Enhanced Skin Lesion Classification Using Fine-Tuned DenseNet201 with Self-Attention Mechanisms

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***Abstract*— Skin lesions, if diagnosed in early stages can be treated and cured properly. Manual screening of images to identify skin lesions is time-intensive and highly prone to human errors. It also needs experts in the field to accurately diagnose the problem which is often not possible in remote areas, thereby, generating a need for automated skin lesion classification using Deep learning techniques. Hence, the paper focuses on skin lesion classification using deep learning across eight classes, employing various models. The work proposed in this paper employs the DenseNet201 model due to its superior accuracy and further fine-tunes and enhances it by integrating self-attention layers between the dense layers. This modification notably improved classification accuracy. By employing self-attention mechanisms, DenseNet201 achieved improved accuracy, highlighting its efficacy in skin lesion classification and outperforming other state-of-the-art methods such as MobileNetV2, DenseNet201, VGG-16, etc with an F-score of 80%. The study underscores the significance of model selection and architectural modifications in enhancing classification performance, particularly in medical imaging applications.**

Keywords*— *skin lesion, medical imaging, deep learning, DenseNet201, self-attention.

I. Introduction

Deep learning stands out in classifying skin lesions, playing an important role in investigating the treatment, diagnosis and even reaching the revolution of dermatology. Automation brings controlled outcomes, provides a basis for scalability, and lowers the tendency of intermittency as the staffing shortage hits geographical areas where the personnel professionally trained in healthcare is few and far in-between. Deep learning models have played a vital role in the process of early detection of health problems and as a result, saved a lot of money on healthcare as well as provided better health outcomes. Through deep learning, specific chapters of dermatology are being studied by finding probable solutions and respective dissemination, which improves the general knowledge of this body of medicine and assistance for both the patients and the global health community.

Besides challenges of the skin lesion classifications using deep learning, they are also accompanied by various tough issues. The most notable issue is often training deep learning models on a few high-quality and various data sets. We spend much on acquiring labeled data, and this takes time. Typically, deep learning models struggle with their inability to be generalized to rare and unrecognized lesions like unique or new diseases. Another problem is the interoperable of the model and the reasoning behind the model's decision. The hidden natures of the deep neural networks, which are usually vague, are central to how they work. Bias and fairness problems can occur; therefore, the diagnoses may show variability in different groups locally. Last but not least, while deep learning models are employed for melanoma diagnosis in clinical settings, regulatory and ethical issues should be taken into account. Such as, therefore, patient-related issues like patient privacy and patient safety need to be considered.

While classification is one of the most advanced machine learning techniques for analyzing and classifying skin abnormalities with the help of image data AI models could be trained on big sets of represented images that could distinguish several types of skin diseases by using patterns and specifics as a point. Deep learning models work on automated detection of skin diseases as well and they accomplish this task with a high level of precision when trained on a sufficient amount of data. It enables the establishment of the disease of skin at the early stage with enough sensitivity and treatment. Deep learning holds a significant place in the domain of dermatology. Deep learning has been demonstrated to be highly accurate in similar tasks - finding abnormalities and distinguishing diffuse lesions. In dermatology, the CNNs learned to catch the differences between benign skin growths (no threat) and malignant skin growths (cancer conditions). In return, after the training, the weights of the CNN would be the more accurate ones in categorizing skin lesions and this paper focuses on developing a similar kind of efficient classification model for the skin lesion classification task. The main contributions of the paper are:

- Enhanced and fine-tuned DenseNet201model by integrated with optimally placed Self-attention layer between dense layers.
- Analysis of placement of self-attention layers at different levels in the model to obtain the best model.
- Implementation and comparative analysis of various state-of-art classification models like MobileNetV2, VGG-16, and DenseNet201, ReseNet152, InceptionResNetV2 with the proposed model.
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II. LITERATURE SURVEY

Kassem, M.A., et al. [1] proposed an evolving algorithm that used deep learning model Google Net models for identifying skin lesions. Outdated methods were inexact and were very difficult to use. With the introduction of the transfer learning technique, their accuracy significantly enhanced and helped in obtaining better automatic skin lesion classification which is a widely used tool for skin cancer scanning and early detection. Amudha, J., et al. [2] discussed a study that showed both ResNet and VGGNets are useful in the task of disease detection, and the ResNet is particularly effective for the recognition of objects. The task of predicting the disease mechanisms is a complex problem that can be divided into several classes; however, the level of accuracy will assist a clinical judgment to ascertain the identification of the disease along with the implementation of the effective treatment.

Shrinithi, S. et al. [3] took images from the sampled skin specimens to detect melanoma in the donated kidneys. They dealt with image pre-processing techniques on images of skin and melanoma for further analysis. In addition to using SVM with the linear kernel for lesion detection, the accuracy of the self-developed algorithm has been gained. So, the research results provided evidence of the usefulness of SVM for melanoma detection in skin images at early stages. Venkatraman et al. [4] discussed a new add-on module in UDR and MDP, which is well-combined with one of the reinforcement learning methods for the segmentation extraordinary efficiency. With the use of a self-supervising mode, this approach concentrates on critical image regions and gets better image segregation results than the conventional procedure as they have shown in the ISIC 2017 data.

Aishwarya, N., et al. [5] came up with a modified YOLO (You Only Look Once) program to carry out complicated resume-like jobs fast and efficiently. Tiny images and expert comparisons helped them tune you only look once (YOLO) to improve the image sharpness and highlight the important parts instead of using whole images. The type of images used (e.g. YOLO v3 or v4) was applied to a test of 4,389 images. Kadirappa et.al. [6] used the EfficientNet-B1 system to classify different skin cancer types. The results showed high performance with 2017 and 2020 images, making it one of the best systems for automated skin cancer detection. Later Azeem et al. [7] came up with a skin cancer detector that was employed using the SkinLesNet model which consisted of multi - a multi-layered convolutional neural network system. So, the SkinLesNet architecture appears the perform that is the same as dermatologist's diagnoses, and the realizable accuracy is also higher than ResNet50 and VGG16.

Alsahafi et al. [8] facilitated by an RCNN-powered deep learning application proposed Skin-Net which is capable of identifying the features of the skin lesions as well as classifying them by exploiting the channel-wise dependencies. During this process, the data sets that are based on the one-eye of a person are converted into an image vector, and the precise values for recognizing them are given. Sindhu et.al. [9] proposed the Resenet50 model for the elimination of diagnostic errors as compared with the rest of the methods, permitting to use of cancer diagnosis using image analysis with not much effort.

Bozkurt, F., et.al. [10] spoke about utilizing the Inception-ResNet-v2 model for advanced cancer classification. Their system provides a wider data set through manipulation, which contributes to efficient disease discrimination, that leads to improved and fastened diagnostic processes. Mohammed et.al. [11] featured customized Xception backbones and soft attention modules, which demonstrate great classification ability, attaining the highest performance up to 2% than the state-of-the-art schemes. Aravindan et.al. [12] proposed a new model utilizing Deep Convolutional Neural Networks (DCNNs), transfer learning, and dataset augmentation techniques that accurately identify skin cancer types from Dermoscopy images. They tested the model on ISIC 2019 and ISIC-2020 datasets with the Efficient Net variants. EfficientNet-B6, outperformed other methods, offering potential for improved skin problem diagnosis in clinical practice.

Maqsood et.al. [13] have invoked the computer-aided Diagnosis (CAD) application that uses deep learning as well as image enhancement techniques to arrive at a clearer diagnosis and reach a diagnostic solution remotely. While they yield better outcomes, those prevail over the others indicating that AI and IoT can offer medical care services. Rajabi et.al. [14] improved skin cancer diagnosis using deep neural networks, including pre-trained models and a modified Alex Net trained with skin images. They employed dropout for performance enhancement Through cross-validation, their model showed a better accuracy boost, showcasing the efficiency of pre-trained networks in diagnosis.

Nazir et.al. [15] used MobileNetV2 and NasNet Mobile having the structure for mobile usage and the two-stage thresholding approach to reach the efficient vision model. An optimization technique assists the monitoring of the variation and in actual sense is the best approach to compare with other techniques. Such an outcome would act as a basis for increasing the level of trust in the system. Hussein et al. [16] created the methods of two ways for skin disease detection. The first employs KNN and Kera’s implementation of pre-trained neural nets such as Alex Net, VGG-16, and VGG-19 that can pull down the depth of details required from the images. The following one points to an adaptation of Alex Net with the grey wolf optimizer that does further fine-tuning. Proven to begin effective diagnosis based on pictures of 4000 cases with ISIC images, both methods were accurate.

Manju et al. [17] adopted DenseNet 169 and ResNet 50 networks using a transfer learning framework. DenseNet 169 took the crown in terms of accuracy, while ResNet 50 was slower and didn't show improved accuracy that much but it did well with high data oversampling. This is an illustration of the power of deep learning in making the early cancer eyeing of the skin more effective, one of which might be utilized in the prevention of disease. The project for the next period is to incorporate additional variables in the model description and overall setup to achieve higher precision. Sulthana, et.al. [18] exhibited one pertinent use of the MobileNet model for skin lesion classification and achieved an accuracy of 89%. Through the use of MobileNetV2, we had computational performance advances by 6%. The paper suggests that as a compression technique without the use of more resources, the S-Mobile could be utilized to reach the aim of improved accuracy.

Chanda et.al. [19] introduced DCENSnet as a novel methodology with three DCNN models and layers for higher precision. We can conclusively assert that DCENSnet is the topper in the test set since it is the method that shows the best results in the everybody first stage when it comes to tattoo recognition and tattoo sectioning. Deng et.al. [20] presented LSNet which is a deep-learning method for classifying skin lesions caused due to various types of skin infections. It adopts a basic local input and a special encoding technique called the Reverse cursor, respectively. In this case, the datasets used are ISIC2018 or ISIC2019, and the LSNet outperforms the current assessment methods. Its capability to achieve a higher accuracy and performance. Several other Deep CNN models have been used in identifying and classifying such problems using images [21, 22]

III. Dataset description

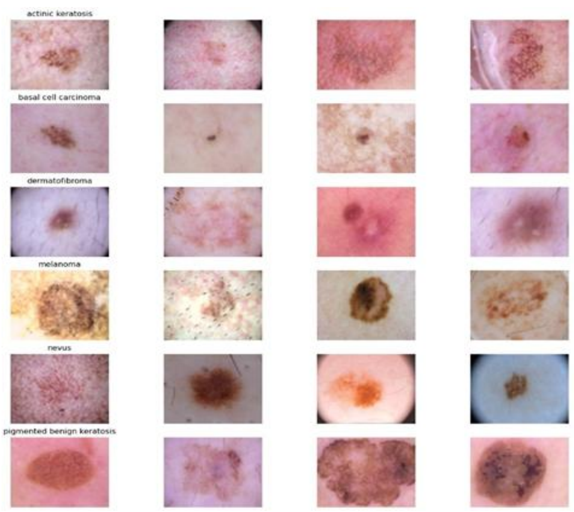

Fig.1: Sample skin lesions Images

The 2019 dataset developed by ISIC carrying over 2500 images of skin lesions is categorized into nine types: Melanoma, Malignant Melanocytic Nevus, Squamous Cell Carcinoma, Basal Cell Carcinoma, Actinic Keratosis, Benignial Keratosis, Dermatofibroma, Bevacizumab Vascular Lesion, and Long-Term Inflammation Squamous Cell Carcinoma. It offers classifying images based solely on visual features or incorporating additional metadata to facilitate model evaluation during the challenge on a separate validation dataset.

IV. Methodology

The overall methodology followed to propose the hybrid architecture of attention attention-enabled DenseNet201 model is presented in Fig 2.

A. Data preparation

In the process, the ISIC 2019 data set was employed for evaluation in the research. This data set contains 8 classes of diseases where there are two benign diseases and four different types of cancer. The classes include Melanoma, Melanocytic Nevus, Basal Cell Carcinoma, Actinic Keratosis, Benign Keratosis, Dermatofibroma, and Vascular Lesion. And there is Squamous Cell Carcinoma and others. Data processing is the application of data augmentation techniques like rotation, flipping, zooming, and color corrections with the essential purpose of increasing the number of types of data and removing the overfitting from the data. We performed the main standardization of the pictures to the uniform measurement standards to ensure the same level for all the figures for keeping the model with the same quality.

The proposed architecture employed the pre-trained DenseNet-201 model and fine-tuned it on the ISIC 2019 dataset by removing the output layer and adding dense layers and attention layers towards the trailing end of the model. DenseNet-201 is a deep convolutional Neural Network that incorporates 201 layers and contains densely connected layers and blocks. This architecture promotes feature reuse and reduces the number of parameters compared to traditional convolutional networks. It includes four dense blocks separated by transition layers that consist of batch normalization, ReLU activation, and pooling operations.

While in self-attention, the focus is on the exact parts of the input sequence that are important to be seen by the model. Among these, the most widely used one is used to calculate a sum product of input elements with matched features where the weight value of features is proportional to the level of matching elements. This technique will assist the model in managing dependency and contextual information in the long-range dependencies while modeling it. For the stated code, a self-attention layer – SeqSelfAttention layer that is applied with sigmoid non-linearity that inserts the model with an ability to encourage it to attend different patterns of the data after transforming the input into an appropriate shape for attention computation.

B. Proposed Architecture

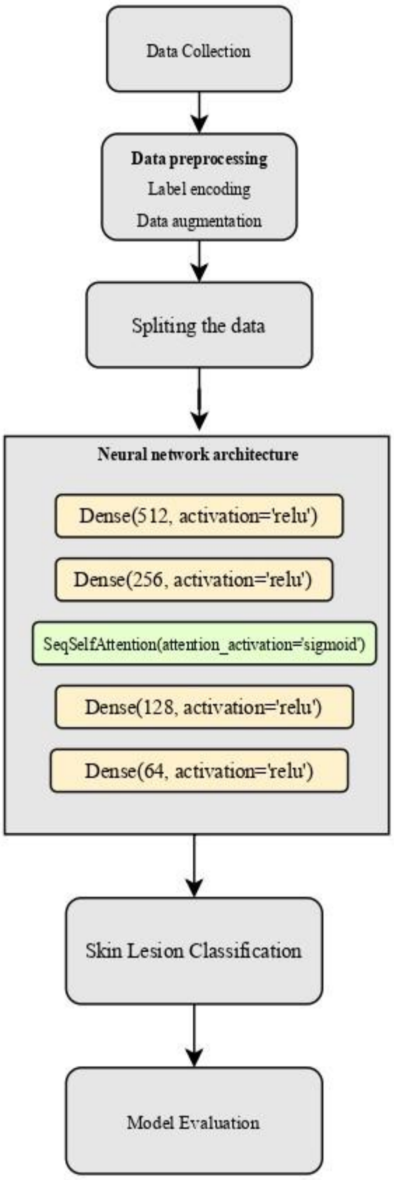

Fig.2: The proposed fine-tuned DenseNet201 model with self-attention mechanism

Transfer learning is implemented by loading the DenseNet201 architecture and preserving the weights of the layers. On top of this, a series of custom layers are added: Its fully connected hidden layer with 512 neurons, reshaped output, and a self-attention layer that helps the model focus on important features, it is then flattened and transformed into a vector that is used with three more dense layers with 256, 128, and 64 neurons, respectively, and dropout in between to produce the final output We have added self-attention layers between the dense layer 1 & 2 and 2&3 and 3&4 dense layers, each one improving the ability of the neural network to concentrate on relevant features at every stage. Self-attention layer in deep learning models decides how input sequence elements are important by calculating attention scores that help to pay more attention to the useful parts. This enhanced the model in the way it captures both far, and near, context, which in return boosted its performance in lesion image analysis and classification. Next, the output layer with a SoftMax function produces a vector of probabilities for each class.

V. Experimental setup

In this work, several deep learning models were implemented to understand their performances on the ISIC 2019 dataset for final model selection and comparative analysis.

TABLE1: PARAMETERS SETTINGS

Training: Validation: Testing	80:10:10
Batch size	32
Image height and width	(75*100)
Activation Function	ReLU, SoftMax
Optimizer	SGD (Stochastic gradient descent)
Loss Function	categorical_crossentropy
Metrics	accuracy, precision, recall, f1-score
No. of epochs	150
steps_for_each_epoch	450 steps

The main state-of-art models implemented were DenseNet201, VGG16, ResNet152, InceptionResNet152 and MoblieNetV2. All the models have been trained and tested on the ISIC 2019 dataset using the same set of parameters as presented in Table 1. The model was trained and validated with 80:10:10 data spilled, using a batch size of 32 and image dimensions of 75x100. Here, we used ReLU and SoftMax activation function, SGD-optimizer, and CategoricalCrossentropy as a loss function. We trained the model for 150 epos and 450 steps per epoch and employed accuracy (Acc), precision (Pr), recall (Re), and F-score (Fs) as evaluation metrics [23].

As mentioned earlier, During fine-tuning we placed self-attention layers between dense layer 2 and dense layer 3. This placement helps the model to be centered on the right input areas; thereby improving feature extraction. The chosen position keeps the performance improvement relatively high while trainable introduced parameters remain low. The presented integration provides a considerable enhancement in classification performance.

TABLE2: PERFORMANCE ANALYSIS OF FINE-TUNED DENSENET201 MODEL WITH SELF-ATTENTION (SA) APPLIED AT DIFFERENT LOCATIONS IN THE ARCHITECTURE

Models	Metrics				
	Pr	Re	Fs	Acc	Loss
DenseNet201 without SA	0.78	0.78	0.77	0.78	0.61
DenseNet201 with SA in Dense Layer (1,2)	0.77	0.77	0.77	0.77	0.94
DenseNet201 with SA in Dense Layer (2, 3)	0.80	0.80	0.80	0.80	0.61
DenseNet201 with SA in Dense Layer (3, 4)	0.79	0.79	0.79	0.79	0.59

Table 2 presents the analysis of the fine-tuned DenseNet201 model with self-attention layers at different locations. It can be seen that by adding a self-attention layer between the Dense Layers (2,3) (as depicted in Fig.2) in model achieved the best overall performance across precision, recall, F1-SCORE, and accuracy, with a notably lower loss.

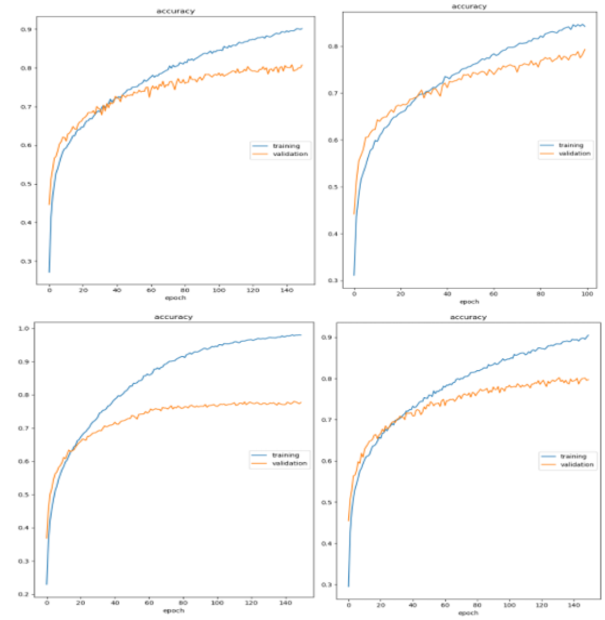

Fig 3: Training and validation accuracies for (a) Densenet201, (b) Dense net (Layer 1&2), (c) Dense net (Layer2&3), Dense net (Layer3&4)

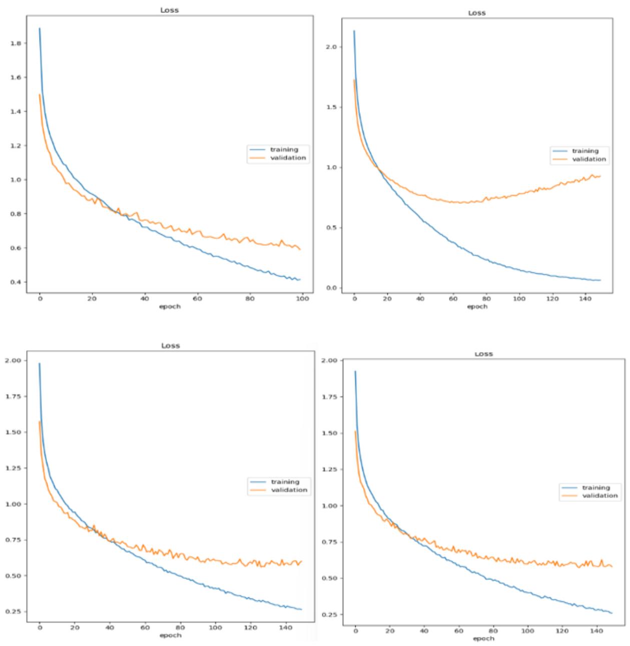

Fig. 4: Training and validation Loss for (a) Densenet201, (b) Dense net (Layer 1&2), (c) Dense net (Layer2&3), Dense net (Layer3&4)

The overall performance of the Proposed architecture leveraged DenseNet201's performance by 2% in terms of F-Score and accuracy by finding a perfect balance between the Recall and Precision values as well.

Loss and accuracy graphs depict how well a model performs during both the training and validation phases across different iterations. The loss graph displays how the error rate decreases as the model becomes more proficient, typically reaching the lowest point. On the other hand, the accuracy graph demonstrates how the model's ability to make predictions gets better, striving to reach a maximum level. These graphs are useful for spotting issues like overfitting, underfitting, and determining the best number of iterations for training.

TABLE3: COMPARATIVE PERFORMANCE OF THE PROPOSED MODEL AGAINST STATE-OF-ART CLASSIFICATION MODELS

Models	Performance Metrics				
	Acc	Pr	Re	Fs	Loss
Densenet201	0.78	0.78	0.78	0.77	0.61
VGG16	0.73	0.74	0.73	0.73	0.74
MobileNetV2	0.60	0.60	0.60	0.59	1.48
InceptionResN etV2	0.60	0.60	0.60	0.60	1.14
ResNet152	0.57	0.57	0.56	0.56	1.23
Proposed Model	**0.80**	**0.80**	**0.80**	**0.80**	**0.61**

As presented in Table 3, for these experiments that classified images into eight types of skin lesion classes and used deep learning models MobileNetV2, DenseNet201, VGG-16, etc. we did the evaluation. The following architectures which are among the characterized ones are like DenseNet201 which has more accuracy than the other models. DenseNet201 demonstrated the best performance across all metrics with the lowest loss, while VGG16 had slightly lower metrics, and MobileNetV2 showed the lowest performance with the highest loss. In this regard, the DenseNet201 model is shifted from one dense layer to the main component by introducing self-attention layers. This helped us increase the performance of the model. This approach focused attention of the model on the most significant features which in turn led to better results with the model's overall performance excelling further than it would have compared to other models. Enhancing the DenseNet201 led to increased accuracy, recall, and F1-score at 80%, proving to be valuable in near-consummate detection and categorization of different types of skin lesions. The integrated self-attention module turned out to be the critical element promoting the accuracy of the model, which may lead to the use of the model as clinical decision-making support in dermatology.

Benchmarking Against Recent Deep Learning Models:

In Comparison with the recent models such as Efficient Net, ResNet50, ResNet101, ResNet152, Inception v3, and Xception, and layouts of attention mechanism in styles of custom model, we observed that our Dense Net 201 model combined with self-attention yielded a better performance in the task of skin lesion classification. While Efficient Net and ResNet variants excelled in transfer learning applications, and many researchers used ensemble approaches to achieve high accuracy on datasets like ISIC 2019, our model achieved notable metrics: Precision (Pr: 0.80, Recall (Re:

0.80, F1-score (Fs: 0.80, Accuracy (Acc: 0.80, and Loss: 0.61. The incorporation of self-attention layers in between the dense layers enhanced the feature extraction and the classification accuracy on 8 classes, which placed our proposed method as a credible solution, in terms of computational efficiency, for discriminating different types of skin lesions.

VI. Conclusion

The proposed study on skin lesion classification using deep learning across 8 classes has analyzed the efficiency of different deep learning models including MobileNetV2; DenseNet201; VGG-16, etc. The Fine-tuned DenseNet201 model with several additional dense layers and self-attention layers at the most optimal position i.e. between dense layer 2 and dense layer 3, is one of the best options for the skin lesion classification because of its accurate degree. DenseNet201's F1-Score was increased by introducing extra layers of self-attention between dense layers, yielding further additional degrees of classification accuracy. It is a testament to the impact of architectural changes to deep learning models for enhancing diagnostic performance. The conclusion drawn from the experiment proves that the adoption of a self-attention mechanism in DenseNet201 is a valuable solution for skin lesion classifications and serves as a valuable contribution to medical imaging and dermatology diagnostics. Further work may extend the results obtained in this work by examining more improvements and modifications in deep learning architectures, especially for medical imaging applications. Even though self-attention layer integration enhancements were introduced to make DenseNet201 simpler for classification, more profound attention architectures like transformers must be explored. Furthermore, using both clinical and thermoscopic images, or the use of patient data would be more precise diagnostic systems. Future work could also be directed towards greater generalization capacity on other datasets and other types of skin and possible elimination of bias and computational cost for actual clinical application.

References

[1] M. A. Kassem, et al., "Skin lesions classification into eight classes for ISIC 2019 using deep convolutional neural network and transfer learning," IEEE Access, vol. 8, pp. 114822-114832, 2020.

[2] N. Gouda et al., "Skin cancer classification using ResNet," in 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA), pp. 536-541, IEEE, Oct. 2020.

[3] S. Shrinithi et al., "Detection of Melanoma Skin Cancer using Thermoscopic Skin Lesion Images," in 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), pp. 240-245, IEEE, Aug. 2021.

[4] R. P. Kumar et al., "Attention-Guided Residual Network for Skin Lesion Classification Using Deep Reinforcement Learning," in 2023 International Conference on Integrated Intelligence and Communication Systems (ICIICS), pp. 1-7, IEEE, Nov. 2023.

[5] N. Aishwarya et al., "Skin Cancer Diagnosis with Yolo Deep Neural Network," Procedia Computer Science, vol. 220, pp. 651-658, 2023.

[6] R. Kadirappa et al., "An automated multi-class skin lesion diagnosis by embedding local and global features of Dermoscopy images," Multimedia Tools and Applications, pp. 1-28, 2023.

[7] M. Azeem et al., "SkinLesNet: Classification of Skin Lesions and Detection of Melanoma Cancer Using a Novel Multi-Layer Deep Convolutional Neural Network," Cancers, vol. 16, no. 1, p. 108, 2023.

[8] Y. S. Alsahafi et al., "Skin-Net: a novel deep residual network for skin lesions classification using multilevel feature extraction and cross-channel correlation with detection of outliers," J.Big Data", vol. 10, no. 1, p. 105, 2023.

[9] M. S. Sivakumar et al., "Deep learning in skin lesion analysis for malignant melanoma cancer identification," Multimedia Tools and Applications, pp. 1-21, 2023.

[10] F. Bozkurt, "Skin lesion classification on dermatoscopic images using effective data augmentation and pre-trained deep learning approach," Multimedia Tools and Applications, vol. 82, no. 12, pp. 18985-19003, 2023.

[11] A. N. Omeroglu et al., "A novel soft attention-based multi-modal deep learning framework for multi-label skin lesion classification," Engineering Applications of Artificial Intelligence, vol. 120, p. 105897, 2023.

[12] J. SM et al., "Classification of skin cancer from dermoscopic images using deep neural network architectures," Multimedia Tools and Applications, vol. 82, no. 10, pp. 15763-15778, 2023.

[13] S. Maqsood et al., "Multiclass skin lesion localization and classification using deep learning-based features fusion and selection framework for smart healthcare," Neural Networks, vol. 160, pp. 238-258, 2023.

[14] A. Faghihi et al., "Diagnosis of skin cancer using VGG16 and VGG19- based transfer learning models," Multimedia Tools and Applications, pp. 1-16, 2023.

[15] V. Dillshad et al., "D2LFS2Net: Multi-class skin lesion diagnosis using deep learning and variance ‐ controlled Marine Predator optimization: An application for precision medicine," CAAI Transactions on Intelligence Technology, 2023.

[16] A. Magdy et al., "Performance Enhancement of Skin Cancer Classification using Computer Vision," IEEE Access, 2023.

[17] H. L. Gururaj et al., "DeepSkin: A Deep Learning Approach for Skin Cancer Classification," IEEE Access, 2023.

[18] R. Sulthana et al., "A novel end-to-end deep convolutional neural network-based skin lesion classification framework," Expert Systems with Applications, vol. 246, p. 123056, 2024.

[19] D. Chanda et al., "DCENSnet: A new deep convolutional ensemble network for skin cancer classification," Biomedical Signal Processing and Control, vol. 89, p. 105757, 2024.

[20] X. Deng, "LSNet: a deep learning-based method for skin lesion classification using limited samples and transfer learning," Multimedia Tools and Applications, pp. 1-21, 2024.

[21] Mol, B., et al., 2023, December. Parkinson's Disease Classification using Hybrid Deep Learning Approach. In *2023 9th International Conference on Signal Processing and Communication (ICSC)* (pp. 591-596). IEEE.

[22] Ganguly, T., et al., 2023, November. Self-attention based ResNet model for Cervical Cancer Detection. In *2023 Second International Conference on Informatics (ICI)* (pp. 1-6). IEEE.

[23] Singh, R.P.et al., 2021. Instance-vote-based motion detection using spatially extended hybrid feature space. *The Visual Computer*, *37*(6), pp.1527-1543.