Multi-Class Classification of Skin Diseases Using ResNet50

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2023 6th International Conference on Information and Communications Technology (ICOIACT) | 979-8-3503-1563-9/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICOIACT59844.2023.10455953

***Abstract*—The World Health Organization (WHO) reports that cancer is one of the leading causes of death globally and is responsible for approximately 10 million deaths yearly. Globally, about 1 in 6 deaths are attributed to cancer. As the body's outermost organ, the skin is vulnerable to various diseases, and accurate diagnosis is crucial for effective treatment. However, limited access to dermatologists and expensive skin biopsies pose challenges to efficient diagnosis. In this research, we utilized the ResNet50 model to classify seven types of skin diseases. We employed the HAM10000 dataset, which consists of images representing disease classes such as akiec, bbc, bkl, df, mel, vasc, and nv. The ResNet50 model was trained and evaluated using accuracy, precision, recall, and F1-score performance metrics. The research findings reveal that the ResNet50 model achieved a high level of accuracy, with an accuracy rate of 91.71% on the test data. The precision, recall, and F1-Score metrics also demonstrated excellent performance, with 91.89%, 92.04%, and 91.87% respectively. These results confirm the model's effectiveness in classifying various skin diseases, demonstrating high precision for accurate identification and high recall for locating all actual instances. The balanced F1-Score emphasizes the model's proficiency in diagnosis, advancing skin disease classification with ResNet50. Overall, these findings contribute to advancing skin disease diagnosis using the ResNet50 model and highlight its efficacy in achieving accurate and reliable classification results.**

Keywords— Dermatological, Convolutional Neural Network, ResNet50, Deep learning, Skin disease classification.

I. INTRODUCTION

The World Health Organization (WHO) reports that cancer is one of the leading causes of death worldwide, responsible for approximately 10 million deaths yearly. It is estimated that cancer accounts for 1 in 6 deaths globally, and it is projected that cancer-related deaths will increase by 45% from 2008 to 2030. Among various types of cancer, skin cancer ranks fifth in prevalence. Skin cancer occurs due to abnormal growth of skin cells and is highly prevalent worldwide [1].

As the primary physical barrier of the body, the skin plays a crucial role in protecting against harmful elements such as ultraviolet radiation and chemicals. It also possesses antibacterial properties that contribute to the immune system's defense against foreign substances and microorganisms. However, exposure to the environment makes the skin susceptible to various diseases. Skin diseases can arise from fungal growth, bacterial infections, allergic reactions, microorganisms affecting skin texture, or abnormal pigment production [2].

Skin diseases encompass a wide range of types and causes. Examples include Actinic Keratoses and Intraepithelial Carcinoma (AKIEC), Basal Cell Carcinoma (BCC), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF), Melanocytic Nevi (NV), Melanoma, Vascular Lesions (VASC), and others.

Dermatology experts typically perform an accurate diagnosis of skin diseases. However, challenges such as limited dermatologist access and insufficient skin health awareness often arise. If left untreated, skin diseases can lead to disabilities, high treatment costs, and even life-threatening conditions. Dermatologists commonly use skin biopsies, which involve taking small tissue samples for laboratory examination, to diagnose chronic skin diseases. However, biopsies can be expensive and cause skin wounds or abrasions [3]. Therefore, developing systems that can assist in efficient skin disease classification is crucial to overcome these limitations.

In the modern era, technological advancements, including computer vision, have significantly impacted various aspects of human life. Computer vision, a branch of artificial intelligence, enables computers to perceive and understand visual inputs like images. Computer vision's progress in healthcare has become a critical issue, with medical professionals utilizing medical image data to aid diagnosis, treatment, and disease identification [4].

Building a system for classifying skin diseases requires the application of machine learning or deep learning methods capable of analyzing image data. Deep learning techniques have shown effectiveness in analyzing medical images, and Convolutional Neural Network (CNN) is a widely used method for image classification. CNNs have demonstrated excellent feature extraction capabilities, particularly in classifying medical images [5].

However, several problems need to be overcome in research on the classification of skin disease types using CNN and CNN-SVM. The limitations of a sizable and representative dataset, class imbalances in the number of samples between skin disease types, complexity in data preprocessing, and developing more efficient models in the CNN architecture are some of the problems faced in this study.

This research aims to develop a system for classifying seven types of skin diseases using the ResNet50 architecture of CNN. The CNN method has been proven to achieve high accuracy in various previous studies of medical image classification. However, several challenges need to be addressed in the research on skin disease classification using CNN. These challenges include the limitation of having a sufficiently large and representative dataset, class imbalance in the number of samples among different types of skin diseases, complexity in data preprocessing, and the development of more efficient CNN architectures.

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II. LITERATURE REVIEW

Using deep learning techniques for skin disease classification has garnered considerable attention in recent years. Numerous studies have been dedicated to developing robust models to classify various skin diseases accurately. This literature review delves into the findings and contributions of relevant research in this domain.

Study [6] examines the use of deep learning for skin cancer detection. Early skin cancer detection is crucial for improving outcomes, but it can be challenging due to similarities between different skin lesions. Deep learning models have shown promise in accurately identifying and distinguishing skin lesions by learning pixel-level details. However, not all models perform equally, with some producing false-positive results. Comparative analysis of various models, including CNN, Resnet-50, VGG-16, Densenet, Mobilenet, Inceptionv3, and Xception, was conducted using the HAM10000 dataset. Results varied, and stacking models performed poorly. Deep learning can improve skin cancer detection, but further optimization is needed.

"Convolutional neural network-based skin image segmentation model to improve classification of skin diseases in conventional and non-standardized picture images" [7] proposed a skin image segmentation model based on CNN and a computer-aided diagnosis system (CAD). Their study aimed to enhance the classification of skin diseases in conventional and non-standardized picture images. The CNN segmentation model was designed to extract skin lesions and separate them from the background automatically. The evaluation results revealed a high sensitivity and specificity of approximately 90% in distinguishing atopic dermatitis.

In this study, [2] proposed an integrated diagnostic framework that combines skin lesion boundary segmentation using deep learning (FrCN) and classification using convolutional neural networks (Inception-v3, ResNet-50, Inception-ResNet-v2, DenseNet-201). The results showed improved classification performance for Inception-ResNet-v2 when using segmented lesions. The classifiers achieved overall weighted prediction accuracies ranging from 81.79% to 89.28% for different skin lesion classes. This integrated diagnostic approach holds promise for enhancing skin cancer diagnosis [2].

The study [8], focused on employing Deep Convolutional Neural Networks (Deep-CNN) to classify melanoma skin cancer from skin lesion images automatically. The study compared the performance of various CNN architectures, including DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, and GoogleNet. While GoogleNet exhibited the best performance among the architectures tested, the study was limited to the classification of melanoma and did not explore the effectiveness of the architecture in recognizing different features, diverse skin types, and various skin diseases. The achieved accuracy of 74.91% in training and 76.08% in testing indicated the potential for further improvements.

The subsequent study [9] aims to classify multi-class skin cancer using the Deep Convolutional Neural Network method. The research applies a CNN model and six transfer learning models, namely ResNet-50, VGG-16, DenseNet, MobileNet, Inceptionv3, and Xception, to the HAM10000 benchmark dataset, which comprises seven types of skin diseases. The study reports accuracy results of 90%, 88%, 88%, 87%, 82%, and 77% for Inceptionv3, Xception, DenseNet, MobileNet, ResNet, CNN, and VGG16, respectively.

Another study [10] employed the Deep-CNN method to detect and classify four types of skin cancer. The proposed model achieved an accuracy of 96.98% for the four types of skin cancer. However, this study utilized a relatively small initial dataset of only 800 images for the four disease classes, indicating an increased dataset size needed to learn more representative features and better differentiate between disease classes.

III. METHOD

A. Research Flow

The stages involved in classifying seven types of skin diseases using the CNN architecture ResNet50 are as follows: (1) Data collection, where a dataset of dermatological images encompassing the seven types of skin diseases is gathered. (2) Data preprocessing, which includes labeling the data, data augmentation to increase dataset variation, image resizing, data normalization, and splitting the dataset into training, validation, and testing subsets. (3) Building the CNN ResNet50 classification model to classify skin diseases using the preprocessed training dataset. (4) Evaluating the model using the validation dataset to assess performance and training progress, utilizing evaluation metrics. (5) Analyzing the results and drawing conclusions, where the evaluated model results are analyzed and compared with other methods, and conclusions are drawn regarding the effectiveness of the model in classifying skin diseases, along with recommendations for dermatology practice.

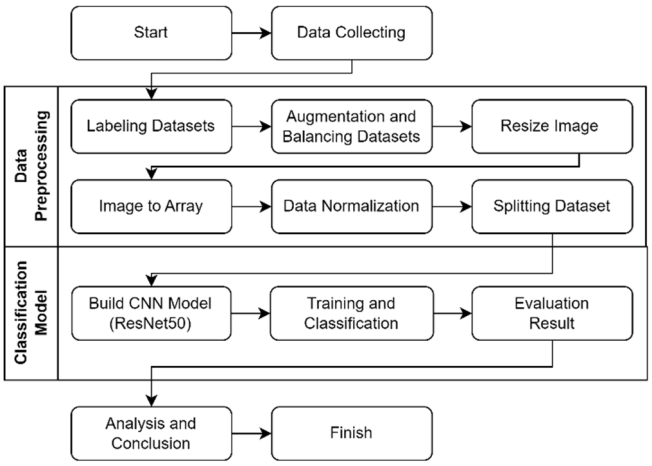

Fig. 1. Research Flow

B. Data Collection

The researchers utilized the HAM10000 dataset from the Harvard Dataverse website for this study. The HAM10000 dataset comprises a vast collection of 10,015 dermatoscopic images representing seven distinct types of skin diseases. Fig. 2 illustrates a representative sample image of the dataset.

Fig. 2. displays sample images of skin diseases from the HAM10000 dataset: (a) Melanocytic Nevi, (b) Melanoma, (c) Benign Keratosis-like Lesions, (d) Basal Cell Carcinoma, (e) Actinic Keratoses and Intraepithelial Carcinoma, (f) Vascular Lesions and (g) Dermatofibroma. The number of datasets can be seen in Table 1.

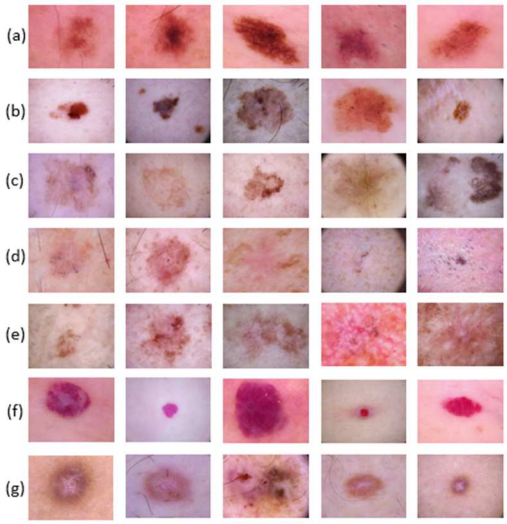

Fig. 2. Sample Dataset Image

TABLE I. NUMBER OF DATASETS

No	Types of disease	Images
1	Melanocytic Nevi	6705
2	Melanoma	1113
3	Benign Keratosis-like Lesions	1099
4	Basal Cell Carcinoma	514
5	Actinic Keratoses and Intraepithelial Carcinoma	327
6	Vascular Lesions	142
7	Dermatofibroma	115

C. Data Preprocessing

1) Dataset Labeling

In this stage, each image in the dataset is separated into folders with labels corresponding to the specific type of skin disease it represents. The results of the labeling process can be seen in Table 2.

TABLE II. LABELING DATASETS

No	Types of disease	Label
1	Actinic Keratoses and Intraepithelial Carcinoma	akiec
2	Basal Cell Carcinoma	bcc
3	Benign Keratosis-like Lesions	bkl
4	Dermatofibroma	df
5	Melanocytic Nevi	nv
6	Melanoma	mel
7	Vascular Lesions	vasc

2) Data Augmentation

Data augmentation is performed to enhance the diversity of the dataset, prevent overfitting, and enrich the variations within the dataset to improve the model's quality. The augmentation techniques applied include rotation, shifting, flipping, zooming, and pixel filling. Examples of the augmentation techniques can be seen in Fig. 3.

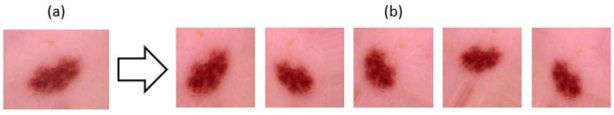

Fig. 3. Examples of image augmentation

In Fig. 3. examples of augmentation applied to one of the dataset images are shown: (a) Image before augmentation and (b) Image after augmentation. Additionally, for each class, the augmentation process generates 3000 images, as shown in Table 3.

TABLE III. DATASET COUNT AFTER AUGMENTATION

No	Label	Images
1	akiec	3000
2	bcc	3000
3	bkl	3000
4	df	3000
5	nv	3000
6	mel	3000
7	vasc	3000

3) Resizing Images

Initially, the collected dataset consisted of images with a resolution of 600x450 pixels. However, to ensure consistency and align with the ResNet-50 architecture, all the images were resized to a uniform size of 224x224 pixels.

4) Converting Dataset to Arrays, Data Normalization, Dataset Splitting

Next, the image dataset was converted into numerical arrays to be processed by the classification model. Additionally, data normalization was applied using the Min-Max method to ensure that pixel values fell within the same range, avoiding the dominance of specific features. Furthermore, the dataset was split into three parts: 80% for training, 10% for validation, and 10% for testing the classification model.

D. Classification of the Model

After preprocessing the dataset, the training and classification processes were conducted to develop a robust model capable of accurately recognizing and classifying various types of skin diseases. The training phase utilized 80% of the dataset to train the model and enable it to learn the distinctive patterns associated with each disease category. To assess the model's performance and prevent overfitting, 10% of the dataset was allocated for validation during the training phase. Subsequently, the remaining 10% of the dataset, known as the testing data, was used to evaluate the final performance of the trained model. This unseen testing data was fed into the model, and the classification results were analyzed to measure the accuracy and effectiveness of disease recognition and classification. The CNN model based on the ResNet50 architecture was constructed and employed during this stage to achieve reliable and accurate classification outcomes.

E. CNN Resnet50

The CNN model based on ResNet architecture includes convolutional layers responsible for extracting features from the skin lesion images. When the skin lesion images are inputted into the model, the convolutional layers of ResNet identify patterns and important features within the images. The extracted features serve as representations that capture significant characteristics, enabling the model to differentiate between different types of skin diseases.

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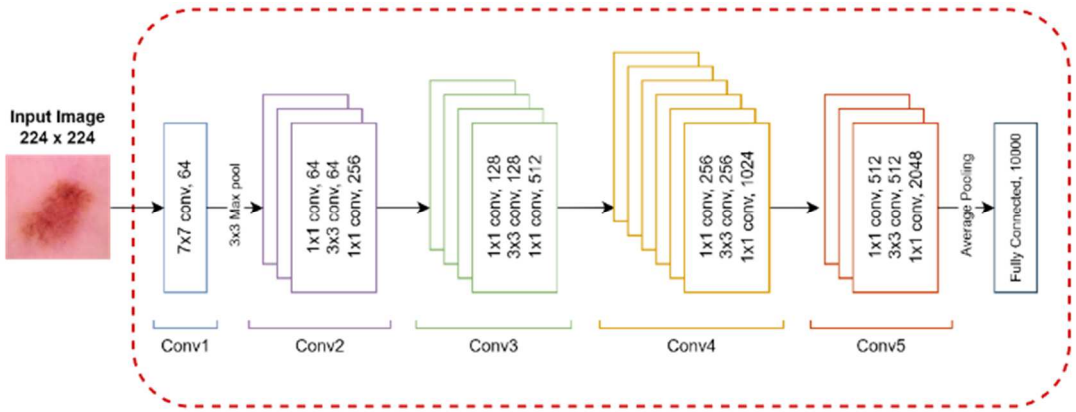

Fig. 4. CNN-ResNet50 Model

The classification layers in ResNet serve as the final layers of the model. They utilize the extracted features to classify the skin lesion images into one of the seven targeted types of skin diseases. Upon completing the classification process, the ResNet model produces predictions for each skin lesion image. The classification process using CNN is illustrated in Fig. 4

F. Model Evaluation

After the classification process is completed, both the CNN models utilizing ResNet50 architectures will generate predictions for each skin lesion image. These predictions are then evaluated using performance metrics such as accuracy, precision, recall, and f1-Score. These metrics are crucial in assessing the model's performance in correctly classifying skin lesion images.

IV. Result and Discuss

A. Results of Model Training and Testing

In this study, we used the ResNet50 model to classify the types of skin diseases. Evaluation of model performance is essential to assess the extent to which the model can accurately recognize and differentiate types of skin diseases. The dataset was divided into 80% for training, 10% for testing, and 10% for validation purposes. The ResNet50 model was trained using the SGD optimizer with a learning rate of 0.001. Additionally, the model was trained for 150 epochs. During the training process, we monitored the training and validation accuracy as well as the training loss to understand how the model progressed during training.

Fig. 5. illustrates the changes in training and validation accuracy throughout the training process. The training accuracy reflects the model's ability to correctly classify the training examples, while the validation accuracy indicates the model's performance on data that was not used during the training. Additionally, the figure displays the training loss changes during the training process. Training loss measures how well the model learns the patterns in the training data, and lower training loss indicates better adaptation of the model to the training data.

B. Performance Metrics of ResNet50 Classification

The evaluation of model performance is crucial in determining the model's ability to accurately identify and distinguish various types of skin diseases. In this section, we will discuss the performance evaluation of the ResNet50 model. For confusion matrix can be seen in Fig 7.

Fig. 6. Confusion matrix of ResNet50 classification accuracy. akiec: Actinic Keratosis, bcc: Basal Cell Carcinoma, bkl: Benign Keratosis, df: Dermatofibroma, mel: Melanoma, nv: Melanocytic Necus, and vasc: Vascular Lesion. The classification results achieved using this model configuration are presented in Table 4.

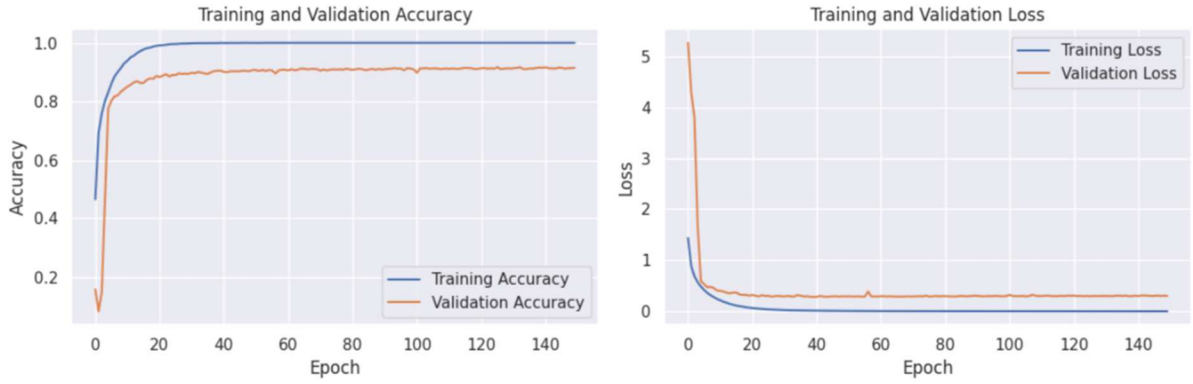

Fig. 5. Training and Validation Accuracy and Loss

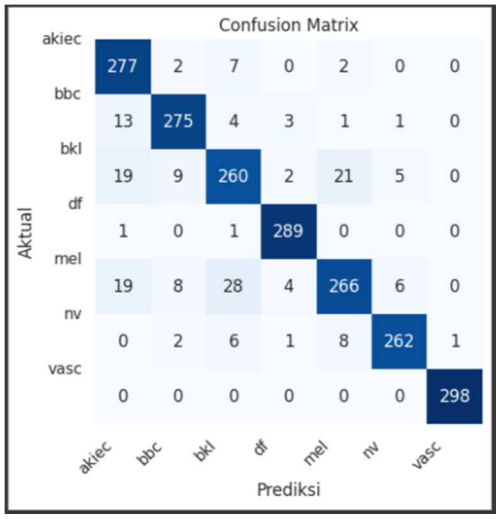

Fig. 6. Confusion matrix

TABLE IV. PERFORMANCE METRICS OF RESNET50 CLASSIFICATION

No	Metric	Value
1	Accuracy	91.71%
2	Precision	91.89%
3	Recall	92.04%
4	F1-Score	91.87%

Table 4 displays the performance metrics of the ResNet50. It achieved an accuracy of 91.71%, indicating its high capability to accurately classify different types of skin diseases. Precision, recall, and F1-score were also calculated to evaluate the model's performance in identifying the desired class and capturing all the true instances. The model showcases excellent precision, recall, and F1-score values of 91.89%, 92.04%, and 91.87%, respectively, demonstrating its balanced ability to correctly identify instances from each class and locate all true instances.

C. Analysis of Accuracy per Class

The analysis was further conducted by examining the accuracy per class achieved by the ResNet50 model. This result provides insights into how well the model can classify individual types of skin diseases. The accuracy rates achieved by the ResNet50 model for each class are presented in Table 5.

TABLE V. ACCURACY PER CLASS

No	Class	Accuracy
1	akiec	95.38%
2	bbc	92.59%
3	bkl	82.28%
4	df	99.31%
5	mel	80.36%
6	vasc	100%
7	nv	93.57%

In this analysis, it is evident that the ResNet50 model achieves high accuracy rates for classes such as akiec, bbc, df, vasc, and nv, with accuracy rates above 90%. This indicates the model's ability to accurately recognize and classify these types of skin diseases with a commendable level of success. However, there are certain classes like bkl and mel that exhibit lower accuracy rates. This suggests challenges in effectively classifying these particular types of skin diseases and highlights the need for further attention in developing improved models in the future.

D. Comparison with Previous Research Studies

In this analysis, we compare the performance of our ResNet50 model with previous studies focusing on skin disease classification on the HAM10000 dataset. Table 6 below presents the comparison between our model's performance and the results of previous research.

TABLE VI. COMPARISON OF RESNET50 MODEL PERFORMANCE WITH PREVIOUS STUDIES

Author	Model	Optimizer	Epoch	Batch Size	Learning rate	Accuracy	Precision	Recall	F1-Score
[11]	InceptionV3	SGD	100	N/A	0.001	88.05%	N/A	N/A	77.84%
	ResNet-50	SGD	100	N/A	0.001	**89.28%**	N/A	N/A	**81.28%**
	DenseNet-201	SGD	100	N/A	0.001	88.70%	N/A	N/A	79.47%
[12]	ResNet-50	Adam	100	16	0.00005	87%	78%	77%	N/A
	InceptionV3	Adam	100	16	0.0001	89%	85%	**80%**	N/A
	Esnsemble	Adam	100	16	N/A	**89%**	**86%**	79%	N/A
[13]	VGG16	Adam	200	32	0.05	87%	87%	87%	87%
	VGG19	Adam	200	32	0.05	85%	85%	85%	85%
	MobileNet	Adam	200	32	0.05	88%	89%	88%	88%
	InceptionV3	Adam	200	32	0.05	**89%**	**89%**	**89%**	**89%**
[9]	VGG-16	Adam	30	32	0.0001	73%	71%	73%	71%
	CNN	Adam	30	32	0.0001	77%	73%	77%	73%
	Resenet-50	Adam	30	32	0.0001	82%	80%	82%	81%
	Mobilenet	Adam	30	32	0.0001	87%	88%	87%	86%
	Xception	Adam	30	32	0.001	88%	88%	88%	87%
	Densenet	Adam	30	32	0.001	88%	88%	88%	87%
	InceptionV3	Adam	30	32	0.0001	**90%**	**90%**	**90%**	**90%**
[6]	InceptionV3	Adam	30	32	0.001	**91%**	**89%**	**89%**	**89%**
	Xception	SDG	30	32	0.0001	91%	89%	88%	88%
	NASNetLarge	SDG	25	32	0.0001	91%	86%	86%	86%
Proposed	**ResNet50**	**SGD**	**150**	**64**	**0.001**	**91.71%**	**91.89%**	**92.04%**	**91.87%**

Table 6 compares the performance metrics of various models, including VGG16, CNN, ResNet50, MobileNet, Xception, DenseNet, NASNetLarge, Inceptionv3, ResNet50v2, and our ResNet50 model. Previous studies reported accuracies ranging from 73% to 90%, with varying precision, recall, and F1-Score. Among these models, our ResNet50 model outperformed the others, achieving the highest accuracy of 91.71%. Additionally, it demonstrated excellent precision, recall, and F1-Score values of 91.89%, 92.04%, and 91.87%, respectively. These findings indicate the superiority of our ResNet50 model in accurately classifying skin diseases and emphasize its potential for improving diagnostic accuracy in this domain.

The above explanation provides an overview of how our ResNet50 model compares to previous studies that employed different models. This table offers clear insights into the performance comparison, highlighting the superior performance of our ResNet50 model in terms of accuracy, precision, recall, and F1-Score. It showcases the effectiveness of our approach in advancing the field of skin disease classification.

Fine-tuning techniques and precise optimization for the ResNet50 model in this study have the potential to yield superior results compared to previous studies. The limitation of the CNN Model in this study is the sensitivity to overlapping data. When there are classes of skin diseases that have similar or overlapping features, the SVM model has difficulty distinguishing between these classes. If similar feature patterns are found across multiple classes, the model will find it difficult to decide on the exact classification. This causes the accuracy results are still less effective and there has not been a significant improvement

V. Conclusion

Based on the analysis of the results of this research, it can be concluded that the ResNet50 model performs well in classifying different types of skin diseases. The model achieved a high level of accuracy, with an accuracy rate of 91.71% on the test data. This indicates that the ResNet50 model is capable of recognizing and distinguishing between various types of skin diseases with good overall accuracy. The performance evaluation of the ResNet50 model using precision, recall, and F1-score metrics also showed impressive results. The precision, recall, and F1-score reached 91.89%, 92.04%, and 91.87%, respectively, demonstrating the model's ability to correctly identify instances from each class and find all true instances.

In comparison to previous studies that utilized models such as VGG-16, CNN, Mobilenet, Xception, Densenet, and Inceptionv3, ResNet50v2, the ResNet50 model not only demonstrated comparable performance but also surpassed them in certain aspects. It achieved higher accuracy and produced better results in classifying different types of skin diseases. Based on these conclusions, it can be stated that the ResNet50 model is very effective in classifying various types of skin diseases with accuracy, precision, recall, and f1-score above 91%. This research contributes to the development and application of machine learning models for skin disease diagnosis, with the potential to enhance speed, accuracy, and efficiency in the diagnostic process.

Further research can be conducted to explore the extent to which the ResNet50 model can be applied to different dermatological datasets, the number of different disease types, and diverse patient populations to assess its general capabilities. In addition, fine-tuning and optimization techniques for ResNet50 models should be explored for potential performance improvements, as well as to overcome the challenges of overlapping classes and complex feature representations.

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