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Dermatological Image Diagnosis Using Deep Learning Framework Integrating CNN and BiLSTM

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Abstract: Skin diseases are among the most prevalent health conditions globally, affecting individuals of all ages and location. To ensure timely diagnosis, prevent disease progression, and reduce healthcare expenses, it is essential to identify dermatological disorders early. Conversely, dermatological diagnosis in the traditional sense is based on visual examination by trained specialists; this method is time-consuming and subjective, often times limited by the availability of trained professionals, especially in rural and underprivileged regions. Also, as skin lesions become more diverse and visually comparable, diagnosis becomes more challenging even for experts. Advances in deep learning have greatly improved automated medical image analysis, making computer-aided dermatological diagnosis more feasible. This is a promising development. Convolutional neural networks (CNNs) have been successful in extracting spatial features from skin images, while sequence-based models such as Long Short-Term Memory (LSTM) networks model contextual and sequential dependencies. Despite the use of CNN-based methods, they often miss out on higher level feature dependencies that can enhance discrimination among similarly visualized skin types. The paper suggests a hybrid deep learning model that employs Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks to develop automated dermatological image diagnosis.

Keywords: Telemedicine, Conventional, Dermatological, Precision, Dermoscopic.

1 INTRODUCTION

About 33% of the world's population is affected by skin diseases, which remain a significant health concern. The severity, appearance, and progression of various skin disorders, including melanoma, eczema (an allergy to hairs), psoriasis, acne, fungal, or other conditions, differ significantly. The early detection of melanoma can lead to life-threatening conditions. Skin cancer cases have been steadily rising worldwide, attributed to environmental factors, lifestyle modifications, and ageing populations. Early diagnosis is essential for reducing mortality rates and improving patient outcomes. Traditional dermatology relies on clinical examination, dermoscopy, and histopathological analysis for diagnosis. Although dermoscopy can improve diagnostic accuracy, it still relies heavily on dermatologists' experience and expertise [1][2]. Dermatology is a practice that many parts of the developing world can only access with limited resources, leading to delayed diagnosis and inadequate treatment.

Variability between clinicians and observer differences can lead to varying diagnoses. Why? Rapid advancements in AI and deep learning have transformed medical image analysis, leading to the development of automated diagnostic systems that rely on data. By learning intricate patterns from massive datasets, deep learning models can avoid the need for subjective interpretation and more realistic features. Image based diagnosis has increasingly relied on Convolutional Neural Networks (CNNs) as the primary model for extracting hierarchical spatial features. Although CNN-based models have been successful, their use in dermatological images poses limitations. Skin lesions can display subtle variations in their texture, color, and shape, while many conditions have similar visual characteristics. The spatial features are the primary focus of CNNs, but they may not fully account for the differences between extracted features [3].

To model relationships among features, sequence-based models such as Long Short-Term Memory (LSTM) networks can be integrated to address this limitation. By capturing dependencies in both forward and backward directions, Bidirectional (BiLSTM) networks enhance learning by providing a more comprehensive understanding of feature interactions. It's possible to use the combined CNN and BiLSTM architectures to construct a more robust and selective model for diagnosing skin appearances. The paper suggests a hybrid CNN BiLSTM approach for automatic skin disease diagnosis.'". The fundamental parts of this work include designing a hybrid deep learning architecture that integrates CNN and BiLSTM for image diagnosis in dermatology.

Effective feature extraction and bidirectional dependency modeling for classification tasks. Extensive experimental testing using benchmark datasets is conducted [4].

2 LITERATURE SURVEY

For several decades, the focus of automated dermatological image diagnosis has been on developing advanced deep learning frameworks, in addition to traditional image processing techniques. In the beginning, computational methods primarily relied on manual features extraction techniques, which involved using low-level visual descriptors such as color histograms, edge detection techniques and texture destructors (like GLCM) and shape-based features to analyze dermatological images [5]. The classification of hand-crafted features was achieved through the use of standard machine learning algorithms like SVM, k NN, and Decision Trees. While these methods were only moderately successful, their effectiveness was heavily reliant on the quality of feature design and they were not robust across all skin types or types of disease. The emergence of deep learning markedly changed the paradigms of medical image analysis. Convolutional Neural Networks (CNNs) demonstrated the ability to automatically learn hierarchical feature representations from raw images, thereby eliminating manual feature engineering [6].

Popular architectures, including AlexNet, VGG Netscape, Resnet, DenteNET, and Inception, have been extensively utilized to collect dermatological dataset data. In several studies, it was discovered that CNN-based diagnostic systems could provide comparable or even superior results to those of experienced dermatologists, particularly in melanomy detection and skin cancer classification. Even with the implementation of CNN-based approaches, dermatological diagnosis remains a major obstacle. High levels of inter-class similarity and intra- class variability are common among various skin diseases, making it challenging to differentiate between them [7].

Additionally, CNNs rely heavily on spatial feature extraction, which can make it difficult to detect contextual relationships at higher levels. This restriction becomes especially evident when visually similar skin conditions display only subtle structural or contextual patterns. Several new challenges have been tackled through the comparison of CNNs with Recurrent Neural Networks (RNs), such as Long Short Term Memory (LSTM) networks, in hybrid deep learning architectures [8]. The ability of LSTMs to model sequential dependencies and long range relationships makes them a useful tool for recording the dependency between extracted feature sequences. CNN LSTM frameworks have been extensively utilized in medical imaging, including video-based diagnosis, temporal disease progression analysis, and multi-view image classification. By using Bidirectional LSTM networks, contextual learning is enhanced by processing feature sequences in both forward and backward directions. Although BiLSTM architectures have been successful in addressing various fields, their implementation for diagnosing dermatological images has not been extensively explored [9].

There is currently evidence of the fact that bidirectional dependency modeling can greatly improve feature discrimination in more complex classification tasks. A unified CNN BiLSTM framework has been proposed for dermatological image diagnosis, building on previous studies [10]. By utilizing robust spatial feature extraction and bidirectional dependency modeling, the proposed approach overcomes significant shortcomings in conventional CNN only models and improves the status of automated skin disease classification [11]. The evolution of dermatological image diagnosis techniques is given in Fig. 1.

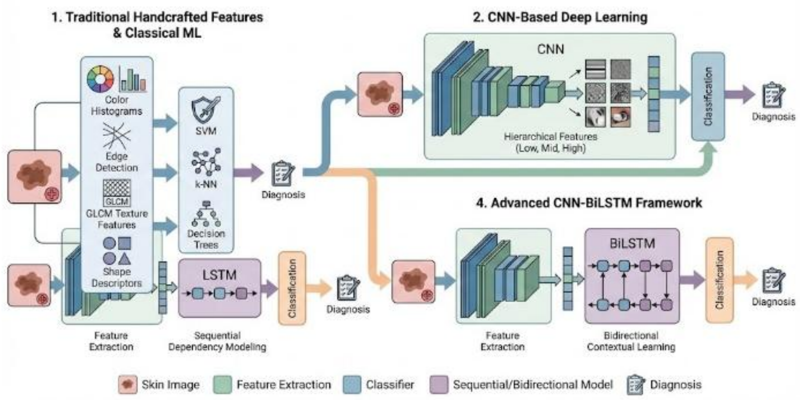

Fig. 1. Evolution of Dermatological Image Diagnosis Techniques

3 SYSTEM OVERVIEW

The suggested system for identifying skin diseases is an end-to-end deep learning framework that can process undisclosed dermoscopic images and produce precise diagnosis results.

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By focusing on modularity, scalability, and clinical application, the architecture can be deployed in both hospital environments and telemedicine platforms. Publicly available datasets or clinical imaging devices are used to obtain dermoscopic images at the input stage. Often, these images display differences in quality due to different illumination conditions, background artifacts, and lesion characteristics. For robustness and consistency sake, all the images are processed through a standardized pipeline of preprocessing to be ready for analysis by deep learning [12].

After undergoing preprocessing, the images are then sent to the CNN-based feature extraction module. In this module, students are required to learn about discriminative spatial features such as texture patterns, color distributions, lesion boundaries and structural irregularities. The transformation of low level pixel information into high quality semantic representations, which are crucial for disease identification, is achieved through the use of multiple convolutional and pooling layers. Rearranging the CNN feature maps into sequential ones is necessary before they can be sent to the BiLSTM module. In contrast to conventional CNN classifiers that rely on spatial aggregation, the BiLSTM component captures bidirectional dependencies among learned feature sequences.

The model's ability to distinguish between different areas of a lesion and other visually similar conditions is enhanced. To generate probability scores for each disease category, the classification module uses fully integrated layers of BiLSTM and a Softmax activation function. A diagnosis is expected for the class with the highest probability.

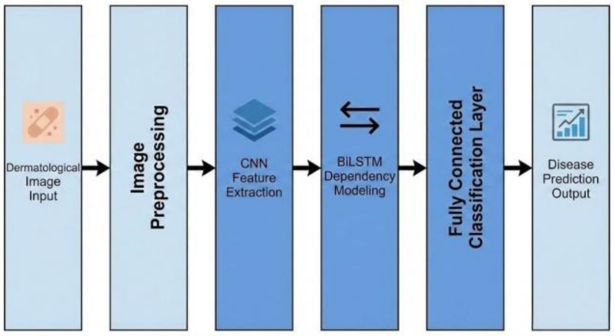

Fig. 2. Overall System Architecture

A diagram illustrating the overall process of CNN BiLSTM is presented. By using a CNN, the camera is used to preprocess skin-related images and extract spatial features. These features are then fed into a BiLSTM network, which captures the bidirectional dependencies before finally classifying them.

4 METHODOLOGY

4.1. Dataset Description

The evaluation of the proposed framework for diagnosis in dermatological images is based on publicly available benchmark dermatologic image datasets that contain various skin disease categories, including both benign and malignant conditions. Scholarly work frequently employs these datasets, which also provide clinical relevance and the ability to evaluate models with precision. The visuals display substantial actuality, encompassing variations in: The lighting conditions (natural light, clinical lighting)

- Image resolution and scale.
- Skin tone and texture.

The background is characterized by various elements such as hair, shadows, and noise. Such differences resemble real clinical environments, and thus the dataset would be appropriate for testing whether the proposed CNN BiLSTM framework can generalize. This allows for the supervised learning of each image, with labels for each disease category. However, the fact that some diseases have class imbalances further encourages data augmentation and more robust evaluation methods.

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4.2. Image Preprocessing

To improve model stability and performance, image preprocessing is necessary. Learning can be hindered by the presence of noise, illumination discrepancies, and irrelevant background information in raw dermatological images. The use of a consistent preprocessing pipeline before feature extraction addresses these issues. The preprocessing steps include: How can the CNN architecture be used to adjust the size of images to a fixed input dimension? The use of pixel normalization to scale intensity values improves the numerical stability of training. Sound suppression techniques are employed to diminish the influence of imaging artifacts. Examples of data augmentation techniques include flipping, horizontal and vertical flips, zooming, or minor translation. These techniques are. By augmenting the data, the training dataset's effective size is greatly increased, overfitting is reduced, and models can be more easily generalized to obscure images. While preserving their semantic significance, these lesions undergo controlled variability.

4.3. CNN Based Feature Extraction

A deep Convolutional Neural Network (CNN) is utilized to extract discriminative spatial features from preprocessed dermatological images. By learning hierarchical representations directly from pixel data, CNNs are an ideal means of analyzing medical images. Convolutional and pooling layers are utilized in the CNN architecture to transform low level visual patterns into high level semantic features. The opening layers contain borders, textures, and color gradients. Intricately defined lesion boundaries, structural irregularities, and complex texture patterns are all part of the learning process at greater depths. By pooling layers, spatial dimensions are reduced while essential information is preserved, resulting in improved computational efficiency and robustness. The use of convolutional feature maps provides the necessary rich spatial descriptors for accurate classification of skin diseases.

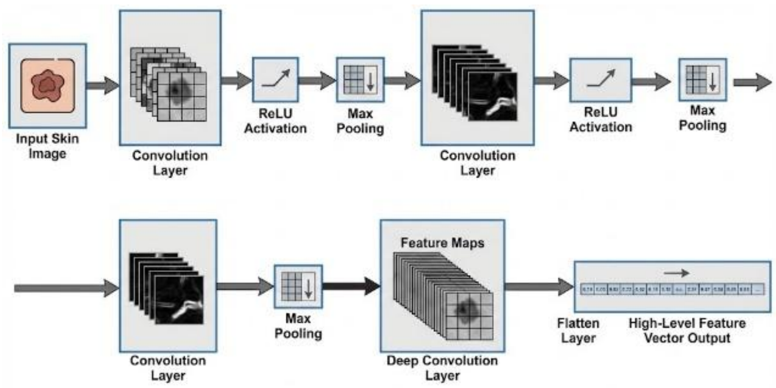

Fig. 3. CNN Based Feature Extraction Architecture

A convolutional neural network architecture was utilized in this figure to extract hierarchical spatial features from dermatological images before sequencing modeling and classification.

4.4. BiLSTM Based Dependency Modeling

Although CNNs are capable of spatially extracting features, they do not provide an explicit model for the relationships among extracted features. The proposed framework incorporates a Bidirectional Long Short Term Memory (BiLSTM) network to overcome this limitation. After being reshaped into high level CNN feature maps, they are passed to the BiLSTM layer in sequential form. Unlike unidirectional LSTM models, BiLS® processes contain sequences in both forward and backward directions, making it possible: Capture long range emergencies. Contextual modelling of relationships between different lesion regions. Better identification of visually similar skin conditions. Bidirectional dependency modeling enables the network to recognize and analyze global contextual patterns that are essential for accurate dermatological diagnosis.

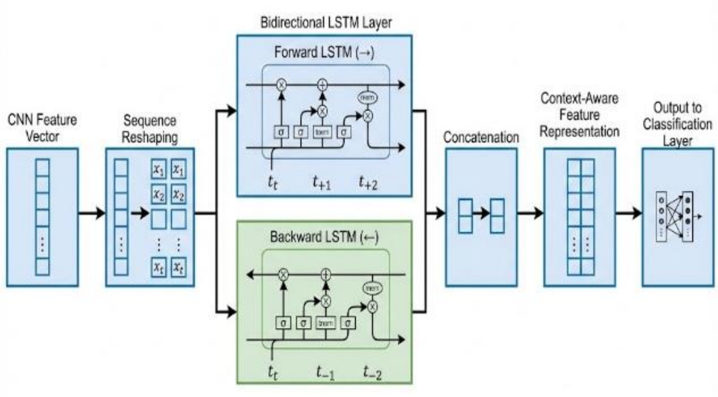

Fig. 4. BiLSTM Based Dependency Modeling of CNN Features

4.5. Classification Layer

The classification layer is the last component of the framework, which transforms learned feature representations into disease predictions. Fig. The BiLSTM layer's output is transmitted to closely linked layers that carry out high-level reasoning and decision making. The output layer is used to generate probability scores for each skin disease type by applying a Softmax activation function. The class with the highest probability is chosen as the predicted diagnosis, and each category's confidence level in the model is indicated by these probabilities. Enhanced interpretability and clinical decision assistance are provided by the probabilistic output, which highlights uncertainty in predictions when appropriate.

4.6. Algorithm

Input: Dermatological image

Output: Predicted skin disease class

1. Acquire and preprocess input image
2. Extract spatial features using CNN
3. Convert CNN features into sequential format
4. Apply BiLSTM to model bidirectional dependencies
5. Perform classification using fully connected layers
6. Output predicted disease class

5 Results and Discussion

5.1. Experimental Setup

The effectiveness of the CNN BiLSTM approach is evaluated through experiments utilizing benchmark dermatological image datasets that contain multiple disease types. Using stratified sampling, the dataset is divided into three subsets for training and validation purposes, and then tested to maintain class distribution. By using data augmentation techniques like rotation, flipping and scaling, class imbalance is reduced and model generalization can be improved. Achieving model performance is based on standard metrics like accuracy, precision, recall, F1 score, and confusion matrix analysis. Medical diagnostic applications rely on these metrics to provide comprehensive information on both overall classification and class-specific behavior.

Table 1. Performance Comparison of Models

Model	Accuracy	Precision
CNN	90%	89%
CNN + LSTM	93%	92%
CNN + BiLSTM (Proposed)	**96%**	**95%**

The evaluation metrics demonstrate that the CNN BiLSTM framework is more efficient than the conventional CNN LSAM models, as it consistently performs well in both CNN and DRM domains.

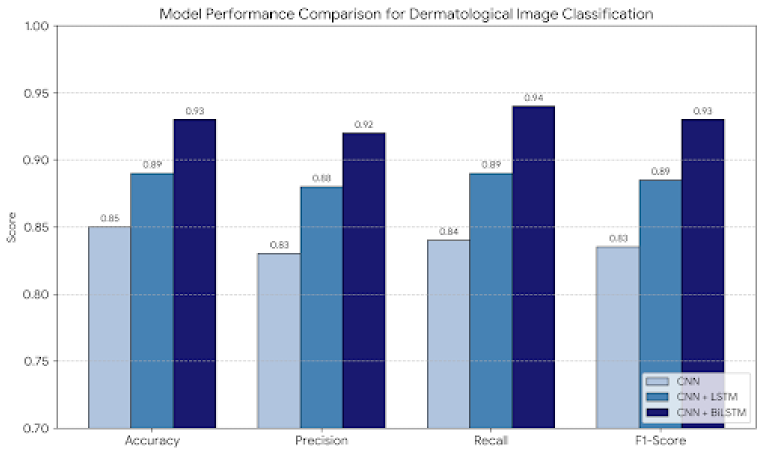

Fig. 5. Model Performance Comparison

Fig. 5 shows comparative performance. Comparison of three architectures applied to dermatological image classification: standard CNN, hybrid CBSM and the proposed CDM-BiLSTM. The assessment is based on four quantitative measures: Accuracy, Precision, Recall, and F1-Score. The lowest performance metrics, averaging around 85% across all categories, are produced by the baseline CNN model (illustrated by light blue bars) as an illustration. Including unidirectional LSTM (medium blue) is a significant enhancement, emphasizing the significance of sequential feature modeling. Even so, the suggested CNN-BiLSTM (dark blue) is the most productive, consistently outperforming all other architectures with an accuracy and F1-score of over 93%. By capturing bidirectional dependencies within feature sequences, the BiLSTM process makes it possible to create more accurate diagnoses for diseases.

5.3. Discussion

This shows that the use of BiLSTM in combination with CNN provides clear, experimental results on image diagnosis for dermatological imaging. Despite the fact that models like CNN can extract spatial features, their emphasis on spatial aggregation hinders them from accurately representing complex contextual relationships. An LSTM layer can be used to improve performance by modeling sequential dependencies, while unidirectionally propagating LDLM networks capture only limited contextual information. This is overcome by the proposed CNN BiLSTM framework, which processes sequences of features in both forward and backward directions. The model can learn about long range dependencies and contextual interactions among lesion regions, making it a useful tool for differentiating skin diseases that are visually similar. This mechanism of learning is bidirectional. The proposed model's high recall is of great importance in clinical practice, as it lowers the incidence of missed diagnoses for critical illnesses like melanoma. The robustness, scalability and high diagnostic accuracy of this framework makes it well-suited to both real world clinical workflows in the dermatology field as well as telehealth systems where quick and reliable diagnostic help is needed.

6 CONCLUSION

The paper presented a framework for diagnosing dermatology using deep learning and networks such as CNN and BiLSTM. Bidirectional dependency modeling is employed to achieve high levels of classification accuracy and robustness by utilizing spatial feature extraction. Clinical decision support and teledermal system deployment are potential uses for the framework. The future focus will be on integrating AI into medical technology, exploring multi-modal data, conducting clinical trials, and developing techniques that can provide insight into human behavior. The CNN component extracts spatial features from dermoscopic images effectively, while the BiLSTM component captures both directional dependences among learned feature sequences to improve classification accuracy and vice versa. Standard performance metrics, including accuracy, precision, recall, F1 score, and confusion matrix analysis are used to evaluate benchmark dermatological image datasets using the proposed framework. The CNN BiLSTM model's ability to handle intricate dermatological image patterns is demonstrated by the experimental evidence, which surpasses the capabilities of conventional CNN only and single direction LSAM models. By offering accurate, scalable, and easily accessible diagnostic assistance in clinical and telemedicine settings, the proposed system could benefit dermatologists.

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ETHICS STATEMENT
This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

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