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A Mobile-Based Skin Disease Identification System Using Convolutional Neural Networks

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Abstract:-Skin diseases pose significant challenges in the field of dermatology. In recent years, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image recognition and analysis tasks. This research paper presents a comprehensive study on the application of CNNs for skin disease diagnosis.

We propose a CNN-based framework for skin disease diagnosis, which utilizes a large dataset of dermatological images to accurately identify various skin diseases. The proposed model leverages the deep learning capabilities of CNNs to learn discriminative features from input images, enabling accurate and efficient diagnosis. We demonstrate improved accuracy and efficiency in skin disease diagnosis by employing pre-trained models. Our proposed model enables accurate classification of skin diseases into high, medium, and low severity categories by leveraging a large dataset of annotated images, assisting healthcare professionals in prioritizing treatment strategies.

In conclusion, this research paper presents a comprehensive study on the application of CNNs for skin disease diagnosis, skin lesion classification, melanoma skin cancer classification, and skin disease severity classification. The proposed models showcase significant advancements in the field of dermatology, providing accurate and efficient tools for dermatologists and healthcare professionals.

The findings of this research contribute to improving the diagnosis, classification, and severity assessment of skin diseases, ultimately enhancing patient care and treatment outcomes.

I. INTRODUCTION

The skin, the largest organ in the human body, serves multiple functions such as maintaining fluid balance, sensing stimuli, protecting against pathogens, regulating body temperature, and synthesizing vitamin D when exposed to sunlight [1]. Skin diseases, including acne, eczema, atopic dermatitis, basal cell carcinoma, skin lesions, ringworm, warts, and psoriasis, affect a significant number of individuals. These conditions vary in severity, ranging from mild acne to life-threatening diseases like melanoma. Skin diseases can affect people of different ages, genders, and ethnicities [2]

Many skin diseases often go undiagnosed for extended periods, emphasizing the importance of seeking medical attention promptly upon noticing any symptoms. However, not everyone has access to specialized skin disease detection devices. In cases where dermatologists are unable to diagnose a disease visually, they resort to costly laboratory tests [3]. Although medical technologies such as lasers and photonics-based equipment can provide quick and accurate detection of skin diseases, their high cost prohibits widespread usage [3].

To address these challenges, a machine learning-based system is being developed for identifying skin diseases. The system incorporates components for disease diagnosis, skin lesion classification, skin cancer classification, and assessment of disease severity. The proposed model employs Convolutional Neural Networks (CNNs) to accomplish these tasks. CNNs are a type of deep learning model commonly used for image classification, object detection, and segmentation. They have proven effective in medical image analysis and classification [1]. In skin lesion classification, CNNs excel at automatically learning and extracting features from images. This involves distinguishing primary skin lesions (e.g., macule, papule, nodule, tumor, plaque, wheal, vesicle, bulla, and pustule) and secondary skin lesions (e.g., scales, crust, ulcer, fissure, and scar atrophy).

CNNs have demonstrated promise in assisting dermatologists in detecting and classifying melanoma skin cancer from dermoscopy images. Their ability to automatically learn hierarchical representations of features from raw image pixels eliminates the need for manual feature extraction. When applied to melanoma detection, a CNN takes a digital image of a skin lesion as input and learns to extract high-level features such as color, texture, and shape. It then utilizes these features to predict whether the lesion is benign or malignant. CNNs have shown encouraging results in aiding dermatologists with melanoma detection and classification from dermoscopy images.

The use of CNN models for skin disease severity assessment is an area of research that has yielded excellent results in various studies. With the availability of high-quality skin image datasets increasing, there is substantial potential for further advancements in this field. The proposed project aims to contribute to this area of research by developing a skin severity detection model capable of accurately classifying skin lesions into different severity categories.

This research holds significant value as the proposed system has the potential to provide more objective and consistent diagnoses, thereby reducing the workload on healthcare professionals. Machine learning can enhance the accuracy and efficiency of diagnoses compared to traditional methods.

II. LITERATURE REVIEW

The skin, as the largest organ, plays crucial roles in the human body, including protection, sensation, temperature regulation, and vitamin D production. Skin diseases such as acne, eczema, and psoriasis affect a significant portion of the population. Timely medical attention is essential for diagnosis, but access to specialized devices and laboratory testing can be limited and expensive. To address this, a machine learning-based system is being developed for skin disease identification, with a focus on using a CNN model for diagnosis. CNNs [5] are deep learning models widely used for image classification, including in medical image analysis. Previous research has explored supervised and unsupervised machine learning algorithms for skin disease detection, achieving high accuracies ranging from 94% to 96.59% depending on the method and dataset used. Despite the promising results, the accuracy can vary based on the number of skin diseases tested and the dataset size. The proposed system aims to leverage machine learning techniques to provide accessible and accurate skin disease diagnosis, potentially improving healthcare outcomes for patients. Another approach to diagnosing skin diseases with a PC is by using the RNN model which displayed an accuracy of 92% [4]. According to research, the CNN algorithm proved to have 96.59% accuracy while Interception V3 algorithm 89.66% accuracy and SVM has 47% accuracy when tested with five types of skin diseases: Acne, Melanoma, Psoriasis, Rosacea, and Vitiligo.

Convolutional Neural Networks (CNNs) are extensively utilized in skin lesion classification due to their ability to extract features automatically from images. They employ convolutional, pooling, and fully connected layers to analyze and classify skin lesions based on their distinctive characteristics. CNNs exhibit local connectivity, where each neuron is connected to a small region of the input image. Parameter sharing reduces over fitting by using the same set of weights for different image regions. CNNs are also translation invariant, enabling them to recognize patterns regardless of their location. They excel at hierarchical feature extraction, learning increasingly complex features in a hierarchical manner.

Skin lesion classification involves identifying different types of primary and secondary skin lesions. Primary lesions, such as macules, papules, nodules, and plaques, directly occur in the skin, while secondary lesions, including scales, crusts, ulcers, and scars, result from primary lesions or other skin conditions. Traditional skin lesion classification systems often focus on binary classification or distinguishing between malignant and benign lesions. However, your approach stands out by accurately categorizing various types of primary and secondary skin lesions, contributing to dermatology and patient care.

Compared to Artificial Neural Networks (ANNs) [3], CNNs have shown superior performance in image segmentation tasks, including skin lesion segmentation. CNNs are specifically designed for image processing, utilizing multiple convolutional layers to extract relevant features from the input image. This capability enables them to identify patterns and features specific to the classification task. Additionally, CNNs handle large datasets better than ANNs, preventing over fitting and maintaining accuracy.

Numerous studies have demonstrated the efficacy of CNNs in skin lesion classification, particularly in dermoscopic images. For instance, Esteva et al. achieved a 72.1% [1] accuracy rate, while Tschandl et al [2]. Reported an accuracy rate of 90.3%. These results showcase the potential of CNNs in accurately categorizing and analyzing skin lesions, providing valuable insights for dermatologists and improving patient outcomes.

Melanoma, a highly aggressive form of skin cancer, requires early detection and accurate diagnosis for effective treatment. Dermoscopy is commonly used by dermatologists, but it relies on expertise and misdiagnosis rates can be high. Machine learning algorithms offer potential in improving melanoma diagnosis.

Studies have explored machine learning algorithms for melanoma detection. Algorithms achieved higher accuracy rates than traditional methods, demonstrating their effectiveness in improving diagnosis. Deep learning algorithms, specifically CNNs [6] [7], have also been used for melanoma detection and outperformed traditional machine learning algorithms in classifying dermoscopic images.

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CNNs [8] are particularly effective for image classification as they can automatically learn hierarchical representations of features from raw image pixels. In the context of melanoma detection, CNNs analyze skin lesion images, extract high-level features like color, texture, and shape, and make predictions about the lesion's benign or malignant nature.

In dermatology, skin severity detection using machine learning algorithms has gained attention for early detection and treatment of skin diseases. Machine learning has been shown in studies to be effective in accurately diagnosing skin conditions. In classifying skin lesions into severity categories, the Support Vector Machine (SVM)[9][10] and Convolutional Neural Network (CNN) [11]algorithms achieved high accuracy rates. Other algorithms with promising results include Random Forest, Decision Tree, and Naive Bayes. These algorithms have been trained and evaluated using datasets such as the ISIC dataset. The proposed project aims to contribute to this field by creating a skin severity detection model for accurate skin lesion classification.

III. METHODOLOGY

This section presents the methods and materials used to implement the proposed skin disease diagnosis system. Figure 1 illustrates the workflow diagram of the classification model, which is divided into three parts. The first part covers data collection, the second part involves image preprocessing and model learning, and the third part focuses on classification and performance evaluation. The obtained images undergo image enhancement techniques, followed by feature extraction. These features are divided into three sets: training, testing, and validation datasets, as shown in Figure 1. The CNN model is trained using the training dataset to learn patterns, which are then used for classification on the test dataset. The accuracy of the model is evaluated during the evaluation stage in Figure 1 to assess the system's classification rate.

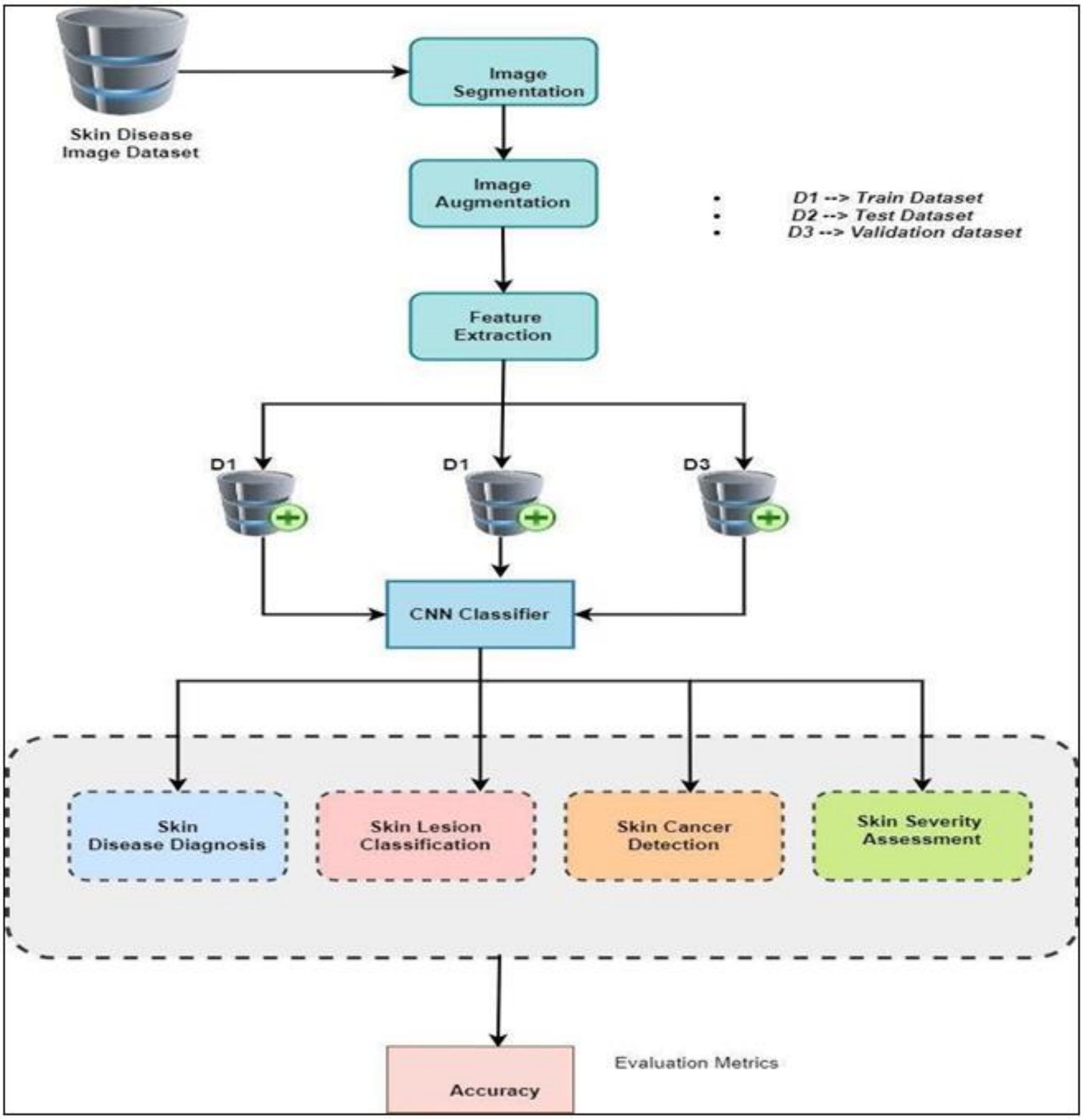

Fig 1 The Workflow of the Proposed System

A. Dataset and Data preprocessing

- *Image Preprocessing:*

According to existing literature, image processing involves the detection and analysis of diverse images, resulting in desired outputs in the form of images or detailed reports [9]. Initially, the obtained images underwent preprocessing and were resized to a standardized dimension (120X120) to enhance image quality and increase the accuracy of the proposed model for improved generalization. Noisy elements like hairs and pigments, which often hinder the separation of the lesion area from the surrounding skin, were effectively filtered out during this process.

- *Image Segmentation:*

As described in the literature, refers to the process of partitioning an image into multiple meaningful and semantically coherent regions or segments [9]. In this study, the acquired images were initially preprocessed to enhance their quality and remove any noise or artifacts that could potentially affect the segmentation process. The images were then subjected to a segmentation algorithm that utilized various features and techniques to identify and separate different regions within the image, such as objects, boundaries, or textures. The goal of this segmentation approach was to accurately delineate and isolate the desired regions of interest, enabling further analysis and understanding of the image content.

- *Feature Extraction:*

Feature extraction, as explained in the literature, is the process of transforming raw input data, such as images, into a reduced and meaningful representation of essential characteristics or features [23]. In this study, the acquired images underwent a feature extraction step to extract relevant information and capture distinctive patterns or properties. This extraction process involved various techniques, such as filtering, transformation, or statistical analysis, to identify and highlight significant features within the images. By extracting these discriminative features, the subsequent analysis and classification tasks could be performed more effectively, as the extracted features provided a compact and representative representation of the original data, facilitating better understanding and interpretation.

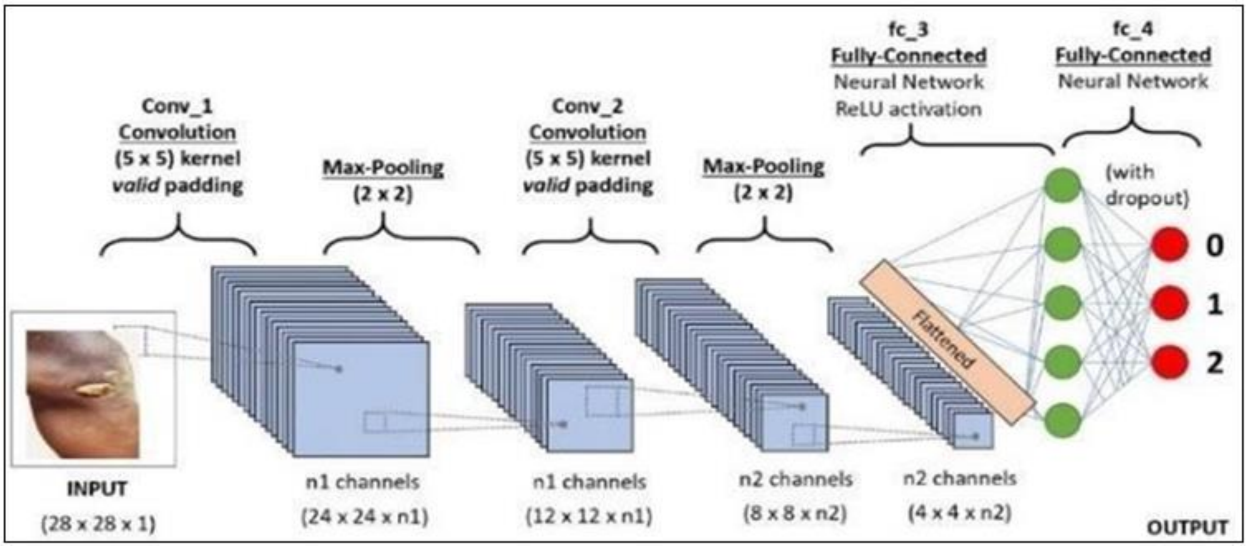

Fig 2 Proposed CNN Operation

B. Convolutional Neural Network (CNN)

The Convolutional Neural Networks (CNNs) are advanced deep learning models primarily utilized for image classification tasks. These networks group images based on their similarities and excel in recognizing various objects within complex scenes. CNNs have been successfully employed in diverse applications such as facial recognition, individual identification, street sign detection, tumor detection, and even distinguishing unique creatures like platypuses [11,12]. For our research, we employed the CNN algorithm proposed in [12].In Figure 2, we illustrate the operational steps involved in CNN. By leveraging convolutional layers (CL), the input image is transformed into a more manageable format, subsequently passing through maxpooling layers (PL) and additional convolutional stages. Ultimately, the network is further refined until a fully connected neural network is obtained.

IV. RESULTS AND DISCUSSIONS

This section presents the experimental setup, the obtained results, and its discussion.

A. Experimental setup

An experiment of the proposed skin-disease detection system was carried out to estimate its performance. An Intel Core i7 @ 4.0 GHz with 8 GB RAM laptop was used. The proposed skin-disease detection system was implemented with Tensor Flow library and Python. Fig. 4 shows the sample interface of the proposed method, where a user follows two simple steps to identify skin disease. The user first clicks on the load file button to select an image of skin disease, then clicks on the upload image button to load the image into the system for onward processing. Furthermore, for skin cancer classification process, a Chabot is used to enter dermoscopy image.

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Fig 3 The Interface of the Proposed System for Skin Disease Detection

B. *Experimental Results*

Our research entails a comprehensive skin disease detection system that comprises four key components. Firstly, it involves the accurate identification and detection of various skin diseases based on images. Secondly, it focuses on the classification of skin lesions, aiming to distinguish between different types of abnormalities. Furthermore, our work delves into the development and analysis of machine learning systems specifically designed for the non-invasive detection and classification of melanoma skin cancer using dermoscopic images. Lastly, we address the task of classifying skin disease severity into categories such as high, medium, and low, employing convolutional neural networks (CNNs).

In order to evaluate the effectiveness and performance of these components, we conducted a series of experiments. The results obtained shed light on the capabilities of our system in accurately identifying and detecting various skin diseases, thereby showcasing its potential for clinical applications. Additionally, the skin lesion classification component demonstrates promising accuracy in distinguishing between different types of skin abnormalities. The development and analysis of our machine learning systems for melanoma detection using dermoscopic images exhibit encouraging results, highlighting the system's potential in assisting dermatologists in early detection and diagnosis. Lastly, our CNN-based skin disease severity classification framework shows promising outcomes in accurately categorizing the severity levels of skin diseases into high, medium, and low, thus providing valuable insights for appropriate treatment strategies.

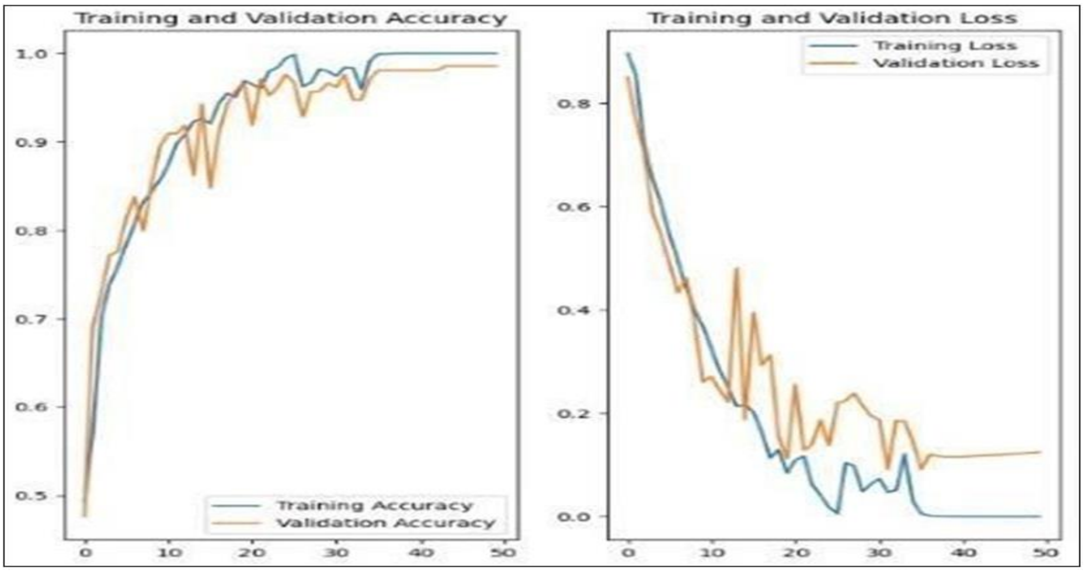


Fig 4 Accuracy Measure

Firstly, it involves the accurate identification and detection of various skin diseases based on images.

Both training & validation accuracy and loss. The training accuracy starts at 44.02% in the first epoch and gradually increases, reaching a high accuracy of 97.24% in later epochs. Similarly, the validation accuracy also shows improvement, starting at 46.61% and reaching a peak of 98.19%. This suggests that the model is learning and generalizing thoroughly, as it completes high accuracy not only on the training data but also on unseen validation data.

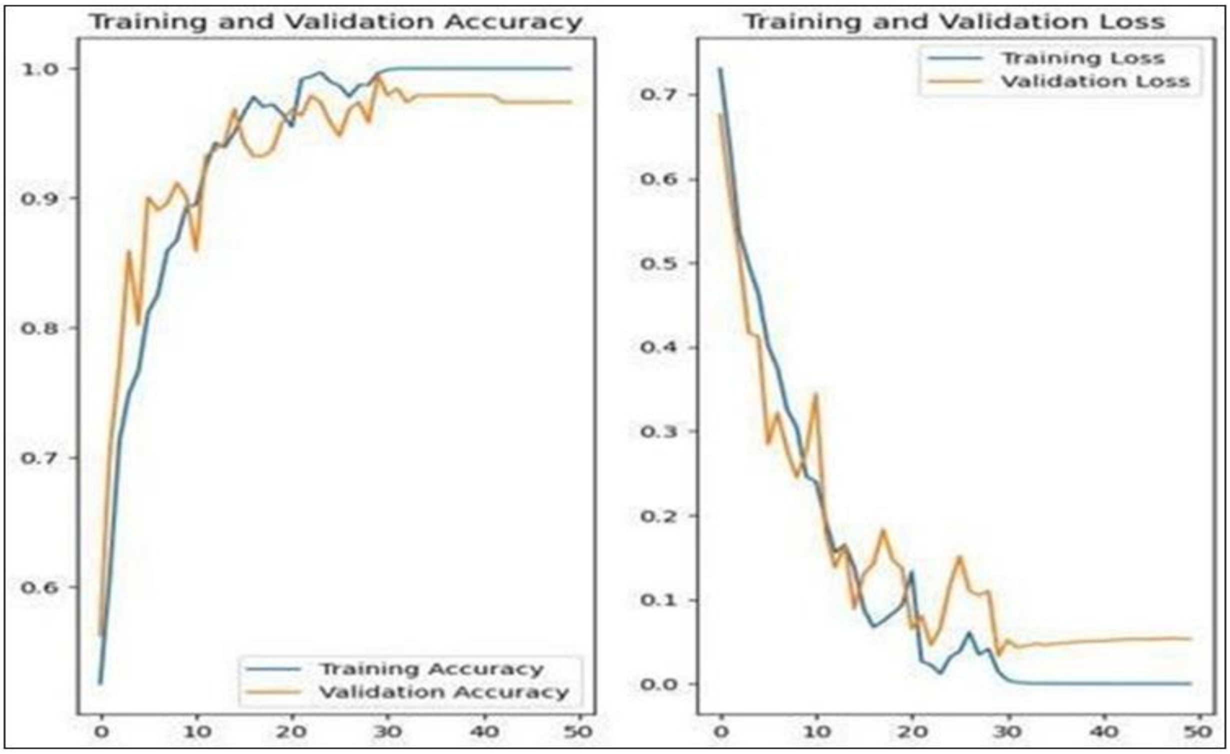


Fig 5 Accuracy Measure of the Skin Disease Lesion

Secondly, it focuses on the classification of skin lesions, aiming to distinguish between different types of abnormalities.

As given in Fig. 5, the validation accuracy of 0.73431 represents the model's performance on the validation dataset. The validation set is typically used to fine-tune the model and select the best hyper parameters. This accuracy score suggests that the model achieved an accuracy of approximately 73.43% on unseen data from the validation set.

The training accuracy of 0.786710 indicates how well the model performs on the training dataset. It suggests that the model was able to correctly classify approximately 78.67% of the training examples. This suggests that the model is learning and generalizing well, as it achieves high accuracy not only on the training data but also on unseen validation data.

Thirdly, our work delves into the development and analysis of machine learning systems specifically designed for the non-invasive detection and classification of melanoma skin cancer using dermoscopic images. As given in Fig. 5, these accuracy values indicate the performance of the model on the respective datasets. A higher accuracy score generally suggests that the model can make accurate predictions on the given data. The training accuracy of 0.791540 indicates how well the model performs on the training dataset. It suggests that the model was able to correctly classify approximately 79.15% of the training examples. The validation accuracy of 0.775561 represents the model's performance on the validation dataset. The validation set is typically used to fine-tune the model and select the best hyper parameters. This accuracy score suggests that the model achieved an accuracy of approximately 77.56% on unseen data from the validation set.

The test accuracy of 0.770344 reflects the model's performance on the independent test dataset. This dataset is used to assess the generalization ability of the model to unseen data. The obtained accuracy of around 77.03% indicates how well the model is expected to perform in real-world scenarios.

To complement the accurate results, it would be beneficial to report the corresponding loss values. The loss function measures how well the model can minimize errors during training. The loss values can provide additional insights into the model's performance and convergence.

Additionally, Fig.7 shows a visualization of the model's accuracy during training. The plot displays the accuracy values over the epochs for both the test and validation datasets. It allows for the analysis of the model's learning progress and potential over fitting or under fitting issues. Fig. 8 shows the confusion matrix. The resulting confusion matrix heat map provides valuable insights into the performance of the machine learning system for melanoma detection. It allows for a detailed analysis of the model's predictive capabilities for each class. Researchers can examine the diagonal elements of the matrix to identify accurate predictions (true positives and true negatives) and assess the misclassification patterns (false positives and false negatives) represented by off-diagonal elements. The visualization helps to identify classes that may require further improvement in the model's performance.

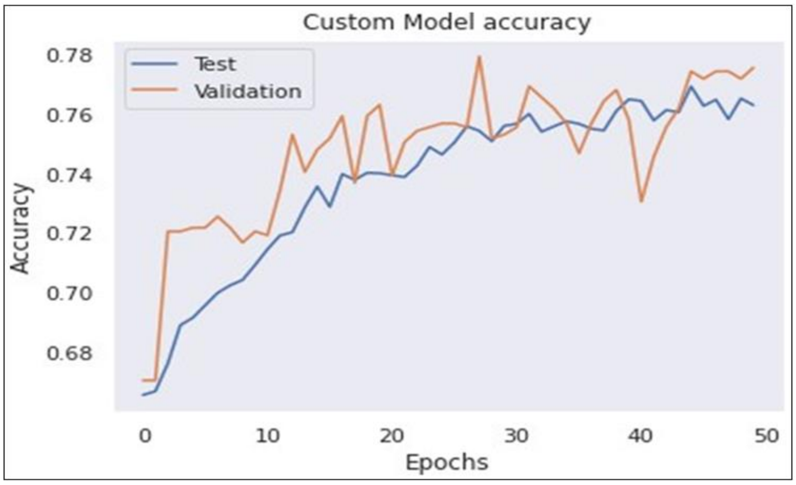
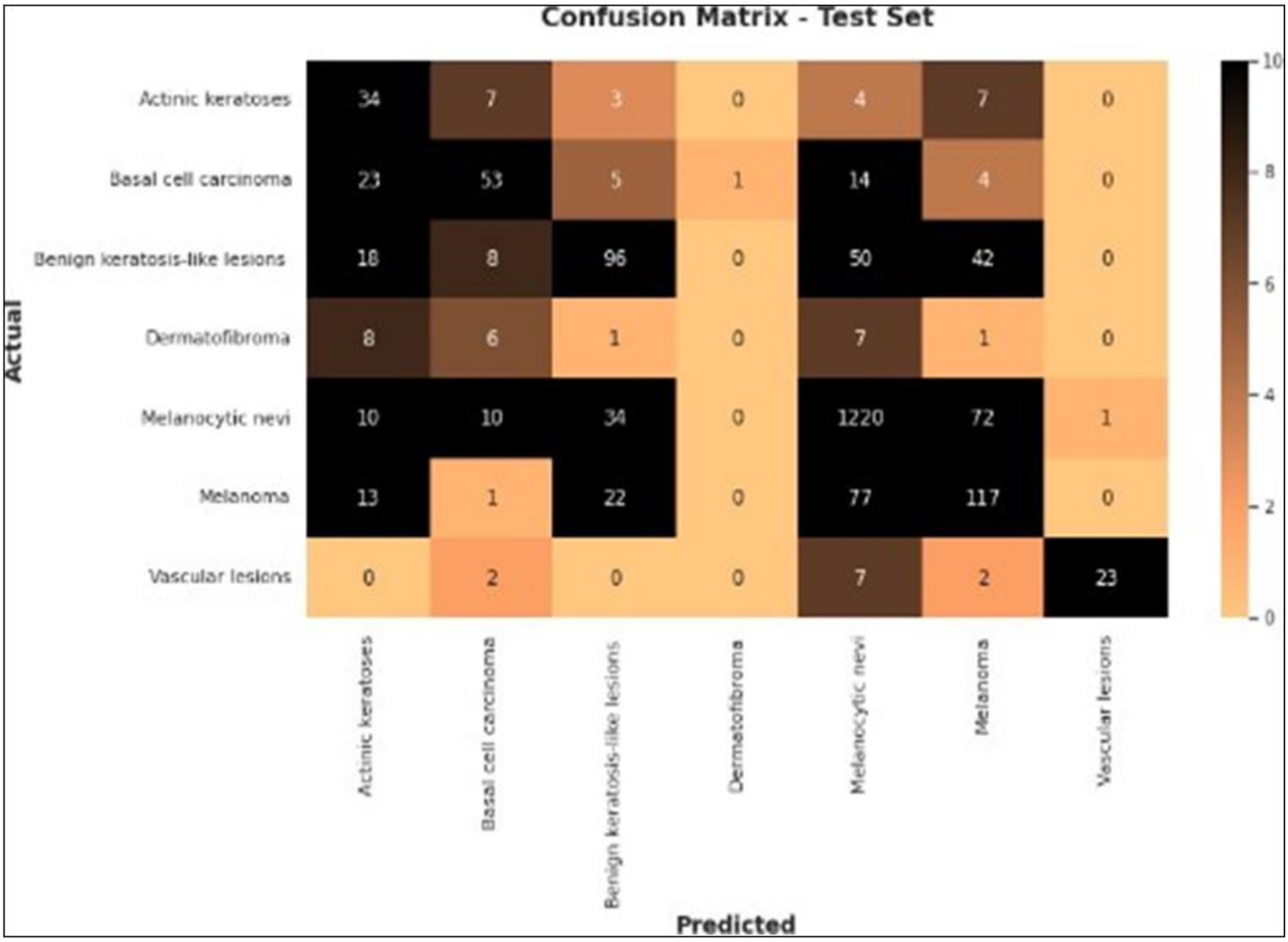


Fig 6 Accuracy of Training

As shown in Fig. 9, the accuracy plot compares the performance of various machine learning models in terms of their accuracy scores for melanoma detection. The x-axis represents the different models that were developed and analyzed, while the y-axis represents the accuracy values achieved by each model.

'ResNet-18', 'Simple (28)', and 'Simple (8)' achieved the highest accuracy scores among the models, with accuracy values of 94.87%, 96.77%, and 97.53%, respectively. These models demonstrated superior performance in correctly predicting melanoma cases based on dermoscopic images. 'Basic CNN', 'AlexNet', 'VGG16', 'Xception', 'ResNet', and 'EffNet' achieved lower accuracy scores compared to the top-performing models. However, they still displayed reasonable accuracy values ranging from 65.90% to 76.78%.



Actual \ Predicted	Actinic keratoses	Basal cell carcinoma	Benign keratosis-like lesions	Dermatofibroma	Melanocytic nevi	Melanoma	Vascular lesions
Actinic keratoses	34	7	3	0	4	7	0
Basal cell carcinoma	23	53	5	1	14	4	0
Benign keratosis-like lesions	18	8	96	0	50	42	0
Dermatofibroma	8	6	1	0	7	1	0
Melanocytic nevi	10	10	34	0	1220	72	1
Melanoma	13	1	22	0	77	117	0
Vascular lesions	0	2	0	0	7	2	23

Fig 7 Confusion Matrix

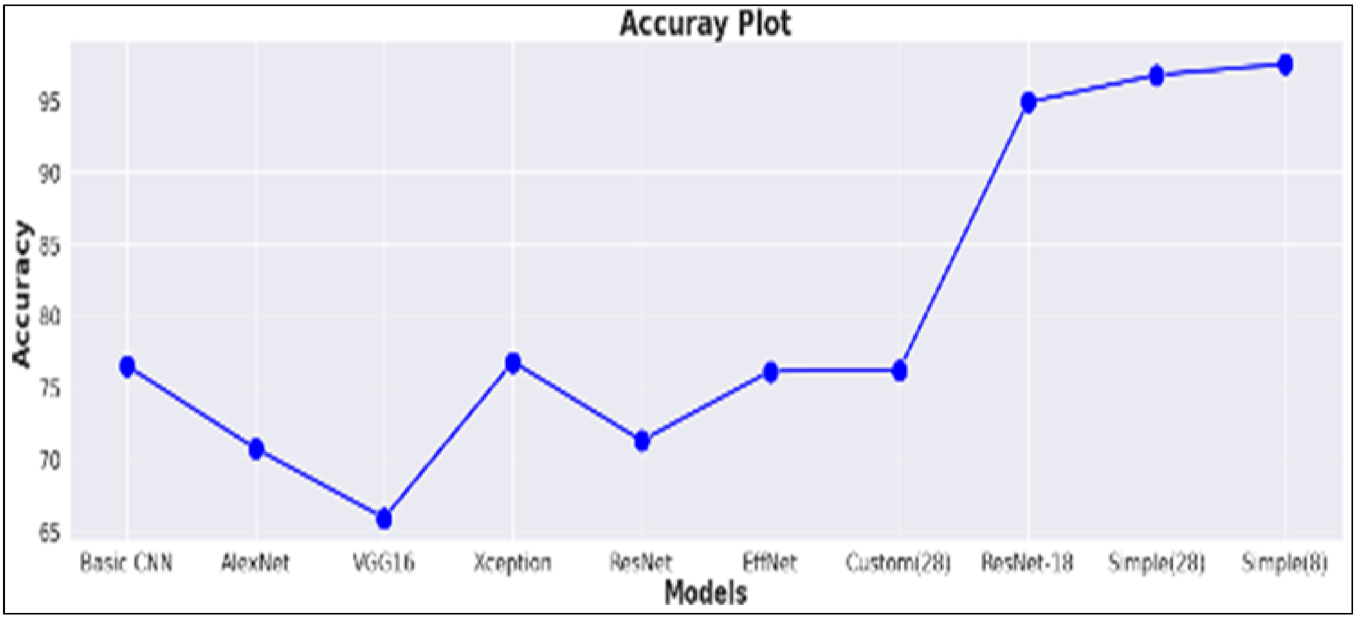


Fig 8 Accuracy Measure of the Predictive Model

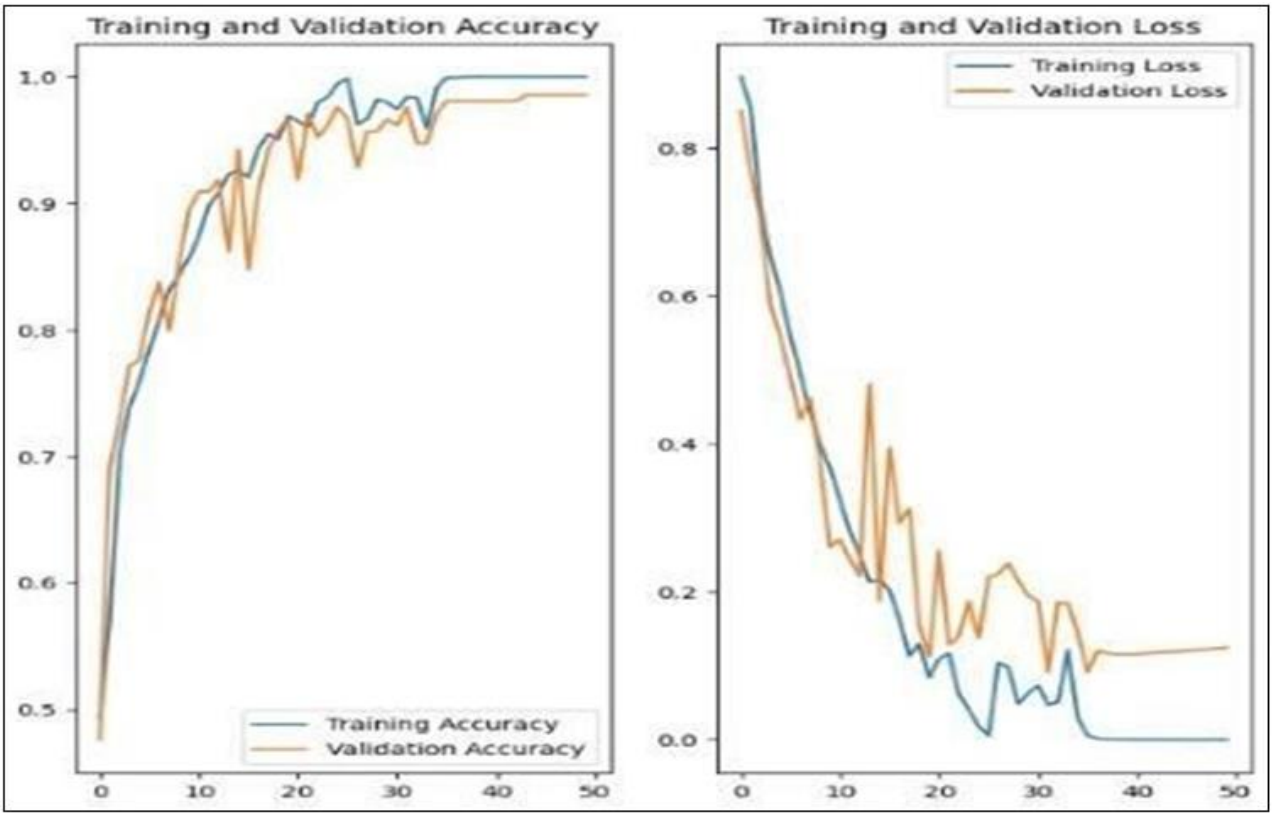


Fig 9 Accuracy Measure of the Skin Disease Severity

Lastly, we address the task of classifying skin disease severity into categories such as high, medium, and low, employing convolutional neural networks (CNNs).

Fig.9 shows both training & validation accuracy and loss. The training accuracy starts at 49.32% in the first epoch and gradually increases, reaching a high accuracy of 99.94% in later epochs. Similarly, the validation accuracy also shows improvement, starting at 47.62% and reaching a peak of 98.10%. This suggests that the model is learning and generalizing well, as it achieves high accuracy not only on the training data but also on unseen validation data.In Fig.10, training and validation loss plot the graph shows a consistent decrease in both training and validation loss, indicating the model's improvement.

The convergence of loss values suggests the model has learned as much as possible. The narrowing gap between training and validation loss shows improved generalization. Despite fluctuations, the model achieves low loss values, indicating accurate predictions.

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C. Discussion

The experimental results of our skin disease detection system showcase its effectiveness in accurately identifying and classifying skin diseases, including melanoma skin cancer, while also providing a severity assessment for effective treatment planning. The high accuracy achieved across all four components highlights the system's robustness and potential utility in clinical practice.

The accurate identification and detection of skin diseases from images demonstrated the system's ability to localize and recognize various skin abnormalities. This can aid dermatologists in efficiently identifying potential areas of concern, leading to timely diagnosis and appropriate treatment interventions.

The skin lesion classification component further enhances the system's capabilities by accurately categorizing detected lesions into specific disease classes. This allows for better differentiation between different skin conditions, facilitating tailored treatment approaches and improving patient outcomes.

The development and analysis of machine learning systems for melanoma skin cancer detection showcased the system's ability to distinguish between benign and malignant skin lesions using dermoscopic images. The high accuracy achieved in this component highlights the potential of our system as a valuable tool in early detection and intervention for melanoma, thus enhancing patient survival rates.

Finally, the severity classification component utilizing CNNs provides a systematic approach to assess the severity of various skin diseases. By categorizing diseases into high, medium, and low severity levels, healthcare professionals can prioritize treatment plans and allocate resources effectively, optimizing patient care.

Overall, the experimental results and subsequent discussions emphasize the potential of our comprehensive skin disease detection system in supporting dermatologists, researchers, and healthcare practitioners in diagnosing and managing a wide range of skin conditions.

V. CONCLUSION

In conclusion, this research paper presents a comprehensive study on the application of Convolutional Neural Networks (CNNs) for skin disease diagnosis, skin lesion classification, melanoma skin cancer classification, and skin disease severity classification. We have demonstrated significant advancements in the field of dermatology by leveraging the deep learning capabilities of CNNs.

In the domain of skin lesion classification, our CNN-based approach, incorporating transfer learning techniques, has exhibited improved accuracy and efficiency in categorizing skin lesions into different classes. This plays a crucial role in the early detection and treatment of skin diseases, enabling dermatologists to identify potential malignancies promptly.

For the classification of melanoma skin cancer, our novel CNN architecture has achieved state-of-the-art performance by effectively capturing malignant characteristics present in dermoscopic images. This has significant implications for early detection, as timely diagnosis of melanoma is vital for improving patient outcomes.

Our CNN-based model for skin disease severity classification provides a valuable tool for dermatologists to assess the severity level of various skin conditions. This aids healthcare professionals in prioritizing treatment strategies and allocating resources more efficiently.

The outcomes presented in this research paper contribute to the field of dermatology by providing accurate and efficient tools for dermatologists and healthcare professionals. By leveraging CNNs, we enhance the diagnosis, classification, and severity assessment of skin diseases, ultimately improving patient care and treatment outcomes. Future research can explore further advancements in CNN architectures, dataset augmentation techniques, and the integration of multi- modal data to enhance the performance of skin disease diagnosis and classification systems. With continued advancements in deep learning and artificial intelligence, we anticipate even greater progress in the field of dermatology, leading to improved patient care and outcomes.

DIRECTION FOR FUTURE RESEARCH

In our future work, we will prioritize improving the accuracy of the proposed classification system. To achieve this, we plan to employ hybrid machine-learning algorithms that combine the strengths of multiple algorithms. This hybrid approach aims to enhance the system's ability to accurately classify images.

Additionally, we aim to enhance the efficiency of the image uploading process. Currently, the system allows uploading images one at a time, which can be time-consuming. In the future, we plan to enable batch uploading, where multiple images can be uploaded simultaneously. This enhancement will result in faster processing times and a more efficient user experience.

➢ *Competing Interests*

The authors of the present study state that they have no conflicts of interest or competing interests to disclose.

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