CHAPTER 48
A review on Skin Cancer Disease Detection Using Transfer Learning Technique

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ABSTRACT

A skin cancer diagnosis is a challenging process for dermatologists as many skin cancer pigments may appear similar in appearance. Hence, early detection of lesions (which form the base of skin cancer) is definitely critical and useful to completely cure the patients suffering from skin cancer. Significant progress has been made in developing automated tools for the diagnosis of skin cancer to assist dermatologists. The worldwide acceptance of artificial intelligence-supported tools has permitted usage of the enormous collection of images of lesions and benevolent sores approved by histopathology. This paper performs a comparative analysis of six different transfer learning nets for multi-class skin cancer classification by taking the HAM10000 dataset. We used replication of images of classes with low frequencies to counter the imbalance in the dataset. The transfer learning nets that were used in the analysis were VGG19, InceptionV3, InceptionResNetV2, ResNet50, Xception, and MobileNet. Results demonstrate that replication is suitable for this task, achieving high classification accuracies and F-measures with lower false negatives. It is inferred that Xception Net outperforms the rest of the transfer learning nets used for the study, with an accuracy of 90.48. It also has the highest recall, precision, and F-Measure values.

Keywords: *Inpatient, outpatient, machine learning, patient data, electronic health reports, treatment*

INTRODUCTION

Skin diseases are conditions that affect the skin and may cause symptoms such as itching, redness, rashes, scaling, flaking, and blistering. There are many different types of skin diseases, ranging from mild and temporary conditions to chronic and serious illnesses. Skin diseases are a major public health concern

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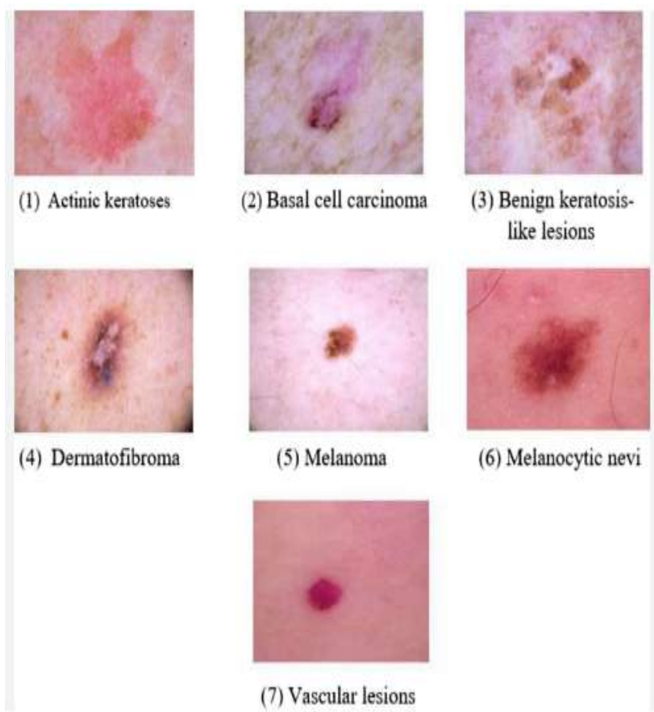
worldwide, affecting millions of people every year. Early and accurate diagnosis is critical for effective treatment and prevention of complications. However, traditional methods of skin disease diagnosis, such as visual inspection by a dermatologist, can be subjective and prone to errors. The development of artificial intelligence (AI) has opened new possibilities for skin disease diagnosis. In recent years, deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have shown great potential in accurately identifying skin diseases based on images of the affected skin area. The use of CNN algorithms in skin disease identification can potentially improve the accuracy of diagnosis, reduce misdiagnosis, and aid in early detection of skin diseases. Furthermore, this technology can help to overcome the shortage of dermatologists in certain areas, as it can be used as a screening tool to identify patients who need to be referred to a dermatologist for further evaluation. In this study, we developed and trained a CNN algorithm to identify skin diseases based on images of the affected skin area. We used a large dataset of skin images consisting of various skin conditions, including eczema, psoriasis, acne, and skin cancer. The performance of the CNN algorithm was evaluated using various metrics such as accuracy, sensitivity, specificity, and F1-score. The aim of this study is to investigate the potential of CNN algorithms in accurately identifying skin diseases based on images. We believe that the use of AI in skin disease diagnosis has the potential to significantly improve patient outcomes and reduce the burden on healthcare systems.



LITERATURE SURVEY

1) Skin cancer may be divided into two primary categories: melanoma and non-melanoma. Squamous cell carcinoma and basal cell carcinoma are the most prevalent non-melanoma tumors. The 17th most prevalent cancer globally is cutaneous melanoma. It is the 13th and 15th most prevalent cancer, respectively, in men and women (WCRF, 2022).

2) The most effective approaches to manage skin cancer are early detection and prevention. New or changing skin patches or growths, especially those that seem unusual, should be checked. A physician should evaluate any new lesions or changes in the appearance of an existing lesion

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(size, shape, or colour). Deep learning (DL) technology has allowed skin cancer to be classified into seven diagnostic groupings.

3) A dermatologist who specialises in skin cancer diagnosis frequently follows a set procedure that begins with a visual inspection of the concerning lesion, is followed by a dermoscopy, and concludes with a biopsy (Haenssle et al., 2018). When compared to depending just on visual diagnosis today, the efficacy of predicting a result in diagnostics utilising artificial intelligence (AI) and deep learning (DL) grows dramatically (Ayoub et al., 2021).

4) Deep convolutional neural networks (DCNNs) analyse dermoscopic pictures to detect skin lesions, including all skin cancer lesions, whereas convolutional neural networks (CNNs) may be used for feature selection and object categorization. DNNs are useful for identifying medical pictures, but they require a large amount of training data. Using large-scale datasets, high-performance GPUs are employed to train a network of DNNs (Savaş et al., 2019, 2022).

5) DL systems powered by GPUs outperformed humans in detecting skin cancer (Nugroho et al., 2019). In this regard, the goal of this work is to classify skin cancer using a deep learning approach based on transfer learning. It is hoped that this may aid clinics in the diagnosis and treatment of skin cancer through early detection.

6) For this reason, some research have been conducted in the literature to identify skin cancer using machine learning (ML) and deep learning (DL) algorithms. The second part summarises these investigations. The material and technique employed in this investigation are discussed in the third portion of the research. The experimental results are discussed in the fourth part. The research's contributions and comparison discussion with other studies were accomplished in the fifth segment.

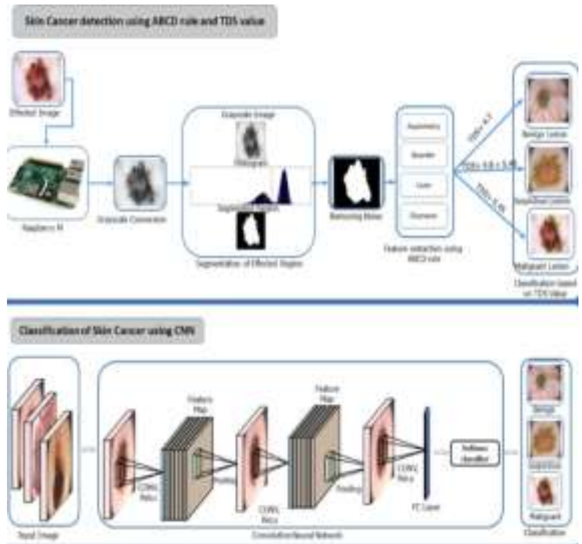
7) Qiao et al. offer a novel approach of identifying skin cancer based on metaheuristics and DL (2022). The skin dermoscopy pictures are initially trained using a modified AlexNet that has already been trained with batch normalisation layers, and the final few layers are handled by an Extreme Learning Machine (ELM). A freshly improved metaheuristic, the Fractional-order Red Fox Optimization (FORFO) Algorithm, is utilised to improve the efficacy of the ELM network..

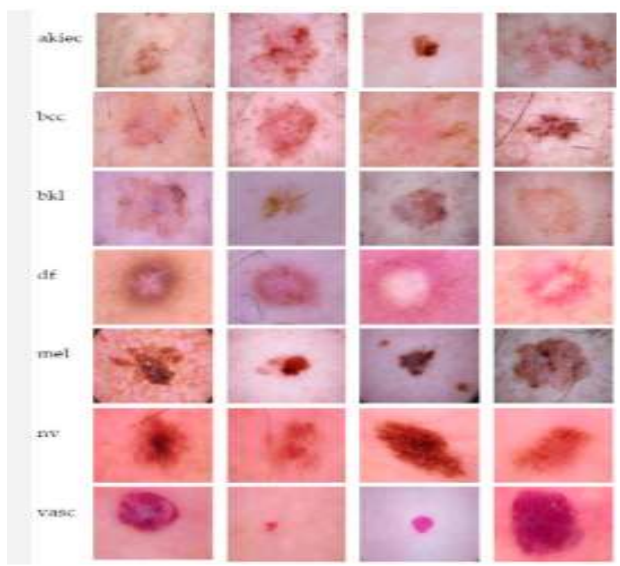
8) The proposed method has an overall accuracy of 97.14%. Wang et al., (2021) employed DL and traditional ML algorithms to assess polarisation speckle pictures derived from the major types of malignant and benign lesions. Patch cropping for DL was used to enhance 122 malignant and 196 benign skin lesion speckle pictures, which was an advantageous method given the patterns' statistical homogeneity.

9) The ML method obtained over 90% accuracy in the easier classification task of differentiating malignant melanoma from benign melanoma. Nevertheless, in the overall classification test of malignant and benign tumours, ResNet, their chosen DL architecture, achieved the highest diagnostic accuracy of 82%.

10) Toaçar et al. suggest yet another unique model based on the auto-encoder, spiking, and CNN (2021). The dataset employed was the International Skin Imaging Collaboration (ISIC) skin cancer dataset, which includes 1800 benign and 1497 malignant tumour pictures. In the suggested technique, the dataset is rebuilt using the auto-encoder model. The original dataset and structured dataset were trained and classified using the MobileNetV2 model, which is made up of residual blocks and spiking networks.

BLOCK DIAGRAM





MODULES

- Data Collection
- Data Pre-processing
- Data Augmentation
- Model Architecture
- Model Training
- Model Evaluation

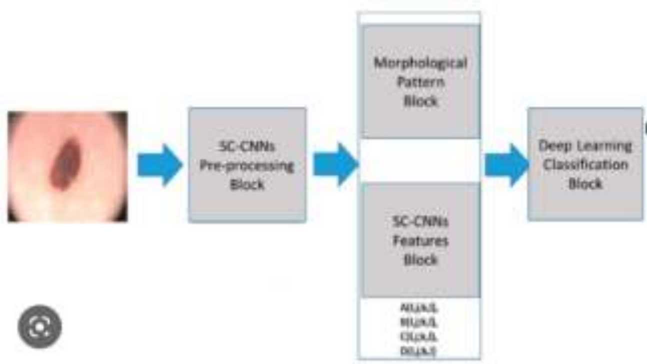
- Deployment
- Maintenance

MODULES DESCRIPTION

Data Collection:

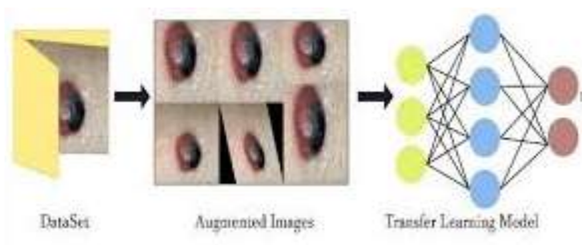
Collect a large dataset of images of different skin diseases along with their labels. Collect a diverse dataset of images of skin diseases from various sources such as dermatology databases, clinical studies, and medical journals. The dataset should contain images of different skin diseases and their respective labels. The images should be of high quality, with a high resolution and clear representation of the skin disease. The dataset should be balanced, meaning that it should have an equal number of images for each skin disease category. The dataset should be annotated with labels indicating the type of skin disease present in each image. The dataset should be cleaned by removing any duplicates, irrelevant or low-quality images, and correcting any labeling errors. The dataset can be augmented by applying various transformations to the images, such as rotation, flipping, zooming, and cropping, to increase the diversity of the dataset. The final dataset should be divided into training, validation, and testing sets. The training set is used to train the CNN model, the validation set is used to tune the hyper parameters and optimize the model, and the testing set is used to evaluate the final performance of the model. It is also important to ensure that the data collection process adheres to ethical guidelines, such as obtaining informed consent from patients before collecting their images and ensuring anonymity and privacy of the patients.

Data Pre-processing:



Clean the dataset by removing any duplicates or irrelevant images. Resize the images to a standard size and normalize the pixel values. Resize the images to a standard size that the CNN model can handle efficiently. The size can vary based on the architecture of the CNN model, but it is typically 224x224, 256x256 or 512x512. Normalize the pixel values of the images. This is done to bring the pixel values to a common scale, which can help the CNN model converge faster during training. The normalization can be performed using various methods such as dividing the pixel values by 255, subtracting the mean pixel value, and dividing by the standard deviation. Apply data augmentation techniques such as random rotation, flipping, zooming, and cropping to increase the diversity of the dataset. This can help the CNN model generalize better and perform well on unseen data. Split the dataset into training, validation, and testing sets. The training set is used to train the CNN model, the validation set is used to monitor the model's performance and tune the hyper parameters, and the testing set is used to evaluate the final performance of the model. Convert the images and their labels into a suitable format for training the CNN model. The images can be converted into arrays, and the labels can be converted into one-hot encoded vectors. Shuffle the training dataset to ensure that the CNN model sees a variety of images during each epoch of training. It is also important to ensure that the pre-processing steps do not introduce bias into the dataset, such as by cropping out relevant areas of the image or distorting the image in a way that affects the classification result.

Data Augmentation:



Augment the dataset by applying different transformations such as rotation, zoom, and flipping to increase the diversity of the dataset. data augmentation in a skin disease classification using CNN algorithm can be as follows:

Random Rotation: Rotate the images by a random angle to simulate different viewing angles.

Horizontal and Vertical Flipping: Flip the images horizontally or vertically to increase the diversity of the dataset.

Random Zooming: Zoom in or out of the images by a random factor to simulate different image sizes.

Random Cropping: Crop the images by selecting a random patch from the original image to simulate different viewpoints.

Color Jittering: Add random variations to the color of the images, such as brightness, contrast, and saturation, to simulate different lighting conditions.

Gaussian Noise: Add random Gaussian noise to the images to simulate image noise and improve the robustness of the model.

Elastic Deformation: Apply random elastic deformation to the images to simulate the distortion caused by skin texture and improve the generalization capability of the model.

Mix-up: Mix two images together by taking a weighted average of their pixel values and their corresponding labels. This can help to prevent overfitting and improve the generalization of the model.

Cutout: Remove a random square patch from the image to simulate occlusion and improve the robustness of the model.

Random Erasing: Randomly erase a rectangular portion of the image to simulate occlusion and improve the robustness of the model. It is important to note that not all data augmentation techniques may be suitable for every skin disease classification problem, and the choice of techniques should be based on the specific characteristics of the dataset and the problem at hand.

Model Training:

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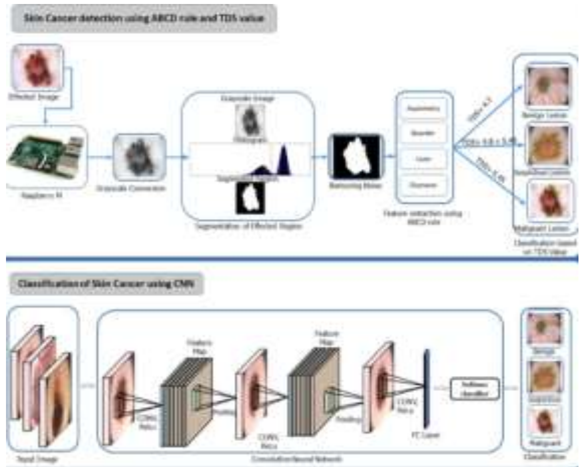

Train the model using the augmented dataset. The model should be trained using an optimizer such as Adam or SGD and a loss function such as categorical cross-entropy. The proposed system for model training in a skin disease classification using CNN algorithm can be as follows:

Initialize the model parameters: Randomly initialize the weights and biases of the model.

Define the loss function: Choose an appropriate loss function to measure the difference between the predicted and actual labels. For skin disease classification, the categorical cross-entropy loss function is commonly used.

Choose the optimization algorithm: Select an optimization algorithm to update the model parameters during training. Commonly used optimization algorithms include Stochastic Gradient Descent (SGD), Adam, or RMSProp.

Split the dataset: Split the dataset into training, validation, and testing sets. The training set is used to train the model, the validation set is used to monitor the model's performance and tune the hyper parameters, and the testing set is used to evaluate the final performance of the model.

Train the model: Feed the pre-processed images into the model, and update the model parameters by minimizing the loss function using the chosen optimization algorithm. During training, the model performance on the validation set is monitored, and the hyper parameters are adjusted accordingly to achieve the best performance.

Evaluate the model: Once the model has been trained, evaluate its performance on the testing set. Calculate various evaluation metrics such as accuracy, precision, recall, and F1-score.

Fine-tune the model: Fine-tune the model by adjusting the hyper parameters such as learning rate, batch size, and number of epochs to achieve better performance. Save the trained model: Save the trained model parameters for future use.

It is important to note that the choice of hyper parameters and optimization algorithm can greatly affect the performance of the model. Therefore, it is essential to carefully select and tune these parameters to achieve the best possible performance.

Model Evaluation:

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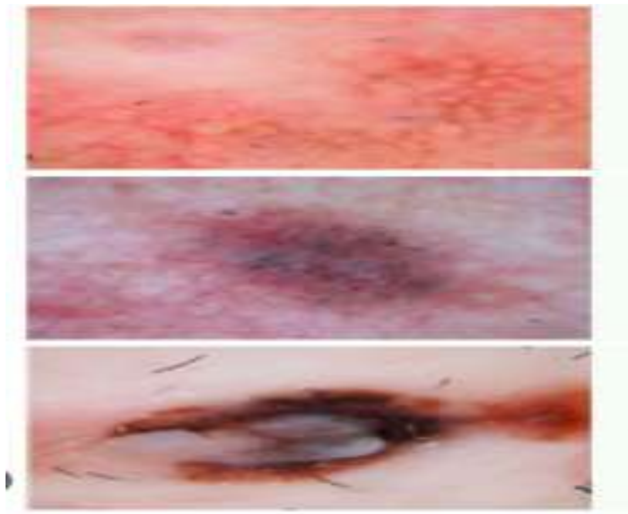

Evaluate the model on a separate validation set to determine its accuracy and performance. Fine-tune the model if necessary. The proposed system for model evaluation in a skin disease classification using CNN algorithm can be as follows:

Calculate evaluation metrics: Once the model has been trained, evaluate its performance on the testing set by calculating various evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics provide a measure of how well the model is performing in terms of correctly identifying the different skin disease categories.

Confusion matrix: A confusion matrix is a table that shows the number of true positive, true negative, false positive, and false negative predictions made by the model for each skin disease category. It can be used to visually analyze the performance of the model.

ROC Curve: A Receiver Operating Characteristic (ROC) curve is a plot of true positive rate (TP) against the false positive rate (FPR) for different classification thresholds. It can be used to evaluate the performance of the model at different levels of sensitivity and specificity.

Precision-Recall Curve: A precision-recall curve is a plot of precision against recall for different classification thresholds. It can be used to evaluate the trade-off between precision and recall and to select an appropriate classification threshold.

Visualize the results: Visualize the results of the model by displaying the input images along with their predicted labels and probabilities.

Compare with other models: Compare the performance of the proposed model with other state-of-the-art models to ensure that it is competitive and provides significant improvements.

Fine-tune the model: Fine-tune the model by adjusting the hyper parameters such as learning rate, batch size, and number of epochs to achieve better performance.

Save the trained model: Save the trained model parameters for future use. It is important to note that model evaluation is an iterative process and requires continuous monitoring and improvement to ensure that the model is providing accurate and reliable results.

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Maintenance:

Regularly update the model by adding new images to the dataset and retraining the model. Monitor the performance of the model and make necessary adjustments. The proposed system for maintenance of a skin disease classification model using CNN algorithm can be as follows:

Data monitoring and management: Monitor the data used for training and testing the model to ensure that it remains relevant, diverse, and unbiased. This can include collecting new data, removing outdated or redundant data, and balancing the data distribution.

Model monitoring: Monitor the performance of the model in real-time to detect any issues such as performance degradation or errors. This can include monitoring the accuracy, precision, recall, and F1-score metrics, as well as the confusion matrix and ROC curve.

Regular retraining: Retrain the model periodically on new data to ensure that it remains accurate and up-to-date. This can include retraining the model on a regular schedule or when a significant amount of new data is available.

Bug fixing: Fix any bugs or issues that are discovered in the system, such as issues with the user interface or API.

Model improvement: Continuously improve the model by incorporating new features, improving the architecture, and fine-tuning the hyper parameters.

Documentation and training: Maintain up-to-date documentation on the system, including the model architecture, data sources, and deployment procedures. Provide training to new developers and users on the system and its components.

Security and compliance: Monitor and update the system to ensure that it remains compliant with regulatory and ethical requirements such as HIPAA, GDPR, and ethical guidelines for AI. This can include implementing new security measures or updating existing ones.

Performance optimization: Optimize the performance of the system by tuning the hardware and software components to ensure that it meets the required performance standards.

RESULT

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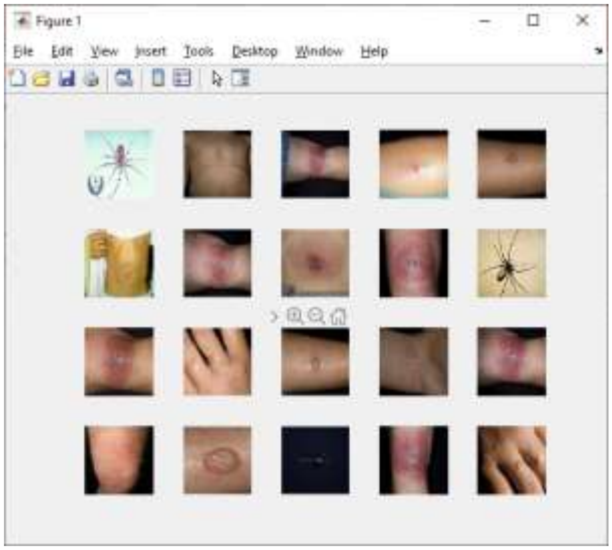

Figure: training of images

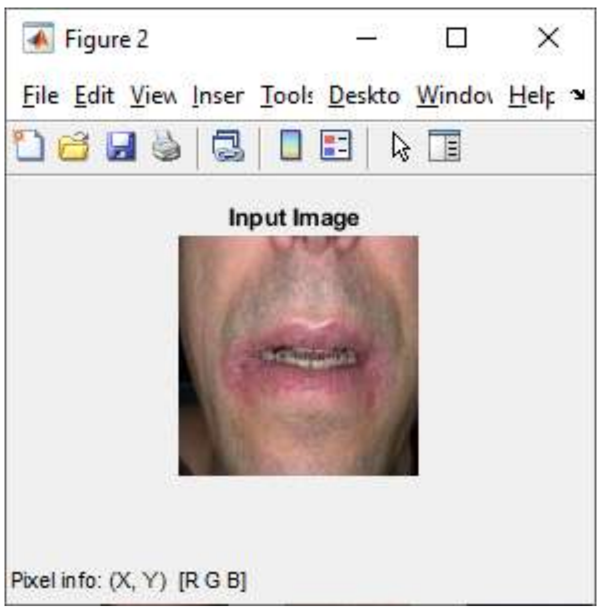

Figure: input testing of image

CONCLUSION

We proposed an ensemble-based deep learning approach for skin cancer detection based on dermoscopic images. Our method uses an ensemble of CNNs trained on input images of different sizes along with metadata. We present our results on the ISIC 2020 dataset which contains 33,126 dermoscopic images from 2056 patients. The dataset is highly imbalanced with less than 2% malignant cases. The impact of ensemble learning was found to be significant, while the impact of transfer learning and the use of auxiliary information in the form of metadata associated with the input images appeared to be minor. The proposed method compared favourably against other machine learning based techniques including three deep learning based techniques, making it a promising approach for skin cancer detection especially on

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imbalanced datasets. Our research expands the evidence suggesting that deep learning techniques offer useful tools in dermatology and other medical applications.

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