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A Convolutional Neural Network Approach for Skin Lesion Classification Using Imbalanced Dataset with Image Augmentation

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Abstract: A significant threat to people's health all over the world is skin cancer. The purpose of this research is to improve the detection of skin cancer by utilizing a CNN classification model that makes use of preprocessing and augmentation techniques. The HAM10000 dataset is used, and the imbalance it contains is addressed by resizing the images to 120×120 pixels and removing hair. Increasing the diversity of datasets through the use of data augmentation techniques is beneficial to the modeling and evaluation processes. In order to achieve the best possible classification of skin lesions, the proposed CNN architecture incorporates layers that have been carefully tuned. The data is divided into three different sets: Training, validation, and testing. The evaluation metrics, which include accuracy, precision, recall, and F1 score, all point to a highly successful performance of 0.932. This analysis demonstrates that the model is superior to other approaches to skin lesion classification, which signifies that it has the potential to be an effective instrument for the early detection of cancer.

Keywords: Convolutional Neural Networks, Deep Learning, Data Augmentation, Image Preprocessing, Skin Lesion Classification

Introduction

Computer-Aided Diagnosis (CAD) systems are essential in healthcare because they improve accuracy and reliability in medical data classification (Dhull *et al*., 2019). These systems aim to aid medical professionals in clinical decision-making, focusing on balancing performance parameters (Dhull *et al*., 2019). A Collaborative Computer-Aided Diagnosis (C-CAD) system has improved radiologists' diagnostic decision-making process (Khosravan *et al*., 2019). Computer-Aided Design (CAD) systems in medicine are highly intelligent and capable of processing complex clinical data and improving diagnostic performance over time (Liew *et al*., 2021; Yanase and Triantaphyllou, 2019). Researchers suggest that machine learning, particularly deep learning, can aid in breast cancer diagnosis, with CAD expert systems exhibiting early detection and stage classification (Liew *et al*., 2021).

The emergence of Computer-Aided Diagnosis (CAD) systems in the field of skin cancer diagnosis, specifically melanoma, presents a promising avenue for further research and exploration. The majority of the time, these systems make use of Artificial Intelligence (AI) techniques in addition to image processing techniques such as segmentation and feature extraction (Maiti *et al*., 2020). Artificial intelligence-based image classification, in particular deep learning algorithms, has demonstrated the potential to differentiate between benign and malignant skin lesions for detection purposes (Goyal *et al*., 2020). On the other hand, these systems are still in the preliminary stages of clinical application, and there is a requirement for methodologies that are more accurate, faster, and more cost-effective (Maiti *et al*., 2020). In terms of execution time, hardware resource utilization, and power consumption, the utilization of dedicated hardware, such as Field-Programmable Gate Arrays (FPGA), for real-time melanoma detection has demonstrated promising results (Barros *et al*., 2020).

In 2020, there were a total of 19.3 million new cancer cases reported, not including nonmelanoma skin cancer. Regrettably, around 10.0 million lives were lost to cancer, excluding nonmelanoma skin cancer. These statistics emphasize the global impact of skin cancer (Labani *et al*., 2021). The Western Pacific region has the highest number of melanoma cases in relation to skin cancer, while the European region has the highest rates of nonmelanoma skin cancers. These findings emphasize the different rates of these conditions in various regions of the world. The prevalence of melanoma and nonmelanoma skin cancers can vary across different regions (Ferlay *et al*., 2021). Receiving a diagnosis of skin cancer, especially melanoma, at an advanced stage can have serious consequences. It can lower the chances of survival and lead to higher treatment costs, as highlighted in a recent study by (Janda *et al*., 2022). Detecting skin cancer at an early stage is crucial due to the significant risk posed by exposure to ultraviolet radiation (Jones *et al*., 2020). However, the current unstructured approach to the detection of skin cancer presents a number of challenges, including the possibility of overdiagnosis and varying levels of care quality. In order to address these issues, more and more people are becoming interested in structured risk assessment and the application of new technologies, such as deep learning techniques, for early detection (Dildar *et al*., 2021).

AI-powered classification of human health problems is an exciting new area. AI can be an important tool for early disease detection (Cahyo and Astuti, 2023). This lets doctors act quickly and correctly. AI can better predict when a disease will start by using machine learning algorithms to look at a huge amount of patient data. This lets doctors be proactive and make personalized treatment plans. AI has the potential to revolutionize disease diagnosis, resource allocation, and healthcare delivery. AI is playing a bigger part in making disease classification and diagnosis more accurate, faster, and easier for more people. AI-driven healthcare innovation gives people the chance to use cutting-edge technologies to lower the number of diseases they have and make their health better (Janda *et al*., 2022). Moreover, the use of AI for skin cancer classification is crucial due to its potential to improve the accuracy and speed of diagnosis, as well as reduce the workload for healthcare professionals (Mridha *et al*., 2023). Integrating AI into healthcare could completely change medicine by allowing people from different fields to work together and always do the best research. The application of Convolutional Neural Networks (CNN) for the classification of skin cancer has demonstrated encouraging results.

When it comes to the task of image classification, CNN (Convolutional Neural Network) is considered a superior option because it provides higher levels of accuracy and precision than humans do (Kumari and Sharma, 2021). As the number of disease classes increased, the classification performance of pigmented skin lesions utilizing CNN improved steadily and, in certain instances, exceeded that of dermatologists (Nugroho *et al*., 2023). By utilizing the architectures of Deep Convolutional Neural Networks (DCNN), which include transfer learning, fine-tuning, ensemble approaches, data generation, and augmentation, it is possible to effectively minimize the insufficiency of labeled data, which is prone to overfitting. Furthermore, these techniques contribute to improving the efficiency of skin lesion classification in general CAD systems (Saeed and Zeebaree, 2021).

Related Works

Using the HAM10000 dataset, Akter *et al*. (2022) investigated deep-learning models for classifying skin lesions. Preprocessing images for training and testing entails resizing them to 224×224 dimensions. Converting images to the float32 data type resulted in rescaling to a 0-1 range. The modeling process used seven deep learning models: Densenet, Mobilenet, Inceptionv3, Xception, VGG16, CNN, and Resnet-50. The study lacked specific details on these models' architecture. In each fold, each model underwent thirty epochs of training. To generate the final model prediction, they used a decision tree classifier model. The study assessed model performance using metrics such as accuracy, precision, recall, and F1 score. The study evaluated seven types of skin lesions using models. A base CNN model with basic features achieved an accuracy of 0.77, while the Inceptionv3 model achieved 0.90.

A study was conducted by Agyenta (2022) for classifying skin lesions using the HAM10000 dataset. They have used multiple techniques for conducting the preprocessing stage. In the beginning, they cropped the images to 224×224 instead of resizing the images. Also, applied color space transformation which is the conversion of a color image into a grayscale image. Skin disease images are represented as RGB images based on the RGB color space where the brightness value of each component is defined by its red, green, and blue intensity values. By converting the RGB image into grayscale, they were able to reduce the complexity of the data and emphasize the prominence of the skin lesion. The hair removal technique is used to improve the quality of the images and remove noise from the images. Finally, two techniques were employed to address the imbalanced nature of skin disease image samples. Undersampling was used to randomly remove some samples while oversampling involved cropping, flipping, and translating the samples randomly to create new image samples that were 4 to 5 times the original image data. The final

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number of images used in the evaluation process was 7283. They evaluated three different models of CNN which were: InceptionV3 85.80%, ResNet50 86.69%, and DenseNet201 86.91%.

In a recent study, Pablo Villa-Pulgarin *et al*. (2022) presented a collection of optimized convolutional neural network models that demonstrate the potential for accurately classifying skin lesions. The models were trained and evaluated using a well-known dataset in the field, called the HAM10000 dataset. This research focuses on enhancing the precision and effectiveness of skin lesion classification, which could result in improved diagnosis and treatment results. The study utilized three transfer learning models: DenseNet-201, Inception-ResNet-V2, and Inception-V3. The dataset was normalized by dividing each value by 255 and converting it to a float. In addition, the models were enhanced with batch normalization layers integrated into the dense blocks. An optimizer called Adamax was used, along with a learning rate scheduler function, to reduce the risk of overfitting. Through parameter tuning, we achieved the best results by using a balanced dataset and fine-tuning transfer learning models. The model showcased exceptional performance, with high accuracy across a dataset containing seven distinct classes. The ISIC 2019 dataset was classified into eight classes using DenseNet-201, along with data augmentation techniques. The optimized DenseNet-201 model achieved an accuracy of 0.98, followed by InceptionResnet V2 with a score of 0.97, and Inception-V3 with an accuracy of 0.96.

Kassem *et al*. (2020) proposed a deep convolutional neural network and transfer learning model and pre-trained GoogleNet. The ISIC 2019 dataset is used for the model evaluation. The public dataset contains eight classes of skin lesions, which are melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, vascular lesions, and squamous. The proposed model is based on a modified GoogleNet architecture that was trained, validated, and tested on skin lesion images. They performed three experiments on the skin lesion dataset. The first experiment used transfer learning and found low sensitivity and precision due to class imbalance. In the second experiment, the authors performed data augmentation to balance the image count, and in the third experiment, they randomly eliminated images. The third experiment yielded the best results, with improved measures across all performance metrics, especially in terms of sensitivity and precision. The accuracy for the first, second, and third experiments was 93.31, 94.2, and 94.92%, respectively.

The studies show how important deep learning is for classifying skin lesions, but they also show that model accuracy is still a problem. Preprocessing and adding data pose significant challenges, particularly with imbalanced datasets. Getting across this gap could greatly improve the accuracy of classification and move computer-aided diagnosis in dermatology forward. Efforts in this direction are very important for making skin lesion classification systems more reliable and useful.

Objectives of Study

The primary objectives of this research are to investigate the effectiveness of using different image augmentation techniques in order to improve the performance of deep learning models on an imbalanced skin lesion dataset. Additionally, focuses on developing a baseline Convolutional Neural Network (CNN) architecture that is specifically developed for the purpose of evaluating augmented images within the context of an imbalanced skin lesion dataset. The implementation of multiple preprocessing steps is the focal point of the study. These steps are essential for preparing the dataset to integrate without any problems with the proposed baseline CNN architecture.

Materials and Methods

The proposed skin lesion classification method has several key steps. Preprocessing the raw data ensures uniformity and readiness for analysis. Next, image augmentation techniques increase dataset diversity and robustness, reducing data scarcity and class imbalance issues. Next, feature extraction and analysis extract discriminative features from the images to characterize skin lesions. This is essential for identifying patterns and distinguishing lesion types. Final classification uses Convolutional Neural Networks (CNN), a cutting-edge deep learning method for image classification. Figure 1 shows how this comprehensive methodology seamlessly integrates each stage to create a robust framework for accurate and reliable dermatological skin lesion classification.

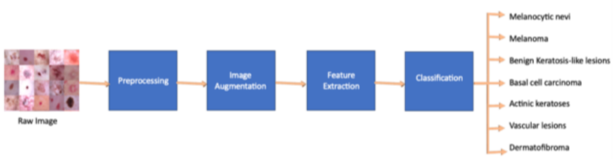

Fig. 1: Process of proposed skin lesion classification method

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Dataset

The HAM10000 dataset, also known as Human Against Machine 10000, is a comprehensive collection of dermatoscopic images of pigmented lesions from various sources (Tschandl *et al*., 2018). The dataset includes a total of 10015 images, each with dimensions of 600×450 pixels. The HAM10000 images were gathered from two different locations, the Department of Dermatology at the Medical University of Vienna, Austria, and the skin cancer practice of Dr. Cliff Rosendahl in Queensland, Australia, spanning a time frame of 20 years. The images represent 7 different classes of pigmented skin lesions, which are: melanocytic nevi (NV), melanoma (mel), Benign keratosis-like Lesions (BKL), Basal Cell Carcinoma (BCC), Actinic Keratoses (Akiec), Vascular Lesions (VSC), and Dermatofibroma (DF), as shown in Fig. 2.

Preprocessing

Preparing data for deep learning models can be challenging because of the large volume and presence of noise. The typical image size utilized for transfer learning models is 224×224 pixels. The dataset was resized from 600×450 to 120×120 pixels, with channel information preserved to fulfill the specified criteria. One of the steps in the preprocessing stage involves hair removal, where images go through multiple processes. The Dull Razor algorithm is utilized in this stage to eliminate hair from the skin and minimize distractions. The images were converted to grayscale and then processed with a black hat filter to improve the visibility of hair follicles against the skin by enhancing dark regions of the image. The process involves converting grayscale images into binary images through binary thresholding (MASK), where pixels are categorized as black or white depending on their intensity in relation to a specified threshold value. Ultimately, the process involves replacing pixels in the mask through a method known as in-painting. This technique is utilized to restore areas of an image that are either missing or damaged by utilizing information from the surrounding areas. Figure 3 shows a sample of an image before and after preprocessing.

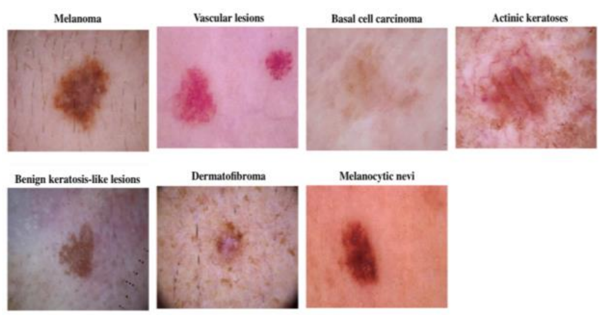

Fig. 2: Types of skin lesions in the HAM10000 dataset

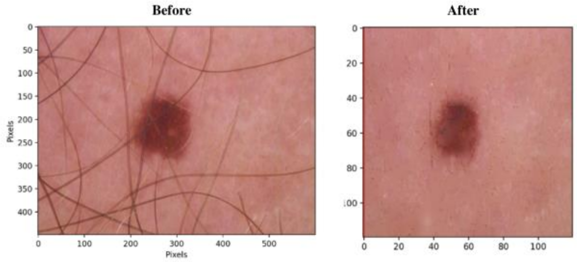

Fig. 3: Image sample before and after the preprocessing stage

Fig. 4: Sample of the image augmentation techniques implemented

Data Augmentation

The HAM10000 dataset contains 7 different types of lesions; however, the number of images in each class is different, which makes the dataset imbalanced for training and testing. While some types of lesions have more than 6,000 images, others have around 100 images, which makes it difficult to use this data for training and testing purposes to evaluate a specific model. The value has assigned class weights to each class based on the number of each class. For instance, if a dermatofibroma lesion had 115 images in the raw dataset, the assigned a class weight of 20 for it so that could randomly augment the images 20 times by using different augmentation techniques such as flip, rotate, random-brightness, random-contrast, motion-blur, median-blur, gaussian-blur, gauss-noise, elastic-transform, clahe, hue saturation value, and shift scale rotation as a sample of the augmentation process shown in.

Figure 4, where the values of these techniques were chosen randomly each time when selected. By implementing that, the dataset size increased from 10015 images to 50785 images. The equation of the image augmentation process is shown in (1), which is the calculation of the total images of each class, which is equal to the summation of the images in that class multiplied by the weight assigned to it and they will give the total number of images in that specific class. Equation (1) is for the summation of all 7 classes after the augmentation that was generated using Eq. (2) and through this calculation got the total image of 50785 which later the dataset set split into training, test, and validation sets. The number of images of each class after the augmentation will follow as these: Melanocytic nevi (6705), melanoma (11130), benign keratosis-like lesions (109,90), basal cell carcinoma (10280), actinic keratoses (6540), vascular lesions (2840), and dermatofibroma (2300).

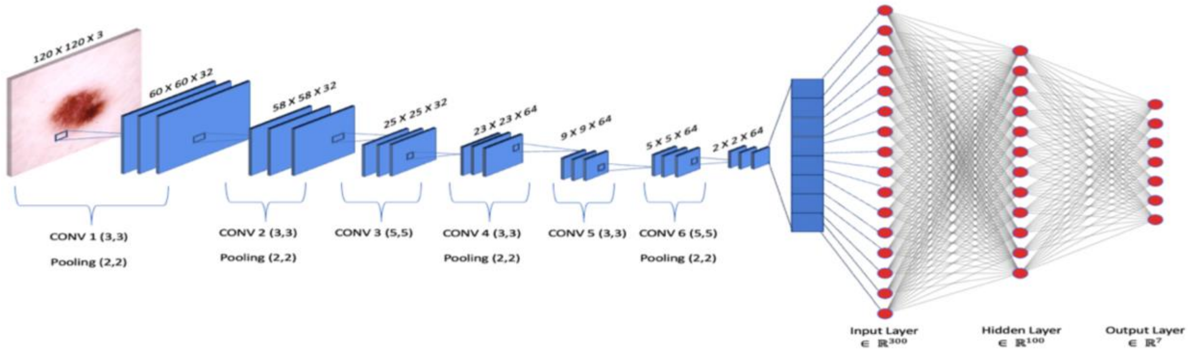

Fig. 5: Proposed CNN model architecture

$$Total_{class_i} = \sum_{j=1}^{N_i} \left(w_i \times x_{i,j} \right) \tag{1}$$

$$Total_{images} = \sum_{i=1}^{C} Totall_{class_i} \tag{2}$$

CNN Model Architecture

Figure 5 shows the proposed architecture of the proposed CNN model. It begins with a preprocessed and augmented 120×120×3 image. The first convolution layer pools the image (2, 2), and after that convolution layer, the kernal size increased to 5×5 to capture more global patterns and more complex features of the image, also preventing overfitting. The upcoming layers will use a kernal size of 3×3. However, in the final layer, the kernal size again increased to 5×5. Batch normalization and dropouts are used between all the layers. As shown in the figure, the first three layers have 32 filters, and the last three layers have 64 filters. The fully connected layers represent the dense network of the nodes; the input layer has a density of 300, the hidden layer has a density of 100, and the output layer has a density of 7, which represents the 7 types of lesions in the dataset.

Model Training and Testing

During the training phase of the proposed model, the augmented dataset is divided into training (70%), testing (15%), and validation (15%) sets. This phase involves optimizing the model's parameters. The hyperparameters tuned for the training are batch size of 32, and the model trained 150 epochs. The model architecture, the model has various layers, which consist of feature extraction, pooling layers for splitting down the sampling, and fully connected layers for classification. Rectified Linear Unit (ReLU) activation functions are applied to capture complex patterns of data. The Adam optimizer is used for parameter updates, leveraging adaptive learning rates for efficient convergence. Throughout training, training, and validation loss and accuracy are monitored to highlight the model's performance. Regularization techniques, such as dropouts, may be applied to reduce overfitting. The testing set is used to further evaluate the model. Metrics such as accuracy, precision, recall, and F1 score are evaluated. A confusion matrix is generated to evaluate the model's performance in classifying images in the test set.

Results and Discussion

Training and Validation Performance

The result of both training and validation is shown in Fig. 6. The model performed very well in the first 60 epochs the validation accuracy is slightly greater than the training accuracy. However, throughout the epochs period, the validation is getting stable and the training is hardly increasing over time as shown in Fig. 6(a) The training and validation loss are also shown in Fig. 6(b). The loss of the training and validation show that the model in the beginning is performing well however, due to the stop of validation accuracy improvement as shown in the accuracy diagram, the validation loss also stops in the middle of the epochs until the end of the training process. The model is performing well based on the validation set, which can be seen that the model can validate unseen data and classify the types of skin during the training process which means the model is learning.

Training and Testing Performance

The testing set is used to evaluate the model further, and the metrics that are evaluated are accuracy, F1 score, precision, and recall. Accuracy evaluation, if the model is using Eq. (3), is the process of dividing all correctly classified samples by the total samples in the training set. Equation (4) shows the precision evaluation. The recall equation is shown in Eq. (5), and F1_score is using Eq. (6). Multiple experiments were conducted, like tuning the hyperparameters by increasing batch sizes to 64 and 128. These batch sizes increased the fluctuation of the validation set, and at the end, also observed overfitting where the training accuracy was

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increasing while the validation was decreasing over time. Further in the experiment, the model did not perform well without data augmentation, which was expected because of the imbalanced dataset, until the best parameters and augmentation equation were found to get the current results.

In the experiment of evaluating the model using different metrics, the test set is used. The metrics evaluation is shown in Table 1, which shows that all of the accuracy, precision, recall, and f1_score have a constant value of 0.932 which shows that the model is performing well in classifying new data. Table 2 is a comparison between the proposed model and approach with previous related works in which they have used different models and architecture of CNN the proposed approach is performing better than the majority of these models by other researchers, which one of the factors is the augmentation process that used in this approach for handling the imbalance dataset that used.

Figure 7, shows the confusion matrix which contains the True positive and False negative evaluation of each class of skin lesion in the dataset predicted by the proposed model. A melanocytic nevi skin lesion is the most misclassified one among all the other types of skin lesion however, the model is performing pretty well for classifying all of the other types:

$$Accuracy = \frac{T_p}{Total\ Samples} \tag{3}$$

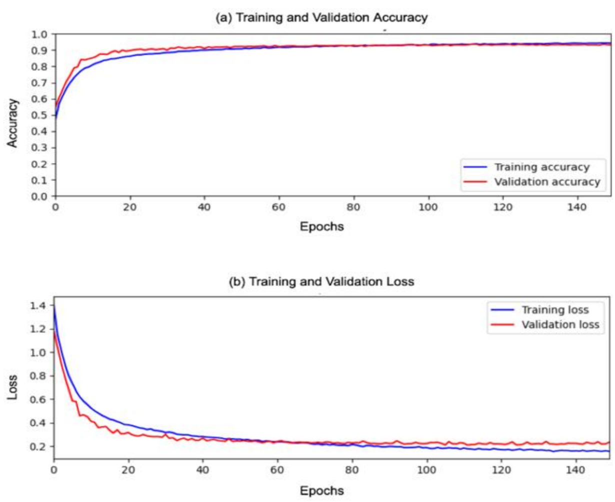

Fig. 6: Training, validation (a) accuracy and (b) loss for the proposed CNN model

Table 1: Proposed model evaluation using a test set

Accuracy	Precision	Recall	F1_score
0.932	0.933	0.932	0.93

Table 2: Proposed model comparison with related works

Author	Model	Dataset	Accuracy
Akter *et al.* (2022)	Inceptionv3	HAM10000	0.90
	Xception		0.88
	Densenet		0.88
	Mobilenet		0.87
	Resenet-50		0.82
	CNN		0.77
	VGG-16		0.73
Agyenta (2022)	InceptionV3	HAM10000	85.80%
	ResNet50		86.69%
	DenseNet201		86.91%
Pablo Villa-Pulgarin *et al.* (2022)	-Optimized DenseNet-201	HAM10000	0.98
	-Optimized InceptionResnet V2		0.97
	-Optimized Inception-V3		0.96
Kassem *et al.* (2020)	GooleNet E-1	ISIC 2019	93.31%
	GooleNet E-2		94.2%
	GooleNet E-3		94.92%
Proposed model	CNN	HAM10000	0.932

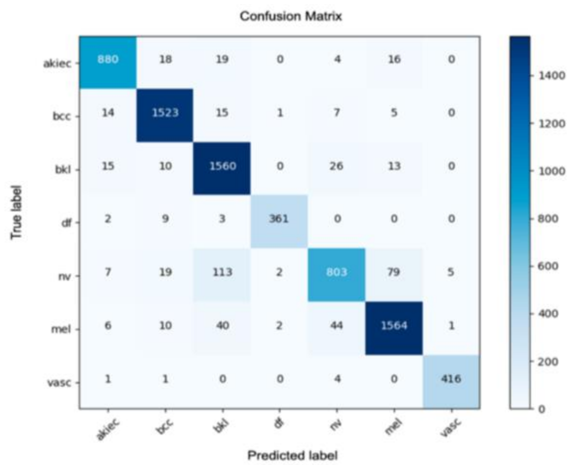

Fig. 7: Confusion Matrix

$$\text{Precision} = \frac{T_p}{T_p + F_p} \tag{4}$$

$$\text{Recall} = \frac{T_p}{T_p + F_n} \tag{5}$$

$$F1Score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

Discussion

In the study conducted by Akter *et al*. (2022), the only data preprocessing used was resizing the image to

120×120 pixels and not implementing any other techniques to either preprocess the images or improve the diversity of the dataset, which led to the low number of accuracies using baseline CNN also the other CNN models that they have used compared to our proposed method are low.

In the Agyenta (2022) study, although they used many techniques in the preprocessing stage in order to select the right images and also remove noise from images by using hair removal techniques however their study didn't stand in evaluation when their models showed a significant overfitting which this causes by having too little number of images that used in training and validation process. The work by Pablo Villa-Pulgarin *et al.* (2022) used multiple data augmentation techniques which by looking at their result we can tell that using image augmentation techniques on imbalanced datasets will help in improving model performance, in their study they did not mention any specific augmentation technique that used. However, they optimized different versions of CNN-based models, not the baseline CNN.

Our proposed model and approach use multiple augmentation and preprocessing techniques which helped increase the diversity of the images and even help the baseline CNN model to perform much better on the imbalanced dataset without having overfitting in the model also gives high accuracy which differentiates the approach from others which is using augmentation and preprocessing and developing new baseline CNN model architecture for evaluation.

Conclusion

Since skin cancer infection and death rates are increasing daily, it is important to use intelligent CAD systems and address this health issue. The deep learning models are performing excellently in classifying multiple types of skin lesions. However, the imbalanced dataset of skin lesions is making the process of using deep learning models such as CNN much harder to perform well. The proposed work focuses on a new CNN model architecture along with using different data augmentation techniques to improve the imbalance dataset that can help train the models to perform better with fewer errors in classifying the skin lesions. The augmentation techniques used were flip, rotate, random-brightness, random-contrast, motion-blur, median-blur, gaussian-blur, gauss-noise, elastic-transform, clahe, hue saturation value, and shift scale rotation with random values. A new CNN model was proposed with different layers. The augmented dataset was divided into train, validation, and test sets. In the process of the model evaluation and used, various metrics are used to evaluate the model such as accuracy, precision, recall, and f1_score with the values of 0.932, 0.933, 0.932, and 0.932 respectively.

Although still working with imbalanced datasets in healthcare is challenging in the future researchers can use unique and different data augmentation that can improve the diversity of datasets to ensure higher accuracy and classification. The limitations of using baseline CNN for image classification using an imbalanced dataset is another challenge which in the future can use different techniques while developing baseline CNN such as using attention-based mechanisms and fuzzy layers to make baseline CNN models perform much better.

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Author's Contributions

Zhyar Yassin Abdalla: Conception and design, data collection, result analysis and interpretation, draft manuscript preparation.

Nor Hazlyna Harun: Conception and design, result analysis and interpretation.

Mohammed Shihab Ahmed Result analysis and interpretation, draft manuscript preparation.

Ethics

The authors confirm that this article has not been published in any other journal. The corresponding author confirms that all the authors have read and approved the manuscript. Additionally, no ethical issues are involved in the manuscript or the dataset, and no conflicts of interest are involved.

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