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A Hybrid CNN-LSTM Framework for the Early Detection of Pox and Similar Skin Conditions

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***Abstract*— Poxviruses are very infectious and can lead to skin blisters as well as other health problems which necessitates early detection to ensure effective treatment. Since the skin lesions caused by different varieties of pox may initially seem identical, it becomes difficult to reliably identify the type of pox. This paper introduces a novel CNN-LSTM hybrid approach for classifying and detecting five types of skin diseases including monkeypox, cowpox, chickenpox, measles and hand, foot, and mouth disease. The suggested technique combines CNN's feature extraction capabilities with the sequential learning process of Long Short-Term Memory (LSTM) networks. The model has an overall accuracy of 97% and an AUC of 99.7%. Grad-CAM analysis demonstrates the system's effectiveness by producing heatmaps that illustrate sections of the picture that influence the projected class score, although the overall performance is slightly reduced for chickenpox. The findings of this study confirmed the proposed system's superiority over pre-trained models, highlighting its potential for rapid and accurate skin condition identification.**

Keywords – Skin lesion, Chickenpox, Monkeypox, CNN, LSTM, Grad-CAM analysis

I. INTRODUCTION

Skin diseases caused by poxviruses and related infections are highly contagious and pose substantial public health concerns. The pox viruses are extremely contagious given that they can spread through biofluid, interaction with contaminated objects, intimate contact with sick people, and consumption of food or drinking water that has been contaminated [1]. These diseases, including monkeypox, cowpox, chickenpox, measles, and hand, foot, and mouth disease (HFMD), manifest as skin lesions that often appear visually similar in their early stages. Despite their distinct viral origins, these conditions share overlapping symptoms, making accurate diagnosis challenging. Early and precise detection is paramount to prevent outbreaks, administer appropriate treatment, and avoid misdiagnosis which can lead to improper vaccination or medication.

Chickenpox, cowpox, monkeypox, and smallpox are classified under distinct virus genera. Smallpox and monkeypox virus belongs to the same viruse group [2]. Cowpox, which is initially very uncommon in humans, mostly transmitted through mice or domestic cats [2]. Monkeypox symptoms are nearly identical to those of chickenpox as they have similar kind of skin lesions in the initial phases, which makes clinical diagnosis extremely challenging [3]. Measles, a viral illness that sometimes becomes more severe than pox, while HFMD is another very common disorder that similarly causes blister-like rashes on different areas of the skin [4]. Since the aforementioned conditions might have very similar physical manifestations in their early stages, it is imperative to provide a quick and precise method for automatically detecting and classifying skin lesions in individuals with these conditions.

Traditional diagnostic methods rely on clinical examination and laboratory testing, which can be time-consuming, costly, and necessitate specialized expertise. Recent advancements in artificial intelligence (AI) and deep learning have demonstrated substantial potential in automating disease detection through medical imaging. Convolutional Neural Networks (CNNs) [5] have been widely employed for feature extraction from medical images, while Long Short-Term Memory (LSTM) [6] networks are effective in learning sequential dependencies. However, existing AI-based approaches either concentrate solely on CNNs or employ pre-trained models, which may lack the capacity to discern both spatial and temporal relationships in skin lesion images.

To address these challenges, this paper proposes a hybrid CNN-LSTM framework for the automated classification of five skin diseases: monkeypox, chickenpox, HFMD, cowpox, and measles. The CNN component extracts spatial features from images, while the LSTM component captures sequential dependencies in the extracted features, augmenting the model's capability to differentiate between similar-looking skin conditions. This approach ensures enhanced accuracy and robustness compared to conventional CNN-based models.

The major contributions of this research article are:

- Development of a hybrid CNN-LSTM model
- Detection and classification of five skin diseases using image data
- A detailed experimental analysis has been provided with Grad-CAM Feature extraction analysis to measure the performance of the proposed system
- A detailed comparison between pre-trained CNN and the proposed model has been done to find the novelty of the proposed work.

II. RELATED WORKS

Several research has been carried out previously based on monkeypox and chickenpox disease prediction using machine learning methods.

K. Kiran et al. [7] implemented an optimized artificial neural network (ANN) model by taking statistical features for detecting monkeypox. The limitation of this work is the model's complexity might make it challenging to comprehend decision-making, which is essential in medical applications. In another work [8], the ResNet50v2 model was used to create a deep learning-based method for classifying mpox lesions in

addition to five other skin disorders. The model found it difficult to distinguish between similar skin disorders, such as chickenpox and monkeypox and the dataset that was used could fail to cover the heterogeneity of skin lesions. Leveraging a time series monkeypox dataset, an ANN model was developed in [9] and compared to LSTM and GRU algorithms to forecast a monkeypox pandemic in five specific nations. The geographic constraint might limit the impact of the research to other areas K. Arora et al. [10] demonstrated the potential of implementing a deep learning (DL) framework to accurately classify chickenpox and monkeypox. Using the Monkeypox Image Dataset, a CNN model was trained using the MobileNetV2 architecture. An image-based deep CNN has been developed in [11] for the recognition of the distinctive skin lesions brought on by the monkeypox virus. One limitation of this work is, the MPXV dataset utilized in this study featured a high proportion of persons with dark skin, which could lead to inaccurate results for other skin colors. In another study [12] authors investigated 13 pre-trained deep learning (DL) models in order to detect the Monkeypox virus and assessed the performance of the models to predict the disease. Two significant drawbacks of this work are that they only employed pre-trained DL models and the dataset size is quite small.

A. Akula et al. [13] examined a dataset that included four classes: normal skin pictures, chickenpox, measles, and mpox and several pre-trained models, including ResNet50V2, Xception, DensNet121, MobileNetV2, to determine the most suited for picture classification. These pre-trained models may sometimes misclassify acne as mpox. Chickenpox and Monkeypox disease were classified in another research work [3] where a four-layer, two-dimensional convolutional neural network (CNN) was implemented. However, the developed model may not work effectively for other datasets. Another study [14] outlines a novel approach to accurately and quickly diagnosing monkeypox using four pre-trained models and the Adam optimization strategy. S. Savaş [15] generated ensemble models For distinguishing visually identical diseases like measles, Mpox, and chickenpox after testing 71 models from pre-trained libraries and filtering out models with unsatisfactory test results. . In another work [16] a model termed PoxNet22 was proposed to categorize monkeypox more precisely than other pox. However, further investigations is required to verify its efficacy and durability in identifying monkeypox.

III. METHODOLOGY

This section depicts the overall approach for classifying five skin diseases: monkeypox, cowpox, chickenpox, HFMD, and measles. We explored adding a fifth class for skin that is disease-free. The loaded data went through a pre-processing pipeline before being separated into training and validation sets. Then, the suggested CNN+LSTM model was trained and verified. After training, the model was assessed by generating test data from the dataset and measuring accuracy, precision, f1-score, and AUC-ROC. In addition, feature explanations were performed using Grad-CAM analysis.

A. Dataset

The dataset with images of all five diseases is being considered in this work. To improve the classification process, this dataset includes various data augmentation techniques such as rotation, translation, reflection, shear, hue, saturation, contrast, brightness jitter, noise, and scaling on the training data. This generates around 7500 images in total. This large amount of image data was split into two parts: 80% for model training and 20% for validation.

B. CNN

Convolutional Neural Networks (CNNs) are multilayer perceptron models capable of extracting and learning complicated features from training data. CNNs excel at image classification, object identification, medical image processing, and facial recognition [17, 18]. The main concept is to take local features from upper levels and transfer them to lower layers to create more complex features.

C. LSTM

Long Short-Term Memory (LSTM) is a more advanced recurrent neural network that uses memory cells and gates to detect temporal connections in sequential input. It successfully manages long-term dependencies and addresses the vanishing gradient issue [19]. LSTMs are frequently used for time-series prediction, voice recognition, and picture classification.

D. Proposed CNN+LSTM Network

In this study, a combined CNN-LSTM method was developed to detect and classify the five types of skin diseases stated above. Figure 1 illustrates the proposed CNN+LSTM architecture. In this combined architecture, CNN is used to extract complex features from images and LSTM is used as a classifier.

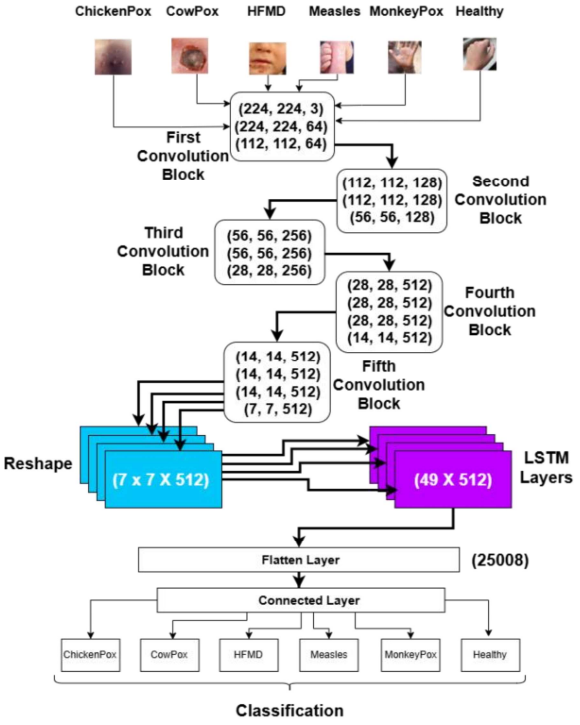


Fig. 1. CNN-LSTM Model Architecture

The proposed hybrid model has 20 layers, including 12 convolutional, 5 pooling, LSTM, fully connected, and output layers with softmax. Each of the first three convolutional blocks is composed of two 2D CNNs and a pooling layer. The

two remaining convolutional blocks each include three 2D CNNs and a pooling layer. A convolutional layer with 3 × 3 kernel and ReLU activation retrieves complicated features, while a 2 × 2 max-pooling layer decreases picture size. The LSTM layer extracts time-related information. The output form of the convolutional block is (None, 7, 7, 512), which is then reshaped to (None, 49, 512) for the LSTM layer. Finally, a fully connected layer divides the images of the diseases (Monkeypox, Chickenpox, Cowpox, Measles, HFMD, and Healthy) into six groups based on time characteristics.

E. Model Evaluation Metrics

To assess the model's performance, accuracy, precision, recall, F1-score, and AUC (Area under the Curve) are utilized. These metrics provide an overview of the model's prediction skills across all classes. ROC curves for each class was generated and presented to demonstrate the trade-off between true and false positive rates. The macro-averaged AUC describes the entire model performance. Individual AUC values for each class are included in ROC curves, together with a baseline random guess curve, to indicate per-class performance. This comprehensive examination demonstrates both overall accuracy and particular class-specific performance.

IV. RESULTS

The training dataset was split into 80% for training and 20% for validation. Table I shows the parameters used for model training.

TABLE I. MODEL TRAINING PARAMETERS

Learning Rate	0.00001
Image Dimensions	224x224
Batch Size	32
Epochs	50
Optimizer	Adam

A. Result Analysis

"Fig. 2" shows the CNN-LSTM classifier's performance, including training and validation accuracy. The model's capacity to learn from the data was demonstrated by the training and validation accuracies, which showed stable accuracy after steady increases during the training phase. At epoch 36, the training accuracy is 99.9% and the validation accuracy is 95.7%.

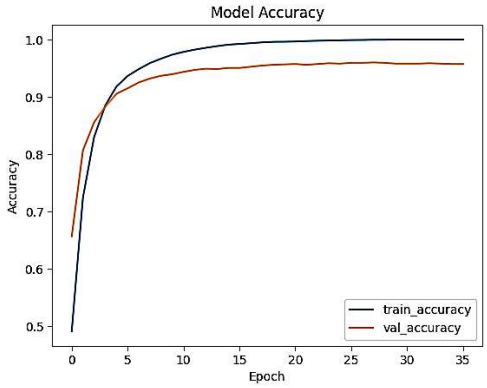
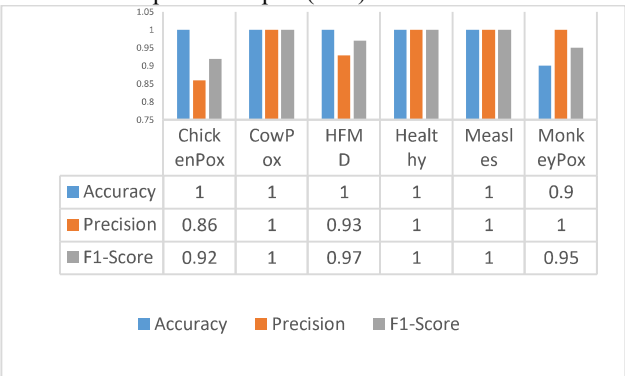


Fig. 2: Evaluation of CNN-LSTM based System's Training & Validation Phase

The model has an overall accuracy of 97%. Figure 3 summarizes and graphically displays the total accuracy, precision, and F1-score of the developed CNN-LSTM architecture for each of the five diseases and healthy skin. Furthermore, the ROC curves between TPR and FPR compare overall performance, which has been depicted in Fig. 4. The AUC value of 99.7% indicates good performance. CNN-LSTM architecture achieved a perfect score (1.0) for all classes except Chickenpox (0.98).



	ChickenPox	CowPox	HFMD	Healthy	Measles	MonkeyPox
Accuracy	1	1	1	1	1	0.9
Precision	0.86	1	0.93	1	1	1
F1-Score	0.92	1	0.97	1	1	0.95

Fig. 3: Performance of the Proposed Network

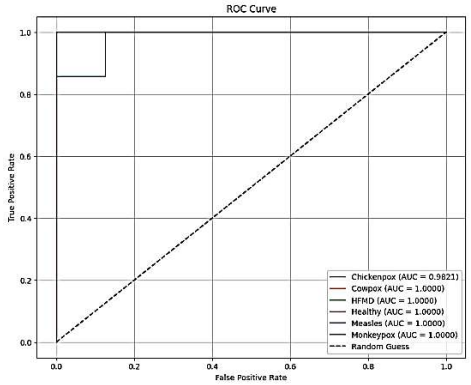


Fig. 4: ROC Analysis of Proposed System

Finally, Grad-CAM analysis has been done. It is a heat map that has been used to visualize thr experimental results. It highlights important regions in an image for prediction after passing through the final layer. Fig. 5 shows the heat map for five skin conditions in CNN-LSTM architecture.

The Grad-CAM visualizations show effective feature extraction in Cowpox, Monkeypox, Measles, and HFMD images, but not in Chickenpox. This aligns with the AUC-ROC analysis, where Chickenpox has a lower AUC. The model's attention is less precise for Chickenpox, indicating reduced performance.

B. Comparison with Pre-trained Models

To evaluate the system's novelty, nine pre-trained CNN models were implemented on the classification dataset. The parameters were kept identical to those of the proposed CNN-LSTM model for fairness. The proposed CNN-LSTM architecture outperformed the CNN-based pre-trained models with the highest test accuracy. The test accuracy results for different models have been depicted in Table II.

TABLE II . ACCURACY COMPARISON BETWEEN PRETRAINED AND PROPOSED MODELS

Model Name	Accuracy (%)
MobileNet	94
DenseNet121	96
DenseNet169	96
VGG16	67
VGG19	95
InceptronV3	95
Xception	94
ResNet50	95
ResNet152	95
Proposed Model	**97**

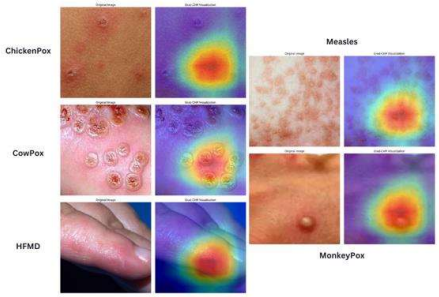


Fig. 5: Original Image vs Grad-CAM Visualization

C. Comparison with Previous Works

Table III presents a comparison of the proposed approach with earlier research. It was clear from the comparison table that the developed CNN+LSTM setup we created performed better overall and had higher predicted accuracy.

TABLE III. COMPARISON WITH PREVIOS STUDIES

Ref.	Disease Detected	Accuracy (%)	Precision (%)
[5]	Mpox	87.13	85.74
[9]	Mpox	89.8	-
[13]	Mpox, Chickenpox, Measles	97.5	-
[10]	Mpox	87.13	85.44
[6]	Mpox, Chickenpox, Measles, HFMD	99.3	99.34
[20]	Mpox	96.56	-
Proposed study	**Mpox, cowpox, chickenpox, HFMD, and measles**	**97**	**97**

V. CONCLUSION

The proposed CNN-LSTM hybrid model effectively classifies five distinct skin diseases—measles, cowpox, chickenpox, monkeypox, and hand, foot, and mouth disease—using advanced feature extraction and time-series analysis. It achieves high accuracy, precision, F1-score, and AUC-ROC of 97%, 97%, 98%, and 99.7%, respectively. The model's interpretability is enhanced by Grad-CAM analysis. It has outperformed some popular pretrained image classification models including ResNet, VGG, DenseNet, MobileNet. However, the dataset's limited size and diversity may restrict generalizability, and the model lacks clinical validation. Future research should expand the dataset to cover diverse demographics and clinical scenarios, enhancing robustness and generalizability and collaboration with medical professionals will ensure clinical reliability and real-world validation.

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