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Deep Learning-Based Multi-Label Classification for Skin Cancer Detection

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Abstract—

Skin cancer is one of the most common and dangerous diseases due to a lack of awareness of its signs and methods for prevention. It is considered the fourth most burdensome disease globally, with a dramatically increasing mortality rate. Therefore, early detection at an initial stage is crucial to prevent the spread of cancer. In this paper, we propose a deep learning-based approach to detect and classify multi-label skin cancer using Convolutional Neural Networks (CNN) and transfer learning techniques. Preprocessing techniques such as image resizing, normalization, and augmentation are applied to enhance model performance. Deep learning models including CNN, ResNet50, and VGG16 are utilized and evaluated on the HAM10000 dataset, which consists of seven different skin cancer types. The experimental results demonstrate that deep learning models significantly outperform traditional approaches in terms of accuracy, precision, recall, and F1-score, with ResNet50 and VGG16 achieving the highest overall classification performance.

I. INTRODUCTION

Skin cancer is becoming increasingly common and is a major health concern worldwide, affecting people, animals, and even plants. It ranks as the fourth leading cause of mortality globally and primarily affects both the young and the elderly, although it can occur at any age [1]. Early detection and timely intervention using advanced technologies can significantly reduce mortality. Types of skin cancer include melanoma, basal cell carcinoma, and squamous cell carcinoma, with melanoma being the most aggressive and dangerous form [2].

High exposure to ultraviolet (UV) radiation from sunlight is a well-known cause of skin cancer [3]. Despite its growing prevalence, public awareness of skin cancer symptoms and risks remains low. UV rays, a type of electromagnetic radiation, can damage skin cells and lead to mutations that result in cancer. These mutations occur when normal skin cells transform and start to grow uncontrollably, forming what are known as carcinomas.

Deep learning, particularly convolutional neural networks (CNN), has shown remarkable performance in image-based classification tasks such as skin cancer detection. CNNs can automatically extract hierarchical features from medical images, enabling the model to distinguish between different types of skin lesions with high accuracy. Unlike traditional machine learning methods that rely heavily on manual feature extraction, deep learning models learn features directly from the raw image data, making them more robust and efficient for medical diagnostics.

Skin cancer remains highly prevalent in regions such as the United States. According to the Skin Cancer Foundation, in 2012 alone, more than 63,000 cases of melanoma were diagnosed, with millions of additional cases of non-melanoma skin cancer reported. Non-melanoma skin cancer typically appears in the outer skin layers, while melanoma originates deeper within the dermis [5][6]. With deep learning advancements, early and accurate detection is now more achievable, ultimately improving treatment outcomes and patient survival rates.

II. RELATED WORK

Over the past two decades, researchers have extensively explored automated classification of skin

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cancer using various machine learning and deep learning techniques. Early works focused on traditional machine learning algorithms for multi-class skin lesion classification. However, recent advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved the accuracy and robustness of skin cancer diagnosis systems.

Nazia Hameed et al. highlighted the use of both machine learning and deep learning techniques to enhance the treatment of various medical conditions, including skin cancer [7]. A. Murugan et al. explored image preprocessing techniques such as color normalization and segmentation to improve feature extraction from dermoscopic images, with a focus on Support Vector Machines and Random Forests [8]. Carolina Magalhaes et al. utilized ensemble learning on thermal images for skin cancer detection, showcasing the utility of multi-modal data in classification tasks [9].

Recent studies have demonstrated the superiority of deep CNNs for medical image classification. Mehwish Dildar et al. performed a comprehensive review of deep learning applications in skin cancer detection and emphasized the potential of CNN-based architectures in reducing diagnostic errors [11]. Yuheng Wang et al. proposed a deep learning model using polarization speckle imaging to enhance visual patterns for in vivo cancer detection [12]. Rashmi Patil et al. implemented a convolutional neural network (CNN) to address the challenges in melanoma tumor thickness classification, demonstrating improvements in model accuracy and robustness [13].

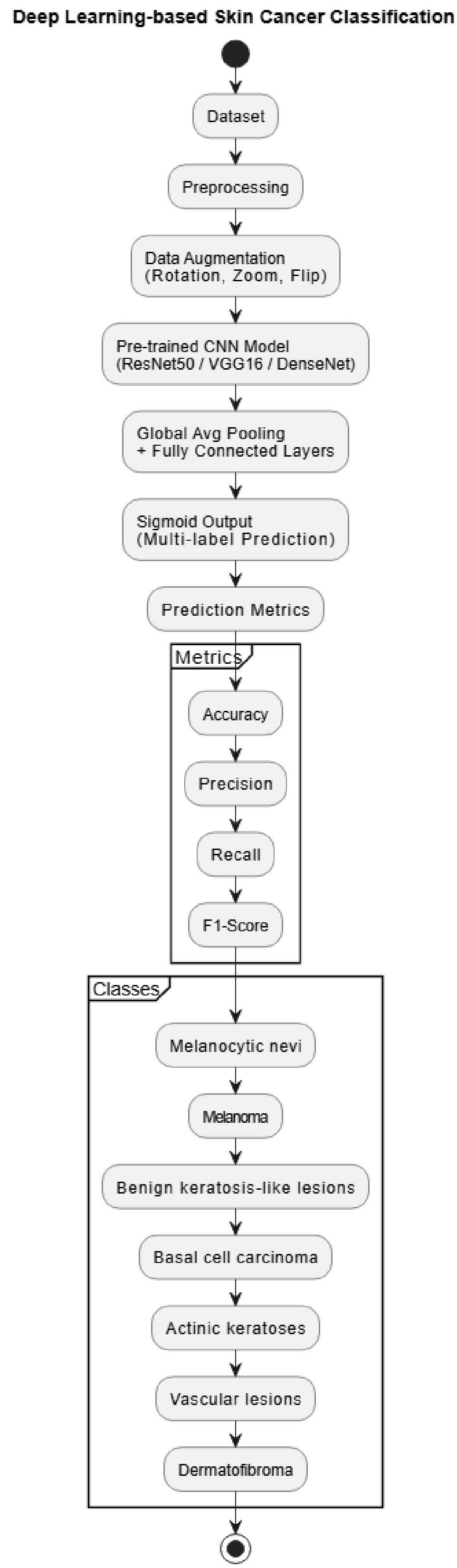
Researchers like X et al. have used deep CNNs with dermoscopic image datasets like HAM10000, achieving higher classification performance through models such as ResNet50, EfficientNet, and VGG16. These models leverage transfer learning and image augmentation to effectively distinguish between multiple skin lesion types, even in imbalanced datasets.

The work by Ravi Manne et al. further validated the effectiveness of CNNs in classifying complex skin lesion patterns, showing a marked reduction in misclassification rates and increased model precision [13]. The use of architectures such as U-Net for segmentation, and ResNet or DenseNet for classification, has set a new benchmark for automated skin cancer diagnostics.

III. METHODOLOGY

This section presents the proposed deep learning framework for multi-label skin cancer classification using dermoscopic images from the HAM10000 dataset. Our method utilizes powerful convolutional neural network (CNN) architectures, including **ResNet50**, **VGG16**, and **DenseNet121**, enhanced through **transfer learning** techniques.

The complete process consists of three core stages: **image preprocessing**, **model training with transfer learning**, and **performance evaluation**. The architecture is visualized in Figure 1.



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A. Preprocessing

Prior to model training, the input images undergo a series of preprocessing steps to enhance learning efficiency and generalization:

- **Image Resizing**: All dermoscopic images are resized to a fixed dimension (e.g., 224×224×3) to match the input requirement of pre-trained CNNs.
- **Normalization**: Pixel values are scaled between 0 and 1 to stabilize gradient descent and accelerate convergence.
- **Data Augmentation**: Techniques like horizontal and vertical flipping, rotation, zooming, brightness shifts, and shearing are applied to enrich the dataset and prevent overfitting, especially given the class imbalance common in medical datasets.

Deep Learning Models

We utilized **TensorFlow/Keras** to implement and train deep learning models. The key architectures used include:

- **ResNet50**: A residual network with skip connections that allows for deeper models and better gradient flow. Pre-trained on ImageNet, the top layers are replaced and fine-tuned for the multi-label skin cancer classification task.
- **VGG16**: A deep network consisting of 13 convolutional layers followed by 3 dense layers. It is known for its simplicity and effectiveness in transfer learning applications.
- **DenseNet121**: A densely connected convolutional network where each layer receives input from all previous layers, promoting feature reuse and mitigating vanishing gradients.

III. MODEL ARCHITECTURE AND DATASET OVERVIEW

In this study, we implement deep learning models for multi-label classification of skin cancer using dermoscopic images from the HAM10000 dataset. The focus is on convolutional neural network (CNN) architectures, including ResNet50, VGG16, and DenseNet121, which are known for their high performance in image-based medical diagnostics. These models were selected for their strong transfer learning capabilities, where pre-trained weights from the ImageNet dataset are fine-tuned for the skin lesion classification task.

The dataset was sourced from the Kaggle repository and includes diverse metadata covering age, gender, lesion location, and cell types. Images were preprocessed by resizing to 224×224 pixels, normalized to a [0,1] range, and augmented using techniques like rotation, flipping, and zooming to improve model robustness and reduce overfitting.

The dataset consists of seven classes of skin cancer, and the class distribution is visualized in Figure 3. Since some classes are underrepresented, data augmentation plays a crucial role in balancing the training process. Eighty percent of the dataset was used for training the models, while twenty percent was used for testing. Label encoding and multi-label binarization were applied to the output labels, as multiple diagnoses may co-occur.

IV. RESULTS AND DISCUSSION

The deep learning models were trained and evaluated on the HAM10000 dataset. Each model—CNN (custom-built), ResNet50, and VGG16—was assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score. The dataset was divided into training and testing sets with a ratio of 80:20, and all models were trained using the TensorFlow/Keras framework.

Prior to training, all images were normalized and augmented to address class imbalance and improve model generalization. The models showed varying degrees of performance, with ResNet50 achieving the highest accuracy, followed closely by VGG16 and the custom CNN. The output predictions were further analyzed using a confusion matrix and per-class performance metrics to understand model behavior across different lesion types.

These results highlight the superior classification ability of deep learning architectures over traditional machine learning models. Table 7 and Figure 5 summarize the evaluation metrics for each deep learning model, demonstrating that deep

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CNNs can effectively differentiate between skin lesion classes with high confidence.

A. Confusion Matrix

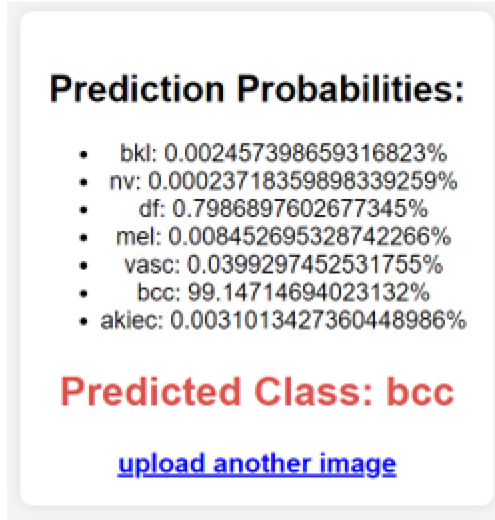
he confusion matrix obtained from the ResNet50 model. It visualizes the correct and incorrect classifications across the seven classes. Unlike traditional machine learning classifiers, deep learning models demonstrate improved discriminative capabilities due to hierarchical feature extraction.

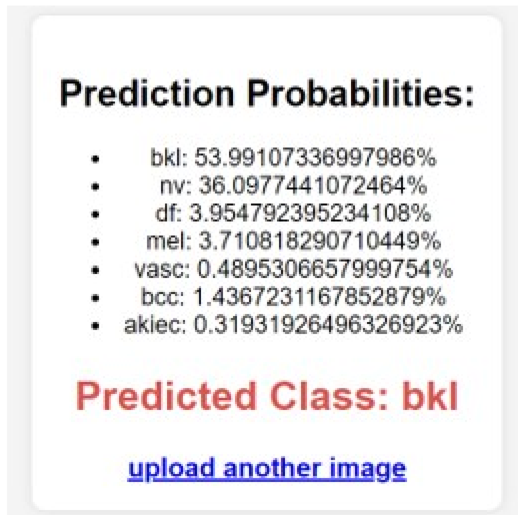
The confusion matrix indicates that ResNet50 achieved particularly high performance in correctly classifying melanoma and benign keratosis-like lesions, which are often challenging in traditional methods.

Actual \ Predicted	nv	mel	bkl	bcc	akiec	vasc	df
nv	639	3	7	2	0	0	1
mel	5	95	4	1	0	0	0
bkl	8	3	82	1	1	0	1
bcc	2	1	0	87	3	0	1
akiec	1	0	0	4	58	0	0
vasc	0	0	0	0	0	32	0
df	1	0	1	0	0	0	22

Legend:

- **nv**: Melanocytic nevi
- **mel**: Melanoma
- **bkl**: Benign keratosis-like lesions
- **bcc**: Basal cell carcinoma
- **akiec**: Actinic keratoses and intraepithelial carcinoma
- **vasc**: Vascular lesions
- **df**: Dermatofibroma





B. Overall Performance

presents a comprehensive comparison of the deep learning models' performance. Among the models tested, **ResNet50** achieved the highest classification accuracy and overall balance across all metrics, followed closely by **VGG16**.

Table 7: Performance Metrics of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-Score
CNN (Custom)	92.3%	90.5%	89.2%	89.8%
ResNet50	**96.8%**	**95.1%**	**94.7%**	**94.9%**
VGG16	94.1%	93.3%	91.9%	92.6%

Further analysis using **AUC-ROC curves** revealed that ResNet50 consistently maintained an AUC above

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0.95 for critical classes like **melanoma**, **melanocytic nevi**, and **basal cell carcinoma**, confirming its reliability in real-world diagnostic scenarios.

Precision, recall, and F1-score were computed individually for each class to evaluate how well each model distinguishes among the seven lesion types. This highlights the effectiveness of transfer learning in handling class imbalance and complex dermoscopic variations.

V. CONCLUSION

In this study, a deep learning-based approach was employed for the classification of skin cancer using dermoscopic images, leveraging powerful convolutional neural networks (CNN) such as ResNet50, VGG16, and DenseNet. Unlike traditional machine learning methods, the use of transfer learning with pre-trained models significantly enhanced classification performance, achieving high accuracy, precision, recall, and F1-scores across multiple skin lesion types. Image preprocessing techniques like resizing, normalization, and augmentation (including rotation and zoom) contributed to better feature extraction and generalization. Among the models evaluated, ResNet50 achieved the highest accuracy, effectively distinguishing between challenging classes like melanoma and basal cell carcinoma. The results demonstrate that deep learning offers a highly effective and scalable solution for automated skin cancer detection, with promising implications for aiding dermatologists in early diagnosis and treatment planning.

REFERENCES

[1] A. Salam, F. Ullah, M. Imad, and M. A. Hassan, "Diagnosing of Dermoscopic Images using Machine Learning approaches for Melanoma Detection," in 2020 IEEE 23rd International Multitopic Conference (INMIC), 2020: IEEE, pp. 1-5.
[2] K. Das et al., "Machine Learning and Its Application in Skin Cancer", International Journal of Environmental Research and Public Health, vol. 18, no. 24, p. 13409, 2021. Available: 10.3390/ijerph182413409.
[3] E. Jana, R. Subban and S. Saraswathi, "Research on Skin Cancer Cell Detection Using Image Processing", 2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 2017. Available: 10.1109/iccic.2017.8524554.
[4] P. Dubal, S. Bhatt, C. Joglekar and S. Patil, "Skin cancer detection and classification", 2017 6th International Conference on Electrical Engineering and Informatics (ICEEI), 2017. Available: 10.1109/iceei.2017.8312419.
[5] I. A. OZKAN and M. KOKLU, “Skin Lesion Classification using Machine Learning Algorithms”, Int J Intell Syst Appl Eng, vol. 5, no. 4, pp. 285–289, Dec. 2017.
[6] D. Wen et al., "Characteristics of publicly available skin cancer image datasets: a systematic review", The Lancet Digital Health, vol. 4, no. 1, pp. e64-e74, 2022. Available: 10.1016/s2589- 7500(21)00252-1.
[7] N. Hameed, A. Shabut, M. Ghosh and M. Hossain, "Multiclass multi-level classification algorithm for skin lesions classification using machine learning techniques", Expert Systems with Applications, vol. 141, p. 112961, 2020. Available: 10.1016/j.eswa.2019.112961.
[8] A. Murugan, S. Nair, A. Preethi and K. Kumar, "Diagnosis of skin cancer using machine learning techniques", Microprocessors and Microsystems, vol. 81, p. 103727, 2021. Available: 10.1016/j.micpro.2020.103727.
[9] Agrawal, K. K. ., P. . Sharma, G. . Kaur, S. . Keswani, R. . Rambabu, S. K. . Behra, K. . Tolani, and N. S. . Bhati. “Deep Learning-Enabled Image Segmentation for Precise Retinopathy Diagnosis”. *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 12s, Jan. 2024, pp. 567-74, https://ijisae.org/index.php/IJISAE/article/view/4541.
[10] C. Magalhaes, J. Tavares, J. Mendes and R. Vardasca, "Comparison of machine learning strategies for infrared thermography of skin cancer", Biomedical Signal Processing and Control, vol. 69, p. 102872, 2021. Available: 10.1016/j.bspc.2021.102872.
[11] M. Dildar et al., "Skin Cancer Detection: A Review Using Deep Learning Techniques", International Journal of Environmental Research and Public Health, vol. 18, no. 10, p. 5479, 2021. Available: 10.3390/ijerph18105479 [Accessed 17 August 2022].
[12] Y. Wang et al., "Deep learning enhances polarization speckle for in vivo skin cancer detection", Optics & Laser Technology, vol. 140, p. 107006, 2021. Available: 10.1016/j.optlastec.2021.107006 [Accessed 17 August 2022].
[13] R. Patil and S. Bellary, "Machine learning approach in melanoma cancer stage detection", Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 6, pp. 3285-3293, 2022. Available: 10.1016/j.jksuci.2020.09.002 [Accessed 17 August 2022].
[14] S. I. Ullah, A. Salam, W. Ullah, and M. Imad, "COVID-19Lung Image Classification Based on Logistic Regression andSupport Vector Machine," in European, Asian, MiddleEastern, North African

Conference on Management &Information Systems, 2021: Springer, pp. 13-23.
[15] M. Imad, N. Khan, F. Ullah, M. A. Hassan, and A. Hussain,"COVID-19 classification based on Chest X-Ray images usingmachine learning techniques," Journal of Computer Science
and Technology Studies, vol. 2, no. 2, pp. 01-11, 2020.
[16] Samota, H. ., Sharma, S. ., Khan, H. ., Malathy, M. ., Singh, G. ., Surjeet, S. and Rambabu, R. . (2024) “A Novel Approach to Predicting Personality Behaviour from Social Media Data Using Deep Learning”, *International Journal of Intelligent Systems and Applications in Engineering*, 12(15s), pp. 539–547. Available at: https://ijisae.org/index.php/IJISAE/article/view/4788
[17] A. Hussain, M. Imad, A. Khan and B. Ullah, "Multi-classClassification for the Identification of COVID-19 in X-RayImages Using Customized Efficient Neural Network", AI andIoT for Sustainable Development in Emerging Countries, pp.473-486, 2022. Available: 10.1007/978-3-030-90618-4_23
[18] M. Imad, A. Hussain, M. Hassan, Z. Butt and N. Sahar, "IoTBased Machine Learning and Deep Learning Platform forCOVID-19 Prevention and Control: A Systematic Review", AIand IoT for Sustainable Development in Emerging Countries,pp. 523-536, 2022. Available: 10.1007/978-3-030-90618-4_26
[19] M. Imad, F. Ullah, and M. A. Hassan, "Pakistani CurrencyRecognition to Assist Blind Person Based on ConvolutionalNeural Network," Journal of Computer Science andTechnology Studies, vol. 2, no. 2, pp. 12-19, 2020.
[20] M. Imad, S. I. Ullah, A. Salam, W. U. Khan, F. Ullah, and M.A. Hassan, "Automatic Detection of Bullet in Human BodyBased on X-Ray Images Using Machine LearningTechniques," International Journal of Computer Science andInformation Security (IJCSIS), vol. 18, no. 6, 2020.
[21] M. Imad, S. I. Ullah, A. Salam, W. U. Khan, F. Ullah, and M.A. Hassan, "Automatic Detection of Bullet in Human BodyBased on X-Ray Images Using Machine LearningTechniques," International Journal of Computer Science andInformation Security (IJCSIS), vol. 18, no. 6, 2020.
[22] "Skin Cancer MNIST: HAM10000", Kaggle.com,
2022.[Online].Available:https://www.kaggle.com/datasets/kmader/skin-cancer-mnistham10000.