Categorization of Integumentary System Disorders using Deep Learning

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***Abstract*— People in today's world are busy and occupied all of the time. We often overlook minor illnesses in our bodies as a result of our fast-paced lives. Skin disease is one of them. It is the most widespread disease on the planet. People generally consider dermatology problems as ephemeral, though that's not always the case. If the skin disease is not appropriately recognized, it might cause serious complications. The project's current models use segmentation techniques such as edge detection; however, our study seeks to diagnose skin disorders with high accuracy rates utilizing Deep learning. Our goal is to use CNN (convolutional neural networks) and transfer learning from the Inception model to identify and categorize skin disorders. This research seeks to inform victims of the potential repercussions and assist doctors in making an initial diagnosis. This is being implemented in both a web application and an Android application.**

Keywords*— *Integumentary system, Deep learning, Diagnosing integumentary system diseases, CNN, Image classification, Computer Vision, Transfer Learning.

I. Introduction

AI is a broad term for intelligence exhibited by machines; we are witnessing a wide-reaching integration of AI into human life in the next few decades. Digital assistants, for example, help us with day-to-day tasks and give us information when we need it. Web searching is becoming increasingly accurate and efficient thanks to AI's predictive capabilities; an example is AI-powered web search. It has increased and can now give you accurate answers to your questions, which would have taken hours of research before. The disease detection or natural catastrophe forecasts are far more accurate than they were twenty years ago.

With the massive amount of data generated every day, it is natural that AI plays an essential role in the future of daily life. Artificial intelligence has been a topic of discussion for a long time, and it seems that it is finally reaching a point in which it can impact our day-to-day lives. Deep learning is a subdivision of AI. It aims at developing algorithms that analyze vast datasets to learn how to perform specific jobs.

Deep learning involves neural networks made up of multiple layers. These networks mimic the behaviour of the brain. Neural networks are at the core, and they provide the best results with unstructured data. This form of AI allows for more accessible training and better returns on investment. There are many advantages; one advantage is the high accuracy it provides with unstructured data. Deep learning outperforms machine learning when it comes to addressing complicated problems. The deep learning models' accuracy is high, and their predictions are close to humans.

Most people do not know how to take care of it when it comes to skin. It is a sensitive and delicate organ that needs care and affection. An estimated 1 in 3 people have a skin disease at any time. The human body has many potential entry points for parasites and bacteria to get inside and infect us with various ailments. Without a proper diagnosis, the disease will likely worsen. Some common skin diseases are eczema, psoriasis, acne, rosacea, and ichthyosis.

Classifying integumentary system disorders using deep learning is one of the most challenging tasks for medical professionals. The accuracy of a computer-based diagnosis for a patient can help save time and money by providing a more accurate diagnosis. An important step in diagnosing a medical condition is to classify it as a certain type of disorder. This classification may be done using, for example, the ICD codes or the DSM-5 codes. To classify the group of International Classification of Diseases (ICD) codes into a suitable category, we use deep learning approach. Our results show that our method outperforms current methods in terms of both accuracy and efficiency.

Our goal is to four classify integumentary system disorders namely Acne, Psoriasis, Ringworm and Eczema using Deep learning. The model is trained using images of each disease as input. The images are fed to the deep learning layers, which adjust the weights of the neurons for every epoch. This model uses an Inception v3 neural network with 48 layers and an additional five dense layers for training photos of distinct classes. After completion of training the testing phase carried out to determine the accuracy of the model.

II. Literature Survey

Integumentary system disorders affect 71 percent of the world's population, almost three-fourths of humankind. Ailments of the integumentary system are the third most prevalent illness, and many who suffer from them do not consider them a significant problem that requires medical attention [2].

Depending on the skin state, the appearance of skin conditions in dermoscopy images might differ significantly. Hair, texture, and bubbles may further obfuscate the distinction between skin infections and neighbouring clear skin. As a result, dermoscopy image classification is a complicated process [4]. We are deploying cutting-edge deep learning technologies to take on this complex task.

When compared towards other ml algorithms, deep learning has been used to perform exceptionally challenging

Fig. 1. Eczema

Fig. 2. Ringworm

Fig. 3. Acne

Fig. 4. Psoriasis

classification and segmentation jobs [32], [33] with great accuracy. The framework of the system is based primarily on convolutional layers [31].

Characteristics in the initial layers of deep learning network topologies are typically broad, while high-level features are often particular. Yosinski et al. [34] demonstrated that using model parameters transmitted from different jobs to initialize networks enhances results compared to arbitrary parameters [24].

[2] Digital dermatology: Skin disease detection model using image processing, this paper uses algorithms like DCT (Direct Cosine Transform), SVD (Single Value Decomposition) and DWT (Direct Wavelet Transform) According to this paper, the attained accuracy for detecting skin disorders is 80%. The model's reliability would have increased greatly if neural networks had been utilized to train the images.

[7] Diagnosis of skin diseases using Convolutional Neural Networks, this paper solely relies on convolutional neural network (CNN) and achieved accuracy of seventy percent. The paper claims that accuracy can be improved if larger dataset is used. The model's accuracy would have improved significantly if the transfer learning approach had been used. Our model was also trained with around one thousand two hundred pictures of skin diseases and tested with two hundred images but achieved around ninety percent accuracy.

[3] Face Skin Disease Detection with Textural Feature Extraction, this paper aims at classifying skin face skin disease detection using K-nearest neighbour algorithm which produced an accuracy of eighty percent. If Deep learning is utilized and transfer learning is implemented then the efficiency of the model would have enhanced greatly.

III. Proposed System

The proposed system seeks to develop a deep learning model to identify integumentary system disorders accurately. The prototype is made available in both web browsers and mobile applications. The proliferation of smartphones has made cameras readily available to everyone; this makes the disease diagnosis more interactive and straightforward. The system is not intended to replace a doctor's participation in the diagnosis completely; rather, it is intended to provide a preliminary diagnosis to understand the condition better. Uploading a picture through a generic camera with ample light is sufficient for recognizing the disease. Fig 1,2,3,4 are the diseases trained in this model. The reason to choose these diseases is that they are widespread among people [14].

A. Model

The dataset was curated from the pictures of the disease on the internet. The model is trained using around three thousand samples. To augment the size of the dataset, we are using the ImageDataGenerator method in TensorFlow framework, which feeds the images in to the model by rotating, shifting the width and height, shear transforming, magnifying, flipping and varying the brightness of the image for every epoch. To further improve the model's accuracy, we are increasing the contrast of the image, which enhances the colours of the image. Any image resolution is tolerable since it will be converted to the standard size for model processing. The model requires inputting age, area of infection, sex to improve the model results further. The enhanced image is passed on to the trained model to receive the output of the disease name. The model predicts the name of the disease with 90.28% accuracy.

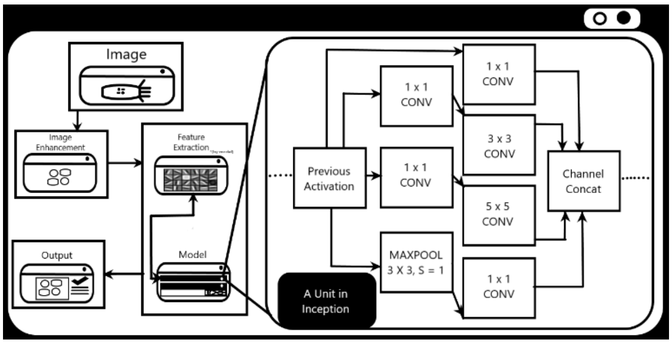

Fig. 5. System Architecture

IV. Methodology

Though other image classification methods are available, like SVM, we use CNN (Convolutional neural networks) because it accurately picks the features from the image through filters and efficiently compares the adjacent pixel. CNN also automatically learns the features of an image which is not the case with other algorithms. The dataset is initially divided into test, train and validation datasets. The train dataset is used to train the model, i.e., it helps the model to understand and recognize the pattern. The test dataset is used to run the trained model to predict the accuracy. The validation dataset is utilized to fine-tune the model's hyperparameters, such as learning rate. The model employs transfer learning method to predict the integumentary system diseases. The advantage of this method is that it improves the accuracy of the model compared to a model trained from scratch. Out of all the neural network models, the proposed system uses the

Inception network developed by Google. The Inception network is trained with a million pictures and the number of convolutional layers are 48.

A. Convolutions

Convolution is a convolutional neural network method that includes the product of a weight matrix with the inputs. The multiplication is done between input data and 2D matrix of values, named filter.

The dot product is used to multiply the corresponding size of the filter in the input with the filter. dot product is the element-wise product of the input and filter's area, always yielding a specific value when totaled. Different types of filters are available as per our requirement, like edge detection filter and sharpen image filter. These filters also have a bias factor that can adjust the bias in a specific layer.as shown in Fig. 6.

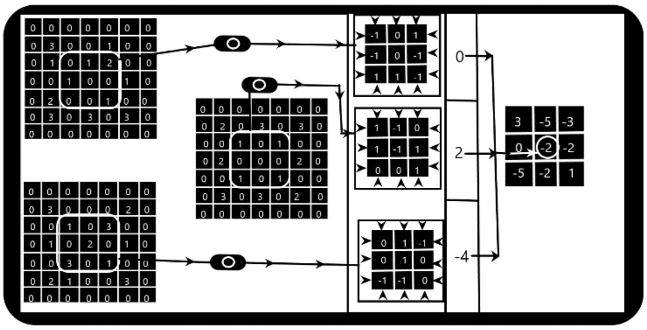

Fig. 6. Working of convolutional layers

The general formula for calculating the output volume involves V is input volume size, F is kernel size, S is stride length, P being padding.

$$\frac{V - F + 2P}{S} + 1$$

Convolutional networks use an activation function, ReLU (Rectified Linear Activation Unit) function is generally used in most neural networks since it offers excellent performance and is easier to train the model. The general equation of ReLU is

$$Re(Z) = \max(0, Z)$$

The ReLU is a widely used activation function which doesn't change the value of the input if it is greater than zero and if the input value is less than zero it outputs the value as zero. The computation of cost for using this activation function is very low in comparison with other activation functions like sigmoid, tanh, etc. Plotting the graph for the below function where x is the input and f(x) is the activation (ReLU) can be observed in Fig.9.

$$f(x) = \begin{cases} 0, for\ x < 0 \\ x, for\ x \geq 0 \end{cases}$$

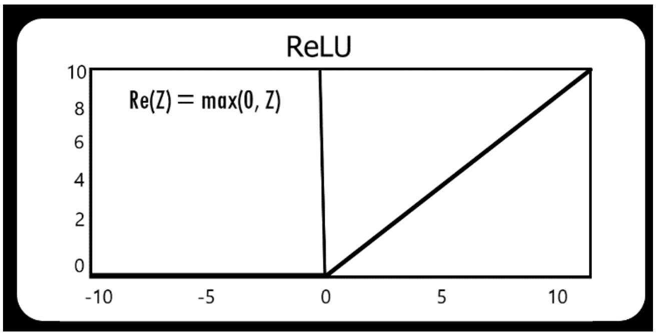

Fig. 7. ReLU graph

Pooling is a technique used to reduce the image size, for example, decreasing from 8x8 image to 4x4 image. As depicted in Fig.10, Max pooling is employed in the Inception network. Based on the stride length, the maximum value in the patch of input image is considered.

$$f_{(u,v)}(I) = {}_{m,n=0}^{\;1}MAX\ I_{(2U+m,2V+n)}$$

In the above equation I is the matrix, U, V are the axes with 2x2 filter and number of pixels shifted also called as stride length is 2. The max of 2x2 filter with stride length of 2 is applied as shown in Fig. 10.

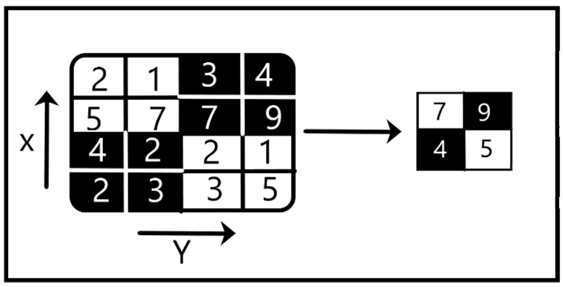

Fig. 8. Max pooling.

1x1 convolution layers are used in the Inception network to decrease the complexity i.e., they are capable of reducing CNN output layers, for example, 8x8x22 can be reduced to 8x8x10, as shown in Fig. 8.

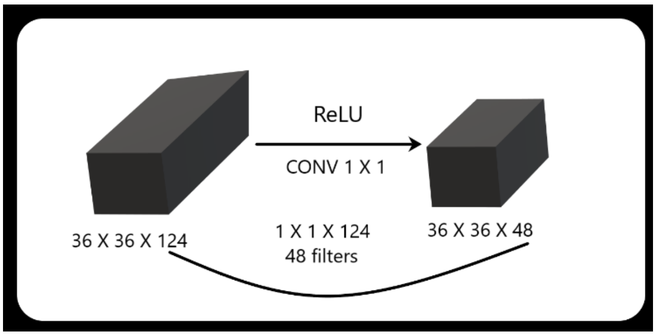

Fig. 9. 1x1 convolution

B. Transfer Learning

The number of images required to train the model is drastically reduced using transfer learning technology. Generally, transfer learning is used when large dataset of pictures are not available. It also helps save the system's resources and does not compromise accuracy. In this paper, we use Inception network v3 though many architectures like VGG and Alexnet are available.

Formal learning is unique to each project and we need to train the model for a specific task. There is no provision for transferring the acquired knowledge to another model. This is a huge drawback since training models again and again for similar projects takes up many resources. Transfer learning enables us to use pre-trained models' information to train new models and even solves challenges like insufficient data for the newer model.

The components used in Inception neural network consists of 1x1 convolution, Max pooling and convolution filters with 3x3 and 5x5 filters which can be observed in Fig. 9,8,6. The architecture of inception can be observed in the Fig.4.

Neural networks are designs with many hyperparameters that may be customized. The first layers capture general information and the following layers concentrate on the individual job. When training again, we can lock specific layers or use fine-tuning for the remainder to fulfill the requirements. With careful study of the architecture, we can use instances of the Inception network as our starting point of the model. With this feature of transfer learning, we can get the best efficiency in minimal time, as depicted in Fig. 11.

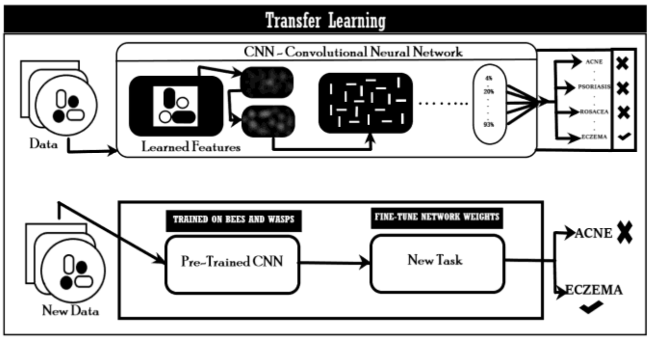

Fig. 10. Transfer learning

The general definition for Domain, Task to understand Transfer Learning definition is as follows, Domain: Let X be the domain and can be defined as X=$\{K, P(L)\}$, where E is feature space, P(L) is marginal distribution and L = $\{l|l_j \in K, j = 1, \dots, n\}$. Task Y is made up of label space W and a decision function g which can be defined as $Y = \{W, g\}$ and g is learned from the data.[35]

The definition of transfer learning is as follows, assuming an observation pertaining to $a^M \in Q^+$ source domain and task i.e., $\{(X_{M_u}, Y_{M_u}) | u = 1, \dots, a^M\}$, and observation about $a^Y \in Q^+$ target domain and task i.e., $\{(X_{N_v}, Y_{N_v}) | v = 1, \dots, a^N\}$, transfer leverages information from the source domain to maximize the efficiency of trained decision functions g^{Y_v} (v = 1,..., a^N) on the target domain [35][36], where a is number domains, X_M is the source domain, Y_M is the source task, X_N target domain, Y_N is the target task and Q is the Iteration or kernel number.

With the help of pooling and applying convolutions, we can adjust the picture's resolution to our project's requirements. The Inception is very flexible in doing so.

As shown in Fig.1. System architecture uses multiple components like convolutions, 1x1 convolutions, and max pooling to form a unit in the Inception network. These individual units are combined to form the Inception network.

SCREENSHOTS

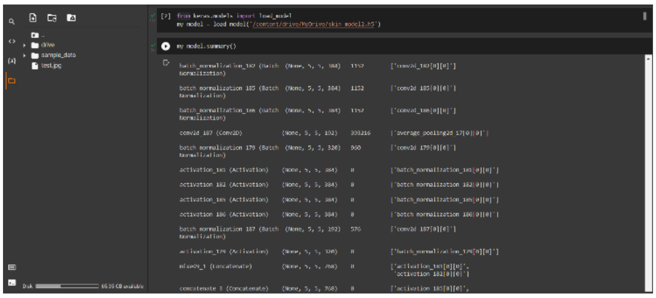

Fig. 11.1 Summary of the model

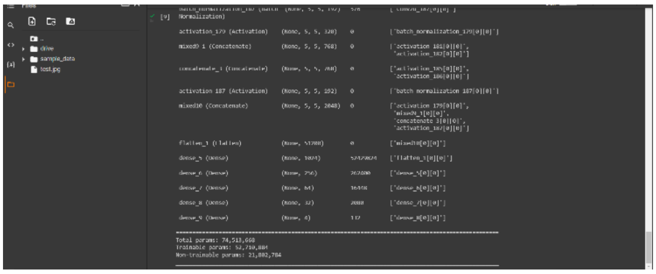

Fig. 11.2 Summary of model

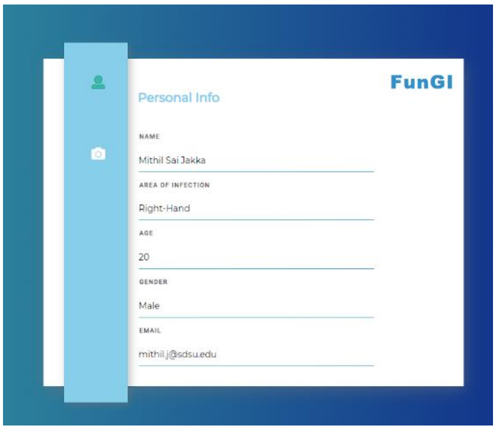

Fig. 12. Entering details of the victim

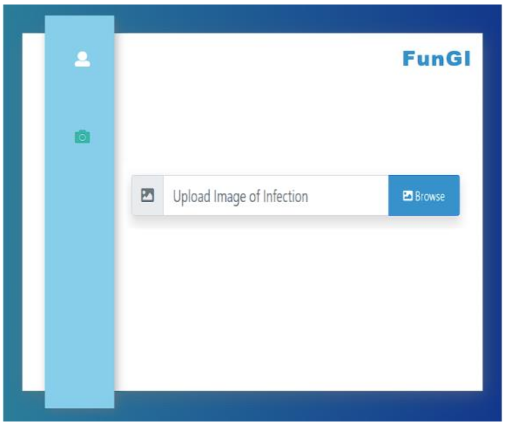

Fig. 13. Uploading the image of the affected area

Fig. 14. Detailed diagnosis of the disease with downloadable report

V. CONCLUSION

This paper explained the method used to detect integumentary diseases by employing Deep learning technology. With the help of transfer learning technique and utilizing Inception neural network, high accuracy can be achieved with a minimal number of images in a dataset. This system cannot replace experts, but it can assist the patient in making a preliminary diagnosis. The model summary is as follows, total parameters: 74,513,668 trainable parameters: 52,710,884 non-trainable parameters: 21,802,784. The prototype created using this method predicted integumentary system disorders with 90.28% accuracy.

VI. FUTURE ENHANCEMENTS

There is ton of scope in research topic. To further improve the model's reliability, regularly spaced shifting and adversarial networks can be employed. The training dataset used in this paper is around one thousand two hundred, to achieve the accuracy above 95% at least for each disease 1500 images i.e., around 7000 images should be used.

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