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Article

Insights into Dermatological Disorders: Understanding Skin Diseases through Medical Image Analysis

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Abstract: Skin disease, from a common disease to a larger problem similar to skin cancers and leprosy, presents significant diagnostic challenges. Easy, accurate, and timely diagnosis is important to successful therapy. This research explores a unique combination of smart computational algorithms to improve the categorization of skin problems. Traditional methods to catch these diseases are very time-consuming as they depend on pathological study, biopsy, and visual inspection resulting in delayed therapy. This study works on developing novel diagnostic techniques by utilizing insights from analysis, which could find out the differences between healthy and unhealthy skin. Furthermore, employing transfer learning involving leveraging pre-trained models like VGG16 and other deep learning models like CNNs, the study handles the complex and diverse nature of skin disease identified in earlier dermatological research. It aims to construct robust automated diagnostic systems, amalgamating findings from existing studies and prior CNN-based models. This paper aims to close the gap between traditional methods and cutting-edge computational techniques to improve the accuracy and speed of skin issues by combining deep learning methods, which may provide good results for the dermatological diagnostic process.

Keywords: skin diseases; Convolutional Neural Networks (CNNs); transfer learning; VGG16

1. Introduction

Skin-related problems spanning from common afflictions to life-threatening conditions like skin cancers and leprosy, pose a significant healthcare challenge globally. Precise and prompt diagnosis continues to be crucial for ensuring successful treatment and determining prognosis accurately. Old traditional methods, reliant on visual inspection, biopsy, and pathological examination, though valuable, can occasionally lead to misdiagnosis and treatment delays.

Recent advancements in medical research have explored innovative diagnostic avenues. Previous research has looked into impedance-based skin measurement [1]. It has shown promise as a non-invasive method. It uses electrical impedance to find differences in bio-electric properties between healthy and infected skin. It can do that because of the differences in the structural and chemical composition of the different skin conditions. Insights from impedance-based identification of skin diseases aim at physicians. It can help prevent the misdiagnosis of conditions like basal cell carcinoma (BCC) and melanoma [2,3]. At the same time, the integration of advanced computational methods, especially deep learning, has also shown a lot of promise in skin image diagnosis and analysis. CNNs and transfer learning techniques, such as pre-trained models like VGG16, present a way to improve the efficiency of skin-related disease classification. These methods allow to extraction of discriminative features of the skin problems from the images. This study suggests combining deep learning with impedance-based techniques to improve the accuracy of dermatological and dermatopathological diagnoses. By combining data from both approaches, this strategy reduces the knowledge gap between conventional methodologies and cutting-edge computation to provide precise, automated diagnosis tools for dermatological disorders [4,5].

Skin disease diagnosis urgently requires both speed and accuracy for optimal patient outcomes. Traditional methods, though valuable, are time-constrained, hindering effective management in a healthcare environment where rapid interventions are crucial. A new approach to skin problem diagnosis has been developed through the use of transfer learning, an AI technique.

2. Motivation

The motivation behind the research is because of the critical need for improved diagnostic methods in the field of dermatology. The complexities involved in skin disease diagnosis always present a significant healthcare challenge. Traditional diagnostic approaches, relying heavily on visual inspection and invasive procedures like biopsies, often lead to misdiagnosis, delays in treatment, and inefficiencies in managing skin conditions.

Skin disease diagnosis urgently requires both speed and accuracy for optimal patient outcomes. Traditional methods, though valuable, are time-constrained, hindering effective management in a healthcare environment where rapid interventions are crucial. The novel aspect of this approach is how cutting-edge computational approaches, especially deep learning techniques like CNNs and transfer learning using trained models like VGG16 are utilized. The goal of this fusion is to develop a new diagnostic paradigm that addresses the limitations of the current approaches.

3. Literature Review

The literature survey reveals a significant body of work dedicated to leveraging deep learning techniques for the automated classification of skin-related issues. One notable contribution involves the CNNs and a diverse dermoscopic image dataset to achieve fast, accurate, and equitable computer-assisted diagnosis [6]. The domain focuses on developing prediction models that take into account several parameters to provide accurate treatment recommendations and diagnosis [7]. A major field of research in skin disease prediction is digital image processing, which helps scientists extract useful diagnostic information from dermatological images [8]. Dermoscopy image classification remains a challenging task for automatic systems; convolutional networks show promise in terms of prediction accuracy. A suggested fusion method regulates the importance of visual information by controlling dermoscopy images and non-image metadata for intelligent skin disease diagnosis. Deep learning model architecture experiments demonstrate superior performance, particularly for rare diseases [9]. Using the DermNet dataset, this study's InceptionV3 model predicts skin conditions such as psoriasis, acne, and eczema with over 78.8% accuracy, indicating the model's applicability to non-medical users [10]. Genetics, aging, hormones, allergies, sun exposure, and environmental factors are all major causes of skin disorders. Although diagnosis is difficult, this study suggests a technique for diagnosing skin diseases using Python, image processing, and the Yolov3 tool [11]. This approach produces trustworthy results fast and does away with the need for a physical examination. The system analyses the affected area, retrieves feature values, and determines the disease using patient images. This strategy is especially helpful for dermatologists who practice in remote areas. The objective is to predict skin diseases with the highest level of accuracy possible [11]. Using machine learning techniques, this paper presents a skin disease module that can classify lesions related to skin cancer, such as melanoma and benign keratosis. Using a Telegram chatbot for prediction, the module trains a MobileNet convolutional neural network on a Raspberry Pi. With a top-2 accuracy of 0.89 and a top-3 validation accuracy of 0.096, the model is a promising tool for dermatologists and users to receive early referrals for managing skin diseases [12]. This study employs deep learning techniques and cutting-edge technology to diagnose skin conditions from infected skin images. For training and model building, MobileNetV2, an architecture for convolutional neural networks, is employed. Since prevention is always preferable to cure, this approach helps medical professionals validate their views and people understand the disease early on, potentially preventing further disease [13]. Ensemble methods for skin disease classification take center stage in another research avenue, discussing the combination of multiple classification models to achieve higher accuracy and robustness in diagnosing different skin conditions [14]. Lastly, a comprehensive review of CNNs is provided, tracing their historical development, exploring applications in various domains, and emphasizing the versatility of 1-D CNNs in diverse applications, including medical imaging and signal processing [15,16]. In [17] the authors propose an automated facial skin disease recognition method using a pre-trained deep-learning model and results in 88% accuracy. In recent times, seeing the growth and development in the field of artificial intelligence mainly in the field of healthcare, the study shows the challenges of diagnosing and identifying facial skin disease with similar symptoms. The solution proposed by the authors includes image preprocessing and a database of 12000 images belonging to 10 classes including 8 diseases, normal skin, and a no-face class. The pre-trained VGG-16 network demonstrates successful classification, and the model achieves 98% accuracy on test images. Another study [18] introduces a skin disease classification approach using models MobileNet V2 and LSTM in deep learning, showing its effectiveness on the HAM10000 dataset produces 85% accuracy. The research suggests the proposed system can significantly help in the diagnosis of skin diseases, reduce complications, and benefit both patients and dermatologists. With an emphasis on melanoma, psoriasis, dermatitis, and herpes, the research develops CNNs for the early diagnosis and prediction of skin diseases [19]. The authors discovered 93.3% accuracy using four CNN classes [20]. Seven networks (Mobilenet, ResNet50, Inception, Xception, VGG 16, and VGG 19) were assembled with 94.1% accuracy in a different study [21]. Table 1 summarizes some existing studies.

Table 1. Existing studies.

Year	Classes	Method	Accuracy
2016 [1]	2 classes	Bio-impedance measurement method	75%
2016 [5]	198 classes	Fine-tuned VGG and CaffeNet.	94.98%
2019 [2]	3 classes	DCNN	95.91%
2020 [3]	4 classes	CNN fine-tuned ResNet152 and InceptionResNetV2	87.42%
2021 [4]	3 classes	CNN	88.83%
2023 [20]	4 classes	CNN	93.3.%
2023 [21]	7 classes	Among the networks on the list are Mobilenet, ResNet50, Inception, Xception, VGG 16, and VGG 19.	94.1%

4. Methodology

The suggested process aims to enhance the accuracy of skin disease prediction by using sophisticated data and methodologies. This method involves applying extensive data collection, employing advanced algorithms to train machines, refining the input variables, selecting and optimizing the models, evaluating their performance through cross-validation, and incorporating cutting-edge technologies like deep learning and ensemble approaches. This methodical technique improves the model's ability to forecast, making it easier to diagnose and treat more efficiently. The proposed workflow is presented in Figure 1.

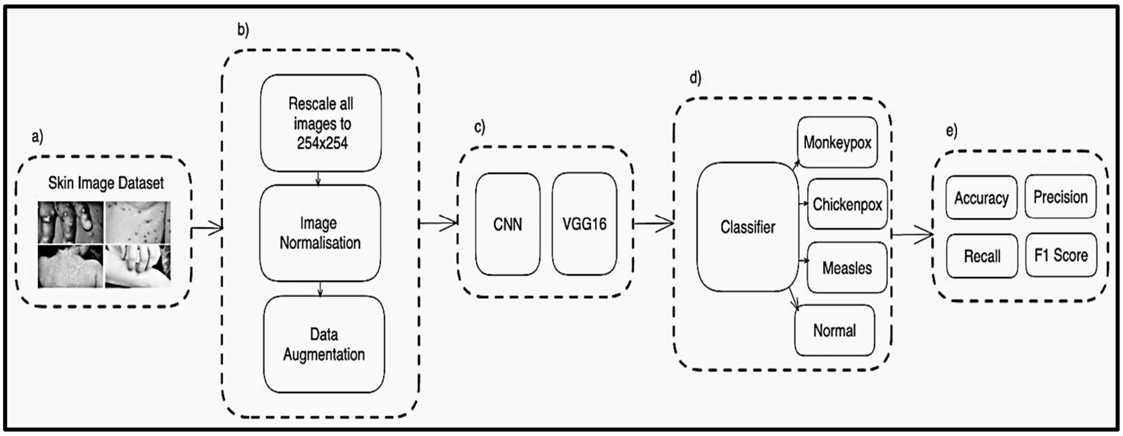


Figure 1. Proposed workflow.

4.1. The Dataset

The dataset [22] used in this study addresses the urgent need for early detection of monkeypox, a concerning outbreak worldwide. Developed by the Department of CSE, Islamic University, Kushtia, Bangladesh, the skin image-based dataset comprises four distinct classes: Monkeypox, Chickenpox, Measles, and Normal. The images for each class have been meticulously collected from various internet-based sources as shown in Figure 2. The rationale behind selecting these specific classes lies in the similarity of skin lesions caused by Monkeypox, Chickenpox, and Measles, which can be challenging to differentiate. The inclusion of a “Normal” class facilitates a comprehensive understanding of healthy skin patterns for effective disease classification.

Figure 2. Example images of the dataset.

4.2. Dataset Preprocessing

The dataset used in this research consists of non-microscopic images of skin diseases. It’s divided into four classes: chickenpox, measles, monkeypox, and normal. The dataset underwent a preprocessing stage before training the model to enhance its viability. This involved resizing images to a uniform dimension of 254×254 pixels, normalization of pixel values to the range [0, 1], and augmentation techniques. Augmentation included random rotation, width and height shifts, and horizontal flips. This process aimed to introduce variability to the dataset. This should prevent overfitting and improve the models’ capabilities.

4.3 Model Architectures

4.3.1. Convolutional Neural Network (CNN) Model

A basic CNN model is specifically designed to analyze the images which makes it handy for tasks like classifying skin diseases. Typically, layers with distinct functions are utilized when developing this type of model: convolutional layers are used to extract features from input images, pooling layers are used to reduce spatial dimensions, and fully connected layers are used to make predictions based on the features extracted. To help the network identify complex patterns, activation functions like ReLU and leaky ReLU are employed to introduce non-linearity into the system. This core CNN structure provides a flexible framework for this type of analysis and plates up as a strong foundation for a variety of image classification problems, such as the analysis of skin diseases as shown in Figure 3.

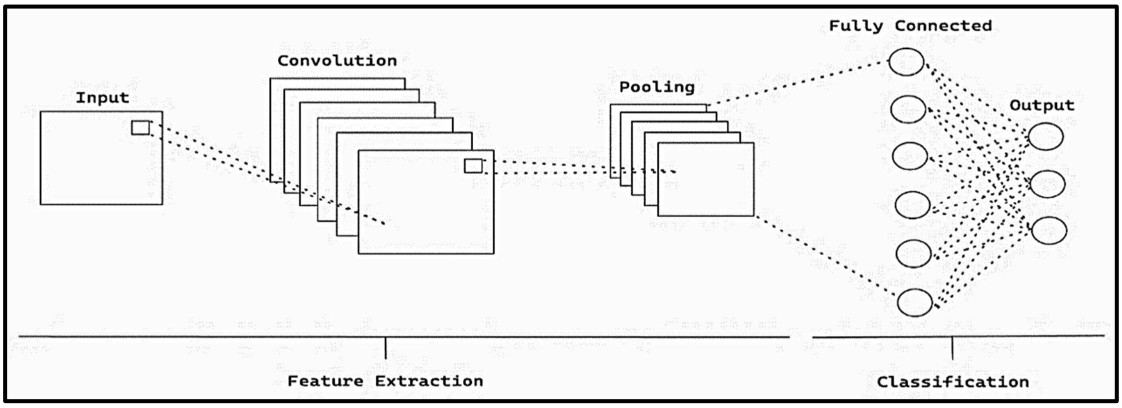


Figure 3. CNN architecture.

4.3.2. VGG16 Transfer Learning Model

The VGG16 model represents an effective CNN architecture recognized for its simplicity and efficacy as presented in Figure 4. Consisting of 16 layers, including convolutional and fully connected layers, VGG16 makes use of the transfer learning model by using previously given weights from the whole ImageNet dataset.

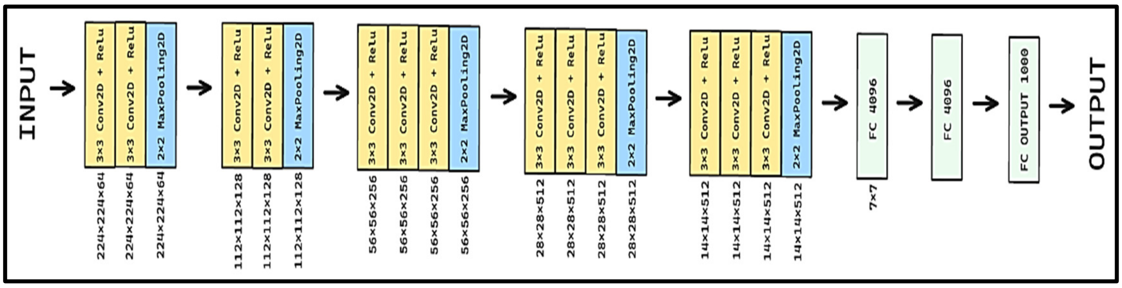


Figure 4. VGG16 architecture.

By pre-training on a large dataset like ImageNet, the VGG16 model gains a deep understanding of huge amounts of visual features which allows it to excel at capturing subtle and complex patterns in images.

4.4. Proposed Solution

4.4.1. Modified Convolutional Neural Network (CNN) Model

The first model developed is a CNN designed from scratch. Three convolutional layers with increasingly larger filters (32, 64, and 128 in this architecture) are followed by dropout layers, batch normalization, and max-pooling to avoid overfitting. The flattened output is then connected to two fully connected layers with 128 and 64 neurons, respectively, incorporating batch normalization and dropout for regularization as presented in Figure 5.

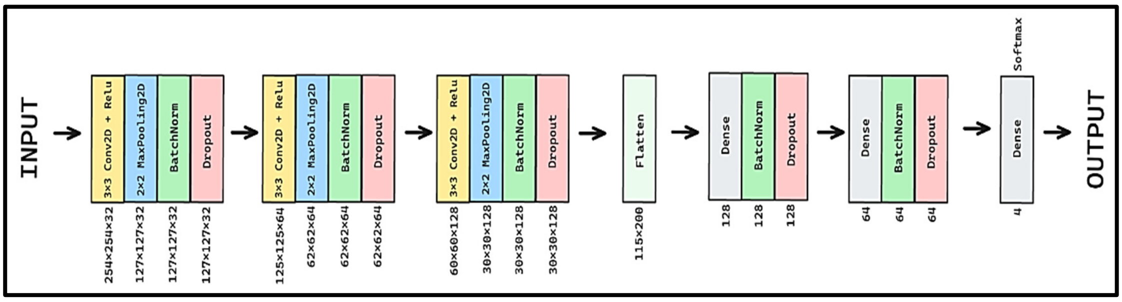


Figure 5. Proposed CNN model architecture.

The final output layer consists of four neurons representing the disease classes, activated by a softmax function. The model was set up using the Adam method for improving its performance, a way of measuring errors called categorical cross-entropy, and it checks how well the model is doing by looking at accuracy.

4.4.2. Modified VGG16 Transfer Learning Model

VGG16, a pre-trained CNNs architecture. The VGG16 model was loaded with weights trained on the ImageNet dataset and its top layers were removed.

A new architecture was built on top of the VGG16 base, comprising a flattened layer, a dense layer with 224 neurons and ReLU activation, and a final output layer with four neurons representing the skin disease classes and activated by a softmax function as shown in Figure 6. The weights of the VGG16 layers were frozen during training to continue with the pre-trained features. Finally, the model was used to compile with the Adam optimizer using categorical cross entropy and loss function. The accuracy of this model was analyzed by the evaluation metric.

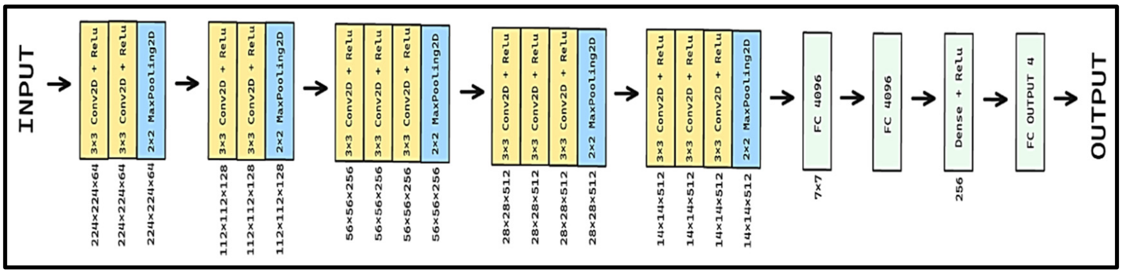


Figure 6. Proposed VGG16 model architecture.

4.5. Training and Evaluation

Both models were trained using a training dataset and estimated using a separate validation dataset. The CNN model was trained till 15 epochs, while the VGG16 model was trained till 30 epochs with early stopping to prevent overfitting. Training progress, including loss and accuracy metrics, was monitored during each epoch. The final models were evaluated on a test dataset to assess their generalization performance on unseen data.

4.6. Evaluation Parameters

After training the models, we subjected them to testing using a reserved test set. The evaluation process involved the use of a confusion matrix to calculate performance metrics, utilizing elements of the matrix to signify both intended and actual classifications. The classification results were categorized into two classes: correct and incorrect predictions. To assess the prediction model, we analyzed four fundamental case studies:

4.6.1. True Positive (TP)

This represents the percentage of true positives accurately identified with a high degree of precision.

4.6.2. False Negative (FN)

Incorrect forecasts fall into this category, identifying situations as malevolent despite the model incorrectly anticipating them to be normal.

4.6.3. False Positive (FP)

Also known as an incorrectly positive prediction, this occurs when the observed assault is in fact, normal.

4.6.4. True Negative (TN)

This represents the percentage of false positives that correctly identify normal situations.

When we have to check how well a task is performing, we look for key metrics: accuracy, recall, F1 score, and precision as presented in Equations (1) to (4). All these metrics help us to find out the performance of the model, these are calculated by analyzing the confusion matrix.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{1}$$

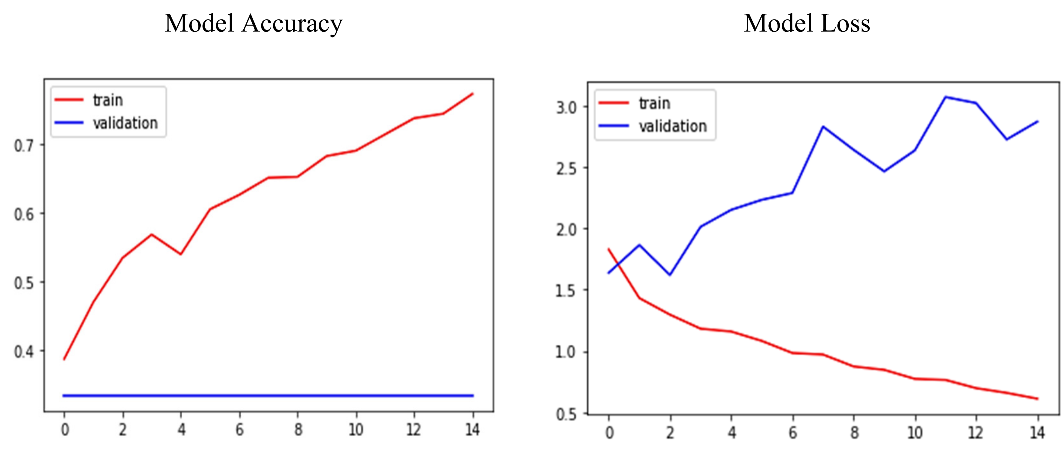
$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$F1 - Score = \frac{2 \times Precision \ \times Recall}{Precision + recall} \tag{4}$$

5. Model Performance Assessment

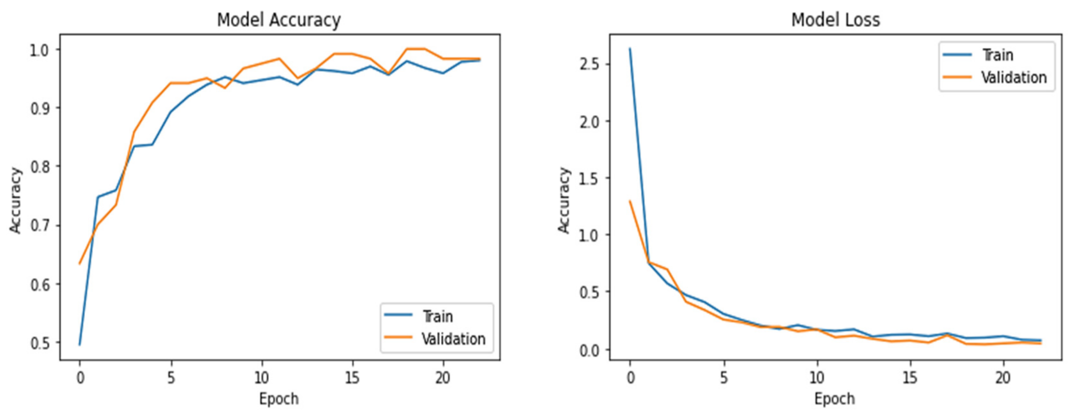
To check how well the models were doing in each epoch, we monitored two things accuracy and loss. We looked at these parameters while the model was in training and during validation. After that, we also created confusion matrices which gave us a closer look at how the model is performing and whether the model classifying the diseases correctly or not as shown in Figures 7 and 8.



(**a**) (**b**)

Figure 7. The trend of loss and accuracy of the CNN model. (a) shows the trend of accuracy and validation accuracy against the number of epochs. (b) shows the trend of loss and validation loss against the number of epochs.

In the analysis of the CNN model, it is observed that, despite an initial increase in training accuracy, the model's performance on the validation set remains stagnant at 33.33%. This discrepancy suggests a potential overfitting issue, indicating that the model may have become too specialized in the training data. Overfitting can be attributed to the limited size of the dataset or the complexity of the chosen architecture. The lack of improvement in validation accuracy over epochs prompts consideration for regularisation techniques or architectural adjustments to enhance generalization.



(**a**) (**b**)

Figure 8. Trend of loss and accuracy of VGG16 model. (**a**) shows the trend of accuracy and validation accuracy against the number of epochs. (**b**) shows the trend of loss and validation loss against the number of epochs.

On the other side, the use of transfer learning with the VGG16 model results in a great improvement. The confusion matrix for the VGG16 model is presented in Figure 9.

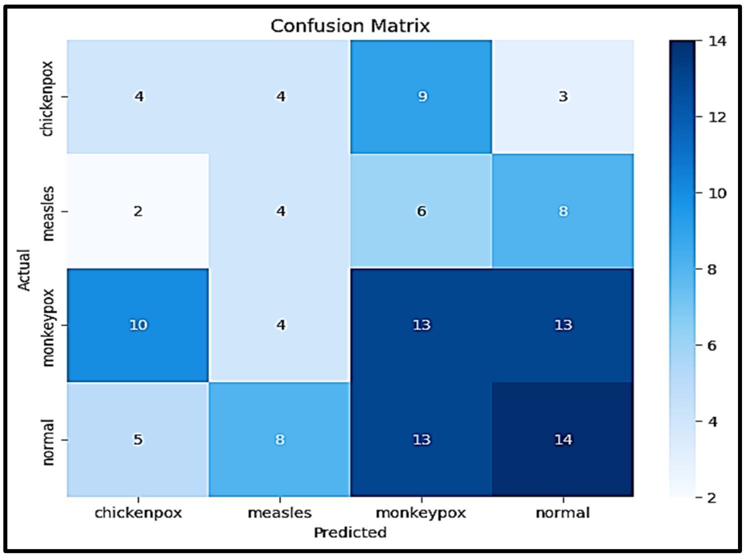


Figure 9. Confusion matrix for the VGG16 model.

This model has extensive knowledge of numerous attributes that are critical for categorizing skin conditions. With the help of this knowledge, the model has the potential to understand the new data it hasn't seen before. In testing, the VGG16 model achieves a great accuracy of 98.33% on the validation set, showing how effective it is to use pre-trained models for tasks like classifying skin diseases. By comparing our two approaches we can see that using a pre-trained model or transfer learning techniques like VGG16 is helpful and provides more accurate results when the dataset size is small.

This study examines the performance metrics of two distinct models, CNN and VGG16, using many assessment criteria. When it comes to training accuracy, VGG16 exhibits much superior performance, reaching an outstanding 99.8%, in contrast to CNN's 78%. Nevertheless, in terms of validation accuracy, VGG16 remains superior to CNN, albeit with a smaller difference, achieving a rate of 98.3% in comparison to CNN's 33%. Although CNN has lesser accuracy, it surpasses VGG16 in recall, precision, and F1 score, demonstrating its capacity to identify meaningful instances in the dataset accurately.

This suggests that although VGG16 performs well in learning patterns during training, CNN may be better at generalizing and catching smaller details in new data, as evidenced by its greater performance in validation measures. These metrics indicate a compromise between the accuracy of the training process and the ability of the model to perform well on unseen data. This highlights the significance of choosing the right model that aligns with the distinctive requirements of the work. VGG16 produced a great result because it already knows a lot from its previous training, however, we can make it better by fine-tuning it or making some changes to how it works. This would help it work well on the data we used for training and new, unseen data.

6. Conclusions

The research on using deep learning for the classification of skin diseases like monkeypox, chickenpox, and measles revealed some interesting findings. The CNN model which was built from scratch faced some challenges with overfitting and resulted in an unacceptable accuracy for classification, while the technique of transfer learning and using a pre-trained model like VGG16 showed higher accuracy and holds great promise for improving dermatological capabilities. Future research it would be beneficial to focus on fine-tuning CNN architectures and exploring larger datasets to further enhance the integration of machine learning into dermatology, making skin disease classification more precise and efficient.

Author Contributions

Conceptualization, D. R., A. G., Y.D.; Methodology: A. J. and S. P.; Software: A. J. and D. R.; Validation: S. P. and A. G.; Writing- original draft preparation: D. R., A. G., A. J., S.P.; Writing-review and editing, resources, supervision, Y. D.; Review and editing, S.C. Sarangi; Supervision, A. A. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The author declares that they have no conflict of interest.

Data Availability Statement

Data will be available upon request.

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