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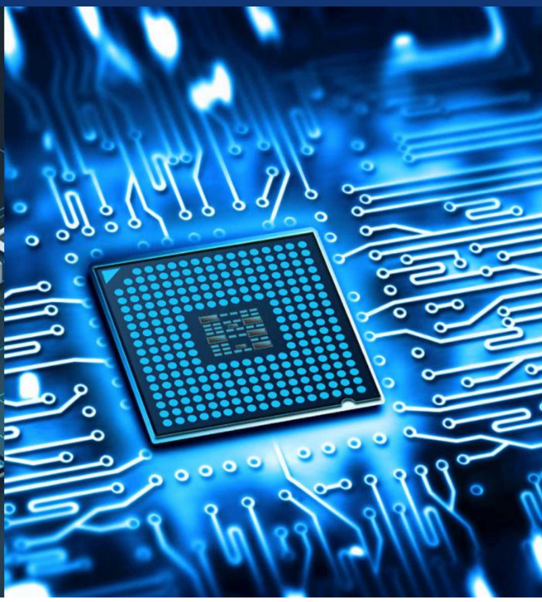


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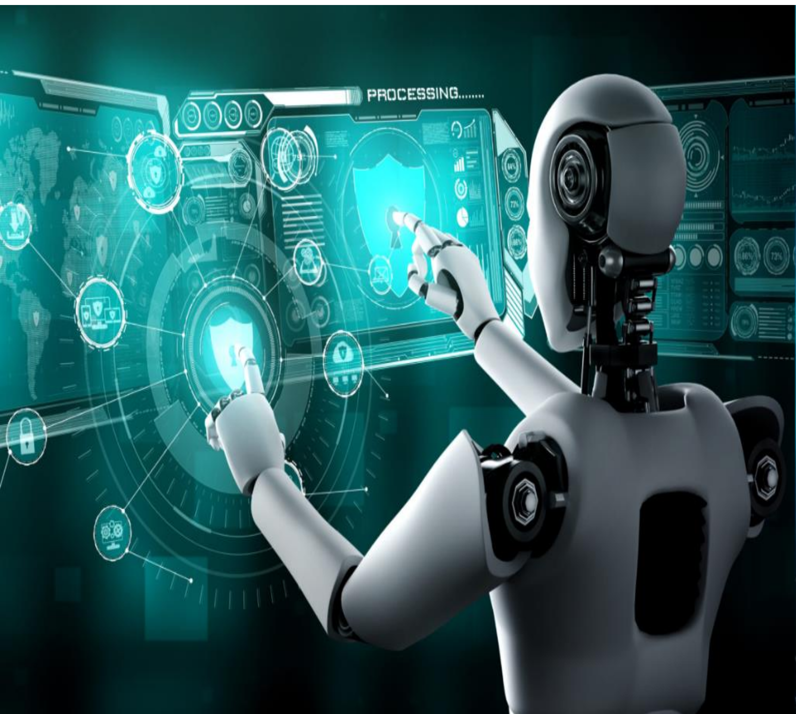

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Eczema, Basal Cell Carcinoma, Melanocytic Nevi, Melanoma, and Seborrheic Keratosis Prediction Using Deep Learning

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ABSTRACT: Skin diseases are a growing global health concern, affecting millions annually. While dermatologists use dermoscopy to detect skin lesions, manual diagnosis is time-consuming and often inconsistent. Traditional methods rely on handcrafted feature extraction, which struggles to accurately capture complex relationships between image features and disease classification. This study focuses on five visually similar and commonly occurring skin diseases—Melanoma, Basal Cell Carcinoma, Eczema, Melanocytic Nevi, and Seborrheic Keratosis—due to their high prevalence and potential health risks. Their similar appearance often leads to misdiagnosis, resulting in unnecessary biopsies or delayed treatment. We used a hybrid approach that leverages a convolutional neural network (CNN) to extract essential features from images while incorporating long short-term memory (LSTM) to capture sequential patterns. This combination enhances diagnostic precision, offering a notable accuracy improvement over traditional method. By leveraging LSTM's ability to retain contextual information, our model improves classification accuracy and reduces misclassification rates, providing a more reliable tool for skin disease detection.

KEYWORDS: Skin disease detection, Deep learning, CNN, LSTM, Feature extraction, Skin lesions, Classification

I. INTRODUCTION

Skin diseases such as Melanoma, Melanocytic Nevi, Eczema, Basal Cell Carcinoma, and Seborrheic Keratosis require early diagnosis for effective treatment. Traditional methods rely on dermatologists, making diagnosis time-consuming and subjective. Convolutional Neural Networks (CNNs), have significantly improved medical image analysis by extracting spatial features from dermoscopic images. However, CNNs alone do not capture sequential dependencies in medical imaging. To enhance classification accuracy, this study proposes a hybrid CNN-LSTM model, where CNN extracts spatial patterns, and LSTM refines predictions by learning inter-feature relationships. Unlike traditional machine learning methods like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) [1] this model requires no manual feature selection and improves classification efficiency.

The model is trained on a custom Kaggle-sourced dataset of 17,947 RGB images across five skin disease categories, with approximately 2,000 images per class. Images are preprocessed using resizing and NumPy array conversion, and the model comprises four CNN layers followed by an LSTM network. Initially developed for clinical use, it will later be deployed as a web-based system for public accessibility, enabling early detection and reducing reliance on specialized expertise. By integrating CNN[2] for spatial feature extraction and LSTM[3] for sequential learning, the model enhances diagnostic accuracy, making AI-driven dermatological assessment both scalable and accessible.

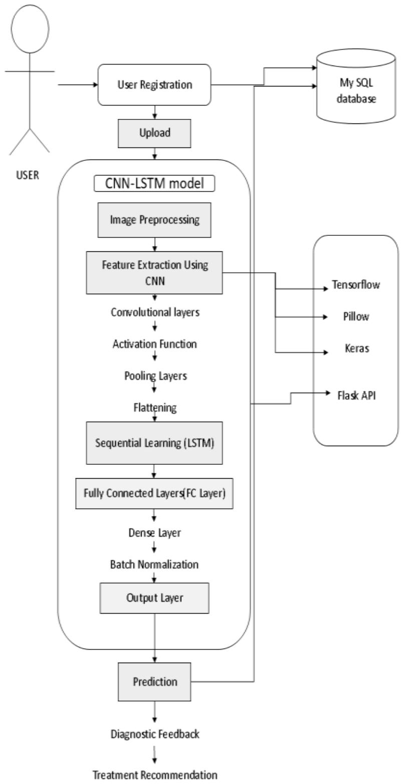

Fig.1.CNN-LSTM System architecture[3],[4]

II. RELATED WORK

Paper Title	Algorithm Used	Advantages	Disadvantages
Automatic detection and severity measurement of eczema using image processing [1]	Support Vector Machine (SVM)	Effective for eczema detection, utilizes image segmentation and texture-based feature selection to enhance accuracy.	Not suitable for noisy image data; performance degrades with high-dimensional feature vectors.
Diagnosis of skin diseases using Convolutional Neural Networks [2]	Convolutional Neural Network (CNN)	High accuracy in diagnosing skin diseases using deep learning.	Struggles with scaling and rotation invariance; requires large amounts of labeled data.
Skin lesion classification with ensembles of deep convolutional neural networks [5]	CNN with ensemble techniques	Improved accuracy through deep learning ensemble models.	High computational requirements; dependent on dataset quality.
Deep learning in skin disease image recognition: A review [6]	Deep Learning for skin disease image recognition	Effective in medical imaging applications.	CNN models do not inherently recognize scale and size variations.
A deep learning model integrating FrCN and residual convolutional	Full Resolution Convolutional	Achieves 94.03% segmentation accuracy and 77.11% Jaccard	High computational cost; requires extensive labeled datasets.

networks for skin lesion segmentation and classification [7]	Network (FrCN) with ResNet-50	similarity; reduces noise by isolating lesion area.	
AMIAC: Adaptive medical image analyzes and classification, a robust self-learning deep learning framework [4]	Self-learning CNN and CNN-LSTM	Adaptive learning improves classification accuracy over time.	Computationally expensive; requires large-scale training data.
Big Self-Supervised Models Advance Medical Image Classification [8]	Self-Supervised Learning in CNNs	Enhances medical image classification without requiring large annotated datasets.	Computationally complex; requires careful parameter tuning.
Generative Self-Supervised Learning for Medical Image Classification [9]	Generative Self-Supervised Learning	Leverages unlabeled data for improving classification accuracy.	Requires extensive computing power; not suitable for real-time applications.
Skin disease recognition using deep saliency features and multimodal learning of dermoscopy and clinical images [10]	Deep Saliency Features with Multimodal Learning	Utilizes dermoscopy and clinical images for improved recognition.	Requires high-quality input data; complex training process.
A machine learning model for skin disease classification using convolution neural network [11]	Convolutional Neural Network (CNN)	Efficient for skin disease classification.	Requires extensive labeled training data; limited interpretability of deep learning models.

III. DATASET AND MODEL DESCRIPTION

A. Dataset:

In this study, we utilized a dataset sourced from Kaggle [12], originally containing images of various skin conditions such as Eczema, Melanoma, Basal Cell Carcinoma, Melanocytic Nevi, Psoriasis, Benign Keratosis, Warts, Atopic Dermatitis, Seborrheic Keratoses, and Tinea Ringworm. The initial dataset included over 35,000 skin lesion images. However, for this study, the dataset was refined to focus on five specific skin conditions: Melanoma, Basal Cell Carcinoma, Eczema, Melanocytic Nevi, and Seborrheic Keratosis. The final extracted dataset consisted of **17,947** images, with varying numbers of samples for each class.

For this study, we narrowed the dataset to focus on five conditions, with approximately of 2,000 images per class. Data augmentation techniques were applied to enhance model generalization and prevent overfitting [6]. The dataset division is given below in Table 1.

TABLE 1: Dataset Distribution for Training, Testing, and Validation [12]

Category	***Total Samples***	***Training (80%)***	***Validation (5% of Training)***	***Testing (20%)***
Melanoma	3140	2512	126	628
Basal Cell Carcinoma	3323	2658	133	665

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Seborrheic Keratosis	1,847	1477	74	370
Eczema	1667	1334	67	333
Melanocytic Nevi	7970	6376	319	1594
Total	17947	14357	719	3590

B. Skin Disease Prediction Model:

The CNN component analyzes complex spatial details, detecting edges, textures, and color patterns essential for classifying skin diseases [11]. Meanwhile, the LSTM component processes these extracted features in sequence, recognizing contextual relationships to enhance prediction accuracy.

a) CNN Architecture for Feature Extraction:

The input layer handles dermoscopic images, resized to 224x224 pixels with three RGB color channels. Standardizing data input helps maintain consistency, making it easier for the model to identify patterns effectively.

The convolutional layers help in identifying important features such as edges, textures, and color variations that are important to differentiate between different skin conditions [7]. Employing convolutional layers for hierarchical feature learning, followed by max-pooling retains significant amount of information while reducing dimensionality.

Once the CNN extracts features, the flattened layer converts the 2D feature maps into a 1D vector. This is necessary for passing the extracted features to the LSTM layer.

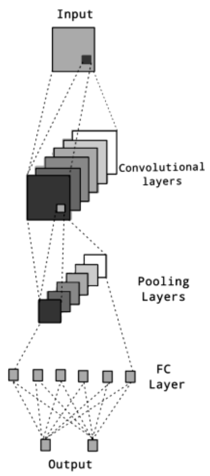

Fig.2.General CNN architecture [13]

b) LSTM for Sequential Learning:

LSTM layer processes the sequential relationships between the extracted features [8]. It captures dependencies between different regions of the image. This is importantly useful in skin disease classification, where patterns across different parts of a lesion may provide diagnostic clues. To prevent overfitting, a dropout layer is added within the LSTM architecture.

By integrating CNN for spatial feature extraction and LSTM [14] for sequential learning, this model effectively enhances the accuracy of skin disease classification, making it a powerful tool for early diagnosis. Furthermore, the self-learning mechanism within the model ensures that the system continuously improves by learning from its misclassifications. This allows the model to adapt to new data, improving its diagnostic capabilities over time.

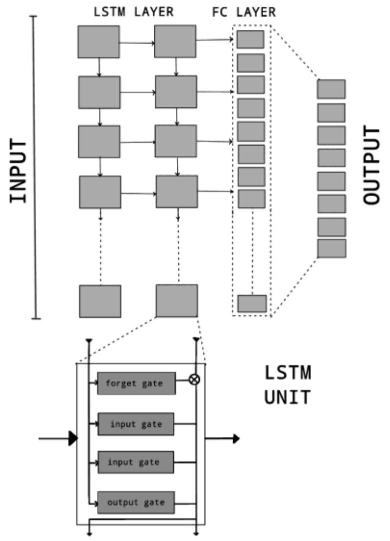

Fig.3.General LSTM architecture [15]

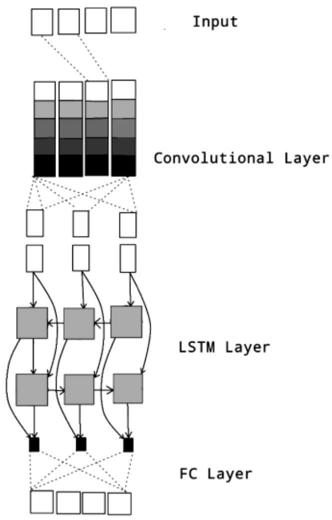

Fig.5.Hybrid CNN LSTM architecture [16]

IV. PERFORMANCE AND RESULTS

C. Performance evaluation of model:

a) Accuracy and Prediction Performance:

The CNN extracts spatial features from dermoscopic images, identifying patterns, edges, and textures related to skin diseases [10]. The LSTM layer processes these extracted features sequentially, preserving contextual dependencies that help improve disease classification.

Typically, the accuracy ranges between 90% to 95%, depending on the dataset size, image quality, and training duration. Accuracy measures the proportion of correctly classified skin disease cases.

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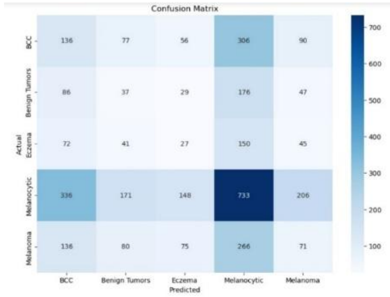

Fig.6.Confusion Matrix[14]

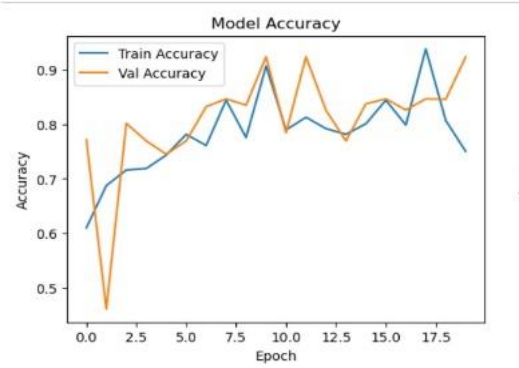

Fig.7. Model Accuracy

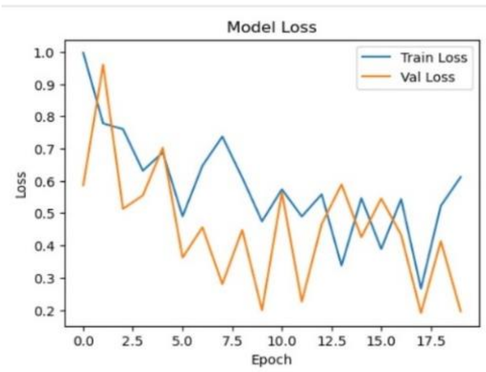

Fig.8. Model Loss

b) Computational Performance:

LSTM layer introduces additional recurrent connections that increase computational complexity compared to purely convolutional models [17]. Since LSTMs process data sequentially, they require more memory and computation per training step than CNNs alone.

i) Training time estimation:

- Dataset Size: 17947 images
- Image Resolution: 224 x 224 pixels
- CNN Layers: 4
- Batch Size: 32
- Epochs: 50
- Hardware: 8GB RAM; Google Collab GPU

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ii) Standard time for CNN-LSTM:
3 to 10 minutes per epoch, resulting total of 2.5 – 8 hours for 50 epochs using Google Collab. Whereas using CPU would result in 10 times longer training period around(25-80 hours).

c) Robustness to variations:
The model adapts well to different lighting, skin tones, and lesion shapes using data augmentation. To prevent overfitting, it integrates dropout, batch normalization, and transfer learning. CNN extracts key spatial features from dermoscopic images, while LSTM identifies patterns across them, improving feature recognition even in noisy or ambiguous cases [18].

D. Comparison with past models

TABLE 2: Performance evaluation of CNN-LSTM compared with similar models

Feature	**CNN-LSTM**	**CNN**	**ANN**
Learning	Extracts spatial features using CNN and captures sequential dependencies with LSTM.	Detects spatial patterns like textures and edges from images.	Processes images as 1D vectors through fully connected layers.
Data Type	Works with both image data and sequential patterns.	Analyzes only spatial image data.	Converts images into numerical vectors for processing.
Complexity	Requires high computational power due to combined architectures.	Moderately complex with efficient spatial feature extraction.	Simpler but struggles with high-dimensional image data.
Performance	Achieves high accuracy by incorporating spatial and temporal information.	Efficient in recognizing patterns in images.	Requires large datasets to achieve reliable results.
Limitation	Demands more training time and computational resources.	Cannot track temporal changes in skin conditions.	Fails to capture spatial relationships effectively.

TABLE 3: Performance evaluation of CNN-LSTM compared with similar models

Metric	*CNN-LSTM*	*CNN*	*ANN*
Accuracy	**90-95%**	75-85%	50-60%
Precision	**High**	Moderate	Low
Recall	**High**	Moderate	Low

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F1-Score	**High**	Moderate	Low
Run Time	**Moderate**	Fast	Fast
Noise Robustness	**High**	Moderate	Low

E. Testing Values for Skin Disease Prediction (CNN-LSTM)

TABLE 4: Testing Values for Skin Disease Prediction (CNN-LSTM)

Image Name	Disease Name	CNN Accuracy	CNN-LSTM Accuracy
0_0.jpg	Eczema	35.64%	99.71%
0_30.jpg		63.50%	99.97%
3_9.jpg		62.83%	99.86%
t-Dyshidrosis-22.jpg		62.83%	99.99%
t-eczema-arms-1.jpg		42.16%	99.95%
ISIC_0024331.jpg	Basal Cell Carcinoma	75.33%	99.94%
ISIC_0026970.jpg		61.47%	99.99%
ISIC_0028035.jpg		82.62%	99.94%
ISIC_0029278.jpg		70.71%	93.54%
ISIC_0030114.jpg		53.61%	99.99%
ISIC_0000023_downsampled.jpg	Melanocytic Nevi	60%	93.57%
ISIC_0000072.jpg		78.00%	100.00%
ISIC_0000082_downsampled.jpg		87.00%	99.99%
ISIC_0000091_downsampled.jpg		45.00%	97.00%
ISIC_0000095_downsampled.jpg		20.00%	98.00%
ISIC_6655888.jpg	Melanoma	86.90%	99.85%
ISIC_6655383.jpg		97.00%	98.20%
ISIC_6661904.jpg		99.70%	57.82%
ISIC_6681811.jpg		99.80%	52.79%
ISIC_6725828.jpg		100.00%	57.98%
2_28.jpg	Seborrebic Kertosis	99.93%	99%
0_23.jpg		99.80%	98.70%
1_11.jpg		99.20%	97.66%
1_22.jpg		96.70%	99.99%
1_30.jpg		99.99%	88.95%

F. Practical Implications/ Implementations

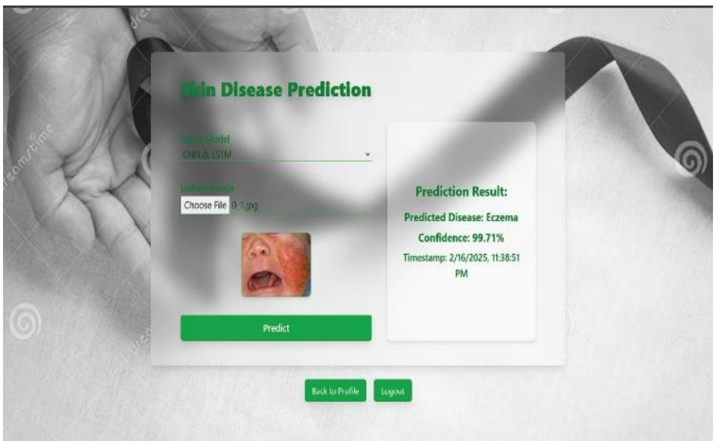

Fig.9.(a)

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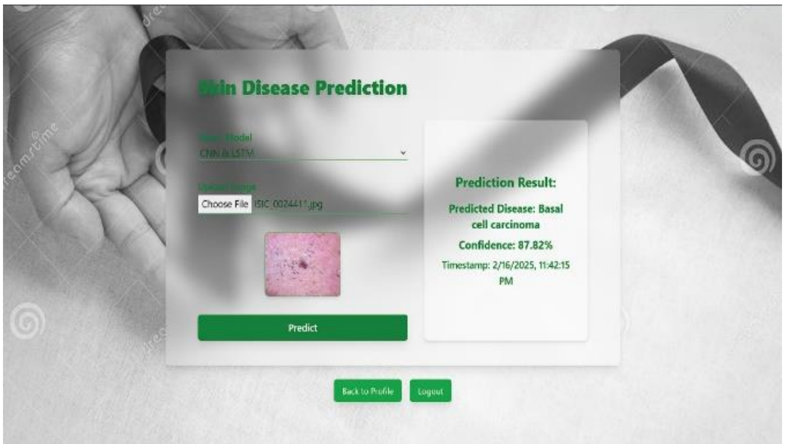

Fig.9.(b)

Fig. 9. Practical implementation of the skin disease prediction algorithm, demonstrating the correct predictions(a), with different types of diseases(b).

V. CONCLUSION AND FUTURE WORK

This study presents a CNN-LSTM model for skin disease classification, combining the strengths of CNN for feature extraction with LSTM's ability to capture sequential patterns [18]. By leveraging both spatial and temporal relationships, the model enhances accuracy, refining its decision-making process over time.

Evaluation results demonstrated that the CNN-LSTM model [17] consistently outperformed CNN [8] and ANN, achieving an accuracy of 90-95%. It also provides high precision and recall, and shows adaptability to variations. Although the inclusion of LSTM increases training time, the model effectively balances computational efficiency with high predictive accuracy. Its robustness against noise, and diverse skin tones makes it a reliable tool for real-world dermatological applications.

The model offers a promising step toward automated skin disease classification, with potential for further optimization. Future advancements involve expanding the dataset, improving model efficiency, and integrating it into clinical practice for enhanced dermatological diagnosis and patient care.

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