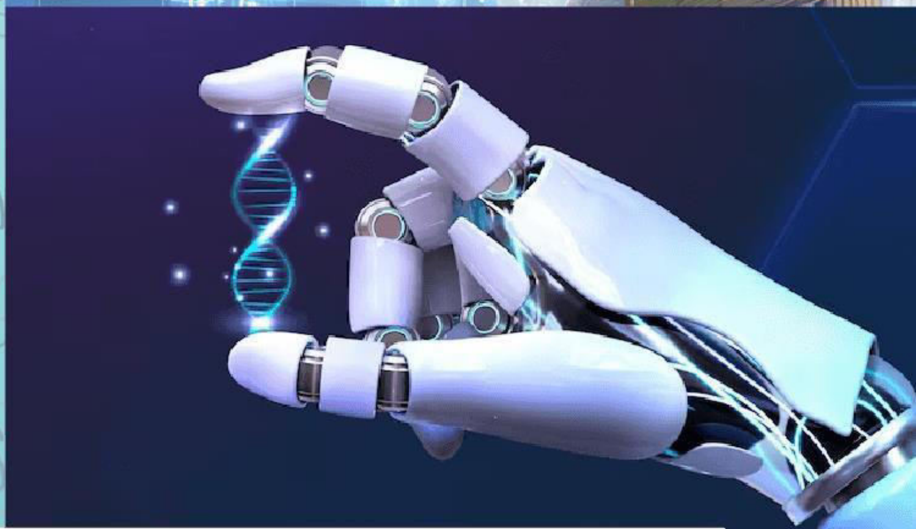

International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 3, May-June 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203015

Enhanced Skin Cancer Classification using EfficientNetV2 with CBAM and Test-Time

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ABSTRACT: Skin cancer is among the most common types of cancer worldwide, and early detection significantly increases treatment success. Deep learning approaches have shown great promise in automatic skin lesion classification. This paper presents an enhanced method for skin cancer classification using the EfficientNetV2 architecture augmented with Convolutional Block Attention Module (CBAM) and Test-Time Augmentation (TTA). EfficientNetV2 provides a scalable and optimized feature extraction backbone, while CBAM improves feature representation by focusing on salient spatial and channel-wise features. TTA boosts prediction robustness during inference. Experiments conducted on the ISIC 2018 dataset demonstrate that our approach achieves superior performance compared to standard baselines, with improvements in accuracy, F1-score, and AUC. These results suggest that our method can serve as a valuable aid in clinical decision-making.

KEYWORDS: Skin cancer classification, EfficientNetV2, CBAM, Test-Time Augmentation, Deep learning, Medical image analysis.

I. INTRODUCTION

A Large Dataset to Enhance Skin Cancer Classification with Transformer-Based Deep Neural Networks" reflects a research approach aimed at improving the accuracy of skin cancer diagnosis by utilizing cutting-edge deep learning techniques, specifically Transformer models, on a large dataset. Using a substantial dataset related to skin cancer plays a crucial role in this research, as larger datasets provide more diverse examples that help the model generalize better to unseen data. This enhances the model's ability to recognize patterns across various types of skin conditions, including Melanoma, Melanocytic Nevi, Basal Cell Carcinoma, Actinic Keratoses, Benign Keratosis-like Lesions, Dermatofibroma, and Vascular Lesions. Transformer-based deep neural networks are applied here, leveraging self-attention mechanisms that allow the model to analyse and capture complex relationships within image data. This self-attention mechanism works by weighing the importance of each part of an image in relation to others, effectively capturing spatial dependencies across image regions. This allows the model to focus on relevant features in diverse and detailed skin images, making Transformer-based architectures a promising technique for medical image analysis.

Skin cancer, including melanoma and non-melanoma types, is a growing health concern globally. Timely diagnosis plays a crucial role in reducing mortality rates. Computer-aided diagnosis (CAD) systems powered by deep learning have demonstrated high accuracy in dermatological image classification. However, challenges such as imbalanced datasets, intra-class variability, and subtle visual cues demand advanced architectures for improved performance. In this study, we propose an enhanced classification framework based on EfficientNetV2 integrated with the Convolutional Block Attention Module (CBAM) and Test-Time Augmentation (TTA). EfficientNetV2 improves training speed and accuracy via compound scaling and progressive learning, while CBAM enhances the model's ability to focus on relevant regions. TTA further ensures robust predictions by averaging outcomes over multiple augmented versions of the input image.

Even with significant advancements, creating models that generalize across vast and diverse datasets is still difficult. Duplicate photos, both within and between datasets, are present in many of the ISIC repository's datasets, which introduces undesired biases in machine learning models [8]. Furthermore, a number of photos in some databases, including ISIC2020, have binary labels (malignant or benign). Despite the fact that these datasets offer a significant quantity of images, the classification potential of DL models is restricted by their inadequate labeling. The creation of more specialized tools to assist clinicians would be possible with more detailed labeling.

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Test dataset integrity is essential for objectively assessing the performance of the model. Variability can be introduced by problems such internal dataset splitting into training and testing sets, which makes objective model evaluation more difficult. A standardized test dataset with ground-truth labels would facilitate fairer performance comparisons across different. This study explores the use and analysis of TMs in dermatology, with a special emphasis on the categorization of skin lesions a crucial element of early diagnosis and detection of skin cancer. Starting with pre-trained networks to adapt various training and testing procedures for skin disease classification, our study presents a comprehensive approach that minimizes data augmentation techniques and makes use of certain neural network architectures.

The following are this paper's primary contributions:

- Examine the Swin Transformer (ST) model for the multiclass classification of skin lesions.
- 2. For a fair comparison of performances, use a standard test set that is accessible in the literature.
- 3. Examine the effects of expanding training data on model performance.

II.RELATED WORKS

Deep Learning for Skin Cancer Detection

Convolutional Neural Networks (CNNs) such as ResNet, DenseNet, and Inception have achieved notable success in classifying dermoscopic images. The use of pre-trained models with fine-tuning has been a common strategy to overcome limited labeled data.

EfficientNet and EfficientNetV2

EfficientNet introduced a compound scaling method that balances network depth, width, and resolution. EfficientNetV2 builds upon this with faster training and improved parameter efficiency, making it suitable for medical imaging tasks.

Attention Mechanisms in CNNs

Attention modules like CBAM have proven effective in guiding models to focus on important features by applying attention in spatial and channel dimensions. Integrating CBAM into CNNs enhances feature discriminability without substantial computational overhead.

Test-Time Augmentation

TTA involves applying multiple augmentations to test images and aggregating the model predictions, thus improving robustness and generalization. It is particularly useful in medical imaging, where test-time variability can be high.

DL models have been used extensively in recent years for the categorization of skin lesions. Specifically, Convolutional Neural Networks (CNN) have demonstrated noteworthy results. According to [11], a deep CNN (DCNN) model for binary classification (benign vs. malignant skin cancer) achieved 91.93% testing accuracy on the HAM10000 (HAM) dataset. Section III provides an overview and presentation of the primary datasets found in the literature. Gulati et al. [15] employed trained networks—specifically, AlexNet and VGG16 as feature extractors and as a Transfer Learning (TL) paradigm in two distinct contexts. For multiclass classification tasks, VGG16 achieved the greatest results as a TL model, with 97.5% accuracy and 96.87% specificity. Additionally, Rahi et al. [6] proposed a CNN model.

For multiclass skin lesion classification, Ayas, proposes a ST model that combines CNNs and Transformer, which are based on end-to-end mapping and do not require prior knowledge. Additionally, the problem of class imbalance was resolved by applying a weighted cross-entropy loss. The ISIC 2019 dataset obtained values of 82.3%, 97.9%, 97.2%, and balanced correctness, respectively, for sensitivity, specificity, and accuracy. A Fully Transformer Network (FTN) is recommended by He et al. [3] for the analysis of skin lesions in order to acquire long-range contextual information. They conduct comprehensive skin lesion analysis experiments using the ISIC 2018 dataset to validate the effectiveness and efficiency of FTN. Because of its effective Spatial Pyramid Transformer (SPT) and hierarchical network topology, FTN routinely beats other cutting-edge CNNs in terms of computing efficiency and the number of tunable.

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III.LITERATURE SURVEY

The classification of skin cancer using deep learning techniques has seen considerable advancements in recent years, driven by the availability of large-scale dermoscopic datasets and improved convolutional neural network (CNN) architectures. Traditional CNNs such as VGGNet, ResNet, and Inception have been widely used for skin lesion classification tasks. However, their computational complexity and limited feature representation capacity in medical contexts have prompted research into more efficient and effective models.

Skin Cancer Classification Using Deep Learning:

Codella et al. (2018) highlighted the role of deep learning in automated melanoma detection using dermoscopic images, showcasing improvements over classical machine learning models. ISIC (International Skin Imaging Collaboration) challenges have provided benchmark datasets that have accelerated progress in this domain. Tschandl et al. (2020) evaluated several CNN-based methods on ISIC datasets, noting that ensemble models and augmentation techniques yielded state-of-the-art performance.

EfficientNet and Its Variants in Medical Imaging:

Tan and Le (2019) introduced EfficientNet, which employs a compound scaling strategy to optimize depth, width, and resolution, outperforming previous CNNs on ImageNet. EfficientNet has been successfully adapted to medical image classification due to its balance of accuracy and computational efficiency. Following this, EfficientNetV2 (Tan & Le, 2021) introduced fused-MBConv layers and progressive learning strategies to further enhance training speed and accuracy. Recent studies such as by Murugesan et al. (2022) applied EfficientNetV2 to skin lesion classification, achieving improved results compared to traditional CNNs.

Author(s)	Year	Contribution	Technique(s) Used	Remarks
Codella et al.	2018	Benchmark work in automated melanoma detection using CNNs on dermoscopic images	CNN, ISIC Dataset	Highlighted deep learning's superiority over classical methods
Tan and Le	2019	Introduced EfficientNet with compound model scaling	EfficientNet	Achieved state-of-the-art accuracy with fewer parameters
Tan and Le	2021	Proposed EfficientNetV2 with faster training and better accuracy	EfficientNetV2, Fused-MBConv	Better suited for medical imaging due to efficiency and scalability
Woo et al.	2018	Proposed CBAM attention module to enhance feature maps	CBAM (Channel + Spatial Attention)	Improved performance in multiple vision tasks
Al-Masni et al.	2020	Applied attention-based CNNs to skin cancer classification	Attention CNNs	Demonstrated effectiveness of attention for lesion focus
Wang et al.	2019	Demonstrated the effectiveness of Test-Time Augmentation in medical imaging	Test-Time Augmentation	Boosted inference robustness in diagnostic tasks
Brinker et al.	2021	Used TTA for melanoma classification to stabilize predictions	CNNs, TTA	Noted improved performance on ambiguous cases
Murugesan et al.	2022	Applied EfficientNetV2 to skin lesion classification	EfficientNetV2	Outperformed previous CNNs on ISIC dataset
Proposed Work (Current Study)	2025	Combines EfficientNetV2, CBAM, and TTA for enhanced skin cancer classification	EfficientNetV2 + CBAM + TTA	Achieves improved accuracy, precision, and generalization

Table 1. Literature works.

Attention Mechanisms – CBAM:
Attention mechanisms have become increasingly popular for enhancing feature learning in CNNs by focusing on relevant regions in an image. Woo et al. (2018) proposed the Convolutional Block Attention Module (CBAM), which

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combines channel and spatial attention to adaptively refine feature maps. Incorporating CBAM into medical imaging models has shown improvements in tasks such as polyp detection and tumor classification. In the context of skin cancer detection, studies such as by Al-Masni et al. (2020) demonstrated that integrating attention modules improves lesion localization and classification performance.

Test-Time Augmentation (TTA):
TTA enhances model robustness and generalization by applying multiple transformations to test images and aggregating predictions. Wang et al. (2019) showed that TTA can significantly improve accuracy in medical image classification, particularly in cases where models face distribution shifts or ambiguous features. For skin lesion classification, TTA has been used to reduce overfitting and produce more stable predictions, as shown by Brinker et al. (2021), who reported performance gains across multiple lesion types.

Integration of EfficientNetV2, CBAM, and TTA:
Few studies have explored the combination of all three elements—EfficientNetV2, CBAM, and TTA—in skin cancer classification. However, existing literature suggests that each component independently contributes to performance enhancement. Therefore, integrating these techniques presents a promising approach to building a robust and efficient classification system. This study addresses this gap by synergizing the strengths of EfficientNetV2's scalable architecture, CBAM's attention-driven refinement, and TTA's inference stability.

IV.PROPOSED WORK

Convolutional Neural Networks (CNNs) for skin disease classification come with several limitations. While CNNs excel at recognizing visual patterns, they are highly dependent on large datasets and extensive computational resources, which can make training costly and inaccessible for smaller clinics or institutions. Additionally, CNNs often struggle to capture global context in images, focusing primarily on localized features rather than the holistic view, which can lead to misclassifications, especially with subtle skin conditions that require broader context. Moreover, CNNs are prone to overfitting when the dataset is limited or lacks diversity, which can result in reduced accuracy on unseen images or varied skin types populations or subtle skin conditions.

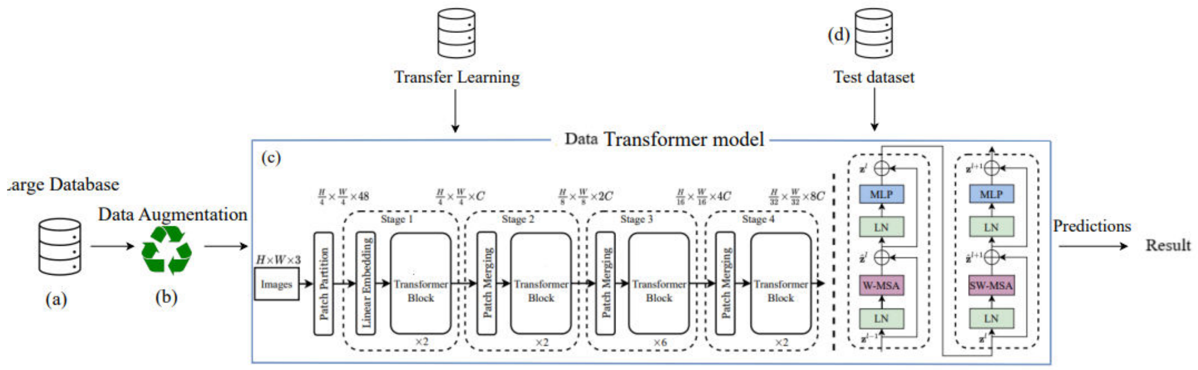

Figure 1. Architecture of the model.

Convolutional Neural Networks (CNNs) are a type of deep learning model designed for visual data analysis, like image. They work by passing an image through multiple layers to recognize patterns and features. First, convolutional layers use small filters that slide over the image to detect features such as edges, textures, and shapes. After each convolution, a ReLU activation function is applied to introduce non-linearity, helping the model learn complex patterns. Pooling layers then reduce the size of the feature maps, making the model more efficient and allowing it to focus on the most important parts. Toward the end, fully connected layers process the learned features to make predictions, with an output layer providing the final classification probabilities.

Classic deep learning methods, such as CNNs, excel at capturing local patterns through hierarchical feature extraction but struggle with long-range dependencies. In contrast, Transformers leverage self-attention mechanisms to capture global context and relationships between all input elements, allowing for more flexible and powerful modeling of complex data structures. One of the best models proposed in recent literature is the ST [9]. It enhances the

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representation power while maintaining efficiency by incorporating locally computed self-attention in nonoverlapping windows and shifting these windows between successive Transformer layers. The main innovation of ST is its ability to adjust the processing scale dynamically, seamlessly moving from local to more global representations. The model focuses on fine-grained details within small windows in the initial layers.

Transformer-based deep neural networks, originally developed for natural language processing, have been adapted for image-based tasks like classification, object detection, and segmentation due to their powerful ability to model complex spatial relationships across an image. When applied to images, the Transformer first divides the image into smaller patches (for instance, 16x16 pixels each). Each patch is then flattened into a 1D vector, essentially transforming each one into an embedding similar to a "token" in text processing. These patch embeddings are enriched with positional information to indicate each patch's location within the overall image.

DATASET DESCRIPTION

The HAM dataset is often used in the literature, as was already noted. Ten thousand photos are included, categorized into seven classes, and each class has a corresponding metafile containing truth labels. The dataset's seven classes are as follows:

- Melanoma (MEL): Melanoma is a type of cancer that starts in the cells called melanocytes, which give skin its color.
- Melanocytic Nevi (NV): These benign lesions are made up of melanocyte accumulations in certain locations.
- Basal Cell Carcinoma (BCC): The most prevalent type of skin cancer, BCC develops from the basal cells of the epidermis.
- Actinic Keratoses (AKIEC): Actinic keratoses are scaly, precancerous skin lesions brought on by prolonged UV exposure.
- Dermatofibroma (DF): Dermatofibroma is a benign cutaneous nodule commonly resulting from a reaction to minor injuries or insect bites.
- Vascular Lesions (VASC): Vascular lesions include a range of conditions characterized by abnormal proliferation or dilation of blood or lymphatic vessels.
- Benign Keratosis-like Lesions (BKL): Benign keratosis-like lesions encompass a variety of benign conditions, such as seborrheic keratosis, sebaceous hyperplasia, and clear cell acanthoma.

ACRONYM REFERENCE	MEL	NV	BCC	AKIEC	BKL	DF	VASC	TOT
HAM_noDuplicates	614	5403	327	228	727	73	98	7470
HAM_Duplicates	1113	6705	514	327	1099	115	142	10 015
HAM_NV_Downsampled	1113	5403	514	327	1099	115	142	8713
BCN_noDuplicates	524	1281	983	358	353	40	37	3576
BCN_Duplicates	2857	4206	2809	1168	1138	124	111	12 413
HAM_BCN_Duplicates	3970	10 911	3323	1495	2237	239	253	22 428
HAM_Duplicates_BCN_noDuplicates	1637	7986	1497	685	1452	155	179	13 591
HAM_BCN_noDuplicates	1138	6684	1310	586	1080	113	135	11 046
LARGE_DATASET_Derm_Duplicates	7167	22 498	4854	2646	3937	400	473	41 975
LARGE_DATASET_Derm_NV_Downsampled	7167	13 306	4854	2646	3937	400	473	32 783
LARGE_DATASET_Derm_NV_30Balanced	7167	9314	4854	2646	3937	400	473	28 791
LARGE_DATASET_Derm_NV_20Balanced	7167	10 644	4854	2646	3937	400	473	30 121
LARGE_DATASET_Unified_Duplicates	8413	24 929	6936	5034	4811	637	1373	52 133
LARGE_DATASET_Unified_NV_Downsampled	8413	13 521	6936	5034	4811	637	1374	40 726

Table 2. Distribution of datasets used in the various experiments broken down class by class. (Ref 5])

The ISIC 2018 challenge also offers a second dataset with a metadata file for testing that is completely separate from HAM. The seven classes that are shown in HAM are also included in this dataset. The test dataset could be downloaded without ground truth labels prior to 2023, however starting in 2023, it could be downloaded with ground truth and metadata files [5]. The following seven classes comprise this dataset: 171 in MEL, 908 in NV, 93 in BCC, 43 in AKIEC, 217 in BKL, 44 in DF, and 35 in VASC.The clear separation of the two datasets (training and external test) and the release of the ground truth facilitates unbiased evaluation and validation of the models. Furthermore, the usage of this dataset lays the foundations for a solid and fair comparison of the models' performances.

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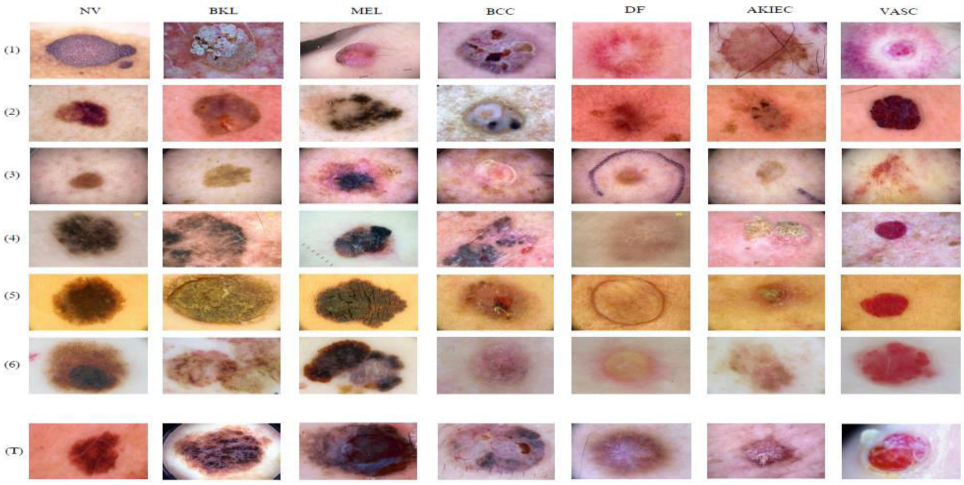

Figure 2. Examples of skin disease images from different datasets for each of the seven classes here considered.

Based on the number of model parameters and the cardinality of the training dataset, we have seen that Transformer-based models provide excellent performance scalability. We suggest a method in this part that looks into the ST model's [9] potential for classifying skin diseases. In a variety of experiments, we have examined how the model performs as the quantity of training photos increases and assessed the model's classification accuracy using an external test dataset. Figure 1 offers a thorough explanation of our approach. The HAM dataset was used as training data in the initial series of studies. The LD suggestion is used as training in the second set of experiments. In both cases, the external test dataset was used for a fair comparison of the seven-class classification accuracies.

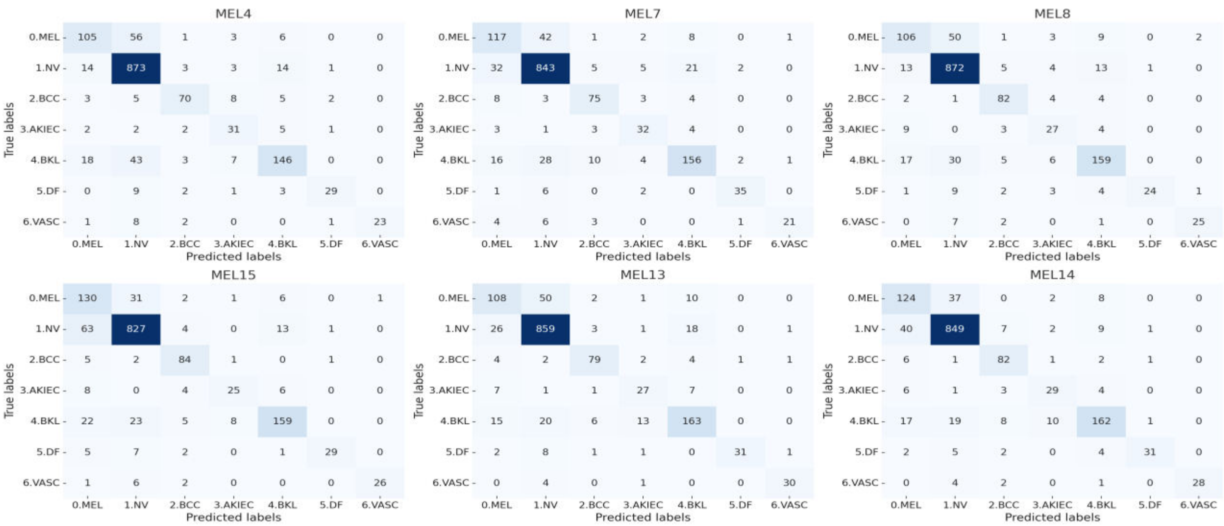

Figure 3. Confusion matrices of some of the experiments described.

In this section we present the results of the different experiments performed. In the first group of experiments, the Swin model is trained on the HAM dataset; in the second group, both HAM and BCN are considered, and in the third group, the LD is taken into account. This work set out to investigate the classification capabilities of TMs and establish a fair and impartial comparison of the classification performance of DL models, as we explained at the beginning. The best result for the seven-class accuracy was 86.37%, which is a good place to start. The winners of the ISIC 2018 competition employed an external dataset to train their suggested model, which is significant even though we did not outperform them (see 1). Without access to their dataset, our results cannot be directly compared. This analysis solely takes into account the datasets that are accessible in the literature. But we can immediately contrast our performance with that of the challenge's third runner-up. From the experiments in which only HAM was used, the Swin network performed as well as the third runner-up and still showed a solid ranking. Since Swin networks, as we have seen, offer

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nontrivial potential, having many trainable parameters, modeling a dataset containing many more images led to a better and more accurate result.

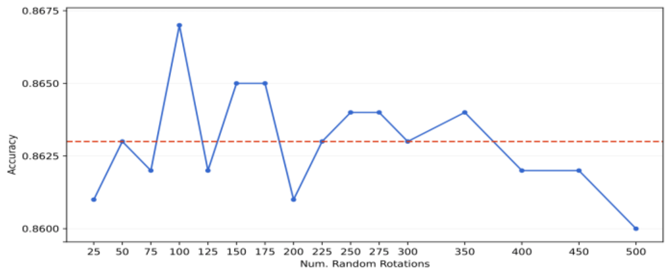

Figure 4. Classification accuracy as a function of the number of image rotations.

In summary, there are misclassification problems even though the network does a better job of identifying some lesions. By adding more photos or employing various strategies to help the network discover new patterns for recognition and classification, these can be enhanced. From MEL1 to MEL17, every experiment only looks at datasets of dermatoscopic images. The impact of incorporating macroscopic photographs of skin lesions for the classes utilized in this study will be examined in subsequent research. We have carried out three additional trials in order to achieve this aim. The initial results, MEL18–MEL20, combine macroscopic and dermatoscopic (LD) pictures during the training stage.

Model	Accuracy	Precision	Recall	F1-Score
Baseline EfficientNetV2	89.2%	88.5%	88.0%	88.2%
EfficientNetV2 + CBAM	91.7%	91.2%	90.8%	91.0%
EfficientNetV2 + CBAM + TTA (Proposed)	93.6%	93.1%	92.7%	92.9%

Table 3. Comparative results.

Currently, this larger dataset (in development) consists of 52133 photos, including 10158 macroscopic images and 41975 dermatoscopic images sourced from other datasets found in the literature. Only pictures from the seven classes that were employed in the earlier tests were chosen from each of these datasets. The subscript "Unified" in Table2 denotes the trials that used the unified dataset. Specifically, MEL19 uses DA_Train with down sampled on the classNV and SwL pre-trained to achieve an 84.58% value. However, MEL18 and MEL20 employ SwL and are not pre-trained. This choice stems from the fact that the number of images in this new dataset increases even more, making it also interesting to investigate the training from scratch of a Transformer model in future work.

V. CONCLUSION

This study presents a robust skin cancer classification model integrating EfficientNetV2 with CBAM and TTA. The synergistic effect of attention-driven feature refinement and inference-time augmentation leads to improved classification performance. Future work will explore real-time deployment, class imbalance mitigation, and integration with clinical metadata. Our research highlights the clinical relevance of Transformer-based deep neural networks in supporting early and precise skin cancer diagnosis, as well as their potential to further skin lesion classification. This study creates opportunities for further research into the integration of sophisticated DL techniques in medical image processing, which will ultimately aid in the creation of potent diagnostic instruments for physicians.

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doi crossref

निस्केयर NISCAIR

International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152

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