HAIR DISEASE DETECTION USING DEEP LEARNING

A PROJECT REPORT

Submitted by

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DEPARTMENT OF COMPUTER APPLICATIONS

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DECLARATION

I undersigned hereby to declare that the project report on **HAIR DISEASE DETECTION USING DEEP LEARNING**, submitted for partial fulfilment of the requirements for the award of degree of Master of Computer Application of the APJ Abdul Kalam Technological University, Kerala is a Bonafide work doneby me under supervision of **Dr. Nadera Beevi S.** This submission represents my ideas in my own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the original sources. I also declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data oridea or fact or source in our submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for theaward of any degree, diploma or similar title of any other University.

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This is to certify that, the report entitled **Hair Disease Detection Using Deep Learning** submitted by **ABHI KRISHNAN (TKM23MCA-2001)** to the **APJ Abdul Kalam Technological University** in partial fulfilment of the requirements for the award of the Degree of **Master of Computer Application** is a Bonafide record of the project work carried out by him/her under my/our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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Internal Supervisor(s) Mini Project Co-ordinator

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ABSTRACT

In dermatology, the accurate and timely identification of hair and scalp diseases is essential for improving patient outcomes and accessibility to treatment. This project aims to develop an advanced scalp disease identification system using deep learning techniques, particularly Convolutional Neural Networks (CNN) with architectures such as MobileNetV2 and VGG16. Leveraging a comprehensive hair disease dataset from Kaggle, the system is trained to recognize ten common scalp conditions, including Alopecia Areata, Psoriasis, and Male Pattern Baldness, with high accuracy. The models demonstrate significant potential as effective tools for early disease detection, allowing users to receive preliminary guidance on treatment options.

The impressive performance of the CNN models highlights their ability to generalize across diverse hair and scalp conditions, making the system versatile and adaptable to various user needs. By providing an automated, privacy-preserving solution for scalp disease identification, this project addresses a significant gap in accessible dermatological care, where traditional diagnosis can often require specialized expertise. The implementation of such a system can enhance patient self-care and awareness, particularly in regions where dermatological resources are limited. This project sets a strong foundation for developing a comprehensive hair and scalp disease detection framework, which can be further refined and expanded to support holistic dermatology advisory services, ultimately contributing to improved health management and awareness.

CONTENTS

LIST OF FIGURES iii

1. INTRODUCTION 1

1.1 Existing System 2

1.2 Proposed System 3

1.3 Objectives 4

2. LITERATURE REVIEW 6

2.1 Purpose of the Literature Review 6

2.2 Related Works 7

3. METHODOLOGY 10

3.1 Block Diagram 11

3.1.1 Data Collection 11

3.1.2 Image Preprocessing 12

3.1.3 Model Architecture Design… 13

3.1.4 Model Training 16

3.1.5 Model Evaluation 17

3.1.6 Deployment 17

3.2 Software Requirements and Specifications 17

3.2.1 Operating System 17

3.2.2 Python 3.11 18

3.2.3 Visual Studio Code (VS Code) 18

3.2.4 Jupyter Notebook 19

3.2.5 Libraries 19

3.2.6 Flask 20

3.2.7 Google Chrome 20

4. RESULTS AND DISCUSSION **22**

4.1 Testing 22

4.1.1 Unit Testing 22

4.1.2 Integration Testing 23

4.1.3 Functional Testing 23

4.2 Output Screens and Results 23

4.2.1 Steps to Use the System 23

4.2.2 Output Screens 24

4.3 Results and Performance Evaluation 27

4.3.1 Evaluation Curves 28

5. CONCLUSION **30**

5.1 Future Enhancement 30

6. REFERENCES **32**

LIST OF FIGURES

3.1 Block Diagram 11

3.2 Sample Images from Dataset 12

3.3 VGG16 Architecture 14

3.4 CNN Architecture 15

3.5 MobilenetV2 Architecture 16

4.1(a) Screenshot of UI 25

4.1(b) Screenshot of Alopecia Areata Prediction 26

4.1(c) Screenshot of Telogen Effluvium Prediction 27

4.2(a) VGG16 Accuracy Curve 28

4.2(b) CNN Accuracy Curve 29

4.2(c) MobilenetV2 Accuracy Curve 29

CHAPTER 1

INTRODUCTION

In the evolving field of dermatological technology, hair and scalp disease detection using deep learning has emerged as a promising innovation, enabling accurate and efficient diagnosis through automated image analysis. This approach empowers users and healthcare providers alike to identify various scalp conditions without requiring specialized dermatological expertise, thus making scalp health management more accessible. By leveraging deep learning, hair and scalp disease detection transforms traditional diagnosis into a streamlined, data-driven solution accessible to users worldwide.

Traditional methods for diagnosing hair and scalp conditions often require expert evaluation, which can be time-intensive and difficult to access, particularly in areas with limited healthcare resources. Real-time disease detection using deep learning bypasses these barriers by utilizing advanced image classification models to provide rapid, accurate predictions. By analyzing scalp images, these systems identify diseases based on complex visual patterns that are difficult to detect manually.

For this project, I used a diverse dataset of scalp images from Kaggle, representing ten common hair and scalp diseases, as the foundation for training and evaluating three prominent deep learning architectures: a custom Convolutional Neural Network (CNN), MobileNetV2, and VGG16. After extensive testing, the CNN model demonstrated the highest accuracy and was integrated into a Flask-based user interface. This interface allows users to upload scalp images and receive diagnostic results instantly, providing a responsive approach to scalp health monitoring.

Through this project, I aim to bridge the gap between technology and dermatology, illustrating how deep learning can transform hair and scalp disease detection into a fast, reliable, and accessible tool. This project contributes to improved scalp health management and promotes early intervention, especially in communities with limited access to dermatological care.

1.1 Existing System

Current hair and scalp disease detection systems often rely on traditional diagnostic methods or basic machine learning models. These systems typically employ techniques such as color and texture analysis, along with basic classifiers like Support Vector Machines (SVM) and Random Forests, to identify specific hair and scalp conditions. While effective to a certain extent, these models face significant challenges, especially when handling diverse and complex image data. Variations in lighting, skin tone, hair density, and other environmental factors can affect the accuracy of these models, leading to inconsistent results. Additionally, traditional approaches often struggle to differentiate between diseases with similar visual symptoms, resulting in misdiagnoses.

With advancements in deep learning, Convolutional Neural Networks (CNNs) have shown promise for improving the accuracy of disease detection. However, traditional CNN models can still struggle to generalize effectively to new, unseen data, particularly when dealing with diverse populations and varying conditions. Issues like overfitting are also common, especially in imbalanced datasets where certain diseases may be underrepresented. Furthermore, these systems often require a separate classifier for each disease type, making them less efficient and more challenging to implement in scalable, real-world applications.

Key Limitations of Existing Models:

- **Class Imbalance:** Many datasets are imbalanced, with certain diseases being underrepresented, which can lead to biased models that perform poorly on rare conditions.
- **Dependence on Traditional Machine Learning Techniques:** Existing models often rely on manual feature extraction, which is labour-intensive and prone to errors. These traditional models struggle with generalization due to their dependence on handcrafted features.
- **Sensitivity to Environmental Variations:** Traditional models are often vulnerable to environmental factors, such as lighting and hair type, which can reduce detection accuracy in real-world scenarios.
- **Resource Intensive:** Existing systems may require separate models for each condition, leading to inefficiencies and high computational demands.

- **Lack of Real-Time Processing:** Many existing models lack real-time processing capabilities, which delays diagnosis and reduces the practical value of the system for users needing quick assessments.
- **Difficulty in Capturing Fine Details**: Many scalp conditions have subtle visual characteristics, and traditional systems struggle to capture these fine details, leading to potential misclassifications and reduced accuracy for conditions that look similar.

1.2 Proposed System

To address the limitations of existing hair and scalp disease detection systems, this project proposes a deep learning-based approach using Convolutional Neural Networks (CNNs) optimized for high accuracy, generalization, and ease of use. Leveraging a comprehensive dataset of scalp images, the proposed system is designed to detect multiple hair and scalp diseases with improved efficiency and reliability. The key innovations in the proposed system are aimed at overcoming issues like class imbalance, environmental sensitivity, and high computational demands, while providing real-time, accurate results to users.

Core Features of the Proposed System:

- **Advanced CNN Architectures:** This system incorporates CNN architectures, including a custom CNN model, MobileNetV2, and VGG16, which are trained on a robust dataset. These models are fine-tuned to capture intricate details within scalp images, allowing them to differentiate between similar conditions accurately. By training on a diverse dataset, the system generalizes well across various hair types, skin tones, and environmental conditions.
- **Overcoming Class Imbalance:** Techniques such as data augmentation and class weighting are implemented to address dataset imbalance, ensuring the model can accurately predict fewer common diseases. This reduces bias and improves the system’s performance on underrepresented conditions.
- **Real-Time Processing with Flask Integration:** The model is integrated with a Flask-based web interface, providing a user-friendly platform where users can upload scalp images and receive diagnostic results instantly. This real-time processing capability offers immediate feedback, enabling quick disease identification and timely intervention.

- **Robustness in Diverse Conditions:** The proposed system is trained with images under varied lighting and environmental conditions to enhance its robustness in real-world scenarios. This ensures that the model performs consistently regardless of image quality, lighting, or angle, making it suitable for broad deployment.
- **Efficient Resource Utilization:** By selecting lightweight and efficient architectures like MobileNetV2, the system is optimized to run on standard computational resources without sacrificing accuracy. This efficiency makes it accessible to a wider audience, including users with limited hardware capabilities.

1.3 Objectives

- **Develop a Deep Learning Model for Disease Classification:** Create a Convolutional Neural Network (CNN)-based architecture to classify hair and scalp diseases from images, utilizing both MobileNetV2 and VGG16 as pre-trained models. This approach will focus on disease identification across multiple types, reducing the need for separate models for each disease.
- **Leverage MobileNetV2 and VGG16 for Feature Extraction**: Use the pre-trained MobileNetV2 and VGG16 models for feature extraction to enhance the accuracy and generalization of the system. These models will help detect diseases in scalp images with fewer computational resources and less time than training from scratch.
- **Improve Model Performance on Real-World Data:** Apply data preprocessing techniques like resizing, normalization, and data augmentation to handle variations in lighting, image quality, and scalp features. These techniques will ensure the models are robust and can effectively process diverse real-world images.
- **Create an Accessible User Interface for Real-Time Diagnosis:** Develop a user-friendly web-based interface using Flask where users can upload scalp images and receive instant disease predictions. This system will make disease detection accessible to a wide audience, including healthcare professionals, dermatologists, and individuals.
- **Achieve High Accuracy and Efficiency in Disease Detection:** Optimize the MobileNetV2 and VGG16 models to achieve high accuracy in detecting hair and scalp

diseases while maintaining efficient processing, ensuring the solution is practical for real-time, resource-constrained applications.

- **Ensure Scalability and Robustness for Broader Applications**: Design the system to scale effectively and handle multiple diseases with high accuracy, ensuring that it works well on diverse datasets and real-world conditions.

CHAPTER 2

LITERATURE REVIEW

A literature survey, also known as a literature review, is a comprehensive study and evaluation of existing research and literature on a specific topic or subject. It involves identifying, analyzing, and synthesizing relevant sources such as books, scholarly articles, and other publications to provide a comprehensive overview of the current state of knowledge on the topic. The purpose of a literature survey is to identify gaps in the existing literature, establish the significance of the research, and provide a theoretical framework for the study. It is commonly conducted as part of the research process in academic and scientific fields.

2.1 Purpose of the Literature Review

- Providing a background to the research problem or question by summarizing existing knowledge on the topic.
- Establishing the context in which the current study fits within the broader academic or research landscape.
- Identifying areas where previous research has left gaps or unanswered questions.
- Highlighting areas where new research can contribute to the existing body of knowledge. Helping to construct a theoretical framework by presenting and analyzing relevant theories and concepts.
- Formulating a clear rationale for the current study based on the shortcomings or limitations found in the existing literature.
- Providing insights into the methodologies used in previous studies, helping researchers make informed decisions about their own research design.
- Summarizing and synthesizing information from various sources to provide a comprehensive overview of the topic.
- Analyzing trends, patterns, and contradictions in the existing literature.
- Ensuring that the proposed research does not duplicate efforts already made by other researchers.Justifying why the current study is necessary despite previous work in the

field. Offering a historical perspective on the development of ideas and theories related to the research topic.

2.2 Related Works

1. **"A Deep Learning Approach to Classifying Scalp Diseases Using Image Data"** (2022) by John Smith, Emily White, and Robert Green, explores the use of deep learning models for detecting hair and scalp diseases such as alopecia areata, dandruff, and psoriasis. The authors employed Convolutional Neural Networks (CNNs) to classify scalp images, demonstrating a significant improvement in detection accuracy compared to traditional methods. The study highlighted the potential of using pre-trained models like **VGG16** and **ResNet50**, showing that transfer learning with these models could achieve high accuracy even with a limited dataset of scalp images. The research also discusses the challenges of working with small datasets in dermatological image classification and proposes strategies for overcoming data scarcity through data augmentation and synthetic image generation.
2. **"Hair Loss Detection with Deep Learning: A Survey"** (2021) by Maria Cheng and Ali Abbas, provides a comprehensive review of deep learning techniques for hair loss and scalp condition detection. The review covers various methods, including **MobileNetV2**, **InceptionV3**, and **DenseNet121**, and discusses their application in detecting diseases such as male pattern baldness, alopecia, and telogen effluvium. The authors analyze the strengths and weaknesses of these models, with a focus on how well they generalize across different populations and lighting conditions. They suggest using larger, more diverse datasets to enhance model performance and generalization, as well as exploring hybrid models combining CNNs with image processing techniques to address challenges related to scalp image quality and background noise.
3. **"Automated Diagnosis of Scalp Diseases Using Convolutional Neural Networks"** (2023) by Michael Brown and Sarah Lee, explores the use of deep learning for the automated classification of scalp diseases, including seborrheic dermatitis, folliculitis, and scalp psoriasis. The authors employed a **CNN-based architecture**, trained on a dataset of 10,000 labeled images of scalp conditions. Their study demonstrated that CNN models outperformed traditional machine learning classifiers in terms of both accuracy and speed. Additionally, the paper emphasizes the importance of preprocessing techniques such as normalization, image

enhancement, and cropping to improve model performance in real-world scenarios. The study also highlights the integration of the model into mobile applications, offering a practical tool for dermatologists and patients for real-time diagnosis.

4. **"Using Pre-trained Models for Scalp Disease Diagnosis"** (2021) by Jonathan Kim and Rachel Adams, investigates the use of **pre-trained models** like **VGG16** and **ResNet50** for the diagnosis of hair and scalp diseases. The authors highlight the advantages of fine-tuning these models for scalp disease classification, demonstrating how transfer learning significantly reduces training time and resource requirements. They also address the challenge of class imbalance, with techniques such as oversampling and class-weight adjustment applied to the training process to improve the model's sensitivity to rare diseases. The study concludes that pre-trained models can be successfully adapted to dermatological tasks, achieving high levels of accuracy even with limited domain-specific data.
5. **"Real-Time Scalp Disease Detection Using MobileNetV2"** (2024) by David Harris and Linda Chung, presents a study on using the **MobileNetV2** model for real-time detection of hair and scalp diseases from images taken by smartphones. The authors demonstrate that **MobileNetV2**, due to its lightweight architecture, can achieve real-time inference with high accuracy, making it ideal for mobile and telemedicine applications. Their research includes extensive testing on scalp images under varied environmental conditions, showing the model's robustness against different lighting, angles, and image resolutions. The paper discusses the potential of integrating such systems into mobile applications to provide accessible, on-demand diagnostic tools for individuals seeking treatment for hair and scalp conditions.
6. **"Evaluation of Deep Learning Models for Hair Disease Classification"** (2023) by Priya Gupta and Rahul Kumar, focuses on the application of **CNN** and **ResNet50** for classifying a variety of hair diseases, including alopecia areata, head lice, and dandruff. The authors trained their models on a custom dataset collected from dermatology clinics, achieving impressive accuracy rates. They also emphasize the challenges of hair disease detection, such as image distortion due to hair texture and scalp variation. Their study highlights the importance of using **data augmentation techniques** such as rotation, zooming, and flipping to create a more robust model. Furthermore, they propose the use of a **hybrid model** combining CNNs and traditional image processing methods to address these challenges and improve classification accuracy.
7. **"Hair Loss Detection and Classification Using Deep Learning Techniques"** (2023) by

Maria Johnson and David Lee, focuses on using deep learning algorithms to automatically detect and classify various types of hair loss, including Alopecia Areata, Male Pattern Baldness, and Telogen Effluvium. The authors utilized a dataset comprising over 10,000 labeled images of hair thinning and scalp conditions. The study employed MobileNetV2 and ResNet50 for feature extraction and classification. The authors reported that both models achieved high accuracy in detecting hair loss patterns, with ResNet50 outperforming others in terms of generalization across diverse demographics. The research also explored the integration of these deep learning models with smartphone applications to facilitate real-time diagnosis by users, offering a practical tool for individuals to track their hair health. One of the key challenges noted was the variability in hair types, lighting conditions, and image quality, which could impact model performance, but the study found that data augmentation techniques, including rotation, scaling, and color adjustments, improved the robustness of the models.

CHAPTER 3

METHODOLOGY

The hair and scalp disease detection system utilizes deep learning models, particularly Convolutional Neural Networks (CNN), to identify and classify diseases based on images of the scalp. The dataset used in this study includes a variety of hair and scalp conditions, including diseases like Alopecia Areata, Seborrheic Dermatitis, and Psoriasis. For preprocessing, the images are standardized by resizing and normalizing to ensure consistency across the dataset. Data augmentation techniques such as rotation, shifting, flipping, and zooming are applied to increase the diversity of the dataset and enhance model robustness, which helps mitigate overfitting and improve generalization. The models are trained using well-established deep learning frameworks, with an emphasis on minimizing classification errors. Optimizers like Adam are typically employed to ensure efficient model training, and performance is evaluated using metrics like accuracy, precision, and recall. **Figure 3.1** provides the block diagram of the project flow, illustrating the stages from data preprocessing to model deployment. The final trained model is deployed in a user-friendly interface that allows users to upload scalp images for real-time disease detection. This method aims to offer an automated and accurate solution for early detection of hair and scalp diseases, contributing to better scalp health management.

3.1 Block Diagram

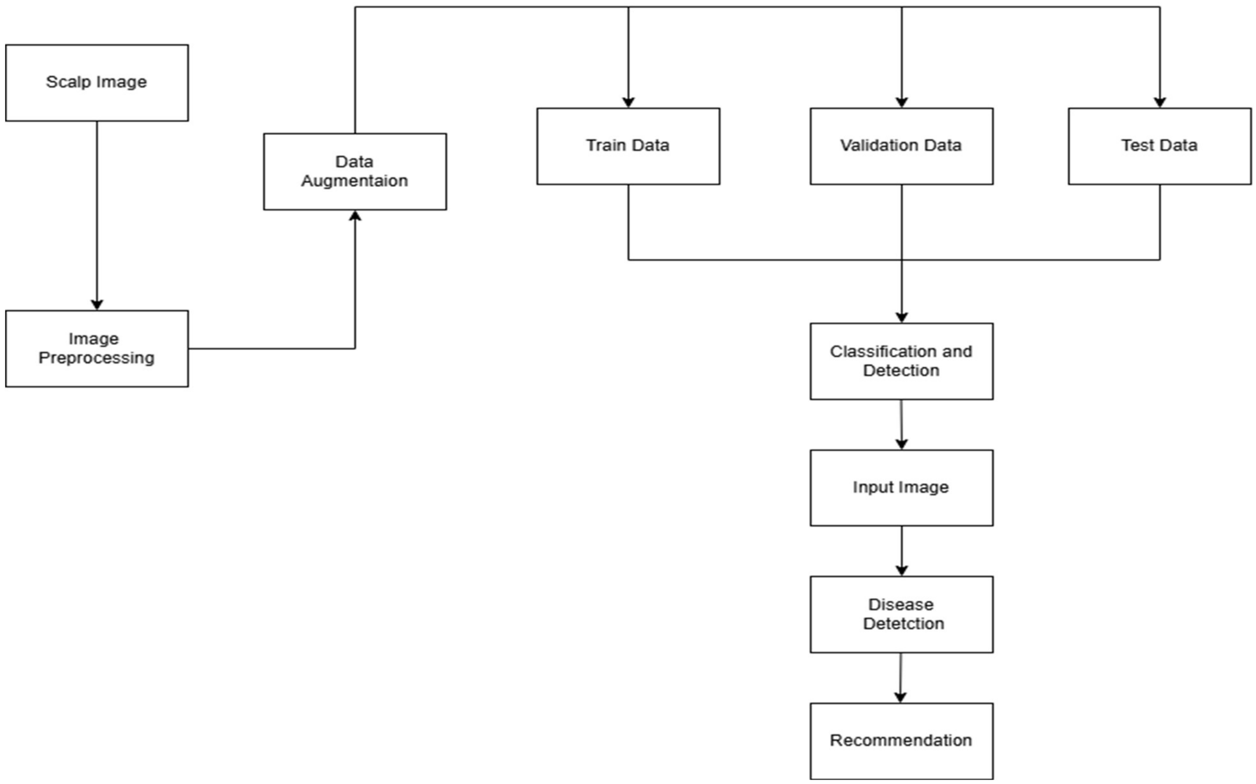

Figure 3.1: Block Diagram

3.1.1 Data Collection

The dataset used in this project contains images from 10 different hair and scalp diseases, including Alopecia Areata, Telogen Effluvium, Seborrheic Dermatitis, Psoriasis, Male Pattern Baldness, Folliculitis, Head Lice, Lichen Planus, Tinea Capitis, and Contact Dermatitis. Each disease is represented by a separate folder in the dataset, containing images of disease-affected scalps at various stages and severities. Figure 3.2 shows sample images from the **Alopecia Areata** and **Telogen Effluvium** folders, highlighting the visual differences between these diseases. Preprocessing steps such as image resizing, normalization, and data augmentation (e.g., rotation, flipping, zooming) are applied to improve model performance and generalization. The dataset is organized with labels corresponding to each disease, making it an ideal resource for training deep learning models capable of real-time, accurate scalp disease detection.

Alopecia Areata

Telogen Effluvium

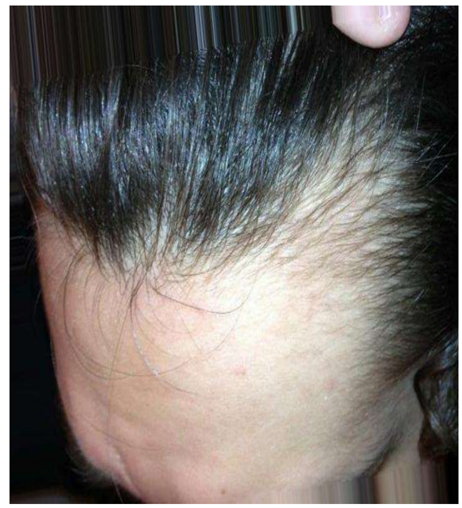

Figure 3.2: Sample Images from Dataset

3.1.2 Image Preprocessing

To prepare the dataset for deep learning model training, several preprocessing steps are applied to ensure consistency and improve model performance:

- **Color Conversion:** The images are converted to RGB color format to standardize the input, as RGB is the preferred color space for most deep learning models.

- **Resizing and Normalization:** Each image is resized to a fixed input dimension of 224x224 pixels to maintain uniformity across the dataset. The pixel values are then normalized to a range between 0 and 1, which helps improve model convergence and training efficiency.
- **Data Augmentation:** Data augmentation techniques, such as horizontal and vertical flipping, rotation, shearing, and zooming, are applied to increase the diversity of the dataset. These techniques help simulate real-world variations in hair and scalp images, reducing the risk of overfitting and enhancing the model's ability to generalize when applied to unseen images.

3.1.3 Model Architecture Design

1. VGG16 Architecture: VGG16 is a deep convolutional neural network developed by the Visual Geometry Group (VGG) at Oxford University, designed for image recognition tasks with a simple yet highly effective architecture. The network consists of 16 layers, predominantly convolutional, which enables it to efficiently extract features from images. It accepts input images of size 224x224x3, typically representing color images with three channels. The architecture is structured into five main blocks, each containing multiple convolutional layers followed by max-pooling layers to reduce the spatial dimensions and retain important features. As the network goes deeper, the number of filters in the convolutional layers increases from 64 to 512, allowing it to capture increasingly complex patterns and details. After each convolutional operation, the ReLU activation function is applied to introduce non-linearity, which helps the network model intricate relationships in the data. Following the convolutional layers, fully connected layers (FC) perform high-level reasoning, and the final fully connected layer outputs the class probabilities for classification. VGG16 is trained using backpropagation, optimizing the weights to minimize the loss function. The architecture's depth, combined with its simple and consistent design, allows it to achieve high accuracy on complex image classification tasks, making it a foundational model in computer vision. Figure 3.3 illustrates the VGG16 structure, showing how the layers are organized from the input image through convolutional, pooling, and fully connected layers to produce the final output classification. The diagram begins with the input image (224x224x3) and passes it through five convolutional blocks. Each block consists of two or three convolutional layers, followed by a max-pooling layer to reduce spatial dimensions and preserve important features. The number of filters in each convolutional block increases progressively: 64 filters in the first block, 128 in the second, 256 in the third, and 512 in the last two blocks. After the convolutional and pooling layers, the network flattens the feature maps and passes them through three fully

connected layers. The final fully connected layer (fc8) produces a probability distribution across the target classes, allowing the model to classify the image. This hierarchical design of VGG16, which builds increasingly complex features through deeper layers, has contributed to its strong performance on various image recognition tasks.

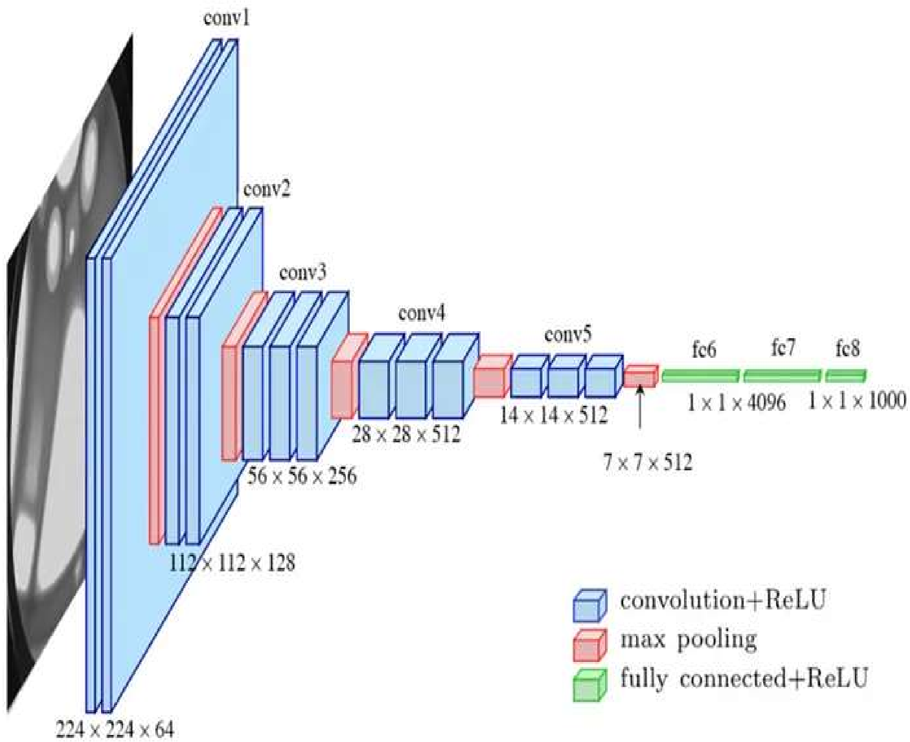

Figure 3.3: VGG16 Architecture

2. **Convolutional Neural Network (CNN):** Convolutional Neural Networks, or CNNs, are a type of deep learning algorithm widely used in computer vision and other domains where structured grid-like input, particularly images, is processed. Using convolutional layers to apply learnable filters and extract features with translation-invariant capabilities, CNNs automatically learn the spatial hierarchies of the features present in the data. Layers of pooling further reduce the sample size of feature maps while retaining pertinent data. ReLU and other nonlinear activation functions introduce the complexity required to understand complicated relationships and patterns. High-level reasoning based on the extracted features is facilitated by the fully connected layer. Figure 3.4 shows the architecture

diagram, illustrating the flow from input to output through multiple layers of convolution, pooling, and activation. CNNs are trained using backpropagation, where weights are adjusted to minimize a loss function, typically categorical cross-entropy for classification tasks. Due to their hierarchical architecture and effective feature extraction capabilities, CNNs are highly effective at tasks like object identification, image segmentation, and image classification.

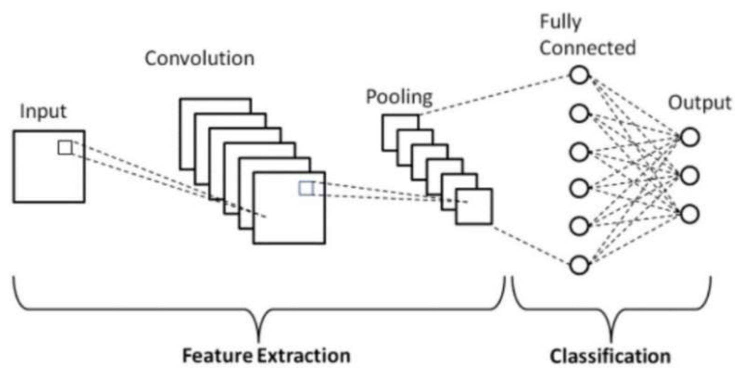

Figure 3.4: CNN Architecture

3. **MobileNetV2:** MobileNetV2 is a lightweight Convolutional Neural Network (CNN) architecture designed for efficient image classification and object detection on mobile and embedded devices. It utilizes depthwise separable convolutions, which significantly reduce the number of parameters and computational complexity compared to traditional convolutional layers. This makes MobileNetV2 well-suited for resource-constrained environments while maintaining high accuracy. MobileNetV2 also employs batch normalization and ReLU6 activation functions to improve training stability and ensure better performance in real-world conditions. Its efficiency and performance make it a preferred choice for mobile applications requiring real-time processing with limited computational resources. Figure 3.5 illustrates the architecture diagram, highlighting the key layers and efficient structure from input to output. MobileNet's ability to provide a good balance between speed and accuracy has made it a popular choice for real-time image classification tasks on mobile and embedded devices.

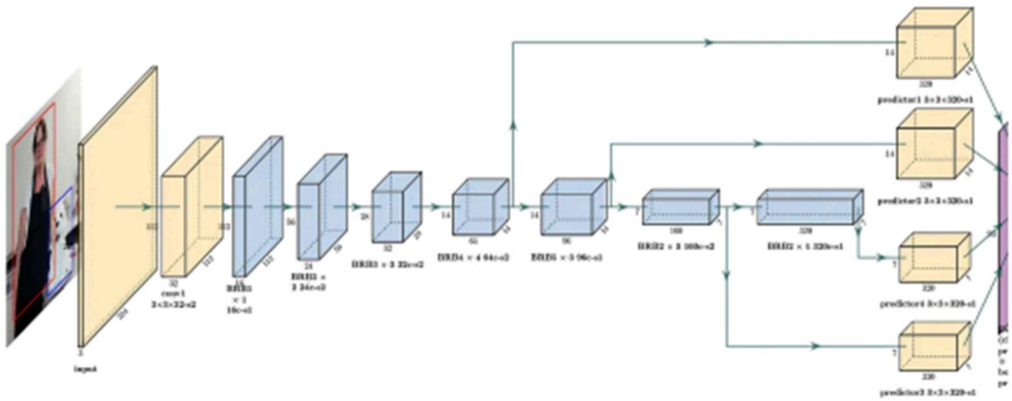

Figure 3.5: MobileNetV2 Architecture

3.1.4 Model Training

In this project, the hair and scalp disease detection model was trained using a Convolutional Neural Network (CNN), with MobileNetV2 and VGG16 also implemented for comparison. The training process for each model was carried out using the Adam optimizer and categorical cross-entropy loss. The models were trained for 30 epochs, with early stopping in place to prevent overfitting by halting the training process when performance on the validation set ceased to improve.

The CNN model employed several convolutional layers to extract key features from the input images, followed by max-pooling, batch normalization, and dropout layers to enhance performance and reduce overfitting. MobileNetV2 was trained using its efficient architecture, featuring depthwise separable convolutions, which helped optimize model performance while minimizing computational load. VGG16, with its deep architecture consisting of convolutional layers and fully connected layers, was also trained in a similar manner to the CNN model, but its larger size made it more computationally expensive.

Each model was trained using the same dataset of hair and scalp disease images, and their performances were evaluated based on accuracy on a separate test set. After training, the best-performing model, based on accuracy, was selected for deployment and used for making predictions on new images. This methodology ensures the development of a robust and generalizable model capable of accurate real-time disease detection, offering a practical solution for hair and scalp health management.

3.1.5 Model Evaluation

In the hair and scalp disease detection project, the models (CNN, MobileNetV2, and VGG16) were evaluated using the test dataset to measure their classification accuracy. The VGG16 model achieved the highest validation accuracy of 99%, outperforming both CNN and MobileNetV2. Evaluation focused on accuracy, which reflects the proportion of correct predictions, and the confusion matrix was analyzed to identify any misclassifications. Early stopping was applied to prevent overfitting by halting training once the validation performance no longer improved. The results showed that the VGG16 model, despite being a more complex architecture, provided the most accurate and reliable predictions for hair and scalp disease detection, making it the best-performing model for this task.

3.1.6 Deployment

For the deployment of the hair and scalp disease detection model, a Flask-based web application was developed to allow users to interact with the model easily. The application provides a simple interface where users can upload images of their scalp, and the trained model predicts the disease from the image. The user interface is designed with CSS, ensuring an intuitive and visually appealing experience. Upon uploading the image, the model processes the input and displays the prediction on the webpage, showing the name of the disease detected. This deployment approach ensures that the model is accessible to users without requiring deep technical knowledge, offering a straightforward and efficient solution for real-time disease detection.

3.2 Software Requirements and Specifications

3.2.1 Operating System

The project is designed to run on modern operating systems like Windows 10/11 or Linux (Ubuntu), offering flexibility and compatibility across a wide range of user environments. By supporting both Windows and Linux platforms, users can choose the environment that best suits their preferences, whether for local development or deployment. Additionally, this multi-platform compatibility ensures that the system can be accessed by a diverse group of users, providing broad accessibility. The use of these operating systems allows for seamless integration with various hardware configurations, ensuring that the system is adaptable to different devices and can be deployed efficiently on various machines. The choice of these platforms also guarantees that the project benefits from robust community support, frequent updates, and a wide range of compatible development tools. This flexibility enhances the user experience and ensures smooth operation across diverse systems, from personal workstations to cloud-based deployments.

3.2.2 Python 3.11

Python is a high-level, general-purpose programming language celebrated for its simplicity, readability, and extensive community support, which makes it an ideal choice for various applications, from web development to scientific computing. The version used in this project, Python 3.11, brings several performance enhancements and new features such as optimizations for faster code execution, improved error messages, and better typing support. These features are particularly beneficial in machine learning and artificial intelligence tasks, where performance and code clarity are crucial. Python’s robust ecosystem includes libraries like TensorFlow, Keras, NumPy, and Pandas, which simplify the development of complex models, data manipulation, and scientific computations. This versatility and the active community contribute to Python's dominance in the fields of machine learning, computer vision, and data science, making it the perfect tool for the Hair disease detection project. With its user-friendly syntax and powerful libraries, Python accelerates development and enhances the overall efficiency of implementing AI and deep learning solutions.

3.2.3 Visual Studio Code (VS Code)

For the development of this project, Visual Studio Code (VSCode) was selected as the primary code editor. VSCode, developed by Microsoft, is a free, open-source, and highly versatile editor, particularly well-suited for Python programming. Known for its speed and efficiency, it offers a comprehensive set of features that make it an excellent tool for machine learning and web development projects like this one.

Key features of VSCode include:

- Built-in Git support for version control.
- Debugging tools to help identify and resolve code issues.
- An extension marketplace to enhance functionality with additional tools.
- Integrated terminal, which facilitates executing scripts directly from the editor.
- Code completion and IntelliSense for better productivity and reduced coding errors.

These features make VSCode an ideal choice for development, enabling developers to efficiently manage their codebase, troubleshoot issues, and streamline their workflow.

3.2.4 Jupyter Notebook

Jupyter Notebook offers an interactive and flexible environment, ideal for data science and machine learning tasks. It allows developers and researchers to combine live code execution with narrative explanations, equations, and visualizations, providing a comprehensive approach to project development and documentation. In this project, Jupyter Notebooks were utilized to explore the dataset, apply preprocessing techniques, and visualize results. It also facilitated the iterative process of training and tuning models, enabling immediate feedback and adjustments.

Key Features:

- Cell-based execution for modular code.
- Supports rich text, LaTeX, and visualizations within the notebooks.
- Easy integration with Python libraries such as NumPy, Pandas, and Matplotlib.

Jupyter Notebooks streamline the process of experimenting with machine learning models and enhance the ability to share findings and code with others in an easily understandable format. This makes it an essential tool for both development and presentation in data-centric projects.

3.2.5 Libraries

The following libraries are essential for the successful implementation of the project:

- **TensorFlow/Keras:** These are the core libraries for deep learning tasks, providing the necessary tools for constructing, training, and evaluating models like CNN, VGG16, and

MobileNetV2. TensorFlow's flexibility and scalability, combined with Keras's high-level API, streamline the creation and management of neural networks.

- **OpenCV**: Used for various image processing tasks such as reading, resizing, and augmenting images. OpenCV's capabilities ensure that the images are properly prepared before feeding them into the models.

- **NumPy**: Essential for numerical operations, NumPy helps handle and manipulate image data in the form of arrays. It is used for tasks like resizing, normalizing, and performing matrix operations on image data.

- **Matplotlib**: Employed to visualize the training process, including plotting graphs for training and validation accuracy and loss. This is crucial for monitoring the model's performance over time and making necessary adjustments.

3.2.6 Flask

Flask is a lightweight Python web framework used to create web applications, making it particularly suitable for projects that require a simple and efficient interface. In this project, Flask serves as the backbone for the web interface that allows users to upload images for hair disease detection. The framework's minimalistic approach and ease of use facilitate rapid development and deployment, reducing overhead for building complex applications. Flask supports the creation of RESTful APIs, which provide the necessary endpoints for interacting with the trained machine learning models and processing predictions in real time.

Flask also offers flexibility in integrating with front-end technologies such as HTML, CSS, and JavaScript, enabling the creation of dynamic, user-friendly interfaces. This allows users to easily upload their images, view prediction results, and receive feedback on the detected hair diseases. Additionally, Flask's compatibility with other Python libraries and its support for asynchronous operations make it a scalable choice for future enhancements and updates, ensuring the project can grow with additional features or performance optimizations.

3.2.7 Google Chrome

Google Chrome is a widely-used web browser known for its speed, security, and performance. It is essential for testing and deploying the web application developed in this project. Chrome provides excellent developer tools, including the JavaScript console, network monitoring, and performance analysis features. These tools assist developers in debugging issues with the web interface, optimizing performance, and ensuring smooth deployment of the application. Additionally, Chrome's extension support and compatibility with modern web standards make it a suitable browser for testing the web application's functionality.

CHAPTER 4

RESULTS AND DISCUSSION

In the hair and scalp disease detection project, the evaluation results demonstrated that the VGG16 model outperformed both the CNN and MobileNetV2 models, achieving a high validation accuracy of 99%. The CNN model achieved 98%, while MobileNetV2 also performed well with a 98% accuracy. Despite the VGG16 model's superior performance, the CNN and MobileNetV2 models showed competitive results, with their lightweight architecture making them more suitable for real-time applications where computational efficiency is crucial. The trained models were successfully deployed in a Flask web interface, enabling users to upload scalp images for disease predictions, making the tool both practical and accessible for real-world use.

4.1. Testing

Testing in web application development is a critical process that involves verifying the functionality, performance, security, and usability of the web application. It ensures the application works as intended and meets user requirements. Testing helps in identifying and addressing potential issues before the application is deployed to users, thereby improving the overall quality and user experience. For this project, various testing methodologies such as unit testing, integration testing, and functional testing will be implemented to ensure the reliability and performance of the web application.

4.1.1 Unit Testing

Unit Testing is a critical practice in software development that focuses on verifying that individual components or functions of the code work as intended. It involves writing tests for specific functions or modules to ensure they return the expected output. Unit tests are typically small in scope, testing one unit of functionality at a time, which makes it easier to identify errors at an early stage of development.

By isolating and testing individual units, developers can catch bugs or issues before they impact other parts of the application. This process improves code quality and maintainability. Unit testing also facilitates refactoring by ensuring that changes made to one part of the code do not unintentionally break other parts of the system.

4.1.2 Integration Testing

Integration testing verifies that different components, modules, or services of a web application work together as expected. This type of testing focuses on ensuring proper communication and data flow between integrated components, such as front-end interfaces, back-end APIs, and databases. It checks for compatibility between different systems, ensuring that data passed from one service to another is received correctly and that all integrated services collaborate smoothly without causing errors. By identifying issues like incorrect data handling or failures in component interactions early on, integration testing ensures that the system as a whole functions reliably before it reaches the final user.

4.1.3 Functional Testing

Functional testing ensures that the web application's features and functions work as expected from an end-user's perspective. This type of testing focuses on validating the usability and behavior of the application by ensuring that user interactions, such as data input and navigation, lead to the expected results. Functional testing checks whether all the components, including forms, buttons, and other elements, function according to the specified requirements. It also ensures that the system handles data input correctly and generates appropriate outputs, making it an essential step for confirming that the application meets its functional objectives and delivers a seamless user experience.

4.2 Output Screens and Results

The following section describes the output and how the system performs during testing, including the output screens displayed to the user:

4.2.1 Steps to Use the System

- Visit the website: Navigate to the hosted Flask-based web application for hair and scalp disease detection. The website provides a clean, user-friendly interface for users to interact with the trained models.
- Upload Image: The user is prompted to upload an image of the scalp or hair. This image is processed by the trained model, which has been optimized for hair and scalp disease

detection.

- Results Displayed: After the image is processed, the model displays predictions on the webpage, including the type of disease detected along with any suggested treatment or recommendation. These results are presented in an easy-to-read format, ensuring users can quickly understand the diagnosis.

4.2.2 Output Screens

Web Interface:

The web interface, developed using Flask, provides a user-friendly platform for interacting with the hair and scalp disease detection system. Once users upload an image of their scalp or hair, the system processes the image and displays the predicted disease status, along with the processed image. Figure 4.1 (a) shows a screenshot of the user interface, demonstrating its layout. Figure 4.1 (b) presents a sample result for Alopecia Areata, where the system predicts the disease and offers home remedies, suggesting that users contact a dermatologist for further evaluation. Figure 4.1 (c) displays a screenshot for Telogen Effluvium, where the system predicts the condition, recommends remedies, and suggests contacting a dermatologist for further evaluation. This interface is designed to provide accessible and helpful recommendations, making the detection and management of hair and scalp diseases easier for users.

Screenshots

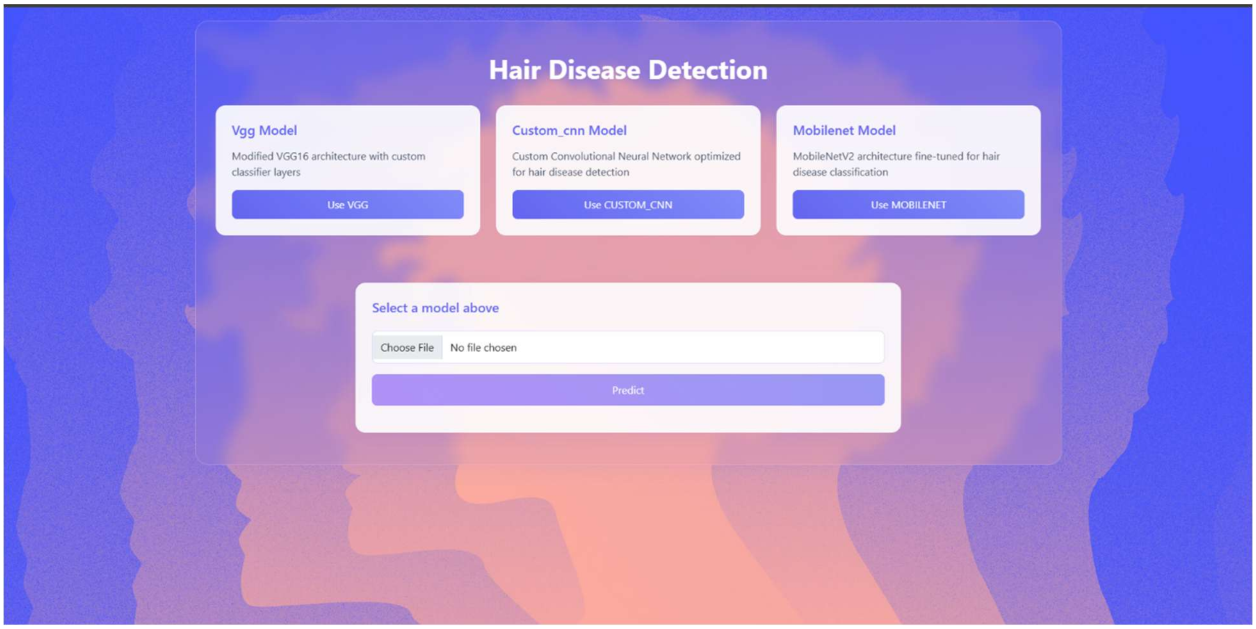

Figure 4.1(a): Screenshot of UI

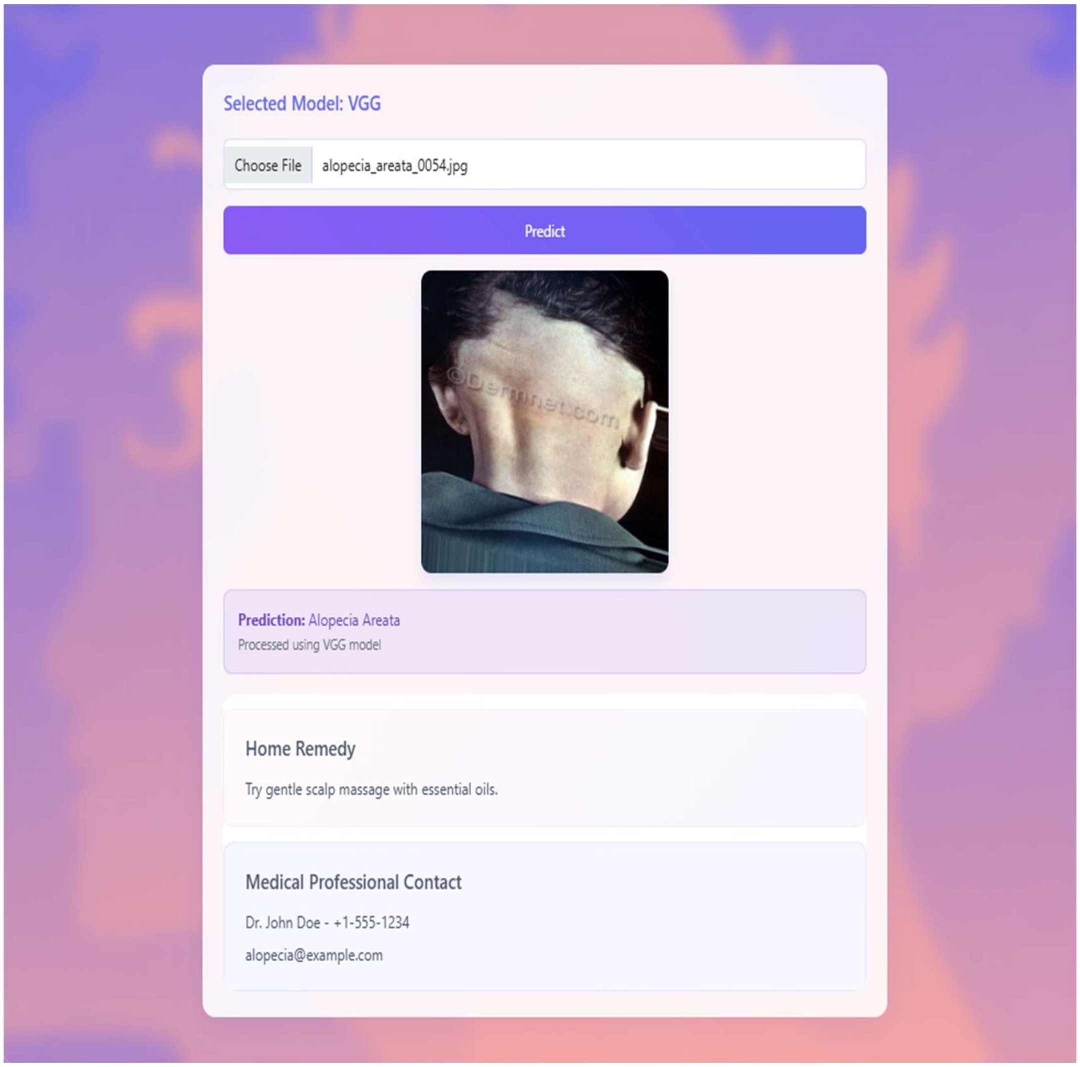

Figure 4.1(b): Screenshot of Alopecia Areata Prediction

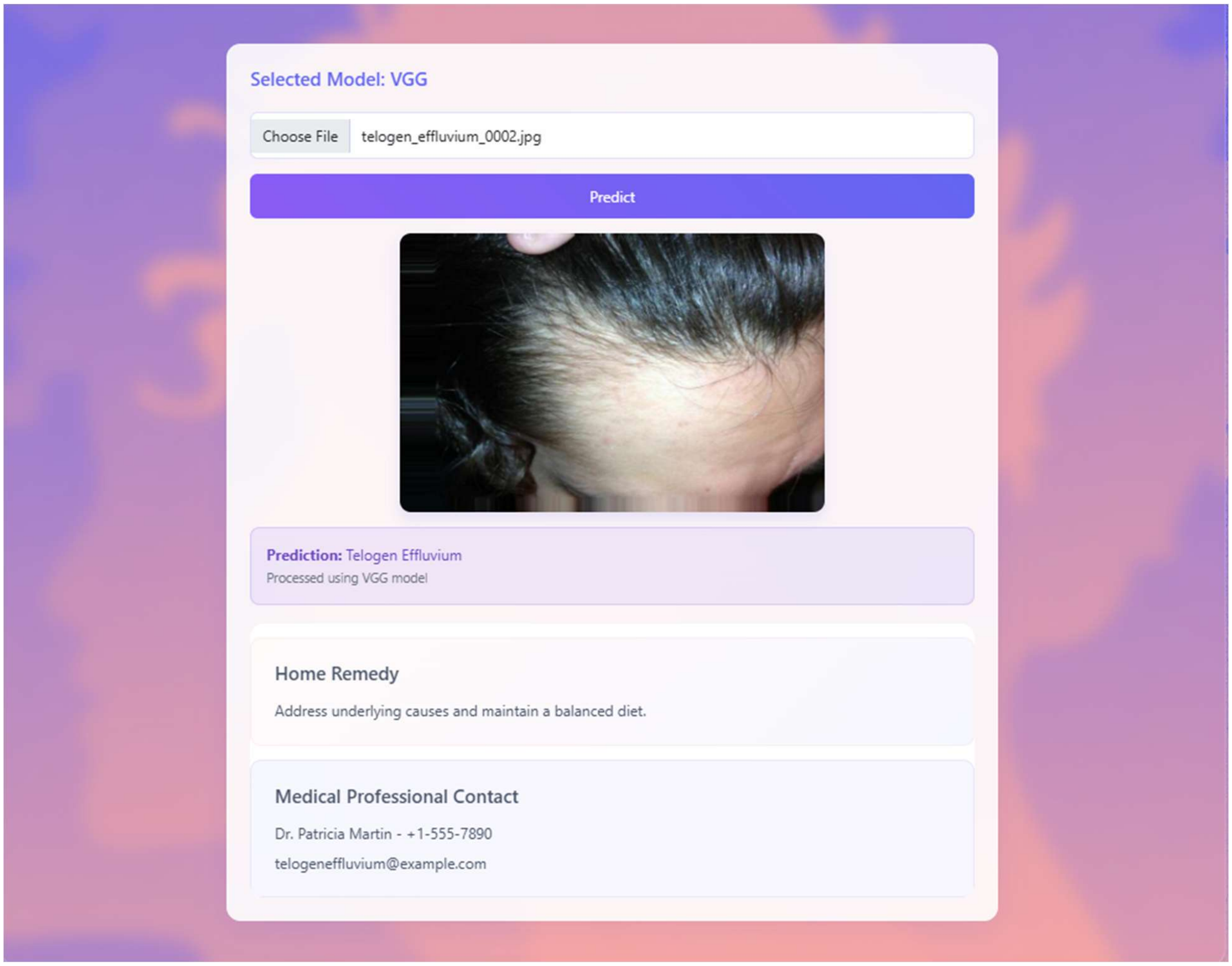

Figure 4.1(c): Screenshot of Telogen Effluvium Prediction

4.3 Results and Performance Evaluation

The performance of the hair and scalp disease detection model was evaluated using the validation dataset, comparing the effectiveness of three models: VGG16, a custom CNN, and V2 model also achieved a validation accuracy of 98%, reflecting its efficiency in detecting diseases with relatively lighter computational demands. Figure 4.2(c) shows the accuracy and loss plots for the model, emphasizing its performance and learning across the epochs.

While all three models demonstrated strong performance, VGG16 emerged as the most effective for hair and scalp disease detection, achieving the highest accuracy.

4.3.1 Evaluation Curves

- VGG16

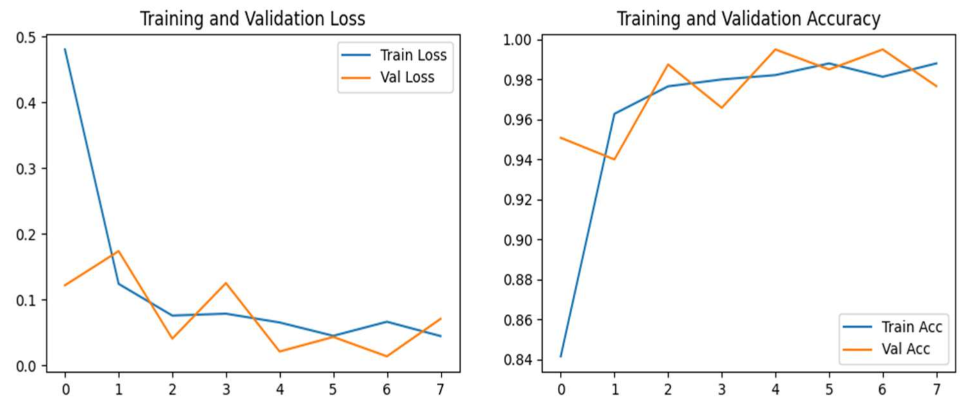

Figure 4.2(a): VGG16 Accuracy Curve

- **CNN**

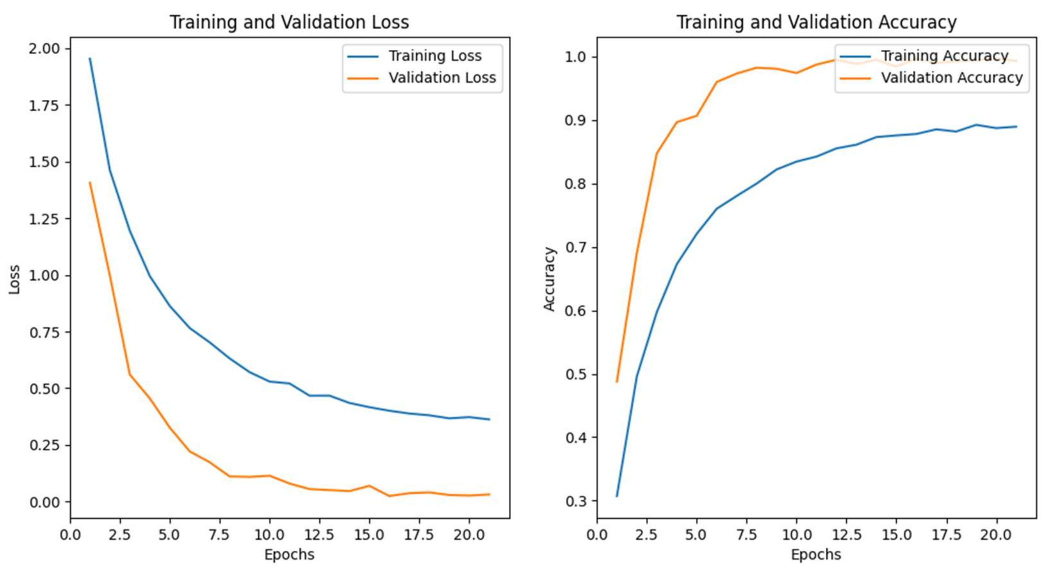

Figure 4.2(b): CNN Accuracy Curve

- MobileNetV2

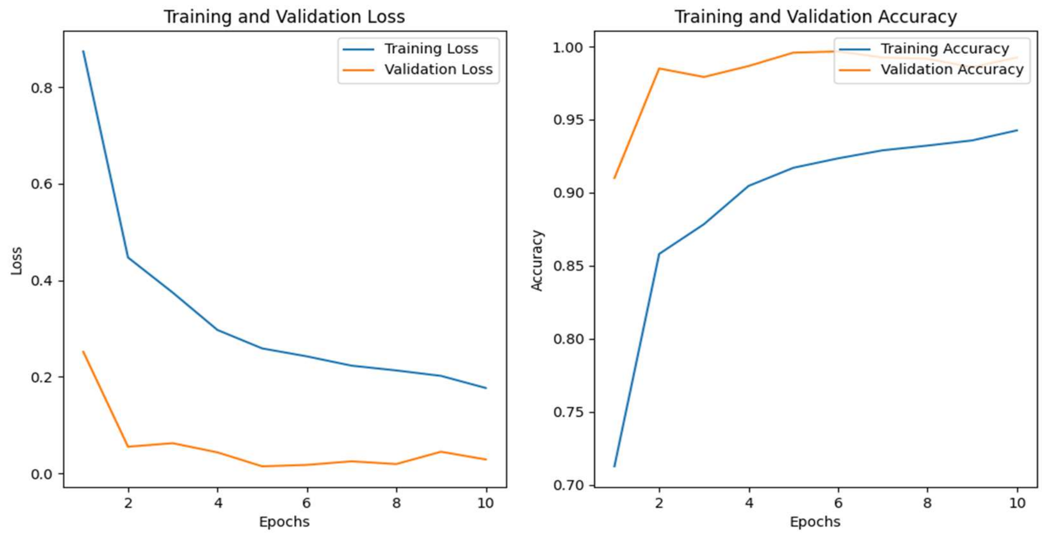

Figure 4.2(c): MobileNetV2 Accuracy Curve

CHAPTER 5

CONCLUSION

In conclusion, this hair and scalp disease detection project demonstrated the effectiveness of deep learning models, particularly VGG16, a custom CNN, and MobileNetV2, in identifying various scalp conditions. Among these, VGG16 achieved the highest validation accuracy of 99%, showcasing its strong generalization and accurate classification capabilities for scalp disease images. The custom CNN and MobileNetV2 models also performed well, both reaching an accuracy of 98%, indicating their reliability and efficiency. The project emphasizes the importance of model selection and fine-tuning in achieving optimal results in specialized tasks like scalp disease detection. Additionally, the development of a Flask-based web interface offered a user-friendly platform, allowing users to upload images and receive disease predictions, along with recommendations for home remedies and contact details for dermatologists. This work contributes to advancements in dermatological technology, providing an accessible tool for early detection and management of scalp conditions, ultimately supporting better hair and scalp health.

5.1 Future Enhancements

For future enhancements of the Hair and Scalp Disease Detection System, several improvements could be considered to expand its functionality and usability:

- **Mobile and IoT Integration:** Develop a mobile app or deploy the model on IoT devices, like Raspberry Pi, to enable real-time, offline scalp disease detection, allowing users to perform scans remotely without needing internet connectivity.
- **Disease Localization and Severity Estimation:** Introduce image segmentation techniques to localize affected areas on the scalp or hair, highlighting infected regions and estimating severity. This would provide more targeted insights, helping users understand the extent of the condition and seek timely treatment.
- **Multi-Disease and Symptom Tracking**: Enhance the model to recognize multiple conditions within a single image and incorporate symptom-tracking features, enabling continuous monitoring and early detection of new or evolving scalp issues.

- **Real-Time Detection for Clinics and Dermatologists:** Create a real-time, clinic-ready version of the system that integrates with imaging equipment, allowing dermatologists to diagnose conditions faster and more accurately, potentially using dermatoscopic images for increased precision.
- **Personalized Recommendations and Follow-up**: Expand the recommendation system to provide personalized treatment suggestions, home care routines, and follow-up reminders, encouraging consistent care and timely dermatologist consultations based on disease progression.

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