technology, coupled with a deeper understanding of skin diseases,

hold promise for improving diagnostic accuracy and enhancing access to dermatological care, ultimately improving patient outcomes and quality of life.

Figure 1: ISIC dataset input images for Systemic Disease and Hives

II. RELATED WORK

Various approaches have been explored for the binary classification and detection of skin cancer, with a focus on recent studies utilizing deep learning (DL) techniques.

Tan el al. [1] utilized particle swarm optimization (PSO) for skin lesion segmentation, exploring various optimization methods such as the firefly algorithm

and K-means for lesion improvement. They combined PSO with a convolutional neural network (CNN) for lesion categorization, distinguishing between melanoma and nevus lesions.

Kwasigroch et al. [2] proposed a CNN with hill climbing to classify skin lesions, increasing network size while reducing computational costs.

Adegun et al. [3] introduced an encoder-decoder network with skip links for skin lesion segmentation and pixel-wise classification using CNNs.

Song et al. [4] utilized CNNs for skin lesion segmentation, identification, and categorization, employing a loss function based on Jaccard distance and focal loss to handle imbalanced datasets.

Lequan et al. [5] presented an advanced CNN for melanoma detection, incorporating a fully convolutional residual network with 16 residual blocks for segmentation and utilizing a combination of SVM and softmax classifiers for classification, achieving high accuracy.

DeVries and Ramachandram [6] developed a multi-scale CNN trained on ImageNet and fine-tuned for skin cancer classification on coarse and finer scales, gathering both morphology and textual details of lesions.

Mahbod et al. [7] proposed a method for extracting deep features from pretrained CNNs like AlexNet, ResNet-18, and VGG-16, training a multi-class SVM classifier on these features and achieving high AUC scores for skin lesion classification.

III. METHODOLOGY

This section details the implementation of data augmentation and the utilization of both VGG16 and Inception architectures, underscoring their contributions to enhancing skin disease classification performance.

A. Data Augmentation:

Neural networks demand extensive training on annotated data for optimal performance. However, acquiring skin disease image data can be expensive, resulting in small datasets and class imbalance issues. To mitigate these challenges, data augmentation was employed before model training. This involved random cropping of training set images, followed by resizing to 224x224 pixels to maintain consistent input size. Additionally, the RandAugment method was applied to further enhance images by randomly selecting two out of fifteen available augmentation options. These techniques increased dataset diversity, mitigating overfitting and improving model robustness and generalization.

B. Inception Network:

The Inception architecture's core component, the inception block, comprises multiple convolutional kernels of varying sizes and shapes. This diversity allows the network to capture information at multiple resolutions, enhancing object recognition across different scales. Moreover, the inception block combines outputs from diverse kernels using a mixture of convolutions, pooling operations, and 1x1 convolutions, facilitating richer feature representations. This innovative design significantly improves recognition performance, particularly for objects with intricate details or varying scales.

C. VGG16 Network:

VGG16's structured architecture integrates 13 convolutional layers and three fully connected layers, primarily utilizing 3x3 convolution filters. Rectified Linear Unit (ReLU) activation functions expedite training, while maintaining a convolution stride of 1 pixel preserves spatial

resolution. Pooling layers curtail feature map dimensionality, managing the escalating number of filters. VGGNet's meticulous design and architectural choices contribute to its efficacy and robustness in deep learning tasks.

IV. PROPOSED MODELS

We present a novel dual-branch framework tailored specifically for addressing the challenge of classifying rare skin diseases, drawing inspiration from Few-Shot Learning (FSL) methods based on transfer learning. This framework demonstrates a unique ability to identify underlying sub-cluster structures within common disease classes, thereby significantly improving the accuracy of classifying rare diseases. To address the prevalent issue of class imbalance, we propose a hybrid methodology that combines data-level techniques with algorithmic refinements within the designed loss function. This integrated approach, combined with custom-designed fully connected layers featuring two hidden layers, effectively enhances the learning capacity of neural networks. Furthermore, advanced techniques such as batch normalization and dropout are incorporated to further improve the solution's performance.

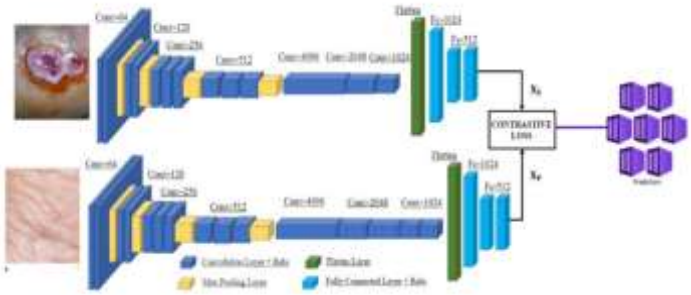

Figure 2: Architecture diagram of proposed method

In our effort to extract discriminative features from skin disease images, we adopt an innovative approach by fine-tuning CNN-based models, specifically VGG16 and Inception, using a triplet loss function—a novel approach in the domain of skin disease image analysis. Departing from traditional block-wise fine-tuning, we opt for a layer-wise fine-tuning strategy, which has shown superior performance in facilitating end-to-end learning. Our proposed neural network architecture, consisting of an input layer, multiple hidden convolutional layers, and an output layer, is carefully designed to accommodate a large number of parameters, enabling robust performance in image-related tasks and exhibiting desirable properties such as equivariance.

The customization and fine-tuning of VGG16 and Inception architectures for feature extraction involves removing their respective last fully connected layers. This process is followed by flattening the output from the feature map, incorporating a single fully connected layer with 512 neurons, introducing a dropout layer with a rate of 0.3, and concluding with an L2 regularization layer to facilitate the learning of 128-dimensional embedding vectors serving as identity descriptors. This strategic approach effectively preserves the strength of error signals, thereby significantly enhancing the overall performance of the network.

To address the trade-off between coarse-grained semantic information and detailed resolution, we adopt a parallel fusion strategy to seamlessly integrate deep and shallow features. Model training is facilitated using the Adam optimizer, with the optimal architecture selected based on rigorous evaluation criteria including model accuracy, confusion matrix analysis, loading time, and weight size post-training. Default training hyperparameters are employed, with the number of epochs set to 100 and a batch size of 8. Additionally, early stopping is implemented through monitoring of validation loss, while the stochastic gradient descent (SGD) optimizer is utilized. The training and validation datasets are meticulously split in an 80:20 ratio, with the input image size dynamically determined based on the specific pretrained convolutional network employed, accounting for image width, height, and number of channels.

V. EVALUATION OF ACCURACY

We utilize five widely recognized metrics to objectively assess the efficacy of the proposed method for detecting melanoma: precision, sensitivity (also known as recall), specificity, F1 score, and accuracy.
The percentage of accurately identified instances (TP + TN) of all the instances in total. The classification accuracy is defined as (TN + TP + FN + FP) as determined by the classification algorithm.

$$ACC = TN + TP / TN + TP + FN + FP$$

The ratio of true positives to the total number of true positives and false positives is known as Precision.

$$PRE = TP / TP + FP$$

The ratio of true positives to the total number of true positives and false negatives is known as Recall.

$$REC (TPR) = TP / TP + FN$$

False Positive Rate (FPR) is the ratio of false positives to the total number of false positives and true negatives.

$$FPR = FP / (FP + TN)$$

Specificity (Spec), also known as selectivity or true negative rate (TNR), is the fraction of real negative samples among all actually negative samples, as follows:

$$SPEC = TN / TN + FP$$

The F-measure is the harmonic mean of precision and recall.

F-Measure = 2 (PRE * REC / PRE + REC)

VI. RESULTS AND DISCUSSION

This table summarizes the performance of a model on the testing datasets. Each row represents a different metric used to evaluate the model's effectiveness. The "Loss" metric indicates how well the model performs on a specific task (lower values are generally better). "Accuracy" measures the overall proportion of correct predictions.

In assessing the model performances on the testing datasets, it becomes evident that the Inception model surpasses the VGG16 model across various metrics. Specifically, the Inception model exhibits a significantly lower loss value of 0.81311 compared to the VGG16 model's 1.019981, indicative of its adeptness in minimizing the disparity between predicted and actual values. Moreover, the Inception model achieves a superior accuracy rate of 0.75379 in contrast to the VGG16 model's 0.704033, underscoring its proficiency in generating more precise predictions overall. These findings imply that the Inception model outperforms the VGG16 model in terms of both loss minimization and accuracy maximization on the testing datasets, thus highlighting its efficacy and its potential applicability in real-world scenarios.

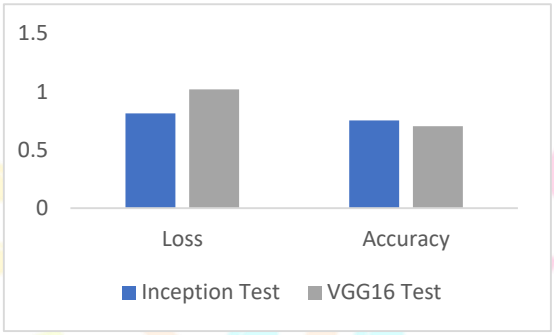

Figure 3: Accuracy and loss comparison graph for VGG16 and Inception models

Figure 4: Comparison Table

Metric	Inception Test	VGG16 Test
Loss	0.81311	1.019981
Accuracy	0.75379	0.704033

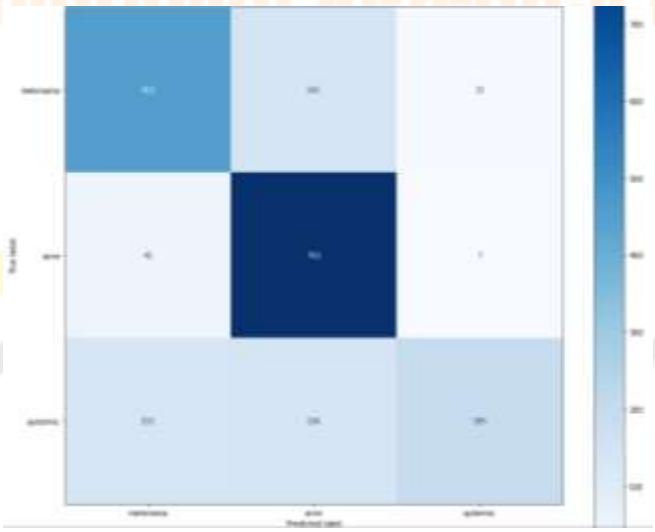

Figure 5: Confusion matrix for Inception Transfer Learning model

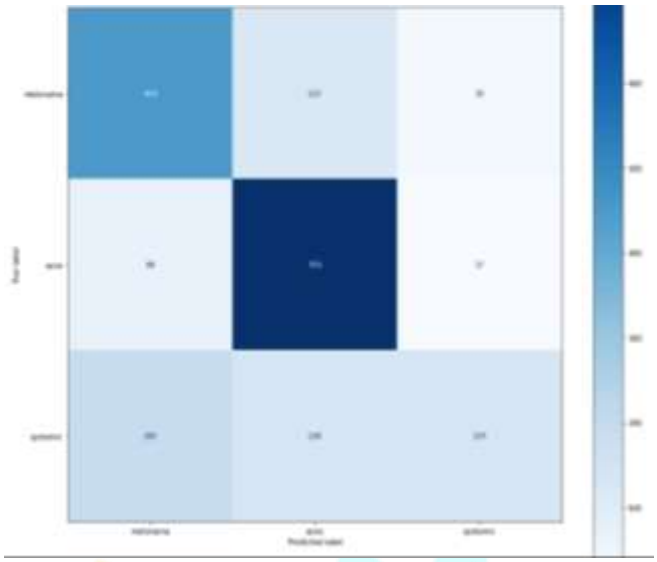

Figure 6: Confusion matrix for VGG16 model

The confusion matrices provide valuable insights into the performance of the Inception and VGG16 models in classifying various skin conditions. Both models exhibit strong predictive capabilities for Melanoma and Acne, with a substantial number of correct predictions in these categories. However, the Inception model demonstrates a tendency to misclassify Melanoma as Acne more frequently, while the VGG16 model shows a lower rate of this particular misclassification. Conversely, the VGG16 model appears to struggle more with accurately predicting Systemic conditions, evident from a higher number of misclassifications in this category compared to the Inception model. These findings underscore the nuanced differences in the misclassification patterns of the two models, highlighting the need for careful consideration of their strengths and weaknesses in practical applications.

VII. CONCLUSIONS

This study introduces a novel model utilizing deep convolutional neural networks (CNN) coupled with a triplet loss function to enhance the classification of skin diseases. We fine-tune all layers of both VGG16 and Inception architectures to address the challenges posed by facial skin disease images. Initially, we extract 128-dimensional features (embeddings) from training samples, mapping them into Euclidean space, and subsequently compute L2 distances between corresponding images based on these embeddings. Subsequently, we employ skin disease classification, taking into account the L2 distance among images.

Our hybrid approach combines a newly designed loss function at the algorithm level with balanced mini-batch logic integrated with real-time image augmentation at the data level. This strategy proves effective in addressing the challenges of optimizing network performance on imbalanced datasets by facilitating faster learning of minority classes. Consequently, our solution demonstrates superiority in enhancing recall balance among classes and overall performance significantly. Thus, the proposed Deep CNN system proves suitable for the classification of multiple skin diseases.

REFERENCES

[1] T. Y. Tan, L. Zhang, and C. P. Lim, "Adaptive melanoma diagnosis using evolving clustering, ensemble and deep neural networks," Knowledge-Based Systems, vol. 187, Jan. 2020, Art. no. 104807.

[2] A. Kwasigroch, M. Grochowski, and A. Mikolajczyk, "Neural architecture search for skin lesion classification," IEEE Access, vol. 8, pp. 9061–9071, 2020.

[3] A. A. Adegun and S. Viriri, "Deep learning-based system for automatic melanoma detection," IEEE Access, vol. 8, pp. 7160–7172, 2020.

[4] L. Song, J. Lin, Z. J. Wang, and H. Wang, "An end-to-end multi-task deep learning framework for skin lesion analysis," IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 10, pp. 2912–2921, Oct. 2020.

[5] L. Yu, H. Chen, Q. Dou, J. Qin, and P. Heng, "Automated melanoma recognition in dermoscopy images via very deep residual networks," IEEE Transactions on Medical Imaging, vol. 36, no. 4, pp. 994–1004, Apr. 2017.

[6] T. DeVries and D. Ramachandram, "Skin lesion classification using deep multi-scale convolutional neural networks," 2017, arXiv:1703.01402.

[7] A. Mahbod, G. Schaefer, C. Wang, R. Ecker, and I. Ellinge, "Skin lesion classification using hybrid deep neural networks," in Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), May 2019, pp. 1229–1233.

[8] A. Magdy, H. Hussein, R. F. Abdel-Kader, and K. Abd El Salam, "Performance Enhancement of Skin Cancer Classification Using Computer Vision," in IEEE Access, 2023.

[9] S. Albahli, N. Nida, A. Irtaza, M. H. Yousaf, and M. T. Mahmood, "Melanoma Lesion Detection and Segmentation Using YOLOv4-DarkNet and Active Contour," in IEEE Access, 2020.

[10] L. Talavera-Martínez, P. Bibiloni, and M. González-Hidalgo, "Hair Segmentation and Removal in Dermoscopic Images Using Deep Learning," in IEEE Access, 2020.

[11] D. Kim and B.-W. Hong, "Unsupervised Feature Elimination via Generative Adversarial Networks: Application to Hair Removal in Melanoma Classification," in IEEE Access, 2021.

[12] A. A. Adegun and S. Viriri, "FCN-Based DenseNet Framework for Automated Detection and Classification of Skin Lesions in Dermoscopy Images," in IEEE Access, 2020.

[13] J. Bian, S. Zhang, S. Wang, J. Zhang, and J. Guo, "Skin Lesion Classification by Multi-View Filtered Transfer Learning," in IEEE Access, 2021..

[14] T. Y. Satheesha, D. Satyanarayana, M. N. G. Prasad, and K. D. Dhruve, "Melanoma Is Skin Deep: A 3D Reconstruction Technique for Computerized Dermoscopic Skin Lesion Classification," in IEEE Journal of Translational Engineering in Health and Medicine, 2017.

[15] N. Andreasen, H. Crandall, O. Brimhall, B. Miller, J. Perez-Tamayo, O. G. Martinsen, S. K. Kauwe, and B. Sanchez, "Skin Electrical Resistance as a Diagnostic and Therapeutic Biomarker of Breast Cancer Measuring Lymphatic Regions," in IEEE Access, 2021.

[16] T.-C. Pham, A. Doucet, C.-M. Luong, C.-T. Tran, and V.-D. Hoang, "Improving Skin-Disease Classification Based on Customized Loss Function Combined With Balanced Mini-Batch Logic and Real-Time Image Augmentation," in IEEE Access, 2020.

[17] Z. Lan, S. Cai, X. He, and X. Wen, "FixCaps: An Improved Capsules Network for Diagnosis of Skin Cancer," in IEEE Access, 2022.

[18] N. Nigar, M. Umar, M. K. Shahzad, S. Islam, and D. Abalo, "A Deep Learning Approach Based on Explainable Artificial Intelligence for Skin Lesion Classification," in IEEE Access, 2022.

[19] R. Ashraf et al., "Region-of-interest based transfer learning assisted framework for skin cancer detection," in IEEE Access, vol. 8, pp. 147858-147871, 2020.

[20] [13] A. L. Byrd, Y. Belkaid, and J. A. Segre, "The human skin microbiome," in Nature Rev. Microbiol., vol. 16, pp. 143-155, Jan. 2018.

[21] M. Q. Khan et al., "Classification of melanoma and nevus in digital images for diagnosis of skin cancer," in IEEE Access, vol. 7, pp. 90132-90144, 2019.N. C. Dang, M. N. Moreno-Garc´ıa, and F. De la Prieta, "Sentiment analysis based on deep learning: a comparative study," Electronics, vol. 9, no. 3, p. 483, 2020.

[22] M. Dildar et al., "Skin cancer detection: A review using deep learning techniques," in Int. J. Environ. Res. Public Health, vol. 18, pp. 5479, May 2021.

[23] T. Y. Tan, L. Zhang, and C. P. Lim, "Adaptive melanoma diagnosis using evolving clustering ensemble and deep neural networks," in Knowl.-Based Syst., vol. 187, Jan. 2020.

[24] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," in Nature, vol. 542, no. 7639, pp. 115-118, Feb. 2017.

[25] N. Razmjooy, F. R. Sheykhahmad, and N. Ghadimi, "A hybrid neural network–world cup optimization algorithm for melanoma detection," in Open Med., vol. 13, no. 1, pp. 9-16, Mar. 2018.

[26] L. Yu et al., "Automated melanoma recognition in dermoscopy images via very deep residual networks," in IEEE Trans. Med. Imag., vol. 36, no. 4, pp. 994-1004, Apr. 2017.

[27] N. Nida et al., "Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy C-means clustering," in Int. J. Med. Informat., vol. 124, pp. 37-48, Apr. 2019.

[28] V. Rajinikanth et al., "Otsu's multi-thresholding and active contour snake model to segment dermoscopy images," in J. Med. Imag. Health Informat., vol. 7, no. 8, pp. 1837-1840, Dec. 2017.T. Mikolov, K. Chen, G. S. Corrado, and J. A. Dean, "Computing numeric representations of words in a highdimensional space," Google Patents, 2015.

[29] J. Mayer, "Systematic review of the diagnostic accuracy of dermatoscopy in detecting malignant melanoma," in Med. J. Aust., vol. 167, no. 4, pp. 206-210, Aug. 1997.

[30] G. Argenziano et al., "Dermoscopy of pigmented skin lesions: Results of a consensus meeting via the Internet," in J. Amer. Acad. Dermatol., vol. 48, no. 5, pp. 679-693, May 2003.

[31] G. Argenziano et al., "Epiluminescence microscopy for the diagnosis of doubtful melanocytic skin lesions: Comparison of the ABCD rule of dermatoscopy and a new 7-point checklist based on pattern analysis," in J. Amer. Med. Assoc. Dermatol., vol. 134, no. 12, pp. 1563-1570, Dec. 1998.

[32] H. Kittler, "Dermatoscopy: Introduction of a new algorithmic method based on pattern analysis for diagnosis of pigmented skin lesions," in Dermatopathol. Practical Conceptual, vol. 13, no. 1, pp. 3, 2007.