

Machine Learning-Based Detection System for Facial Skin Diseases and Ayurvedic Remedies

R.K.A. Risina Rasmith
Department of Computer Science
and Software Engineering
Sri Lanka Institute of Information
Technology
Malabe, Sri Lanka

C.P. Abeywickrama
Department of Computer Science
and Software Engineering
Sri Lanka Institute of Information
Technology
Malabe, Sri Lanka

H.L.D.P. De Silva
Department of Computer Science
and Software Engineering
Sri Lanka Institute of Information
Technology
Malabe, Sri Lanka

K.G. Chamindu Hansana
Department of Computer Science
and Software Engineering
Sri Lanka Institute of Information
Technology
Malabe, Sri Lanka

S. Siriwardana
Department of Information
Technology, Lecturer
Sri Lanka Institute of Information
Technology
Malabe, Sri Lanka

S. Jayaweera
Medical Officer
Government Ayurvedic Hospital
Welipitiya, Sri Lanka

Abstract:- Facial skincare is crucial for overall health, beauty, and wellbeing, as the face serves as a foremost reflection of one's life. Face skin is delicate and more sensitive to damage. Neglecting proper facial skincare can lead to some diseases like acne, dark spots, and other signs of aging. Facial skin diseases are a common health problem that can be found worldwide. Since ancient times, ayurvedic treatments can be found as natural and optimum solutions to cure those diseases and keep the facial skin healthy and glowing. This research introduces an integrated framework to automate face skin disease detection, identify ayurvedic plants, patient data management and telemedicine system, and user interaction within the context of facial skin health. The proposed system utilizes machine learning techniques to identify four facial skin conditions: acne, dark circles, dark spots, and wrinkles into 3 levels. Additionally, it can recognize 20 different ayurvedic plants using leaves, flowers, fruits, and barks and offers ayurvedic remedies through natural language processing (NLP) based emotional awareness chatbot using text and audio messages and enhances patient engagement through a web application using telemedicine system, connecting medical professionals and patients for efficient care delivery. This research aims to reform skincare by combining advanced technology with traditional knowledge, offering holistic solutions to facial skin health. It addresses the need for early face skin disease detection, natural remedies, and seamless patient-professional interaction, eventually promoting a healthy and fair appearance.

Keywords:- Facial Skincare, Disease Detection, Ayurvedic Plants, Telemedicine, Natural Remedies.

I. INTRODUCTION

Facial skincare is an essential component of maintaining a healthy and glowing appearance. The face is often the first thing that others notice about us, and it serves as a reflection of our overall beauty, and wellbeing. However, facial skin is delicate and more sensitive to damage from not only stress, and lack of sleep but also from environmental factors such as sun exposure and pollution. Neglecting proper facial skin care can lead to facial skin diseases such as acne, wrinkles, dark spots, and other signs of aging. In today's fast-paced world, many people struggle to find time to care for their facial skin properly. Moreover, those who do manage to devote time to their skincare routine often rely on chemical products, which can cause damage to their facial skin. Additionally, people often lack the knowledge to determine whether their skincare routine is working properly. However, in this kind of situation, people are unable to choose a better way to take proper care of facial skin.

Fortunately, the practice of Ayurveda offers natural and effective solutions to keep the facial skin healthy and glowing. In ancient times, there were many Ayurvedic methods used for facial care. However nowadays, due to a lack of knowledge and awareness, people often neglect those treatments. Fortunately, with advanced interventions, this gap between traditional Ayurvedic remedies and modern technology can be reduced. By combining the power of technology with the sense of Ayurveda, individuals can achieve healthy and glowing facial skin without the need for harsh chemicals or artificial ingredients. By applying technology, people can now easily access information about Ayurvedic facial skincare practices and plans. Overall, by this approach, individuals can achieve healthy, glowing faces and improve their overall well-being.

This paper presents an implementation of a web application that provides features to identify facial skin diseases, identify ayurvedic plants, and give ayurvedic solutions for particular diseases. Also, there is an NLP-based emotional awareness chatbot that can be used to ask about facial skin diseases, ayurvedic plants, and solutions for particular diseases. Another important feature is the patient data management and telemedicine system which is designed to streamline the process of recording patient data, managing appointments, and facilitating communication between medical professionals and patients..

II. LITERATURE REVIEW

Facial skin health holds a deep influence on an individual's confidence, and overall well-being. However, the journey towards achieving and maintaining flawless skin is filled with challenges. The major challenge is identification of common facial skin conditions such as acne, dark spots, dark circles, and wrinkles. Researchers proposed many solutions to get this challenge to some extent.

In one of the earliest works on acne vulgaris and rosacea skin diseases image classification using gray level co-occurrence matrix and convolutional neural network, Cahya Rahmad et al. (2021) aimed to classify facial skin diseases named rosacea and acne vulgaris in three severity levels: mild, moderate, and severe. They used GLCM filters for feature extraction and Naïve Bayes and Convolutional Neural Network (CNN) for classification. In this research their classification accuracy for GLCM and CNN Resnet-50 are 45.30% and 74.2424% respectively. The dataset contained 479 images [1].

Building on the success of earlier work, Akyeramfo-Sam et al. (2019) developed a web-based skin disease diagnosis application called "medilab-plus" using a convolutional neural network classifier. The selected diseases were atopic dermatitis, acne vulgaris, and scabies. In this proposed system, there were 88% accuracy for atopic dermatitis, 85% accuracy for acne vulgaris, and 84.7% accuracy for scabies [2].

In one of the earliest works, Wirdayanti et al. (2020) investigated the detection of acne-prone skin disease based on its severity in adolescents, adults, and the elderly, both men and women, using textural feature extraction. The method used here is Gray Level Co-Occurrence Matrice (GLCM) with the K-Nearest Neighbor (K-NN) classification method [3].

In one of the earliest works on skin pimple image detection and classification using a hybrid technique, Hameed et al. (2020) developed a method using Naive Bayes Classifier (NBC) and Image Processing. Here, they classified pimples into 3 types named pimples cystic, pimples excoriated, and pimples pustular with the accuracy level of 93.42%. 40 images of each type were considered. They have done feature extraction using Image Processing

techniques. After that, those skin pimples were classified into multiple levels using the NBC method and for performance comparison, Linear Discriminant Analyzer (LDA) classification is used [4].

In one of the earliest works on machine learning-based emotion level assessment using facial action coding system (FACS), Lumini Wickremesinghe et al. (2021) proposed a method to classify levels of emotions in unannotated video clips. To identify levels of emotions, they used the Random Forest algorithm. There were 2 methods and in method I, clusters are shown as neutral, moderate, and peak levels of an emotion using K-Means clustering algorithm. Since that method showed low accuracy on identifying the levels of emotions, they proposed method II. In that method, images were clustered using K-Means clustering which consisted of neutral, peak, and moderate levels of happy, sad and surprise emotions [5].

There are many similar systems to identify Ayurvedic plants. In this research, they used images of leaf samples to identify Ayurvedic plants. To create the dataset, they used 32 different plant species that are used in Ayurvedic, herbal, and traditional medicine. They used image processing and machine learning techniques to do the above task and they used Support Vector Machines (SVM) for classification tasks. 64 samples were utilized for training and 64 samples were used for testing in this system. Entropy, contrast, correlation, solidity, eccentricity, extent, equivalent diameter, mean, and standard deviation are the features used for this training and testing, and their values are taken from the images. They achieved an accuracy of 96.667% using the SVM classifier. [6].

In one of the earliest works on mobile-based assistive tools for Ayurvedic plant identification, Senevirathne et al. (2020) proposed different solutions and methods. Identification of Ayurvedic plants from images of their leaves, flowers, fruits, and bark is a challenging task because quite a bit of preprocessing is required to distinguish the target object from the background. One of the proposed methods is a mobile application that identifies a flower and leaf by its morphological features, such as shape, color, and texture. They used a dataset that consists of 5 categories of flowers and leaves. Each category included 500 images. The perspective is to achieve the highest accuracy for plant identification using image processing. The CNN model achieved 100% accuracy on the training set. They achieved 89% - 96% test accuracy using CNN approaches. 1000 images of local medicinal plants were used for the test. For the datasets of flowers and leaves, the Faster Region Convolution Neural Network (FRCNN) performed the best. This application also provides a Sinhala virtual assistant which enables users to search herbs using the name, which is popular among people, to obtain information about herbs.[7]

Building on the previous work, Jayalath et al. (2019) proposed a similar method for an Ayurvedic knowledge sharing platform with a Sinhala virtual assistant. They used a dataset that contains 500 images for each of the 9 rare medicinal plants. They use deep learning-based CNN approaches and machine learning to identify medicinal plants. They achieved 100% accuracy for the training set and 95% - 99% test accuracy using CNN approaches. They used 5000 images of 9 rare medicinal plants for testing purposes. The number of epochs, or how frequently training takes place, determines how well uncommon medicinal plants may be identified. The accuracy will improve as the number of epochs increases. For Sinhala virtual assistant, they implemented Ayurveda information centralized chatbot which can answer user’s questions relevant to Ayurveda and indigenous medicinal plants. The chatbot analyzes the question that the user asks and provides answers according to that. Also, they used Neural network algorithms to obtain an accurate and efficient response. TensorFlow and Python are used to classify user input and recognize the intent.[8]

In a recent study, Vaishnav (2020) developed a service-oriented chatbot for essential oils using natural language processing. This chatbot is designed to provide users with information about essential oils and their medicinal uses. According to the questions asked by the user, the artifact provides information on essential oils and suggests the use of them. With the help of NLP, the chatbot delivers the users’ application of essential oils and

also suggests solutions to their medical sufferings with these oils. Also, DuckDuckGo API and TensorFlow are used for the advancement of the chatbot [9].

In one of the earliest works on WebRTC conferencing, Nuño et al. (2018) implemented a comprehensive conferencing service that could be used for multi-point e-learning and e-meeting operations. In order to achieve scalability, the platform also makes use of the possibilities of cloud computing. [10].

In a important study, Khalid et al. (2017) implemented a scalable live video conferencing tool using WebRTC. As a signaling server, web sockets were used. It enables any number of colleagues to attend the conference. Without the use of a relay, 92% of the calls were connected over P2P. As a result, just 8% of the calls needed a TURN server to pass NAT. [11].

In an early study, Edan et al. (2017) described the Web Real-Time Communication (WebRTC) technology and the implementation of its clients and server. The major goal is to develop and implement WebRTC video conferencing between browsers utilizing Chrome and (Wired & Wi-Fi) of LAN & WAN networks in a practical implementation. Additionally, a measurement of CPU efficiency, bandwidth usage, and Quality of Experience (QoE) was made. Additionally, a WebSocket-based signaling channel between browsers using the Node.js framework has been developed and put into use. [12].

III. METHODOLOGY

A. System Architecture and Components

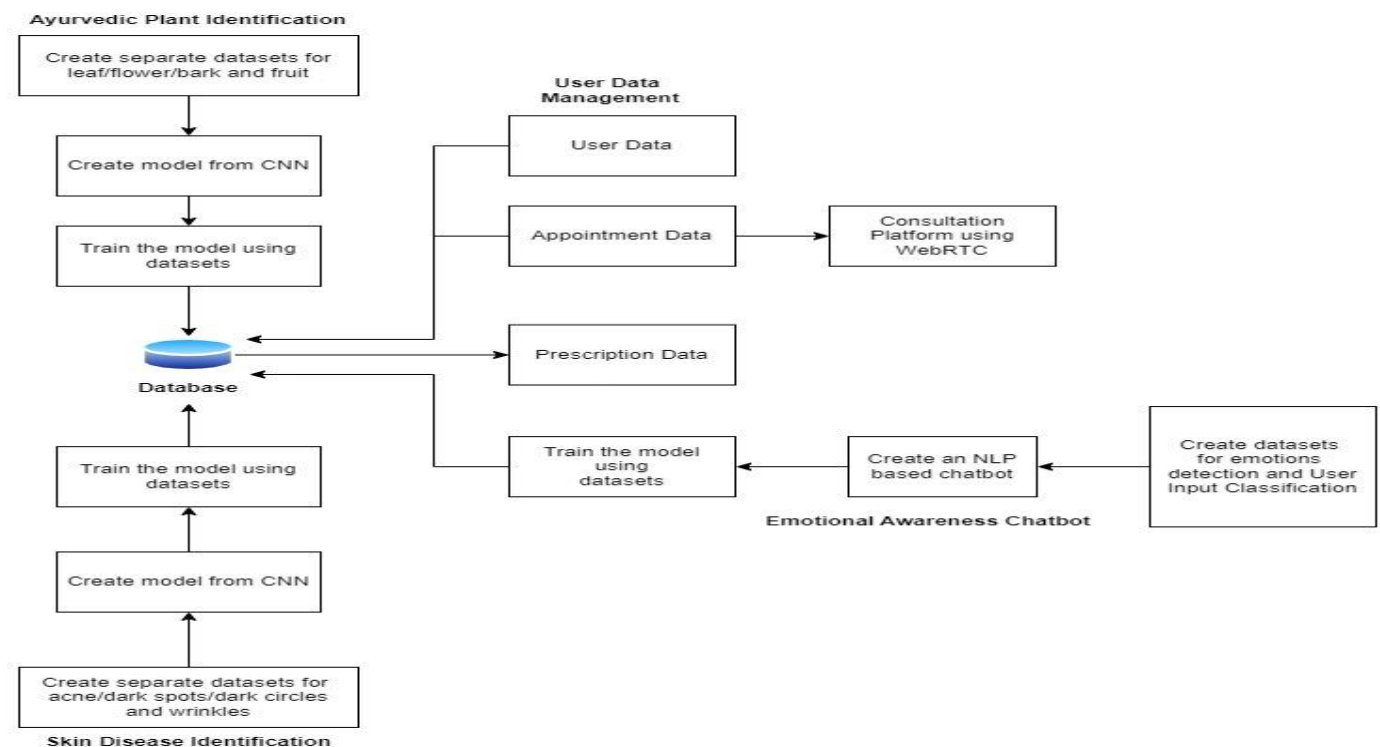


Fig 1 - System Overview Diagram

B. Facial Skin Disease Identification

At first, an extensive study was started and conversations were conducted with various Ayurvedic doctors at the Welipitiya Ayurvedic General Hospital to start the process. Important information about facial skin conditions and the associated Ayurvedic treatments was obtained through these interviews with the Ayurvedic doctors. When considering the face skin diseases side, a survey is used to collect the patients' data and their facial images. After that, those images were divided according to the chosen disease types and the datasets for those categories. Also, some datasets were found from websites like Kaggle. Finally, 427 images dataset for acne, 299 images dataset for dark circles, 285 images dataset for dark spots, and 315 images dataset for wrinkles were found for the research.

The facial skin diseases identification approach uses VGG16 architecture to identify facial skin disease to categorize those diseases into three distinct levels of severity. VGG16 is a well-recognized deep convolutional neural network (CNN) architecture that has been pretrained on a large 'ImageNet' dataset. It has the ability to extract hierarchical features from images. It takes the face images as input and processes them through several convolutional and pooling layers. These layers capture meaningful features from the input images, extract them and eventually learn to recognize relevant patterns of each facial skin disease.

The output from the pretrained layers is flattened into a one-dimensional vector after feature extraction. This stage gets the extracted features ready for fully connected layers to process them further. There is also a dense layer with 256 neurons and Rectified Linear Unit (ReLU) activation. This layer performs additional feature transformation and serves as a hidden layer. 'ReLU' activation adds non-linearity to the model, allowing it to recognize complicated patterns in the data. A dropout layer is added after the initial dense layer to reduce overfitting and enhance the model. Acne, dark spots, dark circles, and wrinkles are the four face skin disorders represented by four neurons of the final output layer. This layer uses the 'softmax' activation function to transform the unprocessed output of the model into class probabilities. The chance that an input image belongs to a particular severity level of a particular skin condition is represented by each output of the neuron.

The 'ImageDataGenerator' offered by 'TensorFlow' is used to apply data augmentation techniques to the training dataset. Rescaling, shearing, zooming, and horizontal flipping are some of these methods. By increasing the variety of the training data, augmentation decreases overfitting and enhances model.

C. Ayurvedic Plant Identification

The main area of interest was Ayurvedic plant-based treatments. These plants were methodically divided into four groups: bark, leaves, flowers, and fruits. These groups included six different plant species for leaves, five different

types for flowers, six different plant species for fruits, and three different species for bark. Twenty distinct plant species were included in all the plant datasets. 913 image datasets for leaves, 2050 image datasets for flowers, 618 image datasets for fruits, and 435 image datasets for bark were gathered as a result of the efforts.

Neural networks come in a variety of forms and are used for machine learning. The Convolutional Neural Network (CNN) is one of the well-known ones. This neural network approach is used to address issues with image presentation. One of the main issues with image presentation is image classification. Images are classified in order of identification. The CNN architectures VGG16, Inception, ResNet, and others are well-known. Although the depth, number of layers, and specific architectural aspects of these designs differ, they all adhere to the fundamental CNN principles.

Convolutional Neural Networks, which have enabled machines to automatically learn and recognize complex patterns and characteristics in visual input, have revolutionized the science of computer vision. This has resulted in remarkable improvements in tasks like image analysis, object detection, and image synthesis. Also, CNN provides high accuracy for image classification and uses several libraries like TensorFlow, Keras, etc.

As the number of training epochs increased to 64, there was a corresponding improvement in model accuracy.

D. Chatbot

The Chatbot Integration component enriches user engagement and interaction by introducing a sophisticated emotionally aware chatbot powered by PHP and JavaScript. The chatbot leverages Natural Language Processing (NLP) techniques to provide dynamic responses and interact with users in a conversational manner. Advanced NLP techniques such as tokenization, entity recognition, and sentiment analysis are employed to process and understand user input. Also, Intent detection algorithms identify the user's purpose and queries. Python and TensorFlow are used to classify user input and identify intent. Additionally, neural network techniques are employed to produce a precise and effective response. Normally, The chatbot interfaces with the Face Skin Diseases Detection System (component 1) to identify skin diseases from images uploaded by users. Integration with the Treatment Recommendations component (component 2) allows the chatbot to provide information about medical plants and natural treatments. Also, it generates responses by combining predefined templates with information extracted from Component 1 and 2 databases. This chatbot engages users in dynamic and context-aware conversations, guiding them through a range of skin health-related queries. Mainly, users can inquire about identified skin diseases, request treatment recommendations, and learn about medical plants. Also, this chatbot can identify users' emotions through the messages and response respond according to those emotions.

```

Administrator Command Prompt
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7488 accuracy: 0.7281 val_loss: 0.7588 val_accuracy: 0.7012 lr: 1.0000e-04
epoch 45/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7387 accuracy: 0.7287 val_loss: 0.8158 val_accuracy: 0.7008 lr: 1.0000e-04
epoch 46/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7297 accuracy: 0.7278 val_loss: 0.7564 val_accuracy: 0.7227 lr: 1.0000e-04
epoch 47/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7481 accuracy: 0.7311 val_loss: 0.7803 val_accuracy: 0.7390 lr: 1.0000e-04
epoch 48/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7405 accuracy: 0.7416 val_loss: 0.8287 val_accuracy: 0.8034 lr: 1.0000e-04
epoch 49/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7618 accuracy: 0.7374 val_loss: 0.7512 val_accuracy: 0.7811 lr: 1.0000e-04
epoch 50/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7379 accuracy: 0.7401 val_loss: 0.8837 val_accuracy: 0.8071 lr: 1.0000e-04
epoch 51/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7405 accuracy: 0.7446 val_loss: 0.7248 val_accuracy: 0.7518 lr: 1.0000e-04
epoch 52/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7408 accuracy: 0.7391 val_loss: 0.8883 val_accuracy: 0.7811 lr: 1.0000e-04
epoch 53/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7205 accuracy: 0.7366 val_loss: 0.7327 val_accuracy: 0.7888 lr: 1.0000e-04
epoch 54/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7217 accuracy: 0.7385 val_loss: 0.7813 val_accuracy: 0.7518 lr: 1.0000e-04
epoch 55/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7218 accuracy: 0.7384 val_loss: 0.7486 val_accuracy: 0.7781 lr: 1.0000e-04
epoch 56/64
17/12/2023 15:56:44.156 [Info] [1] 56s 30/step loss: 0.7224 accuracy: 0.7451 val_loss: 0.7343 val_accuracy: 0.7888 lr: 1.0000e-04
epoch 57/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7237 accuracy: 0.7422 val_loss: 0.7439 val_accuracy: 0.7227 lr: 1.0000e-04
epoch 58/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7211 accuracy: 0.7411 val_loss: 0.7392 val_accuracy: 0.7598 lr: 1.0000e-04
epoch 59/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7362 accuracy: 0.7475 val_loss: 0.6879 val_accuracy: 0.7534 lr: 1.0000e-04
epoch 60/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7381 accuracy: 0.7537 val_loss: 0.7734 val_accuracy: 0.7441 lr: 1.0000e-04
epoch 61/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7295 accuracy: 0.7465 val_loss: 0.7844 val_accuracy: 0.7528 lr: 1.0000e-04
epoch 62/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7295 accuracy: 0.7487 val_loss: 0.7215 val_accuracy: 0.7598 lr: 1.0000e-04
epoch 63/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7291 accuracy: 0.7326 val_loss: 0.7285 val_accuracy: 0.7598 lr: 1.0000e-04
epoch 64/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7278 accuracy: 0.7368 val_loss: 0.7277 val_accuracy: 0.7598 lr: 1.0000e-04
epoch 65/64
17/12/2023 15:56:44.156 [Info] [1] 55s 30/step loss: 0.7229 accuracy: 0.7405 val_loss: 0.6995 val_accuracy: 0.7695 lr: 1.0000e-04
epoch 66/64
    
```

Fig 2 Chatbot

E. Telemedicine Platform

Consultation platform to create communication between doctor and patient is created by using WebRTC. WebRTC, or Web Real-Time Communication, is an open-source technology that empowers web browsers and mobile applications to engage in real-time communication without the need for third-party plugins or installations. The process begins with signaling, where two devices exchange crucial connection information. Once signaling is complete, a Peer Connection is established to manage the communication, handling codec negotiation, encryption, and media stream transmission. Media capture APIs allow access to cameras and microphones, enabling audio and video stream capture. WebRTC manages media processing, including encoding and encryption, and adapts transport protocols based on network conditions, utilizing ICE for NAT traversal, and ensuring secure data transmission with DTLS. In cases where direct peer-to-peer connections are not possible due to firewalls, TURN and STUN servers come into play. Security is a core feature, with end-to-end encryption. Finally, WebRTC provides APIs for media rendering and supports data channels for additional data transmission.

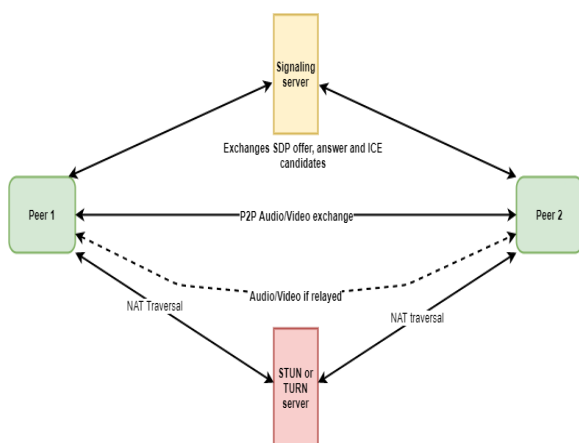


Fig 3 - WebRTC Architecture

In a doctor consultation platform, these features enable secure, real-time video and audio communication between doctors and patients, enhancing the overall telemedicine experience.

IV. RESULTS & DISCUSSION

A. Facial Skin Disease Identification

For facial skin disease detection, there were 2 models that have been developed. The initial model consists of a CNN-based approach and a dataset with 3,500 images that contain acne, dark spots, dark circles, and wrinkles diseases. It had a training accuracy of 75.05%, a validation accuracy of 76.95% a training loss of 72.29%, and a validation loss of 69.95% for 64 epochs. Since the loss is high, the model was enhanced using VGG16.

The developed model which used VGG16 has shown remarkable performance in the task of classifying face skin diseases into three severity levels. It was feasible due to feature extraction, additional feature transformation in dense layers and dropout regularization within that model. The model achieved a training accuracy of approximately 96%, validation accuracy of approximately 90% and a training and validation loss of 14% and 28% respectively for 28 epochs.

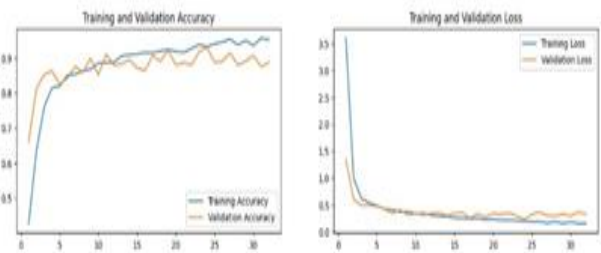


Fig 4 Facial Skin Disease Identification

The created model, which offers a capable solution for skincare analysis, performs well in classifying four facial skin diseases into three severity levels. With the ability to modernize how skin problems are identified and treated, its high accuracy, overfitting mitigation, and generalization capabilities make it a significant tool for dermatological and skincare applications. This is a critical feature since real-world situations frequently involve variance in skin types, ages, and genders. It enables skincare professionals and dermatologists with a powerful tool for quick and accurate analysis. Additionally, future research paths open the door for additional developments and effective use in the field of facial skincare.

B. Ayurvedic Plant Identification

We developed a Convolutional Neural Network (CNN) model to classify a dataset comprising approximately 4000 images encompassing 20 types of plants. The model exhibited impressive performance, achieving a training accuracy of 91.46% and a test accuracy of 91.70%. These results underscore the efficacy of our CNN-based approach in accurately identifying Ayurvedic plants using the images of leaves, flowers, fruits, and barks, demonstrating its potential for applications in traditional medicine and herbal product development. This high level of accuracy highlights the robustness and reliability of our model in distinguishing between various plant species, offering a

promising avenue for future research and practical implementation in the field of Ayurveda and natural medicine.

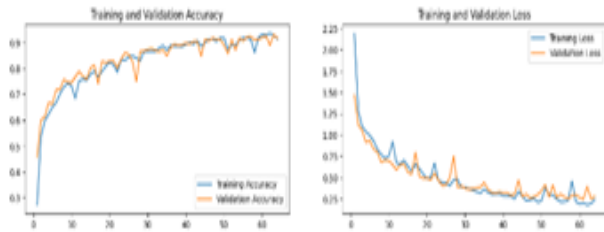


Fig 1 - Plant Identification / Accuracy Graph

C. Chatbot

```

{
  "tag": "disease_identification_category",
  "patterns": ["What are the face skin diseases, you can identify?", "What are the face skin diseases, you can identify?", "What face skin diseases you can identify?"],
  "responses": ["We can identify 4 face skin diseases. They are Acne, darkspot, wrinkles, and dark circles"],
  "context": ""
},
{
  "tag": "disease_types",
  "patterns": ["What are the types of face skin diseases?", "What are the most famous face skin diseases?", "Give me a list of face skin diseases types?"],
  "responses": ["There are so many face skin diseases types. These are some of face skin diseases - acne, eczema, melasma, fungal infections, vitiligo, psoriasis"],
  "context": ""
},
{
  "tag": "disease_in_sri_lanka",
  "patterns": ["What are the face skin diseases have in Sri Lanka?", "What face skin diseases can have in Sri Lanka skin?", "Give me a list of face skin diseases in Sri Lanka?"],
  "responses": ["There are so many face skin diseases types in Sri Lanka. These are some of face skin diseases - acne, eczema, melasma, fungal infections, vitiligo, psoriasis"],
  "context": ""
},
{
  "tag": "disease_conditions",
  "patterns": ["What are the conditions of face skin diseases?", "Give me a conditions related to face skin diseases?", "Any conditions? for face skin diseases?"],
  "responses": ["There are many conditions for face skin diseases. They are lasting conditions, temporary conditions, skin cancer and age-related conditions"],
  "context": ""
}
    
```

Fig 2 - Chatbot / Dataset Structure

The pattern and response elements are the other two parts that make up a tag.

➤ Patterns:

Used to store a straightforward pattern that a Chatbot can use to match what a user may say or input. It's the question's format in this instance.

➤ Responses:

This section provides the user's input response. A template value is defined as a response that the system created.

The chatbot processes user input through the predict_class function, which begins by converting the input sentence into a "Bag of Words" representation — a vector indicating the presence or absence of specific words from the chatbot's vocabulary. The neural network model then uses this vector to make predictions, identifying potential intents or categories the input might belong. Based on a confidence threshold, the function filters out low-probability predictions and sorts the remaining ones by their likelihood. With the most probable intent identified, the chatbot fetches a corresponding response from its predefined dataset, ensuring that the response aligns with the context and content of the user's original input.

V. CONCLUSION

In order to discover and disseminate information on facial skin problems and ayurvedic herbs, cutting edge technologies including Convolutional Neural Network (CNN), image processing, and NLP were applied in this article. With overall accuracy ranges between 85% and 95%, skin disease identification and plant identification were performed using CNN and VGG16 models. Plants used in ayurveda can be recognized by their leaves, flowers, fruits, and barks. With more epochs, skin conditions and medicinal plants can be identified more accurately. NLP was used to create an interactive conversation bot that provides knowledge on ayurvedic medicinal plants and illnesses of the facial skin. In this work, a telemedicine service that enables real-time video-to-video contact between doctors and patients is presented and put into practice. This is done by using WebRTC (Web Real-Time Communication) which offers peer-to-peer protocol that's primarily used over UDP. In future the identification of face skin diseases and ayurvedic plants will be expanded to support more diseases and plants. Also, the system will come as mobile application with ability to capture image and identify disease or plant using mobile phone camera.

REFERENCES

- [1]. Cahya Rahmad, Rosa Andrie Asmara, Alvionitha Sari Agstriningtyas, "Acne Vulgaris and Rosacea Skin Diseases Image Classification using Gray Level Co Occurance Matrix and Convolutional Neural Network," in International Conference on Electrical and Information Technology (IEIT), 2021.
- [2]. Samuel Akyeramfo-Sam, Acheampong Addo Philip, Derrick Yeboah, Nancy Candylove Nartey, Isaac Kofi Nti, "A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks," International Journal of Information Technology and Computer Science, vol. 11, no. 11, pp. 54-60, 2019.
- [3]. Wirdayanti, Irwan Mahmudi, Andi Chairul Ahsan, Anita Ahmad Kasim, Rosmala Nur, Rafifah Basalamah, Anindita Septiarini, "Face Skin Disease Detection with Textural Feature," in 6th International Conference on Science in Information Technology, 2020.
- [4]. Abduladheem Zaily Hameed, Waleed Kareem Awad, Nawar Ahmed Irsan, Azmi Shawkat Abdulbaqi, "Hybrid Technique For Skin Pimples Image Detection and Classification," International Journal of Advanced Science and Technology, vol. 29, no. 3, pp. 4102-4109, 2020.
- [5]. Lumini Wickremesinghe, Dakheela Madanayake, Anuradha Karunasena, Pradeepa Samarasinghe, "Machine Learning Based Emotion Level Assessment," in IEEE 16th International Conference on Industrial and Information Systems (ICIIS), 2021.

- [6]. Tejas D. Dahigaonkar, Rasika T. Kalyane, "Identification of Ayurvedic Medicinal Plants by Image Processing of leaf samples," International Research Journal of Engineering and Technology (IRJET), vol. 05, no. 05, 2018.
- [7]. L. P. D. S. Senevirathne, D. P. D. S. Pathirana, A. L. Silva, M. G. S. R. Dissanayaka, D. P. Nawinna, and D. Ganegoda, "Mobile-based assistive tool to identify & learn medicinal herbs," in 2020 2nd International Conference on Advancements in Computing (ICAC), 2020.
- [8]. A. D. A. D. S. Jayalath, P. V. D. Nadeeshan, T. G. A. G. D. Amarawansh, H. P. Jayasuriya, and D. P. Nawinna, "Ayurvedic knowledge sharing platform with sinhala virtual assistant," in 2019 International Conference on Advancements in Computing (ICAC), 2019.
- [9]. M. Vaishnav, "SERVICE-ORIENTED CHATBOT FOR ESSENTIAL OILS USING NATURAL LANGUAGE PROCESSING," 2020.
- [10]. Pelayo Nuño, F. G. Bulnes, J. C. Granda, F. J. Suárez, and D. F. Garcia, "A Scalable WebRTC Platform based on Open Technologies," Consultation of the Doctoral Thesis Database (TESEO) (Ministerio de Educación, Cultura y Deporte), Jul. 2018, doi: <https://doi.org/10.1109/cits.2018.8440161>
- [11]. Khalid, N. Mahmud, F. Hasan, and Sabbir Hossain Sagar, "P2P video conferencing system based on WebRTC," Feb. 2017, doi: <https://doi.org/10.1109/ecace.2017.7912968>.
- [12]. N. M. Edan, A. Al-Sherbaz, and S. Turner, "Design and evaluation of browser-to-browser video conferencing in WebRTC," IEEE Xplore, Oct. 01, 2017.