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Identification of Skin Cancer Using Machine Learning

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Abstract:. Skin cancer, characterized as a chronic disease, demands time-consuming and costly medical tests for accurate detection, thereby introducing risks associated with treatment delays. Acknowledging the critical need for efficient skin cancer detection, this thesis endeavors to make a significant contribution by proposing an advanced deep learning methodology. The innovative approach involves enhancing the ResNet model with SE modules and integrating a maximum pooling layer within the ResBlock shortcut connection. In comparison to established models (ResNet-50, SENet, DenseNet, and GoogleNet), the proposed method surpasses them in accuracy, parameter efficiency, and computation speed, achieving an impressive average recognition accuracy of 97.48% on a comprehensive 2142-image dataset. This transformative solution aspires to not only revolutionize skin cancer detection but also elevate the standard of patient care in this critical domain.

Keywords: Skin Cancer; Deep Learning; ResNet; Patient care.

1. Introduction

Skin cancer is a prevalent and potentially fatal condition, with an alarming 18.1 million people diagnosed annually [1]. The disease can result from DNA damage in skin cells, leading to genetic alterations that cause uncontrollable cell growth and malignant tumors. Early detection is critical to ensure successful treatment and improved patient outcomes.

Traditionally, dermatologists use visual inspection and biopsies for diagnosing skin cancer. However, these methods have significant limitations. Visual inspection is subjective and heavily reliant on the dermatologist's experience, which can lead to variability in diagnosis. Additionally, it is time-consuming, particularly when assessing a large number of patients, and prone to misinterpretation or delayed detection [2]. The biopsy method, while more definitive, is invasive, painful, and slow. It requires precise handling and processing to avoid false results, and any errors in the pre-sampling, sampling, transportation, or analysis stages can lead to inaccuracies [3].

Recent advancements in technology, particularly computer vision and machine learning, offer promising alternatives for skin cancer detection. These technologies can enhance the efficiency and accuracy of diagnosis by automating the analysis of skin images. Automated systems can support healthcare professionals in making timely and informed decisions, reducing the subjectivity and potential errors associated with manual diagnosis.

This paper proposes a novel machine learning technique to improve the early detection of skin cancer. The method involves analyzing and interpreting skin images using advanced algorithmic classification to identify various types of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma. By utilizing a large and diverse dataset, the proposed model aims to ensure stability and validity in real-world applications.

The integration of machine learning and imaging techniques has the potential to revolutionize skin cancer diagnosis. This approach seeks to overcome the limitations of manual diagnosis, providing a computerized program that can assist medical professionals in accurately identifying and classifying skin cancer types. Such advancements may lead to earlier detection, better treatment outcomes, and more effective overall management of skin cancer [4].

In summary, the study aims to develop an advanced methodology combining machine learning techniques with an extensive dataset to enhance skin cancer recognition. The proposed model has the potential to improve patient care and outcomes by increasing the accuracy, efficiency, and objectivity of skin cancer diagnosis through computational algorithms. This research represents a significant step towards creating intelligent systems that can assist doctors in diagnosing skin cancer more quickly and accurately, ultimately transforming dermatology practices.

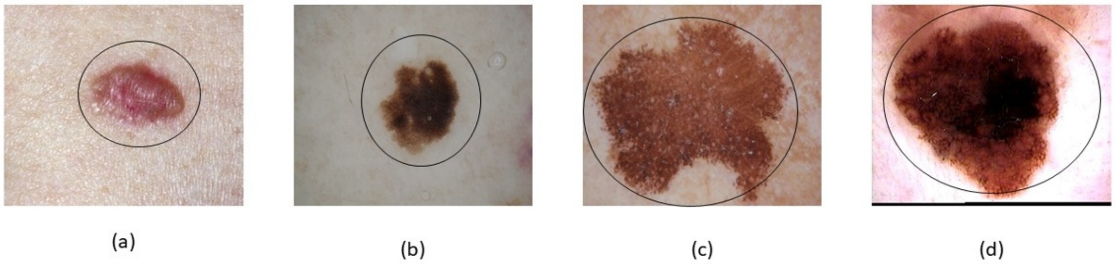

Figure 1. Types of skin cancer

2. Literature Review

This chapter reviews research on machine learning methods for skin cancer identification and classification, highlighting the benefits and challenges of automated approaches. It provides an extensive synthesis of previous research and academic publications in the field of automated skin cancer image processing.

Melanoma, a dangerous type of skin cancer, is primarily caused by ultraviolet ray exposure. Dermoscopy is essential for its diagnosis, but even experienced dermatologists achieve only 75-85% accuracy. Automated systems improve diagnostic efficiency and accuracy by analyzing subtle clues such as asymmetry, color changes, and texture characteristics [5].

Automated dermoscopy photo analysis involves preprocessing, differentiation, and feature extraction/selection. Segmentation significantly impacts subsequent analysis steps. Systems-based analytics can enhance diagnosis accuracy and speed, especially in resource-limited areas. Early identification is crucial to reduce the severity of skin diseases[6].

AI, particularly machine learning (ML) and convolutional neural networks (CNNs), have revolutionized healthcare by improving diagnostic procedures. CNNs are adept at pattern recognition tasks, making them suitable for medical image analysis. AI supports medical diagnosis, treatment, and administrative procedures, demonstrating superior performance compared to traditional methods [7].

Dermatology, reliant on visual analytics, benefits from AI. Various studies have demonstrated the efficacy of AI in detecting skin lesions and classifying them as benign or malignant.[8] developed a CNN-based model outperforming dermatologists in melanoma diagnosis. Han et al. (2021) introduced a hybrid deep acquisition architecture combining CNN and attention processes, achieving satisfactory results on benchmark datasets [9].

Numerous methodologies for skin cancer detection have emerged, including computer-aided diagnosis (CAD) systems and ensemble learning approaches. Schmid et al. designed a CAD system to detect lesion boundaries and quantify their extent. Esteva et al. (2017) and Tshand et al. (2019) showcased the effectiveness of deep learning models in identifying skin lesions .

Publicly accessible dermoscopy image datasets, such as HAM10000, Dermofit, and ISIC, play a crucial role in developing and evaluating deep learning models for skin cancer detection. Codella et al. (2018) conducted a thorough analysis of these datasets, emphasizing their importance for standardization (Codella et al., 2018).

Integrating AI-based decision support platforms into clinical workflows presents challenges, including the need for model transparency and acceptance by physicians. Studies like those by [10]highlight these issues. Additionally, ethical considerations and potential biases in AI models must be addressed to ensure reliable and fair diagnosis [11].

Recent advancements in skin cancer diagnosis involve various machine learning techniques and deep learning models. For instance, Han et al. (2021) explored transfer learning approaches to enhance model performance. Binder et al. (2020) conducted a meta-analysis confirming the clinical usefulness of ML-based methods. Esteva et al. (2020) introduced Dermatologist AI, combining deep learning algorithms with crowdsourced dermatologist expertise [12].

AI-driven diagnostic tools integrated into mobile health technologies expand access to skin cancer screening, particularly in underserved populations. Asgari et al. (2018) demonstrated the potential of mobile health technologies combined with AI for early detection [13].

AI and machine learning methods hold immense potential for revolutionizing skin cancer detection and classification. Despite challenges and ethical considerations, advancements in this field continue to improve diagnostic accuracy and efficiency, offering significant benefits for early skin cancer identification and treatment.

3. Methodology

As result of recent advancements in information and communication technology, as well as medical diagnostics, it is now possible to diagnose illnesses and treat patients more successfully. It is essential to have medical images taken in order to make an early diagnosis and prepare for treatment. In order to identify skin cancer from medical photographs using deep learning algorithms, it is important to do pre-processing, segmentation, and post-processing . Skin cancer detection from medical photographs necessitates the use of a number of different strategies before an algorithm be developed. There are mainly four phases of skin cancer detection:

- Pre-Processing Phase
- Image Segmentation Phase
- Post-Processing Phase
- Classification Phase

3.1. Pre Processing phase

Preprocessing is the first and most time-consuming phase in using medical imaging to identify malignancy, and it is also the most time-consuming step overall. If the original medical photos contain noise, it is possible that they will used. The diagnostic accuracy of medical imaging tests may be compromised a result of background noise. During the pre-processing stage, the amount of noise in raw medical photographs reduced, resulting in higher-quality photographs. Pre-processing techniques can used to generate photos with poor contrast between lesions and healthy skin, as well as photographs with skewed or otherwise warped borders, hair, or black frames. In order to reduce background noise, a variety of techniques are available, including those that use Gaussian noise, Poisson noise, salt and pepper noise, as well as speckle and speck noise, among others. A type of noise reduction approach that use a combination of the adaptive median filter and the adaptive Wiener filter in order to reduce background noise levels.

With the use of pre-processing techniques such as color correction and contrast modulation, noise in medical images can decreased or completely eradicated. In addition to other qualities, hair removal, smoothing, localization, and noise reduction are among the features available. When these pre-processing processes used together, they have the potential to improve the accuracy of skin cancer diagnosis using medical imaging. It is possible to remove hairs from the root of the hair follicle by using a Gaussian filter and a dull Razor, which is a technique known as the Karhunen transform. Other pre-processing techniques are available these days, in addition to non-skin masking include. An image analysis technique that uses pre-processing to identify malignant illness is used to analyze medical pictures. It is possible to detect brain skin cancer lesions using magnetic resonance imaging (MRI) images that have had their contrast altered by the smoothing function. It is possible to take brain tissue from the skull and put it in another location. If skull stripping is done, for example. It is necessary to convert CT scan pictures to grayscale, normalize them, and reduce noise before they can be used to correctly diagnose lung skin cancer. With the use of binary images, it is possible to remove undesired elements from photographs, which may subsequently be converted back into photographs.

The process commences with gathering skin lesion images from various origins, such as medical databases, clinical repositories, or smartphone apps. These images might be captured utilizing diverse imaging devices and under various conditions, resulting in variations in resolution, lighting, and quality.

Standardizing images is crucial for ensuring uniformity across the dataset. This involves actions like resizing images to a consistent resolution, adjusting brightness and contrast, and eliminating artifacts or noise introduced during image acquisition.

Lesion segmentation, a critical step, entails identifying and outlining the boundaries of the skin lesion within the image. Various methods, including thresholding, edge detection, or employing deep learning-based segmentation models, can be utilized for this purpose.

Image enhancement techniques can be applied to enhance the visibility of crucial features within the lesion, such as sharpening edges, improving texture, or adjusting contrast to highlight significant details indicative of malignancy.

Following preprocessing and segmentation, relevant features are extracted from the images to represent each lesion. These features encompass texture descriptors, color histograms, shape characteristics, and other quantitative measures derived from the lesion's appearance.

Normalization and scaling techniques are often employed to ensure comparability of features across different samples, thereby reducing the impact of variations in feature magnitudes on the model's performance.

Data augmentation methods are utilized to augment the dataset's size and diversity artificially. Techniques such as rotation, translation, flipping, or adding noise to images are applied to prevent overfitting and enhance the model's generalization capability.

Ultimately, the dataset is divided into sets for testing, validation, and training. The validation set helps tune hyperparameters and evaluate performance during training, the test set evaluates the performance of the completed model on untested data, and the training set is used to develop machine learning models.

Through these preprocessing steps, researchers ensure that input data is appropriately prepared for subsequent analysis, thereby facilitating the development of more robust and accurate machine learning models for skin cancer identification.

3.2. Image Segmentation phase

A crucial step in the analysis of medical imaging is segmenting the images, which should never be disregarded. A medical picture must be split into multiple interest zones or segments of interest in order to extract the most significant information. Sets up a clear separation between background and main focus in the image. The images are classify medical imagery into four broad categories:

- Segmentation of the general population based on a model.
- Properties of pixels are used to segment the image.
- Market segmentation based on geography.
- When a preset threshold has been reached, segmentation is carried out.

Each category has a set of techniques that can be used in combination with each other. Both histogram-based thresholding algorithms and local and global standards can be used in threshold-based segmentation techniques. This argument has been shown using techniques of maximum entropy, maximum entropy, and Ostu. Watershed segmentation and sowing area expansion are two examples of area-based technologies. For example, fuzzy c-means clustering and Markov field approaches are used in pixel-based segmentation techniques. These methods have been tried under a wide range of conditions. Some of the techniques used in this paper are statistical region growing and clustering, contextual hypergraph, edge detection, fuzzy C-means construction, gradient flow vectors, thresholding of histograms, principal part transformation, approximate modeling, small band graph partitioning. with area fusion band. , and sparse coordination. Combining multiple segmentation approaches can result in a hybrid methodology for segmentation that performs and achieves better accuracy than the separate segmentation methods.

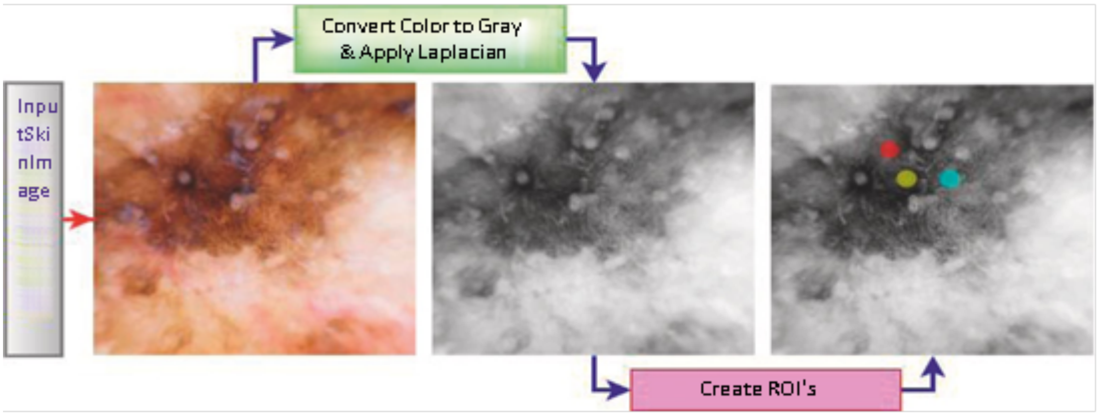

Figure 2. Image segmentation and creating ROI.

3.3. Post-processing phase

During the post-processing step of the pipeline for analyzing medical imaging for skin cancer detection, a significant property of a medical imaging image is discovered and gathered. This is done following picture segmentation and pre-processing. To fulfil the goal of capturing qualities, a number of different approaches have been developed and tested. The broadening of the border and the elimination of the islands, as well as the expanding or closure of operations or the combination of geographical regions, are all popular options. Afterwards, post-processing processes are applied to the picture, and characteristics from the specified region are compiled for further analysis with the goal of identifying illness. Some of the most often used approaches for extracting features are decision boundary features, Fourier power spectrum (FPS), Gaussian derivative kernels , grey level co-occurrence matrix (GLCM), principal component analysis (PCA), and wavelet packet transform.(WPT).

3.4. Classification phase

The deep learning algorithms then used to classify medical photos according to the different types of skin cancer that have been identified once the post-processing stage is completed. Deep learning algorithms have developed in accordance with a number of different ideas. Deep learning approaches may divided into four major categories. The classification strategy entails building and testing a deep learning classifier for skin cancer type identification utilizing images based on their attributes in order to detect different types of skin cancer. In the first stage, photos from the training dataset used to build a deep learning classifier, which then used in the second stage. After a sufficient number of training cycles, the deep learning model that has trained can properly detect the kind of skin cancer in unknown pictures. There are several types of recurrent neural networks (RNNs), including recurrent neural networks (RNNs) and gated recurrent units (GRUs) (GRU).

3.5. Data Annotation

The online database of the European Skin Imaging Partnership (ISIC) provided an average of 2142 (306*7) skin cancer imaging data for this investigation. Basal cell carcinoma, Angio cutaneous, dermatofibroma, actinic keratosis, basal cell carcinoma, benign keratosis, melanocytic nevus, and melanoma are the seven major categories of collected skin tumor datasets. We tested all types of skin cancer in our dataset of 306 photos. Using our benchmark image database, the following skin types are included: An 8:2 ratio is used to randomly separate the collected photos into training and validation sets (1713 training photos and 429 validation images). After data augmentation, a training set of 6,864 images was created. Figure 8 shows what the preprocessing steps look like.

3.6. Experimental Configuration

The specifications of the PC used in this experiment are NVIDIA's GTX 1080Ti graphics card, 64GB RAM, and chip manufacturer's Intel CoreTM i7-8700 CPU. Deep learning algorithms can be trained on networks using the Pytorch graphics processing unit 1.8.0 framework and the Windows operating system. The platform was developed using the integrated computer environment PyCharm2020, Torch 1.8.0 and cuDNN version 11.0.To more completely evaluate the differences between expected and actual results, we conducted experiments using a batch learning approach. We set the weight initialization bias to 0 and set the model's Xavier weight loading scheme and cross-entropy loss. Other parameters include: The model was found to be optimized using Softmax and SGD classifiers. Stochastic Gradient Descent was used to optimize the model, and the size of the model was reduced by 0.1 after 10 iterations. The input image size was standardized to 224 × 224 for training and testing purposes. When the data set has been taken which consist of multiple images and after the size of model was reduced after 10 iterations by 0.1of its reduction. The main reason was to evaluate the difference between expected and actual results, we perform experiments using a batch learning approach. The input images was standardized for training test and testing procedure. For experimental configuration there are some specification of the system which are used in the experiment, in which graphic card, chip manufacturer, different algorithms has been trained on the network. There are some graphics processing unit framework and the windows operating system is used. Then a complete platform is designed which is then used by Integrated computer environment. A total of 51 training periods were performed before the merged model was saved as the final versionto be used in the finished model. Figure 4.2 below shows some improvements

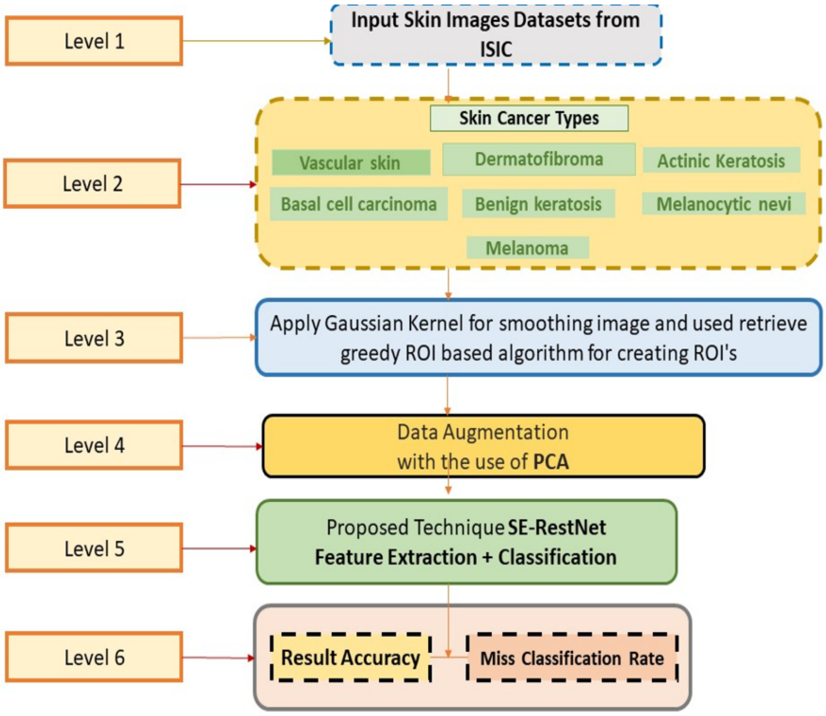

Figure 3. Methodology Framework

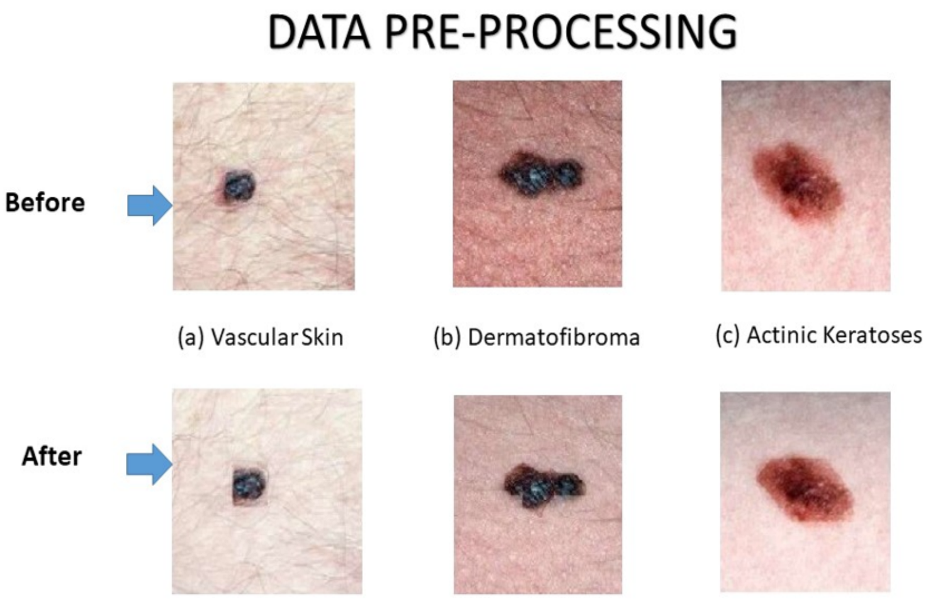

Figure 4. Data pre-processing images of skin cancer different types

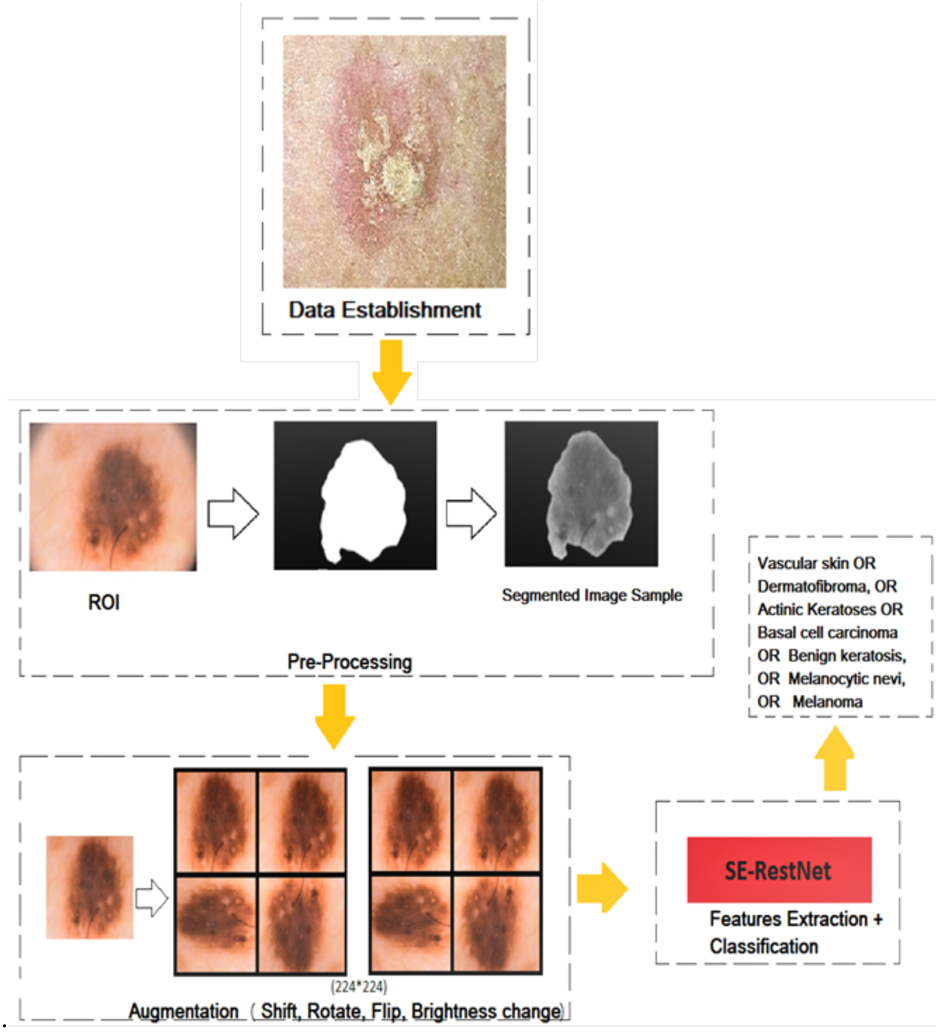

Figure 5. Model

4. Results

Based on the ResNet architecture, this chapter investigates datasets generated using different numbers of SE launch modules. Table 3 shows how the recognition accuracy of the model increases with the addition of one SE module. When more than one SE unit is introduced, the impact on perception is much reduced. When using initial values of all four SE factors, the model performs better and the magnitudes remain within the acceptable range. The SENet connector is also used in this part. Nevertheless, it adds too many parameters and reduces model identification accuracy compared to the simple SENet concatenation created by concatenating four SE launch modules. For this reason, the model in this work was developed using four SE initiation components.

Table 1. Influence of the number of different SE modules on the recognition results

Model	GFLOPs	Params size (MB)	Params	Accuracy (%)
1SE-ResNet	2.578	34.43	9,025,610	92.74
2SE-ResNet	2.578	34.55	9,058,378	90.85
3SE-ResNet	2.579	35.05	9,189,450	90.53

4SE-ResNet	2.579	37.05	9,713,738	94.95
All- ResNet	2.59	37.52	9,836,731	94.01

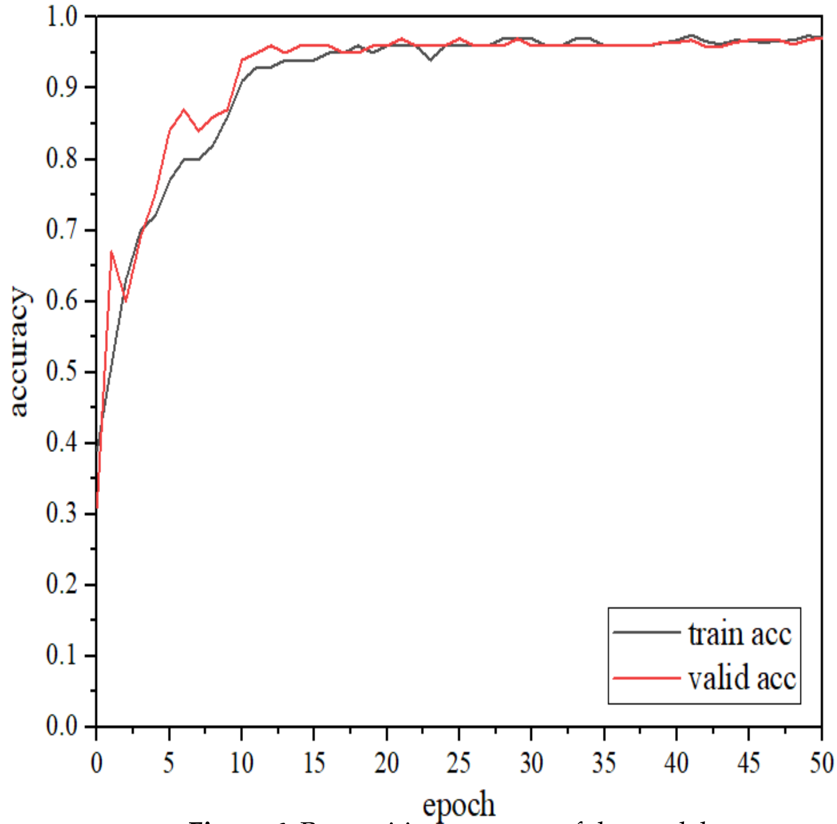

Figure 6. Recognition accuracy of the model

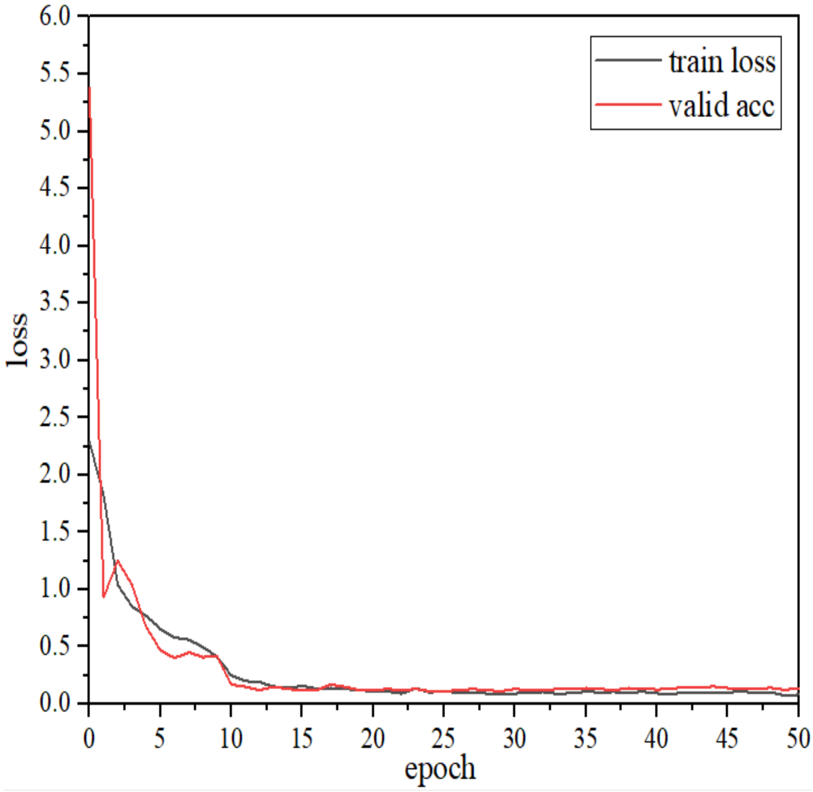

Figure 7. Loss curve of the proposed model

5. Conclusion

This paper introduces cost-effective prognostic tools for skin cancer using advanced deep learning techniques on microscopic and macroscopic images, enhancing biological behavior prediction of early malignancies. The study covers nine skin cancer types, employing digital pathology images from the ISIC. It proposes a multi-functional approach using texture feature datasets, PCA for dimensionality reduction, and various classification algorithms, achieving 97.1333% accuracy with MLP. An improved ResNet model, incorporating a multi-scale model and SE module, attained 97.48% accuracy, outperforming previous models. Additionally, a unique classification model combining convolutional and recurrent neural networks was developed, focusing on nine skin cancer types with augmented ISIC images. This model, involving ResNet-50 and LSTM layers, showed excellent performance in accuracy. These findings underscore the potential of deep learning to improve diagnostic accuracy and patient outcomes in skin cancer detection and treatment, providing valuable tools for dermatologists and healthcare professionals.

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