School of Computer Science and Engineering

VIT-AP

AMARAVATI, INDIA

522237

SKIN DISEASE DETECTION AND CLASSIFICATION USING IoT AND DEEP LEARNING

Project Report

Submitted By:

P. NITHIYASRI (20BCE7035)

POOJITHA GOTTIMUKKALA (20BCE7179)

RAKESH MEHTA (20BCI7051)

HARSHAVARDINI (20BCE7439)

RANJEETA PATHAK (20BCE7188)

MADHAV RAV TRIPATHI (20BCE7109)

Under the Esteemed Guidance of

DR. P. KUPPUSAMY

School of Computer Science and Engineering

Submitted for the Course:

ENGINEERING CLINICS

(EC ID- 230400)

WINTER SEM 2022-2023

ABSTRACT

Skin diseases are among the most common of all human health afflictions and affect almost 900 million people in the world at any point of time. The traditional method of identifying skin diseases involves a biopsy, which can be invasive, time-consuming, and expensive. This experiment of detecting skin diseases is conducted based on deep learning concepts using 2 approaches, with the former one being object detection (using YOLOv7 working principle) and the latter one being the application of transfer learning techniques using convolutional networks such as VGG19, Alex Net and ResNet50. An accuracy of 98.09% is obtained from the VGG19 model, 85.27% is obtained from the Alex Net model, and 76.13% is obtained from the ResNet model. Hence, VGG19 has performed comparatively better than the other 2 approaches. Results obtained from these 2 approaches are displayed with a detailed comparison. Inferences are drawn from the conducted research and future scope for further improvement of the proposed project is inferred.

CONTENT

1. INTRODUCTION

Skin diseases have become increasingly common worldwide in recent years. Factors such as environmental pollution, genetics, climate change, lifestyle changes and use of cosmetic products are some of the major contributors to the development of these diseases. They have made a great impact as other serious medical conditions when assessed by effects on health-related quality of life. They have become increasingly prevalent worldwide, affecting people of all ages, genders, and ethnicities. These conditions can range from mild irritations to severe and life-threatening diseases, such as melanoma. They can have a significant impact on health-related quality of life, causing discomfort, pain, and psychological distress.

Environmental pollution, including exposure to air pollution, UV radiation, and toxins, is one of the major contributors to the development of skin diseases. Studies have shown that exposure to pollution can cause skin aging, pigmentation disorders, and skin cancer. Genetic predisposition also plays a significant role, with some skin diseases having a hereditary component. Climate change is also emerging as a factor, with changes in temperature and humidity levels contributing to skin problems such as eczema and fungal infections. Lifestyle changes, including diet, exercise, and stress levels, can also affect skin health. For example, a diet high in sugar and processed foods can lead to inflammation, which can exacerbate skin conditions such as acne and rosacea. Physical activity can improve overall health and reduce stress, which can have a positive impact on skin health. Conversely, high levels of stress can worsen skin conditions such as psoriasis and eczema. The use of cosmetic products, including makeup, skincare products, and hair care products, is also a significant contributor to skin diseases. Some cosmetic products can cause skin irritation, allergic reactions, and acne breakouts. Furthermore, the use of counterfeit or expired cosmetic products can increase the risk of infection and other adverse effects.

(a) (b) (c)

(d) (e)

Fig. 1. Images of the Skin Diseases Used: (a) Acne (b) Vitiligo (c) Tinea Ringworm Candidiasis (d) Melanoma and (e) Eczema

The existing system of identifying skin diseases uses a biopsy process, where a tissue sample is taken from the affected area and analyzed by physicians. This process can be time-consuming, expensive, and invasive. However, with new advancements and innovations in medical technology, deep learning has emerged as a promising tool for skin disease identification and diagnosis. Deep learning is a type of artificial intelligence that enables computers to learn from data and improve their performance without being explicitly programmed. In the context of skin disease diagnosis, deep learning algorithms can be trained on large datasets of images of skin lesions, enabling them to accurately identify different types of skin diseases. These algorithms can analyze images of skin lesions and generate real-time diagnoses, without the need for invasive procedures such as biopsies. The algorithms can also provide differential diagnoses, identify potential underlying causes, and recommend appropriate treatments.

The use of deep learning algorithms for skin disease diagnosis has several advantages. Firstly, it can provide faster and more accurate diagnoses, enabling earlier interventions and reducing the need for invasive procedures. Secondly, it can improve access to dermatological care, particularly in areas with limited resources, where there may be a shortage of dermatologists. Finally, it can help overcome limitations in human expertise, particularly in the case of rare or complex skin diseases. It has the potential to revolutionize the diagnosis and management of skin diseases.

Accordingly, we have proposed a system for skin disease detection which has been designed using the You Only Look Once (Yolo) algorithm, which is a state-of-the-art deep learning algorithm based on Convolutional Neural Networks (CNNs). Yolo is a real-time object detection algorithm that can detect multiple objects in an image and assign them to their corresponding class. In the context of skin disease detection, Yolo can be trained on a large dataset of images to detect different types of skin lesions and assign them to their respective categories. The system will analyze and process the image data based on various features of the images. It will take in images of skin lesions, pre-process them to enhance their quality, and then input them into the algorithm, which will analyze the images and output the types of skin lesions detected in the images along with their location within the image. The system will utilize computational techniques to analyze the image data and extract relevant features that are indicative of different skin lesions.

Once the system has analyzed the input image, the results will be displayed on a screen. The user can then access the results through a mobile application that has been developed for this purpose. The mobile application will provide detailed information about the detected skin lesion, such as its type, severity, and recommended course of treatment. The mobile application will be designed to be user-friendly and easy to navigate, enabling patients to access their skin disease diagnosis and treatment information quickly and easily.

Altogether, the proposed system based on the Yolo algorithm, in conjunction with the mobile application, has the potential to improve the accuracy and efficiency of skin disease detection and management. By enabling patients to access their diagnosis and treatment information easily and conveniently, this system can improve patient outcomes and reduce the impact of skin diseases on health-related quality of life.

2. LITERATURE REVIEW

Over the years, various researchers have proposed image processing-based techniques for the detection and classification of skin diseases. These techniques are designed to automate the process of skin disease diagnosis and enable early detection, leading to timely treatment and better patient outcomes. Here, we will go through a concise overview of some of the techniques that have been reported in the literature.

Papers [1] and [2] propose an image processing-based method to detect skin diseases. The method takes the digital image of disease affected skin area, then uses image analysis to identify the type of disease. The approach works in the inputs of a color image which is resized to extract features using a pretrained Convolutional Neural Network. In the research paper [1], features have been classified using Multiclass SVM. The system successfully detects 3 different types of skin diseases with an accuracy rate of 100%. The proposed system in paper [2] has used Pycharm based python script for experimental results.

Research paper [3] presents the You Only Look Once (Yolo) algorithms, which are based on DCNNs applied to the detection of melanoma. The Yolo algorithms comprise

YoloV1, YoloV2, and YoloV3, whose methodology first resets the input image size and then divides the image into several cells. According to the position of the detected object in the cell, the network will try to predict the bounding box of the object and the class confidence score. The test results indicate that the mean average precision (mAP) of Yolo can exceed 0.82 with a training set of only 200 images.

The research paper [4] details a process in which input images acquired through an android application are analyzed to predict the presence or absence of a skin disease in a new input image. The application utilizes a question-and-answer format to predict the type of skin disease based on the user's responses. The proposed system then recommends potential treatments, including medication and surgery, based on a trained model for skin diseases like Eczema, Fungal infection, and Urticaria. However, it is important to note that the performance of the question-and-answer application in providing accurate results is not always consistent.

Paper [5] highlights the significance of skin diseases, which have become increasingly common due to environmental changes leading to a rise in skin allergies. The paper proposes the use of image processing and data mining techniques, and experimental results were obtained using the MATLAB tool. The input images were sourced from the dataset. The paper highlights the significance of skin diseases, which have become increasingly common due to environmental changes leading to a rise in skin allergies. The paper proposes the use of image processing and data mining techniques, and experimental results were obtained using the MATLAB tool. The input images were sourced from the dataset.

The methodology presented in [6] involves initially extracting image features as the first step in detecting skin diseases. The accuracy of the system is directly proportional to the number of features extracted from the image, with a higher number of features resulting in greater accuracy. The author has successfully applied this method to identify nine different types of skin diseases with an accuracy of up to 90%.

The proposed system described in reference [7] utilizes various pre-processing techniques, including the use of dull razors and median filters, to eliminate hair and other types of noise from the images. Next, the images are segmented using a technique that sets a pixel limit in order to distinguish between lesions and the background of the image. The system then performs feature extraction, which captures the key aspects of dermatology and epiluminescence microscopy (ELM), such as asymmetry, border irregularity, color variation, and diameter (ABCD). Additionally, the system employs a genetic algorithm (GA) to identify the most discriminative subsets of features, thereby improving the accuracy of classification. The proposed system was evaluated using 100 images from the Dermofit dataset from

Edinburgh Research and Innovation, achieving an average accuracy of 92% and 84% for the classification of benign and malignant skin lesions, respectively.

An automated method using color images and HSV components was implemented in paper [8] to detect malignancy in skin diseases. Its aim is to enable early diagnosis and it includes robust lesion detection through segmentation.

Paper [9] presents an image processing-based approach for diagnosing skin diseases, where digital images of the affected skin area are analyzed to identify the type of disease. The study used 100 skin images from both dermatological disease patients and the internet, with 20 images used for validation and 80 for training. The proposed system achieved a 100% accuracy in detecting three different skin diseases, with a high detection rate for each disease.

Paper [10] proposes a method to analyze skin disease patterns. Images are prepared by removing noise and enhancing pattern visibility. Features are extracted to create a classification model to predict the disease. The system asks the user questions to further determine the disease type and condition using data mining. Finally, the system suggests medical treatment or advice based on the predicted skin disease result.

In Paper [11], a new method is presented for segmenting pigmented skin lesions on standard camera-acquired macroscopic images. The proposed method is simpler than other methods used for dermoscopy, and initial experiments conducted on publicly available datasets of pigmented skin lesion images show promising results. The average segmentation error achieved by this approach is 24.85%, which is better than comparable methods available in the literature, even for illumination-corrected images.

Paper [12] proposes a novel method for border detection of lesions in dermoscopy images. The method involves converting the image to gray-level, modifying the wavelet coefficients using a nonlinear function, and utilizing morphology operators for segmentation. The proposed method shows low border error in most skin lesions compared to recent methods.

Paper [13] presents an automatic method for skin lesion segmentation in macroscopic images using iterative stochastic region merging. The experimental results suggest that the proposed segmentation method can potentially provide more accurate skin lesion segmentations compared to existing methods in the literature. Moreover, the proposed system achieves a segmentation error of under 10% for skin lesions in macroscopic images, which is lower than that of existing methods according to the experimental results.

Paper [14] provides a comprehensive review of recent border detection methods in the literature. The focus is on computational issues and evaluation aspects.

Paper [15] also proposes a skin disease analysis and tracking system based on image segmentation. The system segments the image using the K-means algorithm and applies texture analysis to classify the image into one of three categories. The proposed system achieved 90.89% accuracy, surpassing existing methods. The authors also propose a tracking method for monitoring skin disease progression over time. Paper [16] also proposes an automatic method for skin lesion segmentation and classification applying k-NN classifiers. Firstly, skin images are filtered and segmented using a region growing method. The segmented lesion areas are then represented by color and texture features and classified using SVM and k-NN classifiers, and their fusion. The proposed method achieves promising results on a dataset of 726 samples from 141 images, with F-measure values of 46.71% and 34% for SVM and k-NN classifiers, respectively, and 61% for the fusion of both classifiers. The proposed system shows potential for accurate skin lesion segmentation and classification.

The paper [17] proposes a Detection and Classification system for skin lesion analysis using MATLAB's Image Processing Toolbox. Three segmentation algorithms, namely, semi-automated thresholding, automated thresholding, and k-means were tested on the dataset, and k-means produced the best results. Various features were extracted from the segmented images and normalized before being fed to classifiers like FFBPNN, KNN, and SVM. The KNN classifier achieved a classification rate of 88.18±0.91%, while the SVM classifier achieved a classification rate of 87.27±0.91%. The overall accuracy using FFBPNN was 90.90%. KNN with k=1 performed better than other variations, and linear SVM outperformed SVM with the 'rbf' kernel.

Paper [18] proposes the development of an online children's skin disease diagnosis system. The system includes a database of skin diseases and their symptoms, and it uses a decision tree algorithm for diagnosis. Users can input their symptoms, and the system provides a list of possible skin diseases with accompanying images for reference. The system was evaluated with a sample of 30 children and achieved an accuracy of 90%. The proposed system is expected to improve access to healthcare and help parents make informed decisions about their children's health.

In Paper [19], the focus is on the use of smartphones to capture skin photos and the application of digital image processing and deep learning to categorize skin as normal or abnormal with an average accuracy of 80%. This provides crucial information about a person's current skin condition and possible health risks.

The paper [20] describes a custom image dataset for four skin disease classes and proposes a CNN model, which achieved up to 86% precision and 67% recall. The model was augmented using an image strategy, and a federated learning approach ensured data privacy. Results showed an average accuracy of up to 94.15% among 1000 to 2500 clients. This CNN-based skin disease classification with federated learning is a significant development for secure and accurate identification of human skin diseases.

Paper [21] proposes an expert system using residual neural networks to diagnose major skin diseases efficiently. The system identifies causes and suggests treatments, trained on a dataset from DERMNET, using a 50-layer Residual Neural Network and Python. The system achieved 95% accuracy with an epoch value of 10.

Paper [22] proposes an automated system for detecting 24 types of dermatological diseases using a hybrid ACO-GA algorithm for skin lesion segmentation and TSVM for disease identification. The system achieves 95% accuracy by utilizing ACO and GA algorithms to find optimal cluster centers and comparing testing samples to training samples.

In paper [23], a dataset was created using locally available raw images of human skin with prevalent skin diseases in Pakistan. The dataset was coupled with normal skin, and a multiclass support vector machine system was developed to automatically recognize the skin diseases. Popular texture and frequency domain features, such as Gray Level Co-occurrences Matrix, were used with SVM-based classifiers to identify the diseases from skin images. The system achieved a maximum recognition accuracy of 89.65% on the test set, and it is believed to be the first automated non-invasive system for identifying skin diseases in Pakistan.

In paper [24], carcinoma images were obtained from the Yank Cancer Society Center and DERMOFIT, both widely recognized for their expertise in carcinoma diagnosis. The images were categorized according to the type of carcinoma and a Self-Organizing Map (SOM) and Radial Basis Function (RBF) were combined for recognition and diagnosis. The classification accuracy achieved using this method (88%, 96.15%, and 95.45% for Basal cell carcinoma, malignant melanoma, and squamous cell carcinoma, respectively) was higher than that obtained using KNN, Naive Thomas Bayes, and ANN classifiers. The study also found that the combination of morphology, texture, and color features led to the highest classification accuracy of 93.15%.

The effectiveness of deep convolutional neural networks for image-based skin rash classification is presented in this paper [25]. The study focuses on eight categories, including acne, hives, ringworm, psoriasis, scabies, cellulitis, dermatitis, and normal skin, and the developed applications can only identify skin diseases belonging to these categories. The trained convolutional neural network model used 4,500 sample images and achieved an accuracy rate of 84.89%, indicating good reliability in predicting clinical images of skin rashes.

3. METHODOLOGY

3.1. YOLOv7 WORKING PRINCIPLE

YOLOv7 (You Only Look Once version 7) is an object detection model that uses deep convolutional neural networks to detect and locate objects within an image. It is an improved version of previous YOLO models and is designed to be faster and more accurate.

The working principle of YOLOv7 is based on object detection using deep neural networks. It follows a single-stage object detection approach, where an image is divided into a grid and each grid cell is responsible for predicting the bounding boxes and class probabilities of the objects present within it. The model uses a convolutional neural network to extract features from the image and then applies a series of convolutional and fully connected layers to predict the bounding boxes and class probabilities for each grid cell.

The model uses a backbone of darknet-53, a deep convolutional neural network architecture, to extract features from the input image. The extracted features are then fed into a series of convolutional layers that predict the class probabilities and bounding boxes for each grid cell. The model is trained on a large dataset of annotated images and uses a loss function that penalizes incorrect predictions of object location and classification. During training, the model adjusts its weights to minimize the loss function and improve its accuracy.

YOLOv7 also incorporates several advanced techniques such as feature pyramid networks, spatial attention, and anchor-free object detection to improve its accuracy and efficiency. The feature pyramid network helps the model to detect objects at multiple scales, while spatial attention helps it to focus on relevant regions of the image. The anchor-free object detection technique allows the model to predict the bounding boxes directly without using predefined anchors.

3.2. ARCHITECTURE

<u>STEPS INVOLVED</u>:

5 major steps are involved in the process of deploying classification model on raspberry pi:

1) Training the model: Appropriate features are selected and the model is trained using convolutional neural networks such as VGG-19, AlexNet and ResNet.
2) Converting model to a format suitable for deployment: Once the model is trained, it is converted to a proper deployable format using TensorFlow Lite.
3) Installment of required software: Necessary software including operating system, and dependencies required for the model are installed.

4) Loading model onto Raspberry Pi: Converted model is loaded onto Raspberry Pi using a python script / API.
5) Testing model: Once the model is deployed, test images are passed as input through the model to ensure that it is correctly classifying them

CONVOLUTIONAL NEURAL NETWORKS USED:

1) **VGG19**: VGG-19 (Visual Geometry Group - 19) is a convolutional neural network that is 19 layers deep and uses 3x3 convolutional filters throughout the network. Compared to existing methods, this method has faster training speed, fewer training samples per time and higher accuracy

2) **AlexNet**: AlexNet architecture consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization and fully connected layers along with a softmax layer. Input size in this architecture is fixed due to the presence of fully connected layers. AlexNet overall has 60 million parameters.

3) **ResNet-50**: ResNet-50 is a convolutional neural network that is 50 layers deep (48 convolutional layers, 1 MaxPool layer and 1 average pool layer). These residual neural networks are a type of artificial neural network (ANN) that forms networks by stacking residual blocks.

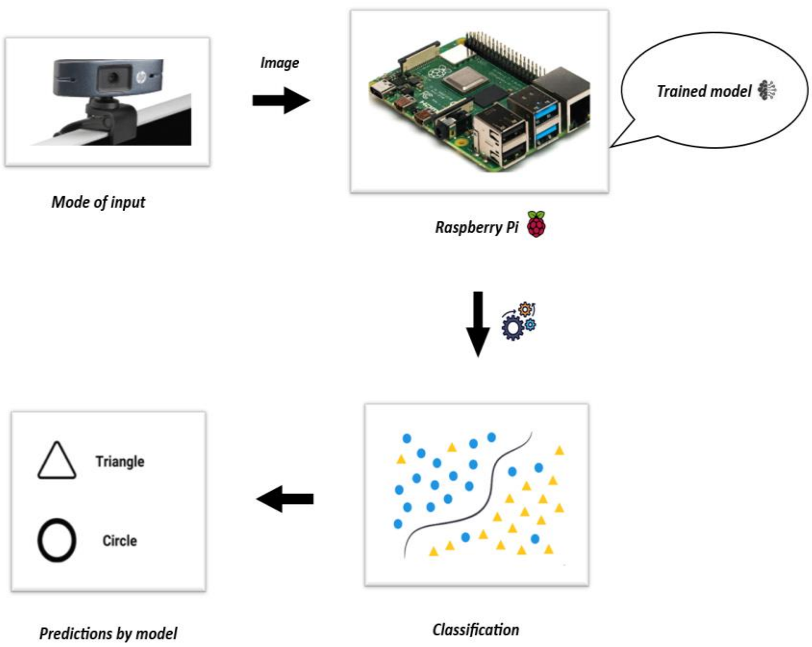


Fig. 2. System

In the perspective of top-down approach, capturing of input image from the user by mode of camera can be considered as an initial step in the architecture. Image can be any affected skin area of the user for which the model is expected to figure out the skin disease that he/she is suffering from. This image is then forwarded as an input to Raspberry Pi in which our previous trained model is deployed. Raspberry Pi has a large and active community of users along with a user-friendly interface which makes it suitable for carrying out image classification. Different CNN algorithms such as VGG19, AlexNet and ResNet are applied on the inputted image and the model predicts the result by classifying the image under one specific skin disease category.

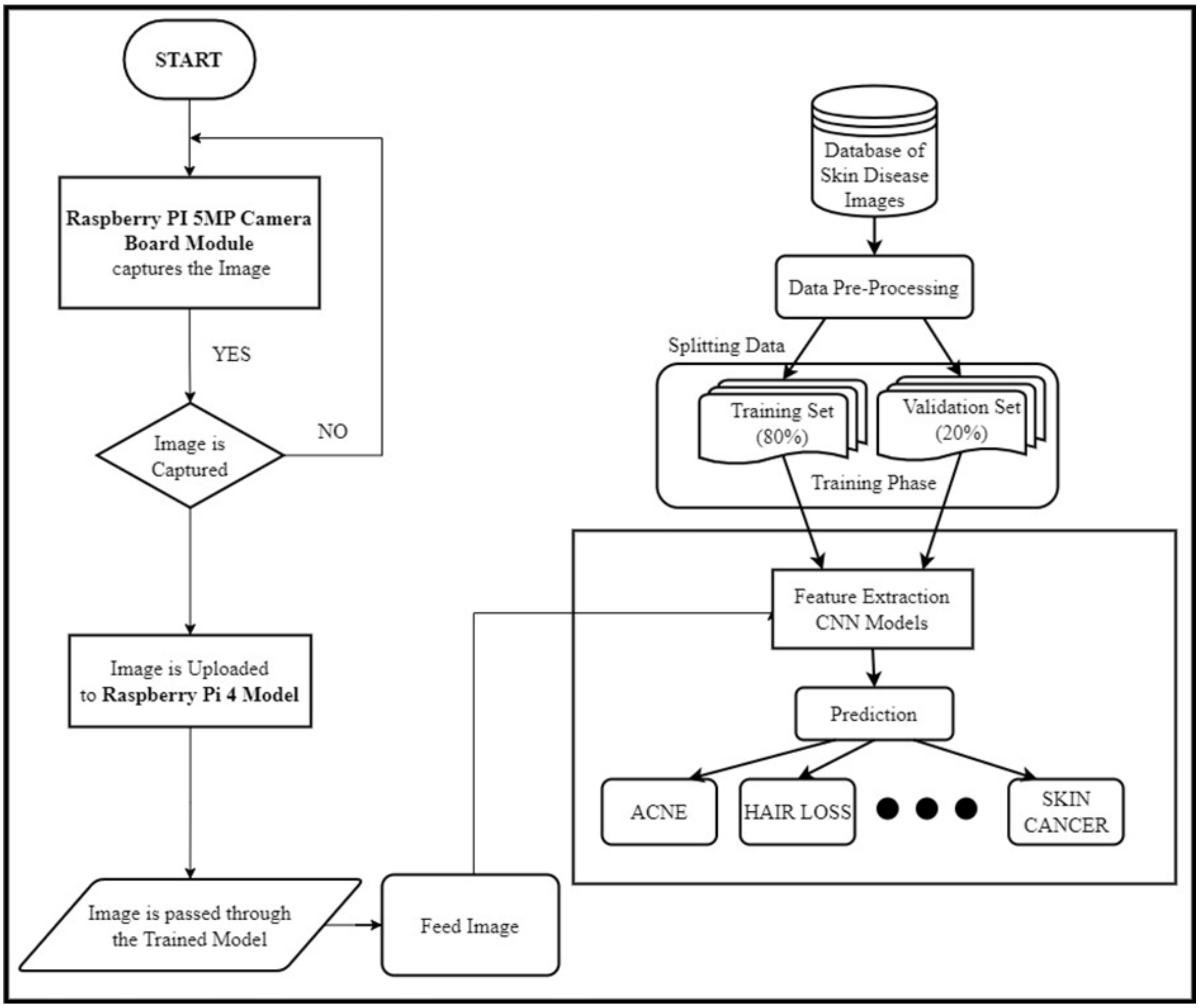


Fig. 3. Flow of the System

3.3. EQUATIONS

$Y = ReLU(W^T * X + b)$ [Convolutional layer]

$Z = Maxpool(Y)$ [Max Pooling layer]

$F = Flatten(Y)$ [Fully connected layer]

$O = Softmax(f(W^T * X + b))$ [Softmax layer]

Where,

Y = Output feature maps of layer / Output feature vector

X = input image / Input feature maps

W^T = Set of learnable convolutional filters (weights)

b = bias vector

In this equation, the input X is convolved with a sequence of filters (W^T) to produce a set of feature maps, which are then downsampled using max pooling to produce a set of pooled feature maps. This process of convolution and pooling is repeated multiple times, with each layer learning increasingly complex representations of the input.

The final pooled feature maps are flattened into a one-dimensional vector, which is then passed through a sequence of fully connected layers to produce the final output(O). Each fully connected layer consists of a set of neurons, each of which is connected to every neuron in the previous layer. The output of each neuron is computed as a weighted sum of the inputs to that neuron, followed by the activation function f.

The final output of the CNN is a probability distribution over the possible classes, which is computed using a Softmax function applied to the output of the final fully connected layer. The Softmax function normalizes the output into a probability distribution, where each element of the vector represents the probability of the input belonging to a particular class.

4. <u>DATASET DESCRIPTION</u>

Data involved in training of this model is extracted from the “Dermnet” dataset of Kaggle. 6 classes from the chosen dataset namely 'Acne and Rosacea Photos', 'Normal', 'vitiligo', 'Tinea Ringworm Candidiasis and other Fungal Infections', 'Melanoma Skin Cancer Nevi and Moles' and 'Eczema Photos' are made use of in order to train the model using different architectures.

Table 4.1. Number of Images in each Class

CLASS NUMBER	CLASS NAME	NUMBER OF IMAGES
0	Acne and Rosacea Photos	1156
1	Normal	808
2	Vitiligo	1566
3	Tinea Ringworm Candidiasis and other Fungal Infections	1300
4	Melanoma Skin Cancer Nevi and Moles	1265
5	Eczema Photos	1235

Below graph represents the number of images of each disease with classes marked from indices 0 to 5 in sequential order of their representation.

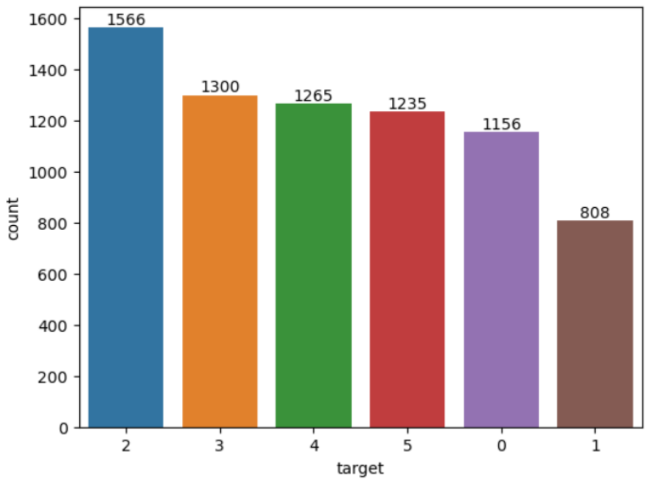


Fig. 4. Number of Images of Each Disease in the Dataset

All images that constitute the dataset are in JPEG format with 3 channels i.e, RGB. The resolutions vary from image to image, and from category to category, but overall, these are not extremely high-resolution imagery. This dataset is framed by the collection of almost all the possible images that can be covered under each disease category, thus ensuring a high level of reliability and image classification rate of the model.

5. RESULTS

5.1. VGG-19 ARCHITECTURE

The precision recall matrix is a table with 6 rows and 5 columns. The rows represent the 6 different classes, and the columns represent precision, recall, F1-score. The first row represents class 0, and the precision, recall, and F1-score values for class 0 are 0.96, 0.99, and 0.97, respectively. Similarly, the precision, recall, and F1-score values for classes 1 through 5 are given in the subsequent rows, and the total number of instances in each class is given in the last column.

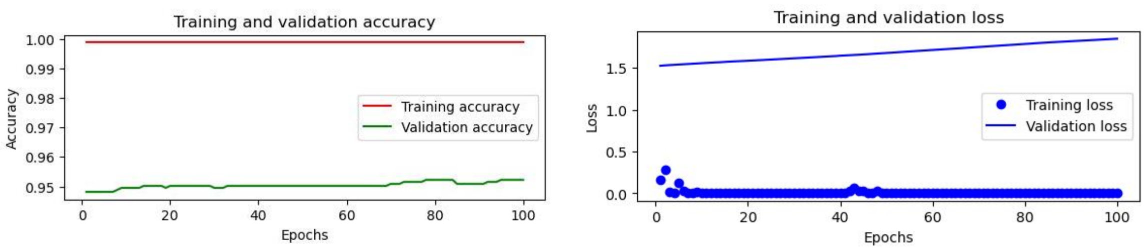
```
46/46 [==============================] - 0s 3ms/step
              precision    recall  f1-score   support

           0       0.96      0.99      0.97       230
           1       0.99      1.00      0.99       158
           2       1.00      1.00      1.00       323
           3       0.98      0.95      0.97       251
           4       1.00      0.97      0.98       266
           5       0.95      0.99      0.97       238

    accuracy                           0.98      1466
   macro avg       0.98      0.98      0.98      1466
weighted avg       0.98      0.98      0.98      1466
```

Fig. 5. Precision recall matrix of VGG-19 Architecture

The accuracy of the model is **98.09%**.



(a) (b)

Fig. 6. Results of VGG-19 Architecture: (a) Accuracy Graph and (b) Loss Graph

5.2. AlexNet ARCHITECTURE

The first row represents class 0, and the precision, recall, and F1-score values for class 0 are 0.84, 0.77, and 0.80, respectively. Similarly, the precision, recall, and F1-score values for classes 1 through 5 are given in the subsequent rows, and the total number of instances in each class is given in the last column.

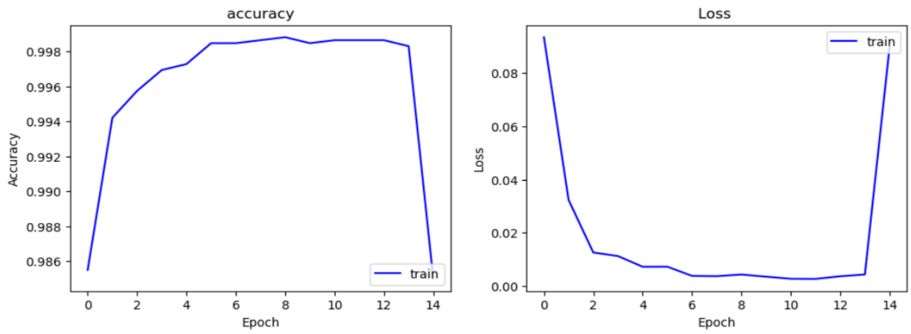
```
46/46 [==============================] - 5s 91ms/step
              precision    recall  f1-score   support

           0       0.84      0.77      0.80       221
           1       0.97      0.93      0.95       176
           2       0.97      0.97      0.97       322
           3       0.74      0.68      0.71       257
           4       0.90      0.91      0.90       245
           5       0.71      0.84      0.77       245

    accuracy                           0.85      1466
   macro avg       0.86      0.85      0.85      1466
weighted avg       0.86      0.85      0.85      1466
```

Fig. 7. Precision recall matrix of AlexNet Architecture

The accuracy of the model is **85.27%**.

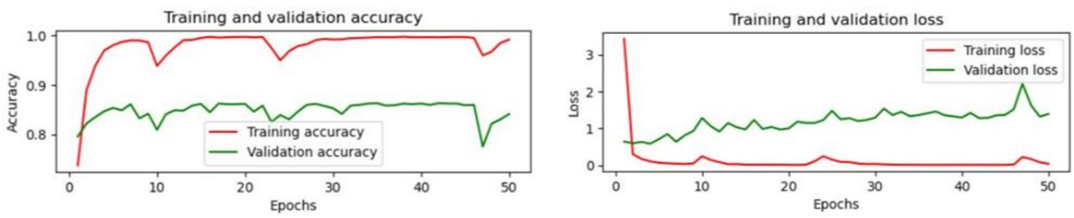


(a) (b)

Fig. 8. Results of AlexNet Architecture: (a) Accuracy Graph and (b) Loss Graph

5.3. ResNet50 ARCHITECTURE

The accuracy of the model is **76.13%.**



(a) (b)

Fig. 9. Results of ResNet50 Architecture: (a) Accuracy Graph and (b) Loss Graph

5.4. INFERENCES

- Out of the 3 architectures used, model trained using VGG19 has exhibited a higher accuracy rate of 98.09%. VGG19 has a simpler architecture compared to other 2 methods which makes it easier to train and comprehend.
- Accuracy of a model can be affected not only by the optimization algorithm used, but also by other crucial factors such as quality and quantity of the training data, the hyperparameters used during training and also the characteristics of the dataset involved.

6. CONCLUSION

Automated detection of skin diseases is crucial for improving public health outcomes by reducing mortality rates, minimizing disease transmission, and preventing the progression of skin conditions. Clinical procedures for detecting skin diseases can be prohibitively expensive and time-consuming. Image processing techniques offer a promising solution to automate dermatological screening at an early stage. Feature extraction is a critical step in accurately classifying skin diseases, and pretrained convolutional neural networks such as VGG19 are effective for this task. Our research successfully designed a skin disease detection system that utilizes computer vision and machine learning techniques, with promising results. The lightweight application we developed can run on low-spec machines and has a user-friendly interface. We successfully implemented the image processing and machine learning algorithms, demonstrating the potential for this system to provide cost-effective and efficient screening for skin diseases.

7. FUTURE SCOPE

This study proposes an automated skin disease detection system to aid in the early detection of skin diseases and assist dermatologists in improving their diagnosis time and accuracy.

- ➔ One of the potential future works is to test the system on a larger dataset consisting of various complexities of skin diseases to enhance the accuracy and efficiency of the algorithm. This can be achieved by adding more diverse and rare types of skin diseases to the existing categories.
- ➔ Moreover, the system can be integrated with advanced technologies such as artificial intelligence, machine learning, and deep learning to improve its diagnosis accuracy and time. For instance, the system can be trained using deep learning techniques such as

Convolutional Neural Networks (CNNs) to learn more sophisticated features from skin images and enhance its classification performance.

➔ Additionally, the system can be further developed to support other languages and regions, making it more accessible and useful for the global medical community. Furthermore, the system can be incorporated with a mobile application, allowing users to capture skin images using their smartphones and receive real-time disease diagnosis.

Altogether, the proposed system has a wide range of future scopes that can be explored to improve its accuracy, efficiency, accessibility, and usability.

8. REFERENCES

[1] Nawal Soliman ALKolifi ALEnezi, 2019, “A Method of Skin Disease Detection Using Image Processing and Machine Learning.” *16th International Learning & Technology Conference 2019.*

[2] Leelavathy S., Jaichandran R., Shobana R., Vasudevan, Sreejith S. Prasad and Nihad, 2020, “Skin Disease Detection Using Computer Vision and Machine Learning Technique.” *European Journal of Molecular & Clinical Medicine, ISSN 2515-8260, Volume 7, Issue 4, 2020.*

[3] Yali Nie, Paolo Sommella, Mattias O’Nils, Consolatina Liguori, Jan Lundgren, 2019, “Automatic Detection of Melanoma with Yolo Deep Convolutional Neural Networks.” *The 7th IEEE International Conference on E-Health and Bioengineering - EHB 2019.*

[4] R. S. Gound, Priyanka S. Gadre, Jyoti B. Gaikwad and Priyanka K. Wagh, 2018, "Skin Disease Diagnosis System using Image Processing and Data Mining." *International Journal of Computer Applications 179(16):38-40, January 2018*.

[5] M. Shamsul Arifin, M. Golam Kibria, A. Firoze, M. Ashraful Amini and Hong Yan, 2012, "Dermatological disease diagnosis using Color-skin images." *International Conference on Machine Learning and Cybernetics, Xian, 2012, pp. 1675-1680, doi: 10.1109/ICMLC.2012.6359626.*

[6] Yasir, R., Rahman, A., & Ahmed, N., 2014, “Dermatological Disease Detection using Image Processing and Artificial Neural Network.” *Dhaka: International Conference on Electrical and Computer Engineering*.

[7] Teck Yan Tan, Li Zhang, Ming Jiang, 2016, “An Intelligent Decision Support System for Skin Cancer Detection from Dermoscopic Images.” *12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD).*

[8] Jyothilakshmi K. K., Jeeva J. B., 2014, "Detection of Malignant Skin Diseases Based on the Lesion Segmentation." *International Conference on Communication and Signal Processing, India.*

[9] Nawal Soliman ALKolifi ALEnezi, 2019, "A Method of Skin Disease Detection Using Image Processing and Machine Learning.", *16th International Learning & Technology Conference.*

[10] A.A.L.C. Amarathunga, E.P.W.C. Ellawala, G.N. Abeysekara, C. R. J. Amalraj, 2015, "Expert System for Diagnosis of Skin Diseases." *International Journal of Scientific & Technology Research VOLUME 4, ISSUE 01*.

[11] Cavalcanti P. G. , Yar, Y., Scharcanski J., 2010, "Pigmented Skin Lesion Segmentation on Macroscopic Images" *Image and Vision Computing New Zealand (IVCNZ), 25th International Conference on Image and Vision Computing*

[12] Sarrafzade, O.; Baygi, M.H.M.; Ghassemi, P., 2010, "Skin Lesion Detection in Dermoscopy Images using Wavelet Transform and Morphology Operation." *17th Iranian Conference of Biomedical Engineering (ICBME2010).*

[13] Alexander Wong, Member, Jacob Scharcanski, and Paul Fieguth, 2011, "Automatic Skin Lesion Segmentation via Iterative Stochastic Region Merging." *Information Technology in Biomedicine.*

[14] M. Emre Celebi, Hitoshi Iyatomi, Gerald Schaefer, William V Stoecker, 2009, "Lesion Border Detection in Dermoscopy Images." *Computerized medical imaging and graphics 33, pp. 148-153.*

[15] Trabelsi O., Tlig L., Sayadi M., Fnaiech F., 2013, "Skin Disease Analysis and Tracking based on Image Segmentation." *Electrical Engineering and Software Applications (lCEESA), 2013 International Conference.*

[16] Sumithra Ra, Mahamad Suhilb, D.S. Guruc, 2015, "Segmentation and Classification of Skin Lesions for Disease Diagnosis." *International Conference on Advanced Computing Technologies and Applications (ICACTA-2015).*

[17] Parnita P. Patil, Prof. Sonali A. Patil, Dr. V. R. Udupi., 2014, "Detection and Classification of Skin Lesion in Dermoscopy Images." *International Journal of Applied Engineering Research.*

[18] Munirah M. Yusof, Ruhaya A. Aziz, Chew S. Fei, 2013, "The Development of Online Children Skin Diseases Diagnosis System.", *International Journal of Information and Education Technology, Vol. 3, No. 2, April 2013.*

[19] Bassma, Rizuan Ahmed Rifat, Md. Kafiul Islam, 2022, “Skin Disease Screening System based on Smartphone Captured Images using Deep Learning.” *11th International Conference on Communications, Circuits and Systems (ICCCAS).*

[20] Md Nazmul Hossen, Vijayakumari Panneerselvam, Deepika Koundal, Kawsar Ahmed, 2022, “Federated Machine Learning for Detection of Skin Diseases and Enhancement of Internet of Medical Things (IoMT) Security.” *IEEE Journal of Biomedical and Health Informatics.*

[21] Moolchand Sharma, Bhanu Jain, Chetan Kargeti, Vinayak Gupta, Deepak Gupta, 2019, “Detection and Diagnosis of Skin Diseases Using Residual Neural Networks (RESNET).” *International Journal of Image and Graphics 21(05).*

[22] Md. Humayan Ahmed, RomanaRahmanEma, Tajul Islam, 2019, “An Automated Dermatological Images Segmentation Based on a New Hybrid Intelligent ACO-GA Algorithm and Diseases Identification Using TSVM Classifier.” *International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT-2019).*

[23] Azeem Iqba, 2019, “Skin Disease Classification using a Multiclass SVM Classifier”

[24] Chaitra T. C., Nisarga R., Srushti N., Sunku Vineela, Rajath A. N., 2020, “Automated System for Prediction of Skin Disease using Image Processing and Machine Learning.” *International Journal of Engineering Research & Technology (IJERT), ISSN: 2278-0181.*

[25] Jannie Fleur Oraño, Francis Rey Padao, Rhoderick Malangsa, 2022, “A Deep Convolutional Neural Network for Skin Rashes Classification.” *Novel & Intelligent Digital Systems: Proceedings of the 2nd International Conference (NiDS 2022), pp.339-348.*