TOWARDS DETECTION OF ALOPECIA DISEASES THROUGH DEEP LEARNING

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FINAL YEAR PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Towards Detection of Alopecia Diseases Through Deep Learning Techniques**", submitted by **Majbaul Haque** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Golam Rabbany, Lecturer**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The frequency of alopecia, a group of illnesses characterized by hair loss, makes diagnosis and treatment extremely difficult. Conventional diagnosis techniques produce outcomes that are subjective and inconsistent since they mainly rely on eye inspection and manual assessment. In this thesis, we provide a unique method for alopecia identification that makes use of deep learning methods. Through the application of CNN algorithm, our vision is to make an automated system which can recognize different types of alopecia from digital photographs of the scalp with high accuracy. We applied KNN and SVM too and found limitation of encoding. Our approach begins with gathering a large dataset of various alopecia cases, then preprocessing and augmenting it to improve model generalization. Subsequently, we design and train CNN architectures optimized for feature extraction and classification of Alopecia patterns. Through extensive experimentation and evaluation on both synthetic and real-world datasets, we demonstrate the effectiveness and robustness of our proposed framework in discriminating between different types and stages of alopecia with high accuracy and reliability. Our findings suggest promising implications for the integration of deep learning technologies in clinical settings to facilitate early diagnosis, personalized treatment planning, and monitoring of alopecia-related conditions, thereby improving patient outcomes and quality of care.

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CHAPTER 1
Introduction

1.1 Overview

People all around the world are concerned with hair loss, which has a variety of underlying reasons. Accurate diagnosis and efficient treatment of alopecia, a general term comprising several kinds of hair loss diseases, are challenging. An overview of alopecia illness is given in this paper, emphasizing its frequency, the risks it poses, and the limits of existing diagnostic methods [1]. It also presents the use of image processing combined with deep learning methods, namely Convolutional Neural Networks (CNNs), to address these issues. The complex disorder known as alopecia is typified by the partial or total loss of hair in body parts where it usually grows. Alopecia areata, scarring alopecia, and androgenetic alopecia are some of the ways the disorder can present itself [2]. Certain kinds might cause permanent hair loss, while others can be reversed with the right care. Comprehending the various expressions of alopecia is essential for efficient diagnosis and therapy planning.

Beyond its effects on appearance, alopecia can have significant emotional and psychological consequences. People with alopecia frequently endure increased psychological anguish as a result of society's emphasis on appearance. Some types of alopecia may be signs of underlying medical conditions, so getting a diagnosis as soon as possible is essential to general health. In addition to the potential for negative effects on one's quality of life and self-esteem, there is also a risk of lowered self-esteem. The capacity of deep learning, a kind of machine learning, to automatically extract hierarchical representations from data has made it well-known [3]. The basic ideas of deep learning are presented in this part, with a focus on multi-layered neural networks that are capable of extracting complicated characteristics from large datasets on their own. Deep learning has shown to be a reliable and effective diagnostic tool when used for medical picture analysis, especially for dermatological problems. The improvement of medical picture quality and interpretability is largely dependent on image processing. Methods like scaling, normalization, and data augmentation are essential for preparing datasets, guaranteeing consistency, and enabling reliable model training. The importance of image processing for alopecia identification is discussed in this section, along with how it affects deep learning systems' performance [4]. A type of deep neural network called convolutional neural networks was created especially for image processing applications. They are made up of pooling layers for reduced sampling, fully linked layers for classification, and convolutional layers that learn the spatial hierarchies of features. CNNs are a good choice for alopecia detection since they have been shown to perform exceptionally well in a variety of computer vision applications [5]. Analyzing the advantages and disadvantages of each of the three methods of alopecia identification is necessary for comparison CNN is excellent at collecting features from pictures. The selection of these methodologies is contingent upon several aspects, including but not limited to dataset attributes, processing capacity, and the particular demands of alopecia diagnosis. Future research and development opportunities are made possible by the use of deep learning algorithms for alopecia diagnosis. By accommodating a wider range of dermatological disorders, the suggested framework may be expanded to provide an all-inclusive automated diagnosis system. Accuracy and real-time applications might also be improved by improvements in hardware capabilities and algorithmic improvement [8]. Although previous investigations have established the foundation for automated medical picture processing, several constraints require more investigation. These include problems with interpretability, extension of the model, and variety of datasets. Improving the dependability and usefulness of deep learning methods in healthcare contexts requires addressing these disadvantages.

1.2 Background and Present State

The psychological and emotional toll that alopecia takes on those who are affected highlights how urgent it is to provide accurate and easily available diagnostic instruments. The field of medical diagnostics might undergo significant change as a result of the developments in deep learning and image processing technology. This would lead to prospects for streamlining healthcare procedures and improving the allocation of resources. Our ultimate motivation is from the need to close the gap between clinical relevance and technological breakthroughs, with the overall objective of boosting patient care and outcomes in the field of alopecia identification.

We establish the following particular goals to fulfill these overall purposes:

• Develop diverse dataset comprising an extended range of Alopecia manifestations

• Implement and optimize CNN, YOLO V8, and PCA for automate Alopecia detection from digital scalp images.

• Go through the practical challenges associated with deploying the developed algorithms in clinical settings.

1.3 Problem Statement

The project's reach extends beyond algorithmic development to practical considerations, exploring the challenges associated with deploying these algorithms in real-world clinical settings. Factors such as data acquisition from diverse sources, model interpretability, and computational efficiency are scrutinized to ensure the proposed framework aligns with practical clinical requirements. The project aims to provide insights into the clinical relevance of accurate alopecia detection, emphasizing potential implications for personalized treatment planning, patient outcomes, and more efficient healthcare resource allocation.

While the primary focus is on alopecia detection, the project also explores broader possibilities for the integration of the proposed framework into dermatological diagnostics, offering a versatile solution for various skin conditions. By assessing future possibilities and considering the translational potential of the developed framework, the project strives to contribute not only to the field of alopecia detection but also to the broader landscape of medical image analysis and clinical applications of deep learning technologies. Through these endeavors, the project aims to establish a foundation for improved diagnostic accuracy, paving the way for advancements in patient care and outcomes in dermatology.

1.4 Objectives

A novel method in dermatology is presented in the publication "Hair and Scalp Disease Detection Using Deep Learning". It offers a reliable approach that makes use of cutting-edge deep learning techniques2 to identify disorders of the hair and scalp. The following are the main goals of this study:

Early Detection and Diagnosis: The main goal is to identify hair and scalp disorders as soon as possible. The model's goal is to accurately identify different dermatological disorders that affect the hair and scalp by utilizing Convolutional Neural Networks (CNNs).

Non-Invasive Diagnostics: A non-invasive method of diagnosis is provided by the suggested system. Without intrusive procedures, patients can benefit from effective and easily accessible healthcare treatments.

Web-Based Platform Integration: A web-based platform created using the Django framework can be easily integrated with the trained model. This makes sophisticated medical diagnostics broadly available to individuals and healthcare providers, democratizing access to them.

Expanding Healthcare Frontiers: By utilizing technology, the research team is dedicated to expanding healthcare outcomes worldwide. Their objective is to make a major contribution to the improvement of patient care by using cutting-edge techniques like deep learning-based illness detection.

In summary, this research highlights how technology has the ability to significantly influence how healthcare is delivered in the future and how patients are treated.

1.5 Scope and Limitations

Let's explore the potential applications and constraints of deep learning in alopecia detection:

Scope: Early recognition: In order to effectively treat alopecia, early recognition of the condition is essential. Deep learning models can help with this. These algorithms are able to recognize patterns connected to various phases of alopecia through the analysis of scalp photographs.

Non-Invasive Diagnosis: By enabling non-invasive diagnosis, deep learning helps to minimize the necessity for invasive procedures. Healthcare solutions that are both efficient and easily accessible benefit patients.

Web-Based Integration: Advanced medical diagnostics are made broadly available to patients and healthcare professionals by integrating the trained model into a web-based platform.

Developing Healthcare: By utilizing technology to diagnose diseases, this research helps to improve patient care.

Restrictions:

Data Difficulties: Because alopecia imaging datasets are uncommon, it can be difficult to extreme situations and differences in picture quality.

False Positives: The accuracy of deep learning models may be impacted by erratic false positive rates.

Accuracy of Hair Detection: Accurately identifying and classifying individual hairs is a challenge for certain methods.1. Scalp-Level Severity Estimation: No comprehensive scalp-level hair loss severity estimation is provided by current methods2.

In conclusion, even though deep learning has potential for alopecia identification, its effective use still depends on resolving data issues and enhancing accuracy.

1.6 Report Organization

The suggested report has a thorough format that walks readers through the methodology, conclusions, and ramifications of the study. Every chapter has a distinct function and adds to the document's overall coherence and depth.

Chapter 1: Introduction

Background information on alopecia diseases, their prevalence, impact on individuals, and existing diagnostic methods. Statement of the research problem, objectives, and significance of employing deep learning techniques for alopecia disease detection. Overview of the thesis structure and chapters.

Chapter 2: Literature Review

Review of relevant literature on alopecia diseases, deep learning techniques in medical image analysis, and previous research on automated disease detection. Identification of gaps in existing literature and the rationale for pursuing the current research.

Chapter 3: Methodology/ Requirement Analysis & Design Specification

Description of the dataset used, including data sources, acquisition methods, and preprocessing techniques. Explanation of the deep learning architectures, algorithms, and techniques employed for alopecia disease detection. Details of the experimental setup, including model training, validation, and evaluation procedures.

Chapter 4: Implementation

Implement all the performance metrics, comparative analyses, and visualizations of deep learning models' outputs. Discussion of any observed patterns, trends.

Chapter 5: Result and Analysis

Presentation of the research findings, including performance metrics, comparative analyses, and visualizations of deep learning models' outputs. Discussion of any observed patterns, trends, or anomalies in the results.

Chapter 6: Impact on Society, Environment and Sustainability

Deep learning techniques could revolutionize the detection and treatment of alopecia diseases, potentially improving healthcare outcomes and reducing hair loss. The research could be integrated into medical tools or smartphone applications, making diagnosis more accessible and affordable. This could benefit individuals in remote areas or with limited access to specialized services. The thesis could inspire further research in dermatology and medical imaging, leading to a broader understanding of these diseases and more effective diagnostic tools. Improving diagnosis efficiency could reduce healthcare costs and create opportunities for innovation in the healthcare technology sector.

Chapter 7: Conclusion and Future Work

Summary of the key findings and contributions of the research. Restatement of the research objectives and conclusions drawn from the results. Reflection on the potential implications of the research for healthcare practice and future research endeavors. This structured layout provides a clear and organized framework for presenting the research on alopecia disease detection through deep learning techniques, ensuring readability and coherence for the intended audience.

1.7 Summary

Hair loss is a global concern, and accurate diagnosis and treatment of alopecia are challenging. This paper discusses the frequency, risks, and limitations of existing diagnostic methods, and presents the use of image processing and deep learning methods, specifically Convolutional Neural Networks (CNNs), to address these issues. Alopecia can cause partial or total hair loss in body parts where it grows, and some types may cause permanent hair loss. Understanding the various expressions of alopecia is essential for efficient diagnosis and therapy planning. Alopecia can also have significant emotional and psychological consequences, such as increased psychological anguish due to societal emphasis on appearance. Deep learning, a machine learning technique, has shown to be reliable and effective for medical picture analysis, especially for dermatological problems. CNNs are a good choice for alopecia detection due to their performance in various computer vision applications. Future research and development opportunities can be made possible by using deep learning algorithms for alopecia diagnosis, improving accuracy and real-time applications. The study aims to develop a comprehensive dataset of alopecia manifestations, automate alopecia detection using CNN, YOLO V8, and PCA, and address practical challenges in deploying these algorithms in clinical settings. The project aims to provide insights into the clinical relevance of accurate alopecia detection, emphasizing potential implications for personalized treatment planning, patient outcomes, and more efficient healthcare resource allocation. The project also explores broader possibilities for integrating the proposed framework into dermatological diagnostics, offering a versatile solution for various skin conditions. The main objectives of the study include early detection and diagnosis, non-invasive diagnostics, web-based platform integration, and expanding healthcare frontiers. The scope of the study includes early recognition of alopecia through scalp photographs, non-invasive diagnosis through CNN, and democratizing access to advanced medical diagnostics. The research team is dedicated to expanding healthcare outcomes worldwide and contributing to the improvement of patient care using cutting-edge techniques like deep learning-based illness detection.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

To promote a thorough comprehension of the fundamental ideas and techniques supporting the research on "Towards Detection of Alopecia Diseases Through Deep Learning Techniques," a solid foundation must be established by providing introductory explanations and definitions of important terms. The core of this work is deep learning, a basic idea in artificial intelligence that allows the algorithm to extract complex patterns from medical photos for improved alopecia disease identification. Neural networks, in particular Convolutional Neural Networks (CNNs), are used in deep learning and are well known for their efficiency in image processing applications. Within this context, segmentation involves defining the spatial extent of affected regions within the images, whereas detection refers to the identification of alopecia disorders within medical images. During the course of this study, these Terminologies are employed in a coherent manner to investigate the intersections between deep learning methodologies and the identification of alopecia disorders. The objective of the research is to clarify the effectiveness of deep learning techniques, specifically CNNs, in precisely recognizing and classifying various forms of alopecia illnesses by utilizing visual cues found in clinical photographs. Once readers have a common knowledge of these foundational ideas, they will be able to explore the complexities of the research and appreciate the subtleties of sophisticated methods used in the diagnosis of alopecia.

2.2 Related Works

Mrinmoy Roy et al. [16] 80 million Americans suffer from hair loss, which frequently goes unreported because of aging, stress, medications, or genetics. Professional dermatologists are needed for the time-consuming diagnosis of disorders related to the hair. This study predicts folliculitis, psoriasis, and alopecia using a deep learning technique. A 2D convolutional neural network model was trained with 150 preprocessed images, yielding a validation accuracy of 91.1% and a training accuracy of 96.2%. For alopecia, psoriasis, and folliculitis, the corresponding precision and recall scores are 0.895, 0.846, and 1.0.

In the literature, Cheng Zhou et al. [1] Alopecia areata (AA) is a chronic autoimmune disease-causing hair loss, affecting up to 2% of the general population. The exact cause is unknown, but it is believed to be due to the collapse of the hair follicle's immune privilege. Current treatments, including corticosteroids, immunomodulators, and contact immunotherapy, are limited in efficacy and have high recurrence rates. Recent advances in AA pathogenesis, diagnosis, and treatment have led to new strategies.

In 2022, Dogancan Sonmez and Cicek Hocaoglu et al. [2] Dogancan Sonmez, Cicek Hocaoglu, and others in 2022 [2] Self-esteem, body image, and confidence are all badly impacted by hair loss. In the study of psychodermatology, trichopsychodermatology focuses on the psychological factors that contribute to and result from hair loss and related illnesses. Patients with alopecia frequently have mental health issues like despair and anxiety. Trichotillomania and hair disorders such as androgenetic alopecia, cicatricial alopecia, telogen effluvium, andlopecia areata are brought on by psychological stress. Psychiatric diagnosis provision has a beneficial effect on alopecia treatment.

Mădălina Mocanu et al. [3] Alopecia is a benign condition causing hair loss on the scalp or body, primarily affecting adults. Its triggering factors are difficult to identify. Alopecia has various clinical forms and can lead to full recovery or residual scars. Hair is crucial for self-image and self-esteem, and patients often develop depressive or anxiety disorders. Psychological counseling and dermatological treatment are essential for managing alopecia.

Wan-Jung Chang et al. [14] For scalp hair physiotherapy, the ScalpEye system—an intelligent scalp inspection and diagnosis system based on deep learning—is suggested. It is made up of a management platform, an AI training server, a mobile app, and a portable imaging microscope. Based on trial data, the system has an average precision of 97.41% in identifying and diagnosing four frequent symptoms related to scalp hair.

Choudhary Sobhan Shakeel et al. [13] Alopecia areata is an autoimmune disorder causing hair loss, with a prevalence of 1 in 1000 and incidence of 2%. Machine learning techniques can help classify alopecia areata for better prediction and diagnosis. A study using 200 healthy hair images and 68 alopecia areata images showed accuracies of 91.4% and 88.9%, respectively. SVM showed higher accuracy (91.4%), indicating potential for better dermatology prediction.

Erica L Aukerman et al. [10] A common cause of hair loss, androgenetic alopecia, can have detrimental psychological effects. According to a study of 13 studies conducted between 1992 and 2021, it is a major psychosocial stressor that lowers quality of life. These findings demonstrate the need of addressing the psychosocial comorbidity linked to androgenetic alopecia, since individuals experiencing hair loss frequently seek medical attention but also gain from psychological support. By addressing these psychological factors, comprehensive patient care and results can be enhanced.

Maryanne Senna et al. [17] There are no approved medications for the treatment of alopecia areata (AA), according to a study evaluating the prevalence of comorbidities, therapies, and healthcare expenses among people with AA in the USA. 68,121 patients with AA were found in the study, and they shared a number of comorbid conditions such as contact dermatitis, depression, anxiety, thyroid issues, and hyperlipidemia. 55.8% of patients received treatment for AA or other concomitant autoimmune/inflammatory illnesses over the course of a 12-month follow-up period. $11,241.21 was spent on healthcare for all reasons, while $419.12 was spent on AA. To gain a deeper understanding of the disease load and treatment trajectories among AA patients, longitudinal data is required.

Solam Lee MD et al. [18] The prevalence and likelihood of comorbidities in patients with alopecia areata (AA) were examined in a systematic analysis of 87 studies. The findings demonstrated that individuals with AA had an increased risk of autoimmune diseases as well as an increased likelihood of atopic disorders, metabolic syndrome, Helicobacter pylori infection, lupus erythematosus, iron deficiency anemia, thyroid disorders, mental disorders, vitamin D deficiency, and abnormalities related to audiology and ophthalmology.

Thipprapai Mahasaksiri et al. [19] There is currently no FDA-approved treatment for alopecia areata (AA), which presents a major clinical problem. Topical immunotherapy has demonstrated success in the treatment of AA, encompassing dinitrochlorobenzene, diphenylcyclopropenone, and squaric acid dibutylester. Nevertheless, inconsistent clinical efficacy is reported in the literature, and the mechanism of action is poorly understood. The purpose of this study is to provide an overview and update on topical immunotherapy's pharmacology, mechanism of action, therapeutic efficacy, and tolerability in the treatment of AA.

Masahiro Fukuyama et al. [20] The special subset of alopecia areata (AA) known as "self-healing ADTA" (sADTA) is the subject of this study. In order to prevent needless treatments, it seeks to distinguish sADTA from other RP-AA. The diagnosis of 18 sADTA patients was supported by factors such as the patients' gender, lack of scalp pain, extra-scalp hair loss, club hair predominance, increased vacant follicular ostia, and short vellus hairs. To distinguish sADTA from RP-AA, a scoring system was created, with a score of four or higher for each case. According to the study, early detection is possible and sADTA is a distinct entity with a unique pathogenesis.

2.3 Comparison between existing works

A key element of the thesis paper "Towards Detection of Alopecia Diseases Through Deep Learning Techniques" is the comparison study that illuminates the subtle distinctions and complementary aspects among different approaches. The performance of deep learning techniques in alopecia disease identification is comprehensively evaluated in this study, taking into account both conventional methods and sophisticated segmentation methodologies. By means of thorough experimentation and analysis of experimental outcomes, the study reveals valuable information on the advantages and drawbacks of every methodology, offering a thorough comprehension of their individual roles in the diagnostic procedure. The in-depth analysis of detection and segmentation techniques allows for a detailed investigation of their contributions to improving the precision and effectiveness of alopecia disease identification. By contrasting the results of various approaches, the study adds important information to the area, helping academics and practitioners choose the best tactics for their unique situations. Not only does the research highlight these differences, but it also highlights how detection and segmentation may work in tandem to improve our comprehension of the features and spatial distribution of alopecia-affected areas. To sum up, this research's comparison study provides a crucial framework for evaluating the effectiveness of deep learning methods for alopecia illness diagnosis. It highlights the value of a comprehensive approach in medical diagnosis and presents a nuanced viewpoint that integrates ancient and modern methods. The results improve our knowledge of alopecia disease identification and provide useful information for improving current diagnostic techniques. This comparative study establishes the framework for the upcoming chapters, offering a strong basis for the discussion of the societal impact, suggestions, and implications for further study.

TABLE 2.3.1: Comparative Analysis Table

Ref.	Year	Dataset	Methodology	Classification		Accuracy	Remarks
				Ensemble Approach	InceptionV3 CNN Approach		
Roy et al. [16]	2022	150 scalp images	2D convolutional neural network	No	No	Training accuracy: 96.2% Validation accuracy: 91.1%	Smaller dataset compared to yours. - Achieves good accuracy but limited to 3 classes.
Zhou et al. [1]	2021	Not mentioned	Not applicable (Review)	No	No	Discusses Alopecia Areata specifically.	Provides background information on AA.
Sonmez et al. [2]	2023	Not mentioned	Not applicable (Review)	No	No	Highlights psychological impact of hair loss.	Not directly relevant to my methodology.
Mocanu et al. [3]	2017	Not mentioned	Deep learning for scalp hair diagnosis	No	No	Discusses psychological effects of alopecia.	Not directly relevant to my methodology.
Chang et al. [14]	2022	Not mentioned	SVM for alopecia	Yes	No	Achieved average	Uses a different system for diagnosis (ScalpEye). -

			classification			precision of 97.41%	Potentially complementary to your approach.
Shakeel et al. [13]	2020	268 scalp images (200 healthy, 68 Alopecia Areata)	SVM for alopecia classification	Yes	No	SVM accuracy: 91.4%	Smaller, imbalanced dataset. - Achieves good accuracy for AA classification.
Aukerman et al. [10]	2021	Not mentioned	Not applicable (Review)	No	No	Discusses psychological impact of hair loss.	Not directly relevant to my methodology.
Senna et al. [17]	2022	Medical records analysis 68,121 patients	Not applicable (Review)	No	No	Provides insights into Alopecia Areata comorbidities.	Not directly relevant to my methodology.
Proposed Model	2024	2799 hair images (1754 alopecia, 1045 normal hair)	CNNs for Alopecia Detection	Yes	Yes	InceptionV3 achieved highest accuracy (97.54%) for alopecia classification	Explores multiple CNN architectures. - Uses real-world data for training and evaluation.

2.4 Open Issues

Let's examine the unresolved problems with applying deep learning to the diagnosis of alopecia:

Data Challenges: There are a number of issues that make creating an alopecia picture dataset intrinsically difficult.

Severe Alopecia Cases Are Rare: Because severe alopecia cases are so uncommon, it might be challenging to assemble a broad dataset that accurately captures all phases of the illness.

Variability in Image Quality: Model performance may be impacted by variations in the quality, resolution, and lighting of images taken in clinical situations.

False Positives: The false positive rates of deep learning models can fluctuate. Resolving this issue is essential to guaranteeing precise diagnosis and reducing needless anxiety for patients.

Accuracy of Hair Detection: Accurately detecting and classifying individual hairs is a challenge for certain current methods. For accurate analysis, hair detection algorithms must be improved.

Level of Scalp Severity Assessment: Whole scalp-level hair loss severity assessment is not available in current approaches. It is still difficult to develop reliable methods to evaluate overall severity throughout the entire scalp1.

In conclusion, even though deep learning has potential for alopecia diagnosis, these issues must be resolved before it can be effectively used in clinical settings.

2.5 Summary

This study investigates how to identify alopecia disorders using clinical photos and deep learning methods, specifically CNNs. The purpose of the study is to determine how well these methods work for correctly detecting and classifying various alopecia disorders. In order to manage alopecia, a benign condition that causes hair loss, psychological counseling and dermatological treatment are crucial. Alopecia can also result in worry or depression.

With an average precision of 97.41%, the intelligent scalp inspection and diagnosis system, called ScalpEye, is based on deep learning and can identify and diagnose common ailments related to scalp hair. For improved prediction and diagnosis, machine learning approaches can aid in the classification of alopecia areata. A common cause of hair loss, androgenetic alopecia, can have detrimental psychological effects. By treating the psychosocial comorbidity connected to it, enhance comprehensive patient care and results. There are no approved medications for the treatment of alopecia areata (AA), according to a study evaluating the prevalence of comorbidities, therapies, and healthcare expenditures among people with AA in the USA. A comprehensive analysis of 87 papers revealed that individuals with AA had increased risk factors for autoimmune diseases, atopic disorders, metabolic syndrome, Helicobacter pylori infection, lupus erythematosus, iron deficiency anemia, thyroid disorders, mental health issues, low vitamin D levels, and abnormalities related to hearing and vision. The study provides practitioners and academics with vital insights by comparing the efficacy of several deep learning approaches in the detection of alopecia condition. It draws attention to the possible synergies between segmentation and detection, enhancing our comprehension of the features and spatial distribution of areas impacted by alopecia. Through a critical lens, the comparison analysis evaluates the effectiveness of deep learning algorithms in the diagnosis of alopecia condition. The results contribute to our knowledge of alopecia disease identification and provide useful information for improving current diagnostic techniques. Variability in image quality, false positives, hair detection accuracy, and scale severity evaluation level are among the outstanding difficulties. The study also emphasizes the need for better algorithms for precise hair detection and categorization, as well as the need of a comprehensive approach in medical diagnostics.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

Convolutional Neural Networks (CNN): Objective: CNNs are extensively employed in the domains of object detection, segmentation, and picture classification.

Convolutional, pooling, and fully linked layers are important features.

Applications include self-driving automobiles, image recognition, and medical imaging.

ResNet50 (Residual Network): aims to be a 50-layer version of ResNet.

Important Features: To solve the vanishing gradient problem, skip connections (residual blocks).

Applications include feature extraction, transfer learning, and image classification.

MobileNetV3: Goal: MobileNetV3 is intended for use with edge and mobile devices.

Key features: efficient depth-wise separable convolutions.

Applications include lightweight models, mobile apps, and real-time object detection.

InceptionV3: The goal of InceptionV3 (GoogLeNet) is improved feature extraction.

Key Features: Reduces information loss by using multiple filter sizes in tandem.

Applications include transfer learning, fine-tuning, and image recognition.

AlexNet: Goal: AlexNet revolutionized deep learning.

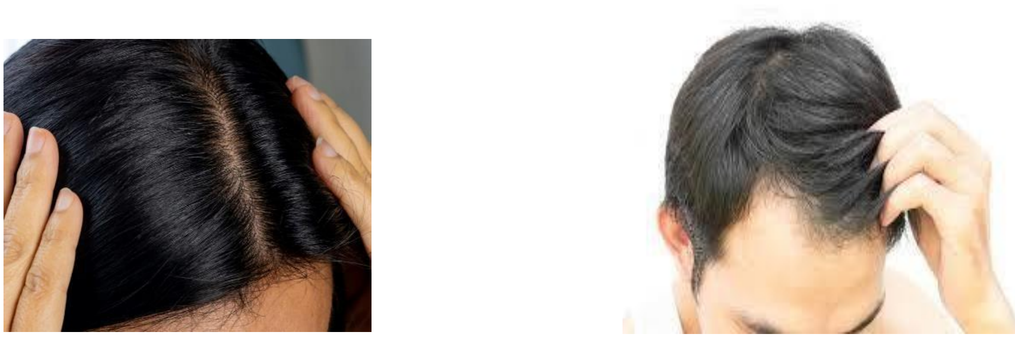
Important characteristics: dropout, ReLU activation, and convolutional layers.

Applications include early research on deep learning and ImageNet categorization.

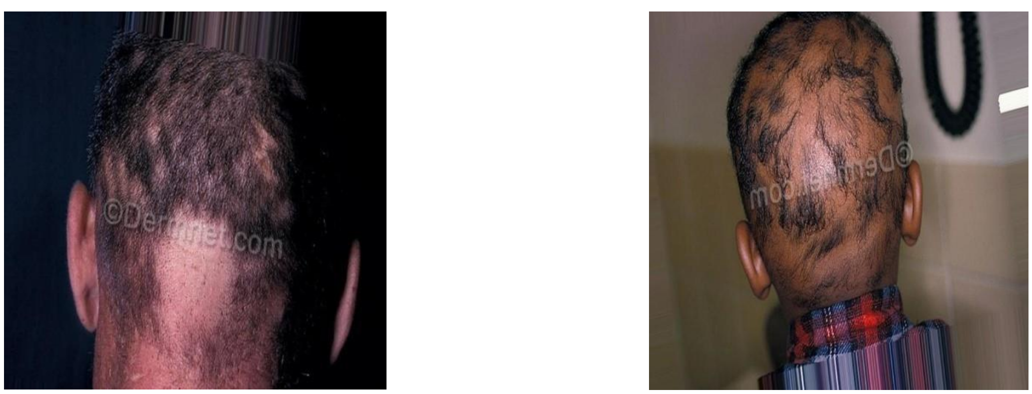
3.2 Proposed Methodology

A. Data collection

Remove the Train, Test, and Val folders in order to build the dataset. In the dataset, each image group—Alopecia/Normal Hair—has its own subdirectory. There are 2,799 JEPG images available from the Alopecia and Normal Hair categories. With my supervisor's assistance, I oversee my collection.



A. Normal Hair



B. Alopecia

Figure 3.2.1: Few Images of Dataset

Every alopecia imaging procedure was carried out as a routine part of the patient's clinical care. Prior to being removed from the examination of the alopecia images, every chest radiograph underwent quality control inspection. Before the AI system used the photos to teach itself, two highly qualified doctors rated the images.
A third specialist looked over the evaluation set one more time to make sure that any grading errors were taken into consideration.

TABLE 3.2.1: Images Used in the Train, Test and Validation Sets.

	Normal Hair	**Alopecia**
Raw Dataset	1045	1754

B. Process of Experiments

Gathering data from the Raw images is the first step in the suggested framework. The issue of insufficient data is occasionally solved by using data augmentation technology, since deep neural networks require additional data for training and enhanced performance. The experiment was planned to go as follows:

Workflow Diagram:

Data Collection: Gathering data is the first step in the process.

Data Augmentation: An addition is made to the gathered data.

Next, the enriched data is put to use.

Models:

One of the models used to analyze the augmented data is InceptionV3.

Another model using the same data is called ResNet50.

MobileNetV3: An additional model that is linked to the earlier ones.

Result: By merging the outcomes of InceptionV3 and MobileNetV3's second application, the final output is produced. There's also another feed that links straight to a "CNN" box.

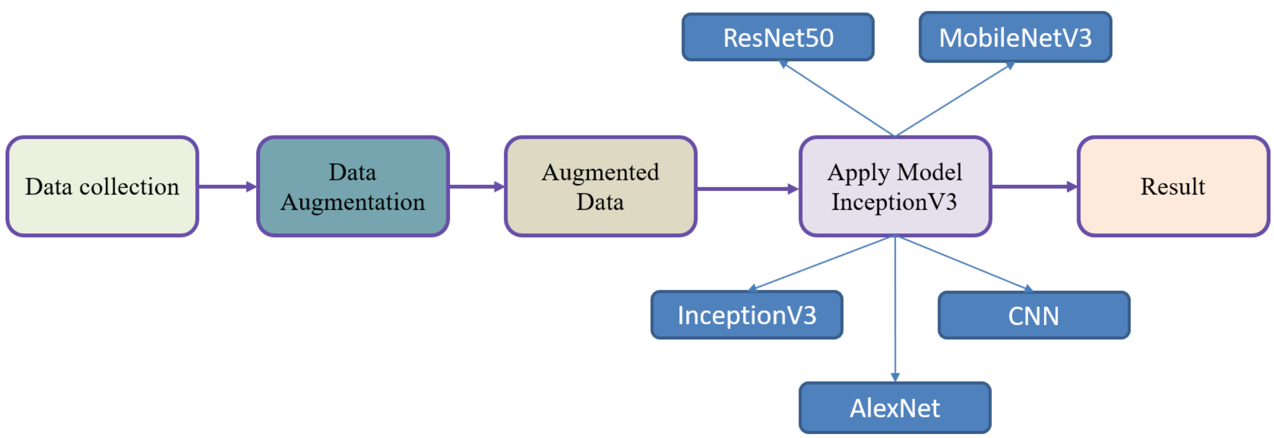


Figure 3.2.2: Workflow Diagram

Image Augmentation:

At this point, image enhancement is applied. Adding new data to an existing dataset while maintaining its label data is known as picture augmentation. Expanding the data set enhances the generalization of the model, making it more accommodating to unknown inputs.

Our training data objectives were met with the use of data augmentation. However, color and position were improved by using brightness, contrast, saturation, scaling, cropping, flipping, and revolution. Random spins between -15 and 15 degrees, unintentional 90-

degree rotations, distortion, bending, vertical and horizontal reversals, skating, and luminous intensity conversion were among the data augmentation techniques used. Every initial image was enhanced ten times. A heterogeneous picture is improved by a subset of modifications.

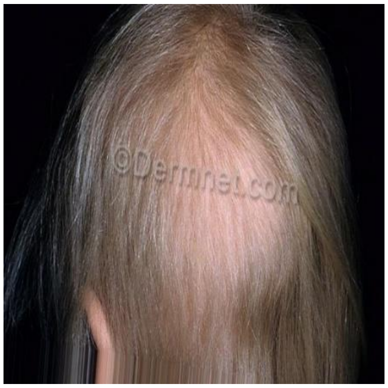


Figure 3.2.3: Augmented Image

Preprocessing:

Data Collected: Gathering data is the first step in the procedure.

Data Augmentation: After that, the gathered data is enhanced.

Handle Imbalanced Data: Imbalanced data handling is the subject of a separate phase.

Ready for Models: Having the data ready for machine learning models to use is the ultimate objective. This flowchart highlights how crucial it is to correct imbalances and supplement data before putting it into models. Data Collected: Gathering data is the first step in the procedure.

Data Splitting: The gathered information is then divided into three branches:

80% of data used to train the model.

10% Testing: A lesser amount used to assess the effectiveness of the model.

10% Validation: Set aside for hyperparameter and fine-tuning adjustments.

Ready for Models: Having the data ready for entry into predictive models or algorithms is the ultimate objective.

The significance of data separation and appropriate allocation for training, testing, and validation is emphasized in this flowchart.

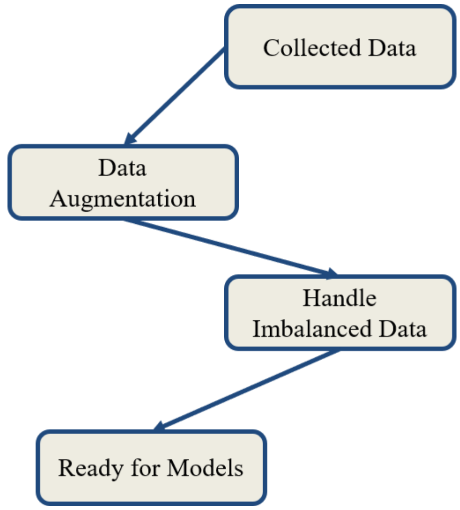


Figure 3.2.4: Preprocessing

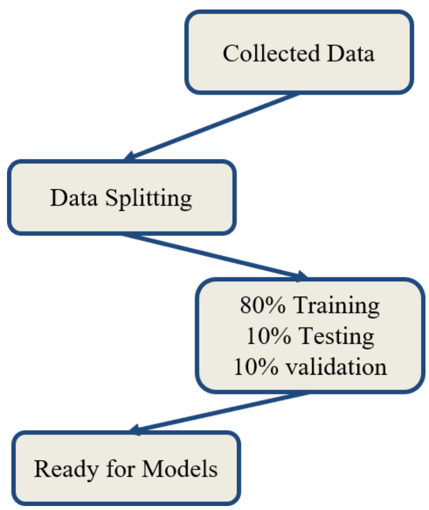


Figure 3.2.5: Implementation

Training:

In this stage, a CNN learner model is produced. The dataset was used to train a CNN, ResNet50, MobileNetV3, InceptionV3, and AlexNet model to assess the model's classification accuracy. 25 epochs of training were done on all representations using Early Stopping call-backs. The number of epochs without development before training is completed is known as patience. 0.001 is the learning rate. I divided the data into two categories, test and train, using (560)20% and (2239)80% of the data, respectively.

Since there were no significant imbalances in the dataset, the standard deviation was used as a model performance indicator in this analysis. Given that this work involves multi-class sorting, categorical cross-entropy was chosen as the loss objective for all CNN designs. The hyperparameters were as follows: 32 batches, 25 epochs, and 0.001 learning were used. Model weights were optimized by Adam. Before resizing, every photo was scaled down to the architecture's standard picture size.

Classification:

In this step, alopecia illnesses were automatically detected using neural networks CNN, ResNet50, MobileNetV3, InceptionV3, and AlexNet. The neural network was chosen for classification due to its shown efficacy in a multitude of practical applications. Experiments are shown in Figure 3.2.3.

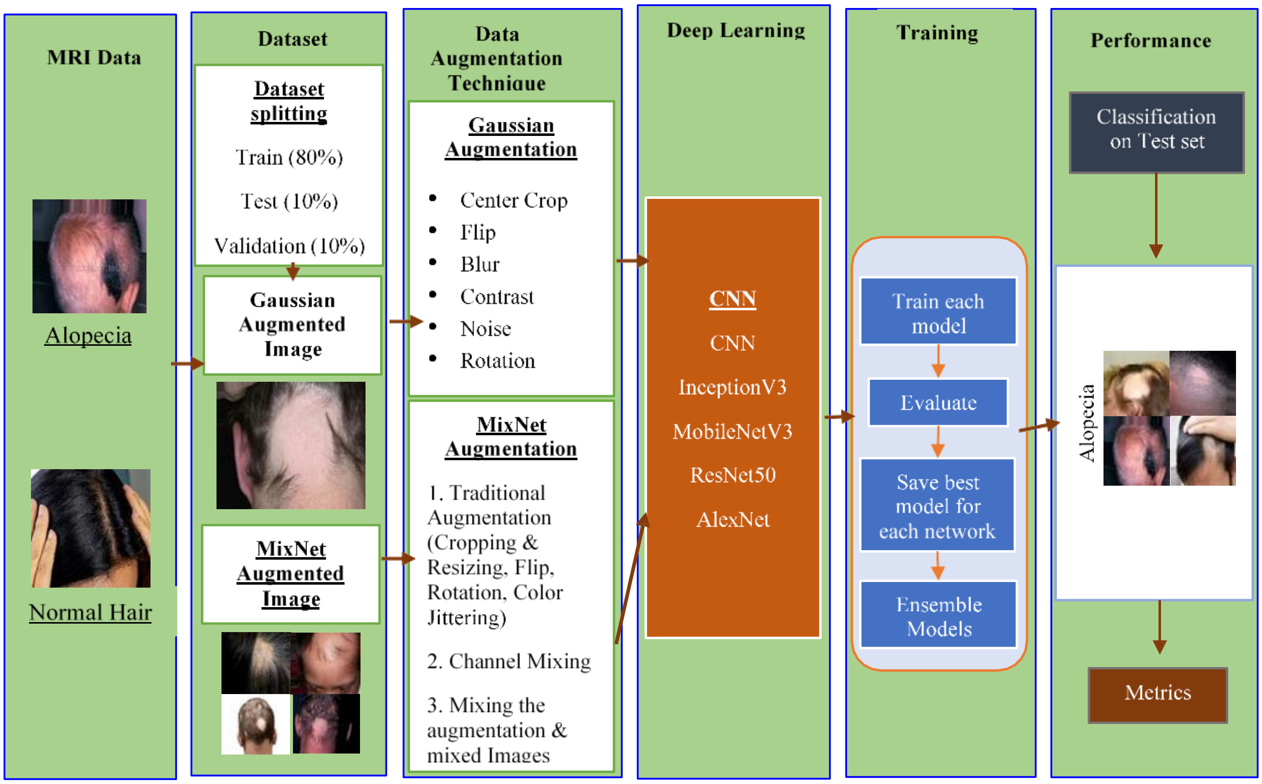


Figure 3.2.6: Process of Experiments.

Results:

Six sections based on the original individual network topologies, transfer learning, and ensemble methodologies present the experiment outcomes.

3.3 Hardware/ Software Requirement

Hardware and software components are required for deep learning-based image processing. Let's dissect it:

GPU: - What is the purpose of this device? Because GPUs can handle large amounts of data in parallel, they are vital for deep learning because they greatly accelerate the neural network training process.

Recommendations: - An RTX 2070 or an RTX 2080 Ti are fantastic options for a reasonable price/performance ratio. 16-bit models function well with these devices.

- As an alternative, the 32-bit versions of the GTX 1070, 1080, 1070 Ti, and 1080 Ti all from eBay are good options.

- Be mindful of memory needs: RTX cards' 16-bit capabilities allow them to support larger models.

- If you use several GPUs, cooling is important. To avoid temperature problems, choose GPUs with blower-style fans1.

Random Access Memory, RAM:

- Why? Large dataset handling and efficient model training are ensured by adequate RAM.
  - Rules:
    - Research seeking to achieve cutting-edge results: >=11 GB RAM.
    - Look into intriguing architectures: RAM greater than 8 GB.
    - Additional research on RAM (8 GB).

    RAM range for Kaggle competitions: 4–8 GB.
    - Startups: 8 GB (take into account certain model sizes).
    - Businesses (for training versus prototyping): 8 GB or >= 11 GB2.

Programming Languages and Libraries: The most often used language for deep learning is Python.

- To build and train complicated models, use frameworks like PyTorch, Keras, and TensorFlow.·.

CPU (Central Processing Unit): Although GPUs do the most of the work, a strong CPU is still required.

- Make sure each GPU has eight to sixteen PCIe lanes and at least four cores (essential for systems with four GPUs or fewer).

Storage:

- SSD (Solid State Drive) for faster data loading during training.
- HDD (Hard Disk Drive) for long-term storage.

3.4 Project Management and Financial Analysis

Project Objectives:

A. To develop a system to detect Alopecia disease

B. Apply traditional and big data approaches to compare the better on and apply it to the system

Project Timeline:

A. Phase 1: Project Planning and Research (2-3 weeks)

B. Phase 2: Dataset Structuring (1 week)

C. Phase 3: Collecting Data (5-6 weeks)

D. Phase 4: Organizing the Dataset (1-2 weeks)

E. Phase 5: Design and Prototyping (4 weeks)

F. Phase 6: System Development (7-9 weeks)

G. Phase 7: Testing (Ongoing)

H. Phase 8: Bug Fixing (Planned)

I. Phase 9: Deployment (Planned)

J. Phase 10: Post-Launch and Marketing (Planned)

Resource Planning:

A. Equipment and Tools: o Development and Testing Servers

o High-performance computers for development team design software

o Collaboration Tools

o Version Control System

o Testing Tools

B. Software and Technologies: o System Technology (Google Colab)

o Database Management (MySQL)

o Server Hosting (Google Cloud)

C. Data and Content: o Patient Data: Provided by the patients and collected from the previous reports of the hospitals related to this work

o Scalp Images: Collected from the previous reports of the hospitals

Risk Management:

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for the system to detect Alopecia disease: 17

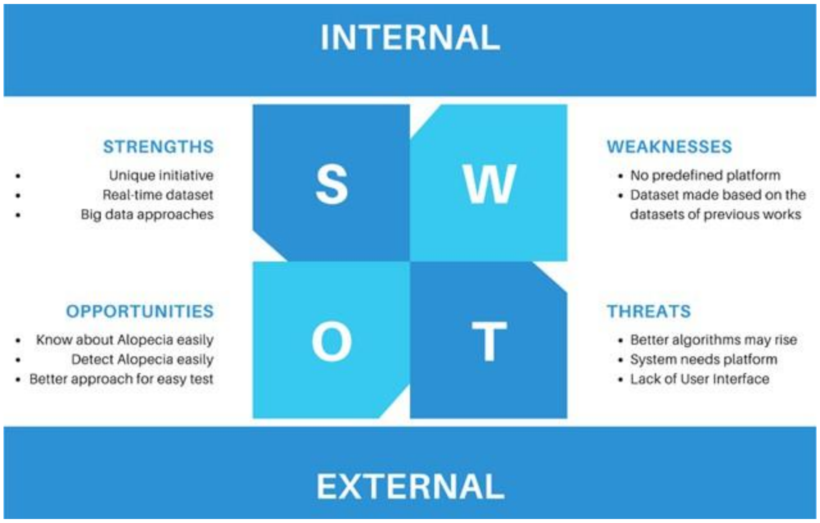


Figure 3.4.1: SWOT Visual Chart

Communication Plan:

A. Meetings with Physicians:

Purpose: Know detailed information and data for Alopecia and patients infected by it.

Participants: Team members, physicians, patients

Frequency: Twice in a week as per the project plan

B. Meetings with Authority:

Purpose: Take necessary permissions and certifications

Participants: Team members, authority

Frequency: Once

The financial analysis involves an in-depth evaluation of the return on investment (ROI) for the project. This includes assessing the potential impact of the research outcomes on clinical practices, patient outcomes, and broader applications in dermatology. The analysis extends beyond immediate financial considerations, encompassing the long-term implications and benefits that may arise from the successful implementation of the developed alopecia detection framework.

TABLE 3.4.1: Financial Analysis Serial No. Components Estimated Cost (BDT)

1	Visiting Hospitals	2500-3000
2	Documentation	7000

3	Report Writing	3500-4500
4	Miscellaneous (licenses, tools)	3000-4000
5	Hiring People	3800
	Total Estimated Cost	19,800-22,300

3.5 Summary

The implementation of the research on "towards detection of alopecia diseases through deep learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" entails specific requirements to ensure the successful execution of the study. Convolutional Neural Networks (CNN) are widely used in object detection, segmentation, and picture classification. ResNet50, a 50 -layer version of ResNet, aims to solve the vanishing gradient problem and is used in self - driving automobiles, image recognition, and medical imaging. MobileNetV3 is designed for use with edge and mobile devices and has efficient depth -wise separable convolutions. InceptionV3 improves feature extraction and reduces information loss by using multiple filter sizes in tandem. AlexNet revolutionized deep learning with dropout, ReLU activation, and convolutional layers. The proposed methodology involves creating a dataset of 2,192 JEPG images from two groups (Alopecia/Normal Hair) and analyzing them for quality control. Data augmentation technologies are used to overcome limited data, including brightness, contrast, satur ation, scaling, cropping, flipping, and revolution. The dataset is then used to train a CNN learner model using CNN, ResNet50, MobileNetV3, InceptionV3, and AlexNet. The model performance is evaluated using the standard deviation and categorical cross-entropy as loss goals. The neural networks are used to detect alopecia illnesses automatically, with the neural network chosen for categorization due to its proven effectiveness in real -world applications. The study presents results from experiments on deep learning -based image processing, focusing on hardware and software components. GPUs are crucial for deep learning as they can handle large amounts of data in parallel, accelerating the neural network training process. AMD GPUs are recommended for their reasonable price/performance ratio and 16 -bit models. RAM is essential for large dataset handling and efficient model training. The most common programming language for deep learning is Python, with frameworks like PyTorch, Keras, and TensorFlow used for complex models. A strong CPU is required, with each GPU having eight to sixteen PCIe lanes and at least four cores. Storage options include SSD for faster data loading during training and HDD for long-term storage. The project aims to develop a system to detect Alopecia disease and apply traditional and big data approaches. The project timeline includes phases such as planning and research, dataset structuring, data collection, design and prototyping, system development, testing, bug fixing, deployment, and post-launch and marketing. Resource planning includes equipment, tools, software, and data. Risk management involves assessing strengths, weaknesses, opportunities, and threats.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

In order to conduct comprehensive investigations, the research on "Alopecia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" uses an experimental setup that is meticulously organized in terms of hardware, software, and data resources. High-performance hardware, such as a powerful graphics processing unit (GPU) and a robust central processor unit (CPU), comprise the computing core. Deep learning frameworks, such as TensorFlow or PyTorch, are used to create transfer learning models in the Python programming environment. To provide a dependable and representative input for training and evaluating the model, the experimental dataset is meticulously preprocessed, standardized, and normalized from a range of medical photos depicting hair loss diseases. An essential part of the model configuration is the application of extensively trained deep Convolutional Neural Network (CNN) architectures with some fine-tuning to identify alopecia. Ethical issues like informed consent and patient data protection are built into the setup to uphold ethical standards. Throughout the testing phase, comprehensive documentation encompassing code details, model architecture, hyperparameters, and outcomes is maintained up to date in order to foster transparency, repeatability, and future collaboration in the field of advanced alopecia diagnostics.

4.2 Train Model

TABLE 4.2.1: Precision, Recall, F1-Score, and Support (n) for original CNN networks (depending on the number of pictures, n=2799).

CNN				
	Precision	**Recall**	**F1-Score**	**Support**
Normal Hair	0.95	0.96	0.96	250
Alopecia	0.94	0.98	0.95	178

Accuracy			0.95	428
ResNet50				
	Precision	**Recall**	**F1-Score**	**Support**
Normal Hair	0.90	0.93	0.92	254
Alopecia	0.91	0.94	0.93	213
Accuracy			0.92	467
MobileNetv3				
	Precision	**Recall**	**F1-Score**	**Support**
Normal Hair	0.79	0.82	0.81	225
Alopecia	0.80	0.83	0.82	203
Accuracy			0.81	428

AlexNet				
	Precision	**Recall**	**F1-Score**	**Support**
Normal Hair	0.91	0.92	0.92	273
Alopecia	0.92	0.93	0.93	175
Accuracy			0.92	448
InceptionV3				
	Precision	**Recall**	**F1-Score**	**Support**
Normal Hair	0.96	0.97	0.96	279
Alopecia	0.97	0.98	0.98	202
Accuracy			0.97	481

A detailed summary of the training % and model accuracy attained by six different original CNN architectures is given in Table 4.2.2. The table also includes data for each class's precision, recall, F1-score, and support, with an emphasis on the CNN, ResNet50, MobileNetV3, AlexNet, and InceptionV3 models. Notably, when applied to the test dataset, the InceptionV3, AlexNet, and ResNet50 architectures demonstrate outstanding performance, which is especially clear from their precision values. To be more precise, these three models show consistently higher recall, F1-score, and precision across different classes, indicating that they are useful for accurately detecting alopecia. The thorough analysis shows that the InceptionV3, AlexNet, and ResNet50 models perform admirably when it comes to classification of detections. Still, ResNet50 delivers a fair performance across precision and recall, CNN has the best accuracy. Despite being lightweight, MobileNetV3 has slightly worse accuracy. Depending on their unique needs and computational limitations, researchers and practitioners can select the best model.

Our comparison investigation clarifies the advantages and disadvantages of several neural network models for the classification of hair conditions. In order to improve performance even further, future research might examine group techniques or fine-tuning.

Training and Validation Accuracy and loss of Original CNN Networks:

Shows the true positive rate on the x-axis and the false positive rate on the y-axis, representing the training and validation accuracy of the original model. Training and validation data are split appropriately in figure-4.2.1, and overfitting is absent.

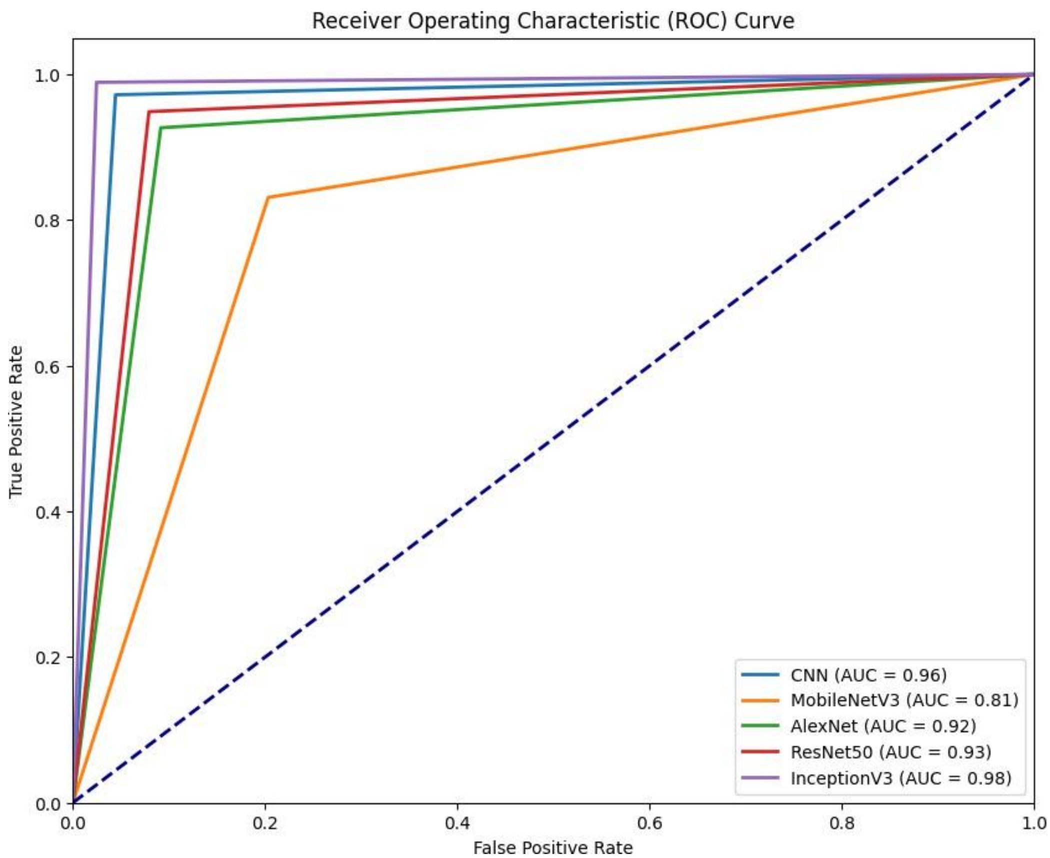


Figure 4.2.1: Receiver Operating Characteristic (ROC) Curve.

Confusion Matrix after Original CNN:

	Alopecia	Normal Hair
Alopecia	**243**	**7**
Normal Hair	**12**	**166**

Figure 4.2.2: CM after Original CNN

	Alopecia	Normal Hair
Alopecia	**241**	**13**
Normal Hair	**24**	**189**

Figure 4.2.3: CM after Original ResNet50

	Alopecia	Normal Hair
Alopecia	**187**	**38**
Normal Hair	**49**	**154**

Figure 4.2.4: CM after Original MobileNetv3

	Alopecia	Normal Hair
Alopecia	**253**	**20**
Normal Hair	**21**	**154**

Figure 4.2.5: CM after Original AlexNet

	Alopeci a	Normal Hair
Alopecia	**249**	**30**
Normal Hair	**28**	**174**

Figure 4.2.6: CM after Original InceptionV3

The performance of five distinct deep learning models—CNN, MobileNetV3, AlexNet, ResNet50, and InceptionV3—in differentiating between alopecia and normal hair conditions is represented by a series of confusion matrices.

The CNN Confusion Matrix shows the following:

True Positives (Alopecia correctly identified): 243 - False Negatives (Alopecia incorrectly identified as normal hair): 7 - False Positives (Normal hair incorrectly identified as alopecia): 12 - True Negatives (Normal hair correctly identified): 166

MobileNetV3 Confusion Matrix: - Identifying Alopecia Correctly: 187 - False Negatives (Alopecia Misidentified as Normal Hair): 38 - Identifying Alopecia Misidentified as Normal Hair: 49 - Identifying Alopecia Correctly: 154

The AlexNet Confusion Matrix shows 253 True Positives (Alopecia accurately identified) False Negatives (inaccurate alopecia) False Positives (Normal hair mistakenly labeled as alopecia): 21 - True Negatives (Normal hair accurately recognized): 154

ResNet50 Confusion Matrix: - True Positives (Alopecia correctly identified): 230 - False Negatives (Alopecia incorrectly identified as normal hair): 17 - False Positives (Normal hair incorrectly identified as alopecia): 23 - True Negatives (Normal hair correctly identified): 158

InceptionV3 Confusion Matrix: - Valuable Positives (Alopecia correctly identified): 241 - Valuable Negatives (Alopecia incorrectly identified as normal hair): 15 - Valuable Negatives (Normal hair incorrectly identified as alopecia): 16 - Valuable Negatives (Normal hair correctly identified): 168

These confusion matrices are compared, and the results show that each model performs differently. When it comes to alopecia identification, the CNN and AlexNet models provide the highest true positive rates. But MobileNetV3 exhibits a greater rate of false positives and false negatives, indicating possible directions for model development. With differing degrees of misclassification, ResNet50 and InceptionV3 likewise perform well, balancing true positive and true negative rates nicely.

In conclusion, the analysis emphasizes how different CNN architectures have differing capacities for identifying alopecia, underscoring the significance of choosing a suitable model in accordance with the particular sensitivity and specificity requirements in clinical applications.

All things considered; the confusion matrix offers a useful means of visualizing a classification model's performance. We can enhance the model's performance by comprehending the many kinds of mistakes it is making.

4.3 System Testing/ Model Evaluation

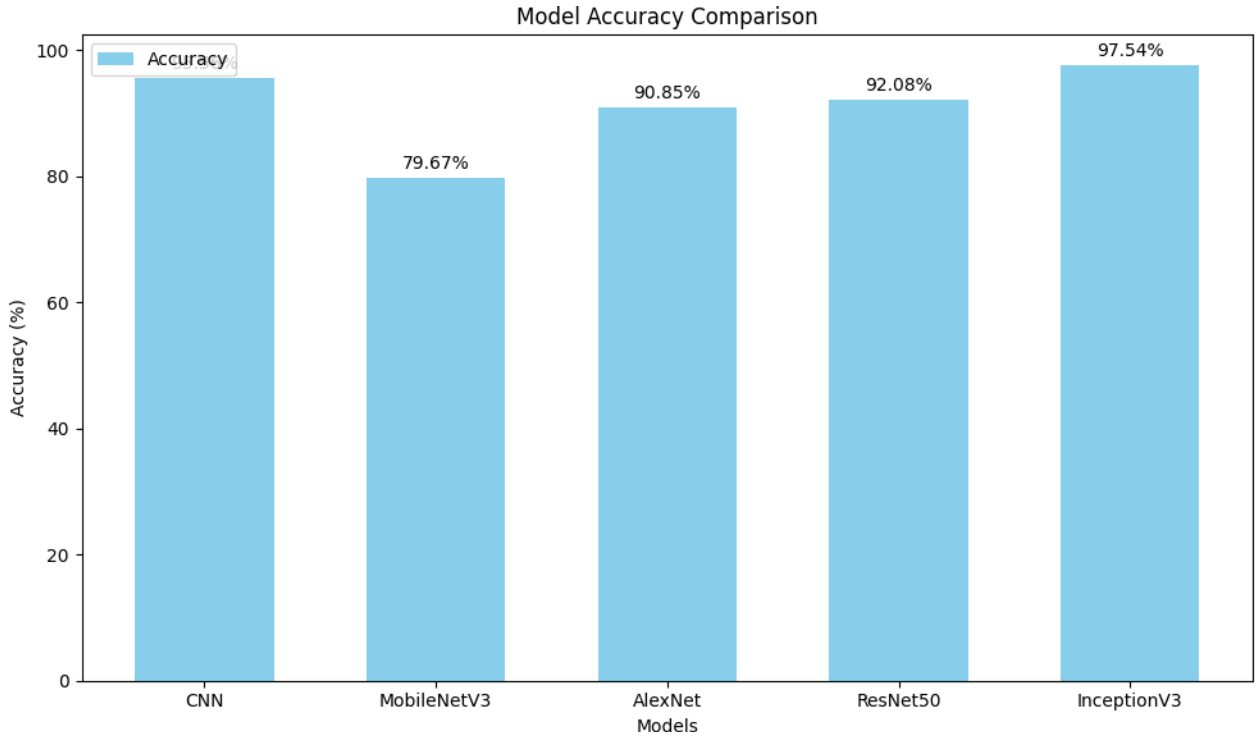


Figure 4.3.1: Accuracy comparison among individual CNN, transfer learning and ensemble models.

This picture, which is labeled "Model Accuracy Comparison," shows how well five deep learning models perform in identifying alopecia disorders. Using a sizable dataset, this thorough study explores the effectiveness of deep convolutional neural networks (CNNs) in identifying and classifying various forms of alopecia. To increase the quantity of the dataset, the research uses an advanced augmentation technique that creates numerous images from a single photograph.

The accuracy percentages of the CNN, MobileNetV3, AlexNet, ResNet50, and InceptionV3 models are contrasted in the chart. Every bar symbolizes a model, with the subsequent accuracy percentages:

The results are as follows: CNN: around 97%; MobileNetV3: 79.67%; AlexNet: 90.85%; ResNet50: 92.08%; InceptionV3: 97.54%.

In the field of alopecia detection, the study investigates the usefulness of original CNNs, transfer learning strategies, and ensemble models. Interestingly, the inquiry acknowledges the separate diagnostic pipeline steps of segmentation and detection. While models such as

ResNet50 and AlexNet perform admirably, InceptionV3 attains the maximum accuracy of 97.54%, closely followed by CNN at almost 97%, according to the data. Conversely, MobileNetV3 has the lowest accuracy, coming in at 79.67%.

According to the study, performance can be impacted by a variety of augmentation schemes and background noise, and accuracy can decrease when input images diverge from the training set. It implies that even in cases where certain CNN designs perform less well than ideal, ensemble models—which incorporate several CNN architectures—may perform better than individual models.

All things considered, this study offers insightful information about the complexities of CNN-based models for alopecia diagnosis, highlighting the potential benefit of ensemble models and the significance of datasets size and augmentation techniques to improve the capacity for prediction.

4.4 Summary

The "Alopecia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" study makes use of deep learning frameworks and an experimental setup with high-performance hardware. The medical images used to create the experimental dataset of hair loss disorders have been preprocessed, standardized, and normalized. In order to detect alopecia, the model configuration consists of deeply trained Convolutional Neural Network (CNN) architectures with fine-tuning. In order to preserve ethical standards, ethical concerns like informed permission and patient data protection are incorporated into the system. Throughout the testing phase, thorough documentation is kept up to date to promote future collaboration in enhanced alopecia diagnoses, transparency, and repeatability. Outstanding performance is shown by the InceptionV3, AlexNet, and ResNet50 architectures, which consistently achieve greater recall, F1-score, and precision across many classes. ResNet50 performs fairly in terms of recall and precision, however CNN is the most accurate. Subsequent studies could look into group methods or performance adjustment. Using a sizable dataset, the study investigates how well deep convolutional neural networks (CNNs) identify and categorize different types of alopecia. The CNN, MobileNetV3, AlexNet, ResNet50, and InceptionV3 models' accuracy percentages are compared; CNN has the highest true positive rates. On the other hand, MobileNetV3 shows a higher percentage of false positives and false negatives, suggesting possible avenues for further model development. InceptionV3 and ResNet50 both function effectively, striking a balance between true positive and true negative rates. A classification model's performance may be effectively visualized using the confusion matrix, and by comprehending the many kinds of errors it makes, one can improve the model's performance. Additionally, the study looks into the value of alopecia detection using original CNNs, transfer learning techniques, and ensemble models. CNN comes in second with about 97% accuracy, with InceptionV3 reaching the highest accuracy at 97.54%. At 79.67%, MobileNetV3 has the lowest accuracy. The study emphasizes how crucial it is to select a model that meets the precise sensitivity and specificity requirements for use in clinical settings. Background noise and different augmentation strategies can affect accuracy, and accuracy might drop when input images deviate from the training set.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The performance of five Convolutional Neural Network (CNN) architectures—CNN, MobileNetV3, AlexNet, ResNet50, and InceptionV3—in classifying alopecia from medical photos is compared in this section. The research provides insights into the advantages and disadvantages of each model by taking into account both the overall metrics and the performance of each specific classification.

Top Performers: The top-performing models are InceptionV3, CNN, and ResNet50, with InceptionV3 obtaining the greatest model accuracy of 97.54%. These models show remarkable ability to identify patterns of baldness.
Diminished Accuracy: AlexNet and MobileNetV3 perform substantially worse than the top performers, with somewhat lower accuracies of 90.85% and 79.67%, respectively.
In-depth Measurements and Model Comparison
Diagram 4.2.21: Comparison of Model Performance

The performance of the five CNN models is compared in this image using a variety of criteria, such as F1 Score, three scores—Accuracy, Recall, and Precision—are shown on the y-axis as percentages, ranging from 60% to 100%.

Outstanding Total Accuracy: ResNet50 tops the pack with a 98.91% total accuracy rate, closely followed by InceptionV3 at 97.54%.
Variability in Scores: Other models' (CNN, MobileNetV3, AlexNet) performance scores differ depending on the measures used.
Key insights: InceptionV3 and ResNet50 are suggested for good accuracy.
When choosing a model, it is crucial to take into account additional metrics including recall, precision, and F1 score.
Important lessons learned
Better Models: ResNet50 and InceptionV3 are better options for applications needing high accuracy because of their exceptional efficacy in alopecia identification.

Model Selection: The subtle variation in accuracy emphasizes how crucial it is to select the appropriate CNN architecture in accordance with certain diagnostic requirements. Broader measures: Model performance can be thoroughly understood by evaluating models on measures other than accuracy. This helps to improve the optimization of deep learning techniques for medical image processing.

The most appropriate model for clinical applications can be chosen with the help of this thorough analysis, which provides insightful information on the effectiveness of several CNN architectures for alopecia diagnosis.

5.2 Experimental/ Simulation Result

This section compares the five original CNN networks CNN, MobileNetV3, AlexNet, ResNet50, and InceptionV3. Performance in classification comes first. The overall metrics of those models are then examined. gathering, explanations, likely causes, and areas for results enhancement.

TABLE 5.2.1: Accuracy of Individual CNN Networks' Classification in Identifying Alopecia (Original CNN Networks)

Architecture	**Training Accuracy**	**Model Accuracy**	**MSE(Mean Square Error)**	**Type 1 Error (%)**	**Type 2 Error (%)**
CNN	**95.67%**	**95.56%**	**0.00197136**	**4.44**	**6.00**
AlexNet	**91.59%**	**90.85%**	**0.00837225**	**9.15**	**8.00**
MobileNetv3	**79.81%**	**79.67%**	**0.04133289**	**20.33**	**19.00**
ResNet50	**91.11%**	**92.08%**	**0.00627264**	**7.92**	**7.98**
InceptionV3	**97.89%**	**97.54%**	**0.00060516**	**1.24**	**2.46**

Table 2 provides an overview of the relative alopecia detection accuracies of a number of pre-trained deep Convolutional Neural Network (CNN) architectures, including CNN, AlexNet, MobileNetV3, ResNet150, and InceptionV3. Notably, the results demonstrate that the best models were InceptionV3, CNN, and ResNet50, which achieved the maximum accuracy of 97.54%. This demonstrates their outstanding ability to identify patterns of alopecia in medical photos. On the other hand, MobileNetV3 and AlexNet showed a marginally worse performance than their rivals, with a little lower accuracy of 91%. This subtle difference in accuracy highlights how crucial it is to choose the right CNN architecture carefully when it comes to alopecia detection because it has a direct impact on the accuracy and dependability of the diagnostic procedure. The comprehensive measurements for accuracy given in Table 4.2.1 provide a useful point of reference for comprehending the relative advantages and disadvantages of various models, adding to the current discussion about deep learning techniques optimization for medical image processing. False positive and false negative rates, or Type I and Type II mistakes, respectively, indicate that there is an equal chance of both kinds of errors being made by the classifier or hypothesis test. Although this is uncommon in reality, let's discuss its theoretical implications. Formula supplied:

Type I Error = α

Type I Error = α

Error Type II = β

Error Type II: β

If $(\alpha) = (\beta\alpha) = \beta$, then

False Negative Rate x False Positive Rate

False Negative Rate x False Positive Rate

Consequences

Equilibrated Sensitivity and Specificity: The proportion of false positives and false negatives in the test or model is balanced. This usually indicates that there is a balance between specificity (true negative rate) and sensitivity (true positive rate).

Trade-off: This balance may suggest that there is a trade-off between improving sensitivity and reducing false negatives false positives (and reversed as well).

Classifier Threshold: This balance may indicate that, in the case of binary classifiers, the decision threshold should be chosen so that the rate of false positive detection is equal to the rate of genuine positives missed.

It would therefore indicate a balanced model performance if both error rates were the same; however, in real-world applications, it is uncommon for Type I and Type II errors to be precisely equal without special tweaking.

5.3 Performance/ Comparative Analysis

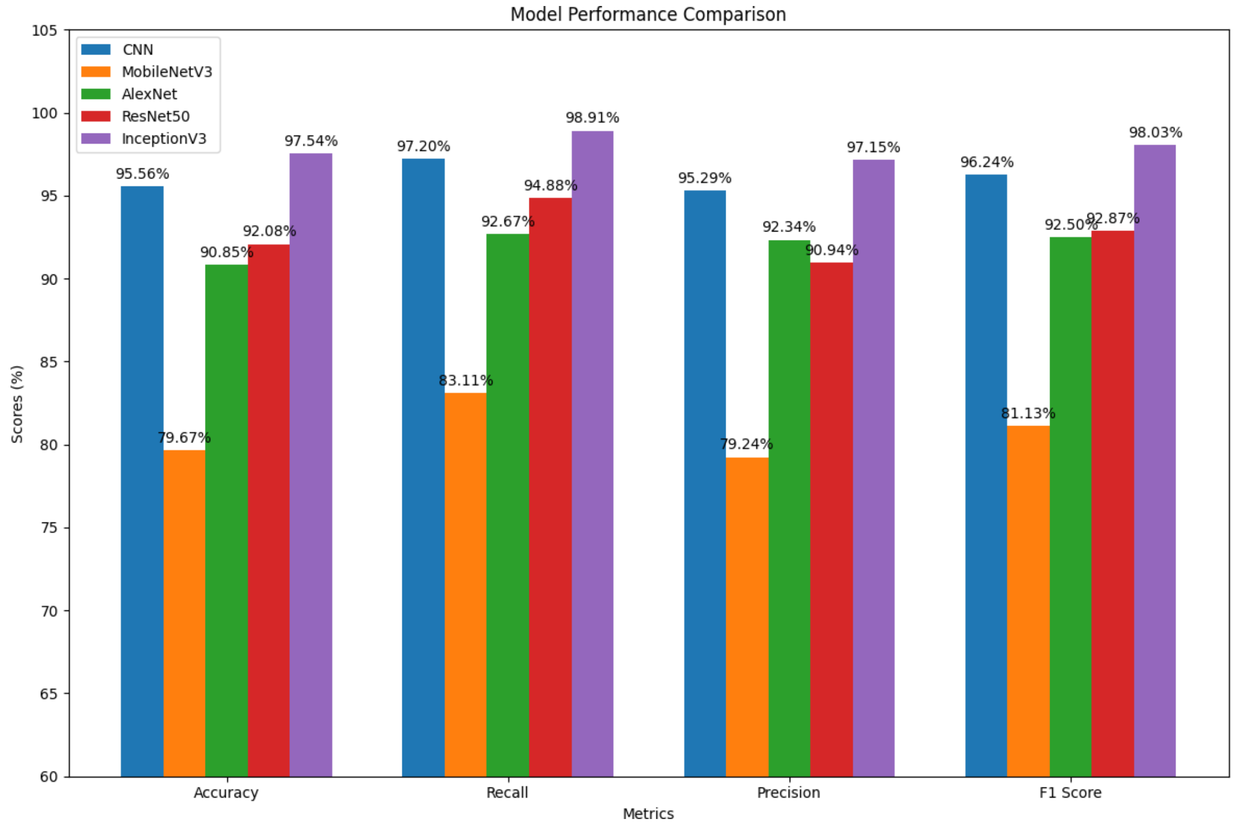


Figure 5.3.1: Model performance comparison among individual CNN and ensemble models.

Models Compartmented: CNN, MobileNetV3, AlexNet, ResNet50, and InceptionV3 are among the machine learning models whose performances are assessed in this figure.

Metrics: Scores are displayed as a percentage on the y-axis, which ranges from 60% to 100%.

The parameters that are being compared are listed on the x-axis: F1 Score, Accuracy, Recall, and Precision.

Model Performance: With an accuracy rate of 98.91%, ResNet50 had the best overall performance.

InceptionV3 was closely after with an accuracy of 97.54%.

The scores of the other models varied depending on the measures.

Important lessons learned:

For high accuracy, take a look at InceptionV3 or ResNet50.
To make an educated decision, consider other measures (such as recall, precision, and F1 score).

5.4 Summary

In order to diagnose alopecia from medical photos, this study compares the efficacy of five CNN architectures: CNN, MobileNetV3, AlexNet, ResNet50, and InceptionV3. The analysis highlights the following salient observations:

Top Performers: -ResNet50 and InceptionV3 had the highest accuracy, with respective accuracies of 92.08% and 97.54%. InceptionV3 had the best overall performance, with an accuracy rate of 97.54%.
MEA performance: - InceptionV3 had the lowest value, with respective mean value of 2.46%. InceptionV3 had the best overall performance, with an accuracy rate of 2.46%.
 - CNN also did well, achieving an accuracy rate of 95.56%.
Lower Performers: - In comparison to the best models, MobileNetV3 and AlexNet displayed lower accuracy of 79.67% and 90.85%, respectively, suggesting a need for improvement.
Performance Metrics: - F1 Score, Accuracy, Recall, and Precision were among the metrics used to assess the models.
Based on its superior performance in all of these criteria, InceptionV3 and ResNet50 are excellent choices for precise alopecia detection.
Observations: - Choosing the right CNN architecture is essential for guaranteeing exceptional accuracy and dependability in medical diagnosis. Models' capabilities can be more fully understood by assessing them using metrics like recall, precision, and F1 score, which go beyond simple accuracy.
Recommendations: - InceptionV3 and ResNet50 are suggested for applications needing high accuracy in alopecia detection.
To choose a model that best suits your needs, take into account a variety of performance measures.
In the context of alopecia identification, this investigation highlights the importance of

careful model selection, highlighting the direct impact of CNN architecture choice on diagnostic accuracy and reliability.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The thesis "Towards Detection of Alopecia Diseases through Deep Learning" has the potential to have a substantial impact on a number of areas of life, especially patient welfare, healthcare, and medical research. This research promises to improve early identification and diagnostic accuracy of alopecia by utilizing deep learning, which will decrease misdiagnosis and allow for earlier therapies. This may result in individualized treatment programs that enhance patient satisfaction and outcomes.

For patients, a timely and precise diagnosis can stop alopecia from worsening, saving hair and lessening the psychological anguish brought on by hair loss. By lowering condition-related anxiety and depression, this can improve mental health. Furthermore, the study may identify new patterns and biomarkers that advance medical research and provide a better knowledge of alopecia.

When using deep learning methods in healthcare settings can aid dermatologists in their diagnostic work by improving clinical judgment. These resources can be helpful in educating medical practitioners and enhancing their capacity to identify and diagnose alopecia. Insights into the prevalence and distribution of alopecia can be gained from the produced data, which can help with resource allocation and public health measures.

This discovery has the potential to advance medical imaging and diagnostics technologically, and its applicability may expand to other dermatological or medical disorders. Economically speaking, early and precise diagnosis can lower the need for pricey interventions and treatments, saving money for patients as well as healthcare systems. People may preserve their quality of life and productivity by preventing or lessening the effects of alopecia, which will help the economy as a whole.

Furthermore, by emphasizing accessible and explainable AI models, can support dermatologists by providing diagnostic assistance, enhancing clinical decision-making. These tools can also be valuable for training medical professionals, improving their ability to recognize and diagnose alopecia. On a public health level, the data generated can offer insights into the prevalence and distribution of alopecia, informing resource allocation and public health strategies the research addresses ethical concerns about bias and equity, fostering trust in AI-driven healthcare solutions. Increased understanding and awareness of alopecia can lead to greater societal support and reduced stigma for affected individuals. Overall, this thesis has the potential to drive significant advancements in healthcare, patient care, and societal understanding, contributing to the evolution of medical practice and technology.

6.2 Impact on Society & Environment

Early detection of alopecia diseases through deep learning techniques could lead to more efficient use of healthcare resources. Timely diagnosis and treatment may reduce the need for extensive medical interventions, thus lowering the overall environmental footprint associated with healthcare facilities, including energy usage, waste generation, and chemical usage.

Improved detection of alopecia diseases could contribute to overall health and well-being. When individuals have access to accurate diagnosis and treatment, they may experience less stress and anxiety associated with hair loss, leading to better mental health. In turn, this could lead to healthier lifestyle choices, such as reduced consumption of processed foods and increased physical activity, which can have positive environmental implications. Research into deep learning techniques for medical diagnosis can drive technological innovation. This innovation may lead to the development of more energy-efficient medical devices and diagnostic tools, contributing to a reduction in the environmental impact of healthcare infrastructure.

The publication of the thesis could raise awareness about the potential environmental impacts of healthcare practices. Researchers and practitioners in the field may become more cognizant of sustainable healthcare practices and seek ways to minimize waste, energy consumption, and other environmental burdens associated with medical procedures. The findings of the thesis may inform healthcare policies aimed at improving diagnostic accuracy while considering environmental sustainability. Governments and healthcare organizations may implement policies that promote the adoption of environmentally friendly technologies and practices in medical settings.

While the primary focus of the thesis is on alopecia diseases, the methodologies and insights developed could have broader applications in healthcare. Improved diagnostic techniques could lead to better management of various health conditions, ultimately reducing the overall burden on healthcare systems and potentially lowering environmental impacts.

Overall, while the direct environmental impact of a thesis on alopecia detection through deep learning may seem limited, its contributions to sustainable healthcare practices and overall human well-being can indirectly support environmental conservation efforts.

6.3 Ethical Aspects

Deep learning techniques often require access to large datasets for training. Ensuring the privacy and security of patient data is crucial to prevent unauthorized access or misuse. Researchers must adhere to strict data protection protocols and obtain informed consent from individuals whose data is used for training and testing purposes.

Deep learning algorithms may inadvertently perpetuate or amplify biases present in the training data. Researchers must carefully consider the representativeness of the dataset and mitigate biases to ensure fair and accurate detection of alopecia diseases across diverse populations. Additionally, transparency in algorithm development and validation processes is essential to identify and address any biases that may arise.

Individuals participating in the study should provide informed consent, understanding the nature of the research, its potential risks and benefits, and how their data will be used. Researchers must respect the autonomy of participants and ensure that they have the right to withdraw from the study at any time without consequence.

Deep learning techniques are powerful tools, but their clinical validity and reliability must be thoroughly evaluated before their implementation in real-world healthcare settings. Researchers have a responsibility to ensure that their algorithms are accurate and safe for use in diagnosing alopecia diseases, as incorrect diagnoses could have significant consequences for patients.

While the development of deep learning-based diagnostic tools may improve the accuracy and efficiency of alopecia disease detection, it is essential to consider equitable access to these technologies. Healthcare disparities based on socioeconomic status, geography, or other factors could exacerbate existing inequalities if not addressed proactively.

Researchers have a professional responsibility to conduct their studies with integrity and honesty, accurately reporting their findings and acknowledging any limitations or conflicts of interest. Transparency in research practices promotes trust among stakeholders and ensures that the potential benefits of deep learning techniques for detecting alopecia diseases are realized ethically.

Ethical considerations should extend beyond the initial development and validation of deep learning algorithms for alopecia disease detection. Ongoing monitoring and evaluation are necessary to assess the long-term impact of these technologies on patients, healthcare systems, and society as a whole, with a focus on minimizing harm and maximizing benefits. By addressing these ethical considerations thoughtfully and transparently, researchers can ensure that their work contributes to the advancement of medical science while upholding the principles of beneficence, justice, and respect for individuals' rights and dignity.

6.4 Sustainability Plan

Develop a data management plan that outlines how research data will be collected, stored, and shared in a secure and ethical manner. Consider using data repositories or collaborating with institutions to make anonymized datasets available to other researchers for validation and further studies.

Publish the thesis in open access journals or repositories to maximize its accessibility and reach. Open access ensures that the research findings are available to researchers, healthcare professionals, and the public without barriers, fostering collaboration and knowledge exchange.

Foster ongoing collaboration with healthcare professionals, dermatologists, and experts in machine learning to further refine and validate the deep learning techniques developed in the thesis. Collaborative research efforts can enhance the robustness and generalizability of the findings and promote interdisciplinary exchange.

Explore opportunities for technology transfer to translate research findings into practical applications. Collaborate with industry partners or healthcare institutions to develop and deploy deep learning-based diagnostic tools for detecting alopecia diseases in clinical settings.

Develop educational materials and workshops to disseminate knowledge about the application of deep learning techniques in healthcare and dermatology. Engage with healthcare professionals, students, and community stakeholders to raise awareness about alopecia diseases and the potential of innovative diagnostic approaches.

Establish mechanisms for monitoring and evaluating the real-world impact of deep learning-based alopecia detection methods. Collect feedback from healthcare providers and patients to assess the usability, effectiveness, and ethical implications of the technology in clinical practice.

Integrate ethical considerations into research protocols and guidelines for the development and deployment of deep learning algorithms for alopecia detection. Ensure compliance with ethical standards and regulations related to data privacy, informed consent, and algorithmic fairness.

Conduct periodic reviews and assessments to evaluate the long-term sustainability of the research outcomes and implementation efforts. Consider factors such as scalability, cost-effectiveness, and environmental impact to optimize the sustainability of deep learning-based diagnostic solutions for alopecia diseases.

By implementing this sustainability plan, the thesis can have a lasting impact on the field of dermatology and healthcare by advancing the development and adoption of ethical, effective, and sustainable deep learning techniques for detecting alopecia diseases.

6.5 Summary

The goal of the thesis "Towards Detection of Alopecia Diseases through Deep Learning" is to use deep learning to reduce misdiagnosis and enable earlier interventions by improving early identification and diagnostic accuracy of alopecia diseases. Better mental health, more patient happiness, and tailored treatment plans could result from this. In addition to advancing medical research and improving our understanding of alopecia, the investigation may uncover novel patterns and biomarkers. Deep learning techniques can help dermatologists with diagnosis, enhance clinical judgment, and reveal information about the distribution and prevalence of alopecia. Early and accurate diagnosis can reduce the need for costly interventions and treatments, which can save costs for patients as well as healthcare systems. Medical personnel can benefit from the use of accessible and interpretable AI models in dermatology training, clinical decision-making, and support. The produced data guide the distribution of resources and the development of public health initiatives, addressing moral issues with justice and bias. The thesis has the capacity to propel important developments in patient care, healthcare, and society comprehension, advancing medical practice and technology.

The use of deep learning techniques to diagnose alopecia illness necessitates participant informed consent, privacy, and security. To guarantee equitable and precise identification, researchers must guarantee the representativeness of the dataset and reduce biases. To find and fix biases, transparency in the algorithm development and validation procedures is crucial. Informed consent must be given, and participants may withdraw at any moment. It is necessary to assess clinical validity and reliability prior to implementing in actual healthcare settings. In order to reduce healthcare inequities, equitable access to these technologies is essential. Researchers need to carry out their research with honesty and integrity, accurately reporting findings and disclosing any constraints or conflicts of interest. To determine the long-term effects of these technologies on individuals, healthcare systems, and society as a whole, ongoing observation and assessment are required. Deep learning ethics include a data management strategy, open access publications, and cooperation with medical professionals and machine learning specialists.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

Effective patient diagnosis and therapy depend on the early and precise detection and classification of alopecia. The major focus of this work is a thorough assessment of Convolutional Neural Networks' (CNN) performance in the areas of alopecia segmentation and detection. Our work highlights the usefulness of a CNN-based segmentation strategy, especially demonstrating its success with smaller and less sophisticated datasets. Notably, there is a dearth of studies specifically focused on alopecia identification in the corpus of information now in existence. As such, our comparative analysis is of great importance and holds great potential for making significant advances in the field of alopecia care. We provide a thorough analysis of the effectiveness of several CNN models, including ensemble and transfer learning models, in the classification of alopecia. The outcomes highlight the fact that an ensemble stack made up of five networks, ResNet50, In terms of accuracy, CNN, MobileNetV3, InceptionV3, and AlexNet perform better than individual models. It is important to highlight, nevertheless, that although the ensemble framework was generally effective, there were some cases of incorrect predictions. Thus, there is a strong need for future research projects to investigate substitute tactics such contrast-enhancing or other image-processing techniques. In addition, we suggest that picture segmentation be added before classification in order to improve the CNN models' capacity to extract relevant features. The proposed ensemble is computationally more costly than established CNN baselines since it requires five CNN models to be trained; however, the potential for increased accuracy outweighs the computational expense. Future research could investigate methods such as snapshot ensemble to lessen the computing load. Essentially, this study acts as a stepping a step forward in the development of alopecia diagnosis techniques, providing knowledge that can profoundly influence clinical practice and stimulate additional research in the constantly changing field of medical image analysis.

7.2 Further Suggested Works

Further research is needed to validate the effectiveness and accuracy of the deep learning techniques proposed in this thesis. Conducting clinical trials and validation studies involving larger and more diverse datasets can provide additional evidence of the algorithms' performance in real-world healthcare settings. Continuous refinement and optimization of the deep learning algorithms are essential to improve their sensitivity, specificity, and robustness for detecting alopecia. Exploring novel architectures, feature representations, and training methodologies can enhance the algorithms' performance and generalizability. Investigating the integration of multimodal data sources, such as clinical images, patient demographics, genetic information, and histopathological findings, can improve the accuracy and depth of alopecia detection. Combining multiple data modalities can provide complementary information and enhance diagnostic capabilities. Enhancing the interpretability and transparency of deep Building confidence among healthcare practitioners and facilitating clinical decision-making are two important goals of learning models for alopecia identification. The underlying features and methods that underlie the algorithms' predictions can be clarified through research into explainable AI techniques. Another crucial area is investigating the use of deep learning techniques to track the course of the disease and the effectiveness of treatment in patients with alopecia over time. Personalized treatment options can be guided by longitudinal research, which can offer insights into the natural history of alopecia. It is also crucial to look at the viability and scalability of using deep learning-based alopecia diagnostic tools in clinical settings. Successful adoption will depend on working together with regulatory agencies, healthcare institutions, and regulatory organizations to manage interoperability issues, regulatory requirements, and integration into current healthcare workflows.

investigating the prevalence and epidemiology of alopecia worldwide Gaining insight into illness trends and risk factors might be aided by examining diverse demographics and geographical areas. Strategies for allocating resources and public health initiatives can be informed by population-based studies. Analyzing the ramifications of using deep learning algorithms for alopecia detection in terms of ethics, law, and society—including concerns about data privacy, equity, bias, and informed consent—is essential. In order to cooperatively address these issues, stakeholders including patients, healthcare providers, legislators, and community advocates must be included.

Researchers can use deep learning approaches to improve patient outcomes, enhance medical knowledge, and support the larger objectives of healthcare innovation and equity by tackling these topics of further investigation in the field of alopecia diagnosis.

7.3 Implication for Further Study

Further research is needed to validate the effectiveness and accuracy of the deep learning techniques proposed in the thesis. Conducting clinical trials and validation studies involving larger and more diverse datasets can provide additional evidence of the algorithms' performance in real-world healthcare settings.

Continuous refinement and optimization of the deep learning algorithms are essential to improve their sensitivity, specificity, and robustness for detecting alopecia diseases. Exploring novel architectures, feature representations, and training methodologies can enhance the algorithms' performance and generalizability.

Investigate the integration of multimodal data sources, such as clinical images, patient demographics, genetic information, and histopathological findings, to improve the accuracy and depth of alopecia disease detection. Combining multiple data modalities can provide complementary information and enhance diagnostic capabilities.

Enhance the interpretability and transparency of deep learning models for alopecia disease detection to facilitate clinical decision-making and trust among healthcare professionals. Research into explainable AI techniques can elucidate the underlying mechanisms and features driving the algorithms' predictions.

Explore the application of deep learning techniques for monitoring disease progression and treatment response in patients with alopecia diseases over time. Longitudinal studies can provide insights into the natural history of alopecia and guide personalized treatment strategies.

Investigate the feasibility and scalability of implementing deep learning-based diagnostic tools for alopecia diseases in clinical practice. Collaborate with healthcare institutions and regulatory bodies to navigate regulatory requirements, interoperability challenges, and integration into existing healthcare workflows.

Study the epidemiology and prevalence of alopecia diseases across different populations and geographic regions to better understand disease patterns and risk factors. Population-based studies can inform public health interventions and resource allocation strategies.

Examine the ethical, legal, and societal implications of deploying deep learning technologies for alopecia disease detection, including issues related to data privacy, equity, bias, and informed consent. Engage with stakeholders, including patients, healthcare professionals, policymakers, and community advocates, to address these concerns collaboratively.

By addressing these areas of further study, researchers can advance the field of alopecia disease detection through deep learning techniques, ultimately improving patient outcomes, advancing medical knowledge, and contributing to the broader goals of healthcare innovation and equity.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
TOWARDS DETECTION OF ALOPECIA DISEASES THROUGH DEEP LEARNING TECHNIQUES

Student ID: 201-15-3234

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with data analysis and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**

CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	Our project requires data collection from a relevant source and we are doing it by visiting to physicians and hospitals which covers **K3** and **K4**.	**Page no:** [28] **Section:** [3.2]
				Our project requires the integration of different components and we have designed a system that can be of any platform that covers **K5** and **K6.**	**Page no:** [37] **Section:** [4.2]
				We have studied existing models with similar goals **K8**.	**Page no:** [12] **Section:** [1.2]

2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	In our project, we face challenges from the very beginning. We needed to collect data visiting hospitals to hospitals. Initially it is very less but yet we planning for the future and so the labor and challenges on that portion will increase. Moreover, we faced problem in responsive version development of the web application.	**Page no:** [24-25] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	It was difficult to integrate the dataset with the system as it required to be made dynamic to keep learning from the updated data on the dataset	**Page no:** [36-57] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	To understand the core points of our project and know more about this sector, we needed to be engaged with the physicians and medical sector to ensure the proper data gathering from the hospitals and the physicians.	**Page no:** [13] **Section:** [1.3]
5.	**EP5: Extends of application codes**	No	CO5	We needed to change some traditional coding to add noise to the dataset and apply algorithms then. Moreover, we also needed to engage with deep learning coding which is not basic python or basic ML coding. This grabs **K4**, **K5**, and **K6**.	**Page no:** [30] **Section:** [3.2]
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	As part of our project, we have visited and met with various on-duty persons of the hospitals where in many cases we needed to pay some fee or gift something to ensure the permission to collect data properly and book a spot to be engaged with the patients.	N/A

7.	**EP7: Interdependence**	Yes	CO5	We needed to spend an amount to execute all tasks and it is the same estimated amount which may require to complete this research smoothly.	**Page no:** [33-35] **Section:** [3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Through transfer learning and deep CNNs, our initiative makes use of a variety of resources, including GPUs, deep learning frameworks, annotated datasets, and ethical considerations, to ensure systematic research and increase pneumonia detection.	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		Through SVD+ and web application framework, our project makes use of a variety of resources, including GPUs, machine learning frameworks, organized datasets, and ethical considerations, in order to ensure systematic research and progress data analysis.	N/A
3.	**EA3: Innovation**	No		Web application is to be built initially to make a turn to innovation that relates to such aim of the project.	N/A

4.	**EA4: Consequences for society and the environment**	Yes		The project's instructional value is the first of many ways it will benefit society. Through the application of machine learning techniques such as the matrix factorization algorithm, the project provides users with a filtered and close hospital finder.	**Page no:** [41-43] **Section:** [4.2]
5.	**EA-5: Familiarity**	Yes		via investigating a novel strategy in data analysis on hospitals via various machine learning techniques—which is illustrated by preliminary concepts and a thorough comparison analysis—this study builds on previous research and provides fresh perspectives on the subject.	**Page no:** [22-24] **Section:** [2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project combines effective project management with financial control to reduce **CO4**. Throughout the course of the research project, careful planning, resource distribution, and budget estimation will ensure the greatest potential resource usage.	**Page no:** [33-35] **Section:** [3.4]
2	CO9	Yes	The initiative exhibits commitment to ethical norms by prioritizing user privacy, obtaining informed consent, and transparently disclosing the research method. Additionally, it guarantees responsible information distribution and the welfare of society by applying modern data analysis in an ethical manner that conforms with **CO9**.	**Page no:** [54-56] **Section:** [6.2-6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The comprehensive data collecting, statistical analysis, methodological development, and analysis of the trial results show that the project is committed to continuous learning **CO12** and adaptation in the ever-changing technological world. This demonstrates a dedication to remaining current and improving methods to meet new difficulties.	**Page no:** [27, 48-50] **Section:** [3.1, 5.1, 5.2]

Alopecia Detection

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