

International Journal of
Engineering Research and Science & Technology



ISSN : 2319-5991

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Machine Learning Algorithms For Skin Disease Prediction

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Article Info

Received: 12-12-2022

Revised: 20-01-2023

Accepted: 25-02-2023

Abstract:

Dermatology is the study and treatment of skin problems. These problems can vary depending on where you are and what season it is because of differences in weather. Human skin is complex, with many different textures, colors, and other features, making it difficult to understand and study. Despite many studies focusing on using computer vision to understand skin, not many have looked at it from a medical perspective. In rural areas where there aren't many doctors, people often ignore skin problems until they get worse. That's why there's a need for a reliable way to automatically detect skin diseases. So, we created a deep learning model, which is a type of machine learning, to tell the difference between healthy skin and skin with problems. Our model can also classify different types of skin diseases, like basal cell carcinoma or melanocytic nevi. Deep learning lets us train our model using large amounts of data quickly. This helps the computer learn how to make accurate predictions about skin problems. We used a type of deep learning called Convolutional Neural Networks (CNNs) because they're good at categorizing pictures. This technology helps support and improve the field of dermatology.

1. Introduction

The skin is the largest organ in the human body. It's made up of layers like the subcutaneous tissues, dermis, and epidermis. Our skin isn't just a covering; it's vital because it senses changes in the environment and protects our internal organs from harmful things like germs, pollution, and sunlight. Various factors, both inside and outside the body, can affect the skin, including genetics, viruses, chemicals, and the immune system. Skin problems can have a big impact on a person's life quality. Sometimes people try

home remedies for skin problems, but if the problem is serious, these remedies can make things worse. Skin problems can spread, so it's important to treat them quickly. Doctors use their experience and judgment to assess symptoms and make decisions about treatment, but if they make a mistake or delay, it can harm the patient's health. That's why it's crucial to find ways to identify skin problems early.

Modern technology has made it possible to develop systems that can monitor the skin for signs of infection early on. There are new tools available that use patterns and

images to diagnose skin disorders quickly and accurately. Machine learning, a type of artificial intelligence, is particularly promising for diagnosing skin diseases. Machine learning can categorize diseases by analyzing pictures. There are many different algorithms that can recognize and predict various types of skin diseases. In healthcare, artificial intelligence (AI) is becoming more important than human operators for automating tasks. The rise of new and complex skin diseases in recent years has raised concerns about the risks they pose to human health. Treating these skin problems early is important because they can spread easily. Exposure to high levels of ultraviolet radiation is a major cause of many skin diseases. The most serious type of skin

cancer is malignant melanoma, but less harmful types can also be treated with therapy. Skin cancer is more common in certain areas of the body and among certain age groups.

Artificial Neural Networks (ANNs) are a type of technology used to analyze and predict data[2]. They are inspired by the structure of the human brain and consist of different types of nodes that perform computations. ANNs use back-propagation to learn from data sets and can achieve accuracy through various methods[2]. However, their accuracy is not always perfect, and they require CPUs with parallel processing capability. ANN results can sometimes be uncertain because they don't provide explanations for their predictions.

2. Literature survey

Advancements in medical image processing have been driven by the combination of technology and healthcare. Techniques like MRI, CT scans, and DSA, which use digital images, help doctors make accurate diagnoses. Many efforts have been made to detect skin diseases more effectively. Here's a summary of recent research:

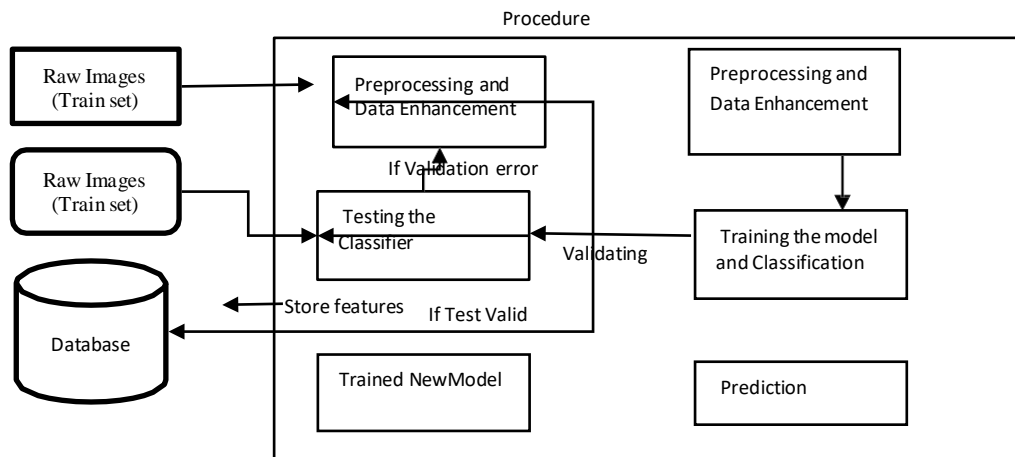
- Ercal et al. [1] used a color metric based on RGB to better distinguish tumors and their surroundings. They used a special method to separate the tumor region from other parts of the image, making it easier to diagnose tumors.
- Cauchy et al. [2] explored using machine learning algorithms to automatically identify dermoscopy patterns and analyze skin lesions. Their use of deep neural networks and image classification algorithms showed promising results.
- Ganster et al. [3] developed a computer-based method to analyze images obtained by ELM. They used segmentation techniques to create a mask of the skin lesion and determined its malignancy based on its shape and characteristics. Grana [4] introduced a mathematical method to evaluate lesion boundaries, considering brightness values along a contour-normal direction at each location. Sigurdsson et al. [5] developed a skin lesion classification system based on Raman spectroscopy. They used a classifier based on neural networks to aid in skin lesion diagnosis by analyzing unique spectral bands.

- Aberg et al. [6] used electrical bio-impedance to distinguish between skin cancer and benign nevi. Their method relied on multi-frequency impedance spectra.

Research indicates that skin disorders rank fourth in global skin burden. To reduce this burden and help patients with early assessments of skin issues, the focus has been primarily on categorizing skin cancer. However, early detection of skin diseases is crucial for successful treatment, though

challenging due to similar symptoms across different diseases. The study presented here introduces a new method for diagnosing common skin lesions, including vascular lesions, basal cell carcinoma, actinic keratoses, benign keratosis-like lesions, melanoma, and dermatofibroma. This method involves pre-processing, deep learning algorithm training, validation, and classification. Experiments conducted on 10,010 photos show that a seven-class classification using Convolution Neural Networks (CNN) with the Keras Application API achieves 93% accuracy.

3. METHODOLOGY

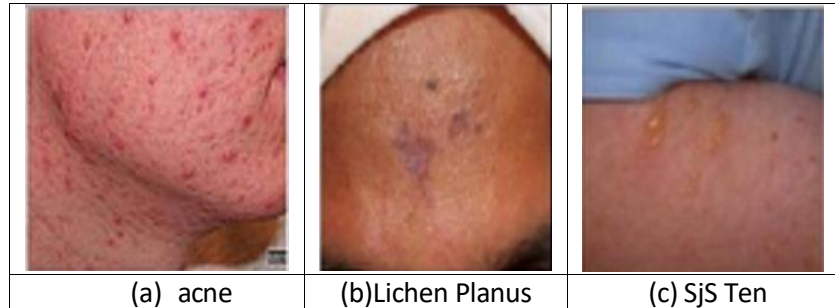


Proposed system

4. Data collection

For this evaluation, we used dermatoscopic pictures retrieved from the SkinCancer-MNIST (Modified National Institute of Standards and Technology Database)-

HAM10000 dataset, which is open to the public. I have a lot of possibilities, but endless. Utilising publically accessible data may be a time and labour saver



Sample images

5. Data Preprocessing

As a general rule, "Trash In-Good Out" applies at this stage [6]. If you want to speed things up, avoid mistakes and dirty data, and validate your dataset using a simple profiling approach [4]. When presented with such data, AI systems often provide subpar results.

5.1 Data Cleaning

Data that isn't clean might lead to errors and skewed outcomes. Therefore, data cleaning is the first stage of data pre-processing. Data cleaning includes completing missing value fills, smoothing data that is noisy by finding and eliminating outliers and discrepancies

5.2 Data Transformation

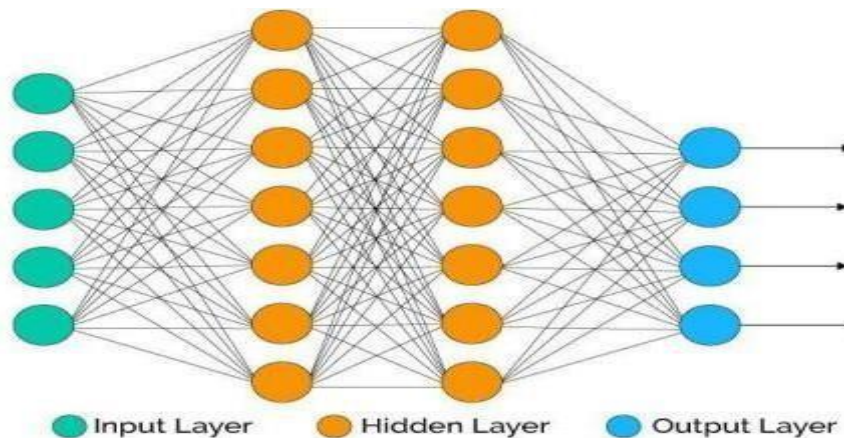
The process of data transformation entails changing the format of data. This process entails changing the values from one representation to another.

6. Algorithm

The Convolutional Neural Network (CNN) is a type of advanced computer system that can learn from data, particularly images. It breaks down the given information into different levels and quickly provides accurate results. Think of it like a detective who looks at clues in layers to solve a mystery.

Imagine a CNN as a series of steps. First, it looks at small parts of the image and combines them to understand the bigger picture. Then, it narrows down the important parts and ignores the rest. This process helps it recognize patterns efficiently, especially in pictures.

CNNs are great for image tasks because they're designed to pick up on important details while ignoring noise. This is done through features like shared information between layers and a technique called pooling, which helps simplify the information.



Fully connected layer

Thanks to powerful computers called Graphical Processing Units (GPUs), training CNNs has become faster. Plus, there's a wealth of labeled data and pre-trained networks available to the public, making it easier for everyone to use CNNs. In building a CNN, we used a tool called Keras Sequential API. It allows us to add layers one after the other, starting from the input. Each layer serves a specific purpose. For instance, the Conv2D layer helps identify different features in the image using filters. Then, the pooling layer simplifies the information, reducing the risk of overfitting (where the model memorizes the data instead of learning from it). To add complexity and make the CNN more adaptable, we introduced non-linearities using activation functions like relu. Also, to prevent the model from focusing too much

on certain details, we used techniques like Dropout, where some connections between neurons are randomly removed during training.

After identifying features, we need to flatten them into a single vector so they can be used by fully connected layers. These layers combine all the information and make predictions about the image, like what objects are in it. Choosing the right settings for training is crucial. We used a loss function called binary cross entropy to measure the difference between predicted and actual labels. For optimization, we employed the Adam Optimizer, which adjusts the model's parameters to minimize loss efficiently. During training, it's important to keep track of how well the model is doing. We used accuracy as a metric, which tells us how often the model predicts

the correct label. Another important factor is the learning rate, which determines how much the model adjusts its parameters during training. We used a technique called

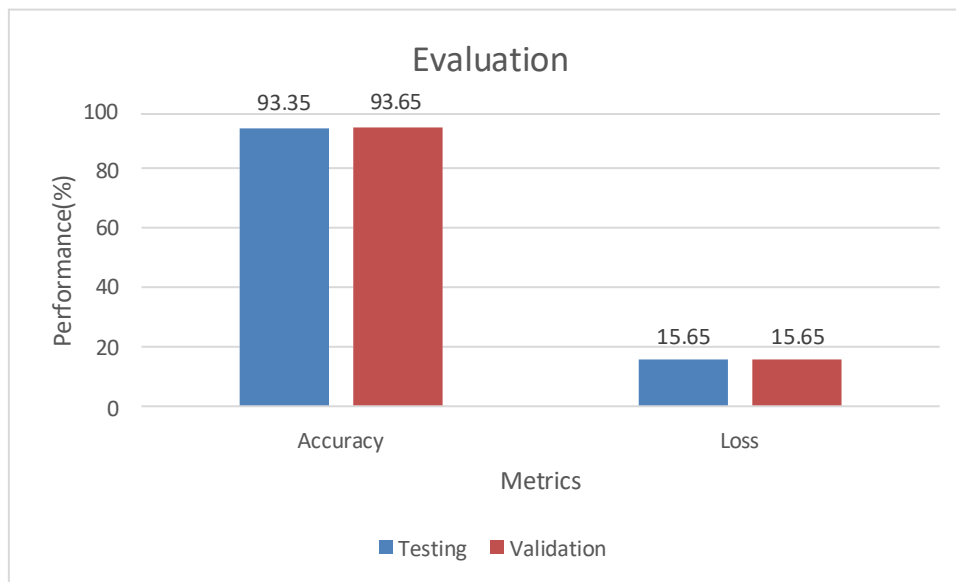
7. RESULTS

The more precise the model, the better. The accuracy and loss acquired are used to assess each model. This requires two levels of precision: Testing and validation precision accuracy. As a prerequisite to this, the Validation set is used for parameter

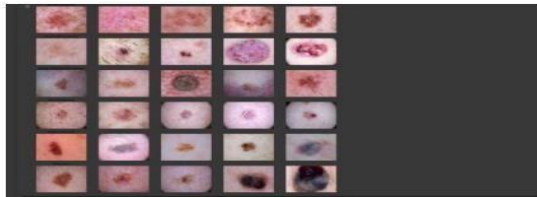
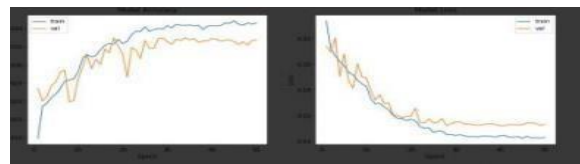
ReduceLROnPlateau to gradually decrease the learning rate as training progresses, helping the model converge to the best solution.

selection; in other words, it is distinct from the Train set. If your model achieves 90% accuracy during training and 89% accuracy during validation, it is anticipated that it will achieve 89% accuracy when presented with fresh data.

S.no	Evaluation		
	Metric/Parameter	Testing	Validation
1	Accuracy	93.35	93.65
2	Loss	15.65	15.65



accuracy



Input images

Predicted image

Graphical plotting

8. Conclusion

Detecting skin diseases is a significant challenge in healthcare, but it's manageable and reversible if detected early. Various methods are used to observe skin diseases, as per research findings. However, there's still a pressing need for early classification of skin diseases. Machine learning algorithms can play a crucial role in diagnosing skin disorders early. They allow users to adjust their skin tone and texture in real-time. Implementing these strategies correctly can

provide essential support and a coordinated approach to prevent skin issues. This will enable both patients and doctors to treat skin conditions more effectively. However, there is limited medical information available for research and practical use. In the future, advancements in AI for identifying skin diseases and the benefits of AI-assisted diagnosis could be explored further with real-time data.

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