RESEARCH ARTICLE OPEN ACCESS

Skin Disease Detection by Convolutional Neural Networks- An Approach

Sounak Nandi
II-year B.Tech Student in Computer Science and Engineering
Heritage Institute of Technology, Kolkata, West Bengal, India

Abstract
Skin diseases are common health problems around the world. The perils of the infections are invisible, which cause physical health distress as well as initiate mental depression. In addition, it sometimes leads to skin cancer in severe cases. Subsequently, diagnosing skin diseases from clinical images is one of the foremost challenging tasks in medical image analysis. Moreover, when performed manually by medical experts, diagnosing skin diseases is time-intensive and subjective. As a result, both patients and dermatologists require automatic skin disease prediction, which makes the treatments plan faster. It can be applied the automatic Grabcut segmentation technique to segment out the affected lesions. For extracting underlying input patterns from the skin images, researchers applied the Gray Level Co-occurrence Matrix (GLCM) and statistical features techniques. Three computationally efficient machine learning techniques, Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) classifiers can be applied using the extracted features for effectively classifying the skin images. There is a massive gap between dermatologists and skin disease patients as many people do not know the types, symptoms, and stages of skin disease. Sometimes it requires a long time to show the signs. For this, it requires early and quick detection. But it may be difficult and expensive to diagnose skin diseases correctly to identify the type and stage of the disease. The automatic computer-aided system based on machine learning approaches has made it possible to detect the types of skin disease more accurately and quickly. Paper presents an intelligent system for automated skin cancer detection using deep learning techniques. The implemented system uses Convolutional Neural Networks (CNNs) to differentiate between benign and malignant skin lesions. Our approach was chosen based on CNNs' proven effectiveness in medical image analysis and their ability to automatically learn hierarchical feature representations.

Keywords: Skin Diseases; Image Processing; CNN; Machine Learning; Skin Types

1. Introduction

The human body is made up of several organs. Skin is one of them. It is the largest organ covering the entire human body [1]. Any disorder that affects human skin is called skin disease [2]. Skin disease is one of the most contagious diseases in the world. According to the World Health Organization (WHO), about 2794 persons in Bangladesh died from skin cancer in 2018 [3]. WHO said that more than 14 million cases diagnosed in world. About 9.6 million deaths occurred globally in 2018 [4]. It is the change of colour or texture of the skin. The causes of skin diseases are viruses, bacteria, allergy, or fungal infections [5]. The genetic factor also causes skin disorders. Generally, skin disease occurs in the thin outer layer of the skin, called epidermis can be visualized by human eyes that cause psychological depression and lead to physical injuries. There are different types of skin lesions: Actinic keratosis (AK), Basal cell carcinoma (BCC), Benign keratosis (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic nevus (NV), Squamous cell carcinoma (SCC), and Vascular lesion (VASC), are shown in Fig. 1. The lesions are different in terms of their symptoms and severity. Some are permanent, and some are temporary and may be painless or painful. Among these skin diseases, melanoma is the most deadly and dangerous type. However, about 95% of skin disease patients can be recovered if identified at an initial state. An automatic computer-aided system can be beneficial to classify skin diseases accurately.

There is a massive gap between dermatologists and skin disease patients as many people do not know the types, symptoms, and stages of skin disease. Sometimes it requires a long time to show the signs.

For this, it requires early and quick detection. But it may be difficult and expensive to diagnose skin diseases correctly to identify the type and stage of the disease. The automatic computer-aided system based on machine learning approaches has made it possible to detect the types of skin disease more accurately and quickly. Many researchers have worked on skin disease classification for the last three decades. The area is so significant and has become a hot research topic. Even though many research papers are done on skin disease detection and classification, there is still a gap to be filled. Most of the previous work is based on a single disease [6-7], and there are different types of skin lesions: Actinic keratosis (AK), Basal cell carcinoma (BCC), Benign keratosis (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic nevus (NV), Squamous cell carcinoma (SCC), and Vascular lesion (VASC). The lesions are different in terms of their symptoms and severity. Some are permanent, and some are temporary and may be painless or painful. Among these skin diseases, melanoma is the most deadly and dangerous type. However, about 95% of skin disease patients can be recovered if identified at an initial state. An automatic computer-aided system can be beneficial to classify skin diseases accurately. There is a massive gap between dermatologists and skin disease patients as many people do not know the types, symptoms, and stages of skin disease. Sometimes it requires a long time to show the signs. For this, it requires early and quick detection. But it may be difficult and expensive to diagnose skin diseases correctly to identify the type and stage of the disease. The automatic computer-aided system based on machine learning approaches has made it possible to detect the types of skin disease more accurately and quickly. Many researchers have worked on skin disease classification for the last three decades. The area is so significant and has become a hot research topic. Even though many research papers are done on skin disease detection and classification, there is still a gap to be filled. Most of the previous work is based on a single disease [6-7], and those that have been done are inadequate for classifying multiple classes [8]. The classification task of multiple classes is very challenging as the skin disease presents more similar behaviour. To develop an automatic classification model for skin diseases classification based on a sufficient number of relevant features with high accuracy. Some researchers proposed a new method that combines two separate data mining approaches into a single unit, as well as an ensemble approach that combines both data mining techniques into a single group. They applied the ensemble deep learning technique on an informative Dermatology publicly accessible dataset ISIC2019 image and categorized skin disorders into seven categories. They observed that the ensemble technique predicted skin diseases more accurately and effectively. Paper presents an intelligent system for automated skin cancer detection using deep learning techniques. The implemented system leverages Convolutional Neural Networks (CNNs) to differentiate between benign and malignant skin lesions. Our approach was chosen based on CNNs' proven effectiveness in medical image analysis and their ability to automatically learn hierarchical feature representations.

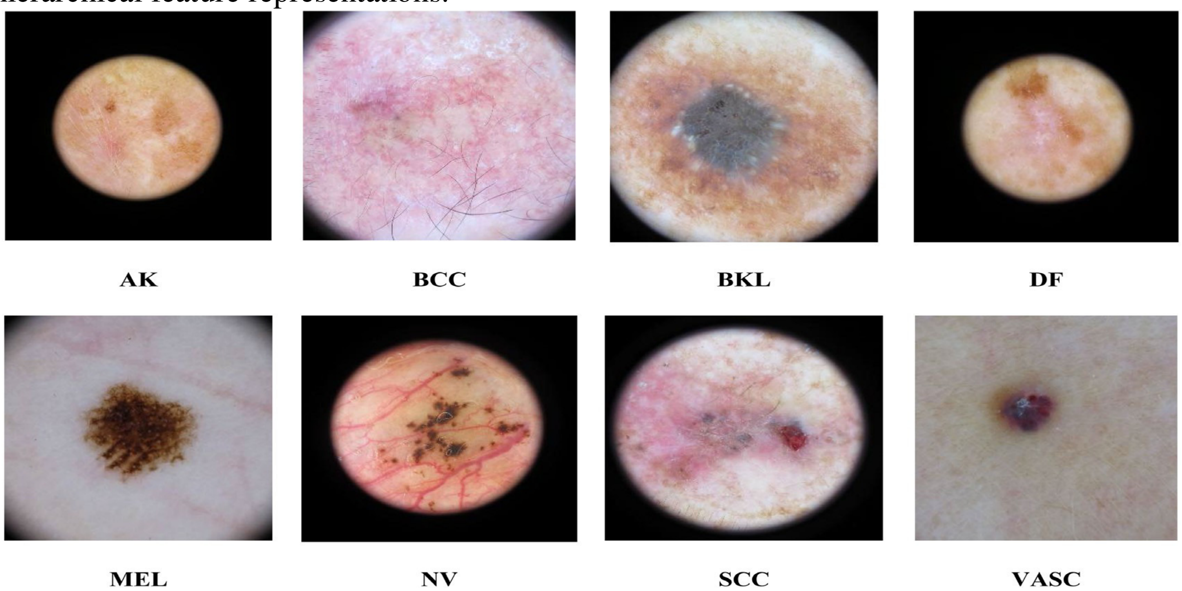

Fig. 1.Sample of Skin Disease Images collected from the ISIC 2019 Challenge Dataset.

2. Literature Review

Many researchers proposed several approaches for the classification of skin diseases. Related works are categorized into different types based on datasets, feature extraction techniques, feature selection techniques, and classification models. This section examined several relevant research articles to discover previous studies' tools and procedures and identify research gaps. Jagdish et al. [9] proposed a model for skin disease detection using image processing methods. They applied fuzzy clustering on 50 sample images with KNN and SVM classification algorithm with wavelet analysis. They showed that the K-Nearest Neighbour classification algorithm works well compared to the Support vector machine (SVM) classification technique with an accuracy of 91.2% and the algorithm identified the type of skin disease using classification methods. But they worked with only 50 sample images containing two classes (basal and squamous disease). Naeem et al. [10] proposed a model to predict skin cancer using image processing strategies and support vector machines (SVMs). They used various pre-handling procedures for clamor evacuation and picture improvement and GLCM method to separate a few highlights in the image. Finally, the classifier classified the images as harmful or harmless. Bandyopadhyay et al. [11] proposed a model combining deep learning (DL) and machine learning (ML). They applied deep neural networks Alexnet, Googlenet, Resnet50, and VGG16 for feature selection and Support Vector Machine, Decision tree, and Ensemble boosting Adaboost classifier for classification. Finally, they carried out a comparative study to identify the best prediction model. Kalaivani et al. [12] proposed a new method that combines two separate data mining approaches into a single unit, as well as an ensemble approach that combines both data mining techniques into a single group. They applied the ensemble deep learning technique on an informative Dermatology publicly accessible dataset ISIC2019 image and categorized skin disorders into seven categories. They observed that the ensemble technique predicted skin diseases more accurately and effectively. AlDera et al. [13] presented a skin disease diagnosis model that take an affected skin image and diagnose acne, cherry angioma, melanoma, and psoriasis. They applied Otsu's method for image segmentation and Gabor, Entropy and Sobel techniques for feature extraction on the dermnet NZ and atlas dermatologico. Finally, they applied Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (K-NN) classifiers for classification, and achieved 90.7%, 84.2%, and 67.1% accuracy, respectively.

3. Methodology

This paper presents an intelligent system for automated skin cancer detection using deep learning techniques. The implemented system leverages Convolutional Neural Networks (CNNs) to differentiate between benign and malignant skin lesions. Our approach was chosen based on CNNs' proven effectiveness in medical image analysis and their ability to automatically learn hierarchical feature representations.

AGUI was also developed to facilitate the use of the system. Multiple steps, including data collection, pre-processing, data standardization and data augmentation are used to prepare the input images for the model to train. Fig.2 shows the flowchart of the implemented proposed system.

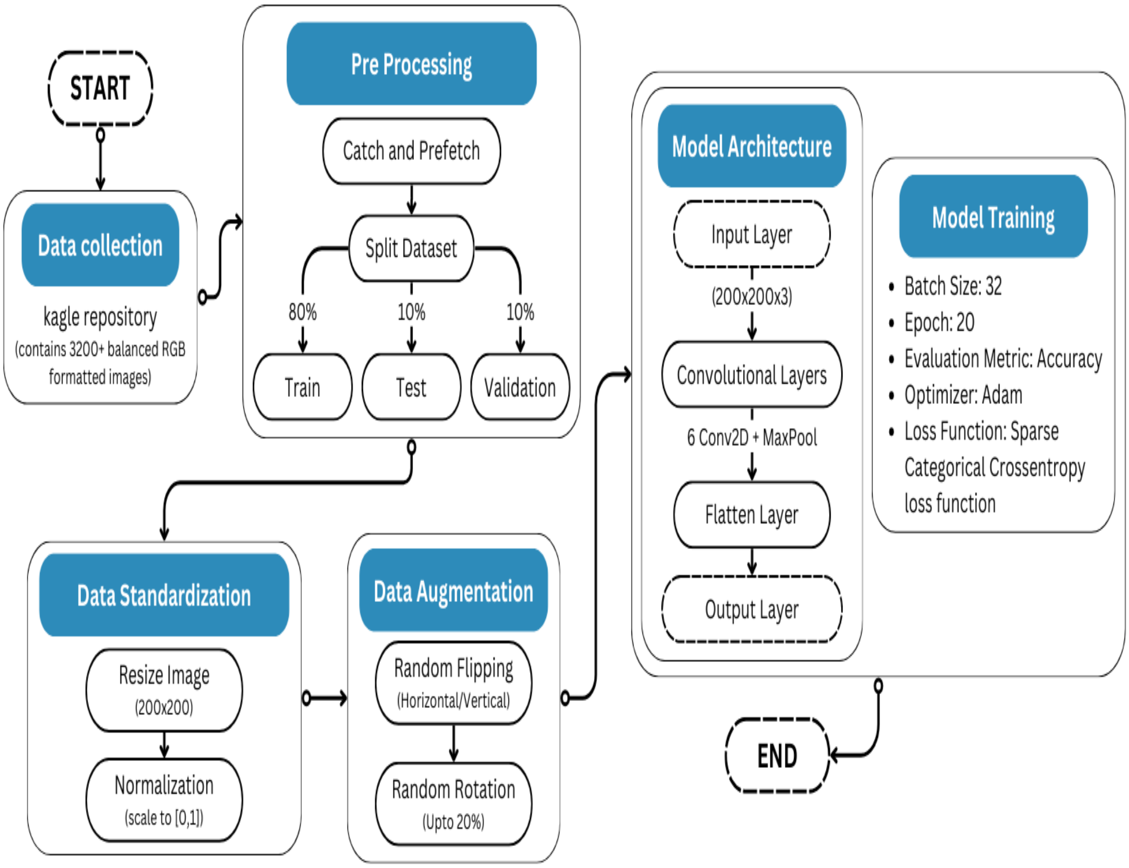

Fig.2 Workflow Diagram of the Skin Disease Prediction model

3.1. Data Collection

This dataset used in this experiment was sourced from the Kaggle repository which is publicly available. It is a widely used dataset in the field of dermatology and skin cancer detection. It contains 3200+ high quality skin disease images in RGBformat. The dataset is balanced in terms of class representation, ensuring unbiased training and evaluation. The data distribution for train and test images is illustrated in fig.3.

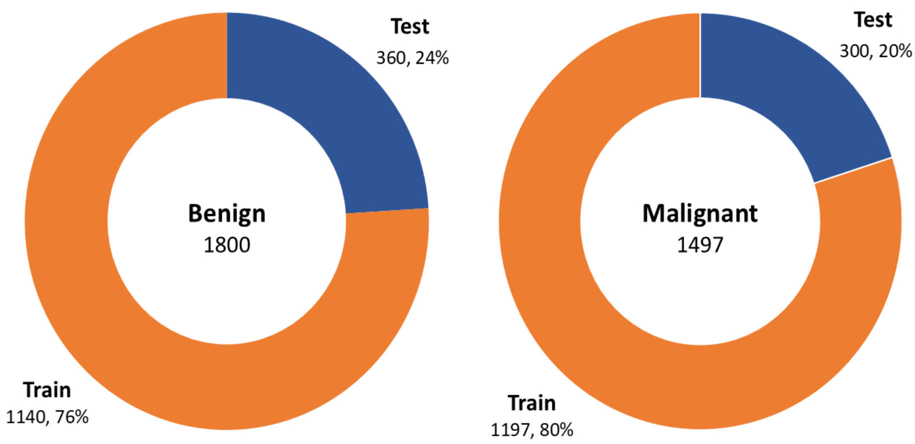

Fig.3Data Distribution for Train and Test in Experimental Dataset

3.2. Pre-processing

Image pre-processing is the very first and important step in image recognition before training a learning model. Pre-processing ensures that the dataset is clean and structured, making itsuitable for the training process. It eliminates inconsistencies such as varying image sizes, scales, or noise, ensuring the model can focus on learning meaningful patterns. The steps involved in pre-processing are describe below.

1. Data Optimization
   Data optimization improves GPU performance during training and reduces training time significantly.
   a) Cache: Stores data in memory after first epoch
   b) Shuffle: Randomizes data order to prevent bias
   c) Prefetch: Prepares next batch while current batch is processing

2. Data Splitting
   Data Splitting prevents over fitting by validating on unseen data. It allows monitoring of model performance during training. Tests model's ability is to generalize to new data.
   a) Training (80%): Used to train the model
   b) Validation (10%): Used to tune hyper parameters
   c) Test (10%): Used for final performance evaluation

3.3. Data Standardization

Standardization was applied to enhance model performance by reducing the disparity between input feature distributions. First each image is scaled to a specific size to provide the model with equal number of pixels for training and predicting, which ensures same number of features can be collected. Since the input images are in RGB format, image normalization is done to equalize the intensity value of each pixel. This ensured uniformity in image size and pixel intensity values, which ranged between 0 and 1 after normalization. The steps are mentioned below:

1. All images were first converted into (200x200) size.
2. To balance the pixel intensity levels the image is normalized. Since the images are in RGB format, each colour channel was normalized separately by scaling intensity values to the range [0, 1].

3.4.Data Augmentation

Data augmentation artificially increases the size and diversity of the dataset. By applying specific transformations (e.g., flips, rotations), the model learns to generalize better to unseen data, reducing over fitting and improving robustness. Random images from the dataset were applied the following transformations.

1. Random horizontal and vertical flips.
2. Random rotations of up to 20%.

3.5.Model

In this study a Convolutional Neural Network (CNN) is used. Convolutional Neural Networks (CNNs) are ideal for tasks like image classification, object detection, and other visual recognition tasks because CNNs automatically learn spatial hierarchies of features (edges, textures, shapes) directly from the images without any manual feature engineering. Unlike fully connected networks, CNNs share weights through filters, drastically reducing the number of parameters and computational cost.

```
input_shape = (32, 200, 200, 3)
n_classes = 2
model = models.Sequential([
    resize_and_rescale,
    layers.Conv2D(32, kernel_size = (3,3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64,  kernel_size = (3,3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax'),
])
model.compile(
    optimizer='adam',
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False),
    metrics=['accuracy']
)
```

3.5.1. Model Architecture

The Convolutional Neural Network (CNN) employed consists of six convolutional layers, each followed by a ReLU activation function and max pooling for dimensionality reduction. The architecture's depth and parameter count were chosen to balance performance and computational efficiency. The Convolutional Neural Network (CNN) architecture used for this study is as follows:

1. Input Layer: Resizes images to (200x200x3) and rescales pixel values to [0, 1].
2. Convolutional Layers: Six Conv2D layers with ReLU activation, followed by max Pooling layers to reduce spatial dimensions. Filters increase from 32 to 64 progressively to capture more complex features.
3. Flatten Layer: Converts 2D feature maps into a 1D vector for the dense layer.
4. Fully Connected Layers: A Dense layer with 64 units and ReLU activation and an output Dense layer with 2 units and a softmax activation for binary classification.

The model was compiled using the Adam optimizer with a learning rate of 0.001 and Sparse Categorical Crossentropy loss function. Training was conducted over 20 epochs with a batch size of 32. Early stopping was implemented to terminate training upon validation loss stagnation. The model's architecture is shown in fig. 4.

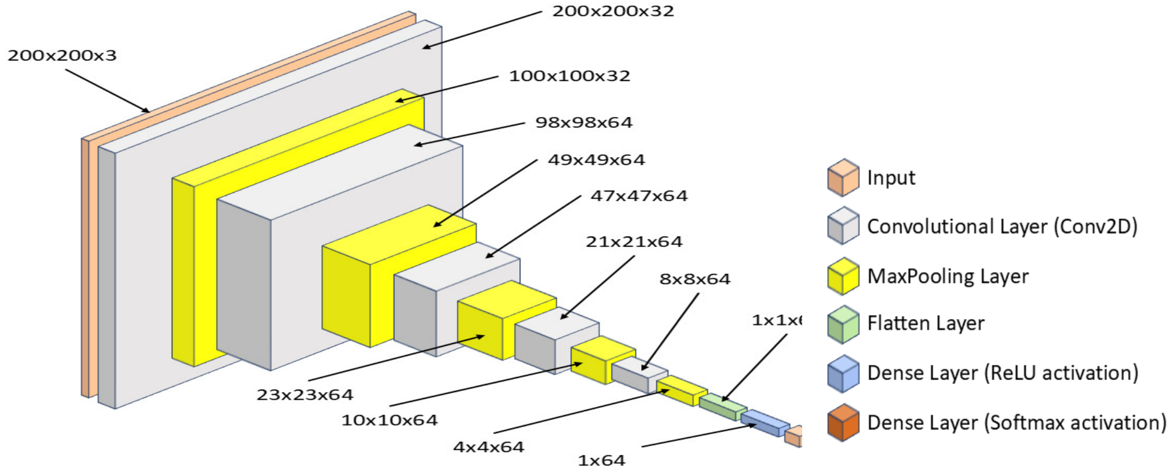

Fig.4The model architecture

4. Result and Discussion

In this section, the results obtained from the proposed methodology are presented below:

1. Training and Validation Accuracy:
   a)Both training and validation accuracy are improving steadily over the epochs, which indicates the model is learning.
   b) The validation accuracy closely follows the training accuracy, with only slight fluctuations. This suggests that the model generalizes well to unseen data and is not over fitting.
2. Training and Validation Loss:
   a) Both training and validation loss decrease consistently over the epochs, which is a good sign.
   b) The validation loss does not diverge significantly from the training loss, indicating that the model is not under fitting or over fitting severely. The training and validation accuracy/loss can be found on fig. 5.

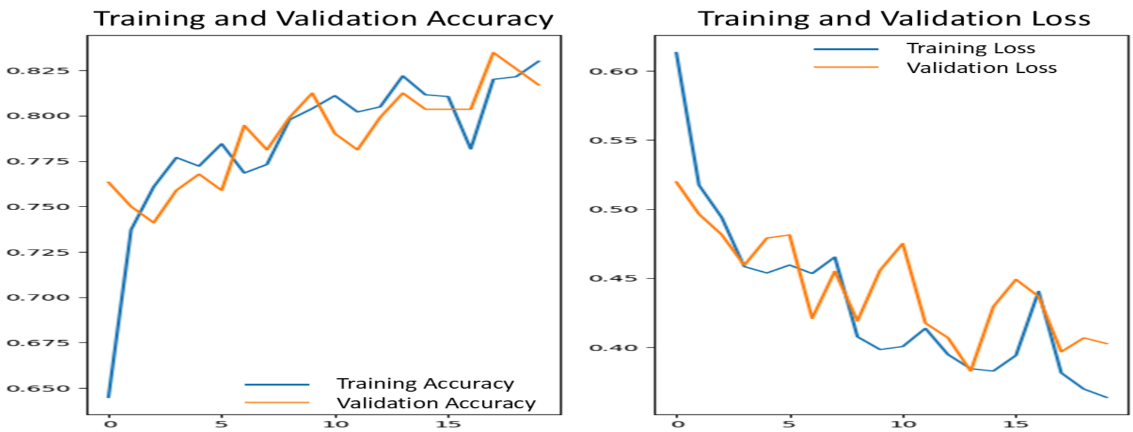

Fig.5 Training and Validation Accuracy/Loss graph of the model

Conclusions

The proposed system is able to detect the skin disease with promising results using computer machine learning techniques. The methodology utilized is carefully quality controlled. The technique includes the utilization of pre-prepared picture recognizers with alterations to distinguish skin images. The measure confirms that the application is without bug and it meets the necessities expressed in the prerequisites report of the system. The overall experimental approach for skin disease detection is used using image processing techniques. The skin images are given into the system for processing. The input image is subjected to image processing process like pre-processing, feature extraction and machine learning based classifier to predict skin disease or not and recommend medicinal guidance based on the skin disease stage.

References

[1] Anatomy of the skin, Stanford children's health, 2021, [Online]. Available: https://www.stanfordchildrens.org/en/topic/default?id=anatomy-of-the-skin 85-P01336.
[2] M.W. Greaves, Skin disease, Britannica, 29, 2020, [Online]. Available: https: //www.britannica.com/science/human-skin-disease.
[3] Bangladesh: Skin disease, 2018, [Online]. Available: https://www. worldlifeexpectancy. com/bangladesh-skin-disease.
[4] Cancer, world health organization, 21, 2021, [Online]. Available: https:// www. who.int/news-room/fact-sheets/detail/cancer.
[5] Md. Al Mamun, Mohammad Shorif Uddin, A survey on a skin disease detection system, Int. J. Healthcare. Inform. Syst. Inform. 16 (4) (2021) 1–17.
[6] C.N. Vasconcelos, B.N. Vasconcelos, Experiments using deep learning for dermoscopy image analysis, Pattern Recognit. Lett. 139 (2020) 95–103.
[7] U.-O. Dorj, K.K. Lee, J.Y. Choi and. M. Lee, The skin cancer classification using deep convolutional neural network, Multimedia Tools Appl. 77 (2018) 9909–9924.
[8] M. Taufiq, N. Hameed, A. Anjum, F. Hameed, m-Skin Doctor: A Mobile Enabled System for Early Melanoma Skin Cancer Detection Using Support Vector Machine, in: eHealth 360◦. International Summit on eHealth, 2017, pp. 468–475.
[9] Jagdis etal., J.A.D.L. Cruz-Vargas, M.E.R. Camacho, Advance study of skin diseases detection using image processing methods, Nat. Volatiles Essent. Oils J. 9 (1) (2022) 997–1007.
[10] Z. Naeem, G. Zia, Z. Bukhari, A healthcare model to predict skin cancer using deep extreme machine, J. NCBAE 1 (2) (2022) 23–30.
[11] S.K. Bandyopadhyay, P. Bose, A. Bhaumik, S. Poddar, Machine learning and deep learning integration for skin diseases prediction, Int. J. Eng. Trends Technol. 70 (2) (2022) 11–18.
[12] A. Kalaivani, S. Karpagavalli, Detection and classification of skin diseases with ensembles of deep learning networks in medical imaging, Int. J. Health Sci. 6 (S1) (2022) 13624–13637.
[13] S.A. AlDera, M.T.B. Othman, A model for classification and diagnosis of skin disease using machine learning and image processing techniques, Int. J. Adv. Comput. Sci. Appl. 13 (5) (2022).

