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Automatic Detection of Skin Diseases Using Convolutional Neural Network Algorithms

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Abstract: Skin diseases are a major health concern in Indone sia and they can seriously impact a patient's quality of life. The problem is aggravated by humid tropical climate, limited access to healthcare facilities, and a lack of trained dermatology personnel. The cases in Indonesia are many, and the diagnosis and treatment of skin diseases are delayed, which makes the patient's condition worse. Based on data from the Ministry of Health (Kemenkes), the prevalence of skin disease in Indonesia is 0.62 cases per 10,000 population with the highest prevalence in Eastern Indonesia. Developing a Skin Disease Detection System Based on Convolutional Neural Network (CNN) algorithms. However, CNN algorithms are widely used in image recognition and classification, and can act as an automatic diagnostic system. This system has been developed to aid in diagnosis and improve patient access to dermatological care, especially for remote communities. Users can reach out for services at any time and any location, a practical solution for treating skin health problems. This study's results are anticipated to lower the diagnostic delays and improve the treatment outcomes while offering quick access to reliable dermatological service. This is a great effort on global level for any skin disease supporting to improve life of human lives from skin health issues.

Keywords: Automated Detection; Skin Diseases; Convolutional Neural Network.

1. Introduction

In Indonesia, skin diseases are a common health issue that significantly impacts the quality of life of affected individuals. With a humid tropical climate, the Indonesian population is particularly vulnerable to various types of skin infections, allergies, and other dermatological conditions. Limited access to healthcare facilities and a shortage of trained dermatological staff further complicate the accurate and timely diagnosis and treatment of skin diseases [1]. This often leads to delayed treatment, which can worsen the patients' conditions. Many cases in Indonesia illustrate this, such as that of a 45-year-old man from Flores Island, East Nusa Tenggara, reported by Kompas [2]. Initially, he noticed painless, non-itchy skin patches and ignored them as they caused no significant discomfort [3]. Living in a remote area with limited access to healthcare services and insufficient information about leprosy, the patches gradually spread, leading to more severe lesions. This delay resulted in nerve damage in his hands, causing numbness and muscle weakness. In addition to this case, there are numerous others in Indonesia where delayed treatment of skin diseases has been reported. These cases underscore the importance of early detection and swift access to healthcare services. Had the diagnosis and treatment been provided earlier, nerve damage could have been prevented or minimized [4][5].

However, the situation described is not unique. According to data from the Ministry of Health (Kemenkes), there were 17,251 registered cases of skin diseases, with a national prevalence rate of 0.62 cases per 10,000 people. Imran Pambudi, Director of the Ministry of Health's Disease Prevention and Control Division, stated that the highest prevalence of skin diseases in 2023 was observed in Eastern Indonesia, with West Papua having the highest prevalence at 13.6 cases per 10,000 people—approximately 22 times higher than the national average. Other provinces with high prevalence rates include Papua (10.77 cases per 10,000 people), Southwest Papua (8.2), North Maluku (6), Central Papua (2.61), Maluku (2.53), South Papua (2.39), North Sulawesi (1.85), Gorontalo (1.34), and West Sulawesi (1.12). Kemenkes aims to reduce the prevalence of skin diseases to less than 1 case per 10,000 people and notes that 8.2% of new leprosy cases in 2023 affected children, while approximately 5.7% of patients already experienced stage-two disabilities. Active case finding efforts continue to identify skin disease sufferers as early as possible. These cases highlight the critical need for early detection and timely treatment, which could be addressed through deep learning algorithms such as CNN-based automatic detection, potentially reducing delays and improving treatment outcomes for patients across Indonesia [6].

In the digital age, the application of deep learning algorithms in healthcare has seen significant advancements, particularly in the diagnosis of skin diseases. Deep learning is a subfield of machine learning whose algorithms are inspired by the structure of the human brain. This structure is referred to as Artificial Neural Networks (ANN). Essentially, it is a neural network with three or more layers of ANN. One method that can be applied in deep learning is classification using Convolutional Neural Networks (CNN) algorithms [7][8][9]. CNN is a type of artificial neural network used for image recognition and classification by applying convolution through filters to extract features from images, which are then processed by subsequent layers to automatically produce a final decision without the need for manual feature extraction [10]. CNN algorithms have proven to be effective in image processing and classification in numerous studies, making them an ideal candidate for deployment in automatic skin disease diagnosis systems. This system can not only enhance diagnostic accuracy by leveraging computational power and machine learning, but also improve the accessibility of skin disease diagnosis, enabling patients in remote areas to receive quick and accurate predictions. The implementation of this system will provide users with convenient access to dermatological services without time and location constraints, offering a practical and efficient solution to global skin health issues [11].

2. Research Method

In this study, the method employed is the Convolutional Neural Network (CNN) algorithm [12]. CNN is a highly effective technique for image processing and has been widely used in various computer vision applications, including skin disease detection [13][14]. This algorithm operates by convolving input images through several layers to extract essential features needed for classification. The process involves multiple stages, such as convolutional layers, pooling layers, and fully connected layers, which together form a deep neural network model [15]. In the scope of this research, CNN is utilized to analyze images of skin lesions and identify patterns associated with different types of skin diseases, including melanoma, squamous cell carcinoma, and vascular lesions. A diagram of the CNN algorithm is shown in Figure 1.

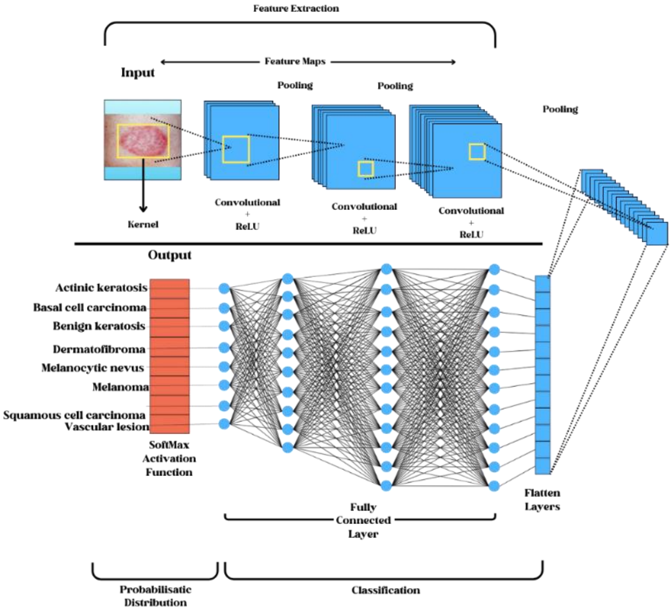


Figure 1. Convolutional Neural Network

The process consists of several key stages, including data collection, data preprocessing, feature extraction, and neural network model training [16]. The stages of the research for skin disease detection using the CNN algorithm follow the workflow presented in Figure 2, which is as follows:

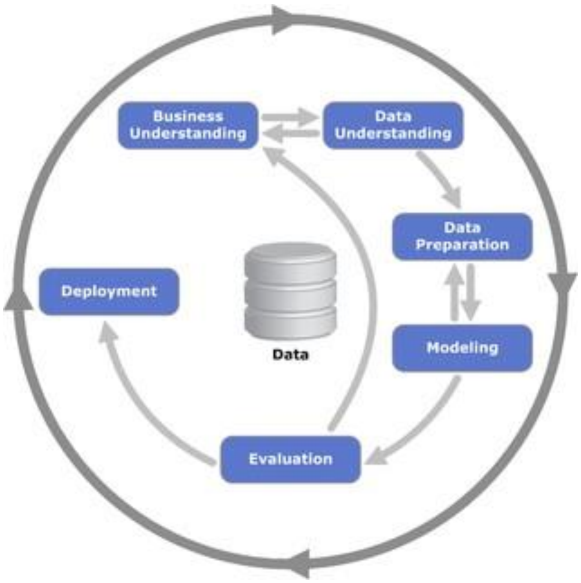


Figure 2. CRISP-DM

2.1 Problem Understanding

The primary goal of this research is to develop a system capable of automatically detecting skin diseases using the CNN algorithm, with the aim of enhancing diagnostic accuracy and improving accessibility to dermatological healthcare services in Indonesia [17]. By utilizing this approach, it is hoped that skin disease detection can be made more efficient and accurate, especially in remote areas.

2.2 Data Understanding

This phase involves exploring the dataset of skin images, which contains various types of diseases. The dataset must be analyzed to understand the number of classes, data distribution, and image quality [18]. A thorough understanding of the data is essential to ensure the model can effectively learn to classify skin diseases based on the provided images.

2.3 Data Preparation

In this phase, the data must be prepared for use in the CNN model. This includes tasks such as data collection, image cleaning (e.g., removing noise), and data augmentation to increase dataset variability and address issues related to data imbalance [19]. Data augmentation techniques, such as rotating and flipping images, can help improve the model's robustness by simulating a more diverse set of inputs.

2.4 Modeling

During this phase, the CNN model is constructed and trained using the prepared data. This involves selecting the appropriate network architecture, fine-tuning hyperparameters, and evaluating the model using metrics such as accuracy, precision, and recall [20]. The model is trained to recognize patterns in the skin images, and performance is continuously assessed to optimize results.

2.5 Evaluation

The outcomes of the CNN model are evaluated to ensure that the model meets the predefined objectives. If the model is not performing at the desired level, this phase may involve revisiting earlier stages to make necessary adjustments and improvements [21]. The evaluation ensures that the model is capable of providing accurate diagnoses in real-world scenarios.

2.6 Deployment

Once the model has been evaluated and approved, it is deployed in an automated detection system through a website-based platform. Users can upload images of their skin, and the system will provide a diagnosis based on the CNN model's predictions [22]. This deployment allows users to access dermatological services easily, making skin disease detection more accessible and efficient.

3. Result and Discussion

3.1 Results

This section describes the implementation of the CNN model and the testing conducted to assess its performance. The process involves several key steps, beginning with data collection and progressing through the application of the CRISP-DM methodology for model development.

3.1.1 Data Collection

The dataset for this study consists of skin disease images obtained from Kaggle. The dataset is divided into eight categories: Actinic Keratosis, Basal Cell Carcinoma (BCC), Benign Keratosis, Dermatofibroma, Melanocytic Nevus, Melanoma, Squamous Cell Carcinoma, and Vascular Lesion. Table 1 below presents the number of images in each class:

Table 1. Number of Images

No.	Class Name	Number of Images
1	Actinic Keratosis	150
2	Basal Cell Carcinoma (BCC)	150
3	Benign Keratosis	150
4	Dermatofibroma	150
5	Melanocytic Nevus	150
6	Melanoma	150
7	Squamous Cell Carcinoma	150
8	Vascular Lesion	150

As indicated in Table 1, the total number of images in the dataset is 1,200, with each image in .jpg and .jpeg formats. These images were used for training, validation, and testing the CNN model.

3.1.2 Implementation of CRISP-DM

The implementation of the CRISP-DM methodology began with problem understanding, where the primary goal was to determine how deep learning techniques, specifically Convolutional Neural Networks

(CNNs), could be utilized to analyze and detect skin diseases from images. This step involved identifying the key requirements and objectives for the system to be developed. Next, in the data understanding phase, the dataset was sourced from secondary sources, such as Kaggle, which provided images of eight classes of skin diseases.

```
filepaths = []
labels = []
classlist = os.listdir(sdir)
for klass in classlist:
    classpath = os.path.join(sdir, klass)
    if os.path.isdir(classpath):
        flist = os.listdir(classpath)
        for f in flist:
            fpath = os.path.join(classpath, f)
            filepaths.append(fpath)
            labels.append(klass)
Fseries = pd.Series(filepaths, name='filepaths')
Lseries = pd.Series(labels, name='labels')
df = pd.concat([Fseries, Lseries], axis=1)
print (df.head())
print (df['labels'].value_counts())
```

```
                                           filepaths             labels
0  /content/drive/My Drive/CNN/resized_images_2/B...  Benign keratosis
1  /content/drive/My Drive/CNN/resized_images_2/B...  Benign keratosis
2  /content/drive/My Drive/CNN/resized_images_2/B...  Benign keratosis
3  /content/drive/My Drive/CNN/resized_images_2/B...  Benign keratosis
4  /content/drive/My Drive/CNN/resized_images_2/B...  Benign keratosis
labels
Benign keratosis           150
Melanocytic nevus          150
Squamous cell carcinoma    150
Melanoma                   150
Actinic keratosis          150
Dermatofibroma             150
Basal cell carcinoma       150
Vascular lesion            150
Name: count, dtype: int64
```

Figure 3. Class Identification

The identification of the classes is shown in Figure 3. It is essential to thoroughly understand the characteristics of the data, such as image resolution, lighting variations, and the presence of noise, to ensure the data quality is adequate for training the model.

```
train_split = .8
test_split = .1
dummy_split = test_split / (1 - train_split)
train_df, dummy_df = train_test_split(df, train_size=train_split, shuffle=True, random_state=123)
test_df, valid_df = train_test_split(dummy_df, train_size=dummy_split, shuffle=True, random_state=123)
```

Figure 4. Pre-processed Data

In the data preparation stage, the dataset was divided into training, validation, and testing subsets. This process also included cleaning the data to remove noise and artifacts that could potentially disrupt the model's training process. Moreover, all images were resized to 224x224 pixels to maintain consistency in input size, which also helps speed up the training process.

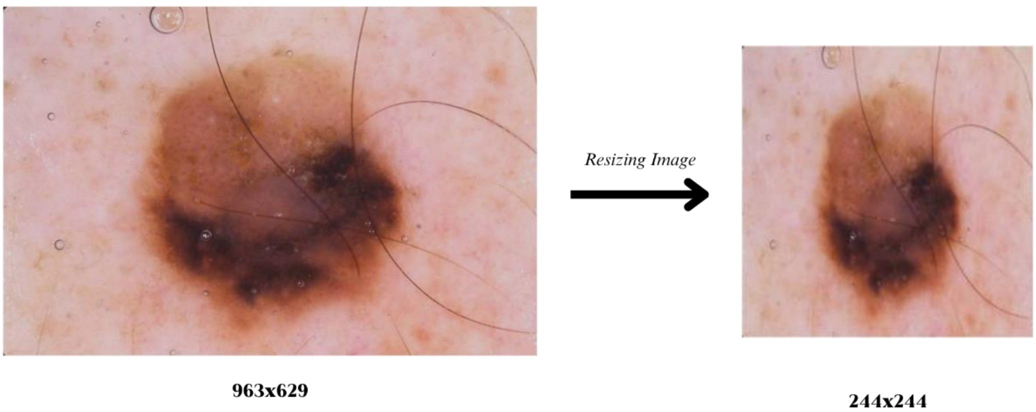


Figure 5. Resizing Image

3.1.3 Model Development

During the modeling phase, a deep learning model was constructed using a pre-trained base model, such as Xception. This model was modified by removing the top layer (include_top=False) and adding custom layers, including a GlobalAveragePooling2D layer and a Dense layer with eight neurons for classification into the eight categories of skin diseases. The model was compiled using the Adam optimizer and categorical cross-entropy as the loss function, with accuracy as the evaluation metric. The training process is depicted in Figure 6.

```
model_name = 'SkinDisease_100'
print("Building model with", base_model)
model = Sequential([
    base_model,
    GlobalAveragePooling2D(),  # Lapisan untuk meratakan output dari base model
    Dense(8, activation='softmax')  # Lapisan output dengan 8 kelas, sesuai dengan jumlah kelas pada dataset
])

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

model.summary()
```

```
Building model with <keras.src.engine.functional.Functional object at 0x7e9ef602bb50>
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 xception (Functional)       (None, 7, 7, 2048)        20861480

 global_average_pooling2d (  (None, 2048)              0
 GlobalAveragePooling2D)

 dense_1 (Dense)             (None, 8)                 16392

=================================================================
Total params: 20877872 (79.64 MB)
Trainable params: 16392 (64.03 KB)
Non-trainable params: 20861480 (79.58 MB)
```

Figure 6. Building a CNN Model

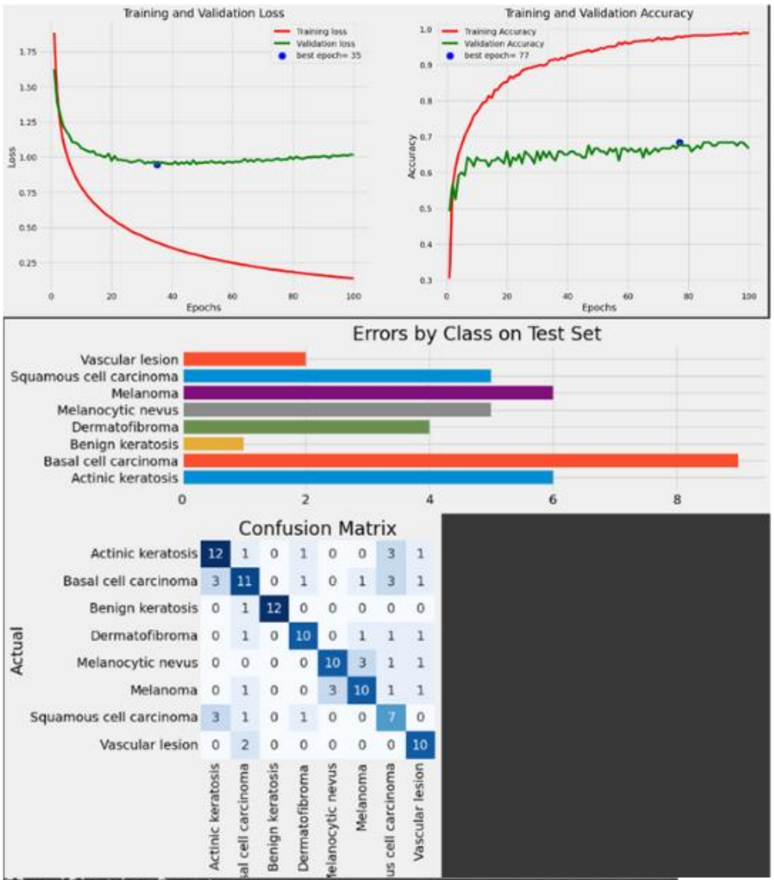
```
epochs =100

history=model.fit(x=train_gen, epochs=epochs, validation_data=valid_gen)
```

```
Epoch 91/100
15/15 [==============================] - 258s 17s/step - loss: 0.1561 - accuracy: 0.9854 - val_loss: 1.0040 - val_accuracy: 0.6833
Epoch 92/100
15/15 [==============================] - 264s 18s/step - loss: 0.1539 - accuracy: 0.9854 - val_loss: 0.9949 - val_accuracy: 0.6833
Epoch 93/100
15/15 [==============================] - 265s 18s/step - loss: 0.1516 - accuracy: 0.9865 - val_loss: 1.0105 - val_accuracy: 0.6833
Epoch 94/100
15/15 [==============================] - 274s 18s/step - loss: 0.1493 - accuracy: 0.9854 - val_loss: 1.0088 - val_accuracy: 0.6833
Epoch 95/100
15/15 [==============================] - 261s 17s/step - loss: 0.1470 - accuracy: 0.9885 - val_loss: 1.0074 - val_accuracy: 0.6833
Epoch 96/100
15/15 [==============================] - 266s 18s/step - loss: 0.1448 - accuracy: 0.9885 - val_loss: 1.0116 - val_accuracy: 0.6750
Epoch 97/100
15/15 [==============================] - 260s 17s/step - loss: 0.1432 - accuracy: 0.9854 - val_loss: 1.0130 - val_accuracy: 0.6833
Epoch 98/100
15/15 [==============================] - 264s 18s/step - loss: 0.1421 - accuracy: 0.9896 - val_loss: 1.0101 - val_accuracy: 0.6833
Epoch 99/100
15/15 [==============================] - 260s 17s/step - loss: 0.1398 - accuracy: 0.9885 - val_loss: 1.0167 - val_accuracy: 0.6750
Epoch 100/100
15/15 [==============================] - 262s 18s/step - loss: 0.1377 - accuracy: 0.9896 - val_loss: 1.0166 - val_accuracy: 0.6667
```

Figure 7. Training the CNN Model

3.1.4 Model Evaluation

The model's performance was evaluated using a Confusion Matrix to analyze the prediction results on the test data. Figure 8 illustrates an accuracy of 68%, which indicates that the model's predictions are reasonably reliable. Although the accuracy could be improved, this result demonstrates the model's potential for skin disease detection.



Classification Report:

	precision	recall	f1-score	support
Actinic keratosis	0.67	0.67	0.67	18
Basal cell carcinoma	0.61	0.55	0.58	20
Benign keratosis	1.00	0.92	0.96	13
Dermatofibroma	0.77	0.71	0.74	14
Melanocytic nevus	0.77	0.67	0.71	15
Melanoma	0.67	0.62	0.65	16
Squamous cell carcinoma	0.44	0.58	0.50	12
Vascular lesion	0.67	0.83	0.74	12
accuracy			0.68	120
macro avg	0.70	0.70	0.69	120
weighted avg	0.70	0.68	0.69	120

Figure 8. Model Evaluation

3.1.5 Deployment

The final phase of the project is deployment, where the trained model is applied to a production environment for real-time or batch prediction. In Python, this involves several critical steps, such as integrating the trained model into a web-based application or other platforms that can handle real-time predictions. After deployment, users can upload images of their skin, and the system will provide a diagnosis based on the model's predictions. The prediction results can then be analyzed and presented to end-users through a user interface or automated system.

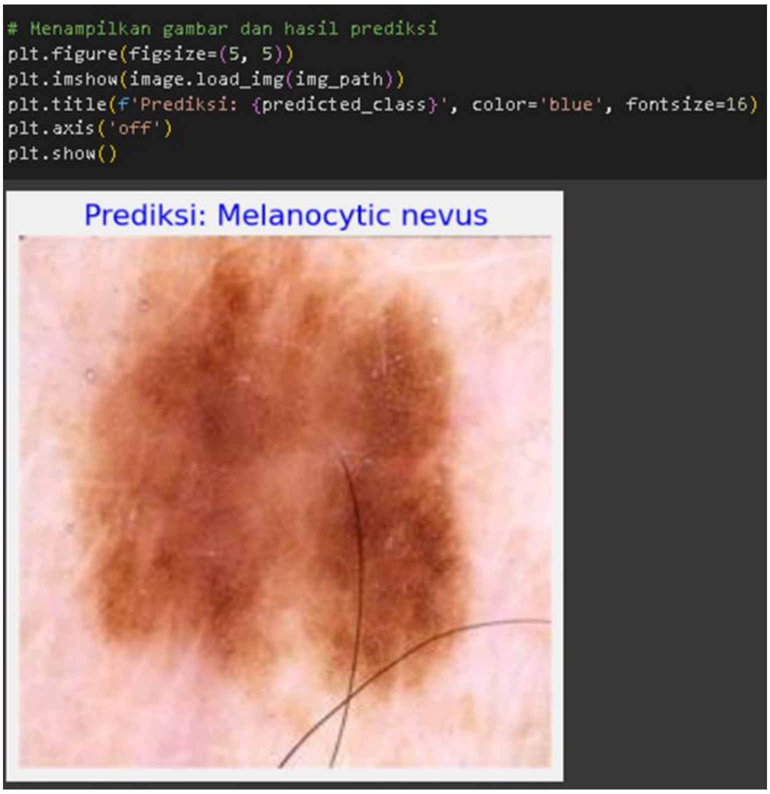


Figure 9. Deployment

The ultimate goal of the deployment phase is to deliver consistent and accurate predictions based on the input data, enabling the model to be applied in practical, real-world applications. This may include automating skin disease diagnosis and assisting healthcare professionals with faster decision-making. The deployment process is illustrated in Figure 9.

3.2 Discussion

The dataset used in this study, obtained from Kaggle, consisted of images of various skin diseases categorized into eight classes. Each class contained 150 images, totaling 1,200 images for training, validation, and testing. This dataset is relatively balanced, which is beneficial for training the model. However, the dataset's images were not all uniform in terms of quality, as real-world datasets often contain variations in lighting, resolution, and noise. This can pose a challenge for the model's ability to generalize across different types of input. Despite these challenges, the dataset proved sufficient for building a robust CNN model, as demonstrated by the model's performance in terms of accuracy.

One of the key steps in developing an effective CNN model was data preprocessing. Images were resized to a consistent size of 224x224 pixels to ensure uniformity across the input data, which is a standard practice in deep learning tasks. Additionally, the data was cleaned to remove any noise or artifacts that could affect the model's performance. Data augmentation techniques were not used in this study, but this could be a potential avenue for improving the model's robustness in future work. Augmentation could help to artificially increase the diversity of the dataset, which might improve the model's ability to handle variations in real-world scenarios. In the model training phase, a pre-trained Xception model was used as the base for transfer learning. This approach is effective as it leverages the knowledge gained from training on large datasets like ImageNet, which improves the model's performance on smaller, specialized datasets like the one used in this study. By modifying the base model to suit the skin disease detection task, the resulting CNN model was able to learn important features associated with skin diseases. The use of the Adam optimizer and categorical cross-entropy loss function contributed to the model's efficient training process.

The CNN model achieved an accuracy of 68% during evaluation, which is a promising result considering the complexity of skin disease classification. While this accuracy is not yet optimal, it is indicative of the model's potential in distinguishing between different types of skin diseases. There are several factors that may have influenced this result. First, the model may have struggled to differentiate between similar-looking skin lesions, especially given the limited size of the dataset. Some skin diseases may exhibit similar visual characteristics, making them difficult to distinguish even for advanced machine learning models. Another factor that could have impacted model performance is the quality and consistency of the images in the dataset. Although the dataset was fairly representative, variations in image resolution, lighting, and background noise may have hindered the model's ability to learn clear patterns. These challenges are common in real-world datasets, and future improvements in data quality and preprocessing techniques could lead to better results.

Despite the current performance, several strategies could be employed to enhance the model's accuracy. First, the dataset could be expanded by including more images for each class, as a larger dataset typically allows the model to better generalize to unseen data. Additionally, incorporating data augmentation techniques, such as rotating, flipping, or adjusting the brightness of images, could further diversify the dataset and improve the model's robustness. Moreover, the model's architecture could be fine-tuned by experimenting with different pre-trained models or adjusting hyperparameters such as the learning rate, batch size, or the number of layers in the neural network. Techniques like fine-tuning or adding more convolutional layers could allow the model to extract more complex features and improve its performance in distinguishing between similar skin lesions.

The deployment of the trained CNN model into a real-time, web-based system is a significant step toward making automatic skin disease detection accessible to users. Once deployed, the system allows users to upload images and receive instant diagnoses. This approach can be particularly beneficial in regions where access to dermatological expertise is limited, such as rural or remote areas. Although the model is capable of providing preliminary diagnoses, it is important to note that it should not replace professional medical advice. The model's predictions should be used as a tool to assist healthcare providers rather than as a standalone diagnostic tool. Future work could include integrating the model with a user-friendly interface that provides additional support, such as explanations for the predictions or links to further medical resources.

4. Related Work

In recent years, the application of Convolutional Neural Networks (CNNs) for medical image classification, particularly in dermatology, has garnered significant attention due to their ability to achieve high accuracy in disease detection from images. Several studies have explored the use of CNNs for skin disease classification, leading to significant advancements in automated dermatological diagnosis. One of the key studies in this field is by Wu *et al*. (2019), who compared different CNN algorithms for face skin disease classification. They demonstrated that CNNs are highly effective in classifying common skin conditions based on clinical images, achieving promising results in terms of accuracy and robustness. The study's findings align with the growing use of CNNs in dermatology for accurate skin disease detection, especially for conditions like acne and eczema [8]. Additionally, Lemieux *et al*. (2022) proposed geometric deep learning techniques, which combine CNNs with other machine learning methods to improve the accuracy of protein-protein interaction predictions. Although their focus was on protein interactions, the concept of hybrid deep learning models has potential applications in dermatology, such as improving the performance of CNNs by integrating them with other algorithms for enhanced skin disease classification [3].

Another study by Asiri *et al*. (2023) explored the transition from traditional CNN models to Involutional Neural Networks for brain tumor diagnosis, highlighting the growing interest in refining CNN architectures for medical image classification tasks. While this work focuses on brain tumor detection, it demonstrates the potential for CNN refinements, such as Involutional Neural Networks, to enhance accuracy in other medical fields, including dermatology [5]. Similarly, Alali *et al*. (2019) used CNNs for polarity classification in Arabic dialects, a task that also required the model to handle large volumes of varied data. Their findings underscore the utility of CNNs in handling complex datasets, a feature that is crucial for dermatological applications where skin lesion images can vary significantly in appearance [1].

In terms of skin disease detection, Back *et al*. (2021) developed a robust classification system for herpes zoster using deep neural network ensembles. Their research highlighted the importance of using ensemble techniques in improving classification performance for skin diseases, especially in real-world applications where individual models may struggle with certain classes of lesions. Ensemble methods, which combine multiple CNN models, could also be leveraged to improve skin disease detection, particularly for diseases that are visually similar but require nuanced classification [9].

Further research by Pan *et al*. (2019) discussed the energy-efficient implementation of CNNs using Cellular Neural Networks in non-volatile memory systems. While this study primarily focused on hardware optimization for CNNs, it underscores the importance of improving the efficiency of CNN models, which can be particularly beneficial when deploying skin disease detection systems on mobile or embedded devices for real-time diagnosis [4]. This is particularly relevant for telemedicine applications, where rapid processing and low power consumption are essential.

In a similar vein, Ghosh *et al*. (2023) introduced a two-phase evolutionary approach to optimize CNN architectures for medical image classification. Their work demonstrates how architectural optimizations can enhance model performance, which is directly applicable to skin disease classification, where variations in lesion morphology and background noise can impact model accuracy [6]. This idea is further explored by Zhang *et al*. (2019), who used spiking echo state networks in CNNs for time series classification. Although their study focused on time-series data, the concept of using novel neural network structures for classification could be applied to skin disease detection to address the challenges of lesion variety and image noise [10].

Pham *et al*. (2020) also introduced customized loss functions combined with real-time image augmentation to enhance skin disease classification accuracy. This study emphasizes the importance of balancing the data during training, especially for imbalanced datasets where certain skin diseases may be underrepresented. Techniques such as real-time data augmentation and balanced mini-batch training could be valuable additions to improve the CNN model's performance in classifying less common skin diseases [14]. In their study, Verma *et al*. (2021) developed a hybrid deep neural network model for the digital diagnosis of hand, foot, and mouth disease. Their research underscores the importance of hybrid models in enhancing diagnostic performance across multiple types of diseases, suggesting that similar approaches could be adopted to integrate various CNN models and improve skin disease detection systems [22].

The use of CNNs for skin disease classification has become a well-established area of research, with numerous studies demonstrating their effectiveness. However, challenges such as dataset imbalance, data quality, and model generalization remain. Further improvements in CNN architectures, ensemble methods, and data augmentation techniques could provide even more accurate and robust systems for skin disease detection. The integration of such methods into real-world applications holds great promise for improving healthcare accessibility, especially in remote areas where dermatological services are limited.

5. Conclusion

Based on the discussion, results, and testing conducted through the application of Convolutional Neural Networks (CNN) for skin disease detection, it can be concluded that the developed model achieved an accuracy of 68% on the validation data. Although this accuracy is not yet optimal, the results demonstrate that the model is capable of recognizing and classifying various types of skin diseases with a reasonably reliable performance. An accuracy of 68% indicates that the model is able to provide relevant and useful results in the context of automatic skin disease detection. This model utilizes the Xception architecture as a feature extractor, augmented with pooling layers and an output layer for classifying eight types of skin diseases. With 100 epochs of training, the model demonstrated adequate performance in processing dermatological images and providing useful predictions for clinical applications.

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