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"Heal-Derm": Diabetic Skin Infections Detection System through a Mobile Application

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***Abstract* - Public health in Sri Lanka has considerable obstacles due to the prevalence of undiagnosed diabetes and a lack of awareness of diabetic diseases. Many people do not become aware of having diabetes until it's already had terrible effects. In this study, we present a mobile application that uses image processing and machine learning techniques to identify and track common skin diseases linked to diabetes, such as cellulitis, Acanthosis nigricans, nail abnormalities, and foot ulcers. The mechanisms that are already in place exclusively concentrate on foot ulcers, ignoring other significant illnesses. By giving users a way to evaluate their diabetes and spot potential skin infections through changes to their body or skin, the smartphone application intends to empower people with diabetes. People can seek appropriate treatment, lower their risk of complications, and possibly save lives by quickly identifying these illnesses. The suggested solution calls for specific domain knowledge in dermatology, medical imaging, image processing, and machine learning. This study intends to improve diabetes care and the avoidance of diabetic skin infections by addressing the limitations in current detection systems.**

Keywords: diabetes, image processing, machine learning, dermatology, mobile application.

I. INTRODUCTION

Diabetes mellitus, a chronic metabolic disorder affecting millions of people worldwide, poses significant health challenges. Among its various complications, diabetic foot ulcers, acanthosis nigricans, nail defects, and cellulitis are commonly observed. These conditions not only impact the quality of life for individuals with diabetes but also increase the risk of serious complications and lower limb amputations. Accurate and timely detection of these complications is crucial to initiate appropriate interventions and prevent further deterioration. In this research paper, we present a novel approach that utilizes machine learning (ML) models to identify diabetic foot ulcers, acanthosis nigricans, nail defects, and cellulitis, while also providing severity levels and suitable diagnostics. Moreover, we have developed a user-friendly mobile application that allows individuals to capture wound images and upload them for analysis by the ML models, enabling seamless interaction and accessibility for users. This integrated approach aims to improve the early detection and management of diabetes-related complications, leading to better healthcare outcomes and enhanced patient empowerment.

II. LITERATURE REVIEW

A) Managing diabetes using mobile applications that utilize image processing

The study aims to develop a user-friendly, comprehensive, and fully integrated web and mobile-based Clinical Decision Support and Monitoring System (CDSMS) for the screening, diagnosis, treatment, and monitoring of diabetes mellitus (DM) diseases in primary care. The system will be based on evidence-based guidelines and will be tested in two stages: usability, understandability, and adequacy. The trial will involve 10 primary care physicians and 450 patients, with eligible participants assigned to intervention and control groups. The system will make recommendations on patient monitoring, diagnosis, and treatment, and patients will be monitored for 6 months. Clinical and laboratory outcomes will be assessed in person or online[1].

B) Diabetic foot ulcer detection using neural networks

Diabetic foot ulcers (DFUs) are a prevalent and debilitating complication of diabetes, causing significant morbidity and posing a considerable burden on healthcare systems worldwide. In recent years, advancements in mobile technology have opened new possibilities for the early detection and management of DFUs. This literature review aims to explore the feasibility of developing a mobile application utilizing the normal mobile phone camera for the detection of DFUs, in contrast to the thermal camera-based system presented in Fraiwan's 2017 study[2]. In their feasibility study titled "Diabetic Foot Ulcer Mobile Detection

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System using Smart Phone Thermal Camera," Fraiwan (2017) proposed a novel approach for DFU detection. The researchers utilized a thermal camera integrated with a smartphone to capture thermal images of the foot, aiming to identify regions of abnormal temperature associated with DFUs [3]. Through the analysis of thermal patterns, the system demonstrated promising results in terms of accuracy and feasibility for DFU detection[4]. However, the reliance on a specialized thermal camera limited the accessibility and widespread adoption of the technology. Developing a mobile application for DFU detection using a normal mobile phone camera offers several advantages over the thermal camera-based approach[5].

Another advantage is the user convenience provided by mobile applications. They are easily accessible, intuitive to use, and familiar to most of smartphone users, facilitating widespread acceptance and adherence to the detection process. Additionally, developing a mobile application allows for seamless integration with electronic health records (EHR) systems, enabling healthcare professionals to efficiently manage and monitor patient data[6].

However, developing a mobile application with a normal camera for DFU detection poses challenges. One significant challenge is the development of robust image processing algorithms that can accurately identify and segment DFUs from images captured by a normal mobile phone camera.[7] Machine learning techniques, such as deep learning, may prove useful in this regard. Lighting and environmental factors, such as shadows, reflections, and ambient temperature, must also be carefully considered and accounted for in the development of the mobile application.

C) Acanthosis Nigricans detection using neural networks

The research paper titled "Diabetic Acanthosis Nigricans Detection using Neural Networks" by Meghana Madhukar Phiske presents a study on the application of neural networks for the detection of diabetic acanthosis nigricans (DAN), a skin condition commonly associated with diabetes. The paper explores the use of machine learning techniques, specifically neural networks, to develop an automated system capable of accurately identifying DAN from images. By leveraging a dataset of DAN images, the researchers trained a neural network model to learn and recognize the characteristic patterns and features of DAN. This research highlights the significance of leveraging advanced technologies like neural networks to enhance the detection and management of diabetes-related complications[8]. Diabetic acanthosis nigricans (DAN) detection using neural networks is a significant area of research that aims to provide an automated and efficient approach for identifying this dermatological manifestation in individuals with diabetes. The research paper by Meghana Madhukar Phiske.focuses on the development of a neural network-based algorithm to detect DAN[9].

Another research paper by Yangkui Zhai contributes to the detection of DAN using neural networks by employing a similar methodology. This study also utilizes CNNs for feature extraction and employs a classification model for DAN detection. The authors explore the effectiveness of different CNN architectures and evaluate their performance using a comprehensive dataset of clinical images[10].

In conclusion, the research papers Meghana Madhukar Phiske and Yangkui Zhai provide valuable insights into the use of neural networks for the detection of DAN[9]. These studies demonstrate the potential of employing advanced machine learning techniques to automate the identification of this dermatological manifestation in individuals with diabetes. Such advancements hold promise for improving early diagnosis and intervention, ultimately enhancing patient care and management of DAN[10].

D) Cellulitis due to diabetics detection using neural networks

Cellulitis, a skin infection caused by cuts or scratches, is higher in people with diabetes due to impaired immune and circulatory system function. A study by Healy (2017) found that people with diabetes had a 2.5 times higher risk of developing cellulitis than those without the disease. Image processing has not been extensively studied for identifying cellulitis[11].

This research is being conducted to detect Cellulitis caused by diabetes using a mobile phone camera. In here it will process the image and detect whether it is caused by diabetes, and it will produce the medical instructions to follow the people.

For instance, Sadiq et al study .'s from 2021 created an image processing method to identify diabetic patients' foot ulcers[12]. The algorithm had a detection accuracy of 90.83% for foot ulcers. But it is not used to detect cellulitis. In this research, it is improved and used to detect Cellulitis as well. According to the research of Cellulitis by Brandon D. there is an approach to detect cellulitis from thermal images in previous stages [13]. But the accessibility is very low. In our system we are processing images using mobile phone camera, so the accessibility is much higher

E) Determination of RGB in Fingernail Image As Early Detection of Diabetes Mellitus

This research aimed to determine the component color RGB on fingernails as an early detection of diabetes mellitus.

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Results showed overlapping range numbers of RGB in all categories, and the detection of diabetes mellitus needs improvement. The study used auto check GCU rapid test and blood glucose auto check glucose strips to obtain blood glucose data. Fingernail images were obtained using a Canon Ixus 285 HS 20, 2 MP digital camera under lighting. The analysis stage aimed to obtain the range number of component fingernail colors to determine blood glucose levels into categories of normal, prediabetes, or diabetes. The study used a two-step process of data retrieval, data processing, and data analysis. The range number of RGB histograms showed overlaps in all three types of histograms and categories. Overlapping in RGB may occur due to lighting intensity, but the effect of lighting was minimized by using a box with a lamp during data retrieval [14].

Table I: Comparing existing applications and our application features

	B	C	D	E	"Heal-Derm"
Early detection	Yes	Yes	Yes	Yes	No
Detecting DFU	No	Yes	No	No	Yes
Detecting AN	Yes	No	No	No	Yes
Detecting Cellulitis	No	No	No	Yes	Yes
Detecting Nail Infections	No	No	Yes	No	Yes
Compressive diagnosis	Yes	Yes	Yes	No	Yes
Patients' Empowerment	No	Yes	No	No	Yes
Accessibility	No	No	No	No	Yes
Accuracy	Yes	Yes	Yes	Yes	Yes

III. METHODOLOGY

A) Module Discussion

1) Detection of Diabetic Foot ulcers and Provide related recommendations

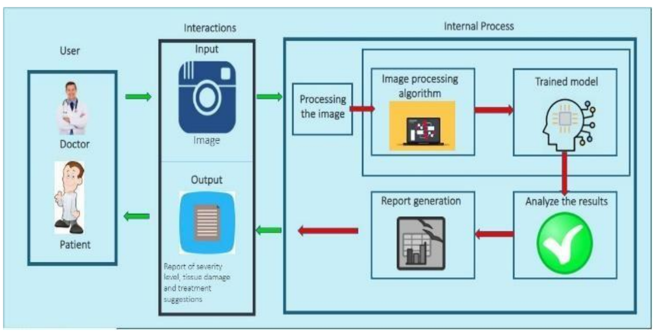

Figure 1: Component diagram of DFU detection model

To detect and classify diabetic foot ulcers, abnormal foot ulcers, healthy skin, and normal wounds, we developed a mobile application using React Native and employed a Convolutional Neural Network (CNN) model. The methodology involved several steps, including dataset collection, model architecture selection, model training, and integration into the mobile application. For dataset collection, we gathered a diverse set of wound images from various sources. The dataset consisted of four classes: abnormal foot ulcers, diabetic foot ulcers, healthy skin, and normal wounds. To ensure consistency, each image was preprocessed by resizing it to a standardized dimension of 224x224 pixels using OpenCV [10].The chosen model architecture for this study was MobileNetV2, a lightweight CNN model designed specifically for mobile applications. We leveraged the pretrained MobileNetV2 model, which had been trained on the ImageNet dataset, as an initial feature extractor. To adapt the model for our classification task, the last few layers were replaced with custom classification layers, including a Global Average Pooling layer and two Dense layers. The weights of the base model were frozen to preserve the learned features, while only the custom layers were fine-tuned during training. To train the model, the dataset was split into training and testing sets, with a ratio of 80:20. The training set was used to train the model over 20 epochs, employing a batch size of 32. The Adam optimizer was utilized, and categorical cross entropy was employed as the loss function. The model's performance was continuously monitored using accuracy as the evaluation metric. After training, the model's performance was evaluated using the testing set. This evaluation involved measuring the test loss, which indicates the dissimilarity between predicted and actual labels, and the test accuracy, which represents the proportion of correctly classified wound images.

2) Detection of Acanthosis Nigricans(AN) and detecting severity level

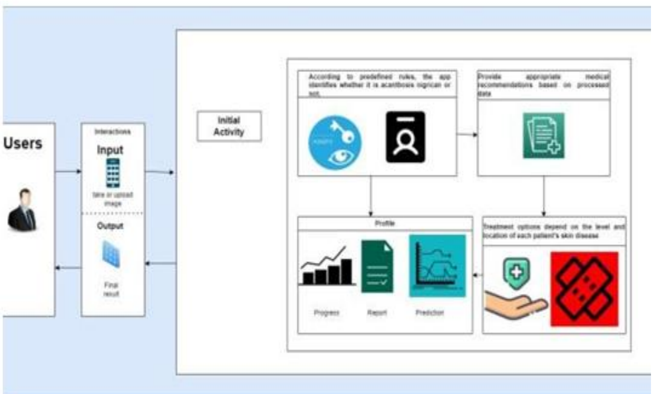

Figure 2: Component diagram of AN detection model

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A smartphone application was developed to differentiate between diabetic acanthosis nigricans and healthy skin. Data set collection, model architecture selection, model training and integration into the mobile application were all steps in the technology. Review the literature on diabetes prevalence, skin infections and health care systems in Sri Lanka to gain insight into the status and knowledge gaps. Field. Collect studies, medical literature, and related research papers. To learn more about diabetes, skin infections and caregivers' experiences, perspectives, and challenges, talk to them. The model for Identifying Infection consists with custom CNN with the VG668 architecture: The chosen model architecture is a custom convolutional neural network (CNN) with the VG668 architecture. This architecture may have been specifically designed or adapted for the task of identifying skin infections caused by diabetes. The specific details of the VG668 architecture are not provided in the given information, but it is likely optimized for handling image data and extracting relevant features for infection detection.

Used tensorFlow and keras that are widely used deep learning frameworks that provide a high-level API for building and training neural networks. TensorFlow is known for its flexibility, scalability, and production readiness, while Keras offers a user-friendly interface and abstraction for defining and training deep learning models. By using these frameworks, the model development process was streamlined and benefits from the extensive libraries, tools, and community support available.

Jupyter Notebook and Google Colab are popular choices for Integrated Development Environments (IDE)s in developing machine learning models. Jupyter Notebook provides an interactive computational environment that allows for code execution, data visualization, and documentation within a single interface. Google Colab, on the other hand, offers a cloud-based environment with free access to GPU resources, making it suitable for training deep learning models. Using these IDEs facilitates code development, experimentation, and collaboration.

Mobile App was developed using React Native, Node.js, and Visual Studio Code (VS Code): The mobile app is developed using React Native for the front end, Node.js for the backend, and Visual Studio Code (VS Code) as the integrated development environment (IDE). React Native is a popular framework for building cross-platform mobile applications using JavaScript. It allows for the development of native-like mobile apps that can run on both iOS and Android platforms. Node.js is used for the backend to handle server-side logic and provide APIs for communication between the mobile app and the server.

Model architecture is consisted with convolutional layers with ReLU activation function, pooling layers, MaxPooling2D layers, Dropout layers, and a Flatten layer. Convolutional layers are responsible for extracting relevant features from the input images by applying convolutional filters. ReLU activation function is used to introduce nonlinearity and enhance the model's ability to capture complex patterns. Pooling layers, such as MaxPooling2D, are used to reduce the spatial dimensions of the feature maps, allowing the model to focus on the most important information. Dropout layers are employed to mitigate overfitting by randomly disabling a fraction of the neurons during training. Finally, a Flatten layer is used to convert the multidimensional feature maps into a 1D vector, which is then fed into dense layers for classification.

3) Detecting cellulitis caused by diabetes and providing instructions

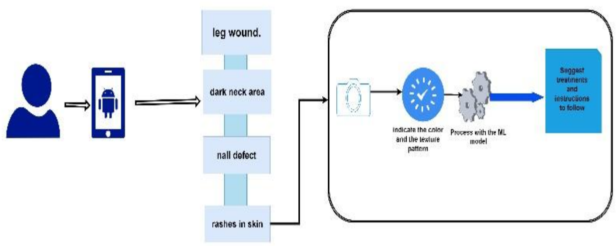

Figure 3: Component diagram of cellulitis detection model

Review literature on diabetes incidence in Sri Lanka, skin infections, and healthcare systems to understand existing knowledge and gaps in the field. Gather relevant research articles, medical journals, and reports. Interview diabetes experts, individuals with skin infections, and caregivers to understand their experiences, perspectives, and challenges. Conducted a cost-benefit analysis to see whether the suggested mobile application would improve the early detection and treatment of skin infections brought on by diabetes in Sri Lanka. Considering things like lower healthcare expenses, better healthcare outcomes, and easier access to diagnosis and treatment. Compared to the expenditures of developing and implementing the mobile application, weigh the possible rewards.

Model for Identifying Infections contains custom CNN with VG668 architecture. Tensorflow and Keras were used as frameworks during development. React Native on the front end with Node.js, the backend and Convolution2D layers with ReLU activation function used with pooling layers, MaxPooling2D layers, Dropout layers, Flatten layer are used as techniques to create the model.

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4) Detecting Nail Defects caused by Diabetic and Providing solutions

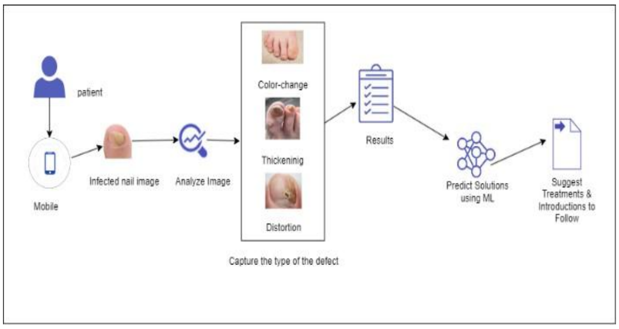

Figure 4: Component diagram of nail defects detection model

Customized the primary model for identification was CNN. CNN was chosen because it is one of the most fundamental deep learning models and can distinguish between input images. Due to the wide variety of tools, libraries, and community resources it contains, TensorFlow is predominantly employed in this context. Then, abstractions and building blocks are provided by Keras for the creation of machine learning code. Due to its straightforward but comprehensive GUI, maplotlib was used to plot the results. The training and testing sets were divided into 80% and 20%, respectively. The layers that make up the data model's foundation are as follows 6 - Convolution2D layers with ReLU activation function, 6 – Max Pooling 2D layers, 1 - Flatten layer (to get output in the set of numbers) and 2 Dense layer 'SoftMax' activation function (to change the output into a probability). Due to the problem's size and abundance of data and parameters, the optimizer "Adam" was utilized. to acquire the best results, various Optimizers were tested with the model. In here mainly used two classes to identified diabetic nail or non-diabetic nail, using CNN model able to identify infection nail with good accurate. The parameters of batch size, learning rate, and epochs were hyperparameter tuned. A lower number was initially picked with a steady increase in value because research has shown that greater values for learning rate and batch size do not always produce higher results. A brute force approach was employed to determine the optimal epochs. To preprocess the data, it was shuffling, resizing, and rescaling. A 256*256 image was used since it matched the model parameter.

IV. RESULTS AND DISCUSSIONS

A) Detecting Diabetic Foot Ulcers

The model's predictions, indicating whether the wound is a diabetic foot ulcer, abnormal foot ulcer or healthy skin were presented to the user in the mobile application's interface. The following results were produced by the model after the training.

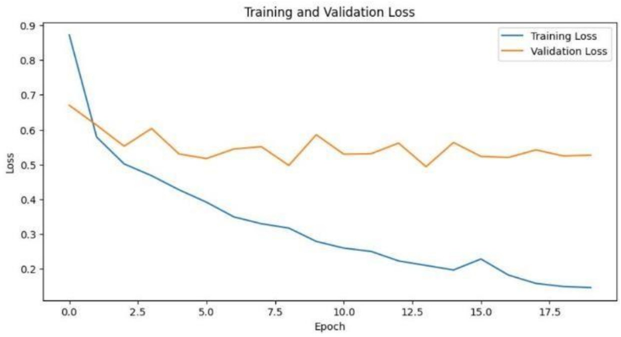

Figure 5: Training and validation accuracy of DFU detection model

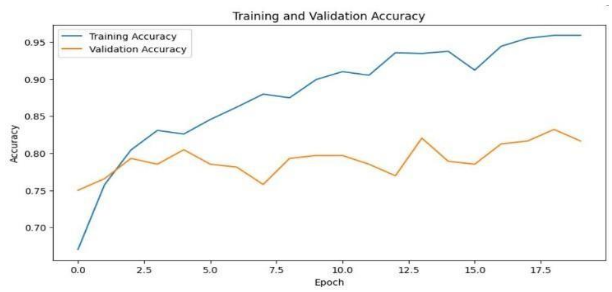

Figure 6: Training and validation loss of DFU detection model

This involved dataset collection, model architecture selection, model training using the MobileNetV2 model, and integration into a mobile application for real-time wound classification. This approach allowed to effectively detect and classify different types of wounds, empowering users to receive prompt feedback and enabling early intervention and appropriate medical care for diabetic foot ulcers.

The following prediction probability was captured when an abnormal diabetic foot ulcer image is inserted to the trained model.

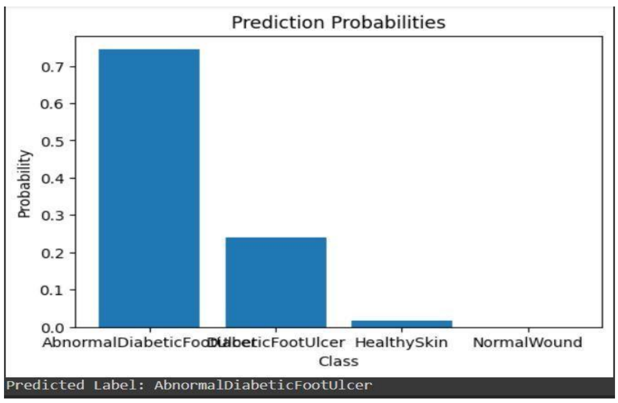

Figure 7: Prediction of DFU detection model

B) Detecting Acanthosis Nigricans

Accuracy for Training and Validation graph shows accuracy on the y-axis and the total number of epochs on the x-axis. A higher number of epochs causes the accuracy to

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fluctuate, but it has no detrimental effects. With 40 epochs and a batch size of 32, the model achieved a training accuracy of 94.37%.

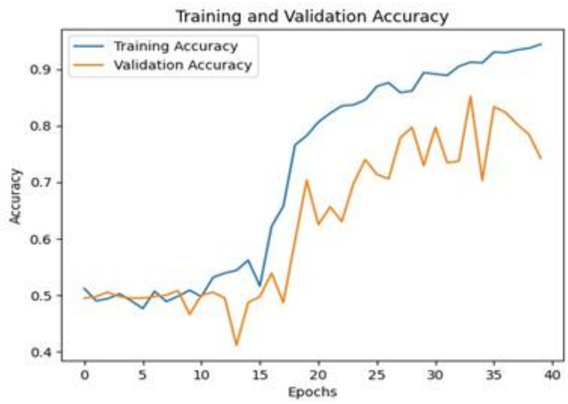

Figure 8: Training loss of AN detection model

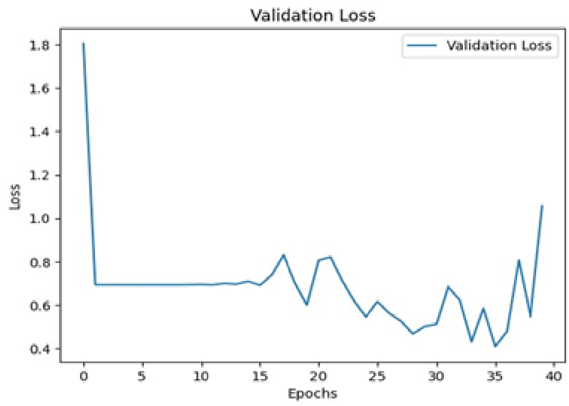

Figure 9: Validation loss of AN detection model

```
[9] img_path = '/content/drive/MyDrive/datasets/Test/acanthosis nigricans/1.jpg'
    img_arr = cv2.imread(img_path)
    img_arr = cv2.resize(img_arr, (img_size, img_size))
    img_arr = np.array(img_arr) / 255.0

    prediction = model.predict(np.array([img_arr]))
    if prediction[0][0] > 0.5:
        print('The image is acanthosis nigrican.')
    else:
        print('The image is healthy skin.')

    1/1 [==============================] - 0s 256ms/step
    The image is acanthosis nigrican.
```

Figure 10: Prediction of AN detection model

C) Detecting cellulitis

Figure 11 represents the training and validation accuracy chart. The y-axis depicts the accuracy for the graph. The xaxis depicts the number of epochs. As it is clear from the graphs with a large number of epochs, accuracy fluctuation gets higher. It is apparent that many epochs does not negatively affect accuracy .87% training accuracy was able to be reached using this model as shown in the examples and predictions. 15 epochs and 32 batch size are the hyper parameters used in this model.

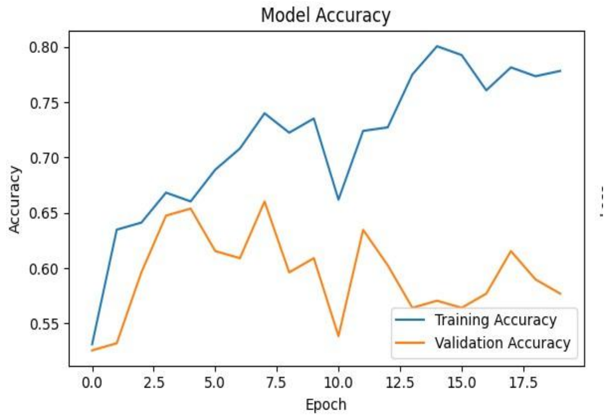

Figure 11: Accuracy chart of Cellulitis detection model

The following figure shows the result of the model.

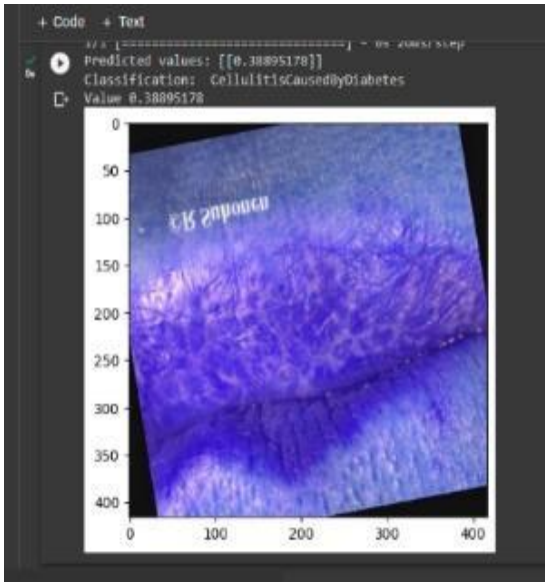

Figure 12: Results of cellulitis detection model

The table shows the how accuracy is increased and how los is dicreased while the training acording to the last 5 epochs.

Table II: Cellulitis detection model accuracy

Epoch	Loss	accuracy	Val_loss	Val_accuracy
10/15	0.6269	0.6644	0.4936	0.8976
11/15	0.5896	0.6924	0.1706	0.9731
12/15	0.6280	0.6431	0.6623	0.5927
13/15	0.5678	0.7031	0.7980	0.5399
14/15	0.5850	0.6977	0.7152	0.4871
15/15	0.5529	0.7137	0.3753	0.8718

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D) Detecting Nail Defects caused by Diabetic and Providing solutions

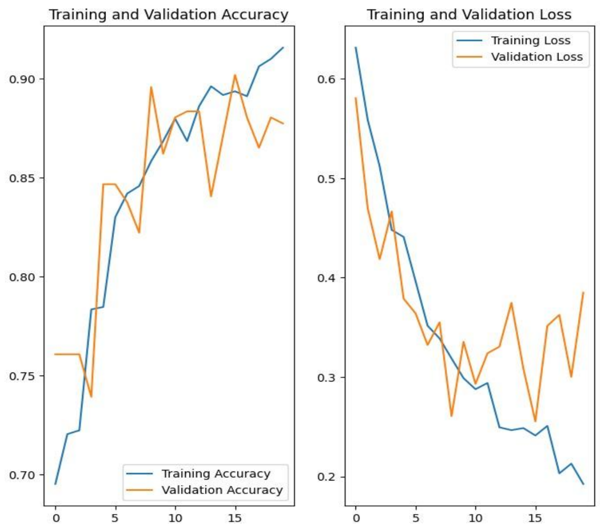

Figure 13: Test Accuracy Chart Of Nail Defects Detection Model

The above figure 13 represents training and validation accuracy with the loss. The y-axis depicts the accuracy for the first graph and the loss for the second graph. The x-axis depicts the number of epochs. As is clear from the graphs, with many epochs, loss and accuracy fluctuation gets higher. It is apparent that many epochs do not negatively affect accuracy or loss. 91.56% training accuracy and 87.73% test accuracy were able to be reached using this model as shown in the examples and predictions.

Figure 14: Results of nail defects detection model

V. CONCLUSION

This research paper is performed to provide solutions and medical prescriptions to diabetic patients who are having four major skin infections which includes diabetic foot ulcers, AcanthosisNigricans, cellulitis due to diabetics and nail defects due to diabetics. In this research four CNN models are developed to find the best suited solutions and predictions. When considering outputs provided by four models which are used for image classification, all the models were provided with considerable accuracy levels. Some additional research has also been done for the purpose of mapping the actual infected area and for measuring the severity level. To map actual infected areas, data preprocessing techniques were used and implemented and finetuned a custom-made python operation to provide the severity level. To increase object detection accuracy, the authors are willing to train data sets using You Only Look Once (YOLO) v5 object detection model and willing to increase the early detection feature of diabetic skin infections in future.

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