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SKIN DISEASE CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

Skin disease is one of the pivotal ailments which mankind is battling with. Many skin diseases if not discovered and curbed in time eventually lead to cancer, which is a deadly disease or maims the affected individual. Identification of these diseases often relies on the expert knowledge of the doctors and skin biopsy results in which sometimes the accuracy and prediction is deficient, and it takes time. Traditional methods of diagnosis face some limitations of time and accuracy. To combat such problems, our paper develops a Convolutional Neural Network (CNN) based classification model for skin-related conditions. The use of CNN algorithms in the process of diagnosing skin conditions has delivered outstanding results. The computer-aided results are fast and help deliver an instant overview of the disease. Experts can quickly identify skin health-related problems by uploading images through this portal with ease. We can predict precise values by combining MobileNet classifiers with Convolutional Neural Networks (CNN) at an accuracy rate of 96.99%.

Keywords: *Skin Diseases, Convolutional Neural Network, Deep Learning, classification, MobileNet, skin lesions.*

1. INTRODUCTION

Skin diseases pose a significant global health problem as they can affect every individual irrespective of age or sex. Furthermore, the increasing burden of such conditions has been linked to the surroundings and changes in one's way of living. It is worth mentioning that certain populations such as Indians experience a great deal of this burden, they are believed to be among the top ten most burdened countries around the globe. In contrast, the data from studies in the India suggest that a significant portion of the population, about one out five, has some form of dermatitis (type of skin disease). There are certain causes for skin abnormalities, such as illness of the immune system, imbalance of normal levels of hormones, alteration of cell dynamics, and others.

The clinical assessments showed that as children's ages increased, the softness, smoothness, and general quality of their skin often decreased. Due to these variations in skin development, children's skin may be more susceptible to inflammation and irritation (Zhuang, D., et al., 2022). Children are more prone to skin diseases due to their frequent minor skin injuries, exposure to pathogens, and physical agents like extreme heat or cold.

Medical professionals and governments alike frequently fail to consider the personal impact that skin diseases have on their patients. They were directed towards illnesses thought to be more dangerous. Skin disorders are becoming increasingly common due to several factors, including the global warming trend, the HIV epidemic, shifting societal lifestyles, moving away from home, and increased usage of industrial toxins. But with the advancement of technology like artificial intelligence it has been possible to achieve the impossible. AI is the simulation of human logic in a machine that allows one to think, reason and in such a way that it solves complex issues and makes decisions as a human being (He, Y., and Peng, D., 2022). Population health has been a major concern, which is why information technology specialists have been working on making AI technology to help prevent such health problems.

With advancement in technologies for diagnosing skin disease, the need for quick and accurate diagnosing of skin diseases has grown. Deep learning methods such as the Convolutional Neural Networks (CNNs) and MobileNet architecture have been developed among other apparatus to enhance the diagnosis of skin diseases and they are just a fraction of the many artificial intelligence developments for the automated ascertainment of skin diseases. These advancements are helpful in the interpretation of the dermoscopy images of lesions, which in turn offers a hope to the alleviation in the diagnosis complexities in the future. However, the extent to which such sophisticated models can be utilized to enhance the clinical practice as clinical applications, depends on the ease of use of the final solution for the users, and the means of its installation. In this context, we describe a web based deep learning system using Flask that performs diagnostic analysis in real time incorporating advanced CNN. The application proved to be very useful in classifying skin diseases images when the patients uploaded the images since it employed the deep learning convolutional neural networks methods (Mahbod, A., et al., 2019) and (Kaur, S., et al., 2024). Furthermore, the performance of the model is improved by the addition of our own CNN model which is designed for quick and precise diagnosis.

In the last few years, there has been an increasing application of many sophisticated deep-learning neural networks including MobileNet and LSTM for advanced skin disease diagnostic tools and their classification. Nevertheless, more focus has been given to one factor concerning the research that can be improved the imaging processing techniques that are used to detect skin disorder lesions in the wireless imaging devices which, in turn, enhanced many other diagnosis techniques. Another aspect of the noise effect on skin lesions classification using deep convolutional neural networks is a challenge for specialists. Advancements in technology in this area have both positive and negative aspects about improving diagnosis. In addition, it is observed that convolutional neural networks are viable and effective in the mobile-based skin lesions classification to ease the diagnosis of skin diseases (Ramella, G., 2020). Moreover, also the multi-scale multi- network ensembles in the re-training methods for skin lesion classification tasks have already proven their effectiveness thus raising the need for the different ways to widen the diagnostic Success.

2. LITERATURE REVIEW

Several researchers advocate the use of image-processing-based methodologies for diagnosing diverse skin conditions. In this context, the current paper reviews various documented methodologies and proposes a structured approach to utilize colored photographs for diagnostic purposes, without requiring specialized expertise. Consistent with most diagnostic systems, a skin disease detection system typically operates in two stages: an initial phase focused on segmenting the affected skin region, and a subsequent classification phase. The segmentation phase leverages various image-processing techniques, such as k-means clustering and color direction methods (e.g., color harmony), to isolate and identify abnormal skin regions. The second phase utilizes artificial neural networks to classify the specific type of disease. This two-stage framework was able to segment a person into six skin abnormality types with an accuracy of 95.99% and classify it with an accuracy of 94.016%. (Wu, H. et al., 2020).

The other approach focuses on peak detection in images which aids in lesion localization in its early stages. This method transcends traditional classification, as it utilizes deep learning to enforce even more specific classification. As a result of these procedures, 22,501 out of approximately 23,000 images examined intended for this research, mostly from DermNet, were considered feasible. These images represented 23 major disease classes, each of which included 642 sub-classes. However, after some of the subclasses were considered redundant or unnecessary they were removed, thus leaving a final collection of 21,844 images with 622 subcategories. Moreover, ISIC has files of 24,000 images containing hand annotations that are sorted into seven leading categories of diseases and has been very important for development of deep neural networks architectures using transfer learning techniques (Ray, A. et al., 2020).

Furthermore, with the increasing concern over skin cancer, there has been significant spending on developing technology for diagnosis, thereby leading to complex classification. For example, a very basic system for classifying skin was developed for classifying moles into benign and malignant. The Inception V3 and DenseNet-201 models belong to the family of deep convolutional neural networks (CNN) architecture that this system is constructed upon. For instance, Inception V3, which is one of the most popular models in image recognition, is well-known for its multi-scale processing capabilities which entails the combination of 1X1, 3X3 and 5X5 convolution layers and thereby makes feature extraction possible at various visual resolutions. In this study, Inception V3 also performed reasonably well in skin lesion classification with top-5 classification accuracy of 93.7 percent, and top-1 accuracy of 77.9 percent on the ImageNet database. In an attempt to improve the accuracy more, as well as, meet more the objectives of the project that relates to its specificity, additional retraining of the layers of the Inception V3 was performed. The CNN architecture comprises different Inception modules as stated before that aim to enhance model performance. All in all, 27 epochs for Part A and 20 epochs for Part B of the model were spent and they proved to be hazardous as DenseNet-201 is another strong architecture which opts for high classification results by having dense connections in its four connected blocks for better learning ability and effective utilization of parameters.

As a follow-up investigation, Malliga, S. et al 2020 examined the various deep learning algorithms which can be adopted to detect and classify skin viral diseases, skin bacterial infections, skin fungal infections, and certain allergies. It is worth highlighting that the use of laser technology in combination with medical photonics has made the detection of these skin disorders more feasible. However, the cost and complexity of such diagnostic tools remain prohibitive. Malliga's goal was to test cost-effective approaches for addressing skin disorders caused by melanoma, nevus and seborrheic keratosis. In this regard, the authors followed a methodology that is well known and use the Alexnet architecture which is commonly used for high-level image classification tasks in computer vision. Kyle has mentioned in one of his papers that there are three convolutional layers and five fully connected layers in the AlexNet architecture which allows the network to be able to learn complex features from images. Melanoma (439), Nevus (551), and Severoboric Keratosis (413) were the classes under which the images in the training dataset were defined by the students. Since AlexNet contains several convolutional kernels, it is easy for the model to implement the strategy of image processing with RGB of size 256 by 256 pixels. Using this configuration, AlexNet is capable of making predictions regarding an image being correlated with a specific class of illness which suggests that guidance for improvement of the predictive accuracy of the model has been established.

When put together, these methods open the possibility of deep learning and advanced image processing techniques integration for making highly accurate, convenient, and easily scalable systems for detecting and classifying skin diseases.

3. DATA DESCRIPTION

The dataset, which was obtained via Kaggle, is made up of unprocessed photos of skin lesions categorized into seven classifications that correspond to various skin conditions. There were multiple photos with different qualities available in each class. Images were preprocessed to enhance quality and standardize dimensions prior to model training, guaranteeing uniformity across the dataset. In order to classify these preprocessed photos and guarantee that the CNN model could train on reliable results, they were fed into the model.

Table 1: Distribution of Dataset

Serial No.	Class	Number of Samples	Number of Training Samples	Number of Validation Samples
1	Actinic Keratoses	327	301	26
2	Benign Keratosis	1099	1024	75
3	Basal Cell Carcinoma,	514	484	30
4	melanoma	1113	1074	39
5	Dermatofibroma	115	109	6
6	melanocytic nevi	6705	5954	751
7	vascular Naevus	142	131	11
Total		*10,015*	*9,077*	*938*

This dataset has a moderate imbalance, whereby the majority class, Melanocytic Nevi, samples 6,705 examples, and some classes have very minimal samples, such as Dermatofibroma and Vascular Naevus. The data have been divided to ensure there is a 90 percent use of samples for training the model and 10 percent for validation, which supports better model training and evaluation.

4. METHODOLOGY

A series of processes designed to craft a deep learning- powered algorithm for skin disease classification and recognition. It begins with harvesting an extensive dataset featuring high-quality images detailing every spectrum of skin illness in multiple different images. On top of these images lay a basis for this project training and testing to produce an effective deep machine. A variety of ordinary and common dermatologic problems to more unusual conditions are presented in the closely selected images. Once the set of images is collected, the deep learning architecture of the model is described with detail. Selection of a proper type of architecture setting is essential for the successful classification of skin diseases (Kawahara, J., et al., 2016) and (Chopra, S., et al., 2024). The architecture for dermatological image analysis is more involved and has to be designed and built with careful attention to detail to the factors mentioned earlier. The selected design is further refined and modified in order to conform to the specific requirements of the classification of skin diseases.

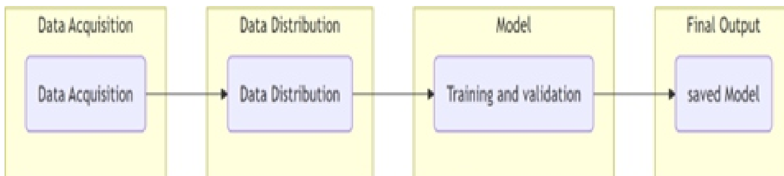

Figure 1: Overview of methodology

4.1. Data Collection

The dataset used to execute this project, "Skin Cancer MNIST: HAM10000," can be downloaded from Kaggle. There are images in this rich dataset from a wide scope of dermatology and are adequately appropriate for training models related to classification in skin cancer (Mader, K. S., 2018).

4.2. Data Preprocessing

Some preprocessing techniques were applied to make the data compatible with our model using the Keras preprocessing library. The batches were divided into 10 images each for more efficient training of the model. This batching allows the model to update its weight only after processing an entire batch, which stabilizes and makes the weight update consistent.

4.3. Data Analysis

Input data was not fed directly into the model without properly understanding the nature of data in the dataset. There are images of different diseases such as Melanocytic Nevi, Actinic Keratoses, Basal Cell Carcinoma, Melanoma, Benign Keratosis, Dermatofibroma, and Vascular Naevus providing a wide view of pathology of dermatology. Each image in the dataset comes with a ground truth classification about the skin lesion that is being depicted.

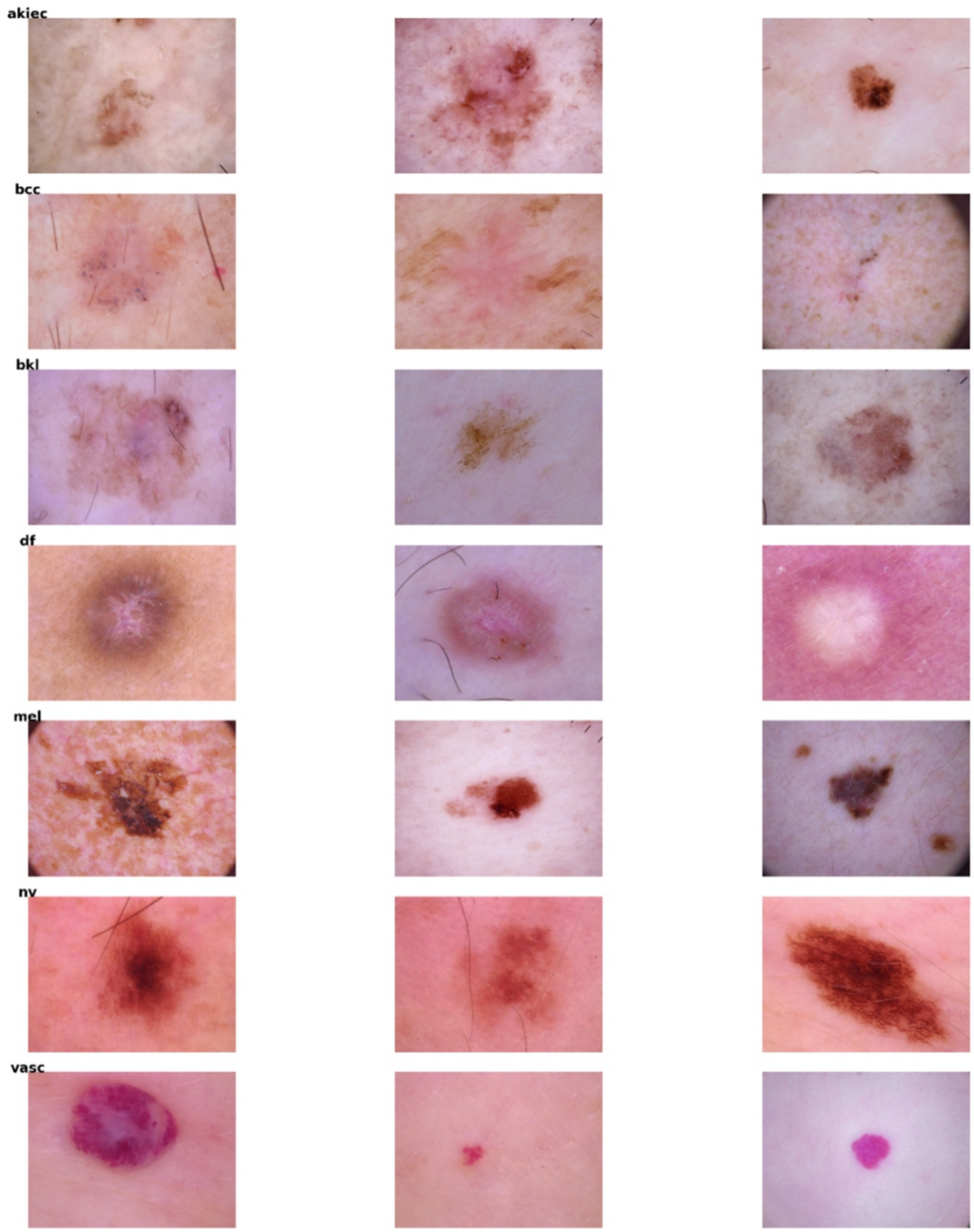

Figure 2: Sample Data

4.4. Data Visualization

A Graphical representation which is visual representation of dataset representing a graphical summary of the main characteristics of the dataset used by our model as shown in Figure 3. Each bar represents a feature or category of the dataset, which can easily be compared as their respective values or frequencies are represented.

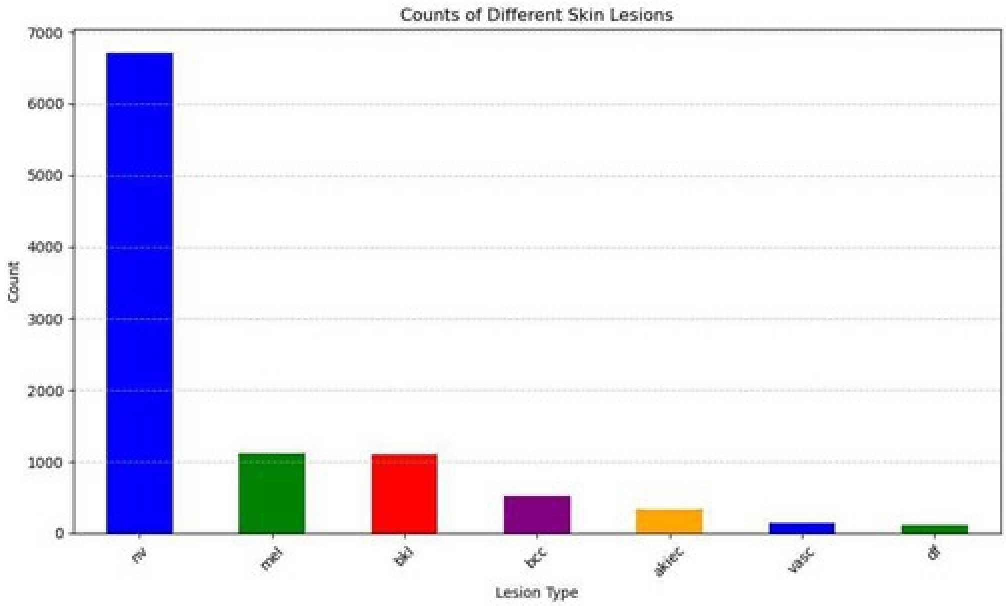

Figure 3: Count of Different Skin Lesions

4.5. Proposed Model

In this paper, we design a CNN architecture to be efficiently applied for the multi-class task of image classification into any seven categories regarding image recognition. With the size of input pixels set to 224*224 and three colors of RGB capturing a myriad of features in the images. The architecture begins with a convolutional layer that uses 32 filters, each of which applies a 3*3 kernel to extract low-level features like edges and textures. The convolution operation can be mathematically represented as:

$$(I * K)(x, y) = \sum_a \sum_b I(a, b) . K(x - a, y - b)$$

where 'I' is the input and 'K' represents kernel/filter.

The feature maps are then down sampled by a max pooling layer, which reduces both the overall computational complexity and the size of the spatial representations while preserving crucial information. The definition of the maximum pooling operation is:

$$P(i, j) = \max \{A[x, y] : (x, y) \in \text{pooling region}\}$$

The network can capture more intricate patterns and hierarchies in the data by repeating this procedure methodically and increasing the number of filters to 64 in the deeper layers.

A dropout layer is added so that instead of depending on patterns, the model can learn more general traits, after the initial pooling layer to improve the model's resilience and prevent overfitting. A mathematical definition of the percentage of neurons that are randomly lost during training is:

$$\text{dropout}(x) = \begin{cases} 0 & \text{with probability } p \\ \frac{x}{1-p} & \text{with probability } (1-p) \end{cases}$$

For classification tasks, the network design consists of several convolutional layers, pooling layers, and a flattening layer that converts the 3D outputs into a one-dimensional vector. Then, it is transferred into a dense layer with 126 units, using the ReLU activation function to enforce non-linearity which can be defined as:

$$f(x) = \max(0, x)$$

and enable learning more complex relationships between the features. The output layer contains seven units representing classes, utilizing the softmax activation function at the end of the architecture, such as:

$$softmax(p_i) = \frac{e^{p_i}}{\sum_{q=1}^{K} (e^{p_q})}$$

This function would turn out the output in terms of a probability distribution regarding the likelihood of the corresponding class, therefore ensuring perfect multi-class classification. Based on the conclusion reached here, the presented model based on deep learning powers boosts the accuracy for the tasks of image classification. These are, respectively, useful for different real applications-both in agricultural areas or health and autonomous systems in need of accurate categorization regarding images.

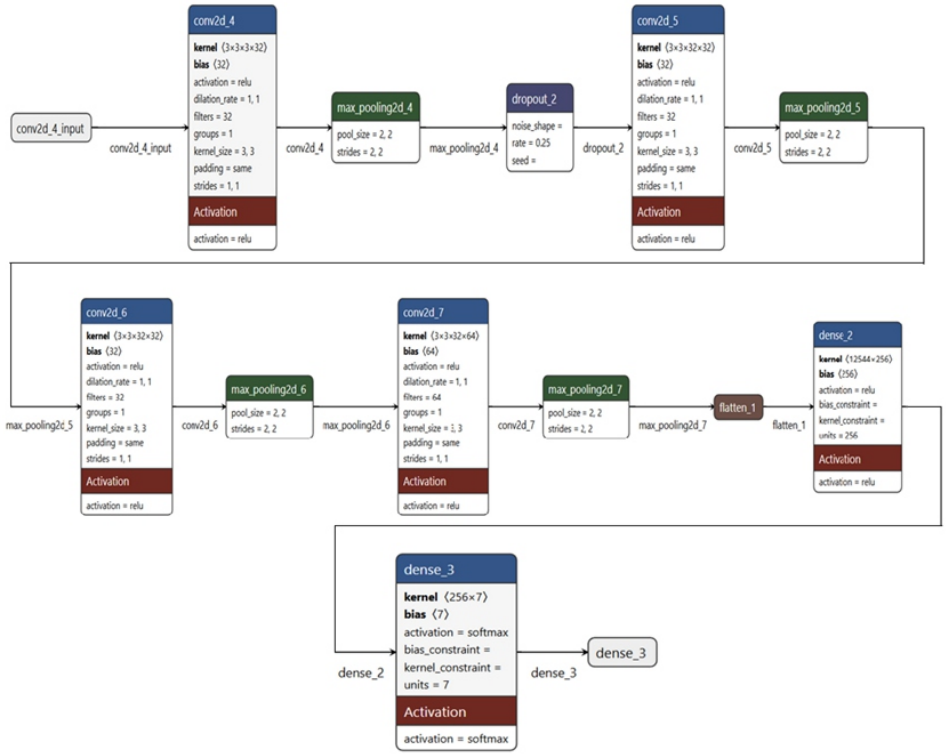

Figure 4: Model Architecture

4.6. Accuracy

This paper discusses the application of Convolutional Neural Networks for skin disease detection is presented. The system identifies and predicts the kind of skin illness classification algorithms. The name of the disease detected, and the safety precautions are displayed by the system after the detection. Using this feature, the system can predict skin conditions in real- world settings with a high accuracy of 96.99%. Figure 5(a) represents the accuracy values in the model, and Figure 5(b) represents the loss values of the model.

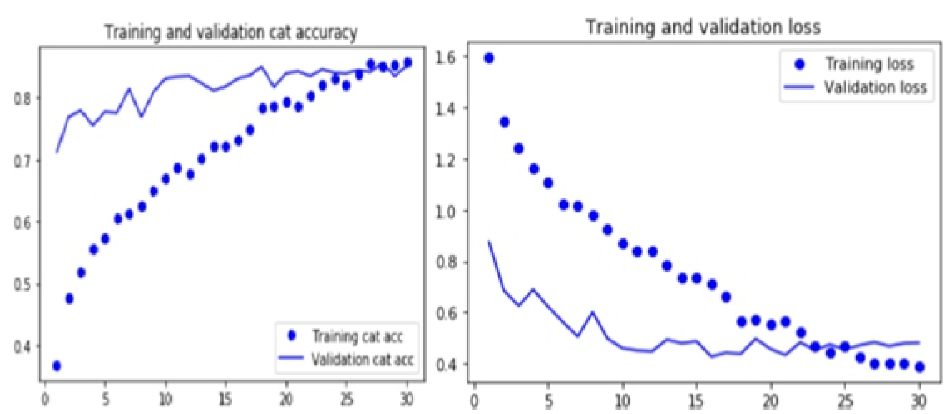

Figure 5(a): Training and validation cat accuracy (b) Training and validation loss values of the model

The accuracy achieved by our model is 96.99% that even surpasses all previously suggested models as shown in Table 2. This indicates improvement in performance, thereby suggesting that the model proposed is effective for use and that this further shows superiority in the given subject.

Table 2. Performance comparison of previous models

Source	ACC	Sensitivity	Specificity	AUC
(Han, S. S., et al., 2018)	86.4 ±3.5	85.5 ± 3.2	91% ± 0.01	–
(Esteva, A., et al., 2017)	72.1 ± 0.9%	–	91%	–
(Li, Y. and Shen , L., 2018)	90.20%	69.30%	90.20%	84.80%
(Serte, S. and Demirel, H., 2019)	83%	62%	88%	96%
(Hameed, N., et al., 2020)	96.47%	99.50%	98.17%	–

5. CONCLUSION

Studies into skin disease classification with the help of Convolutional Neural Networks (CNNs) have clearly shown the potential these deep learning architectures hold for enhancing the diagnostics in dermatology. The use of a stronger architecture of CNN with an excessively curated dataset, classifies skin diseases into seven different categories with high accuracy and reliability. This solution also offers and predicts a contribution to dermatologists in clinical practice towards better diagnosis and accurate results with reduced possibilities of human intervention while detecting diseases linked to the skin. Specifically, the emphasis on the usage of high-quality diversified datasets suggests the further works on data collection and data preprocessing from medical images to enhance the models' robustness. Future work will include developing the model into other skin diseases and extending the use of explainable AI techniques to make predictions more interpretable. The model will be further enhanced in robustness through domain adaptation with medical experts involved. In addition, it is also possible to add patient demographics and medical histories to the model to refine the diagnostic process and bring forward customized treatment recommendations.

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