JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

SKIN DISEASE CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

Sakshi Zagade, Shruti Sakpal, Dr. Santoshi Pote, Merrin Mary Solomon
Department of Data Science, Usha Mittal Institute of Technology,
SNDT Women's University, India

Abstract

The skin being the largest organ in the human body, comprises the epidermis, dermis, subcutaneous tissues, blood vessels, lymphatic vessels, nerves, muscles etc. Allergies, Pigmentation, Fungal development, bacteria, and microbes are some of the major grounds for the causation of several variations of skin diseases in humans. Such infections have chances of worsening as time progresses if proper treatment is not provided immediately. Hence, skin diseases or infections must be nursed promptly with the aim of avoiding the proliferation of such illnesses which might have fatal repercussions in the future. Advanced techniques and procedures for the classification of such illnesses based on Artificial Intelligence and machine learning models are now in increasing demand in the industry. But not all of them are freely available for the commoners. For that reason, the proponents came up with the suggestion of a Convolutional Neural Networks (CNN) based model for the identification of different skin diseases. We introduce a multiclass CNN model that helps categorize Healthy skin and skin being affected by 23 different classes of skin diseases. Our Purpose of the project is to detect the category of skin disease easily with increased accuracy. The first stage includes the image of the skin illness being subjected to various kinds of pre-processing techniques which is followed by feature extraction. Then the second stage involves Deep learning algorithms to identify diseases on the basis of analyzation and observation of the skin. The proposed system is highly beneficial in rural areas where access to dermatologists is limited.

Keywords: CNN, Feature extraction, Deep Learning, Skin diseases, Fast API

1. INTRODUCTION

With an approximate surface area of 20 square feet, the skin is the largest organ in the body. In addition to helping to control body temperature and shielding us from germs and the environment, skin also allows us to feel touch, heat, and cold. One of the most prevalent categories of disorders that individuals of all ages deal with is skin disease. The skin plays a significant role in maintaining the core temperature and in general, protecting our body from various skin maladies which is why the skin being healthy or illness-free is of extreme importance.

The diagnosis of skin conditions mostly depends on the dermatologists' experience and the findings of skin biopsies, which is, usually, a very time-consuming process. Even though skin diseases may seem harmless, they can pose a serious health risk if not treated effectively. Early symptoms of numerous diseases are similar, so diagnosing them at an early stage is challenging.

As technology continues to advance, as well as with different data mining approaches, treatments of skin predictive classification are becoming increasingly accurate and highly predictive. Consequently, automated assessment of these illnesses has become more valuable because of its capacity to provide accurate results faster than human analysis involving clinical laboratories. The goal of this topic is to develop an automated image-based system for skin disease detection and classification, which will improve diagnostic accuracy and alleviate the scarcity of human specialists. [1]

Skin disease classification is a crucial field of study because of the high prevalence of skin diseases and the need for accurate and timely diagnosis. Deep learning-based techniques, such as convolutional neural networks (CNNs), have produced encouraging results in accurately classifying skin diseases. CNNs are a kind of neural network that can automatically learn features from input data, making them well-suited for image classification tasks. [6] The first step in developing a CNN-based skin disease classification model is data acquisition. This involves collecting a large dataset of skin disease images that are labeled with their corresponding disease categories. The quality and diversity of the dataset are critical for the model's performance. [6,7] Once the data is acquired, it is pre-processed to remove noise and enhance image quality. The pre-processed images are then split into training, validation, and testing sets.

The next step is model development, which involves designing a CNN architecture that can learn features from the input images and put them in the appropriate disease category. The architecture typically comprises several convolutional layers for feature extraction from the input images., followed by pooling layers that lessen the number of dimensions in the feature maps. After being flattened, the convolutional layers' output is fed into fully connected layers that perform the final classification. The model is trained using the training set and validated using the validation set. Once the model is trained and validated, it is tested on the testing set to evaluate its performance. Developing a CNN-based skin disease classification model involves several steps, including data acquisition, pre-processing, and model development, and has the ability to greatly increase the precision and effectiveness of diagnosing skin diseases.

2. RELATED WORKS

The field of skin disease classification using Convolutional Neural Networks (CNN) has witnessed significant advancements, with several notable studies contributing to the understanding and improvement of this critical domain.

In a study conducted by Velasco et al. (October 2019), titled "A Smartphone-Based Skin Disease Classification Using MobileNet CNN," the authors introduced a novel approach to skin disease identification. They employed a CNN MobileNet model along with App Development, showcasing the potential of mobile technology in facilitating efficient and accessible disease classification. Their emphasis on oversampling and data augmentation techniques highlighted the importance of preprocessing strategies in achieving optimal classification accuracy. [1]

Amit R.S. and colleagues, in their research on "Potato Plant’s Disease Classification using CNN and Transfer Learning" (July 2022), explored the transferability of CNNs to agricultural contexts. Their work demonstrated that Transfer Learning models, when applied to plant pathology, offer simplicity in implementation coupled with a high degree of accuracy. This cross-disciplinary application underscores the adaptability of CNNs in diverse domains, including agriculture. [2]

In the realm of medical image analysis, Kritika Sujay Rao et al. delved into "Skin Disease Detection using Machine Learning." Their research focused on the application of Convolutional Neural Networks; a deep learning paradigm well-suited for image-based tasks. Their emphasis on the role of validation data in refining the accuracy of the system sheds light on the crucial aspect of dataset quality in skin disease classification. [3]

A noteworthy contribution by A. Kalaivani and Dr. S. Karpagavalli involved the "Detection and classification of skin diseases with ensembles of deep learning networks in medical imaging." The researchers employed a multi-model ensemble approach, combining various deep-learning techniques to achieve a remarkable accuracy of 96.1 percent. This approach reflects the potential of ensemble methods in enhancing the resilience of models used to classify skin diseases. [4]

Lastly, the study by Ashwaq Alsayed and team on the "Classification of Apple Tree Leaves Diseases using Deep Learning Methods" introduced insights from the application of ResNet-V2, a CNN architecture. Their findings emphasized the effectiveness of the Adam optimizer in transfer learning, and they suggested that increasing the number of instances could further improve classification accuracy, offering valuable insights for fine-tuning CNN models in skin disease classification. [5]

These diverse studies collectively contribute to the evolving landscape of skin disease classification utilizing CNNs, providing valuable insights, methodologies, and potential avenues for further research and improvement in this critical field.

3. PROPOSED MODEL

3.1 Dataset

This machine learning project starts with data collection. Data that we can use as a training dataset. In this case, we collected images of different skin diseases. The dataset was acquired through Kaggle which contains 19500 dermatologically tested images of 23 different skin diseases. The 23 different conditions of skin disorders that have been included in our dataset are as follows:

1. Acne and Rosacea Photos
2. Actinic Keratosis Basal Cell Carcinoma and other Malignant Lesions
3. Atopic Dermatitis Photos
4. Bullous Disease Photos
5. Cellulitis Impetigo and other Bacterial Infections
6. Eczema Photos
7. Exanthems and Drug Eruptions
8. Hair Loss Photos Alopecia and other Hair Diseases
9. Herpes HPV and other STDs Photos
10. Light Diseases and Disorders of Pigmentation
11. Lupus and other Connective Tissue diseases
12. Melanoma Skin Cancer Nevi and Moles
13. Nail Fungus and other Nail Disease
14. Poison Ivy Photos and other Contact Dermatitis
15. Psoriasis pictures Lichen Planus and related diseases
16. Scabies Lyme Disease and other Infestations and Bites
17. Seborrheic Keratoses and other Benign Tumors
18. Systemic Disease
19. Tinea Ringworm Candidiasis and other Fungal Infections
20. Urticaria Hives
21. Vascular Tumors
22. Vasculitis Photos
23. Warts Molluscum and other Viral Infections

3.2 Data Pre-processing

There are 19500 dermatoscopic images in this dataset. The data is divided into training data, which consists of 15500 images overall, and testing data, which consists of 4000 images, using a random (rand) function. In which the training data is further divided into 90% as actual training dataset (215 images) and the remaining 10% as validation dataset (25 images). For Data cleaning and preprocessing, we will be using tf data set and data augmentation. The dataset under consideration exhibits a slight imbalance, with certain skin diseases having a higher frequency than others. We employed data augmentation, a technique that balances the data and produces additional images by rotating or transforming the preexisting data, to solve such issues.

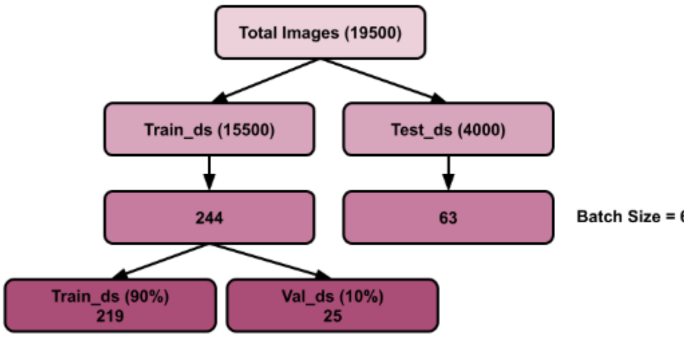

Fig.1. Dataset Distribution

Figure 2 shows some sample images from the dataset

Fig.2. Sample Dataset

3.3 Model Building

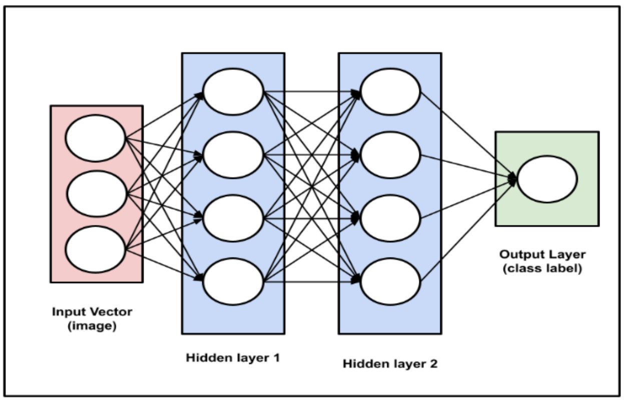

Fig.3. CNN Architecture

Once the dataset is acquired and pre-processed, a significant step in our skin disease classification project involves model building using Convolutional Neural Networks (CNNs). CNNs are considered a standard and effective approach for image classification tasks. Leveraging this deep learning architecture, our objective is to train the model to recognize patterns and features indicative of different skin diseases.

This stage focuses on building a Convolutional neural network and training that network on the train dataset. Followed by measuring the accuracy on the test dataset. CNN (Convolutional Neural Network) is a particular kind of deep learning method that's mainly employed for image identification and classification jobs. CNN's many layers include convolutional, pooling, and fully connected layers. To extract features from the image, a sequence of learnable filters is convolved with the input image in the convolutional layers. The feature maps created by the convolutional layers are subsequently down-sampled by the pooling layers. The classification operation is then carried out by the fully linked layers using the extracted features.

Similarly, this model comprises a set of different layers and the first layer is resize and rescale. Two distinct operations that are frequently carried out on images as part of the pre-processing step are referred to as resizing and rescaling. Resizing is the process of altering an image's dimensions while preserving its aspect ratio. When the input images are not all the same size, this can be helpful. On the other hand, rescaling is the process of altering an image's range of pixel values. Usually, this is done to guarantee that the pixel values fall inside a specific range, such 0 to 1. The input data can be normalized in this way to enhance the training process and the model's functionality. The second layer performs data augmentation which is required as we might not have enough diverse set of images, so we rotate, flip, and adjust contrast to create more training samples.

The third layer is the actual convolutional layer whose function is to execute the mathematical operation of convolution to extract features from input data, such as an image. Convolution works by moving a small filter or kernel over the input data and computing a dot product between the filter and a small area of the input at each place. A new output tensor is created as a result of this procedure, and it comprises details on the existence and positioning of different features in the input data. By learning the filter during training, the convolutional layer may automatically identify important patterns in the input. We employed the activation function "relu," which is commonly used for the hidden layers because it's very fast to compute.

The pooling layer is the next layer in our model. A pooling layer is used to reduce the spatial dimensions of the input image while conserving the important features. There are two types of pooling layers: Max Pooling and Average Pooling. The most prevalent kind of pooling layer and also the one which we implemented in our model is termed a max pooling layer, which divides the input image into a number of non-overlapping rectangular sub-regions and outputs the highest value of each sub-region. [6,10]

Then the result of the previous layer needs to go through the Flattening layer which is a process of transforming the output from the convolutional layers into a one-dimensional feature vector that can be fed into a fully connected layer for classification or regression. The fully connected layers require a 1-dimensional input vector, whereas the convolutional layers produce a 3-dimensional tensor, necessitating this flattening step. Important spatial information from the input picture is retained in the flattened feature vector, but in a way that the fully connected layers can handle it.

The dense layer is the next layer which is a fully connected layer that comes after the convolutional and pooling layers. The convolutional and pooling layers' newly discovered features are used by the dense layer to categorize the input image. Every neuron in the earlier layer is connected to every neuron in the present layer by a dense layer, resulting in a matrix multiplication operation that produces a vector of scores that indicates the likelihood that the input image belongs to each potential class. The SoftMax activation function, which normalizes the scores and generates a probability distribution over the various classes, is often fed the dense layer output. The predicted class for the input image is then determined by selecting the class with the greatest probability. [6]

3.4 Methodology and Implementation

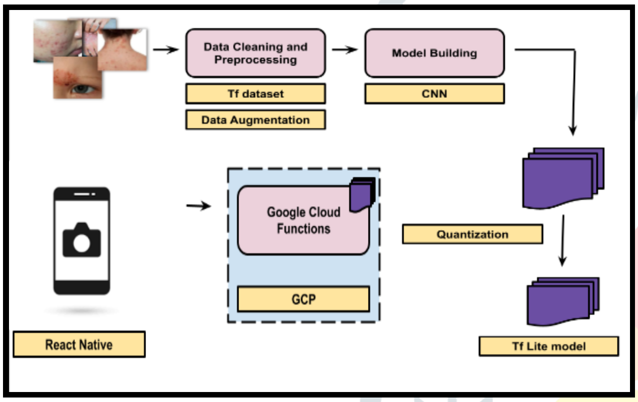

Fig.4. Methodology

Following the training phase, the next step is to export the trained model onto our disk for further deployment. This exportation process ensures that the model is preserved and can be readily accessed for subsequent phases of the project.

Moving forward, we delve into the concept of ML Ops, where we employ Tensor Flow serving (TF serving). A Tensor Flow server is configured to run on top of the exported model, and this server is then invoked from a FastAPI. This integration ensures seamless and efficient serving of the trained model, laying the foundation for the operationalization of machine learning processes.

The subsequent phase involves mobile app development, a pivotal step to make the skin disease classification accessible and user-friendly. To deploy the model on a mobile application, we employ quantization and conversion techniques to transform the model into a Tensor Flow Lite (tf lite) format. This optimized version of the model serves as the core component for the mobile app, enhancing efficiency and responsiveness. [7]

The Android application is crafted using Java, ensuring compatibility with a wide range of devices. This application becomes a user-friendly interface for individuals seeking quick and precise categorization of various skin diseases. Users can input a picture of the affected region of their skin into the prototype. The application, through image processing techniques, swiftly analyses the input image, providing an almost instantaneous output by displaying the detected skin disease.

In summary, our project integrates data acquisition, model building with CNNs, ML Ops with TF serving, and mobile app development to create a comprehensive system for efficient and user-friendly skin disease classification. The seamless flow from dataset acquisition to mobile application demonstrates a holistic approach aimed at providing timely and accurate assistance in identifying skin diseases.

4. RESULTS AND DISCUSSION

Convolutional Neural Networks (CNNs) stand out as a formidable tool in the realm of model building, particularly for image classification tasks. Their superiority over traditional Artificial Neural Networks (ANNs) lies in their ability to capture intricate patterns and hierarchical features present in images. The robustness and accuracy exhibited by CNNs make them a preferred choice when constructing models for image-related applications.

In our project, we successfully leveraged the power of CNNs to achieve a commendable model accuracy of 69 percent. This accuracy is a testament to the effectiveness of CNNs in discerning complex patterns within skin disease images. However, it is important to note that the accuracy of any image classification model is intricately tied to the size and quality of the dataset used for training. Our achievement of 69 percent accuracy underscores the significance of a carefully curated dataset in the model development process.

The observed accuracy is not a fixed metric; rather, it is influenced by various hyperparameters. These hyperparameters include learning rates, optimizer functions, activation functions, dropouts, batch size, and more. Fine-tuning these parameters becomes crucial in optimizing the model's performance, and their careful consideration contributes to the overall effectiveness of the skin disease classification system.

To enhance user interaction and convenience, our application features an intuitive front end, as depicted in the attached images. Users are presented with two convenient options: capturing an image through the camera or uploading one from the gallery. Once an option is selected, the chosen image is transmitted to the backend, where the CNN structure is applied. The backend processing involves the intricate analysis of the image using the trained model. Subsequently, the final output or result is presented to the user, offering a swift and precise categorization of the skin condition.

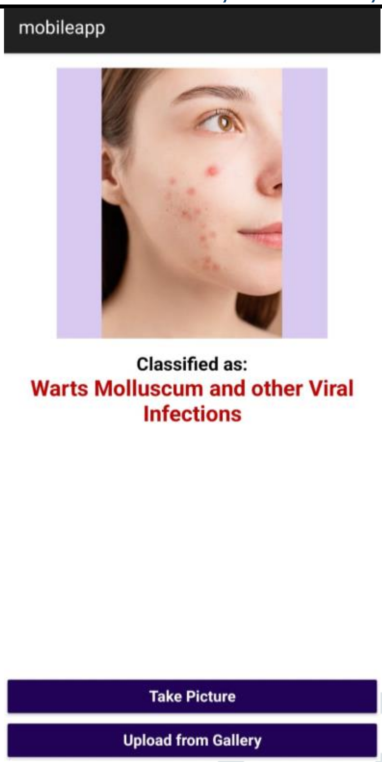

Fig.5. Mobile App Result (1)

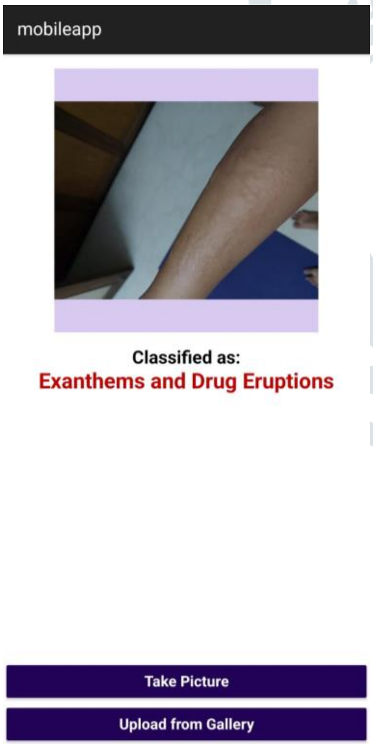

Fig.6. Mobile App Result (2)

5. FUTURE WORK

India boasts a rich heritage of traditional natural remedies and authentic medicinal practices that have been integral to its culture. These natural remedies, deeply rooted in traditional medicine, continue to hold immense value as potent medicinal resources in the country. They have proven effective in alleviating troublesome symptoms and have been a reliable source of healthcare for generations.

However, with the rapid pace of modernization, there is a growing concern that the upcoming generations may lack awareness about the potent remedies available at home. These remedies, often derived from natural sources, have the potential to address health issues at their early stages, providing quick and effective relief. Recognizing this gap in knowledge, our application seeks to bridge the generational divide by not only detecting and classifying skin diseases but also by offering insights into relevant home remedies that can be employed for holistic well-being.

Skin diseases can be influenced by various factors, both direct and indirect. These factors include environmental conditions, food allergies, irritants, genetic makeup, certain diseases, and the immune system. Additionally, the geographical location of an individual can play a vital role in understanding the root cause of a skin condition. For instance, in urban areas like Delhi, where issues like eczema and allergies are exacerbated by toxic air, there is a growing concern about the impact of the environment on skin health. This application can be implemented to further use the user's location as one of the parameters in classifying skin diseases, offering a more tailored and contextualized healthcare solution.

This system can also help in providing the user with the nearby hospitals and dermatologists details which would be helpful. This feature can serve as a valuable resource, facilitating prompt medical attention and further enhancing the user's experience with a seamless transition from disease detection to medical consultation.

In essence, our application not only leverages technology to identify and classify skin diseases but also integrates traditional wisdom and local context. By incorporating home remedies and considering geographical factors, it strives to empower users with a comprehensive healthcare solution that aligns with India's rich tradition of natural remedies while addressing the evolving healthcare needs of the present generation.

6. CONCLUSION

In conclusion, the Skin Disease Classification using CNN project represents a significant stride in leveraging advanced technology for healthcare. The utilization of Convolutional Neural Networks has proven instrumental in achieving a commendable level of accuracy in the classification of skin diseases, offering a robust solution for timely diagnosis. The project not only showcases the power of CNNs in discerning complex patterns within medical images but also emphasizes the potential for technology to enhance healthcare accessibility. By providing a user-friendly interface for skin disease detection and classification, this project contributes to the productivity and responsiveness of medical diagnostics. Beyond its technical achievements, the project has broader implications for healthcare, bridging the gap between cutting-edge technology and the critical need for accurate and quick disease identification in the field of dermatology.

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