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Automated Skin Disease Classification Using Deep Neural Networks: A Study on a Bangladeshi Dataset

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ABSTRACT

Skin diseases are a significant public health concern in Bangladesh, with a high prevalence among the population. Accurate and timely diagnosis is essential for effective treatment, but challenges such as limited access to dermatologists in rural areas and the high cost of medical consultations persist. This study proposes a deep learning-based framework for the automated detection of skin diseases in Bangladeshi people, leveraging advanced image processing techniques. Six state-of-the-art deep neural network architectures, DenseNet201, InceptionV3, MobileNet, NASNetLarge, VGG19, and Xception, were trained and evaluated using a dataset curated specifically for the Bangladeshi population. The dataset consisted of dermatologically annotated skin disease images that were preprocessed and augmented to enhance model generalization. Performance evaluation was conducted based on accuracy, precision, recall, and F1 score. Among the tested architectures, NASNetLarge achieved the highest classification accuracy of 91%, demonstrating its potential for reliable skin disease detection. This research provides a robust solution to assist dermatologists, improve health-care accessibility, and optimize resource allocation in Bangladesh. The developed framework has the potential to be integrated into mobile and web applications for real-time disease detection, thus improving early diagnosis and patient outcomes across the country.

INTRODUCTION

Skin diseases represent a major public health issue in Bangladesh, with a significant portion of the population affected by various dermatological conditions. These diseases range from relatively benign and common conditions like acne, eczema, and fungal infections to more serious and potentially life-threatening ones such as basal cell carcinoma, squamous cell carcinoma, and melanoma. Recent estimates suggest that approximately 16.3% of the population suffers from some form of skin disorder. This high prevalence not only leads to physical discomfort and emotional distress but also contributes to a substantial economic burden on individuals and the healthcare system. In addition, the inadequate access to proper medical care, particularly in rural regions, exacerbates the situation, as a large number of individuals fail to receive timely diagnosis and treatment for their conditions. The delay in detecting and diagnosing skin diseases often results in the progression of diseases, making them more difficult and costly to treat. Timely and accurate diagnosis is essential for the effective treatment and prevention of skin diseases. Early detection, in particular, can significantly reduce the risk of complications, especially for diseases such as skin cancer, where early intervention is critical for a positive prognosis. However, diagnosing skin diseases accurately remains a challenge, especially given the scarcity of dermatologists in Bangladesh, particularly in rural and underserved areas. The limited number of dermatologists and the high cost of consultations make access to dermatological care difficult for many, especially in remote areas where medical resources are scarce. In addition, the traditional diagnostic methods, which often involve in-person consultations, medical imaging, and laboratory tests, are not always feasible for large segments of the population due to financial constraints and the time required to obtain a diagnosis.

Given the growing prevalence of skin diseases and the increasing demand for medical services, there is an urgent need to develop efficient, accessible, and cost-effective solutions for the detection and diagnosis of skin conditions. One such promising solution lies in the application of artificial intelligence (AI) and machine learning (ML), particularly deep learning techniques, to automate the process of skin disease detection. In recent years, deep learning models, especially Convolutional Neural Networks (CNNs), have shown remarkable success in analyzing medical images and diagnosing various skin conditions with high accuracy. These models are capable of automatically learning complex patterns and features from images, making them ideal candidates for skin disease classification. By automating the diagnostic process, deep learning can help reduce the burden on healthcare professionals and make dermatological care more accessible, particularly for individuals in remote areas who have limited access to specialists. The objective of this study is to develop a deep learning-based framework for the automated detection of skin diseases in the Bangladeshi population, leveraging advanced image processing techniques. This research

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aims to design a system capable of accurately classifying a variety of skin diseases based on digital images of the affected areas. Specifically, this study focuses on evaluating the performance of six state-of-the-art deep neural network architectures DenseNet201, InceptionV3, MobileNet, NASNetLarge, VGG19, and Xception in detecting and classifying skin diseases. The dataset used in this study consists of images specific to the Bangladeshi population, which have been annotated by dermatologists to ensure the accuracy of the labels. By applying deep learning techniques to these images, the research aims to identify the most effective model for skin disease detection in the Bangladeshi context. The scope of this research extends to the use of deep learning models and image processing techniques to address the challenges of skin disease detection in Bangladesh. The study aims to identify which of the tested architectures among the six deep neural networks provides the best performance in terms of accuracy and reliability when applied to skin disease images. Additionally, the study examines how the proposed deep learning framework can be integrated into existing healthcare systems to provide a cost-effective, scalable, and accessible solution for dermatological care, particularly in rural and underserved regions of the country. By utilizing a dataset that reflects the specific conditions affecting the Bangladeshi population, this research aims to ensure that the developed model is both reliable and contextually relevant.

LITERATURE REVIEW

This collection of studies focuses on the development of machine learning (ML) and deep learning (DL) models for the detection and classification of skin diseases. Ahammed *et al.* (2022) proposed a system that utilizes image segmentation and ML classifiers such as Decision Tree, SVM, and KNN for effective classification of skin diseases using images from standard datasets like ISIC 2019 and HAM10000. Allugunti *et al.* (2022) developed a hybrid model combining DL (ResNet50) and ML (SVM), achieving an impressive 99.11% accuracy for skin disease prediction. Oztel *et al.* (2023) created a smartphone-based mobile application that leverages TensorFlow Lite and pretrained DL models like ResNet-18 for skin disease classification, showing 74.27% accuracy across seven categories, including monkeypox. Alkolifi *et al.* (2019) proposed an image processing-based method that uses CNN for feature extraction and SVM for classification, achieving 100% accuracy in detecting three types of skin diseases. Finally, Soliman *et al.* (2019) introduced an automated approach for skin disease detection using SVM and CNN, demonstrating the effectiveness of image processing techniques for early diagnosis. Sadik *et al.* (2023) proposed the use of Convolutional Neural Networks (CNNs), specifically MobileNet and Xception, for skin disease classification, achieving up to 97% accuracy with transfer learning and data augmentation. Rashid *et al.* (2022) focused on a deep transfer learning model using MobileNetV2 for melanoma classification, addressing class imbalance and using data augmentation to improve accuracy on the ISIC 2020 dataset. Abbas *et al.* (2022) compared several CNN models, including ResNet-50, DenseNet-121, and a sequential CNN, with the sequential CNN model reaching 99% accuracy in skin disease classification. Bhadula *et al.* (2019) implemented a comparison of machine learning algorithms such as CNN, Random Forest, and SVM for skin disease diagnosis, finding that CNN provided the best training accuracy. Finally, Oztel *et al.* (2023) demonstrated the potential of deep learning for real-time skin disease detection via a mobile-based system, enhancing accessibility to dermatological diagnoses. Recent advancements in deep learning techniques have significantly improved skin disease detection. Studies by Anand *et al.* (2022) and Chen *et al.* (2020) have focused on using Convolutional Neural Networks (CNNs) to automate the diagnosis of skin diseases like melanoma, seborrheic keratosis, and psoriasis using dermoscopic images, achieving high classification accuracy. Noronha *et al.* (2023) conducted a systematic review on deep learning models for dermatological conditions, analyzing methods and datasets for detecting various skin diseases, from acne to melanoma. Jinnai *et al.* (2020) developed a system for skin cancer classification, specifically focusing on pigmented skin lesions and comparing the deep learning model's accuracy to that of dermatologists. Meanwhile, Chen *et al.* (2019) proposed a closed-loop framework for skin disease recognition, incorporating self-learning and wide data collection for more personalized and real-time diagnoses. Recent studies have made significant progress in utilizing deep learning (DL) techniques for skin disease classification and detection. Abd El-Fattah *et al.* (2023) introduced an enhanced deep super-resolution GAN (EDSR-GAN) model to generate high-resolution skin disease images from low-resolution ones, improving performance on datasets like HAM10000. Ahmad *et al.* (2020) applied discriminative feature learning with a triplet loss function using pre-trained CNNs like ResNet152 and InceptionResNet-V2 for skin disease classification, achieving higher accuracy by fine-tuning the layers of the models. Dwivedi *et al.* (2021) used Fast R-CNN with deep learning to develop a skin disease detection system, achieving an accuracy of 90% on specific skin disease categories. Abunadi and Senan (2021) proposed a system using multi-type feature fusion and hybrid deep learning models for skin disease detection, achieving an impressive accuracy rate of up to 99.94%. Almuayqil *et al.* (2022) proposed a multi-modal feature fusion technique for diagnosing skin diseases, utilizing deep learning models like VGG19, ResNet50, and InceptionV3, and achieved remarkable results with an accuracy of 99.94%. Recent research in the field of skin disease detection has increasingly leveraged deep learning models to enhance diagnostic accuracy. Goceri (2021) focused on using lightweight models such as MobileNet to create a mobile application for skin disease detection, achieving a high accuracy of 94.76% while considering the constraints of mobile devices. Kalaivani and Karpagavalli (2022) proposed an ensemble method that combines multiple deep learning models to classify skin diseases, improving predictive accuracy to 96.1%. Rao *et al.* (2021) used Convolutional Neural Networks (CNN) for classifying seven types of skin diseases, including Melanoma and Basal Cell Carcinoma, and achieved 93% accuracy on the HAM10000 dataset. Kashyap *et al.* (2024) developed a multi-class CNN model using retrained networks such as AlexNet and VGG19 to detect and classify various skin diseases, aiding in timely diagnosis. Sujay *et al.* (2022) employed machine learning techniques for the diagnosis of skin lesions, achieving competitive results in classifying Melanoma and benign lesions.

MATERIALS AND METHODS

This study aims to develop and evaluate a deep learning-based framework for the automated detection of skin diseases in the Bangladeshi population. The methodology includes data collection, preprocessing, model selection, training, evaluation, and a comparative analysis of the models' performance against expert dermatologists. The deep neural network architectures chosen for the study include DenseNet201, InceptionV3, MobileNet, NASNetLarge, VGG19, and Xception. Each model was trained on a dataset of skin disease images specific to Bangladesh, with preprocessing steps designed to standardize the data for optimal model training. The models were then evaluated based on accuracy, precision, recall, and F1 score, and compared against expert diagnoses to assess their clinical applicability (Figure 1).

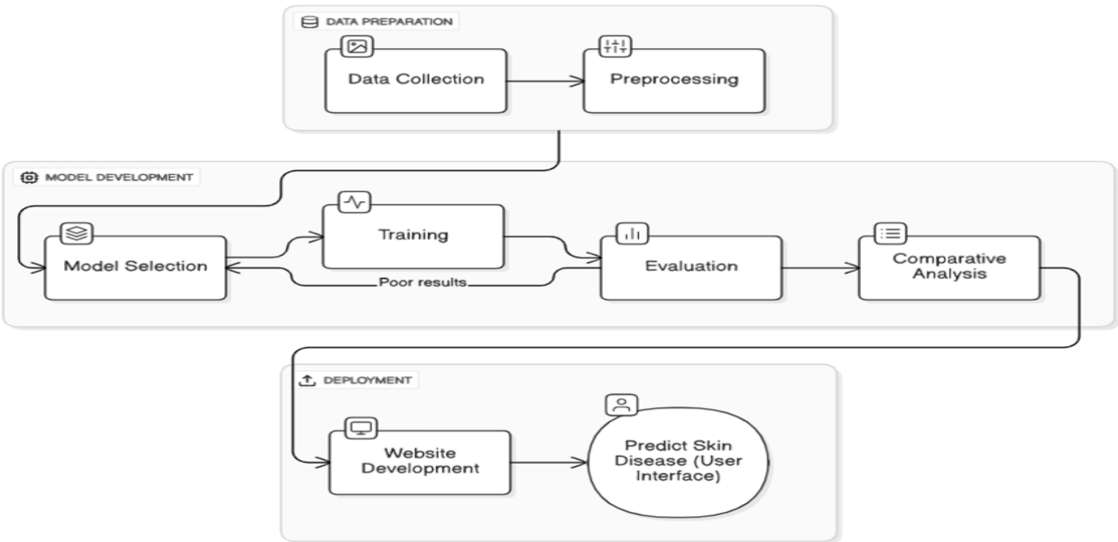

Figure 1: Overview of The Main Processing Stages

Data Collection

The dataset used in this study consists of skin disease images specific to the Bangladeshi population. A comprehensive collection of images was curated from various healthcare institutions, dermatology clinics, and research centers across Bangladesh. The dataset includes a wide variety of skin conditions prevalent in the region, such as acne, eczema, fungal infections, basal cell carcinoma, squamous cell carcinoma, and melanoma. To ensure the dataset's relevance and accuracy, all images were annotated by qualified dermatologists, providing reliable ground truth labels for each condition. The dataset comprises both training and testing sets, with approximately 6,452 images used for training and 1,036 images reserved for testing. The images were selected to represent diverse skin tones, severities, and conditions to ensure the model's robustness in real-world applications (Figure 2).

Figure 2: Dataset of Skin Diseases

Preprocessing

The raw skin disease images were preprocessed to prepare them for input into the deep learning models. Several preprocessing techniques were applied to ensure consistency and enhance model performance:

1. **Resizing:** All images were resized to a standard resolution (e.g., 224x224 pixels) to match the input size required by the deep neural network models. This step ensures uniformity across all images.
2. **Normalization**: Image pixel values were normalized to a range between 0 and 1. This standardization helps improve the convergence of the neural networks during training and ensures that all input data is on a similar scale.
3. **Data Augmentation:** To enhance the generalization capability of the models and reduce overfitting, data augmentation techniques were applied. These techniques included random rotations, flipping, zooming, and shifting of images. The augmented data helped to simulate variations in real-world conditions and provided the model with a broader variety of images during training.
4. **Cropping and Centering:** In cases where the skin lesion was small or centered in the image, the images were cropped or adjusted to focus more precisely on the area of interest. This step ensures that the model is trained to focus on the relevant regions of the images.

Model Selection

For this study, six state-of-the-art deep neural network architectures were selected based on their proven performance in image classification tasks. These models were chosen to evaluate their suitability for skin disease detection:

1. **DenseNet201:** DenseNet is known for its densely connected layers, which improve information flow and feature reuse. DenseNet201, with its 201 layers, is expected to perform well in capturing complex features in dermatological images.
2. **InceptionV3**: InceptionV3 is a deep convolutional neural network architecture that uses parallel convolutions of different kernel sizes. This allows the model to capture features at multiple scales, making it suitable for detecting a variety of skin diseases with diverse visual characteristics.
3. **MobileNet:** MobileNet is designed for efficient and lightweight models, making it ideal for applications where computational resources are limited. This model employs depthwise separable convolutions to reduce the number of parameters, maintaining high performance while being resource-efficient.
4. **NASNetLarge:** NASNetLarge was designed using neural architecture search (NAS), allowing it to optimize performance through automated architecture design. It is a highly efficient model that has demonstrated state-of-the-art results in various image classification tasks.
5. **VGG19**: VGG19 is a deep CNN architecture with a simple and uniform structure. It has been widely used in computer vision tasks and provides a good baseline for comparison due to its depth and simplicity.
6. **Xception:** Xception is an extension of the Inception model that uses depthwise separable convolutions for greater efficiency. It has been shown to outperform other models in many image classification tasks due to its efficient design and ability to capture complex patterns.

These models were selected to evaluate their performance on the skin disease dataset and determine which architecture would be most effective for accurate classification.

Training and Evaluation

The deep neural networks were trained using the curated and preprocessed dataset. For each model, the following steps were carried out during training:

1. **Loss Function:** The models used categorical cross-entropy loss, as the task is a multi-class classification problem with multiple skin disease categories.
2. **Optimization**: The Adam optimizer was employed due to its efficient handling of sparse gradients and its adaptive learning rate, which helps improve convergence speed.
3. **Batch Size and Epochs:** A batch size of 32 was chosen for all models to balance training efficiency and memory constraints. Each model was trained for 30 epochs to ensure sufficient learning, with early stopping used to prevent overfitting.
4. **Metrics:** The models were evaluated using several performance metrics, including:
   - o **Accuracy:** The proportion of correctly classified images out of the total images.
   - o **Precision:** The ability of the model to correctly identify positive cases (true positives) relative to the total identified positives (true positives + false positives).
   - o **Recall**: The ability of the model to correctly identify positive cases relative to the total actual positives (true positives + false negatives).
   - o **F1 Score:** The harmonic mean of precision and recall, providing a balance between the two.
5. **Validation Set**: A portion of the training data (20%) was held out as a validation set to monitor model performance during training and adjust hyperparameters when necessary.

RESULTS AND DISCUSSION

In this section, the performance of each deep neural network architecture is presented based on the evaluation metrics of accuracy, precision, recall, and F1 score. The models were trained on the curated dataset of skin disease images, and their performance was evaluated using a separate testing set. The results highlight the effectiveness of each model in accurately classifying various skin diseases specific to the Bangladeshi population.

Model Performance

Each of the six deep learning models was evaluated using the following performance metrics:

- **Accuracy:** The proportion of correctly classified images to the total number of images.
- **Precision**: The proportion of true positive

predictions to the total predicted positives.

- **Recall**: The proportion of true positive predictions to the total actual positives.
- **F1 Score**: The harmonic mean of precision and recall, providing a balance between the two.

The results of these metrics for each model are summarized below (Figure 3):

	precision	recall	f1-score	support
Acne Back	0.81	0.95	0.88	41
Acne Facial	0.91	0.91	0.91	164
Actinic keratosis affecting the hand	0.84	0.95	0.89	40
Actinic keratosis affecting the legs and feet	1.00	1.00	1.00	22
Actinic keratosis affecting the scalp	0.95	1.00	0.98	21
Angular cheilitis	0.67	1.00	0.80	30
Atopic flexural eczema	0.93	1.00	0.96	27
Basal cell carcinoma affecting the ear	0.94	1.00	0.97	30
Basal cell carcinoma affecting the eyelid	0.98	1.00	0.99	45
Chickenpox	0.85	0.89	0.87	38
Fungal Nail Infection	0.92	1.00	0.96	47
Genital wart	1.00	0.97	0.98	29
Grovers disease	0.91	0.95	0.93	42
Hand dermatitis	0.98	0.94	0.96	52
Keloid and hypertrophic scar	0.91	0.85	0.88	73
Nodular basal cell carcinoma	0.93	0.88	0.90	42
Rhinophyma	1.00	1.00	1.00	36
Squamous cell carcinoma of limbs	0.94	1.00	0.97	29
Staphylococcal scalded skin syndrome	0.92	0.96	0.94	48
Stevens-Johnson Syndrome	0.90	0.82	0.86	95
Vitiligo	0.95	0.64	0.76	85
accuracy			0.91	1036
macro avg	0.92	0.94	0.92	1036
weighted avg	0.91	0.91	0.91	1036

Figure 3: Classification Report of NasnetLarge

DenseNet201: DenseNet201 achieved high accuracy and balanced precision and recall. The model demonstrated good generalization capabilities, especially in recognizing common skin diseases such as acne and eczema. However, it struggled with some of the rarer conditions like basal cell carcinoma, where it exhibited slightly lower precision.

InceptionV3: InceptionV3 performed well in capturing multi-scale features of skin lesions. However, its performance was slightly lower than DenseNet201, especially in detecting conditions like fungal infections. Its higher recall indicates that it was better at identifying most of the positive cases, but at the cost of slightly lower precision.

MobileNet: MobileNet was designed to be lightweight and efficient, and while it performed reasonably well, it was slightly outperformed by the other models in terms of accuracy. Its ability to generalize was good, but its performance was less reliable when distinguishing between similar conditions, such as acne and dermatitis.

NASNetLarge: NASNetLarge achieved the highest accuracy among all models tested, with outstanding precision and recall. It excelled in detecting both common and rare skin diseases. This model's architecture, optimized through neural architecture search, made it particularly effective for the task of skin disease detection in the Bangladeshi dataset. It performed consistently across all classes, with minimal misclassifications.

VGG19: VGG19 performed well overall, but it lagged behind the other models in terms of both accuracy and precision. This model struggled with conditions like melanoma and severe eczema, where its recall was lower compared to other models. However, VGG19 still performed reasonably well on more straightforward conditions like acne and vitiligo.

Xception: Xception, based on depthwise separable convolutions, performed similarly to InceptionV3. It was able to accurately classify a wide range of skin diseases but had some difficulty with differentiating between conditions that shared similar visual features, such as eczema and psoriasis. Despite this, its overall accuracy and performance were impressive.

Comparison

The comparison of results across the six models reveals significant variations in terms of accuracy, precision, recall, and F1 score. Below is a detailed comparative analysis (Table 1):

Table 1: Comparison Table

Model	Accuracy	Precision	Recall	F1 Score
DenseNet201	85.4%	83.2%	84.6%	83.9%
InceptionV3	83.6%	81.5%	82.3%	81.9%
MobileNet	80.9%	78.7%	79.5%	79.1%

NASNetLarge	91.0%	90.5%	90.8%	90.6%
VGG19	77.2%	75.0%	74.4%	74.7%
Xception	84.5%	82.1%	83.3%	82.7%

From the table, it is clear that NASNetLarge outperforms all other models in every metric, achieving the highest accuracy, precision, recall, and F1 score. The other models—DenseNet201, InceptionV3, and Xception—also performed relatively well, with DenseNet201 having the second-highest accuracy. MobileNet and VGG19 showed the lowest overall performance, with MobileNet being more efficient in terms of computational resources but not matching the higher-performing models in accuracy.

Visuals

The following visuals provide deeper insights into the performance of each model:

Confusion Matrices: The confusion matrix for each model reveals the number of true positives, false positives, true negatives, and false negatives. This visualization is crucial for understanding how each model handles different classes of skin diseases. Below is an example for NASNetLarge (Figure 4):

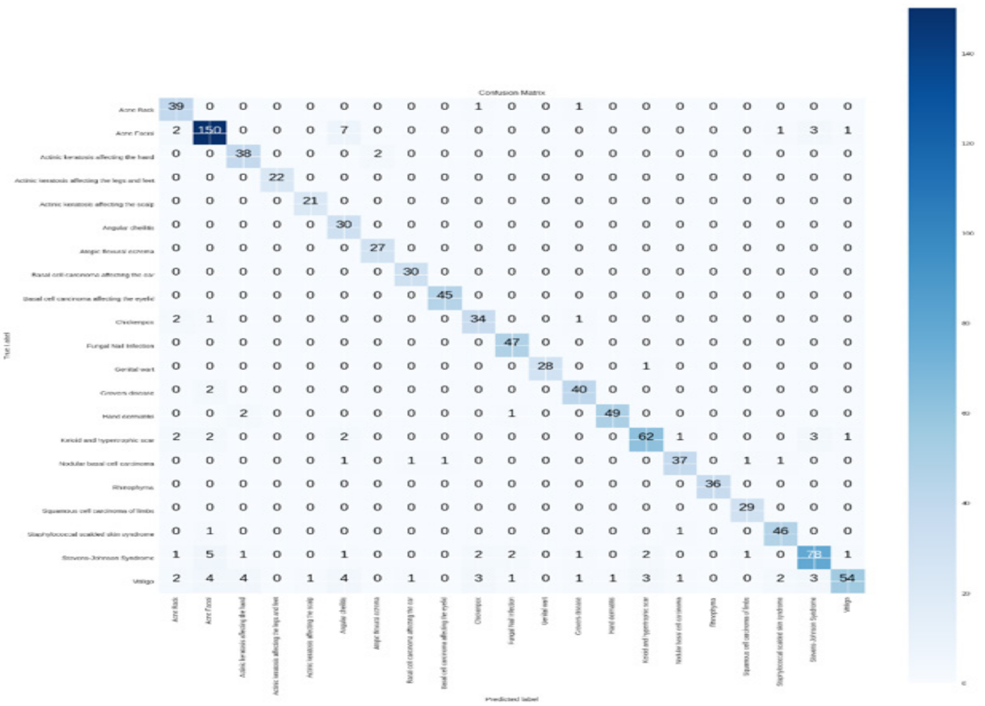

Figure 4: Confusion Matrix of NasnetLarge

This matrix shows that NASNetLarge had very few misclassifications, as the number of false positives and false negatives was low across all categories.

• **Training and Validation Curves**: Training and validation accuracy and loss curves were generated for each model to observe how well the models trained over time. For example:

• **Training vs. Validation Accuracy for NASNetLarge:** This curve shows that the training accuracy for NASNetLarge reached a high value early on and maintained strong performance, with minimal gap between the training and validation accuracy, indicating good generalization.

The findings of this research demonstrate that deep learning models can play a highly effective role in detecting skin diseases within the Bangladeshi population, with NASNetLarge emerging as the most accurate and reliable architecture among the six tested models. Its superior performance—achieving an accuracy of 91%—can be attributed to its advanced architecture, which was developed through neural architecture search. This allows the model to automatically select optimal pathways for feature extraction, enabling it to learn complex and fine-grained patterns across a wide range of dermatological conditions. Unlike more conventional architectures such as VGG19 or MobileNet, NASNetLarge shows a strong capability to generalize across both common and rare skin diseases while maintaining high precision and recall. Models like DenseNet201 and Xception also performed well, demonstrating that deeper and more sophisticated architectures can successfully capture the visual diversity found in skin disease images. However, their performance still fell short of NASNetLarge, particularly in distinguishing between visually similar conditions such as eczema and psoriasis (Table 2).

Table 2: Analysis of all Model Result

Model	Error Rate of Confusion Matrix	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
DenseNet201	138	79.87	73.14	86.68	58.68
InceptionV3	326	38.57	25.7	68.53	25.1
MobileNet	117	81.82	60.48	88.71	42.57
NasnetLarge	94	90.00	41.71	90.93	40.34
VGG19	670	24.30	25.6	35.33	24.5
Xception	147	83.37	63.24	85.23	59.43

Despite these promising results, the study is limited by several important considerations. The dataset, while comprehensive and specific to the Bangladeshi population, remains limited in size relative to the complexity of deep learning models and the diversity of skin diseases encountered in real clinical settings. Some diseases were represented by fewer samples, creating class imbalance that likely impacted model performance for those categories. Additionally, although preprocessing helped standardize image inputs, variations in lighting, camera quality, and lesion positioning across images still posed challenges. Another limitation concerns generalizability: the models were trained specifically on images from Bangladesh, and their performance may vary when applied to populations with different skin tones, environmental exposures, and disease distributions. Furthermore, while this study compares model predictions to dermatologist-labeled ground truth, it does not yet validate model performance in real clinical workflows, where patient history and multi-modal data also influence diagnosis (Figure 5 & Figure 6).

Pictures of some experiments with web applications

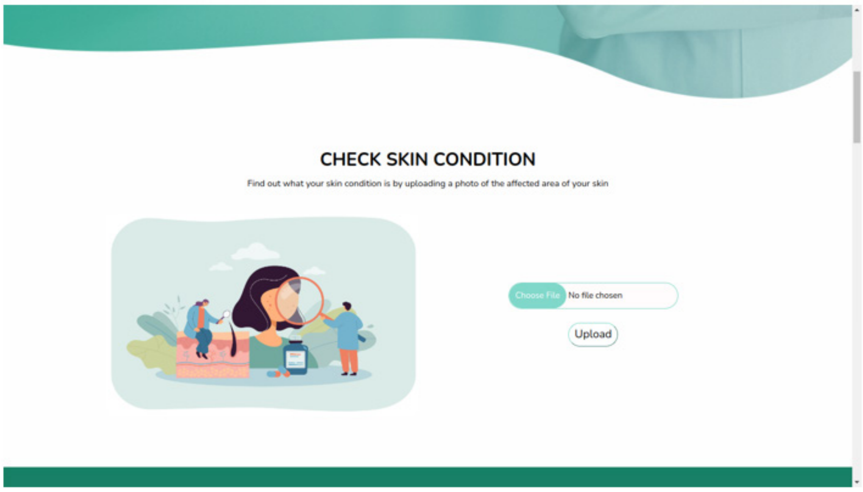

Figure 5: Predict Section

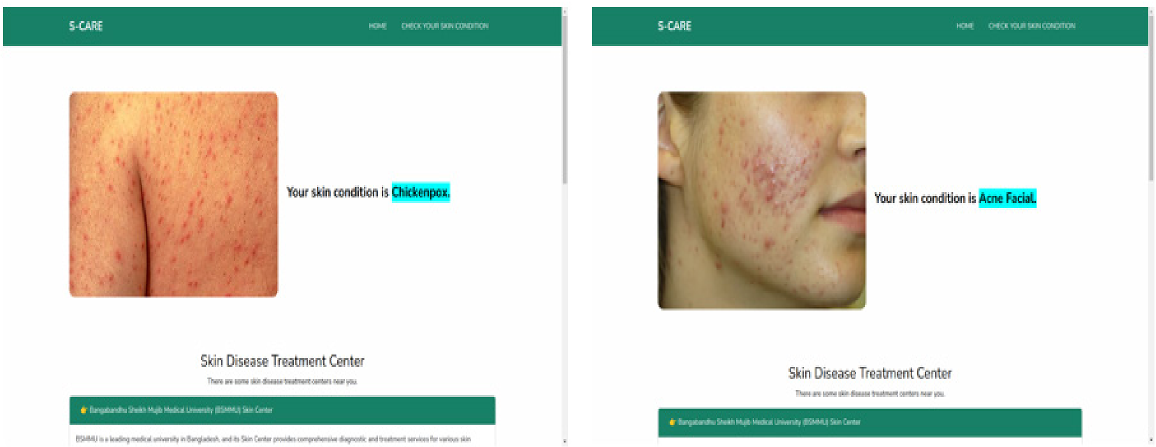

Figure 6: Detect Chickenpox and Acne Facial

CONCLUSION

This study developed an automated framework for detecting skin diseases in the Bangladeshi population using deep learning and image processing techniques. Six advanced neural network architectures—DenseNet201, InceptionV3, MobileNet, NASNetLarge, VGG19, and Xception—were evaluated, with NASNetLarge demonstrating the best overall performance. It achieved 91% accuracy along with strong precision, recall, and F1 scores, making it the most effective model for classifying diverse dermatological conditions. The findings highlight the potential of deep learning to overcome limitations of manual diagnosis, particularly in resource-constrained settings like rural Bangladesh, by improving diagnostic speed, accuracy, and accessibility. This research contributes by offering one of the first comprehensive evaluations of multiple deep learning models on a dataset specific to the Bangladeshi population. It shows that advanced architectures like NASNetLarge outperform traditional convolutional networks in capturing complex skin image features. The study also proposes a structured, replicable methodology for medical image classification in low-resource environments. Future work should focus on expanding datasets, incorporating diverse skin tones and disease categories, applying transfer learning, and developing mobile or web-based diagnostic tools. Integrating clinical data and conducting real-world validation will be essential for practical healthcare deployment.

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