

SKIN DEEP ADVANCED MODEL

FOR ACCURATE SKIN DISEASE DIAGNOSIS

A PROJECT REPORT

Submitted by

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PANIMALAR ENGINEERING COLLEGE
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PROJECT COMPLETION CERTIFICATE



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TO WHOMSOEVER IT MAY CONCERN

This is to certify that Ms. DEVI K (Reg No: 211421104053), Ms. AKSHAYA V (Reg No: 211421104016), Ms. HEMASREE R (Reg No: 211421104097), students of final year B.E., (COMPUTER SCIENCE ENGINEERING) of "PANIMALAR ENGINEERING COLLEGE" has completed their major project with great success at our concern, under the Title: "SKIN DEEP ADVANCED MODEL FOR ACCURATE SKIN DISEASE DIAGNOSIS" from JANUARY 2025 to MARCH 2025.

Their project is found to be relevant regarding their stream and they had submitted a copy of the project report to us. During their Project period we found their sincere and hard working and possessing good behaviour and moral character.

We wish them grand success in future endeavours.

For SPIRO PRIME TECH SERVICES,

A handwritten signature in black ink.



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ABSTRACT

The mortality rate due to skin cancer is high, particularly in Western nations. Early detection of skin cancer cures the disease and prolongs human life. A common non-invasive technique for detecting skin cancer is a dermoscopy examination. Individual judgments by dermatologists determine the diagnosis, and the visual analysis of dermoscopy images requires additional inspection time. Current skin cancer classification algorithms rely solely on spatial information. However, they lack spectral domain data for lesion classification, leading to suboptimal model performance. This paper introduces novel hand-crafted features derived from cepstrum, spectrogram, and image-domain techniques to enhance skin cancer classification accuracy. These hand-crafted features incorporate both spectral and spatial information. Additionally, a newly developed 1-D multi-headed convolutional neural network (CNN) is trained using these features to classify skin lesions using the challenging HAM10000 and Dermnet datasets. The performance of the proposed network is compared with other state-of-the-art approaches on the same datasets. According to experimental results, the proposed network achieved an accuracy of 88.57% on the Dermnet dataset and 89.71% on the HAM10000 dataset. Implementing this approach could improve the accuracy of clinical diagnosis.

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LIST OF ABBREVIATIONS

CNN - Convolutional Neural Network

IOU- Intersection Over Union

AI - Artificial Intelligence

SGD - Stochastic Gradient Descent

STFT - Short Time Fourier Transform

DFT - Density Functional Theory

RAM - Random Access Memory

AUC - Area Under the Curve

SSD - Solid State Drive.

TP - True Positive

TN - True Negative

FP - False Positive

FN – False Negative

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CHAPTER 1

INTRODUCTION

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INTRODUCTION

Skin cancer, one of the most fatal diseases globally, requires early detection to improve patient outcomes significantly. Dermoscopy, a non-invasive diagnostic technique, depends on dermatologists' expertise, often leading to inconsistent interpretations and increased inspection time. To address these challenges, automated classification systems have been proposed.

Existing models typically rely on spatial data from dermoscopy images, which limits their performance. The absence of spectral domain information, which captures texture, frequency components, and lesion structure, hampers their efficacy. To overcome this, a novel technique integrating spectral and spatial data is proposed. Hand-crafted features like cepstrum, spectrogram, and image-domain-based representations are combined to enrich lesion analysis.

A 1-D multiheaded CNN is developed to classify skin lesions using these features. Experiments on HAM10000 and Dermnet datasets demonstrate superior performance compared to state-of-the-art methods, achieving accuracy rates of 88.57% and 89.71%, respectively. These results highlight its promise for clinical use, aiming to enhance skin cancer diagnostics with robust, automated solutions.

1.1 OVERVIEW OF THE PROJECT

Skin cancer is a highly prevalent and life-threatening condition, with its incidence rising due to factors like UV radiation and artificial tanning. Early detection is vital for improving survival rates, as timely diagnosis significantly enhances outcomes. Traditional diagnostic methods, such as the ABCD rule and seven-point checklist, rely heavily on dermatologists' expertise, making them subjective and prone to variability. Additionally, distinguishing between skin lesion types is challenging due to similarities in texture and pigmentation, often leading to misdiagnosis or delays.

To overcome these limitations, artificial intelligence (AI) and deep learning technologies have emerged as effective solutions. A novel system employing a 1-D multiheaded convolutional neural network (CNN) integrates both spatial and spectral features for enhanced diagnosis. Utilizing datasets like HAM10000 and Dermnet, the model achieves improved classification accuracy, offering a reliable, non-invasive diagnostic tool. This AI-driven system accelerates diagnostic speed, enhances precision, and reduces reliance on manual interpretation, making early detection more accessible and efficient.

1.2 PROBLEM STATEMENT

Skin cancer is one of the most prevalent types of cancer worldwide, with its incidence steadily increasing over the years. Artificial Intelligence (AI) and Deep Learning techniques have emerged as promising tools in the field of medical image analysis, offering automated and efficient solutions for disease diagnosis and classification. In recent years, researchers have focused on leveraging these technologies to develop robust algorithms capable of accurately identifying various types of skin cancer based on dermatoscopic images. By harnessing the power of AI and Deep Learning, healthcare professionals can enhance diagnostic accuracy, reduce workload, and ultimately, contribute to better patient care. This paper explores the advancements in skin cancer classification using AI and Deep Learning

techniques, highlighting their potential impact on dermatology practice and public health.

1.3 NEED FOR THE PROJECT

Skin diseases are a pervasive global health issue, affecting millions of individuals across various demographics. Traditional diagnostic methods, which often rely on visual assessments by dermatologists, can be subjective and inconsistent, leading to potential misdiagnoses. Furthermore, access to specialized dermatological care is limited in many regions, particularly in rural and underserved areas, resulting in delayed or inaccurate diagnoses. This delay can exacerbate conditions, leading to more severe health outcomes. Therefore, there is a critical need for an automated, accurate, and accessible diagnostic tool that can provide consistent and timely diagnoses. Such a tool would not only enhance the accuracy of skin disease detection but also democratize access to dermatological care, ensuring that individuals, regardless of their location, can receive early and accurate diagnoses, ultimately improving patient outcomes and quality of life.

1.4 OBJECTIVE OF THE PROJECT

The primary objectives of the project are multifaceted. Firstly, it aims to develop a highly accurate and reliable diagnostic model for skin diseases, reducing the reliance on subjective visual assessments by dermatologists. Secondly, the project seeks to enhance healthcare accessibility by providing a tool that can be used remotely, making dermatological care available to individuals in underserved areas or those unable to visit a dermatologist. Thirdly, the project aims to support dermatologists by offering a preliminary diagnostic tool, allowing them to focus on more complex cases and improving overall efficiency. Lastly, the project strives to improve patient outcomes through early and accurate diagnosis, enabling timely and appropriate treatment. By achieving these objectives, the project aims to

significantly impact the field of dermatology, improving both the quality and accessibility of skin disease diagnosis and treatment.

1.5 SCOPE OF THE PROJECT

The scope of the project is comprehensive, encompassing several key components. It begins with the collection and preprocessing of a large and diverse dataset of skin disease images, ensuring representation across different skin types and 2 conditions. The project then focuses on the development of an advanced deep learning model, specifically utilizing Convolutional Neural Networks (CNNs), to accurately classify various skin diseases. This involves designing the network architecture, selecting appropriate hyperparameters, and rigorously training the model. Following development, the model's performance will be validated using metrics such as accuracy, precision, recall, and F1-score to ensure its reliability. The project also includes the creation of a user-friendly application, accessible via mobile or web platforms, allowing users to upload images and receive diagnostic results. Finally, the project encompasses continuous maintenance of the model, ensuring it remains accurate and up-to-date in real-world settings.

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

2.1.1 TITLE: DETECTION AND CLASSIFICATION OF SKIN DISEASES USING DEEP LEARNING.

AUTHOR: D.A. Vineela.

YEAR OF PUBLISHING: 2023

This paper explores a deep learning-based approach for skin disease classification using CNNs and three pre-trained models AlexNet, ResNet, and InceptionV3. It addresses challenges in distinguishing skin diseases, emphasizing automation to reduce human intervention. Results show ResNet outperforms other models in classification accuracy.

2.1.2 TITLE: SKIN DISEASE PREDICTION USING DEEP LEARNING.

AUTHOR: Adarsh Jadhav, Shivani Hardade

YEAR OF PUBLISHING: 2022

The paper presents a deep learning-based method for predicting and classifying skin diseases using convolutional neural networks (CNNs) and the HAM-10000 dataset. It achieves high accuracy in diagnosing conditions like melanoma, benign keratosis, and basal cell carcinoma. The study highlights the benefits of AI-assisted dermatology in improving diagnosis speed and accuracy while reducing reliance on manual biopsies. The model demonstrates 97.05% accuracy, showing promise for future clinical applications and telemedicine.

2.3 TITLE: SKIN DISEASE DETECTION USING DEEP LEARNING

AUTHOR: Srushti

YEAR OF PUBLISHING:2020

The paper presents a skin disease detection system using deep learning and image processing. It proposes a user-friendly application that utilizes smartphone cameras for diagnosis, making dermatological assessments more accessible and affordable. The system processes images using filters and machine learning models, specifically artificial neural networks (ANNs) implemented in Python with Keras, OpenCV, and Tkinter. The study aims to improve early detection of skin diseases like Nevus and Ringworm while minimizing reliance on dermatologists

2.4 TITLE: SKIN DISEASE DETECTION USING DEEP LEARNING

AUTHOR: Sruthi Chintalapudi, Vikas Prateek Mishra

YEAR OF PUBLISHING:2021

The paper discusses a deep learning-based system for detecting skin diseases using convolutional neural networks (CNNs). It proposes a user-friendly web portal where users can upload images for analysis, classifying conditions such as melanoma and basal cell carcinoma. The approach aims to provide an accessible, cost-effective alternative to traditional lab-based diagnoses, achieving 91.74% training accuracy and 87.33% validation accuracy.

2.5 TITLE: SKIN DISEASE DIAGNOSIS USING DEEP NEURAL NETWORK AND LARGE LANGUAGE MODEL.

AUTHOR: Xia, Deneng

YEAR OF PUBLISHING:2023

The paper explores a skin disease diagnosis system that integrates deep neural networks with large language models (LLMs). It introduces SkinDiseaseChat, a chat-based diagnostic tool that combines image classification (ResNet, VGG, DenseNet) with an interactive LLM (VisualGLM) to enhance user engagement and interpretability. The system achieved 93% validation accuracy on the HAM10000 dataset and provides an accessible, AI-powered alternative for diagnosing skin conditions.

2.6 TITLE: NOVEL MIXED DOMAIN HAND-CRAFTED FEATURES FOR SKIN DISEASE RECOGNITION USING MULTIHEADED CNN.

AUTHOR: Anurodh Kumar, Amit Vishwakarma

YEAR OF PUBLISHING:2024

The paper proposes a novel skin disease recognition method using a 1-D multiheaded convolutional neural network (CNN) combined with hand-crafted features from spatial, spectrogram, and cepstrum domains. It improves classification accuracy on the HAM10000 and Dermnet datasets, outperforming existing methods with an accuracy of 89.71% and 88.57%, respectively. The approach enhances early skin cancer detection by integrating spatial and spectral data, offering a more effective diagnostic tool.

2.7 TITLE: CONVOLUTIONAL NEURAL NETWORK BASED APPROACH TOWARDS MOTOR IMAGERY TASKS EEG SIGNALS CLASSIFICATION

AUTHOR: S. Chaudhary, S. Taran, V. Bajaj, and A. Sengur

YEAR OF PUBLISHING: 2019

This paper presents a convolutional neural network (CNN)-based method for classifying motor imagery tasks using EEG signals. The study aims to enhance brain-computer interface (BCI) applications by improving the accuracy and efficiency of EEG signal classification.

2.8 TITLE: A SURVEY ON IMAGE DATA AUGMENTATION FOR DEEP LEARNING

AUTHOR: C. Shorten and T. M. Khoshgoftaar

YEAR OF PUBLISHING: 2019

This survey provides a comprehensive review of image data augmentation techniques used in deep learning. It discusses various augmentation methods, their effectiveness in improving model performance, and their applications in different computer vision tasks.

2.9 TITLE: GRAPH-BASED INTERCATEGORY AND INTERMODALITY NETWORK FOR MULTILABEL CLASSIFICATION AND MELANOMA DIAGNOSIS OF SKIN LESIONS IN DERMOSCOPY AND CLINICAL IMAGES

AUTHOR: X. Fu, L. Bi, A. Kumar, M. Fulham, and J. Kim

YEAR OF PUBLISHING: 2022

This research introduces a graph-based neural network model for multilabel classification of skin lesions using dermoscopy and clinical images. The study focuses on improving melanoma diagnosis by leveraging intercategory.

2.10 TITLE: PROGRESSIVE TRANSFER LEARNING AND ADVERSARIAL DOMAIN ADAPTATION FOR CROSS-DOMAIN SKIN DISEASE CLASSIFICATION

AUTHOR: Y. Gu, Z. Ge, C. P. Bonnington, and J. Zhou

YEAR OF PUBLISHING: 2020

This paper proposes a novel method combining progressive transfer learning and adversarial domain adaptation to improve cross-domain skin disease classification. The approach aims to enhance model generalization when dealing with different datasets, addressing challenges in medical image analysis due to domain shifts.

2.11 TITLE: ARTIFICIAL INTELLIGENCE IMAGE CLASSIFICATION FOR DIAGNOSIS OF SKIN CANCER: CHALLENGES AND OPPORTUNITIES

AUTHOR: Manu Goyal¹, Thomas Knackstedt², Shaofeng Yan³, and Saeed Hassanpour

YEAR OF PUBLISHING: 2023

This review explores the development of AI-enabled computer-aided diagnostic systems for skin cancer detection. It highlights the increasing need for AI assistance due to rising skin cancer cases, low awareness, and limited clinical expertise. The study discusses publicly available skin lesion datasets, deep learning algorithms for distinguishing malignant from benign lesions, and the use of dermoscopic, clinical, and histopathology images. Despite promising accuracy claims, AI systems are still in early clinical application stages. The review also examines challenges and future opportunities to enhance AI-driven dermatological diagnostics.

2.12 TITLE: DETECTION AND CLASSIFICATION OF SKIN CANCER BY USING A PARALLEL CNN MODE

AUTHOR : Noortaz Rezaoana, Mohammad Shahadat Hossain, Karl Andersson

YEAR OF PUBLISHING: 2020

This paper proposes an automated technique for skin cancer classification using deep learning and image processing. It focuses on early detection to improve treatment outcomes by leveraging Convolutional Neural Networks (CNNs) to classify nine types of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma. The study enhances dataset size through image augmentation and employs transfer learning to improve accuracy. The proposed CNN model achieves a weighted average precision of 0.76, recall of 0.78, F1-score of 0.76, and an overall accuracy of 79.45%, demonstrating its potential in aiding early diagnosis.

2.13 TITLE: LAYER-SPECIFIC MODULES DETECTION IN CANCER MULTI-LAYER NETWORKS

AUTHOR: Xiaoke Ma , Wei Zhao, and Wenming Wu

YEAR OF PUBLISHING: 2023

This paper introduces LSNMF, a novel graph clustering algorithm for multi-layer networks using Nonnegative Matrix Factorization (NMF). It extracts and decomposes vertex features into common and layer-specific components, ensuring better structural characterization. LSNMF outperforms existing methods in accuracy and robustness, effectively identifying stage-specific modules linked to functional enrichment and patient survival.

2.14 TITLE: SKIN LESIONS CLASSIFICATION AND A REVIEW

AUTHOR: Marzuraikah Mohd Stofa, Mohd Asyraf Zulkifley, Muhammad Ammirul Atiqi Mohd Zainuri

YEAR OF PUBLISHING: 2021

This paper reviews deep learning-based approaches for automated skin disease diagnosis, addressing challenges in lesion complexity. It analyzes classification techniques, lesion detection methods, and evaluates 12 CNN models using accuracy, specificity, sensitivity, and AUC.

2.15 TITLE: CLASSIFICATION OF SKIN DISEASE USING DEEP LEARNING NEURAL NETWORKS WITH MOBILENET V2 AND LSTM

AUTHORS: Parvathaneni Naga Srinivasu, Jalluri Gnana SivaSai, Muhammad Fazal Ijaz, Akash Kumar Bhoi, Wonjoon Kim, James Jin Kang

YEAR OF PUBLICATION: 2023

This article presents a deep learning-based approach for classifying skin diseases using MobileNet V2 and Long Short-Term Memory (LSTM) networks. The proposed model combines the strengths of MobileNet V2 for efficient feature extraction and LSTM for handling sequential data, allowing for accurate skin disease classification. The approach aims to improve diagnostic accuracy, efficiency, and real-time applicability in clinical settings. The study highlights the potential of integrating advanced neural network architectures for better skin disease detection and classification.

CHAPTER 3

THEORITICAL BACKGROUND

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3.1 IMPLEMENTATION ENVIRONMENT

3.1.1 SOFTWARE REQUIREMENTS

Operating System: Supports both Windows and Linux, enabling flexibility for development and deployment based on user preference.

Simulation Tool: Anaconda with Jupyter Notebook is required for creating and managing deep learning environments, allowing for streamlined data analysis and code execution.

Programming Language: Python is the core language due to its versatility and rich ecosystem for machine learning and deep learning frameworks.

3.1.2 HARDWARE REQUIREMENTS

Processor: Intel i3 processor is specified, offering sufficient performance for general deep learning tasks, though higher configurations may be more efficient.

Hard Disk: A minimum of 400 GB storage ensures ample capacity to handle datasets, models, and other necessary files.

RAM: At least 4 GB RAM is essential for smooth operation during model training and execution; higher RAM capacities can improve performance.

3.2 EXISTING SYSTEM

Skin cancer has a high fatality rate, especially in Western countries. Early detection of skin cancer prolongs human life and is helpful to cure disease. Dermoscopy inspection is a frequently utilized noninvasive method to diagnose skin cancer. Visual inspection of dermoscopy images takes more inspection time, and the decision is based on the individual perception of dermatologists. The existing methods for skin cancer classification utilize only spatial information. However, the spectral domains of information are missing to classify skin lesions. Therefore, the performance of the existing models is moderate. To improve the performance of skin cancer classification, this work proposed novel hand- crafted features formulated using image-, spectrogram-, and cepstrum-domain features.

The developed hand-crafted features use spatial as well as spectral information. Furthermore, the developed hand-crafted features are given as input to a newly developed 1 multi-headed convolutional neural network (CNN) for the classification of skin lesions, using the challenging HAM10000 and Dermnet datasets. The performance of the proposed network is compared with the other existing state-of-the-art methods on the same dataset. From the experimental analysis, the proposed network achieved an accuracy of 89.71% on the HAM10000 dataset and an accuracy of 88.57% on the Dermnet dataset. The proposed method may be used to enhance the performance of clinical diagnosis measurement.

3.3 PROPOSED SYSTEM

The Proposed system aims to revolutionize skin disease diagnosis by leveraging advanced deep-learning techniques. Using Convolutional Neural Networks (CNNs) implemented with TensorFlow, our system will analyze skin images to accurately classify and diagnose various dermatological conditions. The process begins with users uploading skin images through a Django-based interface, ensuring ease of access and user-friendly interaction. Once uploaded, the images undergo pre-processing to enhance quality and standardize format, crucial for effective CNN-based analysis. The CNN model, trained on a diverse dataset of annotated skin images encompassing various diseases and conditions, will then perform feature extraction and classification..Upon classification, the system will provide detailed diagnostic reports, including probable conditions, confidence levels, and recommended actions such as further consultation or treatment. User feedback and iterative model improvement are integrated to enhance diagnostic precision over time.

3.4 DATASET DESCRIPTION

A. DATASETS

1) HAM10000 DATASET: The dataset [46] has 10500 images altogether, each measuring 224 by 224 pixels, and is separated into seven classes. Melanoma (nv), melanocytic nevi (mel), dermatofibroma (df), benign keratosis (bkl), basal cell carcinoma (bcc), actinic keratoses (akiec), and vascular (vasc) are the seven categories. Of the total number of photos, there are 6705 in the nv class, 327 in the akiec class, 514 in the bcc class, 1099 in the bkl class, 1113 in the mel class, 142 in the vasc class, and 115 in the df class. There are many different types of photos in the dataset, including dermoscopic and clinical images. Nevertheless, these photos are not of particularly high quality overall. There is significant imbalance in the dataset. Samples for every dataset class are shown in Fig 3.4.1

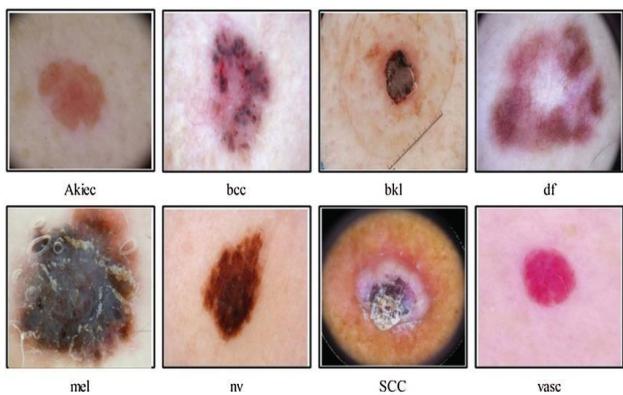


Fig 3.4.1 HAM10000 Dataset

2) DERMNET DATASET: About 19,500 photos with a wide range of pixel sizes make up this collection. This work chooses seven of the 23 categories since they are highly variable and have varying resolutions. Eczema pictures (ep), nail fungus (nf), basal cell carcinoma (akbcc), actinic keratoses, vascular tumors (vt), melanoma skin cancer (msc), seborrheic keratoses (sk), and urticaria hives (uh) are the seven categories that have been established. There are 1235 photos in the ep class, 1040 in the nf class, and 1149 in the akbcc class. There are 482 photos in the vt class, 463 in the msc class, 1371 in the sk class, and 212 in the uh class. All of the pictures are in JPEG format and have three RGB channels. Nevertheless, these photos are not of particularly high quality overall. All photos are resized to 128×128 pixels in order to preserve consistency in image dimensions. Each class's samples are shown in Fig.3.4.2



Fig 3.4.2 Dermnet Dataset

B.CEPSTRUM:

Cepstral analysis is a powerful tool in medical image processing because it extracts deep-level frequency features that are useful for identifying skin cancer, melanoma, and other lesions. By combining it with other techniques, such as spectrogram analysis, the classification accuracy of skin disease detection can be significantly improved.

$$\text{DFT}^{-1}\{\log|\text{DFT}\{f(x,y)\}|\}=C(x,y)$$

Cepstral analysis is a signal processing technique used to extract meaningful features from images (or signals). It transforms an image into a new representation that highlights certain patterns, which can be useful for classification—like identifying different skin lesions.

C.SPECTROGRAM:

For the analysis of 1-D signals, including speech and biological signals, spectrograms are widely used. Nevertheless, spectrograms are now used in a relatively small number of computer vision applications [13]. An image is subjected to a 2-D STFT in order to obtain its spectrogram. The magnitude of the STFT coefficients is then squared. The STFT can be used to calculate the spectrogram of any signal $f(n_1, n_2)$. Any signal $f(n_1, n_2)$ has the following spectrogram $S(n_1, n_2, w)$.

$$S(n_1, n_2, w) = |\text{STFT}(f(n_1, n_2)(m_1, m_2, w))|^2 = |F(m_1, m_2, w)|^2$$

where m and w are discrete and quantized as a result of the fast Fourier transform technique being used to produce DFT, and $w(n_1, n_2)$ is a window function. By fusing the two planes using maximum magnitude selection, $S(n, w)$, a 2-D shape, is created from $S(n_1, n_2, w)$, a 3-D object.

3.5 ARCHITECTURE DIAGRAM

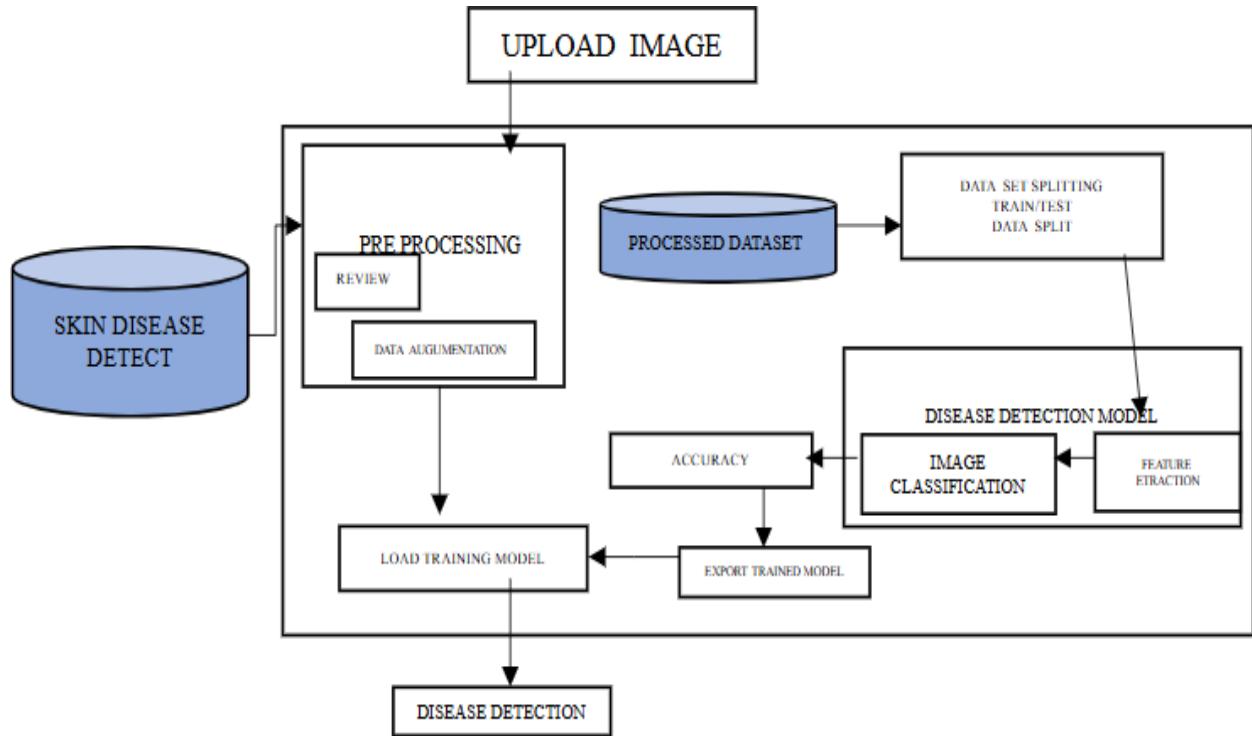


Fig 3.5.1 Architecture Diagram

The Skin Disease Detection System begins with the user uploading an image of the affected skin. The image then undergoes a pre-processing stage, which includes reviewing the image quality and applying data augmentation techniques to enhance and diversify the dataset. Once processed, the images are stored in a processed dataset, which is then split into training and testing sets for model development. During this phase, the model is trained using the processed dataset, and its accuracy is evaluated to ensure reliable predictions. The trained model is then exported for real-world usage. Finally, the system utilizes the trained model to analyze new images and detect potential skin diseases, providing accurate and efficient results.

3.6 USECASE DIAGRAM

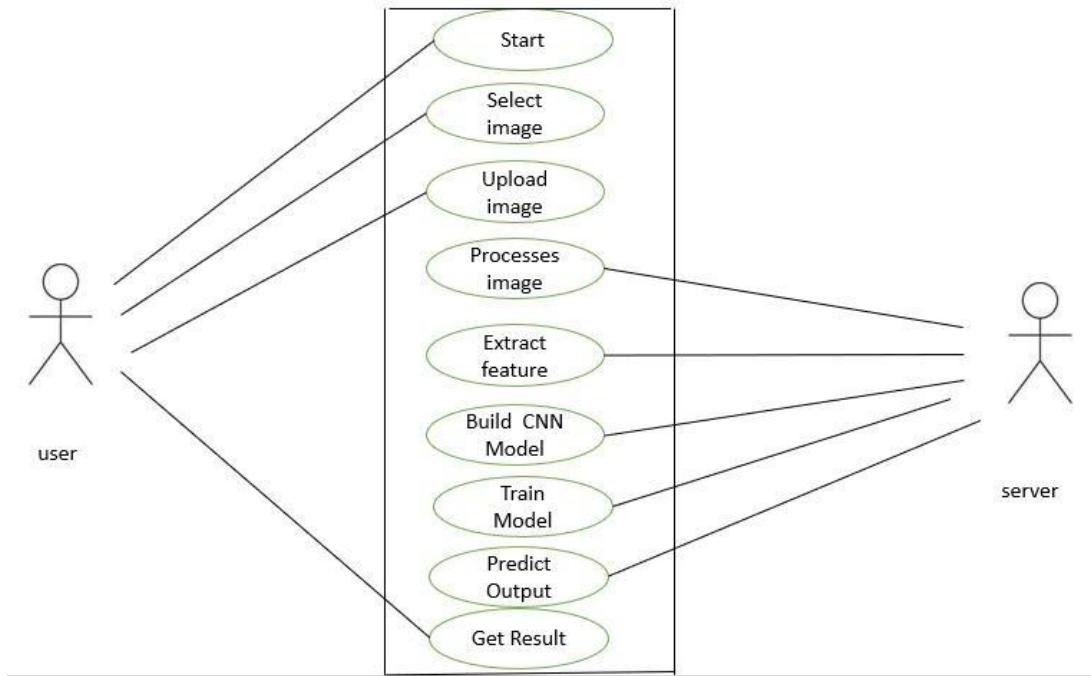


Fig 3.6.1 Usecase Diagram

User represents the individual initiating the process, such as a dermatologist, clinician, or technician. Server acts as the backend that processes the input and generates the diagnosis. The system is initiated when the user begins the process. The user selects the image of the suspected skin lesion. The image is uploaded to the system for analysis. The server preprocesses the image (e.g., resizing, normalization) to make it suitable for the CNN model. Important patterns such as lesion texture, color, and borders are identified using feature extraction methods within the model. The system utilizes its pre-trained Convolutional Neural Network (CNN) for analyzing the extracted features. For some iterations, the model refines itself with the enriched data, ensuring accurate predictions. (This might only apply during initial or periodic updates to improve the model.) The model classifies the lesion into specific categories. The diagnosis or classification result is delivered back to the user.

3.7 ACTIVITY DIAGRAM

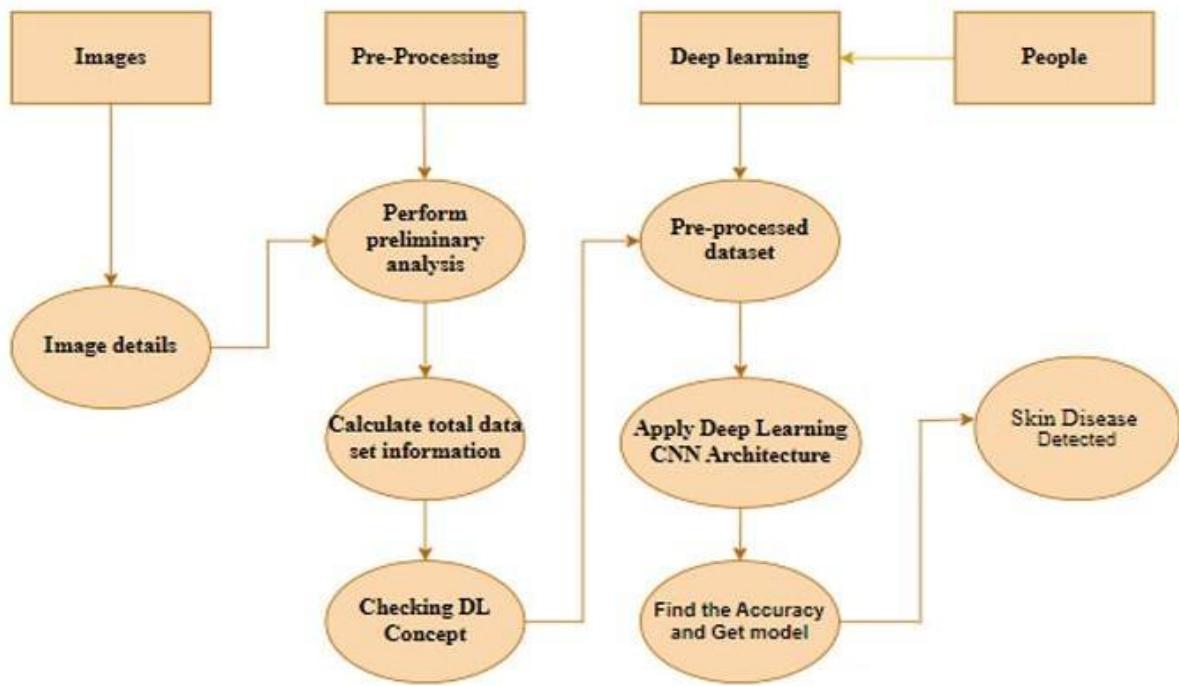


Fig 3.7.1 Activity Diagram

Activity is a particular operation of the system. Activity diagrams are not only used for visualizing dynamic nature of a system but they are also used to construct the executable system by using forward and reverse engineering techniques. The only missing thing in activity diagram is the message part. It does not show any message flow from one activity to another. Activity diagram is some time considered as the flow chart. Although the diagrams looks like a flow chart but it is not. It shows different flow like parallel, branched, concurrent and single.

3.8 SEQUENCE DIAGRAM

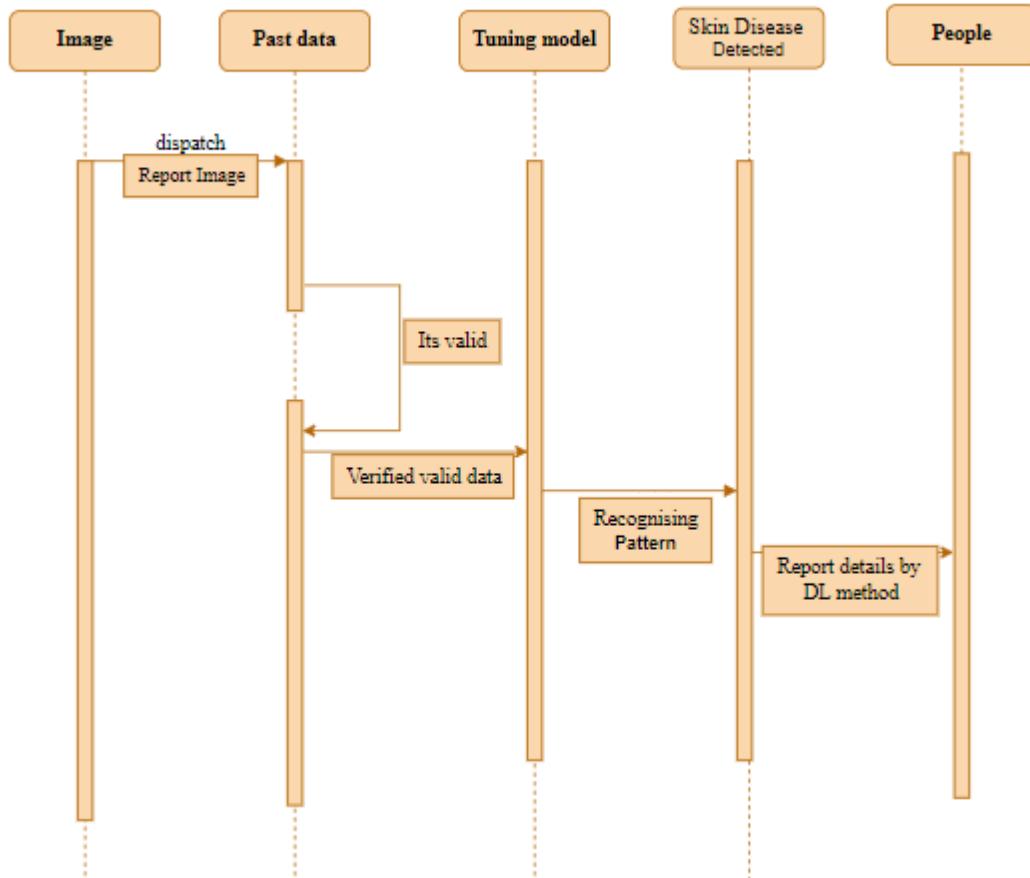


Fig 3.8.1 Sequence Diagram

Sequence diagrams model the flow of logic within your system in a visual manner, enabling you both to document and validate your logic, and are commonly used for both analysis and design purposes. Sequence diagrams are the most popular UML artifact for dynamic modelling, which focuses on identifying the behaviour within your system. Other dynamic modelling techniques include activity diagramming, communication diagramming, timing diagramming, and interaction overview diagramming.

3.9 COLLABORATION DIAGRAM

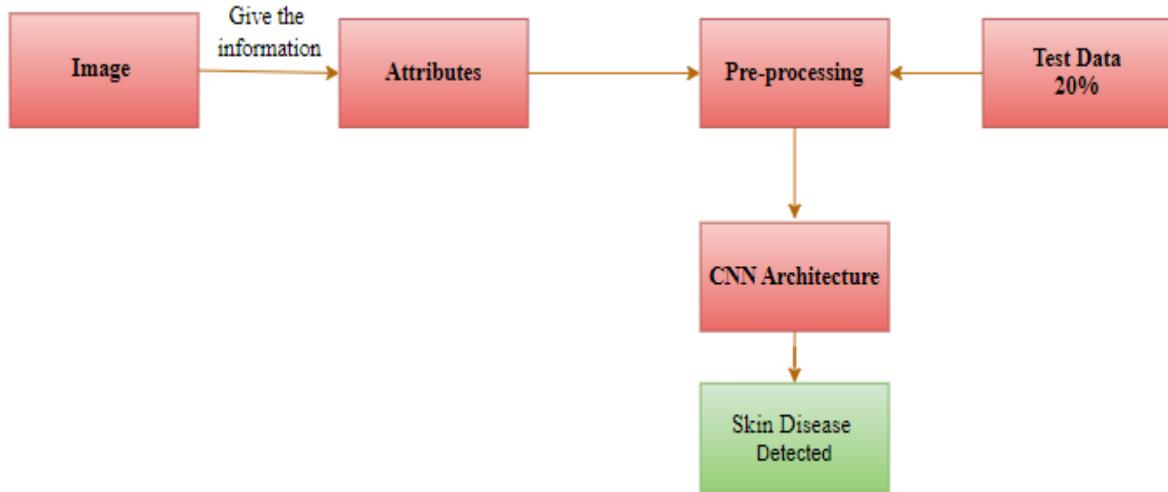


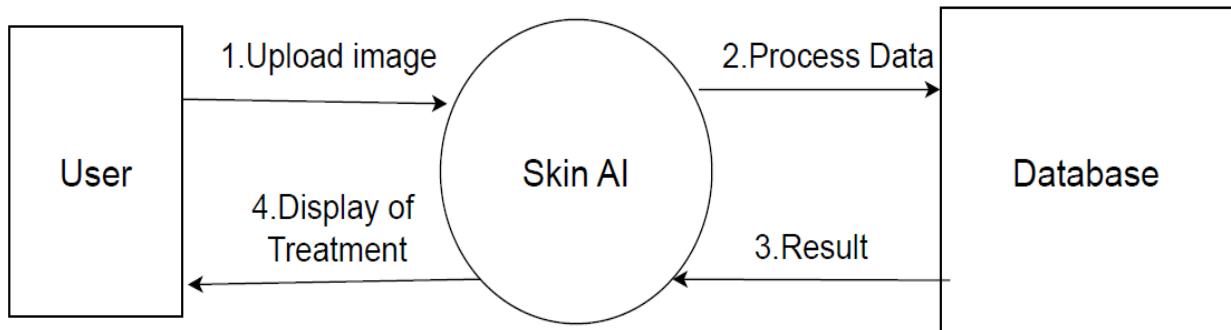
Fig 3.9.1 Collaboration Diagram

A collaboration diagram shows the objects and relationships involved in an interaction, and the sequence of messages exchanged among the objects during the interaction.

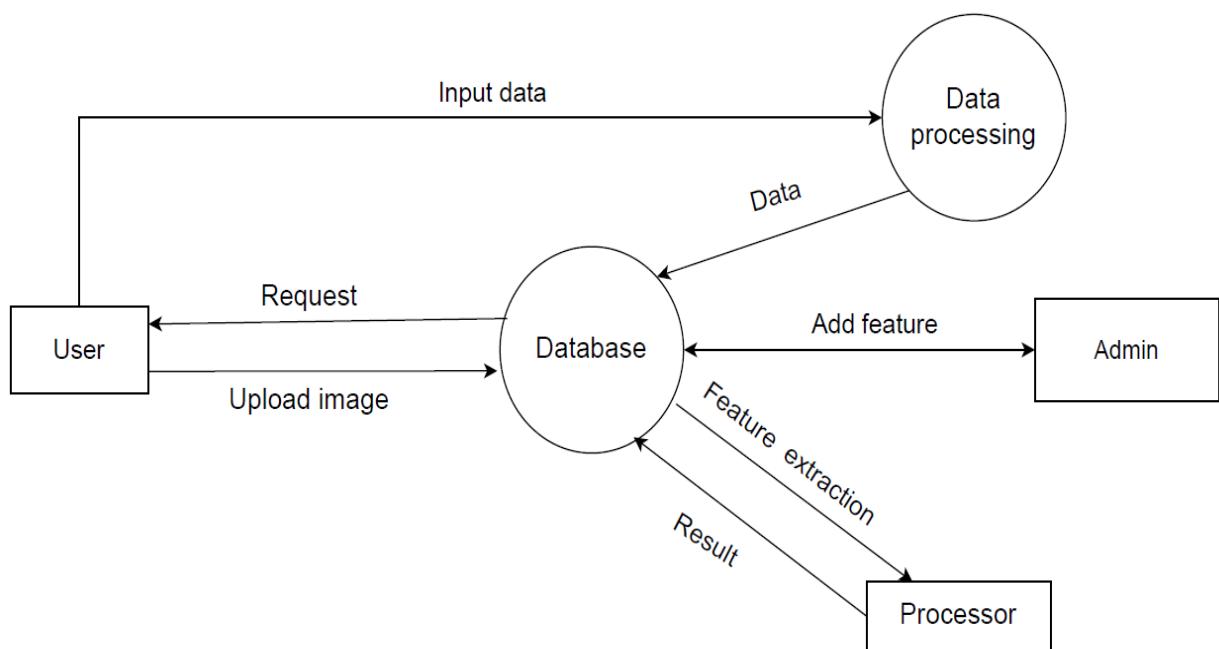
The collaboration diagram can be a decomposition of a class, class diagram, or part of a class diagram. It can be the decomposition of a use case, use case diagram, or part of a use case diagram.

The collaboration diagram shows messages being sent between classes and objects (instances). A diagram is created for each system operation that relates to the current development cycle (iteration).

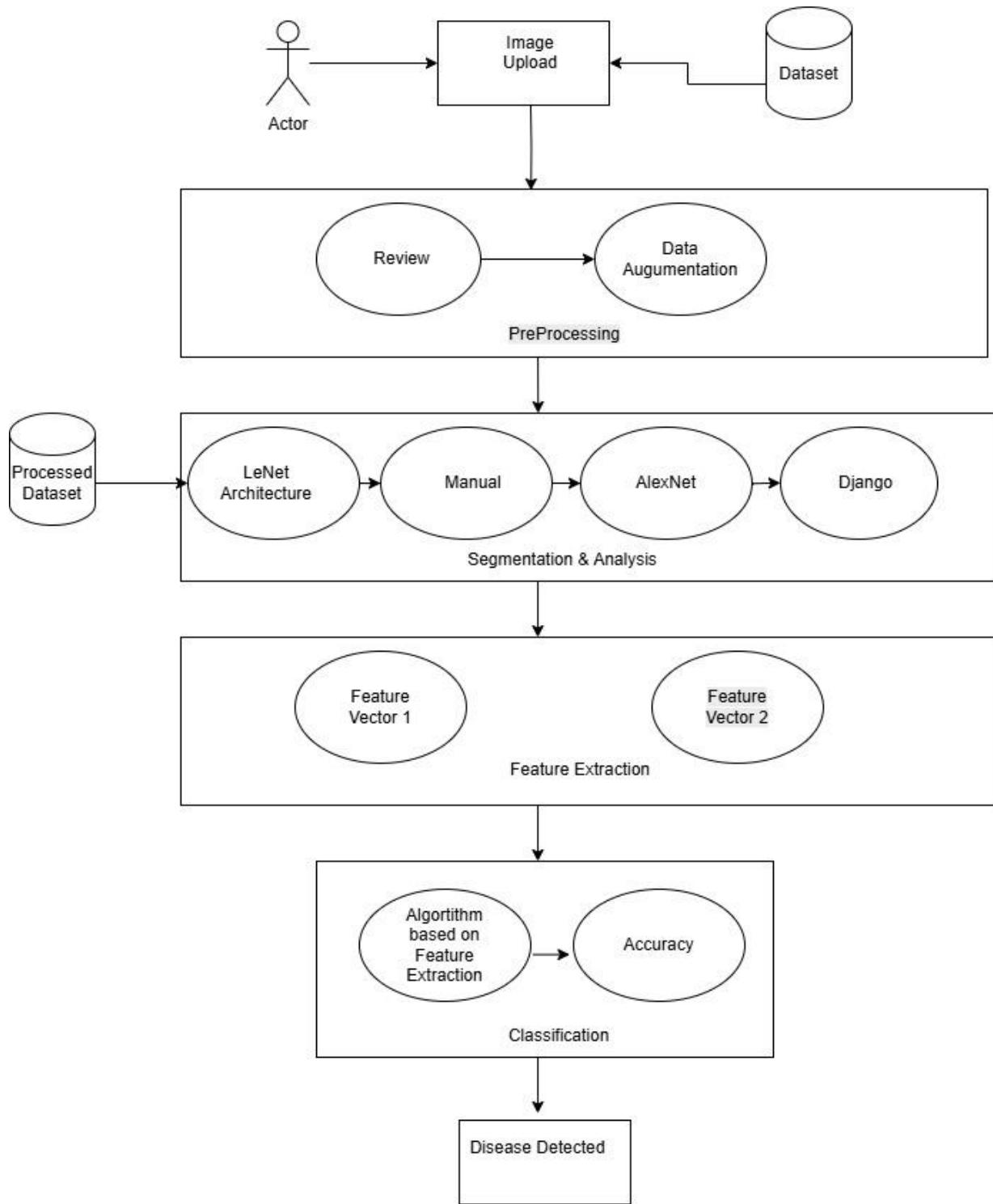
3.10 DATA FLOW DIAGRAM



DFD – Level 0



DFD – Level 1



DFD – Level 2

The DFD illustrates data flow across preprocessing, feature extraction, model classification, and prediction in skin disease classification.

CHAPTER 4

SYSTEM IMPLENETATION

CHAPTER 4

SYSTEM IMPLEMENTATION

4.1 LIST OF MODULES

This project includes certain modules listed as:

1. Data Analysis
2. Manual Architecture
3. LeNet Architecture
4. ALEXNET Architecture
5. Deployment

WORK FLOW

- 1. DATA GATHERING:** This initial step involves collecting dermoscopy images and relevant datasets that showcase skin lesions, such as HAM10000 and DermNet.
- 2. DATA PREPROCESSING:** Images undergo preprocessing techniques like resizing, normalization, and noise reduction. Spectral data may be enriched to improve classification performance.
- 3. CNN ALGORITHM:** A Convolutional Neural Network (CNN) is built, integrating spatial and spectral features for enhanced analysis of skin lesions.
- 4. TRAINING MODEL:** The CNN model is trained using preprocessed data to learn distinctive features and patterns of various skin diseases.
- 5. TESTING MODEL:** The trained model is evaluated on unseen test sets to ensure its reliability and accuracy in diagnosing skin conditions.
- 6. PREDICTION:** The final model is applied to new dermoscopy images for diagnosing skin lesions, aiming to differentiate between benign and malignant

conditions with high accuracy.

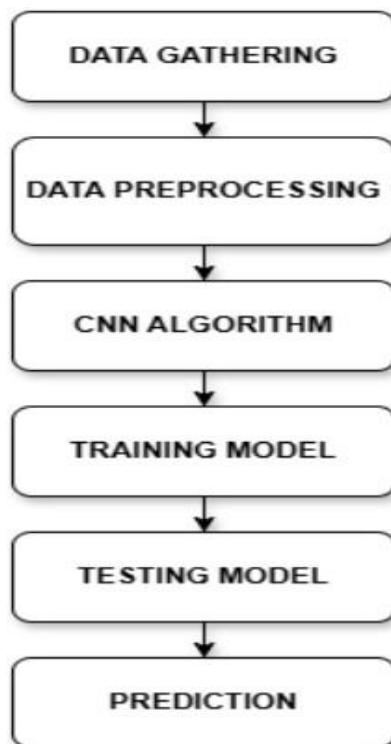


Fig 4.1.1 Work Flow Diagram

4.2 MODULE DESCRIPTION

IMPORT THE GIVEN IMAGE FROM DATASET:

We have to import our data set using keras preprocessing image data generator function also we create size, rescale, range, zoom range, horizontal flip. Then we import our image dataset from folder through the data generator function. Here we set train, test, and validation also we set target size, batch size and class-mode from this function we have to train using our own created network by adding layers of CNN.

TO TRAIN THE MODULE BY GIVEN

1. Data Analysis

Data analysis is the process of cleaning, changing, and processing raw data, and extracting actionable, relevant information that helps businesses make informed decisions. The procedure helps reduce the risks inherent in decision-making by providing useful insights. The data analysis process, or alternately, data analysis steps, involves gathering all the information, processing it, exploring the data, and using it to find patterns and other insights.

In data analysis we analyse the data that how the image data is available. We analyse how many data are available and we check whether the normal data is available corresponding to the mask data.

2.Manual Architecture

Skin Disease classification involves the categorization of skin lesions based on various visual and clinical features to aid in accurate diagnosis and treatment planning. In manual architecture, this process typically relies on the expertise of dermatologists who visually inspect and analyze skin lesions. Dermatologists employ their knowledge and experience to assess key characteristics such as asymmetry, border irregularity, color variation, diameter, and evolving changes in the lesion's appearance. The manual classification system often includes different types of skin cancer, such as melanoma, basal cell carcinoma, and squamous cell carcinoma, each exhibiting distinct visual cues. Dermatologists may also incorporate dermoscopy, a non-invasive technique using a handheld device with magnification and light, to enhance their examination. This meticulous manual examination, guided by established diagnostic criteria, plays a crucial role in early detection and effective management of skin cancer, highlighting the significance of human expertise in the classification process. However, the advent of computer-aided diagnostic tools and artificial intelligence has shown promise in augmenting these efforts by providing additional support through automated analysis of skin lesions.

3. Le-Net Architecture

LeNet, short for "LeNet-5," is a classic convolutional neural network (CNN) architecture developed by Yann LeCun in the early 1990s. While LeNet is renowned for its role in image classification tasks, it can be adapted for image segmentation applications like skin cancer detection. Here's a high-level overview of how LeNet can be modified for this purpose:

1. Input Image: The input to the network is a skin cancer image, typically in grayscale or color, depending on your dataset and requirements.
2. Preprocessing: Preprocess the input images as needed. Common preprocessing steps include resizing to a consistent input size, normalization, and data augmentation.
3. LeNet Architecture: LeNet consists of a series of convolutional and pooling layers followed by fully connected layers. For skin cancer detection, you will need to modify the architecture to produce pixel-wise masks instead of classification.
4. Convolutional Layers: Retain the convolutional layers from the original LeNet architecture. These layers are responsible for learning hierarchical features from the input image.
5. Pooling Layers: Keep the max-pooling layers from the original LeNet. Pooling helps reduce the spatial dimensions of feature maps.
6. Encoder-Decoder Modification: Modify the fully connected layers of the original LeNet into an encoder-decoder architecture for segmentation. Remove the final fully connected layers that were used for classification.
7. Decoder: Design a decoder portion that mirrors the encoder. It consists of transposed convolutional (also known as deconvolutional) layers that upsample the feature maps back to the original image size.
8. Activation Function: Apply an appropriate activation function, such as sigmoid (for binary segmentation) or softmax (for multi-class segmentation), to the output layer of the decoder to obtain pixel-wise masks.
9. Loss Function: Define a suitable loss function for segmentation tasks, such as binary cross-

- entropy or categorical cross-entropy, depending on the nature of your data.
10. Optimization Algorithm: Utilize an optimization algorithm, like stochastic gradient descent (SGD), Adam, or RMSprop, to train the network by minimizing the defined loss function.
 11. Training Data: Train the network using a labeled dataset of skin cancer images and their corresponding pixel-wise masks.
 12. Post-processing (Optional): Depending on the quality of the masks, you may apply post-processing techniques such as morphological operations (erosion, dilation) or connected component analysis to refine the s.
 13. Evaluation: Evaluate the performance using standard metrics like Intersection over Union (IoU), Dice coefficient, or pixel accuracy.

It's essential to note that while LeNet can serve as a starting point for tasks, modern architectures, such as U-Net or FCN (Fully Convolutional Network), are generally more suitable for due to their specialized design for pixel-wise predictions. These architectures often yield better results and are more commonly used in contemporary computer vision tasks, including medical image.

4. DEPLOY

Deploying the model in Django Framework and predicting output

In this module the trained deep learning model is converted into hierarchical data format file (.h5 file) which is then deployed in our django framework for providing better user interface and predicting the output.

Django

Django is a high-level Python web framework that enables rapid development of secure and maintainable websites. Built by experienced developers, Django takes care of much of the hassle of web development, so you can focus on writing your app without needing to reinvent the wheel. It is free and open source, has a thriving and active community, great documentation.

4.3 ALGORITHM DESCRIPTION

CONVOLUTIONAL NEURAL NETWORK

A Convolutional neural network (CNN) is one type of Artificial Neural Network. A Convolutional neural network (CNN) is a neural network that has one or more convolutional layers and are used mainly for image processing, classification, and also for other auto correlated data.

TYPES OF CNN:

- ALEXNET
- LENET

1. ALEXNET

AlexNet architecture consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. 2. Each convolutional layer consists of convolutional filters and a nonlinear activation function ReLU. 3. The pooling layers are used to perform max pooling. AlexNet contained eight layers; the first five were convolutional layers, some of them followed by max-pooling layers, and the last three were fully connected layers. It used the non-saturating ReLU activation function, which showed improved training performance over tanh and sigmoid.

ARCHITECTURE OF ALEXNET

Convolutional layers:

Convolutional layers are the layers where filters are applied to the original image, or to other feature maps in a deep CNN. This is where most of the user-specified parameters are in the network. The most important parameters are the number of kernels and the size of the kernels.

Pooling layers:

Pooling layers are similar to convolutional layers, but they perform a specific function such as max pooling, which takes the maximum value in a certain filter region, or average pooling, which takes the average value in a filter region. These are typically used to reduce the dimensionality of the network.

Dense or Fully connected layers:

Fully connected layers are placed before the classification output of a CNN and are used to flatten the results before classification. This is similar to the output layer of an MLP.

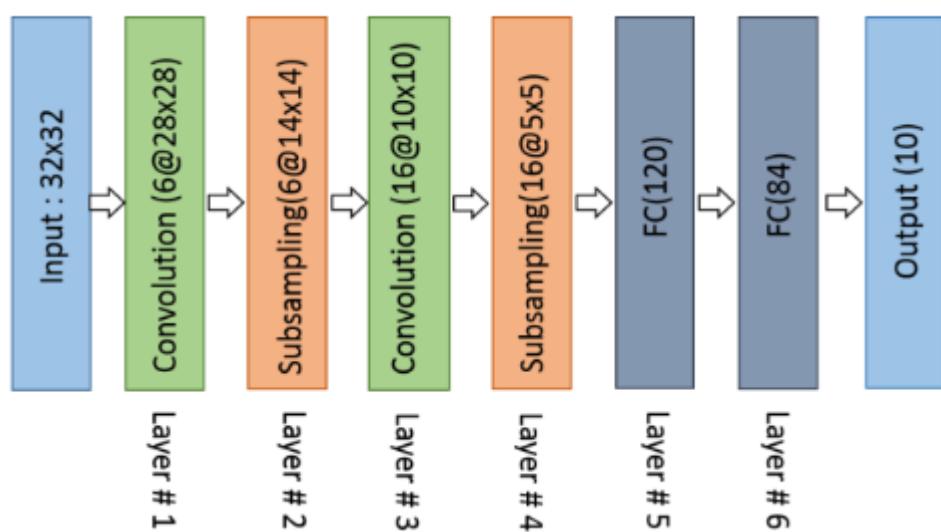


Fig 4.3.1 Architecture of AlexNet

2. LENET

As a representative of the early convolutional neural network, LeNet possesses the basic units of convolutional neural network, such as convolutional layer, pooling layer and full connection layer, laying a foundation for the future development of convolutional neural network. As shown in the figure (input image data with 32*32 pixels) LeNet-5 consists of seven layers. In addition to input, every other layer can train parameters. In the figure, Cx represents convolution layer, Sx represents sub-sampling layer, Fx represents complete connection layer, and x represents layer index.

ARCHITECTURE OF LENET

Convolutional layers

Convolutional layers are the layers where filters are applied to the original image, or to other feature maps in a deep CNN. This is where most of the user-specified parameters are in the network. The most important parameters are the number of kernels and the size of the kernels.

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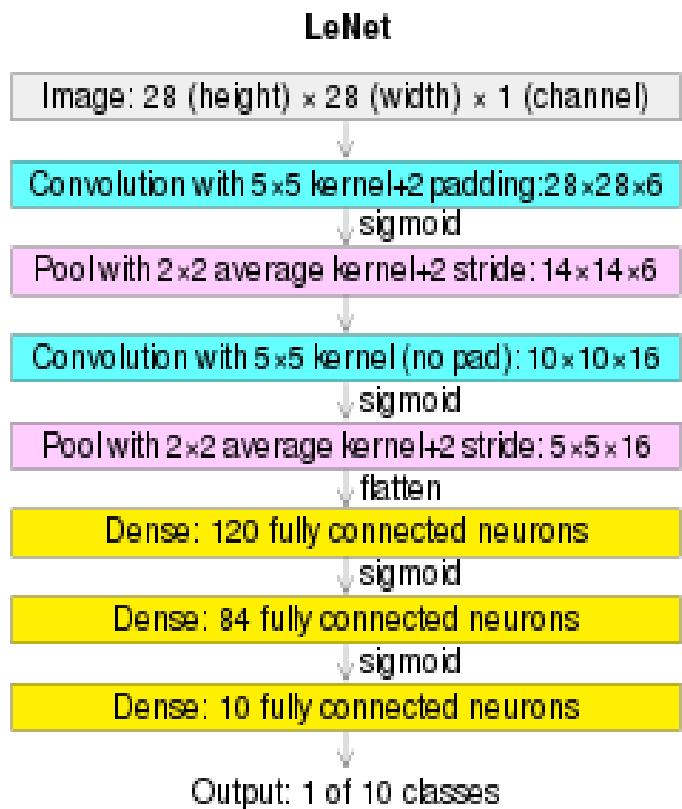


Fig 4.3.2 Architecture of LeNet

CHAPTER 5

RESULTS AND DISCUSSION

CHAPTER 5

RESULTS AND DISCUSSION

5.1 PERFORMANCE TESTING:

Testing is an essential phase in the software development lifecycle to ensure the Sports Shot Classification System performs accurately, meets defined requirements, and delivers consistent results under diverse scenarios. Below is a structured approach to testing the system.

TYPES OF TESTING

1. Unit Testing

a) Video Frame Processing:

Test video frame extraction to ensure the correct frame rate is maintained (e.g., 30 FPS).

Verify that frame resizing (e.g., 224×224 resolution) and normalization are performed correctly for model input.

b) Deep Learning Model Inference:

Test the system's ability to process frames through architectures like VGG, AlexNet, and LeNet, and return accurate predictions.

c) Feature Extraction:

Validate the spatial feature extraction capabilities of CNNs to ensure patterns like player movements and shot mechanics are captured effectively.

2. Integration Testing

a) Video Acquisition Integration:

Verify that the system correctly captures video streams for shot classification.

b) Model Integration:

Test the integration of CNN models (e.g., VGG, AlexNet) to ensure smooth

processing and classification of shot types like goals and assists.

c) User Interface Integration:

Ensure the user-friendly interface displays real-time classification results and allows interaction with system settings.

3. System Testing

a) End-to-End Functionality:

Test the full pipeline from video capture to classification and result display to ensure seamless functionality.

b) Error Handling:

Validate system behavior for edge cases, such as corrupted video frames or incorrect input formats.

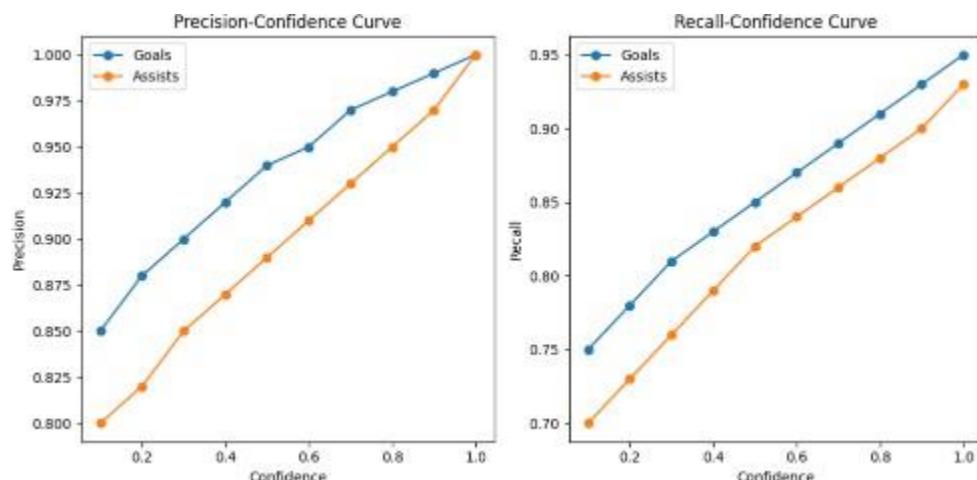


FIG.5.1.1 : P-GRAFH AND R-GRAFH

4. Performance Testing

a) Classification Speed:

Measure the inference time of the model to ensure real-time shot classification.

b) System Load Handling:

Verify that the system processes multiple video streams simultaneously without performance degradation.

5. Security Testing

a) Data Privacy:

Ensure that video data is securely transmitted and stored, meeting data protection standards.

b) Access Control:

Verify that only authorized users can access the system or modify settings.

6. Usability Testing

a) User Interface:

Test the usability of the graphical interface for broadcasters, analysts, and coaches.

b) User Feedback:

Gather feedback from users to improve system interaction and ease of use.

7. Edge Case Testing

a) Low Resolution:

Test the system's performance with low-quality video inputs or frames with poor lighting conditions.

b) Ambiguous Frames:

Evaluate model accuracy with edge cases like overlapping players or unclear shot

8. Regression Testing

a) Model Updates:

Perform tests after retraining or optimizing CNN architectures to ensure stable performance.

b) Interface Compatibility:

Verify the system's compatibility after UI or backend updates.

9. White Box Testing

a) Code Analysis:

Review the implementation of CNN architectures (e.g., VGG, AlexNet) for logical errors and optimization.

b) Model Efficiency:

Test individual layers of the deep learning models for performance consistency.

10. Black Box Testing

a) Shot Categorization:

Test the system's ability to classify sports shots into predefined categories without knowledge of the internal algorithms.

b) User Scenarios:

Simulate real-world scenarios, such as analyzing live video streams of a match.

5.2 TEST CASES AND REPORTS

Test Case ID	Test Case Description	Expected Results	Actual Results	Status
TC001	Image Upload	Image is uploaded successfully	Image uploaded successfully	Pass
TC002	Image Processing	Image is resized and normalized corrected	Image resized and normalized correctly	Pass
TC003	Feature Extraction	Features like texture and color extracted	Features extracted accurately	Pass
TC004	Model Training	Model trains without error	Model trained successfully	Pass
TC005	Model Testing	Model predicts skin condition with > 90% accuracy	Model achieved 91% accuracy	Pass
TC006	Result Display	Diagnosis confidence score displayed	Diagnosis and confidence score displayed	Pass

Table 5.2.1 Test Cases and Status of Testing

The above are some of the important test cases that are to be run to ensure smooth functioning of the system.

This structured testing approach ensures that the Skin Disease Classification System meets performance, security, and usability standards, guaranteeing robust and reliable functionality.

5.3 RESULTS AND DISCUSSION

The proposed one-dimensional (1-D) multiheaded convolutional neural network (CNN) is implemented in Python and run on a 3.20 GHz central processing unit with 256-gigabyte solid-state storage. Performance of the model is evaluated with different metrics including accuracy, F1 score, precision, specificity, sensitivity, and area under the curve (AUC). Two widely used datasets, HAM10000 and Dermnet, are employed for multiclass skin lesion classification.

Data augmentation and class balancing strategies are applied for improving model performance. Both of the datasets have 4,375 dermoscopy images that are divided into training, testing, and validation subsets. That is, 80% of the images are kept for training, 12% for testing, and 8% for validation. The model takes hand-crafted features from spatial, spectral, and cepstrum spaces as input. Performance of the proposed method is assessed using the mean and the standard deviation of the evaluation metrics as well as the 95% confidence interval for statistical reliability.

Parameters	Without data augmentation	With data augmentation
Acc (%)	86.28±0.36	89.71 ± 0.24
Sen (%)	86.06±0.32	89.24 ± 0.20
Pre (%)	85.94±0.20	89.00 ± 0.24
Spe (%)	89.42±0.40	92.68 ± 0.20
F1 Score	0.8600±0.04	0.8912 ± 0.02
AUC	0.9128±0.03	0.9340 0.03

Table 5.3.1 Analysis of the network on the test set for the HAM10000 dataset

Results

1. Dataset Utilization:

The datasets consist of 4,375 dermoscopy images for each database, categorized into training (80%), testing (12%), and validation (8%) sets.

Preprocessing techniques like resizing, normalization, and data augmentation (e.g., flipping, rotation) were applied to enhance the quality and diversity of the images.

2. Feature Integration:

The model combines spatial features (image domain) and spectral features (spectrogram and cepstrum) to enrich the representation of skin lesions.

Various combinations of spatial and spectral features were tested, such as:

- Image + Cepstrum
- Image + Spectrogram
- Image + Cepstrum + Spectrogram

3. Performance Metrics:

Metrics like Accuracy, F1 Score, Precision, Specificity, Sensitivity, and AUC were used to evaluate the model.

The proposed model achieved 88.57% accuracy on the DermNet database and 89.71% accuracy on the HAM10000 database

4. Statistical Analysis:

The results were validated using statistical tools, calculating the mean and standard deviation at a 95% confidence interval to ensure reliability.

Discussion

1. Model Efficiency:

The integration of spatial and spectral features significantly improved classification accuracy compared to models relying solely on spatial data.

The handcrafted features (cepstrum, spectrogram) provided richer information about lesion texture and structure, enhancing diagnostic precision.

2. Comparison with Existing Techniques:

The proposed model demonstrated superior performance in multiclass skin lesion classification, addressing limitations of traditional methods that lack spectral domain information.

3. Clinical Applicability: use, potentially assisting dermatologists in early detection and diagnosis of skin diseases.

4. Future Directions:

Expanding datasets and incorporating multimodal approaches (e.g., patient-reported symptoms) could further improve the model's robustness and applicability.

Precision Calculation

Precision indicates how many of the predicted positive samples are actually positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Where:

TP (True Positives): Correctly predicted positive samples.

FP (False Positives): Incorrectly predicted positive samples.

Recall Calculation (Sensitivity or True Positive Rate)

Recall measures how many of the actual positive samples were correctly identified.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score Calculation (Harmonic Mean of Precision and Recall)

The F1 Score balances precision and recall, providing a single measure of model performance.

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1 Score Calculation Verification:

$$\text{AlexNet: } \frac{2 \times 0.96 \times 0.95}{0.96 + 0.95} \approx 0.955 \Rightarrow 95.5\%$$

$$\text{LeNet: } \frac{2 \times 0.90 \times 0.89}{0.90 + 0.89} \approx 0.895 \Rightarrow 89.5\%$$

Accuracy Calculation

Accuracy measures how many of the total predictions were correct.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

AlexNet achieved the highest performance with a precision of 96%, recall of 95%, F1 Score of 95.5%, and remarkable accuracy of 99.70%,

LeNet performed reasonably well with 90% precision, 89% recall, and 96.47%

CHAPTER 6

CONCLUSION AND

FUTURE WORK

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

This study highlights how dermatologists benefit from automated skin lesion classification for decision-making. The authors proposed a novel method by combining image, spectrogram, and cepstrum domain features to create enhanced hand-crafted features. These features captured both spectral and spatial information, crucial for analyzing challenging dermoscopy images. A 1-D multiheaded CNN model was then applied to classify skin lesions using the concatenated features as input. The results demonstrated improved performance metrics, including Accuracy, Specificity, Precision, Sensitivity, AUC, and F1 scores, surpassing other state-of-the-art methods. Notably, the approach achieved 88.57% accuracy on the Dermnet dataset and 89.71% on HAM10000. Looking ahead, the methodology could be extended to analyze various biological signals and medical imaging datasets, advancing healthcare applications beyond skin lesions.

Advanced CNN models have shown significant promise in enhancing the accuracy of skin disease diagnosis. By utilizing sophisticated architectures like ResNet, Inception, and DenseNet, these models have achieved high precision in distinguishing between various skin conditions, including both benign and malignant lesions. The ability of these models to extract and interpret complex features from skin images has led to improved diagnostic performance compared to traditional methods.

6.2 FUTURE ENHANCEMENT

Enhance Data Diversity: Enhancing data diversity is essential for improving model accuracy and fairness, especially in medical diagnosis. Expanding datasets to include a wider range of skin tones, ages, and conditions ensures the model can generalize better across real-world scenarios. Addressing class imbalances prevents the model from favoring certain categories, reducing bias and improving reliability. Techniques like data augmentation and synthetic data generation help create a more balanced dataset, leading to fairer and more effective predictions. Ultimately, a diverse dataset enhances the model's robustness, making it more inclusive and adaptable to different populations.

Develop Interpretability Methods: Developing interpretability methods for Convolutional Neural Networks (CNNs) is essential for ensuring their reliable use in clinical settings. Since CNNs function as "black boxes," it is crucial to create techniques that provide insights into how decisions are made. Methods such as saliency maps, Grad-CAM, and feature visualization help highlight which parts of an image influence predictions, allowing clinicians to verify and validate results. This transparency builds trust, ensuring that medical professionals can confidently integrate AI models into their workflows. By improving interpretability, these models become more accountable, enhancing their adoption and effectiveness in real-world healthcare applications.

APPENDICES

APPENDICES

A1. SDG GOALS

The "Skin Deep Advanced Model for Accurate Skin Disease Diagnosis aligns with several United Nations Sustainable Development Goals (SDGs) by addressing health, innovation, and inclusivity. Here's how:

1. SDG 3: Good Health and Well-being

Impact: The project enhances early detection and diagnosis of skin diseases, including skin cancer, which is critical for improving patient outcomes. By leveraging AI, it reduces diagnostic errors and supports timely treatment, contributing to better healthcare delivery.

2. SDG 4: Quality Education

Impact: The project contributes to medical education by offering a tool for training healthcare professionals in dermatology. It aids in understanding diagnostic techniques and promotes learning through AI-driven insights.

3. SDG 9: Industry, Innovation, and Infrastructure

Impact: The project promotes technological innovation in healthcare by integrating advanced AI models like CNNs for skin disease diagnosis. It fosters the development of robust healthcare infrastructure and encourages research in AI-driven medical solutions.

4. SDG 10: Reduced Inequalities

Impact: By automating skin disease diagnosis, the model ensures equitable access to quality healthcare, especially in underserved regions where dermatologists may be scarce. It reduces disparities in healthcare delivery by providing consistent and reliable diagnostic support.

5. SDG 17: Partnerships for the Goals

Impact: The project encourages collaboration between healthcare providers, AI researchers, and policymakers. It supports partnerships aimed at improving healthcare systems and advancing AI applications in medicine.

A2. SOURCE CODE

MANUAL NETWORK

```
import os
import glob
import numpy as np
from tensorflow.keras.preprocessing.image
import ImageDataGenerator
from tensorflow.keras.models import Sequential
from PIL import Image
from tensorflow.keras.layers import Convolution2D
from tensorflow.keras.layers import MaxPooling2D
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Activation
from keras.callbacks import ModelCheckpoint
import matplotlib.pyplot as plt
dermatofibroma_disease
'DATASET/TRAIN/dermatofibroma_disease'
basal_cell_carcinoma 'DATASET/Train/basal_cell_carcinoma_disease'
melanoma = 'DATASET/Train/melanoma_cancer'
vascular_lesion_cancer = 'DATASET/Train/vascular_lesion_cancer'

def plot_images(item_dir, n=6):
    all_item_dir = os.listdir(item_dir)
```

```
item_files = [os.path.join(item_dir, file) for file in all_item_dir][:n]
```

```
plt.figure(figsize=(80, 40))
for idx, img_path in enumerate(item_files):
    plt.subplot(3, n, idx+1)
    img = plt.imread(img_path)
    plt.imshow(img, cmap='gray')
    plt.axis('off')
plt.tight_layout()
```

```
def image_details_print(data,path):
    print('===== Images in: ', path)
    for key,values in data.items():
        print(key,':\t', values)
```

```
def images_details(path):
    files=[f for f in glob.glob(path + "./", recursive=True)]
    data={}
    data['Images_count']=len(files)
    data['Min_width']=10**100
    data['Max_width']=0
    data['Min_height']=10**100
    data['Max_height']=0
```

```
for f in files:
    img=Image.open(f)
    width,height=img.size
    data['Min_width']=min(width,data['Min_width'])
    data['Max_width']=max(width, data['Max_width'])
```

```
data['Min_height']=min(height, data['Min_height'])
data['Max_height']=max(height, data['Max_height'])

image_details_print(data,path)
print("")  
print("TRAINING DATA FOR dermatofibroma_disease:")
print("")  
images_details(dermatofibroma_disease)
print("")  
plot_images(dermatofibroma_disease, 10)
print("")  
print("TRAINING DATA FOR basal_cell_carcinoma:")
print("")  
images_details(basal_cell_carcinoma)
print("")  
plot_images(basal_cell_carcinoma, 10)
print("")  
print("TRAINING DATA FOR melanoma:")
print("")  
images_details(melanoma)
print("")  
plot_images(melanoma, 10)
print("")  
print("TRAINING DATA FOR vascular_lesion_cancer:")
print("")  
images_details(vascular_lesion_cancer)
print("")  
plot_images(vascular_lesion_cancer, 10)
```

```

train_datagen=ImageDataGenerator(rescale=1./255,shear_range=0.2,zoom_range=0
.2,horizontal_flip=True)
training_set=train_datagen.flow_from_directory('DATASET/Train',target_size=(22
4,224),batch_size=32,class_mode='categorical')
test_datagen=ImageDataGenerator(rescale=1./255)
test_set=test_datagen.flow_from_directory('DATASET/Test',target_size=(224,224),
batch_size=32,class_mode='categorical')
Classifier=Sequential()
Classifier.add(Convolution2D(32,(3,3),input_shape=(224,224,3),activation='relu'))
Classifier.add(MaxPooling2D(pool_size=(2,2)))
Classifier.add(Flatten())
Classifier.add(Dense(38, activation='relu'))
Classifier.add(Dense(20, activation='softmax'))
Classifier.compile(optimizer='rmsprop',loss='categorical_crossentropy',metrics=['ac
curacy'])
model_path = "MANUAL.h5"

```

```

callbacks = [
    ModelCheckpoint(model_path,           monitor='accuracy',           verbose=1,
    save_best_only=True)
]
epochs = 10
batch_size = 512
import matplotlib.pyplot as plt

```

```

def graph():
    #Plot training & validation accuracy values
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])

```

```

plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()

graph()
import matplotlib.pyplot as plt
def graph():
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Test'], loc='upper left')
    plt.show()

graph()

```

ALEXNET:

```

import warnings
warnings.filterwarnings('ignore')
import tensorflow
import tensorflow as tf
print(tf._version_)

import keras
import keras.backend as K
from keras.models import Model
from keras.layers import Input, Dense, Conv2D, Conv3D, DepthwiseConv2D,
SeparableConv2D, Conv3DTranspose

```

```

from keras.layers import Flatten, MaxPool2D, AvgPool2D, GlobalAvgPool2D,
UpSampling2D, BatchNormalization

from keras.layers import Concatenate, Add, Dropout, ReLU, Lambda, Activation,
LeakyReLU, PReLU

from time import time
import numpy as np
from keras.callbacks import ModelCheckpoint
from tensorflow.keras.callbacks import EarlyStopping
import warnings
warnings.filterwarnings('ignore')
from tensorflow.keras.preprocessing.image
import ImageDataGenerator

train=ImageDataGenerator(rescale=1./255,shear_range=0.2,zoom_
range=0.2,horizontal_flip=True,validation_split = 0.2)
train_data=train.flow_from_directory(directory
'DATASET/TRAIN',target_size=(224,224),
batch_size=32,class_mode='categorical')

def alexnet(input_shape, n_classes):
    input = Input(input_shape)

    # actually batch normalization didn't exist back then
    # they used LRN (Local Response Normalization) for regularization
    x = Conv2D(96, 11, strides=4, padding='same', activation='relu')(input)
    x = BatchNormalization()(x)
    x = MaxPool2D(3, strides=2)(x)
    x = Conv2D(256, 5, padding='same', activation='relu')(x)
    x = BatchNormalization()(x)

```

```
x = MaxPool2D(3, strides=2)(x)
x = Conv2D(384, 3, strides=1, padding='same', activation='relu')(x)
x = Conv2D(384, 3, strides=1, padding='same', activation='relu')(x)
x = Conv2D(256, 3, strides=1, padding='same', activation='relu')(x)
x = BatchNormalization()(x)
x = MaxPool2D(3, strides=2)(x)
x = Flatten()(x)
x = Dense(4096, activation='relu')(x)
x = Dense(4096, activation='relu')(x)
output = Dense(n_classes, activation='softmax')(x)
model = Model(input, output)
```

```
model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accuracy'])
y', tensorflow.keras.metrics.Precision())])
```

```
return model
```

```
input_shape = 224, 224, 3
n_classes = 20
K.clear_session()
model = alexnet(input_shape, n_classes)
model.summary()

import matplotlib.pyplot as plt
import numpy as np
plt.figure(figsize=(20, 8))
plt.plot(history.history['accuracy'])
```

```
for i in range(epochs):
```

```
    if i%5 == 0:
```

```
plt.annotate(np.round(history.history['accuracy'][i]*100,2),xy=(i,history.history['accuracy'][i]))
```

```
plt.title('Model accuracy')
```

```
plt.ylabel('Accuracy')
```

```
plt.xlabel('Epoch')
```

```
plt.show()
```

LENET:

```
import warnings
```

```
warnings.filterwarnings('ignore')
```

```
import tensorflow
```

```
import tensorflow as tf
```

```
print(tf._version_)
```

```
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Conv2D
```

```
from tensorflow.keras.layers import Convolution2D
```

```
from tensorflow.keras.layers import MaxPool2D
```

```
from tensorflow.keras.layers import MaxPooling2D
```

```
from tensorflow.keras.layers import Flatten
```

```
from tensorflow.keras.layers import Dense
```

```
from tensorflow.keras.layers import Dropout
```

```
from tensorflow.keras.layers import Activation
```

```
MODEL=Sequential()
```

```
MODEL.add(Convolution2D(filters=32, kernel_size=(3,3), strides=(3,3),  
input_shape=(224,224,3), padding='valid', activation='relu'))
```

```
MODEL.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='valid'))
```

```
MODEL.add(Convolution2D(filters=128, kernel_size=(3,3), strides=(3,3),  
padding='valid', activation='relu'))
```

```

MODEL.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='valid'))
MODEL.add(Flatten())
MODEL.add(Dense(256, activation='relu'))
MODEL.add(Dense(20, activation='softmax'))

OPT = tensorflow.keras.optimizers.Adam(0.001)

MODEL.compile(optimizer=OPT, loss='categorical_crossentropy', metrics=["accuracy", tensorflow.keras.metrics.Precision(), tensorflow.keras.metrics.Recall()])

MODEL.summary()
model_path = "LENET.h5"

M=ModelCheckpoint(model_path,monitor='accuracy',verbose=1,
save_best_only=True, mode='max')
import matplotlib.pyplot as plt
import numpy as np
plt.figure(figsize=(20, 8))
plt.plot(WORKING.history['accuracy'])
for i in range(epochs):
    if i%5==0:
        plt.annotate(np.round(WORKING.history['accuracy'][i]*100,2),xy=(i,WORKING.history['accuracy'][i]))
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.show()

KERAS:
from keras.models import load_model
from PIL import Image, ImageOps

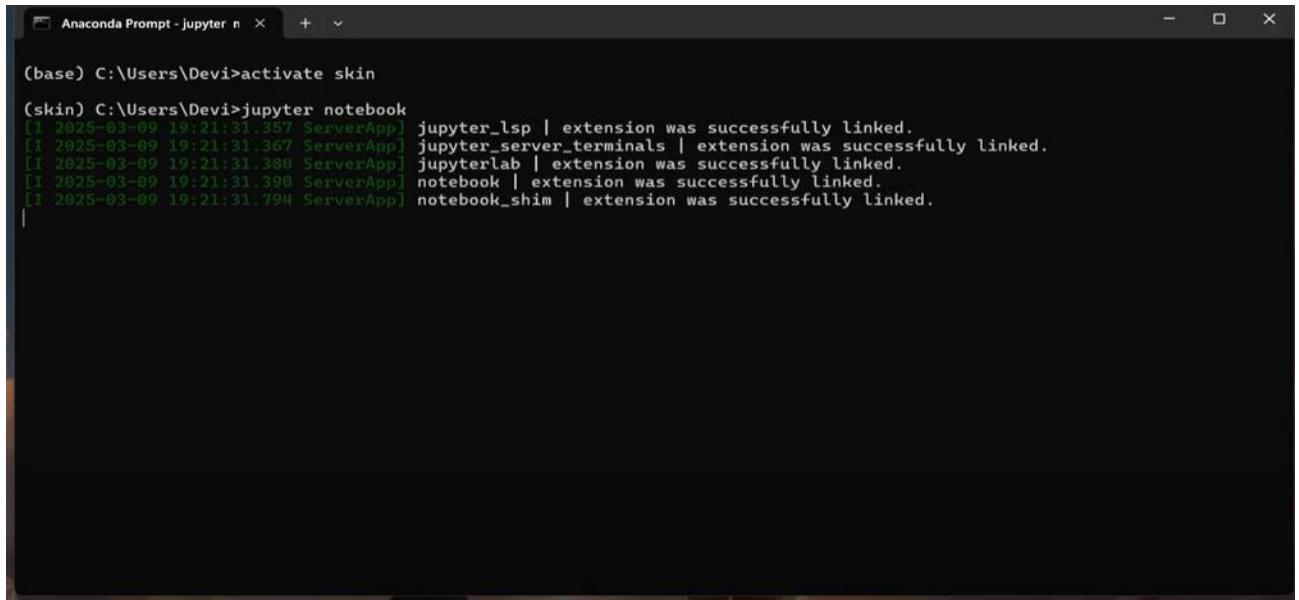
```

```

import matplotlib.pyplot as plt
import numpy as np
model = load_model("keras_model.h5")
data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
def check_images(item_dir):
    count = 0
    all_item_dir = os.listdir(item_dir)
    item_files = [os.path.join(item_dir, file) for file in all_item_dir]
    #print(item_files)
    image_name = list(item_files)
    for i in range(len(image_name)):
        print(i+1)
        image = Image.open(image_name[i]).convert("RGB")
        #print(image)
        image = ImageOps.fit(image, (224, 224), Image.ANTIALIAS)
        image_array = np.asarray(image)
        data[0] = normalized_image_array
        classes = ['FRACTURE', 'NOT_FRACTURE']
        prediction = model.predict(data)
        idd = np.argmax(prediction)
        if classes[idd] == 'FRACTURE':
            print(f"{image_name[i]} : FRACTURE")
            #count = count+1
        else:
            print(f"{image_name[i]} : none")
            os.remove(image_name[i])
    #else:
        #print(F"TOTAL : {i+1}\nCORRECT : {count}")
check_images('DATASET/TEST/FRACTURE')

```

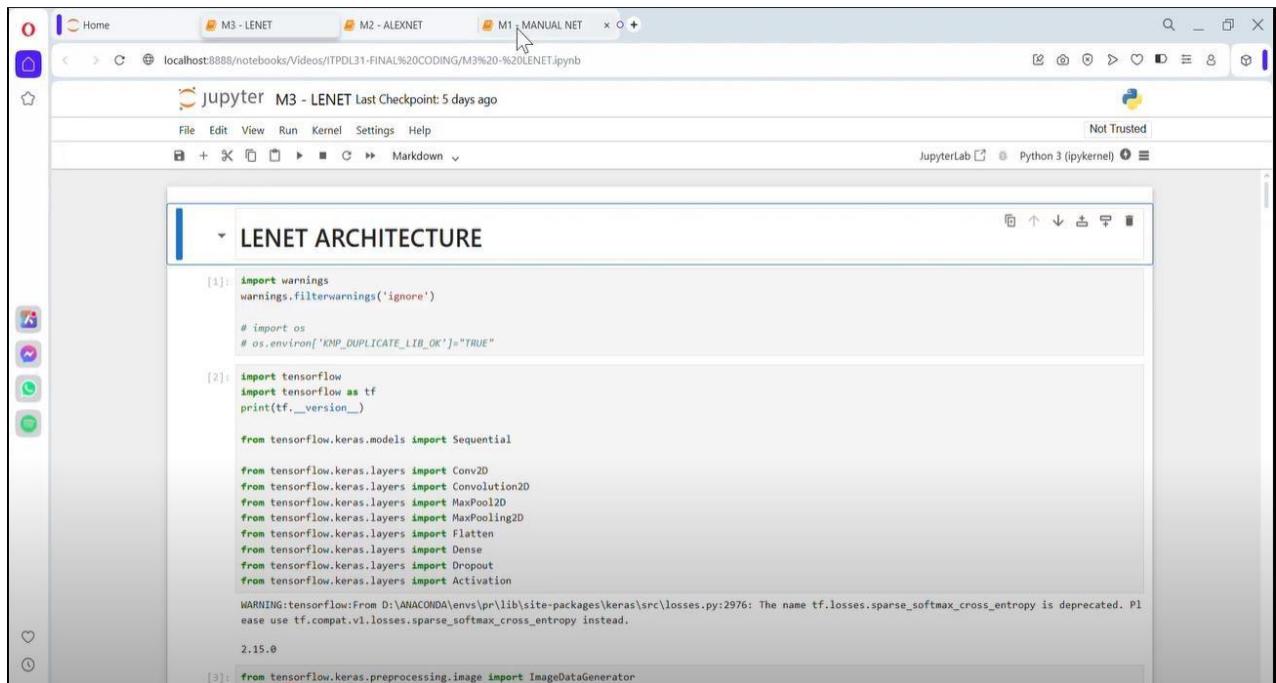
A3. SCREENSHOTS



```
Anaconda Prompt - jupyter n × + ▾

(base) C:\Users\Devi>activate skin
(skin) C:\Users\Devi>jupyter notebook
[I 2025-03-09 19:21:31.357 ServerApp] jupyter_lsp | extension was successfully linked.
[I 2025-03-09 19:21:31.367 ServerApp] jupyter_server_terminals | extension was successfully linked.
[I 2025-03-09 19:21:31.380 ServerApp] jupyterlab | extension was successfully linked.
[I 2025-03-09 19:21:31.390 ServerApp] notebook | extension was successfully linked.
[I 2025-03-09 19:21:31.794 ServerApp] notebook_shim | extension was successfully linked.
```

Fig A.3.1 Jupiter Notebook



The screenshot shows a Jupyter Notebook interface with three tabs at the top: 'M3 - LENET', 'M2 - ALEXNET', and 'M1 - MANUAL NET'. The current tab is 'M3 - LENET'. The notebook title is 'jupyter M3 - LENET Last Checkpoint: 5 days ago'. The code cell contains the following Python code:

```
[1]: import warnings
warnings.filterwarnings('ignore')

# import os
# os.environ['KMP_DUPLICATE_LIB_OK']= "TRUE"

[2]: import tensorflow
import tensorflow as tf
print(tf.__version__)

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import Convolution2D
from tensorflow.keras.layers import MaxPool2D
from tensorflow.keras.layers import MaxPooling2D
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Activation

WARNING:tensorflow:From D:\ANACONDA\envs\pr\lib\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.

2.15.0

[3]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

Fig A.3.2 Lenet Architecture

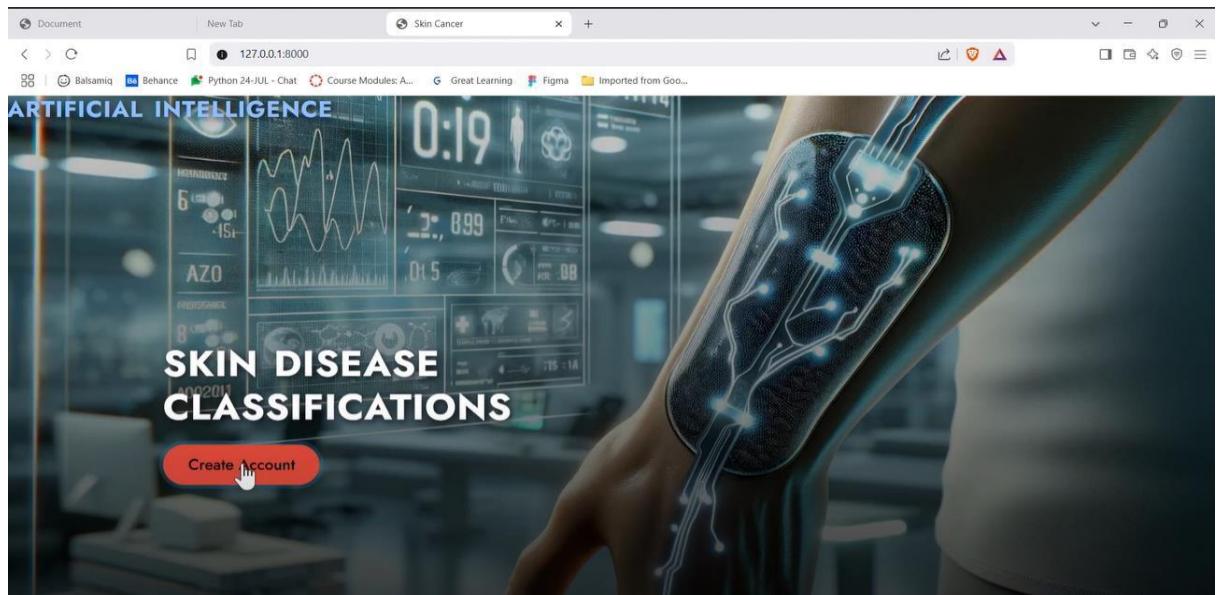


Fig A.3.3 Account Creation

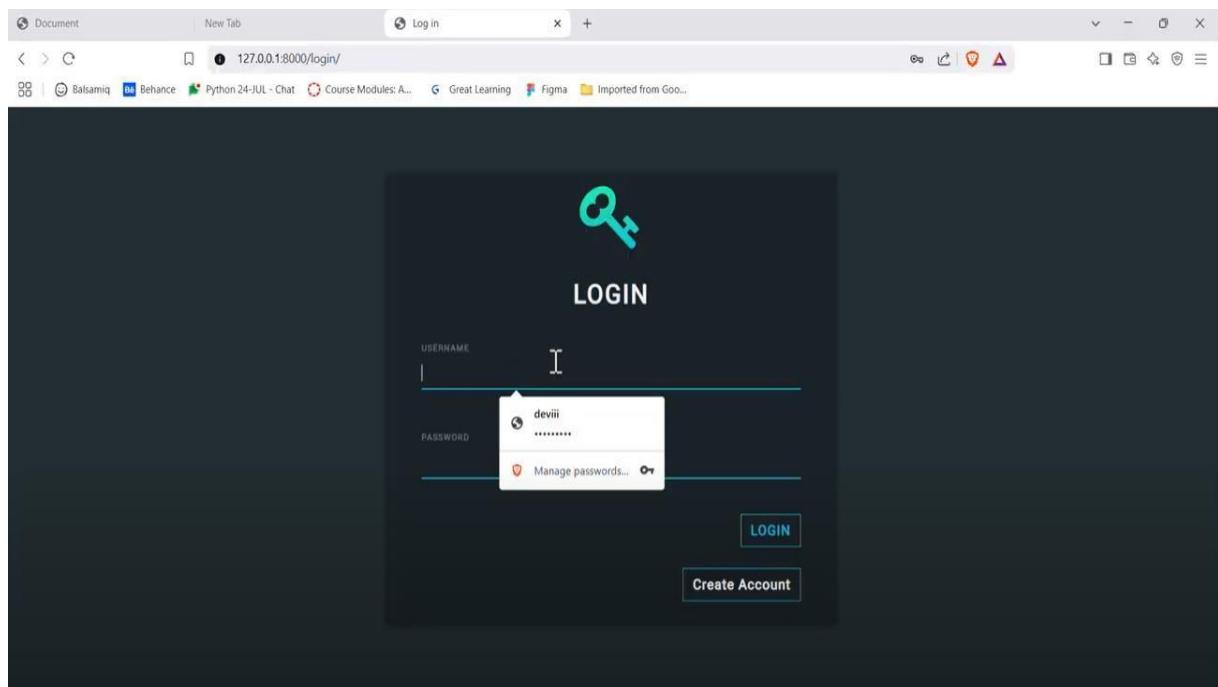


Fig A.3.4 Login Creation

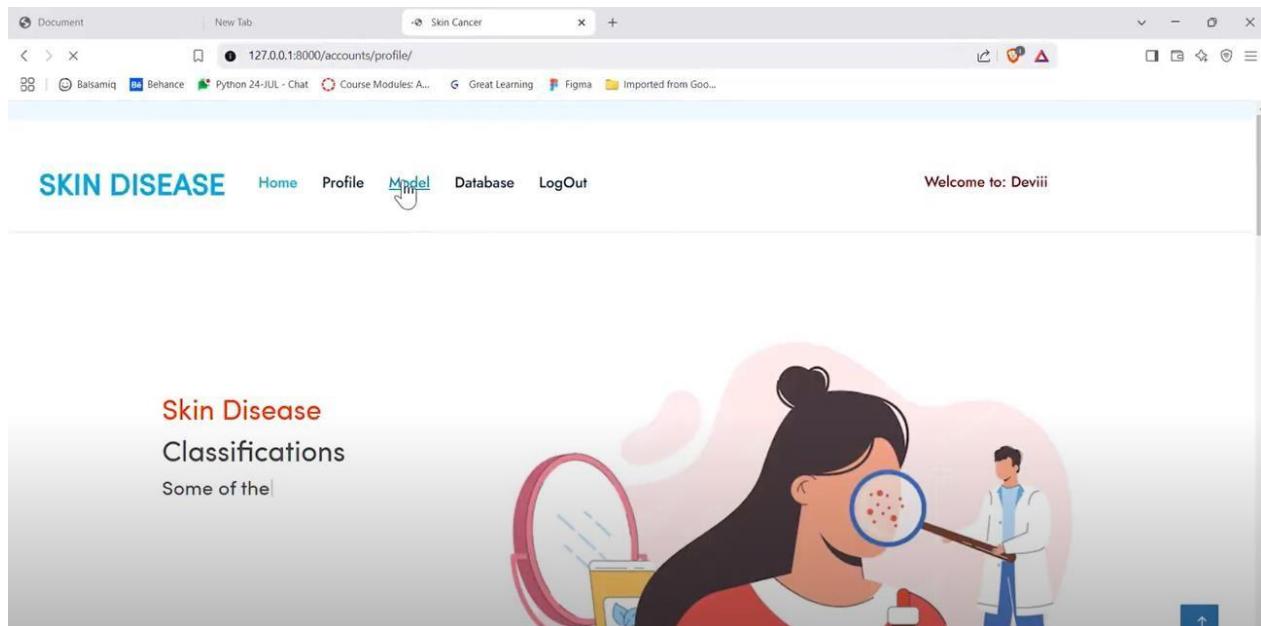


Fig A.3.5 Home Page

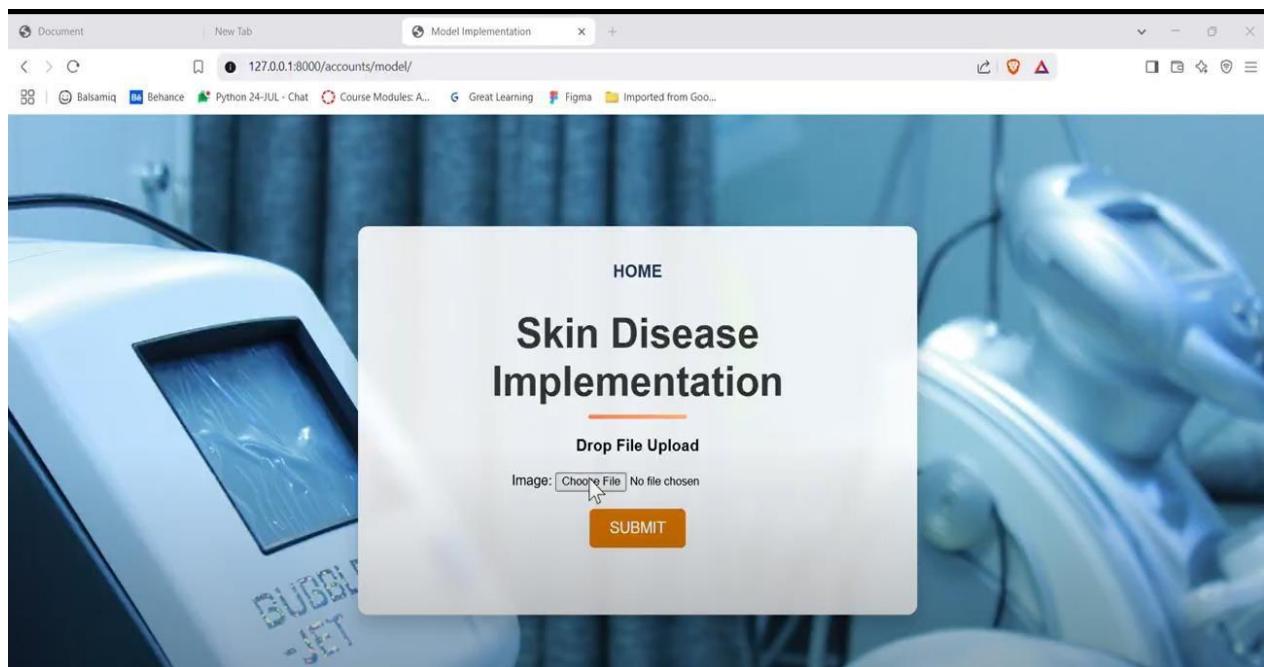


Fig A.3.6 Photo Uploading

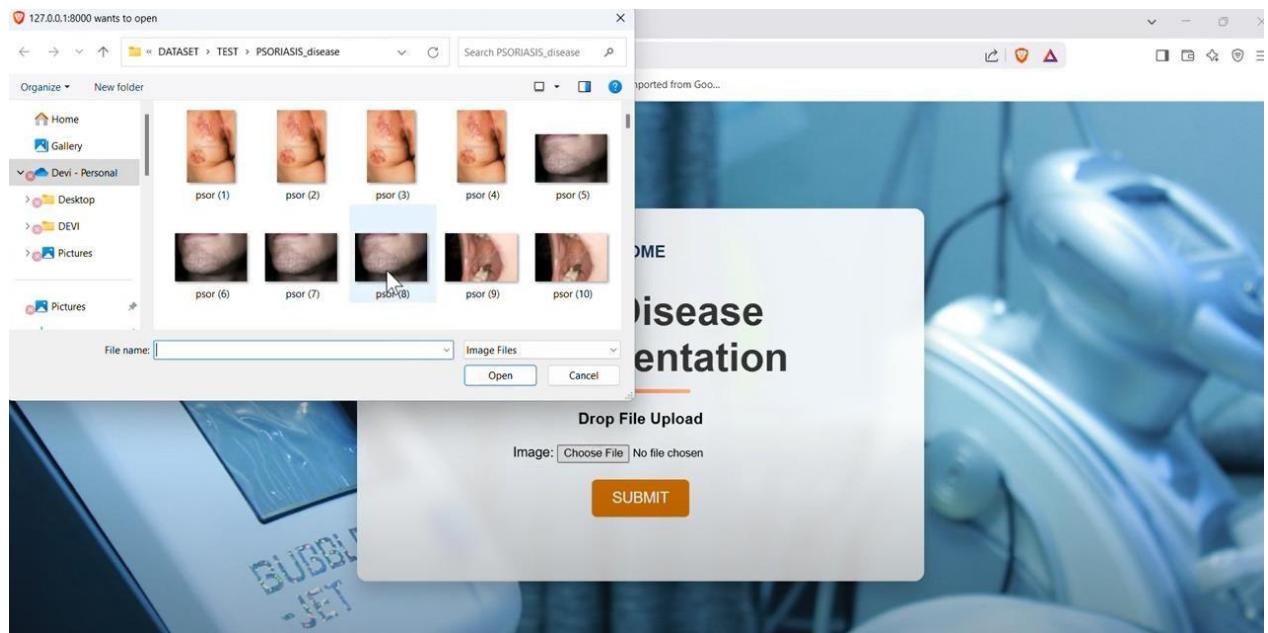


Fig A.3.7 Selection Of Photos

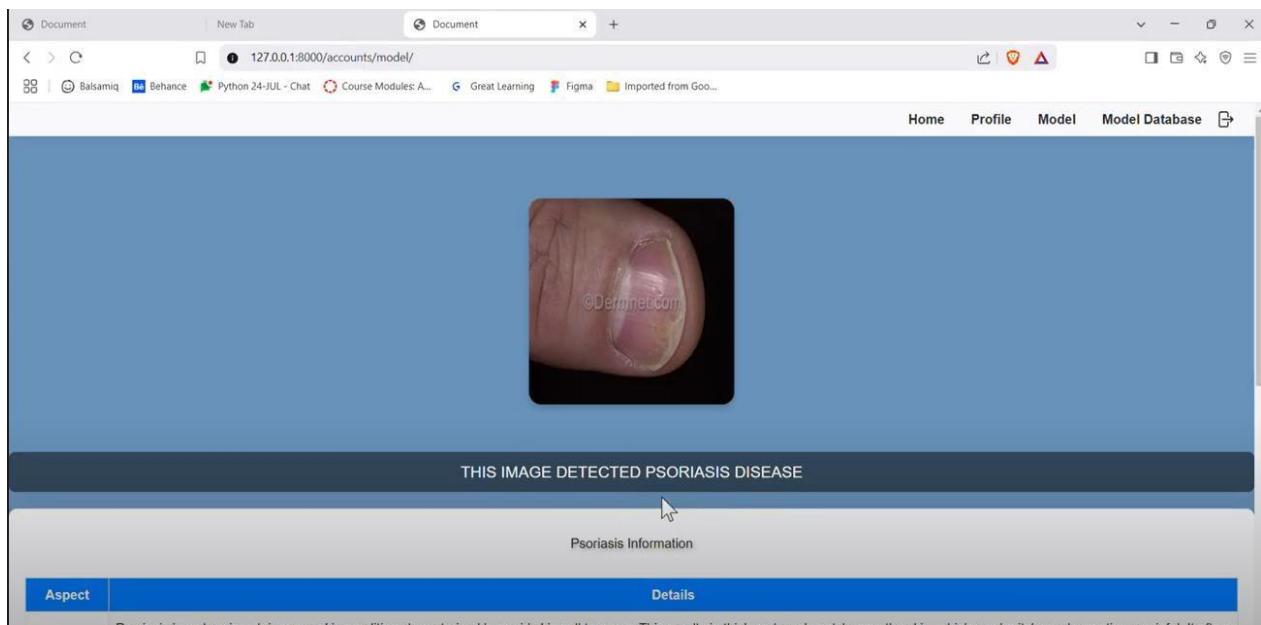


Fig A3.8 Disease Detection

The screenshot shows a web browser window with two tabs open. The active tab is titled 'Document' and has the URL '127.0.0.1:8000/accounts/model/'. The browser's address bar also displays this URL. The page content is a user interface for a medical or diagnostic application. At the top, there is a navigation bar with links for 'Home', 'Profile', 'Model', and 'Model Database'. Below this, a dark blue header bar contains the text 'THIS IMAGE DETECTED PSORIASIS DISEASE'. The main content area is titled 'Psoriasis Information' and features a table with three columns: 'Aspect', 'Description', and 'Details'. The 'Aspect' column contains categories like 'Description', 'Prevention', and 'Precautions'. The 'Description' row provides a general overview of psoriasis. The 'Prevention' row lists steps to reduce flare-ups, including maintaining a healthy weight, avoiding smoking, following a balanced diet, managing stress, and avoiding skin injuries. The 'Precautions' row lists ways to protect the skin from sun exposure and use moisturizers regularly. A cursor arrow is visible, pointing towards the 'Details' column of the table.

Aspect	Psoriasis Information	
Description	Psoriasis is a chronic autoimmune skin condition characterized by rapid skin cell turnover. This results in thick, red, scaly patches on the skin, which can be itchy and sometimes painful. It often affects areas such as the scalp, elbows, knees, and lower back.	
Prevention	While psoriasis cannot be entirely prevented, the following steps may help reduce flare-ups: <ul style="list-style-type: none">- Maintain a healthy weight- Avoid smoking and excessive alcohol consumption- Follow a balanced diet- Manage stress- Avoid skin injuries and infections	
Precautions	<ul style="list-style-type: none">- Use mild, non-irritating skin products- Avoid harsh soaps and skin care products- Protect your skin from excessive sun exposure- Use moisturizers regularly	

Fig A3.9 Disease Description

A4. PLAGIRISM REPORT



Page 1 of 10 - Cover Page

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skin paper.docx

Mizoram University

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6 Pages

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SKIN DEEP ADVANCED MODEL FOR ACCURATE SKIN DISEASE DIAGNOSIS

1

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Abstract—The mortality rate due to skin cancer is high, particularly in Western nations. Early detection of skin cancer cures the disease and prolongs human life. A common non-invasive technique for detecting skin cancer is a dermoscopy examination. Individual judgments by dermatologists determine the diagnosis, and the visual analysis of dermoscopy images requires additional inspection time. Current skin cancer classification algorithms rely solely on spatial information. However, they lack spectral domain data for lesion classification, leading to suboptimal model performance.

This paper introduces novel hand-crafted features derived from cepstrum, spectrogram, and image-domain techniques to enhance skin cancer classification accuracy. These hand-crafted features incorporate both spectral and spatial information. Additionally, a newly developed 1-D multiheaded convolutional neural network (CNN) is trained using these features to classify skin lesions using the challenging HAM10000 and Dermnet datasets. The performance of the proposed network is compared with other state-of-the-art approaches on the same datasets. According to experimental results, the proposed network achieved an accuracy of 88.57% on the Dermnet dataset and 89.71% on the HAM10000 dataset. Implementing this approach could improve the accuracy of clinical diagnosis.

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17
23
5

I. INTRODUCTION

10 Skin cancer is one of the most prevalent and fatal diseases in the world, with the highest mortality rate in the Western world. Early detection is crucial, with early treatment substantially improving the outcome and survival rate for the patient. Dermoscopy examination is one such common non-invasive technique for the diagnosis of skin cancer. Traditional diagnostic methods, however, rely heavily on the experience of the dermatologist, leading to

inconsistency in interpretation and increased inspection time. Automated skin cancer classification systems have therefore been suggested to assist in the diagnosis to counter such issues.

Existing classification models predominantly depend on spatial information extracted from dermoscopy images. However, these models' absence of spectral domain information often hampers the performance. Spectral information can provide rich information regarding the texture, frequency components, and structure of skin lesions, which can be utilized to enhance classification performance.

This paper proposes a new technique that integrates spectral and spatial information to improve skin cancer classification. We propose hand-designed cepstrum, spectrogram, and image-domain-based features to obtain an overall representation of skin lesions. We also develop a 1-D multiheaded convolutional neural network (CNN) that is trained on the enriched features to perform skin lesion classification. We experiment with the proposed model on two benchmark datasets, HAM10000 and Dermnet, and it performs better than state-of-the-art techniques. Our method achieves an accuracy rate of 88.57% on the Dermnet database and 89.71% on the HAM10000 database, which makes it promising for clinical use.

Using spectral-domain information and implementing an innovative CNN architecture, our method can improve the reliability and accuracy of automatic skin cancer detection. The proposed framework can be employed as an effective assistant for dermatologists, with the potential for increased speed and accuracy in diagnosis, thus improving patient outcome

[1] This work improves skin cancer classification by using handcrafted features that mix spatial and spectral data. A novel 1-D multiheaded CNN trained on the HAM10000 and Dermnet datasets surpasses previous models, with 89.71% and 88.57% accuracy, respectively. The strategy may enhance clinical diagnosis.

[2] Skin conditions affect millions of people globally and can result

- 5 in risks like skin cancer as well as psychological discomfort. Poor optical acuity in skin disease images makes diagnosis difficult in the absence of sophisticated equipment and medical specialists. In
- 6 order to classify skin diseases, this paper suggests a deep learning method utilizing CNN architecture and three pre-trained models: AlexNet, ResNet, and InceptionV3. Images of burns and cuts, which are frequently misclassified by current approaches, were utilized in conjunction with a dataset that included seven disorders,
- 12 such as melanoma, nevus, and seborrheic keratosis. By eliminating
- 24 the need for manual feature extraction and data reconstruction, deep learning increases classification efficiency.

15
9

[3] Dermatology is complicated and challenging to diagnose, particularly in developing nations where therapy is costly. According to the WHO, skin conditions are the most prevalent non-communicable illnesses in India. Smartphones that use machine learning and image processing provide a cost-effective method of disease diagnosis. To identify skin conditions, the suggested system uses an application that analyzes and processes the photos with the help of artificial intelligence. Image processing

- 11 used to process the photos, and machine learning is used to produce the outcome.

[4] To identify different skin conditions, including sexually transmitted infections, this study investigates image categorization using deep learning. A trained algorithm examines the afflicted skin patches in photographs uploaded by users to a portal.

- 13 Convolutional neural networks are used in the technique to identify diseases and extract features. All you need for a rapid and affordable diagnostic is a camera and a computer. The kind, severity, and spread of the disease are among the results.

[5] Using the multimodal LLM VisualGLM in conjunction with image classification models on the HAM10000 dataset, this thesis investigates the application of large language models (LLMs) for the diagnosis of skin diseases (93% validation accuracy). Conventional AI techniques lack interaction but rely on deep networks such as ResNet and VGG. Our chat-based technology interacts with users, offers clarifications, and adds more information to improve diagnosis. This study shows the potential of LLMs in medicine, integrating AI-based image interpretation with human-in-the-loop interaction to improve diagnosis accuracy.

III. PROPOSED SYSTEM

The methodology for Skin Disease Classification using Artificial Intelligence Techniques is structured to ensure a systematic approach in the development and implementation of an efficient and accurate diagnostic system. The primary objective is to utilize

state-of-the-art deep learning models to assist in the early and precise detection of skin diseases, thereby improving patient

outcomes. This methodology consists of several key stages, including data collection, preprocessing, model development, training, and evaluation.

A. Data Collection and Preprocessing

The dataset used for training the model consists of a diverse range of dermatological images representing various skin conditions. These images are gathered from publicly available sources and medical repositories. Preprocessing techniques such as image resizing, normalization, and augmentation are employed to enhance the quality of input data and improve model generalization.

B. Model Creation and Instruction

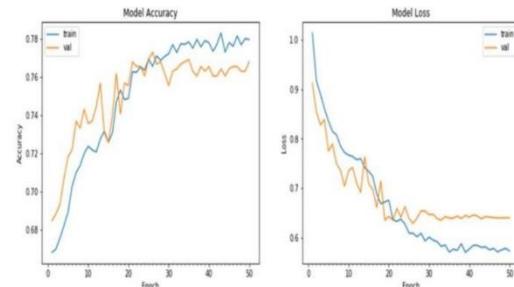
TensorFlow is used to implement a Convolutional Neural Network (CNN) for classification. The model architecture includes key layers such as Convolutional, max pooling, Flatten, Dropout, and Dense layers, which help in feature extraction and classification. The dataset is divided into training and testing sets, ensuring a balanced learning process. The training phase involves optimizing model parameters using an appropriate loss function and optimizer, such as categorical cross-entropy and Adam

C. Model Evaluation and Prediction

Once trained, the CNN model is evaluated using accuracy, precision, recall, and F1-score to measure its effectiveness. The trained model is then tested on unseen images to classify skin disease and non-skin disease conditions. The final classification results are analyzed, and potential improvements are identified for further refinement.

This methodology ensures a structured and efficient approach to developing an AI-driven diagnostic system for automated skin disease classification, aiding in telemedicine and dermatological applications.

Graph 1



Graph 1 represents the Data Loss and Accuracy Vs Epoch

IV. MACHINE LEARNING MODELS.

X.

AI and Deep Learning have transformed medical image analysis, providing automated and efficient diagnosis. The technologies are improving accuracy, decreasing workload, and enhancing patient care.

- 14 Data Science, an interdisciplinary science that brings programming, statistics, and domain expertise together, is crucial for AI innovation. AI mimics human intelligence, empowering machines to learn, reason, and forecast results. Deep Learning, a category of AI, employs neural networks to process enormous datasets with time-improving capabilities. CNNs, commonly applied to medical imaging, distinguish between malignant and benign skin lesions with high accuracy.
- 4 Artificial intelligence-based dermatology devices help physicians reduce errors and speed diagnosis. Future developments will address enhancing model interpretability, resolving ethical issues, and bringing AI into practice. Pivoting around overcoming such challenges as data privacy, algorithmic bias, and regulatory clearance will be key to safe AI adoption. By enhancing these technologies, AI can greatly improve skin cancer detection and therapy.

Table 1

Aspect	Merits	Demerits
Accuracy & Precision	CNNs trained on diverse datasets ensure accurate classification. TensorFlow optimizes model performance.	High computational power is needed for complex feature extraction. XI. XII. XIII.
Usability	The django-based interface allows easy image uploads, improving accessibility.	Requires specialized knowledge for model fine-tuning. XIV.
Processing Efficiency	Pre-processing techniques standardize images, improving input quality and reliability.	The model may struggle with unseen data, affecting generalization.
Continuous Learning	User feedback and updates enhance diagnostic accuracy over time.	Requires significant computational resources, making it impractical for low-power environments.

Table 1 Describes the Merits and Demerits

V. MODULE DESCRIPTION

The module begins with importing and preprocessing skin image datasets using Keras' image data generator. Techniques like resizing, rescaling, zooming, and flipping enhance image quality and standardization. To provide an organized method for CNN-based classification, the dataset is separated into training, testing, and validation sets. Verifying dataset balance, especially between normal and afflicted skin photos, requires data analysis. These structured inputs are then used to train the CNN model, increasing illness detection precision and accuracy.

Manual classification relies on dermatologists analyzing skin lesions based on asymmetry, border irregularity, and color variations. While dermoscopy aids in manual diagnosis, AI-driven models enhance accuracy and efficiency. The LeNet-5 CNN architecture is adapted for skin disease classification, involving convolutional, pooling, and encoder-decoder layers. Activation functions, loss functions, and optimization algorithms like Adam or SGD fine-tune the model's performance. The trained model is evaluated using metrics like IoU and Dice coefficient to ensure reliability.

Finally, the trained model is deployed using the Django framework, allowing users to upload images for real-time disease detection. Django provides a secure, efficient, and user-friendly web interface, enhancing accessibility for medical diagnosis.

VI. PREPROCESSING OF THE DATASET

1) HAM10000 Dataset: The dataset [46] contains 10500 images altogether, each with a size of 224 by 224 pixels, and is divided into seven classes. Melanoma (nv), melanocytic nevi (mel), dermatofibroma (df), benign keratosis (bkl), basal cell carcinoma (bcc), actinic keratoses (akiec), and vascular (vasc) are the seven classes. Out of the total count of photos, there are 6705 of class nv, 327 of class akiec class, 514 in the bcc class, 1099 in the bkl class, 1113 in the mel class, 142 in the vase class, and 115 in the df class. There are numerous different types of photographs in the dataset, including dermoscopic and clinical images. Samples for each dataset class are presented in Fig. 1.2) Approximately 19,500 images of a large variety of pixel sizes comprise this dataset. This paper selects seven of the 23 classes because they are very variable and contain varying resolutions. Eczema images (ep), nail fungus (nf), basal cell carcinoma (akbcc), actinic keratoses, vascular tumors (vt), melanoma skin cancer (msc), seborrheic keratoses (sk), and urticaria hives (uh) are the seven categories that have been defined. There are 1235 photos in the ep class, 1040 in the nf class, and 1149 in the akbcc class.

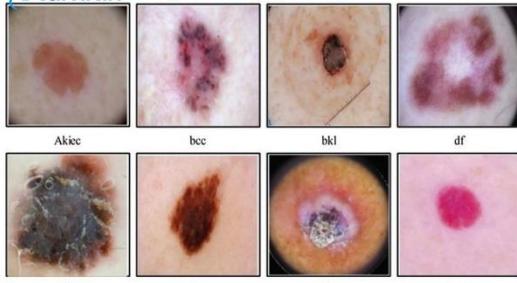


Fig. 1 illustrates the HAM10000 dataset's class-wise skin lesions.



Fig. 2: Images of the DermNet dataset's class-wise skin lesions

There are 482 images in the vt class, 463 in the msc class, 1371 in the sk class, and 212 in the uh class. All of the images are JPEG and have three RGB channels. However, these images are not of particularly good quality overall. All images are resized to 128 × 128 pixels to maintain consistency in image sizes. Each class's samples are illustrated in Fig. 2.

B.CEPSTRUM:

A chain of processes is utilized to achieve a signal's cepstrum. Initially, a Fourier transform is used to transform a provided signal into a frequency domain. The resultant term must then be subjected to a logarithmic operation. The result is then passed through an inverse Fourier transform. After an inverse Fourier transform, the ultimate signal that is produced is in the cepstrum domain. Any signal $f(x, y)$ has the cepstrum $c(x, y)$ as follows [12]:

$$\text{DFT}^{-1}\{\log|\text{DFT}\{f(x, y)\}|\} = C(x, y)2 \quad (1)$$

where the magnitude operation is denoted by $||$. Concatenating the columns of $C(x, y)$ to create a single column that transforms the 2-D form of $C(x, y)$ into 1-D. $C(n)$, which is one of the components of the proposed new mixed domain hand-crafted features. A picture's cepstrum gives more specific information regarding that image. This compressed data may be trustworthy for classifying the different types of skin lesions.

C.SPECTROGRAM:

In the analysis of 1-D signals, such as speech and biological signals, spectrograms are commonly employed. However,

now employed in a relatively limited variety of computer vision applications[13]. A spectrogram is a visual and qualitative representation of the frequency range of a signal as it changes with time. An image undergoes a 2-D STFT to obtain its spectrogram. The absolute values of the STFT coefficients are squared. The STFT may be utilized to compute the spectrogram of any signal f (n_1, n_2). Any signal f (n_1, n_2) possesses the following spectrogram $S(n_1, n_2, w)$ [18]: where m and w are discrete and quantized due to the fast Fourier transform technique being utilized to generate DFT, and $w(n_1, n_2)$ is a window function. With the combination of the two planes through maximum magnitude selection, $S(n, w)$, a 2-D shape, is formed from $S(n_1, n_2, w)$, a 3-D object. Concatenating the columns of $S(n, w)$ into a vector $S(n)$ gives the 1-D version of the same.

VII. FEATURE EXTRACTION

1-D multiheaded CNN was utilized employing Python on 3.20 GHz CPU having 256 GB SSD to discriminate multiclass skin lesions based on the HAM10000 and DermNet databases. 4,375 images per database were utilized, splitting them into 80% training, 12% testing, and 8% validation. Data augmentation mechanisms like rotation, zoom, cropping, and flip were utilized for balancing training examples and enhancing generalization.

The model learns spatial (image), spectrogram, and cepstrum features, and the best performance is obtained with the concatenation of all three types of features. In comparison, spatial features alone gave the worst performance. The model was trained with the Adam optimizer for 30 epochs, batch size 32, and dropout rate 0.25 to avoid overfitting. Performance was measured in terms of accuracy (Acc), F1-score, precision (Pre), specificity (Spe), sensitivity (Sen), and AUC.

Evaluation yielded that data augmentation enhanced classification performance by 3-4% and AUC by 2-3%. The mean absolute error (MAE) in DermNet and HAM10000 was 0.1257 and 0.1142, respectively, indicating a high level of classification performance. Model training time was 1.42 hours, with an average prediction time of 1.29 seconds.

A confusion matrix evaluation identified that the model effectively classified akiec, bkl, df, and mel lesions, while NV lesions presented the highest misclassification rate. Feature concatenation strongly minimized false negatives and false positives, enhancing diagnostic accuracy.

Comparative assessments in Table 1 shows that the integration of spatial, spectrogram, and cepstrum features immensely surpassed the utilization of spatial features only. The robustness of the model was validated through low standard deviations in performance metrics, indicating stability.

In summary, the suggested 1-D multiheaded CNN successfully distinguishes between skin lesions, where feature concatenation enhances diagnostic quality and stability. The efficiency of the model, supplemented by data augmentation and fine-tuned feature extraction, is a good sign for its implementation as an automatic skin cancer diagnosis tool. In future research, further enhancing generalization and diminishing misclassification, especially for the difficult lesion class NV, would be worthwhile.

Parameters	Without data augmentation	With data augmentation
Acc (%)	86.28±0.36	89.71 ± 0.24
Sen (%)	86.06±0.32	89.24 ± 0.20
Pre (%)	85.94±0.20	89.00 ± 0.24
Spe (%)	89.42±0.40	92.68 ± 0.20
F1 Score	0.8600±0.04	0.8912 ± 0.02
AUC	0.9128±0.03	0.9340 0.03

Table 2 Analysis of the network on the test set for the HAM10000 dataset

VIII. RESULTS AND DISCUSSION

The suggested network is executed on the Python platform on the computer with the CPU at 3.20 GHz, 256 GB SSD. Accuracy (Acc), F1 score, precision (Pre), specificity (Spe), sensitivity

⑧ Sen, and the area under the curve (AUC) score are the performance metrics used to contrast the performance of the suggested 1-D multiheaded CNN. The performance parameters are calculated mathematically in the following way.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

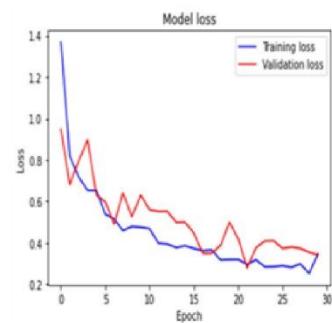
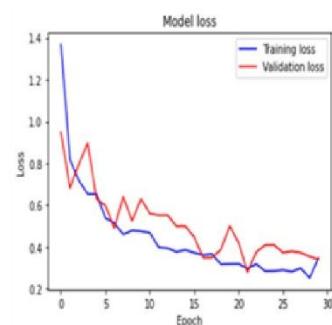
HAM10000 and Dermnet databases are used to classify multiclass skin lesions in the following way. Data augmentation is first used to augment the small sample of photographs for every class. Second, the training sample photos for every class in the datasets are balanced. 4375 dermoscopy images for every dataset are used for experimental investigation. Eight percent of all the

③ ④ images are used for the training set, twelve percent for the test set, and eight percent for the validation set. Second, the utilization of the spatial-, frequency-, and cepstrum-domain features is used to produce new hand-crafted features. Spatial (image), spectral (spectrogram and cepstrum), and concatenation of different groups of the spatial and spectral features (image and cepstrum, image and spectrogram, and image, cepstrum, and spectrogram) have been used as the inputs to the proposed network with both ⑤ ⑥ datasets to test the performance of the network. Based on the mean and standard deviation at the 95% confidence interval, the performance of the proposed network is evaluated [16]. The proposed methods section deals with the details of the generation of the handcrafted elements

⑦

⑧

GRAPH 2



Graph 2 Data loss of each model vs Epoch

IX. CONCLUSION

Dermatologists can discover that the automated classification of skin lesions assists them in making decisions. In this work, the authors have classified skin lesions into various classes using the HAM10000 and Dermnet datasets. This is done by concatenating image, spectrogram, and cepstrum domain features to develop new hand-crafted features. The spatial and spectral data present in the final concatenated features can be used to extract detailed information from the challenging dermoscopy image files. The suggested 1-D multiheaded CNN is then utilized to classify skin lesions by taking concatenated features as the input. Compared with other state-of-the-art methods on the same dataset, experimental results indicate that the proposed methods have better Acc, Spe, Pre, Sen, AUC, and F1 scores. The accuracy of the proposed method was 88.57% on the Dermnet dataset and 89.71% on the HAM10000 dataset. In the future, different biological signals (ECG, EMG, PCG, EEG, etc.) and images (CT, X-ray, MRI, etc.) will be employed to confirm the efficiency of the proposed methodologies for further challenging datasets related to skin lesions and other healthcare-related problems.

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A5. PAPER PUBLICATION



Letter of Acceptance

Dear Author

This is to inform you that your presentation proposal titled "[Early Detection of Parkinson's Disease through Vocal Features](#)" submitted to the **International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI – 2025)**, which will be held on **January 20-22, 2025** at Surya Engineering College, Erode, Tamil Nadu, India, has been accepted as a result of blind reviews.

International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI – 2025) aims to provide an interdisciplinary platform for researchers from both academia and industries and lends itself to the integration of recent research works in the field of development and deployment of Multi-Agent Systems and promote agent-oriented approach and tools to solve the potential challenges in collaborative applications.

On behalf of the organization committee, I would like to congratulate you.

Author Details:	Anandha Ponni P, Avaniya Seireena, Shiny R M
Paper ID:	ICMSCI-967
Affiliation:	St.Joseph's College of Engineering, India.

Please feel free to contact us if you have any questions or require further information regarding the conference.

Congratulations once again, and we anticipate an engaging and productive conference.

With Best Regards,

Conference - ICMSCI 2025.

Yours' Sincerely,



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