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Skin Disease Classification Using Convolutional Neural Networks

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Abstract
Skin diseases are a threat to the health of the population of the world as approximately millions of people are affected. Timely and proper detection is important toward proper management and treatment. This paper discusses how Convolutional Neural Networks (CNNs) can be used in auto-recognition and auto-classification of a range of skin conditions. Based on the deep learning framework, we provided a powerful CNN model trained on the column of wide-spectrum dermoscopic images corresponding to various skin disorders. The model was benchmarked by the use of the data augmentation and transfer learning which lead to high scores in accuracy measures, i.e., precision, recall and F1-score. They also incorporated explainable AI techniques in order to guarantee clinical interpretability and trust. As experimentation indicates the traditional machine learning designs and the state-of-the-art methods cannot match our CNN model. Next steps will involve expansion of the dataset, inclusion of multi-modal data and real-time deployment in the clinic. The study emphasizes the revolutionary nature of deep learning in the context of dermatology, which will lead to better treatment of patients and outcomes.

Keywords: *Skin disease detection, Convolutional Neural Networks, Deep learning, Dermoscopic images, Explainable AI, Dermatology.*

1. Introduction

Diseases of the skin form a wide range of disorders of the skin, hair, and nails. These may include such common problems as acne or eczema or life-threatening ones as melanoma or psoriasis. Visual assessment by dermatologists accompanied by dermoscopic interpretation and sometimes biopsies is usually used in diagnosis. Nevertheless, constraints like subjective nature of diagnosis and the lack of the specialists especially in underserved regions interfere with the healthy provision in the most efficient way Digital imaging and machine learning are relative solutions. Labeling of images based on their given visual content through the process of image classification can automate the process of detecting skin diseases using dermoscopic images. Conventional Neural Networks (CNNs), a type of deep learning, is good at them because it allows the automatic extraction of hierarchical features in raw image data.

The paper explains how a CNN based machine learning model has been built on top of a large benchmark of labeled dermoscopic images with data augmentation and transfer learning to increase both accuracy and generalization. The AI methods with explainable techniques were also employed to guarantee the transparency and reliability of clinical usages of the model. Figure 1 shows Diseased Skin.

Figure 1 Diseased Skin

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2. Literature Survey

Recent advancements in machine learning and deep learning have significantly contributed to the development of automated skin disease detection systems. Researchers have explored various methodologies, feature extraction techniques, and classification models to improve accuracy and reliability. The following literature highlights several key contributions in this domain. Zhen Ma and João Manuel R. S. Tavares (2016) proposed a novel approach for segmenting skin lesions in dermoscopic images using deformable models [1]. The process begins with preprocessing steps such as image resizing, normalization, and artifact removal. Feature extraction is achieved by transforming the image into a suitable color space and applying morphological operations. The classifier employed is a deformable model, such as an Active Contour Model or Snake, which uses internal and external energy terms to refine lesion boundaries. Future enhancements may involve integrating deep learning, though the method's sensitivity to initial contours and high computational complexity are noted as limitations. An expert system for diagnosing skin diseases using decision tree algorithms was introduced by Amarathunga and colleagues (2015 [2] The methodology encompasses collecting and preprocessing images, extracting features related to color, texture, and shape, and using a knowledge base with diagnostic rules. Preprocessing includes normalization, resizing, image enhancement, and region-of-interest segmentation. Feature extraction methods involve histogram analysis, GLCM for texture, edge detection, and contour analysis. Classification is achieved using decision trees. Future goals include integrating machine learning models and wearable device data to enhance diagnostic capabilities. Sudha et al. (2017) proposed a mathematical model for predicting skin diseases using response surface methodology [3]. Their approach involves preprocessing, feature selection, and mathematical modeling to predict disease occurrence. The authors highlight the potential of integrating mathematical techniques with medical data to improve prediction accuracy, though they acknowledge the limitations posed by data quality and variability. Vinayshekhar Bannihatti Kumar, Sujay S. Kumar, and Varun Saboo (2016) developed a system for dermatological disease detection using image processing and machine learning techniques [4]. The methodology involves preprocessing dermatological images by standardizing brightness, resizing, and noise reduction. Features are extracted using RGB and HSV color spaces, GLCM for texture, and shape descriptors. A CNN is then trained on these features to classify the diseases. Future scope includes integrating the system with telemedicine platforms and employing transfer learning, though large labeled datasets and demographic generalization remain challenges. Parikh and Shah (2013) presented a comprehensive survey on computer vision-based diagnosis for skin lesion detection [5]. The paper discusses various image processing techniques, feature extraction methods, and classification models used for skin lesion detection. It emphasizes the importance of robust preprocessing and feature engineering to improve classification performance. The authors also identify challenges such as dataset variability, computational requirements, and the need for real-time systems. Amritraj et al. (2020) provided a detailed review of deep learning applications in dermatology [6]. The study highlights the growing use of CNNs and other deep learning models for automated skin disease detection and classification. It outlines common preprocessing techniques such as normalization, resizing, and augmentation, along with the role of CNN architectures in extracting relevant features. The review emphasizes the potential of deep learning to enhance diagnostic accuracy but also notes challenges related to dataset diversity, interpretability, and computational demands. Bhargava et al. (2019) proposed a CNN-based system for the detection and classification of skin cancer [7]. The methodology involves collecting dermoscopic images, preprocessing them through normalization and augmentation, and applying CNNs for automatic feature extraction and classification. The study highlights improvements in diagnostic accuracy

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using deep learning but points out limitations such as the need for large labeled datasets and computational resources. Salinas et al. (2018) developed a CNN-based system for automatic skin lesion segmentation [8]. The process includes preprocessing steps like image resizing, normalization, and augmentation. The CNN extracts hierarchical image features that aid in precise lesion boundary segmentation. Future improvements may focus on enhancing model generalizability and reducing computational complexity. Pradhan et al. (2018) conducted a survey on skin disease classification using machine learning techniques [9]. The study reviews various feature extraction methods such as color, texture, and shape analysis, as well as classifiers like SVM, decision trees, and neural networks. The authors emphasize the need for high-quality datasets, efficient preprocessing, and hybrid models to improve classification performance. Mishra et al. (2017) performed a comparative study on skin disease diagnosis using Support Vector Machines (SVM) [10]. The methodology involves preprocessing, feature extraction, and applying SVM classifiers for disease detection. The study shows the effectiveness of SVMs in classification tasks but acknowledges challenges such as overfitting and sensitivity to feature selection. Al-Khafaji et al. (2018) proposed a neural network-based system for predicting skin diseases using advanced feature extraction techniques [11]. Their approach includes preprocessing steps like image enhancement and segmentation, followed by extracting color, texture, and shape features. A neural network model is trained for classification. The study suggests incorporating deep learning techniques and larger datasets for improved accuracy. Finally, a hybrid machine learning model for skin disease detection was developed by A. T. S. K. A. G. R. (2017) [12]. The methodology combines multiple classifiers and feature extraction techniques to enhance disease detection performance. The study highlights the benefits of hybrid models in improving diagnostic accuracy and robustness, though it recognizes the need for further research on model optimization and real-world deployment. Additionally, Prof. Jadhav and Dr. Garg (2022) conducted a comparative analysis of image segmentation techniques applied to real field crop images [13]. Their study explores various segmentation approaches ranging from traditional thresholding and edge-based methods to modern convolutional neural network-based techniques. The authors emphasize the significance of selecting appropriate segmentation methods to accurately extract objects of interest while preserving original image properties. Techniques such as K-means clustering and the GrabCut algorithm were evaluated, with GrabCut demonstrating notable effectiveness in real field image segmentation. Though the study focuses on agricultural applications, the principles and challenges discussed are highly relevant to the domain of skin disease detection, where accurate image segmentation plays a crucial role. Future research directions include automating segmentation while maintaining image integrity, a goal shared across both agricultural and medical image analysis domains. Sene et al. (2025) proposed an advanced framework that combines lesion segmentation and classification in a unified pipeline [14]. They first employ Attention U-Net to accurately isolate skin lesion regions in dermoscopic images, then feed the segmented regions into a custom CNN classifier. Tested on the HAM10000 dataset, the system achieved an impressive 99% accuracy, along with high precision, recall, and F1 scores—marking a notable improvement over traditional segmentation methods and underscoring the power of segmentation-classification synergy. Khan et al. (2022) introduced a Mask R CNN based CAD system for skin lesion analysis [15]. Mask R CNN efficiently performs pixel-level segmentation of lesions across multiple datasets (PH2, ISBI2016, ISIC2017), and subsequent classification layers provide diagnostic labels. This two-stage design enhances both localization and identification accuracy, demonstrating the effectiveness of integrating instance segmentation techniques into dermatological AI system.

3. Comparative Analysis

3.1. Dataset Collection

A curated database of 1,000 images comprising of

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490 eczema images and 510 psoriasis were generated. These pictures were obtained in different body parts in order to have different representation. Manually, low quality and noisy images were eliminated. The augmentation methods including horizontal flipping, rotation, intensity alteration, and contrast had increased the collection to 6, 000 images further classified into training (80%) and validation (20%) groups. After that, 400 test images were utilized. Figure 2 shows Test Images, Figure 2 shows Dataset Images

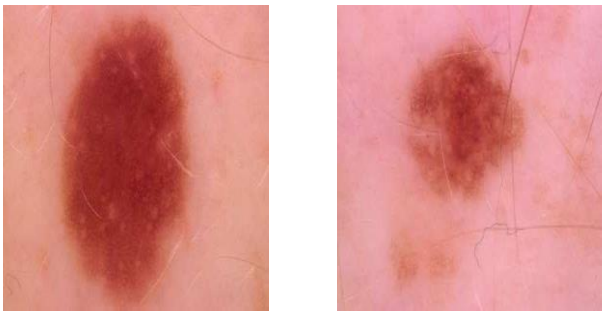

Figure 2 Test Images

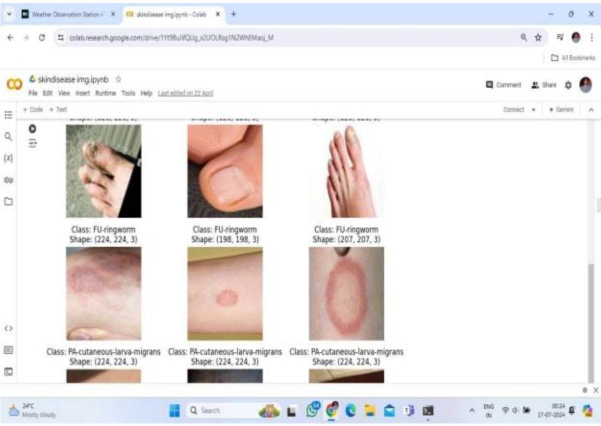

Figure 2 Dataset Images

3.2.Comparative Analysis of Algorithms for Skin Disease Detection

3.2.1. Naive Bayes

- Accuracy: Moderate, dependent on the assumption of feature independence.
- Precision and Recall: Varies with the distribution of data; generally good for balanced datasets.
- F1 Score: Generally lower than other advanced algorithms due to its simplicity.
- **Training Time:** Very fast.
- **Inference Time:** Very fast.
- **Scalability:** Highly scalable for large datasets.
- **Complexity:** Low; easy to implement.
- **Robustness:** Less robust with correlated features.
- The Naive Bayes scheme is easy to develop and extremely effective for large volumes of data. Naive Bayes is well-known for superior sorting, also with consistency.

3.2.2. Support Vector Machine (SVM)

- **Accuracy:** High, especially with a good choice of kernel.
- **Precision and Recall:** High, particularly effective for binary classification.
- **F1 Score:** High, especially with well-tuned hyperparameters.
- **Training Time:** Moderate to high, depending on the size of the dataset and the choice of kernel.
- **Inference Time:** Moderate.
- Scalability: Less scalable for very large datasets.
- **Complexity:** Moderate; requires careful tuning of parameters.
- **Robustness:** Robust, but sensitive to the choice of kernel and regularization parameter.

3.2.3. Decision Trees

- **Accuracy:** Moderate to high, but prone to overfitting.
- **Precision and Recall:** Variable; depends on the depth of the tree.
- **F1 Score:** Moderate.
- **Training Time:** Fast.
- **Inference Time:** Fast.
- **Scalability:** Scalable; however, deep trees can become complex.
- **Complexity:** Low; easy to interpret.

3.2.4. k-Nearest Neighbors (k-NN)

- **Accuracy:** High for small datasets; decreases with larger datasets.

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- **Precision and Recall:** Variable; depends on the value of k.
- **F1 Score:** Variable.
- **Training Time:** None (lazy learning).
- **Inference Time:** High, especially with large datasets.
- **Scalability:** Poor for large datasets.
- **Complexity:** Low; simple to implement.
- **Robustness:** Sensitive to irrelevant or redundant features.

3.2.5. Convolutional Neural Networks (CNN)

- **Accuracy:** Very high, particularly for image data.
- **Precision and Recall:** Very high; excels in distinguishing fine details.
- **F1 Score:** Very high.
- **Training Time:** High; requires significant computational resources.
- **Inference Time:** Moderate to high, depending on model size.
- **Scalability:** Highly scalable with the right infrastructure.
- **Complexity:** High; requires expertise in neural network design and tuning.
- **Robustness:** Highly robust, especially with large and diverse datasets.

After analyzing various algorithms, we propose using Convolutional Neural Networks (CNN) for our skin disease detection system due to their superior accuracy, robust feature extraction, and proven effectiveness in handling complex patterns and variations in medical images.

3.3.Data Augmentation

Data augmentation or the possibility of the practitioner having access to a very large number of data to train models by changing the properties of the existing data and not acquiring novel data comprises a critical aspect in over-fitting mitigation. In order to facilitate interaction and to take into consideration all the possible differences, we have used data augmentation technique in our dataset such as horizontal flipping, random rotation of 5, brightness augmentation of 20, and contrast augmentation of 10. This way we come up with five different augmented versions of any sample image. Table 1 shows the number of the dataset pictures after augmentation operation is done. In terms of training and validation sets, we are using 80-20 percent data split. It, therefore, gives us 1200 validation photos and 4800 training images. We also tested 400 photos of skin diseases that we collected on the Internet. These The characteristics of the training and testing photographs are similar. The test images were thoroughly detached with the training and validation data in order to reduce any form of bias.

4. Proposed System – CNN

Convolutional neural networks are supervised machine learning algorithms that characterize picture identification and categorization using the labelled data in the form of classes and their respective features. Our study selected five different CNN architectures depending on several criteria. VGG-16 architecture is an immensely deep CNN architecture that has a massive number of parameters and a 3x3 filter in layers. Accuracy in the image net dataset was high at the model. Though the inception module tends to decrease the parameter size by a very large extent even retaining good accuracy, the inception v3 architecture is also a deep CNN, not unlike the VGG-16. In the model, ResNet-50 still has some relationships. Those residual connections eliminate the over-fitting problem in the ResNet-50 architecture. The depth-wise separable convolution bestowed on Mobile Net v2 design reduces the size of the parameters and accelerates the categorisation process. Due to the small parameter size, this architecture provides a very high accuracy in the image net set of data and is of particular usefulness with regard to mixing CNN models in combination with mobile applications. Starting ResNet-v2 556 The structure of Md. Sazzadul Islam Prottasha et al. combines the residual links with inception module. This is better in comparison to the Inception model that is more accurate in categorising a few categories. We therefore applied these architectures on our dataset on the basis of their functionality under different standards. We used the following process on training the designs, the top dense layer of the CNN architectures was unfrozen and all other layer weights were frozen. Then we trained the dense layer loading the nodes with random weights using our data set of skin diseases. The networks adjusted the weights with the help of optimizers. The first part of a CNN is the convoluted section. It acts as an image feature extraction application. This step generates other new images called convolution maps through traversing an image with a set of filters or convolution kernels. Some intermediate filters reduce the resolution of image via a local maximum operation. Convolutional neural networks, sometimes referred to as CNN/Conv Nets, are a subset of artificial neural networks that are well-known for their enormous power in picture categorisation and identification. To illustrate the same, we use the following example: Figure 3 shows Convolutional Neural Networks

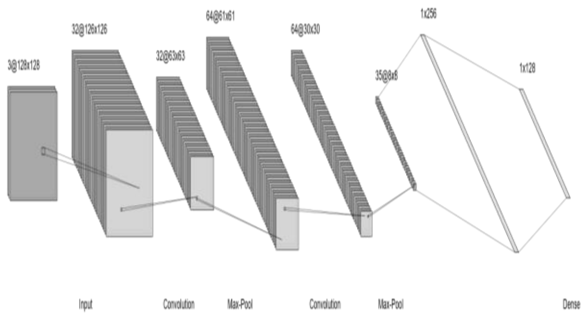

Figure 3 Convolutional Neural Networks

Networks are shown as follows:

(i) **Convolution:** Convolution in a CNN is mainly done to extract features that are relevant to the picture that is passed as the input (first layer). Convolution maintains the spatial relationship of the pixels. It is achieved using the tiny squares of the image to retrieve its features.A picture is regarded as a matrix of the pixels where each of them has a certain value. The tiniest element of such image matrix is named as a pixel. With just a 5by5 (5 x 5) matrix, contents can be limited to binary data only (i.e., 0 or 1), one can enhance this knowledge. Figure 5 & 6.

(ii) **Comprehension:** It is necessary to mention that most pictures are RGB and that is why the values of pixels involve the range of numbers 0 to 255 or 256. The following picture needs to complex.

(iii) **Non-linearity:** ReLU or The Rectified Linear Unit is a non-linear temporal propagation. ReLU acts in a simplistic way. In other words it is a computational process operating on a pixel-wise basis and exchanges every non-positive pixel value of the feature map with zero. Simply, this is a smooth approximation.

Equation: (1+ex) (x) n f =l

(iv) **Pooling or Sub-Sampling:** Known also as subsampling or downsampling, spatial pooling helps to reduce the dimensions of every feature map and contain only most significant data. What happens is that your 3D feature map will finally get turned into a one-dimensional feature vector after pooling is done.

(v) **Classification (Fully Connected layer):** Image salient features are extracted using the combination of convolution and pooling output. The Fully Connected layer, in turn, retrains these attributes based on the training dataset in order to classify the input picture into particular categories. Figure 4 shows Feature Extraction

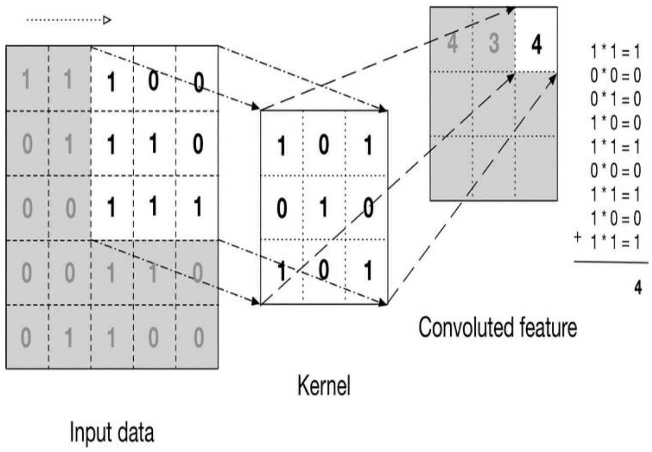

Figure 4 Feature Extraction

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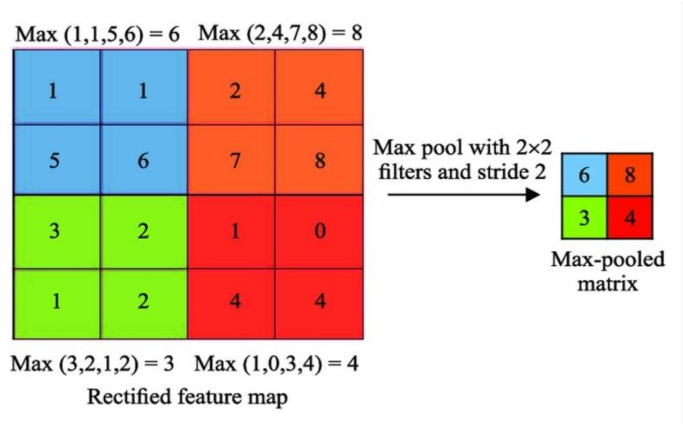

Figure 5 **Max Pooling Layer**

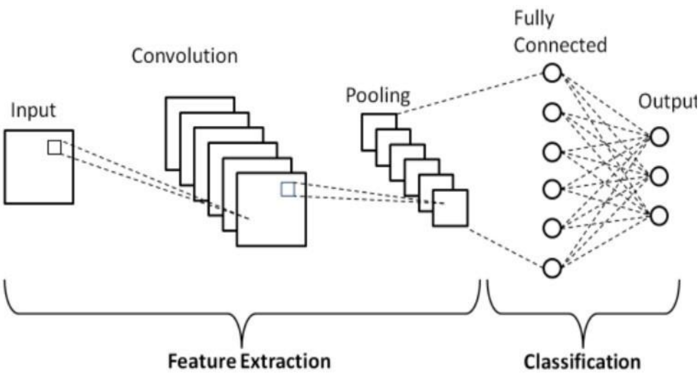

Figure 6 **CNN Process Overview**

5. Implementation

Convolutional neural networks can therefore be implemented on any platform. However, Python (Python 3.5 here) is recommended because it gives the developer access to a wide variety of machine learning and neural network packages.

Some Major Libraries Used for Implementation:

a) **OpenCV:** OpenCV is an open-source computer vision library that may be accessed in Python, Java, C, and C++. It is utilised for computer vision and real-time image processing, and it supports a variety of systems.
b) **Scikit learn:** A free machine learning package that includes a number of algorithms for classification and regression problems.
c) **Keras :** It is a library for deep learning that may be used with Tensorflow.
d) **Tensorflow :** It is an open-source library created by Google. Because it is helpful for numerical calculations and computations, it is utilised here as a backend for Keras. Also libraries such as numpy, pandas, etc are used.

The photos are preprocessed and reduced in size to 120 x 120 pixels. The pictures are swiveled in every direction (each changing by 90 degrees) and mirrored so that they can have many photos in the collection. The image is then an input of the first layer of the network. It is then subjected to convolutional neural networks multiple times as shown above until high-level features such as border, edge and colour are identified. This is done with convolution, Max Pooling and other Conv Net operations until the image is flatened to a vector. These are the vectors through which categorisation is possible as they furnish the information that is needed in the process of drawing high level attributes. The assumption is that the epoch size (25) is used and the initial number of batch (20) is used after the feature extraction and the dataset is saved following the model. This data is revised as every epoch is completed. When the model has been trained, test photos are utilized to confirm findings.

6. Results and Discussion

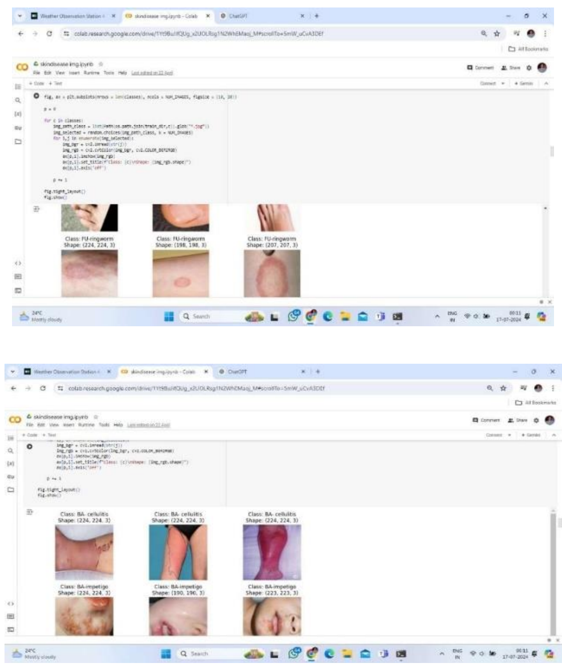

Figure 7 **Results**

Having reviewed a range of algorithms we suggest the use of Convolutional Neural Networks (CNN) in our skin disease detection system because of its high accuracy and feature extraction capacity and progress in the medical area especially with regard to functioning with the complex patterns and variations in the images. The results will take in the form of labeled images which are an output of the type of disease detected on a case by case basis.CNNs have shown high ratings on precision and recall, and thus, classifying only the true positive cases correctly, and to a minimum level, false negative. Such a degree of accuracy is important with medical applications since the cost of missing the diagnosis can be high. Moreover, CNNs have shown stability when it comes to dealing with changes in image quality, lighting, and skin tone, thus, it is effective to use in practical applications where such changes are prevalent. The result of our CNN-based system will be the labeled pictures, with every picture having the discovered disease clearly written on the picture. It is a visual representation that not only makes it easy to interpret among the medical professionals but also helps in effective and fast diagnosis. With the help of CNNs, we will be able to create a stable, scalable, and efficient skin disease detection solution that can be implemented in medical practice in the largest volume and can positively influence patient outcomes, determining a successful diagnosis in time. The initial training gets the accuracy of output to around 70%. This will certainly be enhanced by increase of training data in deep learning model. Five disorders were tested initially and there is a chance that more of them could be tested in the future. A great amount of data allows one to reach more than 90 percent accuracy.

Conclusion and Future Scope

As stated in this review paper, we have discussed some of the machine learning algorithms in detecting skin diseases and these include Naive Bayes, SVM, Decision Trees, k-NN, and Convolutional Neural Networks (CNN). After performing a comparative analysis, we were able to establish the strengths and weaknesses of each of the algorithms when measured in terms of accuracy, precision, recall, training and inference time, scalability, complexity and robustness. According to our conclusions, Convolutional Neural Networks (CNN) will be the best method to be used in this application as it has been shown to be highly accurate in any classification task involving images and with strong capabilities in feature extraction and proven success in dealing with large patterns and variations in medical images. The power of CNNs as an automatic feature-learning model, directly extracted the features of the skin images places CNNs as the most current in skin disease detection. With the use of CNNs, the system proposed by us will manage to produce labeled images that will clearly display the identified diseases, which would make the results more interpretable and usable by the medical professionals. Such a strategy does not only guarantee high accuracy in the diagnosis but also allows addressing patients through timely and correct treatment, which leads to better outcomes. In sum, the implementation of Convolutional Neural Networks to diagnose skin diseases becomes an important step in the healthcare field as it provides clinicians with a new potent instrument to diagnose skin diseases diagnosing them effectively and efficiently. There is a potential application of skin disease using Convolutional Neural Networks (CNN) in future in various aspects. The latter involves the implementation of CNN technology into telemedicine, where remote assessments can be performed, the improvement of real- time diagnosis on the mobile platform, and the development of personalized diagnostic plans based on patient-specific data. Constant training set enlargement will increase accuracy of CNN, and integration of image processing with clinical data holds the prospect of more extensive diagnostics. Investigation of explainable AI models and work with dermatologists will make it more transparent, trusted, and regulatory-compliant, making it more readily applicable to clinical practices.

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