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Skin Diseases Detection using Deep Learning

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Abstract: Skin disease diagnosis is a complex task requiring specialized expertise due to the diversity of dermatological conditions. Convolutional Neural Networks (CNNs) offer a promising solution by automating diagnosis through pattern recognition in medical images. This study explores CNNs' effectiveness in skin disease detection, focusing on the impact of data augmentation on model performance. Initially, a CNN model achieved 76% training accuracy and 85% testing accuracy. With data augmentation—using techniques like rotation, flipping, and scaling—these figures improved to 81% and 87%, respectively. These transformations expanded the dataset, enhancing the model's ability to generalize by mimicking real-world conditions. This process combats overfitting and helps the model learn robust features crucial for accurate diagnosis. The CNN architecture utilized multiple convolutional layers to extract essential features from images, followed by pooling layers to reduce dimensions and prevent overfitting. Fully connected layers then consolidated these features for final classification. The model's evaluation involved metrics such as accuracy, precision, recall, and F1 score, highlighting the augmented model's superior performance. This research underscores the significance of data augmentation and pre-processing in developing reliable diagnostic tools. The study's findings suggest that CNNs can aid dermatologists by providing accurate, efficient diagnoses, particularly valuable in areas with limited access to healthcare expertise. Future work aims to refine these models further, ensuring their interpretability and integration into clinical settings, thereby enhancing patient care and outcomes.

Keywords: Augmentation, Convolutional Neural Network (CNN), Data pre-processing, Deep learning, Dermatology, Diagnostic accuracy, Healthcare innovation, Machine learning, Medical imaging, Skin disease.

I. INTRODUCTION

Skin disease recognition poses a significant challenge in the medical field, exacerbated by rising pollution levels and poor dietary habits, which have contributed to an increase in patients with skin-related issues. Unhealthy skin not only impacts physical well-being but also damages self-confidence, emphasizing the importance of regular and proper skin monitoring for early detection. Skin diseases can impose a heavy emotional and psychological burden on patients, often exceeding the physical discomfort they cause. According to the World Health Organization (WHO) [1], skin diseases continue to be the fourth leading cause of nonfatal disease burden worldwide. The early detection of skin-related diseases is crucial, as they can progress to more severe health issues such as cancer if left untreated. Detecting skin diseases is inherently challenging due to the similarity in appearance and common symptoms shared among many conditions, such as rashes or itching. This overlap makes it difficult to differentiate between diseases without a thorough examination. In this context, deep learning offers promising solutions for developing effective systems capable of classifying various skin diseases. Convolutional Neural Networks (CNN), in particular, have emerged as the most efficient for image-related tasks, including image classification and object detection [2]. CNN can automatically and adaptively learn spatial hierarchies of features from input images, making them well-suited for tasks where local patterns and structures are crucial. In the present work, a deep learning-based model has been proposed for the classification of various skin diseases, leveraging the strengths of CNN. The model's architecture is designed to extract and learn discriminative features from skin images, enabling accurate classification of different conditions. Data augmentation techniques such as rotation, flipping, and scaling were applied to the dataset to enhance the model's ability to generalize to unseen data. This approach enriched the dataset, improved training accuracy, and maintained high testing accuracy, underscoring the importance of data pre-processing in deep learning. The model was evaluated using metrics such as accuracy, precision, recall, and F1 score. Initially, the CNN model achieved a training accuracy of 76% and a testing accuracy of 85%. After applying data augmentation techniques, the training accuracy improved to 81%, with the testing accuracy reaching 87%. These results highlight the effectiveness of data augmentation in enhancing model performance and robustness. The augmented model demonstrated superior accuracy compared to the baseline, indicating its efficacy in detecting a wide range of skin conditions. The implications of these findings in clinical practice are significant. CNN-based systems with augmented data can assist dermatologists in making accurate and efficient diagnoses, potentially streamlining the diagnostic process and reducing the workload on healthcare professionals. Moreover, such systems can improve patient outcomes by facilitating early detection and treatment of skin diseases. Ongoing research is essential to further refine and optimize CNN models for real-world applications, including the exploration of advanced augmentation techniques and interpretability methods to ensure reliability and trust in clinical settings. In conclusion, this study underscores the effectiveness of CNN in skin disease detection, demonstrating that augmented data can lead to a notable improvement in accuracy, achieving up to 87%. These advancements hold great promise for enhancing dermatological diagnosis and improving patient care outcomes, marking a significant step forward in computer-aided medical diagnostics. The use of deep learning, particularly CNN, for skin disease classification represents a crucial development in addressing the growing burden of skin diseases and improving the quality of life for affected individuals.

II. Literature Review

This chapter reviews the application of Convolutional Neural Networks (CNNs) in detecting various diseases through medical imaging, demonstrating their substantial effectiveness and accuracy in a range of medical diagnoses. The literature highlights significant advancements in deep learning, particularly CNNs, for various disease detection and classification tasks across different domains.

A. Applications in Medical Imaging

Retinal Diseases: For retinal diseases, M. Bhandari *et al.* (2023) [3] emphasized that CNNs achieve a diagnostic accuracy of 94.29%, which is crucial for preventing blindness through early detection and precise analysis of retinal images. The study utilized a deep learning framework to analyse retinal fundus images, identifying signs of diabetic retinopathy, age-related macular degeneration, and other retinal conditions. The high accuracy rate demonstrates the potential of CNNs to revolutionize the field of ophthalmology, providing tools for early diagnosis and effective management of retinal diseases.

COVID-19: In the context of the COVID-19 pandemic, F. Rustam *et al.* (2021) [4] employed

CNNs to classify the severity of COVID-19 from chest X-rays, achieving an impressive 99.5% accuracy. This application is particularly significant as it showcases the potential of CNNs in diagnosing lung-related issues and aiding in timely treatment decisions. The model's ability to accurately distinguish between different stages of COVID-19 can assist healthcare providers in making informed decisions regarding patient care and resource allocation during pandemics.

Liver Diseases: Additionally, H. Che *et al.* (2021) [5] developed a deep learning system for classifying non-alcoholic fatty liver disease from ultrasound images, achieving over 90% accuracy. This underscores the reliability of CNNs in liver disease diagnosis and highlights the efficiency of real-time, cost-effective imaging methods enhanced by AI. By providing a non-invasive and accurate diagnostic tool, CNNs can help in the early detection and management of liver diseases, potentially reducing the need for more invasive procedures like biopsies.

Pneumonia: X. Gu *et al.* (2018) [6] proposed a novel computer-aided diagnosis (CAD) system utilizing fully convolutional networks (FCN) and deep convolutional neural networks (DCNN) for identifying pneumonia in chest X-rays, achieving an accuracy of 80.48%. Despite the relatively lower accuracy compared to other studies, this research highlights the continuous improvement and potential of deep learning models in medical diagnostics. The use of FCN and DCNN in tandem exemplifies the innovative approaches being developed to enhance disease detection.

Brain Tumors: R. İncir *et al.* (2024) [7] demonstrated the effectiveness of transfer learning models in brain tumor diagnosis, with EfficientNetV2-M achieving an impressive accuracy of 98.01%, and further enhanced to 98.41% when combined with Inception-V3. Similarly, M. Toğaçar *et al.* (2020) [8] introduced BrainMRNet for brain tumor classification, achieving 96.05% accuracy. These studies highlight the critical role of CNNs in neuroimaging, offering high accuracy in detecting and classifying brain tumors, which is essential for timely and effective treatment.

Lung Nodules: Y. Gu *et al.* (2018) [9] developed a 3D CNN for lung nodule detection in CT scans, achieving high sensitivity and an AUC of 0.7967. The three-dimensional aspect of this model allows for a more comprehensive analysis of CT scans, improving the detection rates of lung nodules and potentially leading to better outcomes in lung cancer diagnosis and treatment.

B. Applications in Agriculture and Food Quality

Plant Diseases: J. Ma *et al.* (2018) [10] used a DCNN for recognizing cucumber leaf diseases, achieving 93.4% accuracy. The application of CNNs in agriculture demonstrates their versatility and effectiveness beyond medical imaging. By accurately identifying plant diseases, these models can help farmers take timely actions to protect crops, thereby improving yield and reducing losses.

Fruit Classification: A. Patino-Saucedo *et al.* (2018) [11] employed a modified AlexNet for tropical fruit classification, reaching 99.56% accuracy. The high precision of CNNs in distinguishing between different types of fruits can significantly aid in the automation of sorting and grading processes in the agricultural industry. Similarly, S.-H. Wang *et al.* (2020) [14] presented an 8-layer CNN for fruit classification, achieving 95.67% accuracy, further demonstrating the capability of CNNs in this domain.

Nut Grading and Quality Inspection: A. Sivaranjani *et al.* (2019) [12] optimized cashew nut grading with a deep CNN, achieving 97.7% accuracy. This application shows how CNNs can be utilized for quality control in the food industry, ensuring that products meet certain standards before reaching consumers. R. Sustika *et al.* (2018) [13] compared different CNN architectures for strawberry quality inspection, finding VGGNet to be the most accurate. The ability to accurately grade and inspect food products can enhance efficiency and consistency in the food supply chain.

III. METHODOLOGY

Convolutional Neural Networks (CNN) have emerged as a powerful tool for automatic feature extraction and image classification in various domains, including medical diagnostics. This study explores the application of CNN in the challenging field of skin disease detection, where accurate diagnosis is crucial yet often complicated by the visual similarity and overlapping symptoms of different conditions. The CNN architecture utilized in this research includes 3 convolutional layers, each followed by an activation layer, and 3 max pooling layers. A flatten layer reshapes the extracted features before feeding them into a dense layer, which incorporates dropout and L2 regularization to improve model robustness and prevent overfitting. The CNN model is trained and evaluated on a secondary dataset comprising 2084 training images and 377 testing images, categorized into 5 distinct classes representing various skin diseases.. Without data augmentation, the CNN model achieves accuracies of 76% and 85% on the training and testing datasets, respectively. Upon applying augmentation techniques, these accuracies improve to 81% and 87%. Performance evaluation metrics such as accuracy, recall, precision, and F1 score are utilized to comprehensively assess the model's performance in skin disease detection. The results underscore the effectiveness of CNN in accurately classifying skin diseases, demonstrating their potential as a valuable tool in dermatological diagnostics. This research contributes to advancing automated diagnostic systems, aiming to enhance the efficiency and accuracy of skin disease diagnosis in clinical practice. Within the proposed framework, a deep learning model has been developed to focus on five commonly encountered skin diseases: atopic dermatitis, melanoma, tinea (ringworm), basal cell carcinoma (BCC), and warts along with other viral infections. This model leverages the capabilities of Convolutional Neural Networks (CNN) to accurately diagnose these conditions from images. The dataset used for this study comprises 2,084 images in the training set and 377 images in the testing set, collected from an online repository dedicated to educational and research purposes.

Kaggle (https://www.kaggle.com/datasets/riyaelizashaju/skin-disease-classification-image dataset). These images were carefully curated to represent a wide range of visual characteristics associated with the targeted skin diseases. The images were classified both with and without data augmentation to assess the impact of augmentation on the model's performance. Data augmentation techniques such as rotation, flipping, and scaling were applied to artificially expand the dataset, introducing variability that mimics real-world conditions. This process is critical in enhancing the model's ability to generalize and perform well on unseen data. Fig. 1 illustrates a selection of images from this dataset, providing a visual overview of the diverse types of skin conditions included. This visual representation helps in understanding the variety and complexity of the images the model is trained on, showcasing the different manifestations of each skin disease. The augmentation process, by adding slight variations to the training images, aims to improve the model's robustness and its capability to handle different cases effectively. The schematic representation of the proposed model's workflow is depicted in Fig. 2, detailing the steps involved in the data augmentation, training, and evaluation processes. The workflow begins with the pre-processing of the raw images, including resizing, normalization, and augmentation. The pre-processed images are then fed into the CNN model, which consists of several convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. During the training phase, the model learns to identify distinguishing features of each skin condition from the augmented dataset. The training process involves optimizing the model's parameters to minimize the loss function, which measures the difference between the predicted and actual labels. Regular evaluations on the validation set ensure that the model is not overfitting and is capable of generalizing well to new data. The performance of the model is finally evaluated on the testing set, using metrics such as accuracy, precision, recall, and F1 score to provide a comprehensive assessment. The results from the experiments indicate that data augmentation significantly improves the model's performance, leading to higher accuracy and better generalization to unseen data. In summary, the development of this deep learning model for skin disease diagnosis highlights the critical role of data augmentation in enhancing model performance. By systematically applying augmentation techniques, the model's ability to accurately classify various skin conditions is significantly improved, demonstrating the potential of CNN in medical image analysis and the importance of robust training methodologies in developing reliable diagnostic tools. Within the proposed framework, a deep learning model has been developed to focus on five commonly encountered skin diseases.

- *Atopic Dermatitis (Eczema):* Atopic Dermatitis, commonly known as eczema, is a chronic skin condition characterized by dry, itchy, and inflamed skin. It often affects young children but can occur at any age. Eczema is not contagious but can lead to other allergic conditions such as asthma and hay fever. It typically appears on the face, neck, hands, and in the creases of the elbows and knees. Management of atopic dermatitis includes regular moisturizing, avoiding irritants, and using medicated ointments or creams to control inflammation and itching.
- *Melanoma:* Melanoma is a serious type of skin cancer that originates in melanocytes, the cells that produce melanin, the pigment responsible for skin colour. It can develop on any skin surface but is most commonly found in areas exposed to the sun, such as the arms, back, face, and legs. Melanoma is known for its high potential to spread (metastasize) to other parts of the body, making early detection and treatment crucial. Symptoms include changes in existing moles, such as asymmetry, irregular borders, colour changes, diameter growth, and evolving shape or size. Treatment options include surgical removal, immunotherapy, targeted therapy, chemotherapy, and radiation therapy.
- *Tinea (Ringworm):* Tinea, commonly referred to as ringworm, is a fungal infection that presents as an itchy, circular rash with a clear centre and a red, scaly border. Despite its name, it is not caused by a worm but by dermatophyte fungi. Ringworm can affect various parts of the body, including the scalp (tinea capitis), body (tinea corporis), feet (tinea pedis or athlete's foot), and groin (tinea cruris or jock itch). It is contagious and can spread through direct contact with an infected person or animal, or through contaminated objects. Treatment involves antifungal medications, which can be topical or oral depending on the severity and location of the infection.
- *Basal Cell Carcinoma (BCC):* Basal Cell Carcinoma is the most common type of skin cancer. It arises from the basal cells, which are located in the deepest part of the epidermis. BCC typically develops in sun-exposed areas such as the face, neck, and arms. It often appears as a pearly or waxy bump, a flat, flesh-coloured or brown scar-like lesion, or a sore that heals and then reopens. BCC is usually slow growing and rarely spreads to other parts of the body. However, it can cause significant local damage if not treated. Treatment options include surgical excision, Mohs surgery, cryotherapy, and topical medications.
- *Warts and Other Viral Infections:* Warts are benign skin growths caused by the human papillomavirus (HPV). They can appear on any part of the body but are most common on the hands, feet (plantar warts), and genitals (genital warts). Warts are typically small, rough, and skin-coloured but can vary in appearance. They are contagious and can spread through direct contact with an infected person or contaminated surfaces. Other viral infections affecting the skin include herpes simplex virus (cold sores and genital herpes) and varicella-zoster virus

(chickenpox and shingles). Treatment for warts may include over-the-counter remedies, cryotherapy, laser treatment, or prescription medications. Other viral infections are managed with antiviral medications and symptomatic relief measures.

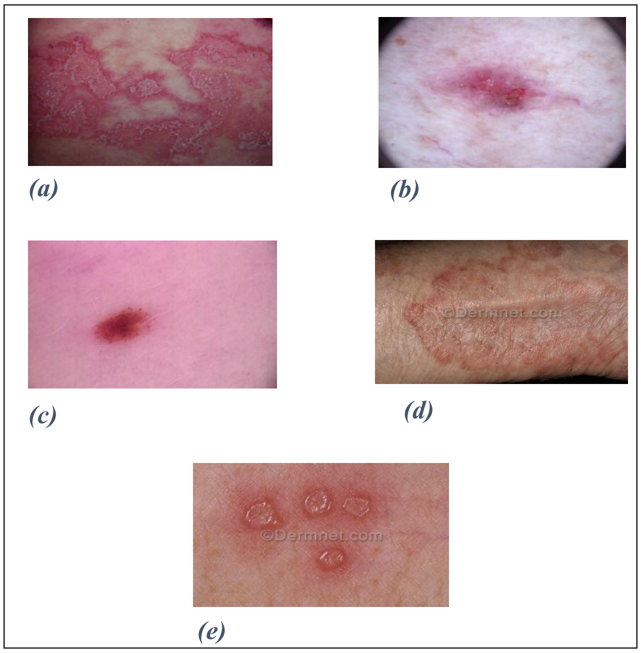


Fig. 1: Showing the Samples of Images of Skin Diseases (a) Atopic Dermatitis, (b) Melanoma, (c) Tinea (Ringworm), (d) Basal Cell Carcinoma (BCC), and (e) Warts Along with Other Viral Infections

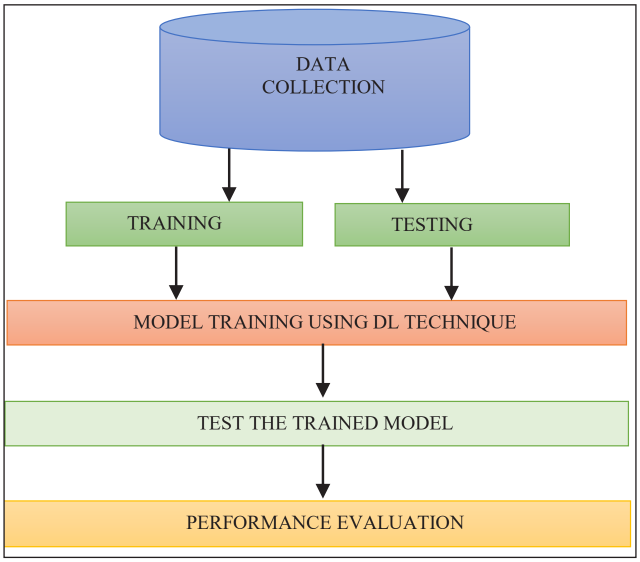


Fig. 2: Research Methodology for the Skin Diseases Detection using CNNs

A. Deep Learning (DL)

Deep Learning (DL) represents a specialized branch within the realm of machine learning (ML), aiming to replicate the intricate processes of the human brain when processing data and generating patterns to inform decision-making. Positioned as a more sophisticated extension of ML techniques, DL is often referred to as deep neural learning or deep neural networks. This methodology harnesses multi-layered architectures comprising nonlinear units, with each subsequent layer leveraging the outputs of its predecessors as input [11].

B. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) represent a specialized form of artificial neural networks (ANNs) leveraging perceptrons, a machine learning algorithm, for supervised learning tasks, particularly in data analysis. CNNs excel in handling complex tasks involving images, sounds, texts, videos, and more, primarily focusing on visual imagery analysis. They boast a sophisticated architecture that requires minimal pre-processing. Renowned for their shift invariance and translation invariance owing to shared-weights architecture, CNNs stand out as a preferred choice for predictive tasks, enjoying widespread adoption over other algorithms. Comprising an input layer, an output layer, and multiple hidden layers, CNNs' hidden layers typically feature convolutional layers that perform convolutions via dot product operations. The common activation function employed is the rectified linear unit (RELU), followed by additional convolutional layers such as pooling layers, fully connected layers, and normalization layers. These layers are referred to as hidden layers because the activation function and final convolution layer [12] conceal their inputs and outputs. The fundamental architecture of CNNs is illustrated below in Fig. 3.

Convolutional Layer: The convolutional layer processes input from the previous layer by convolving it with a kernel, similar to how neurons respond in the human body. Different images of Skin diseases serve as input, and the convolution operation computes the dot product of original pixel values with defined filter weights. This process generates a summarized result representing the observed pixels.

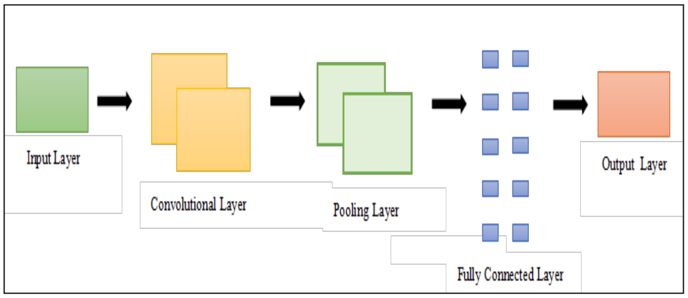


Fig. 3: Basic Architecture of Convolutional Neural Networks (CNNs)

Activation Layer: Following the convolutional layer, the resulting matrix, which is smaller than the original image, passes through an activation layer. This layer introduces non-linearity, crucial for the network to train itself via backpropagation. Typically, the ReLU activation function is employed to achieve this.

Pooling Layer: Another key component of CNNs is the pooling layer. This layer further reduces the matrix size through down-sampling. By passing a filter over the previous layer's results, it selects specific values (often the maximum value, known as max-pooling), aiding faster and more efficient training by focusing on essential information within each image feature.

Fully Connected Layer: The output of previous layers, represented as a one-dimensional vector, serves as input to this layer. Its output is a list of probabilities for various labels associated with the image, such as Actinic keratosis Atopic dermatitis. The label with the highest probability indicates the classification or detection decision.

Output Layer: In CNNs, the output layer receives flattened input from other layers, transforming it into the desired number of classes for the problem at hand. The architecture may include multiple activation and pooling layers, depending on the specific CNN design.

C. Performance Evaluation

The model's performance will be evaluated based on various metrics derived from its confusion matrix, as outlined below:

True Positive (TP): Instances where the model correctly predicts positive values, indicating that both the actual class and the predicted class are positive.

True Negative (TN): Instances where the model correctly predicts negative values, indicating that both the actual class and the predicted class are negative.

False Positive (FP): Instances where the model incorrectly predicts positive values, despite the actual class being negative.

False Negative (FN): Instances where the model incorrectly predicts negative values, despite the actual class being positive.

Accuracy: Accuracy is a straightforward measure representing the ratio of correctly predicted observations to the total observations.

	Actual Result		
Predicted Result		LOW	HIGH
	LOW	True Positive	False Positive
	HIGH	False Negative	True Negative

Precision: Precision indicates the ratio of correctly predicted positive observations to the total predicted positive observations.

Recall: Recall represents the ratio of correctly predicted positive observations to all observations in the actual positive class.

F1 Score: The F1 Score is the harmonic mean of Precision and Recall, considering both false positives and false negatives. These performance metrics can be calculated as depicted in the table below.

Parameter	Formula
Accuracy	(TP + TN)/ (Total Cases)
Recall	TP / (TP + FN)
Precision	TP / (TP + FP)
F1 Score	(2 * Recall * Precision) / (Recall + Precision)

IV. RESULTS AND DISCUSSION

In the proposed study, a dataset consisting of 2,084 images in the training set and 377 images in the testing set was collected from Kaggle (https://www.kaggle.com/datasets/riyaelizashaju/skin-disease-classification-image dataset). The dataset encompasses four classes of skin conditions: Atopic dermatitis, Melanoma, Tinea (ringworm), Basal Cell Carcinoma (BCC), and Warts along with other viral infections. To enhance the dataset and improve the performance of the Convolutional Neural Network (CNN) model, data augmentation techniques were employed. These techniques, including rotation, flipping, and scaling, were used to artificially increase the number of images and introduce variability that helps the model generalize better to unseen data. Following the augmentation process, the dataset was split into training and testing sets, with 80% of the images used for training the model and the remaining 20% reserved for testing. This split ensured that the model was trained on a substantial portion of the data while being evaluated on a separate set to assess its performance accurately. A CNN-based model was developed to classify the images into the respective skin condition categories. Initially, the model was trained without data augmentation, achieving a training accuracy of 76% and a testing accuracy of 85%. However, after applying data augmentation techniques, the training accuracy improved to 81%, and the testing accuracy increased to 87%. This improvement highlights the effectiveness of data augmentation in enhancing the model's ability to learn and generalize from the training data. The CNN model was trained for 35 epochs with a batch size of 32. During training, the model parameters were optimized to minimize the loss function, which measures the discrepancy between the predicted and actual labels. The training and validation accuracy graphs, depicted in Fig. 4, show the progression of the model's performance over the epochs. Similarly, Fig. 5 illustrates the training and validation loss graphs, providing insights into the model's learning process. The validation loss being very low and the validation accuracy being higher than the training accuracy indicate that the model has generalized well to unseen data, avoiding overfitting. To further assess the performance of the model, confusion matrices were generated. Table I presents the confusion matrix without data augmentation, while Table II shows the confusion matrix with data augmentation. These matrices provide a detailed breakdown of the model's predictions, allowing for an analysis of its accuracy in classifying each skin condition. The confusion matrix with data augmentation demonstrates improved accuracy across all classes, reinforcing the benefits of augmentation techniques. In addition to accuracy, various performance metrics were calculated to measure the effectiveness of the model, including precision, recall, and F1 score. Precision indicates the proportion of true positive identifications among all positive identifications, recall measures the model's ability to detect all actual positives, and the F1 score provides a harmonic mean of precision and recall. For the proposed model, the values for these metrics were 0.87, 0.8, and 0.8, respectively. These metrics underscore the model's balanced performance in identifying different skin conditions. Precision, recall, and F1 score are particularly important in medical diagnosis, where the cost of false positives and false negatives can be high. High precision ensures that the model is accurate when it predicts a certain skin condition, reducing the likelihood of misdiagnosis. High recall indicates that the model can identify most cases of a condition, which is crucial for early detection and treatment. The F1 score, as a combined measure, provides a comprehensive view of the model's overall performance, balancing both precision and recall. The implications of these findings for clinical practice are significant. CNN-based systems with data augmentation can aid dermatologists in making more accurate and efficient diagnoses. By automating the initial screening process, these systems can reduce the workload on healthcare professionals and allow them to focus on more complex cases. Moreover, such systems can be deployed in areas with limited access to specialized dermatological care, providing a valuable tool for early detection and intervention. Furthermore, the use of data augmentation techniques to improve model performance is a critical aspect of this study. Augmentation not only increases the quantity of data but also introduces variability that helps the model learn more robust features. This is particularly important in medical image analysis, where the diversity of visual manifestations of diseases can be challenging for models trained on limited datasets. By augmenting the data, the model becomes more adept at handling different cases, leading to better generalization and higher accuracy. Ongoing research is essential to further refine and optimize CNN models for real-world applications.

This includes exploring advanced augmentation techniques, such as synthetic data generation and domain adaptation, to further enhance the diversity and quality of training data. Additionally, developing methods to enhance model interpretability is crucial for clinical adoption. Techniques such as saliency maps and attention mechanisms can help clinicians understand the model's decision-making process, fostering trust and facilitating the integration of AI into clinical workflows.

V. Conclusion

The study demonstrates the effectiveness of CNN in skin disease detection, highlighting the significant improvement in accuracy achieved through data augmentation. The proposed model, with a training accuracy of 81% and a testing accuracy of 87%, showcases the potential of deep learning in medical diagnostics. The comprehensive evaluation metrics, including precision, recall, and F1 score, further validate the model's performance. These advancements hold great promise for enhancing dermatological diagnosis and improving patient care outcomes, marking a significant step forward in computer-aided medical diagnostics. The integration of CNN into clinical practice represents a transformative development in healthcare, leveraging the power of deep learning to deliver more accurate efficient, and accessible diagnostic services.

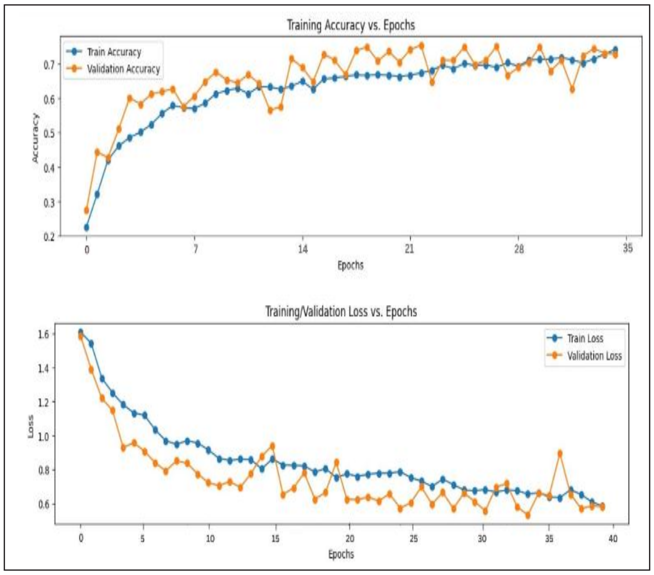


Fig. 4: Showing Training Accuracy and Validation Loss over Epochs without Applying Augmentation

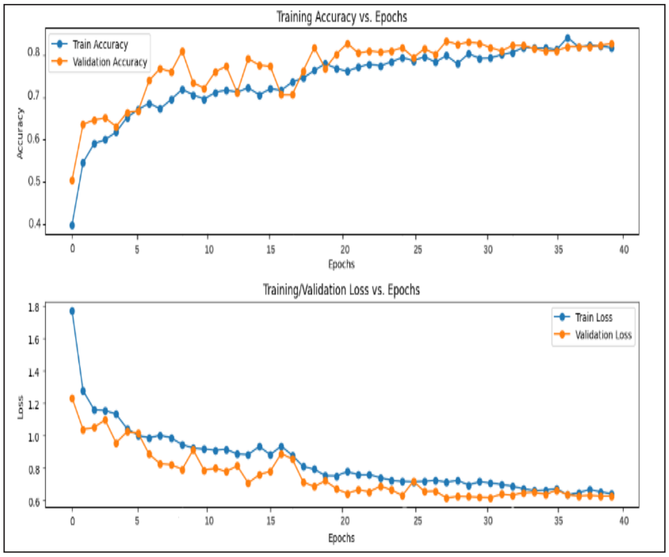
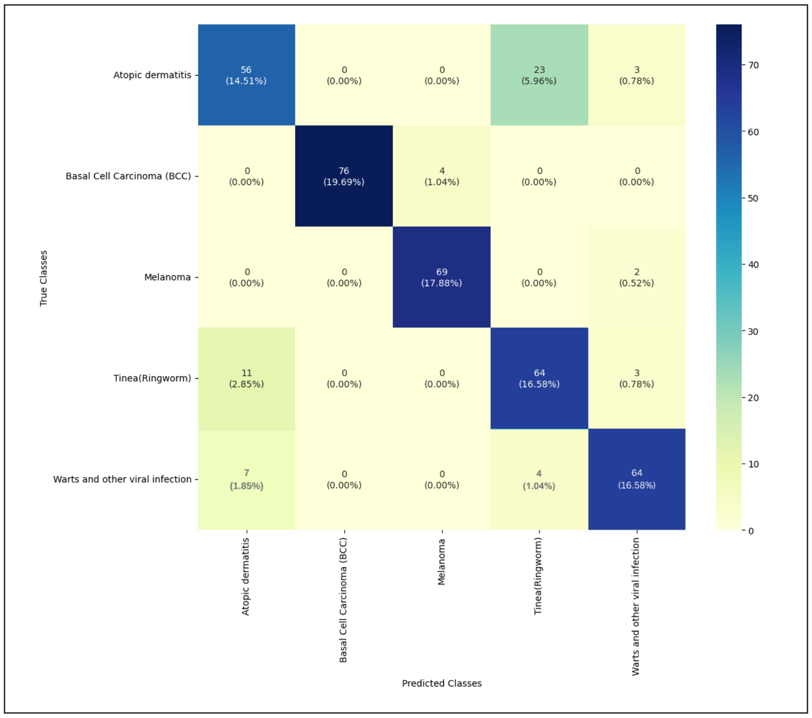


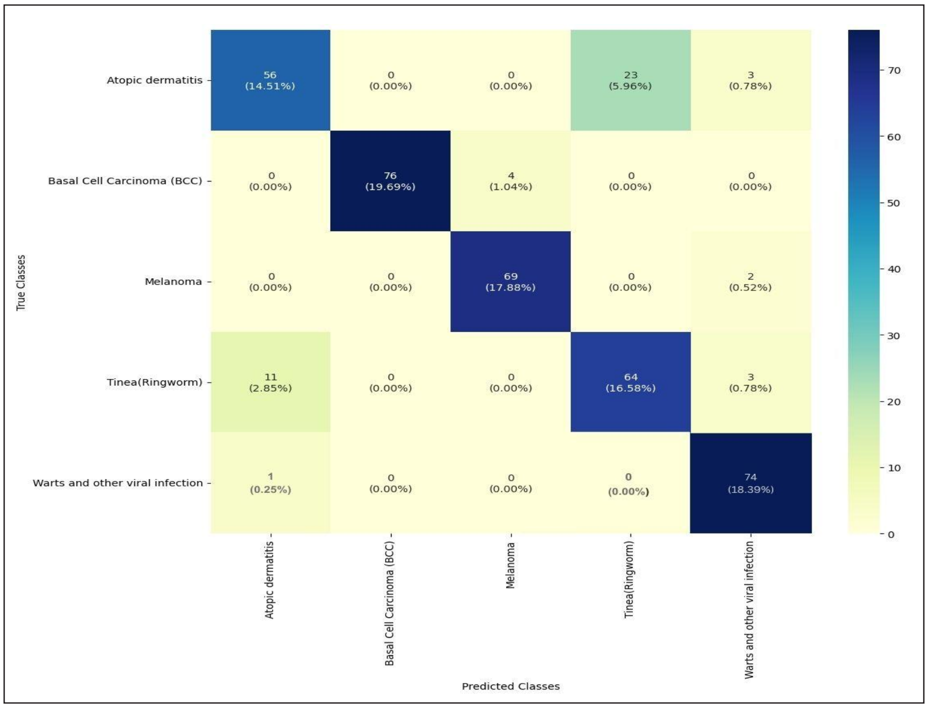
Fig. 5: Showing Training Accuracy and Validation Loss over Epochs After Applying Augmentation

TABLE I: CONFUSION MATRIX FOR MODEL WITHOUT APPLYING AUGMENTATION



True Classes \ Predicted Classes	Atopic dermatitis	Basal Cell Carcinoma (BCC)	Melanoma	Tinea(Ringworm)	Warts and other viral infection
Atopic dermatitis	56 (14.51%)	0 (0.00%)	0 (0.00%)	23 (5.96%)	3 (0.78%)
Basal Cell Carcinoma (BCC)	0 (0.00%)	76 (19.69%)	4 (1.04%)	0 (0.00%)	0 (0.00%)
Melanoma	0 (0.00%)	0 (0.00%)	69 (17.88%)	0 (0.00%)	2 (0.52%)
Tinea(Ringworm)	11 (2.85%)	0 (0.00%)	0 (0.00%)	64 (16.58%)	3 (0.78%)
Warts and other viral infection	7 (1.85%)	0 (0.00%)	0 (0.00%)	4 (1.04%)	64 (16.58%)

TABLE II: CONFUSION MATRIX FOR MODEL AFTER APPLYING AUGMENTATION



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Tinea(Ringworm)	11 (2.85%)	0 (0.00%)	0 (0.00%)	64 (16.58%)	3 (0.78%)
Warts and other viral infection	1 (0.25%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	74 (18.39%)

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