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Skin Cancer Diseases Classification using Deep Convolutional Neural Network with Transfer Learning Model

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ABSTRACT: Skin cancer ranks among the most prevalent forms of cancer globally, contributing to millions of fatalities. Its primary cause lies in the uncontrolled mutation growth within DNA. Early detection is pivotal for enhancing treatment success rates. Modern medical practices leverage technology extensively, with intelligent systems aiding in the analysis and classification of skin conditions. Detecting infection rates accurately poses challenges due to the intricate texture of skin and the visual similarities of diseases. This study aims to analyze biomedical datasets containing pre-existing illness data to develop an effective method for distinguishing skin cancer as either malignant or benign. Leveraging ResNet-50 deep learning architectures, we classify the dataset. With a dataset comprising training images, our model achieves an accuracy of 86.66%. This accuracy may further improve with increased epochs.

KEYWORDS: Skin Cancer, Intelligent-systems, Resnet-50, Malignant, Benign.

I. INTRODUCTION

Skin cancer emerges as a pressing concern in the 21st century, with its incidence steadily rising. Ranked as the third most common cancer, it stands as a significant contributor to non-accidental deaths among individuals aged 20–39[1,2]. Furthermore, melanoma cases have surged by 53% over the past decade, primarily attributed to UV exposure [3]. Timely detection of skin lesions assumes paramount importance to forestall metastasis and fatal outcomes. Nonetheless, discerning various skin lesions poses challenges, even for seasoned dermatologists, owing to their nuanced distinctions. The imperative for prompt and precise diagnosis is underscored by its potential to avert metastasis and fatal consequences [4]. Despite this urgency, distinguishing between many skin lesions remains daunting, even for experts [5]. To enhance the accuracy and efficiency of skin cancer diagnosis while mitigating reliance on invasive biopsy procedures, a pioneering deep learning model was devised, leveraging transfer learning and data augmentation techniques. It's noteworthy that this study does not constitute an ablation study, as the proposed model's evaluation did not entail the removal or alteration of individual components to assess their impact on overall performance.

Skin cancer, as the most prevalent type of cancer in the present era, is particularly active due to the expansive coverage of the human body by the skin, which serves as the body's largest organ. Broadly categorized into benign (noncancerous) and malignant (cancerous) types, the former typically exhibits slow growth and limited spread, exemplified by conditions like seborrheickeratoses and dermatofibromas. In contrast, malignant tumors grow rapidly, invade healthy tissues, and metastasize throughout the body, posing significant health risks. Notable examples include melanoma and squamous cell carcinoma.

Early detection is paramount for successful treatment, often necessitating invasive biopsy procedures. However, computer-based technologies offer a promising alternative for efficient, cost-effective, and non-invasive detection of skin cancer symptoms. Deep learning techniques, such as ResNet-50, play a pivotal role in this endeavor, leveraging their ability to analyze, recognize, and categorize images in datasets. ResNet-50, in particular, with its deep architecture and pre-training on a vast dataset like ImageNet, excels in image recognition and object detection. Combined with other image analysis techniques, these deep learning algorithms enhance the speed and accuracy of skin cancer detection.

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The application of ResNet-50 in a developed algorithm yields an impressive accuracy rate of 86.66% in identifying the type of skin cancer, while also enabling precise modifications to images of afflicted skin. This underscores the potential of deep learning in revolutionizing skin cancer diagnosis, offering hope for improved outcomes and reduced burdens on patients and healthcare systems alike.

As an initial step, it is exploited to identify suspicious skin lesions using a non-invasive method. Figure 1 showssomesampleimages ofvarious skincancers.

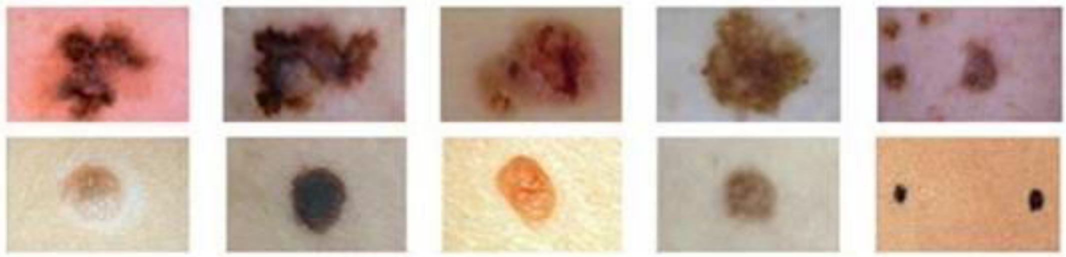

Figure1: Some samples of Skin cancer and normal images.

II. LITERATURESURVEY

With the use of training datasets, neural networks have been utilized to identify skin cancer. A thorough comprehensive assessment of deep learning approaches for the early diagnosis of skin cancer has been successfully carried out in the past. Research is being done to understand how a learning model is trained with pre-processed and trained datasets. The model is taught to comprehend the image's lesion attributes, including symmetry, colour, size, form, and others, which are then employed to both identify skin cancer and discriminate benign from malignant skin cancer. The procedures mostly entail gathering datasets, which is followed by cleaning datasets. Segmentation and feature extraction from the dataset are subsequent processes, followed by training datasets, testing, and training the model. The image collection of skin cancer is received with forecasts of its accuracy, specificity, and sensitivity. The detection uses a variety of traditional deep learning techniques, including generative adversarial neural networks (GAN) for skin cancer, artificial neural networks (ANN), convolutional neural networks (CNN), and Kohonen self-organizing neural networks (KNN). Convolution neural network (CNN) architectures have been used by several researchers to analyse datasets on skin cancer in an effort to improve methods for early skin cancer detection. In fact, CNN is quite accurate in identifying the type of skin cancer when applied to the Image dataset. The authors of [6] first proposed CNN for the analysis of skin lesions in dermoscopy pictures. Using deep CNN with the International Skin Imaging Collaboration (ISIC) dataset, they were able to attain an accuracy of 80.3%. The data is divided using a convolutional-deconvolutional architecture. On the same dataset, a different team of researchers employed CNN based on symptomatic feature extraction [7]. In this study, the properties of the affected skin cells are obtained following the segmentation of the dermoscopic pictures utilizing the feature extraction technique. The categorization of skin cancer based on vision has been reported in a publication. They employed the VGG16 and CNN [8]. An accuracy of 78% was achieved after working on three distinct training techniques. In that system, three models were employed: a deep convolutional neural network, logistic regression, and a tailored, pretrained VGG16. On the 2742 dermoscopic pictures from the ISIC dataset, a team of researchers also used a region-based CNN with ResNet152 [9].

A study published in the Journal of Medical Internet Research in 2018 that used a ResNet-50 model to classify skin lesions as malignant or benign with an accuracy of 89.9%. Additionally, research utilizing SVM and sequential models were carried out, with the obtained accuracy above 75%. The software "Design and implementation of Skin Cancer Predictor system applying Machine Learning Algorithms on Live cloud architecture" was built. It is extremely challenging to automatically detect different skin lesion states from medical dermoscopy images. past research papers propose a cascading new deep learning network-based integrated model for segmenting and categorizing skin lesions. A special full resolution neural network is used in the initial stage to segment the boundaries of skin lesions from dermoscopy pictures (FrCN). The segmented lesions are then submitted to a deep residual network for classification.

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[10] In order to categorize skin cancer, YessiJusman, Indah Monisa, DhimasDharmawan, and KunnuPurwanto proposed a Multilayer Perceptron in 2021. This model included a modified CNN with VGG16. Based on their analysis of the HAM10000 dataset, they found that VGG16 operates considerably more quickly than Multilayer Perceptrons [11]. NourAburaed, Mina Al-Saad, WatiqMansoor, AlavikunhuPanthakkan, and Saad Ali Aminin 2020 developed a classification system for skin cancer that made use of VGG16 and VGG19[12]. The accuracy rate of ResNet-101 architecture and Inception-v3 architecture were compared in 2019 by OnurKöse, Feyza YILMAZ, and Ahmet DEMR, who found that the latter was more prevalent than the former "Deep learning for skin cancer detection: a systematic review" by Han et al. (2020) [13] is a review of existing studies that have used deep learning for the detection and diagnosis of skin cancer. The authors conducted a comprehensive search of the literature and identified a total of 35 studies that met their inclusion criteria. The review found that deep learning has the potential to improve the accuracy and efficiency of skin cancer detection compared to traditional methods. However, the authors also noted that the performance of deep learning models can vary significantly depending on the specific characteristics of the dataset and the type of skin cancer being detected. Overall, the review found that deep learning models were most accurate for detecting melanoma. However, the accuracy of these models was lower for the detection of other types of skin cancer, such as basal cell carcinoma and squamous cell carcinoma. The authors concluded that further research is needed to improve the performance of deep learning models for skin cancer detection and to address issues such as dataset bias and generalizability to real-world settings. "A deep learning-based approach for skin cancer diagnosis using dermoscopic images" by Akay et al. (2019) [14] is a study that investigated the use of deep learning for the diagnosis of skin cancer using dermoscopic images. The authors developed a convolutional neural network (CNN) model using a dataset of over 100,000 images of skin lesions, including both benign and malignant tumors. The study found that the CNN model performed well for the diagnosis of squamous cell carcinoma, with accuracy rates of 84.6%, respectively. The authors concluded that the use of deep learning for the diagnosis of skin cancer using dermoscopic images is a promising approach that has the potential to improve the accuracy and efficiency of skin cancer diagnosis. However, they also noted that further research is needed to optimize the performance of these models and to address issues such as dataset bias.

III. MOTIVATION

Cancer poses a severe threat to human life, often leading to fatalities, and among the various types, skin cancer emerges as one of the rapidly escalating malignancies that can result in death. Several factors contribute to its onset, including smoking, alcohol consumption, allergies, infections, viruses, physical activity, environmental changes, and exposure to ultraviolet (UV) light. UV rays, especially from the sun, have the capacity to damage the DNA within skin cells, predisposing individuals to skin cancer. Additionally, abnormal swellings in the body can also trigger skin cancer development.

Given its association with a higher mortality rate, estimated at 50%, early detection of skin cancer is crucial. Timely diagnosis allows for simpler treatment options like excision, significantly reducing the risk of death. Conversely, delayed diagnosis is linked to an increased risk of fatality. To mitigate the mortality rate associated with skin cancer, there's a pressing need for non-invasive and efficient systems for detecting skin lesions early. Early detection can be instrumental in saving lives, underscoring the urgency for the development and implementation of effective skin lesion detection systems.

IV. PROPOSED SYSTEM

The model utilizes ResNet-50 to identify and classify images as malignant or benign. ResNet-50 is a deep learning model renowned for its proficiency in image recognition, object detection, and picture categorization. With its 50 layers, ResNet-50 has been extensively trained on a vast dataset of one million images from the Image Net database, providing a robust foundation for classification tasks.

Despite the advantages offered by dermatoscopy in improving the diagnosis of pigmented skin lesions compared to visual examination, the availability of modest-sized and insufficiently diverse datasets poses challenges for training neural networks. However, artificial neural networks, when trained on dermoscopy images, hold promise for automating the identification of pigmented skin lesions, potentially enhancing diagnostic accuracy and efficiency. The

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proposed system diagram is shown in below Figure 2:

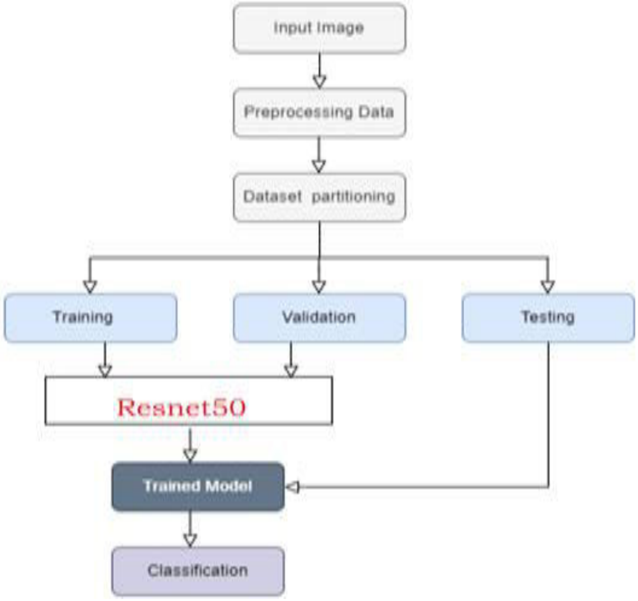

Figure 2: Proposed system diagram

4.1 ResNet-50:
ResNet50 stands out as a potent image classification model, capable of achieving cutting-edge performance when trained on extensive datasets. Its groundbreaking feature lies in the integration of residual connections, which facilitate the learning of residual functions mapping input to output. This innovation enables the network to delve into much deeper architectures without succumbing to the issue of vanishing gradients.The architecture of ResNet50 as comprises four main components: convolutional layers, identity blocks, convolutional blocks, and fully connected layers. The convolutional layers play a pivotal role in feature extraction from the input image, while the identity and convolutional blocks process and transform these features. Finally, the fully connected layers are employed for the ultimate classification decision.

The convolutional layers within ResNet50 consist of multiple convolutional layers followed by batch normalization and ReLU activation functions. These layers are instrumental in extracting various features from the input image, including edges, textures, and shapes. Subsequently, max pooling layers are applied to reduce the spatial dimensions of the feature maps while retaining crucial features.The identity block and convolutional block serve as fundamental building blocks within ResNet50. The identity block follows a straightforward path, passing the input through convolutional layers and adding it back to the output. This mechanism empowers the network to learn residual functions effectively. Meanwhile, the convolutional block resembles the identity block but incorporates a 1x1 convolutional layer to decrease the number of filters before the 3x3 convolutional layer.The culmination of ResNet50 lies in its fully connected layers, responsible for the final classification decision. The output of the last fully connected layer undergoes a softmax activation function, generating the probabilities for each class, thereby facilitating the conclusive classification. Further, Figure 3 demonstrates internal details of ResNet-50 CNN model,whereasFigure 4depictsthebasicflow diagramofthetypicalResNet-50 CNN model.

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Structural Details of ResNet-50 Model

- A convolution with a kernel size of 7 x 7 and 64 different kernels all with a stride of size 2 giving us 1 layer.
- Next we see max pooling with also a stride size of 2.
- In the next convolution there is a 1 x 1, 64 kernel following this 3 x 3, 64 kernel and at last a 1 x 1, 256 kernel, these three layers are repeated in total 3 time so giving us 9 layers in this step.
- Next we see kernel of 1 x 1, 128 after that a kernel of 3 x 3, 128 and at last a kernel of 1 x 1, 512 this step was repeated 4 time so giving us 12 layers in this step.
- After that there is a kernal of 1 x 1, 256 and two more kernels with 3 x 3,256 and 1 x 1, 1024 and this is repeated 6 times giving us a total of 18 layers.
- And then again a 1 x 1, 512 kernels with two more of 3 x 3, 512 and 1 x 1, 2048 and this was repeated 3 times giving us a total of 9 layers.
- After that we do an average pool and end it with a fully connected layer containing n nodes and at the end a softmax function so this gives us 1 layer.

Figure 3: Internal structural details of theResNet-50architecture.

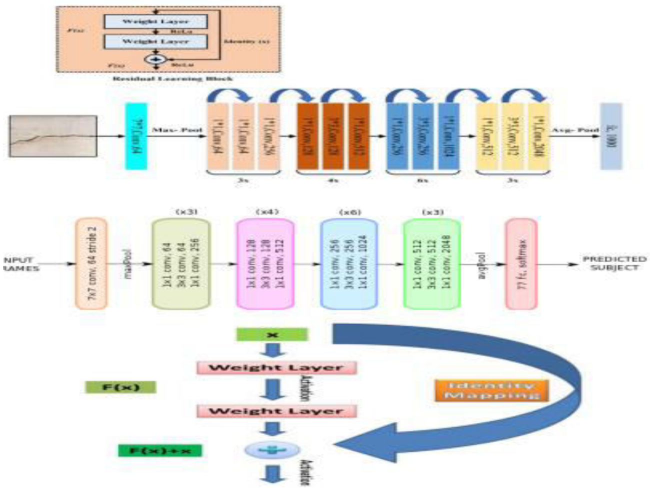

Figure 4: ResNet-50 neural network architecture

Deep learning has emerged as a valuable tool in the advancement of computer-aided diagnosis for detecting skin lesions. However, one of the challenges in applying deep learning methods in the medical domain is the scarcity of high-quality and large-scale open datasets. This limitation is inherent in the medical field due to privacy concerns, preventing many clinics and hospitals from publicly sharing their data. Nevertheless, several researchers have managed to overcome these barriers by pushing the boundaries of technology.

Platforms like the ISIC Archive have facilitated access to data, enabling the utilization of convolutional neural networks (CNNs) for medical diagnosis, particularly in the field of skin lesion detection. Two prominent research trends can be observed in this domain: one involves utilizing CNN architectures with transfer learning to mitigate data availability limitations, while the other leverages larger, unlabeled datasets through unsupervised learning techniques, followed by supervised learning for classification. The approach presented in this work adopts the former strategy, employing transfer learning due to the lack of a larger dataset.

The proposed approach entails developing a hybrid CNN model that integrates features from pre-trained ResNet-50 architectures for skin lesion detection using dermoscopic images. Initially, the dermoscopic image is fed as input to

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both selected CNN models. The output of the final max pooling layer is the average pooling layer of ResNet-50 are then selected and passed through new fully connected (FC) layers with ReLU activation functions. Subsequently, a new FC layer is constructed to fuse the features generated from the previous layers. Additional FC layers are employed to extract more salient features, culminating in a final FC layer with softmax activation function for classification.

The proposed hybrid CNN model is retrained using 80% of the dataset, while the remaining 20% is used for validation. Detailed structural diagrams and algorithmic steps of the proposed classification scheme are provided for clarity in the article. This approach showcases a novel methodology for skin lesion detection, leveraging the strengths of multiple CNN architectures to improve classification accuracy.

V. RESULTS

5.1 Dataset Description

The dataset utilized in this study comprises skin mole images categorized as Malignant and Benign. In total, the dataset consists of 4946 images. Among these, 2637 images are allocated for training, while 681 images are designated for testing purposes. Furthermore, the training dataset constitutes 80% of the total images, with the remaining 20% allocated for testing.

The performance of the model is analyzed by using the confusion matrix. This will specifythe performance of classification models for given test data. This will specify the values for test data that are known. This matrix is divided into two attributes such as predicted values and original values along with an overall number of predictions.

5.2 Performance Metrics

The performance of the model is analyzed by using the confusion matrix. This will specifythe performance of classification models for given test data. This will specify the values for test data that are known. This matrix is divided into two attributes such as predicted values and original values along with an overall number of predictions.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

True Negative (TN): The prediction value is false and actual value is also false.

True Positive (TP): The prediction value is true and actual value is false. False Positive (FP): The predicted value is true and actual value is false. FalseNegative (FN):Thepredictedvalueisfalse andactualvalueis true.

Accuracy:

The accuracy metric is one of the simplest Classification metrics to implement, and it can be determined as the number of correct predictions to the total number of predictions.

It can be formulated as:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

To implement accuracy metric, we can compare ground truth and predicted values in a loop, or we can also use the scikit-learn module for this. Firstly, we need to import the accuracy_score function of the scikit-learn library as follows: from sklearn.metrics import accuracy_score

Here, metrics is a class of sklearn. Then we need to pass the ground truth and predicted values in the function to calcul ate the accuracy.Although it is simple to use and implement, it is suitable only for cases where an equal number of samples belong to each class.

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Precision:

The precision metric is used to overcome the limitation of Accuracy. The precision determines the proportion of positive prediction that was actually correct. It can be calculated as the True Positive or predictions that are actually true to the total positive predictions (True Positive and False Positive).

$$Precision = \frac{TP}{(TP + FP)}$$

Recall or Sensitivity:

It is also similar to the Precision metric; however, it aims to calculate the proportion of actual positive that was identified incorrectly. It can be calculated as True Positive or predictions that are actually true to the total number of positives, either correctly predicted as positive or incorrectly predicted as negative (true Positive and false negative).
The formula for calculating Recall is given below:

$$\text{Recall}= \frac{TP}{TP+FN}$$

F1-Scores:

F-score or F1 Score is a metric to evaluate a binary classification model on the basis of predictions that are made for the positive class. It is calculated with the help of Precision and Recall. It is a type of single score that represents both Precision and Recall. So, the F1 Score can be calculated as the harmonic mean of both precision and Recall, assigning equal weight to each of them.
The formula for calculating the F1 score is given below:

$$F1 - score = 2 * \frac{precision * recall}{precision + recall}$$

Figure 5 shows some sample images for which cancer is detected.

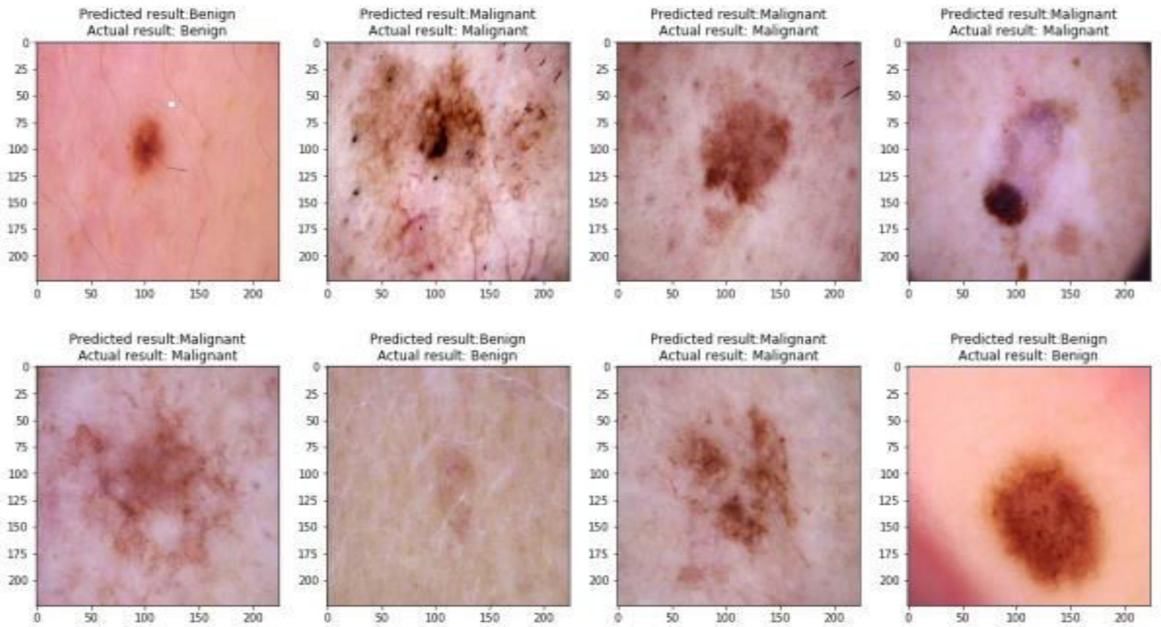

Figure 5: Sample images for which cancer is detected.

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Table 1 presents the performance metrics of various DL models.

Table 1: Comparison of DL Models

Model/Metric	**Accuracy**	**Precision**	**Recall**	**f1-score**
ANN	72.12	0.62	0.71	0.69
CNN	86.23	0.81	0.83	0.82
ResNet-50	99.45	0.96	0.97	0.96

VI. CONCLUSIONS

This article underscores the significance of automated classification methods in supporting the detection of skin cancer. Various approaches were discussed to enhance prediction accuracy, offering valuable insights for the medical field. However, challenges persist, particularly in dealing with the diverse clinical images influenced by factors like different cameras and environmental conditions. The study employed a CNN model, specifically utilizing ResNet-50, which demonstrated satisfactory performance in classifying two types of skin cancer. Furthermore, the article presented techniques for the decision-making process in model selection, offering a systematic framework applicable across diverse applications. The work showcased a methodology for constructing a ResNet-50 model and conducted experiments to evaluate its performance based on metrics such as accuracy, precision, recall, and F-measure. Overall, the study provides a promising avenue for leveraging deep learning models in skin cancer detection, contributing to advancements in medical diagnosis and treatment.

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