Islamic University Of Lebanon
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Report Of
Skin Diseases Detection

ELBC803

Embedded Systems Design

Spring 2023 – 2024
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1. Abstract

Skin diseases are more common than other diseases. Skin diseases may be caused by fungal infection, bacteria, allergy, or viruses, etc. The advancement of lasers and Photonics based medical technology has made it possible to diagnose the skin diseases much more quickly and accurately. But the cost of such diagnosis is still limited and very expensive. So, image processing techniques help to build automated screening system for dermatology at an initial stage. The extraction of features plays a key role in helping to classify skin diseases. Computer vision has a role in the detection of skin diseases in a variety of techniques. Due to deserts and hot weather, skin diseases are common in Saudi Arabia. This work contributes in the research of skin disease detection. We proposed an image processing-based method to detect skin diseases. This method takes the digital image of disease effect skin area, then use image analysis to identify the type of disease. Our proposed approach is simple, fast and does not require expensive equipment other than a camera and a computer. The approach works on the inputs of a color image. Then resize the of the image to extract features using pretrained convolutional neural network. After that classified feature using Multiclass SVM.

To diagnosing the different types of skin diseases is an exigent process even for better-experienced skin doctors, while there are several reasons for an increase in such conflicts, foremost among them is the reduction of these types of diseases. This paper proposed Deep learning. Nowadays diagnosing diseases through modern technology becomes easy to access and convenient. Due to the emergence of smartphone analysis and providing results in less time. This system will utilize computational techniques to analyze, process, and relegate the image data predicated on various features of the images. Skin images are filtered to remove unwanted noise and process it for enhancement of the image. Using a machine-learning algorithm (Convolutional Neural network) can predict the type of disease and show in the output to the IOT page of the predicted disease.

2. Introduction

Composed of epidermis, dermis, and subcutaneous tissues, skin is the largest organ of human body, containing blood vessels, lymphatic vessels, nerves, and muscles, which can perspire, perceive the external temperature, and protect the body. Covering the entire body, the skin can protect multiple tissues and organs in the body from external invasions including artificial skin damage, chemical damage, adventitious viruses, and individuals' immune system. Besides, skin can also avoid the loss of lipids together with water within epidermis and dermis so that skin barrier function can be stabilized. In spite of defense and barrier function, skin is not indestructible in that skin tends to be constantly influenced by a variety of external and genetic factors. Currently, there are three main types of skin diseases appearing in human body, including viral skin diseases, fungal skin diseases, and allergic skin disease. Despite the fact that these types of skin diseases can be cured at present, these diseases indeed have brought trouble to patients' life. Nowadays, the majority of conclusions on the patients' existing symptoms are drawn mainly based on doctors' years of experience or their own subjective judgments, which may lead to misjudgments and consequently delay the treatment of these. Therefore, it is of great theoretical significance and practical value to study how to extract symptoms of diverse skin diseases on the basis of modern science and technology. Under this circumstance, effective and accurate identification of the types of skin diseases can be achieved to prescribe treatment according to patients' symptoms .

In the ever-evolving landscape of healthcare, Artificial Intelligence (AI) is emerging as a powerful force that is reshaping the way we approach medical diagnostics. Among its numerous applications, AI is making significant strides in the realm of skin disease diagnosis. The transformative role of AI in diagnosing skin diseases, exploring its potential, applications, and the profound impact it has on patients, dermatologists, and the healthcare industry as a whole.

3. Review of Literature

Several researchers have proposed image processing-based techniques to detect the type of skin diseases. Here we briefly review some of the techniques as reported in the literature.

A system is proposed for the dissection of skin diseases using color images without the need for doctor intervention. The system consists of two stages, the first the detection of the infected skin by uses color image processing techniques, k-means clustering and color gradient techniques to identify the diseased skin and the second the classification of the disease type using artificial neural networks. The system was tested on six types of skin diseases with average accuracy of first stage 95.99% and the second stage 94.016%.

In the method of extraction of image features is the first step in detection of skin diseases. In this method, the greater number of features extracted from the image, better the accuracy of system. The author of applied the method to nine types of skin diseases with accuracy up to 90%. Melanoma is type of skin cancer that can cause death, if not diagnose and treat in the early stages.

The author focused on the study of various segmentation techniques that could be applied to detect melanoma using image processing. Segmentation process is described that falls on the infected spot boundaries to extract more features.

The work proposed the development of a Melanoma diagnosis tool for dark skin using specialized algorithm databases including images from a variety of Melanoma resources.

Similarly, discussed classification of skin diseases such as Melanoma, Basal cell carcinoma (BCC), Nevus and Seborrheic keratosis (SK) by using the technique support vector machine (SVM). It yields the best accuracy from a range of other techniques. On the other hand, the spread of chronic skin diseases in different regions may lead to severe consequences.

Therefore, proposed a computer system that automatically detects eczema and determines its severity. The system consists of three stages, the first effective segmentation by detecting the skin, the second extract a set of features, namely color, texture, borders and third determine the severity of eczema using Support Vector Machine (SVM).

A new approach is proposed to detect skin diseases, which combines computer vision with machine learning. The role of computer vision is to extract the features from the image while the machine learning is used to detect skin diseases. The system was tested on six types of skin diseases with accurately 95%.

4. Problematic

1. *****Accessibility and Affordability**:*** How can skin disease detection technologies be made more accessible and affordable to underserved populations, particularly in developing countries or remote areas?

2. *****Accuracy and Reliability**:*** What are the current limitations and challenges in achieving high accuracy and reliability in automated skin disease detection algorithms, and how can these be addressed?

3. *****Interpretability and Explainability**:*** How can machine learning models for skin disease detection be made more interpretable

and explainable to assist dermatologists in understanding the rationale behind their decisions?

4. ***Data Privacy and Security**:* What are the implications for patient privacy and data security in the collection, storage, and analysis of medical images for skin disease detection, and how can these concerns be effectively addressed?

5. ***Bias and Fairness**:* How can bias and fairness issues be mitigated in skin disease detection algorithms to ensure equitable and accurate diagnosis across diverse patient populations?

6. **Integration with Healthcare Systems**: What are the challenges and opportunities in integrating automated skin disease detection tools into existing healthcare systems to enhance diagnosis, treatment, and patient care?

7. ***Patient Empowerment and Education**:* How can skin disease detection technologies empower patients to take a more active role in managing their skin health through early detection, education, and selfmonitoring?

8. ***Validation and Clinical Adoption**:* What are the key considerations in validating and clinically adopting new skin disease detection technologies, and how can these processes be streamlined to accelerate their implementation in clinical practice?

9. ***Long-term Monitoring and Management**:* How can skin disease detection tools be adapted for long-term monitoring and management of chronic skin conditions, such as psoriasis or eczema, to optimize treatment outcomes and patient quality of life?

10. ***Collaboration and Multi-disciplinary Approach**:* What are the benefits of interdisciplinary collaboration between dermatologists, data scientists, engineers, and other stakeholders in advancing the field of skin disease detection, and how can synergies be maximized to drive innovation and progress?

5. Description of The Dataset

We compiled our dataset by collecting images from different websites specific to skin diseases. The database has 3000 images of every disease (Normal images, Melanoma images, Eczema images and Psoriasis images). Fig 1 shows some of the sample images from our dataset.

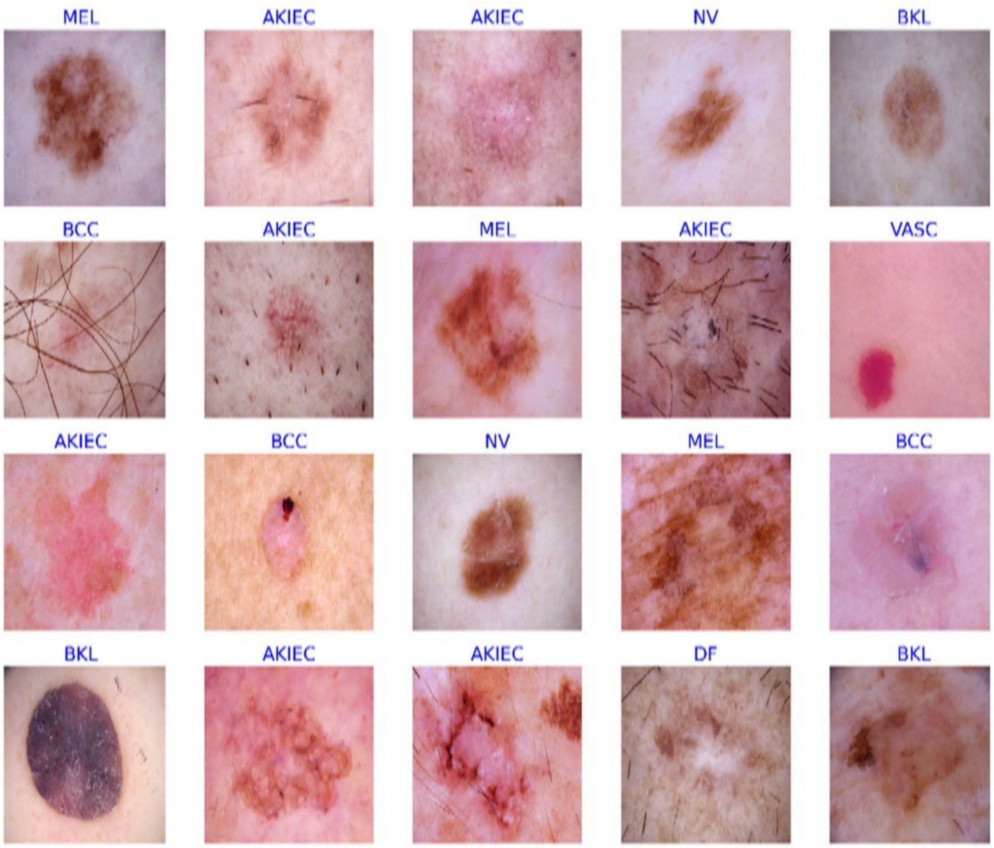

Figure 1 samples of data images

6. Methodology

In this section, the methodology of the proposed system for detection, extraction and classification of skin diseases images is described. The system will help significantly in the detection of melanoma, Eczema and Psoriasis. The whole architecture can be divided into several modules comprising of preprocessing, feature extraction, and classification. The block diagram of the system is shown in Fig 2.

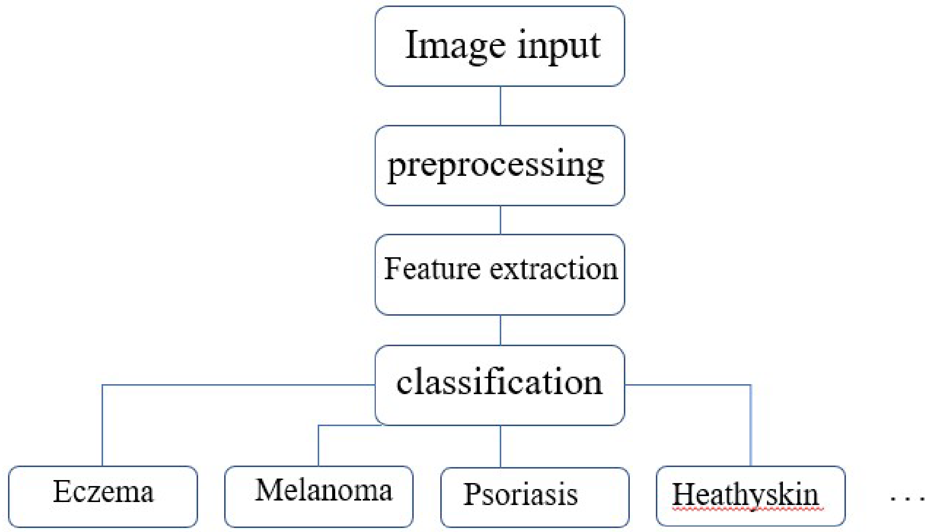

Figure 2 The block diagram of the system

.1 Preprocessing:

Achieving high performance of skin disease detection system requires overcoming some major difficulties. Such as creating a database and unifying image dimensions. In the following section, the technique used in image resizing is explained.

.2 Image Resizing:

To resolve the problem of different image sizes in the database an input image is either increase or decrease in size. Unifying the image size will get the same number of features from all images. Moreover, resizing the image reduces processing time and thus increases system performance.

Figure 3 Example of Original image of Eczema database.

Figure 4 Example of resizing image of Eczema database.

.3Feature Extraction:

At the beginning, Convolutional Neural Network (CNN) is a set of stacked layers involving both nonlinear and linear processes. These layers are learned in a joint manner. The main building blocks of any CNN model are: convolutional layer, pooling layer, nonlinear Rectified Linear Units (ReLU) layer connected to a regular multilayer neural network called fully connected layer, and a loss layer at the backend. CNN has known for its significant performance in applications as the visual tasks and natural language processing 8.

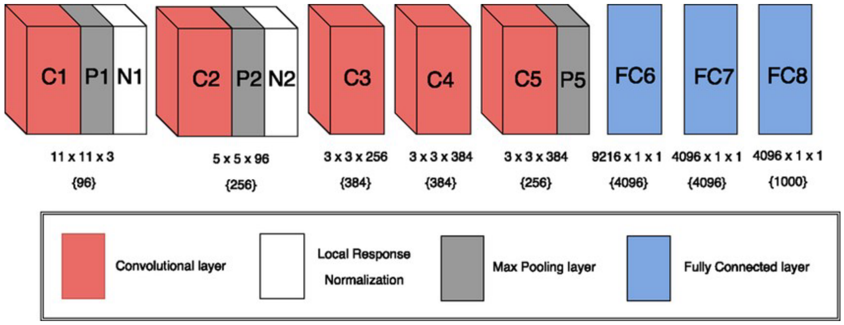

Figure 5 AlexNet block diagram [8].

AlexNet is a deep CNN model, developed by Krizhevsky et al. [8], to model the 2012 ImageNet for the Large Scale Visual Recognition Challenge (ILSVRC-2012). AlexNet consists of five convolutional layers; where a nonlinear ReLU layer is stacked after each convolutional layer. In addition, the first, second, and fifth layers contain maxpooling layers, as shown in Figure 5. Moreover, two normalization layers are stacked after the first and the second convolutional layers. Furthermore, two fully connected layers at the top of the model preceded by softmax layer. AlexNet was trained using more than 1.2 million images belonging to 1000 classes [8]. We proposed feature extraction from a pretrained convolutional neural network. Because it is the easiest and robust approach to use the power of pretrained deep learning networks.

.4Classification

is a computer vision method. After extracting features, the role of classification is to classy the image via Support Vector Machine (SVM). A SVM can train classifier using extracted features from the training set.

7. The code of project

.1 App Code :

```
from flask import Flask, request, jsonify, render_template
import numpy as np from PIL import Image from
tensorflow.keras.models import load_model
```

```
app = Flask(__name__) model =
load_model('model.h5')
class_labels    =      ['Actinic      keratosis',     'Atopic        Dermatitis',    'Benign
        keratosis', 'Dermatofibroma', 'Melanocytic nevus',
          'Melanoma',        'Squamous     cell     carcinoma',    'Tinea  Ringworm
        Candidiasis', 'Vascular lesion'] @app.route('/') def home():
   return render_template('index.html') @app.route('/predict',
methods=['POST'])
def predict():
   file = request.files['image']     img =
Image.open(file.stream).convert("RGB")     img = img.resize((150, 150))  #
Resize image to match model input shape     img_array = np.array(img) /
255.0     img_array = np.expand_dims(img_array, axis=0)    predictions =
model.predict(img_array)    predicted_class = np.argmax(predictions[0])   #
return the predicted class (or disease label)    return jsonify({'prediction':
class_labels[predicted_class]}) if __name__ == '__main__':
   app.run(debug=True)
```

.2 train Model

```
import tensorflow as tf from tensorflow.keras.preprocessing.image
import ImageDataGenerator

# Directory containing your dataset organized into subdirectories by class train_data_dir
= 'dataset/train'

# Example of ImageDataGenerator with augmentation
train_datagen = ImageDataGenerator(
   rescale=1./255,           # Rescale pixel values to be between 0 and 1
rotation_range=20,        # Random rotation up to 20 degrees     width_shift_range=0.2,
# Randomly shift images horizontally by 20%     height_shift_range=0.2,    # Randomly
shift images vertically by 20%     shear_range=0.2,          # Shear intensity (shear angle
in radians)     zoom_range=0.2,           # Randomly zooming inside pictures by 20%
horizontal_flip=True,     # Randomly flip images horizontally     fill_mode='nearest'
# Strategy for filling in newly created pixels
```

```
)

# Generating batches of augmented data from the directory train_generator
= train_datagen.flow_from_directory(
   train_data_dir,           # Target directory
target_size=(150, 150),    # Resizes all images to 150x150
batch_size=32,            # Size of the batches of data
   class_mode='categorical'   # Since it's a multi-class classification
)

# Define your model
model = tf.keras.models.Sequential([     tf.keras.layers.Conv2D(32, (3, 3),
activation='relu', input_shape=(150, 150, 3)),     tf.keras.layers.MaxPooling2D(2,
2),     tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
tf.keras.layers.MaxPooling2D(2, 2),     tf.keras.layers.Conv2D(128, (3, 3),
activation='relu'),     tf.keras.layers.MaxPooling2D(2, 2),
   tf.keras.layers.Flatten(),
   tf.keras.layers.Dense(512, activation='relu'),     tf.keras.layers.Dense(9,
activation='softmax')  # Adjust to match the number of classes in your dataset
])

# Compile the model
model.compile(loss='categorical_crossentropy',
           optimizer='adam',
           metrics=['accuracy'])

# Train the model history = model.fit(     train_generator,
steps_per_epoch=train_generator.samples // train_generator.batch_size,
epochs=10  # Adjust the number of epochs as needed
)

# Save the trained model
model.save('model.h5')
```

.3 Web Code

```
<!DOCTYPE html>

<html lang="en">


<head>

   <meta charset="UTF-8">
```

```
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<title>Skin Disease Detection</title>
<style>
    /* Styles for Header, Main, and Footer */
body {          font-family: Arial, sans-serif;
margin: 0;          padding: 0;
background-color: #f4f4f4;
    }

    header {          background-
color: #1e88e5;          color:
white;          text-align: center;
padding: 20px;
    }

    main {
padding: 20px;
text-align: center;
    }

    footer {          background-
color: #333;          color: white;
text-align:                center;
padding: 10px 0;          position:
fixed;               width:  100%;
bottom: 0;
    }
```

```
/* Styles for Dropzone */
.dropzone {             display: inline-
block;             padding: 20px;
border: 2px dashed #aaa;             border-
radius: 5px;             cursor: pointer;
transition: border-color 0.3s ease;
        }

        .dropzone:hover {
border-color: #888;
        }

        #image-preview img {                  max-width:
100%;              height: auto;              border-radius:
5px;              box-shadow: 0px 2px 5px rgba(0, 0, 0,
0.1);             margin-top: 20px;
        }

        /* Styles for Result and Loading */
        #result {
margin-top: 20px;
text-align: center;
        }

        #loading {
display: none;
margin-top: 20px;
        }
```

```
              /* Button Styles */         button {
padding: 10px 20px;             background-color:
#1e88e5;             color: white;             border:
none;             border-radius: 5px;
cursor: pointer;             transition: background-
color 0.3s ease;             display: none; /*
Initially hidden */             margin: 0 auto; /*
Center horizontally */
        }

        button:hover {
background-color: #1565c0;
        }

        /* Additional Style */
        .show {
            display: block !important;
        }

    </style>
</head>

<body>
    <header>
        <h1>Skin Disease Detection</h1>
    </header>
    <main>
        <form id="upload-form" enctype="multipart/form-data">
```

```
<div class="dropzone" onclick="selectImage()"
ondragover="event.preventDefault()" ondrop="dropHandler(event)">
    Click or Drop Image Here
    <input id="image-upload" type="file" name="image"
  accept="image/*" style="display: none;" onchange="displayImage(this)"
capture>
  </div>
 </form>
 <div id="image-preview"></div>
 <div id="loading">Predicting...</div>
 <div id="result"></div>
 <button id="clear-button" onclick="clearResult()">Clear</button>
</main>
<footer>
 <p>Powered by AI</p>
</footer>
<script>
 function selectImage() { document.getElementById('image-
upload').click();
 }

 function displayImage(input) {
if (input.files && input.files[0]) {
var reader = new FileReader();

    reader.onload = function (e) { var img =
new Image(); img.onload = function() {
if (img.width >= 450 || img.height >= 450) {
var canvas = document.createElement('canvas');
var ctx = canvas.getContext('2d'); canvas.width
```

```
= 300;                          canvas.height = 300;
ctx.drawImage(img, 0, 0, 300, 300);
                        document.getElementById('image-preview').innerHTML          =         '<img
src="' + canvas.toDataURL() + '" />';
                    } else {
                        document.getElementById('image-preview').innerHTML          =         '<img
src="' + e.target.result + '" />';
                    }
                    document.getElementById('clear-button').classList.add('show');
predictDisease(input.files[0]);
                };                  img.src =
e.target.result;
            }

            reader.readAsDataURL(input.files[0]);
        } else {
            // If no file is selected (e.g., the file input is reset), clear the image preview
            document.getElementById('image-preview').innerHTML = '';
document.getElementById('clear-button').classList.remove('show');
            // Clear result if no file is selected
clearResult();
        }
    }



    function    predictDisease(imageFile)    {
var     formData     =     new     FormData();
formData.append('image', imageFile);
```

```
// Display loading indicator
document.getElementById('loading').style.display = 'block';
document.getElementById('result').innerText = '';
fetch('/predict', {
method: 'POST',
body: formData
})
.then(response => response.json())
.then(data => {
// Hide loading indicator
document.getElementById('loading').style.display = 'none';
document.getElementById('result').innerText = 'Predicted disease: ' +
data.prediction;
// Highlight prediction result
document.getElementById('result').classList.add('predicted'); })
.catch(error => {
console.error('Error:', error);
// Hide loading indicator and display error message
document.getElementById('loading').style.display = 'none';
document.getElementById('result').innerText = 'Error predicting disease.
Please try again.';
// Add error class for styling
document.getElementById('result').classList.add('error');
});
}

function dropHandler(event) {
event.preventDefault(); var file =
```

```
event.dataTransfer.files[0];
displayImageFromFile(file);
        }

        function displayImageFromFile(file) {
var     reader     =     new     FileReader();
reader.onload = function (e) {
                document.getElementById('image-preview').innerHTML          =          '<img   src="'
            + e.target.result + '" />';                  document.getElementById('clear-
button').classList.add('show');
                predictDisease(file);
            }
            reader.readAsDataURL(file);
        }

        function clearResult() {
            document.getElementById('image-preview').innerHTML = '';
document.getElementById('result').innerText = '';
document.getElementById('result').classList.remove('predicted', 'error');
document.getElementById('clear-button').classList.remove('show');
            // Reset file input to clear the selected file
            document.getElementById('image-upload').value = '';
        }
    </script>
</body>

</html>
```

8. The method of work

Step 1 :

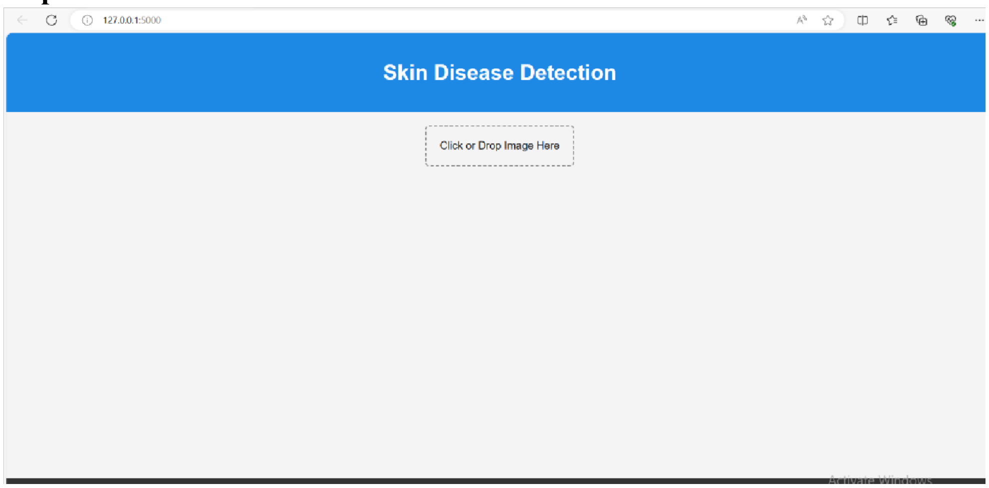

Figure 6 step 1 of program

Step 2 :

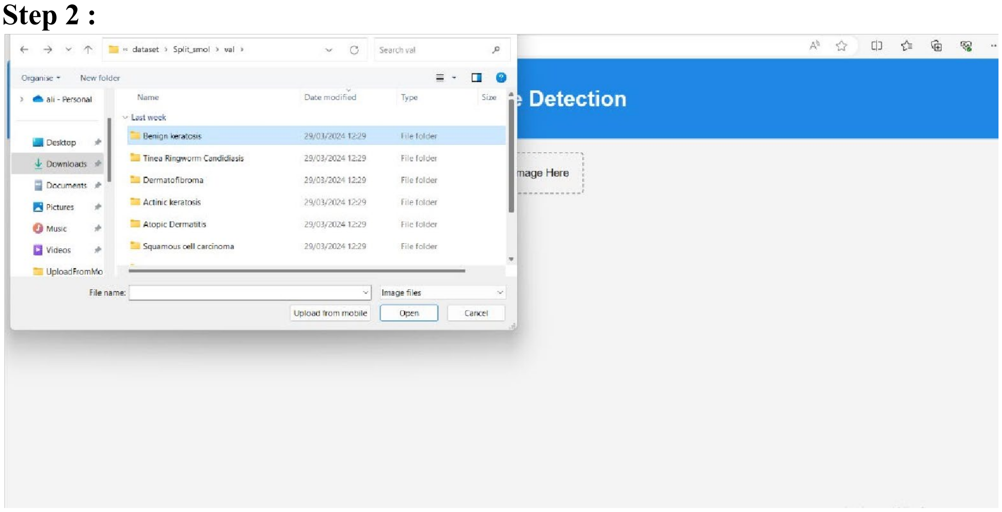

Figure 7 step 2 of program

Step 3 :

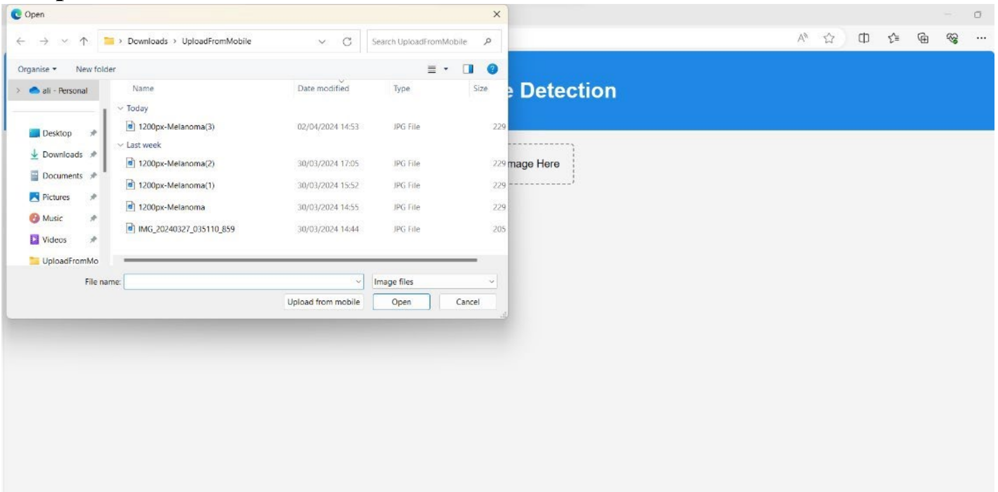

Figure 8 step 3 of program

Step 4 :

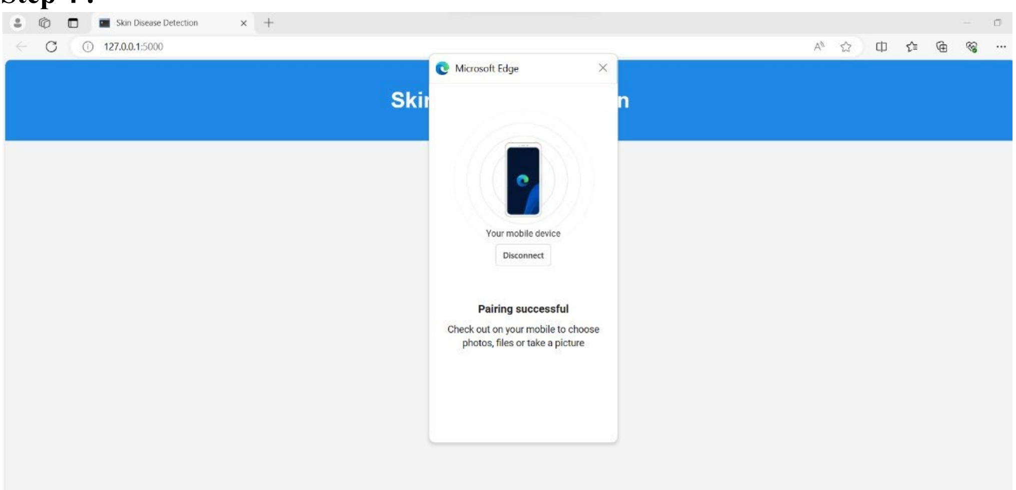

Figure 9 step 4 of program

Step 5 :

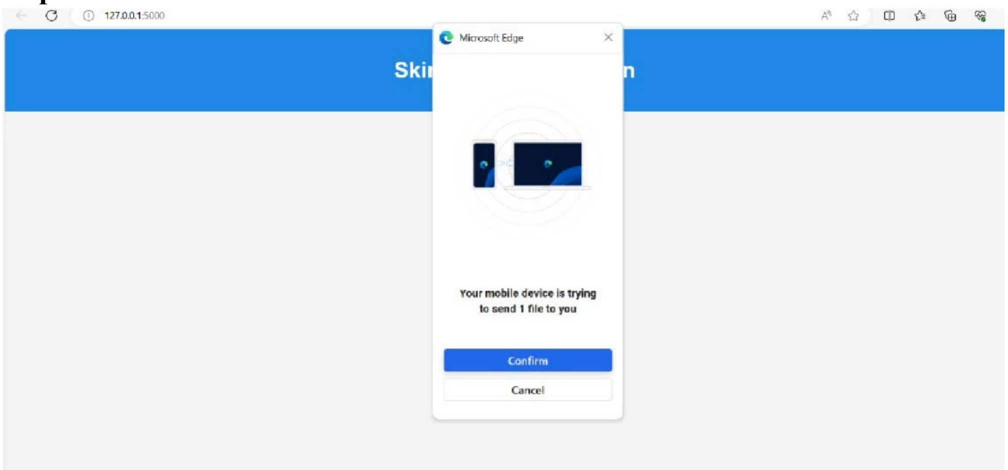

Figure 10 step 5 of program

Step 6 :

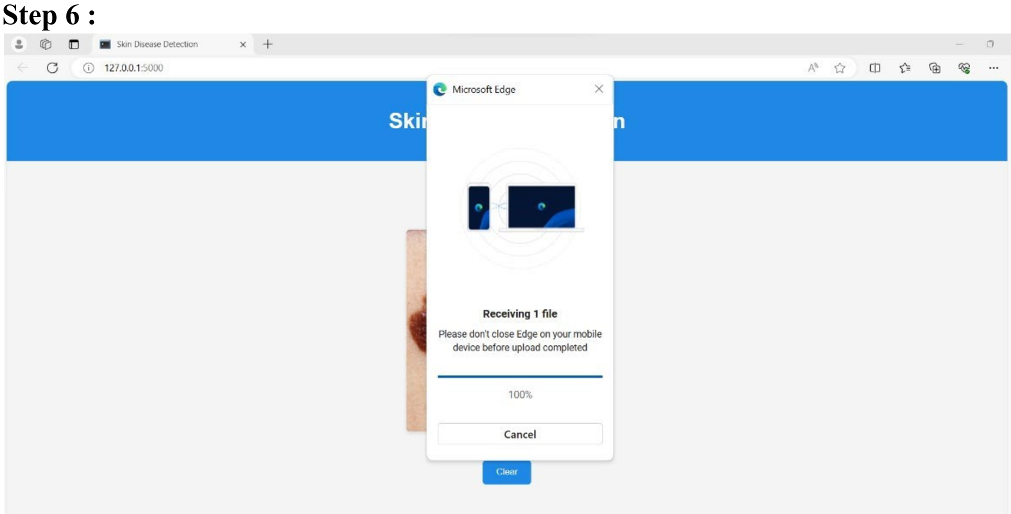

Figure 11 step 6 of program

Step 7 :

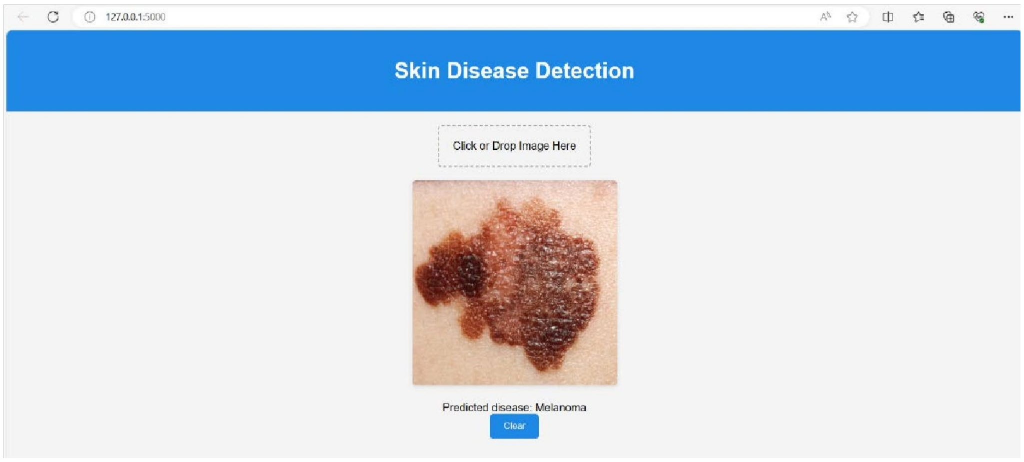

Figure 12 step 7 of program

9. The Future of AI

The future of skin disease diagnosis with AI is bright. As AI algorithms become more sophisticated and data sets grow, we can expect:

1.Enhanced early detection and diagnosis of skin conditions.

2.Personalized treatment plans tailored to each patient.

3.Improved access to dermatological care, especially in underserved areas.

4.Enhanced patient engagement and education through AI-driven apps and resources.

5.More efficient and streamlined workflows for dermatologists.

AI in skin disease diagnosis is not a replacement for the expertise of healthcare professionals but a powerful tool that augments their capabilities. The synergy between human knowledge and AI's analytical prowess offers a new era of precision and efficiency in dermatological diagnostics.

10. Conclusion

Artificial Intelligence has already begun to transform the field with its ability to enhance accuracy, early detection, and accessibility, AI is poised to revolutionize how we diagnose and manage skin conditions. The collaboration between AI and dermatologists represents an exciting frontier in healthcare, offering the potential to improve patient outcomes and enhance the overall quality of dermatological care. As AI continues to evolve, so does the future of skin disease diagnosis.

Unlock the Future of Skin Disease Diagnosis with **TeamD.AI** Ready to experience a revolutionary approach to skin health? **TeamD.AI** is your trusted AI-powered app for precise and early skin disease diagnosis. Experience the future of skin disease diagnosis with **TeamD.AI App** and take charge of your skin's well-being!

11. References

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2. Self-Paced Balance Learning for Clinical Skin Disease Recognition Jufeng Yang;Xiaoping Wu;Jie Liang;Xiaoxiao Sun;Ming-Ming Cheng;Paul L. Rosin;Liang Wang Year: 2020

3. H. Gupta, H. Bhatia, D. Giri, R. Saxena, and R. Singh, Comparison and Analysis of Skin Lesion on Pretrained Architectures Comparison and Analysis of Skin Lesion on Pretrained Architectures no. July 2020, doi: 10.13140/RG.2.2.32161.43367.

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